

DOCTORAL THESIS

Integrated Sensing and User
Localization in Reconfigurable
Intelligent Surfaces-Assisted
Dynamic Rich-Scattering
Environments

Anum Umer

TALLINN UNIVERSITY OF TECHNOLOGY
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Integrated Sensing and User Localization in Reconfigurable Intelligent Surfaces- Assisted Dynamic Rich-Scattering Environments

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Declaration:

Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

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TALLINNA TEHNIKAÜLIKOOL
DOKTORITÖÖ
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**Lõimitud tuvastamine ja lokaliseerimine
peegeldusterikkas keskkonnas
ümberkonfigureeritavate tarkade
pindade abil**

ANUM UMER



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List of Publications

The present Ph.D. thesis is based on the following publications that are referred to in the text by Roman numbers.

Publications

- I A. Umer, I. Mürsepp, M. M. Alam, and H. Wymeersch, "Reconfigurable Intelligent Surfaces in 6g Radio Localization: A Survey of Recent Developments, Opportunities, and Challenges," *IEEE Communications Surveys & Tutorials*, vol. 27, no. 6, pp. 3526–3560, 2025
- II A. Umer, I. Mürsepp, and M. M. Alam, "Reconfigurable Intelligent Surfaces in Dynamic Rich Scattering Environments: BiLSTM-Based Optimization for Accurate User Localization," in *2024 3rd International Conference on 6g Networking (6gNet)*, pp. 122–126, 2024
- III A. Umer, I. Mürsepp, and M. M. Alam, "Adaptive RIS Configuration Design With Environmental Sensing for User Localization in Dynamic Rich Scattering Environment," *IEEE Transactions on Mobile Computing*, vol. 25, no. 7, pp. 9770–9783, 2026

Under Review

- IV A. Umer, I. Mürsepp, and M. M. Alam, "Integrated Sensing, User Location and Orientation Estimation in RIS-Assisted Dynamic Rich Scattering Environment," *IEEE Transactions on Wireless Communications (Under review)*, 2026

Author's Contributions to the Publications

- I **Publication I:** In this paper, I was the first author. I provided a comprehensive survey of reconfigurable intelligent surfaces (RIS) for sixth generation (6G) radio localization, reviewing their capabilities, deployment scenarios, and recent advancements in RIS-assisted localization techniques. I presented a taxonomy of RIS based localization approaches and I discussed key challenges, limitations, and future research directions for integrating RIS into 6G networks. I identified the research questions for systematic literature review, I defined the search string and identified the appropriate databases to find the most relevant literature, I filtered it on the basis of predefined inclusion and exclusion criteria, I prepared the figures and tables, and I wrote the manuscript with supervisors' guidance, and I revised it based on reviewers' comments.
- II **Publication II:** In this paper, I was the first author. I defined the problem of user equipment (UE) localization in a downlink single-input-single-output (SISO) RIS-assisted communication system in an indoor rich-scattering environment (RSE). I presented a codebook-based approach for optimizing RIS configurations in dynamic RSE to improve UE localization accuracy. I proposed a data-driven model to learn the relationship between varying wireless channels and RIS configurations and I created and tested a codebook for RIS configurations that improved UE localization accuracy. I wrote the experiments code and conducted simulations for data generation, I wrote the code for data processing, I designed the model and used the data to train and test the model. I analyzed the results and evaluated the performance of the proposed approach, I prepared the figures and tables, I wrote the manuscript with supervisors' guidance, and I revised it based on reviewers' comments.
- III **Publication III:** In this paper, I was the first author. I addressed the problem of adaptive RIS configuration design for UE localization in downlink SISO and multiple-input-multiple-output (MIMO) RIS-assisted communication system in an indoor RSE. I proposed an adaptive learning-based localization approach using a data-driven model to capture temporal correlations in measurements and sequentially update RIS configurations. I wrote the experiments code and conducted simulations for data generation, I designed the model and used the data to train and test the model. I wrote the codes for baseline approaches, I trained and tested them with the simulated data and evaluated their performance against proposed approach. I prepared the figures and tables, I wrote the manuscript with supervisors' guidance, and I revised it based on reviewers' comments.
- IV **Publication IV:** In this paper, I was the first author. I addressed the problem of uplink UE location and orientation estimation in indoor RSEs for a MIMO RIS-assisted communication system. I proposed an approach to adaptively sense the environment with the help of RIS and to sequentially design the RIS configuration, BS beamforming and UE beamforming vectors, using the sequence of pilot transmissions from the UE to the BS. I wrote the experiments code and conducted simulations for data generation, I trained a data-driven network based controller and used data to train and test it. I derived the Bayesian Cramér-Rao lower bound (BCRLB) based estimator for UE location and orientation estimation in the RSE; supervisors reviewed and verified the derivation. I wrote the codes for baseline approaches, I trained and tested them with the simulated data and evaluated their performance against proposed approach. I conducted experiments to evaluate the proposed approach under various RSE condi-

tions to test its robustness. I prepared the figures and tables, I wrote the manuscript with supervisors' guidance, and I revised it based on reviewers' comments.

Abbreviations

2D	two dimensional
3D	three dimensional
5G	fifth generation
6G	sixth generation
AI	artificial intelligence
ANN	artificial neural network
AoA	angle-of-arrival
AoD	angle-of-departure
BCRLB	Bayesian Cramér-Rao lower bound
Bi-ARULN	Adaptive RIS-Assisted User Localization Network
biLSTM	bidirectional long short-term memory
Bi-SEN	Scattering Estimation Network
BO	Bayesian Optimization
BS	base station
CDF	cumulative distribution function
CNN	convolutional neural network
CRB	Cramér-Rao bound
CRF	conventional radio frequency
CRLB	Cramér-Rao lower bound
CS	compressive sensing
CSI	channel state information
DFL	device-free localization
DL	deep learning
DNN	deep neural network
DSP	digital signal processors
FIM	Fisher information matrix
FPGA	field-programmable gate arrays
GDoP	geometric dilution of precision
GNSS	global navigation satellite systems
IoT	internet of things
ISAC	integrated sensing and communication
JCAL	joint communication and localization
LoS	line-of-sight
LSTM	long short-term memory
MCRB	misspecified Cramér-Rao bound
MIMO	multiple-input-multiple-output
MISO	multiple-input-single-output
ML	machine learning
MLE	maximum likelihood estimation
mmW	millimeter wave
MSE	mean square error
MUSIC	multiple signal classification
NLoS	non-line-of-sight
OEB	orientation error bound
OFDM	orthogonal frequency division multiplexing
OTFS	orthogonal time frequency space
PEB	position error bound

REB	rotation error bound
RF	radio frequency
RIS	reconfigurable intelligent surfaces
RL	reinforcement learning
RMSE	root mean squared error
RSS	received signal strength
RSE	rich-scattering environment
RSEs	rich-scattering environments
RNN	recurrent neural network
RTT	round-trip time
SIM	stacked intelligent metasurfaces
SIMO	single-input-multiple-output
SISO	single-input-single-output
SL	sidelink
SLAC	simultaneous localization and communication
SLAM	simultaneous localization and mapping
SNR	signal-to-noise ratio
SO	scattering object
SOs	scattering objects
STAR	simultaneously transmitting and reflecting
TDoA	time-difference-of-arrival
THz	terahertz band
ToA	time-of-arrival
TOF	time-of-flight
UAV	unmanned aerial vehicle
UE	user equipment
UL	uplink
UWB	ultra wide band
VLP	visible light positioning

1 Introduction

Wireless communication networks are undergoing a fundamental transformation with the advent of sixth generation (6G) systems. Among the most critical capabilities envisioned for 6G is centimeter-level radio localization, the ability to determine the position and orientation of a user equipment (UE) with high accuracy, low latency and minimal infrastructure overhead [5]. Achieving this goal in complex environments, such as indoor spaces and rich-scattering environments (RSEs) populated by multiple dynamic scatterers, represents one of the most demanding technical challenges in modern wireless research [6, 7, 8].

Reconfigurable intelligent surfaces (RIS) have emerged as a pivotal technology for 6G localization. A RIS consists of a planar array of passive or active electromagnetic elements whose reflection, transmission, or absorption properties can be tuned electronically [6, 7]. By controlling the phase and amplitude of the reflected signals, a RIS can reshape wireless propagation to create favorable channel conditions for communication, sensing, and localization. Crucially, RIS can create low cost, low power virtual anchor points through controllable reflections, enabling accurate localization with fewer physical base stations (BSs) and extending coverage into non-line-of-sight (NLoS) areas that are inaccessible to traditional systems [8]. In hybrid-mode operation, RIS can sense as well as reflect the signals, enabling it to perform environmental sensing alongside assistance in communication and localization [9]. It can, thus, assist in integrated sensing and communication (ISAC) implementation with the integration of sensing, localization and communication within a unified framework, enabling more efficient spectrum usage, improved situational awareness, and enhanced system performance, which are expected to be key capabilities in 6G networks.

Despite their promise, the deployment of RIS for UE localization in dynamic RSEs, where multiple scattering objects (SOs) move along unpredictable or partially predictable trajectories, introduces significant technical challenges. The wireless channel in such environments is highly nonlinear and varies in time, making it difficult to obtain accurate channel models or rely on static RIS configurations [10, 11, 12]. Furthermore, existing localization approaches predominantly rely on simplified channel assumptions, fixed RIS configurations, or scattering-agnostic models, all of which degrade in performance when the propagation environment changes continuously [13]. Therefore, there is a need for adaptive methods that can sense the environment, intelligently design RIS configurations, and accurately estimate UE location parameters.

1.1 Problem Statement and Research Questions

A dynamic RSE is characterized by multiple simultaneously active SOs, representing, for example, human occupants or moving machinery, whose positions vary over time and whose collective effect on the wireless channel is analytically intractable via conventional cascaded channel models. This setting is representative of indoor deployment scenarios such as industrial facilities, warehouses, and smart buildings. In a dynamic RSE, three interrelated difficulties compound the localization problem. First, the relationship between the RIS configuration, the channel observed at the UE, and the UE location is nonlinear and environment-dependent, ruling out closed-form analytical solutions. Second, the channel changes continuously as the SOs move, meaning that a fixed RIS configuration or a static RIS configuration selected during an offline calibration phase may quickly become suboptimal. Third, localization accuracy must be maintained despite these temporal variations without requiring frequent offline retraining or exact knowledge of the SO' positions.

Informed by these observations, the thesis pursues four research questions:

- **RQ1:** What is the current state of research on RIS-assisted radio localization in 6G networks and what are the key developments, opportunities, and challenges in the field?
- **RQ2:** How can a codebook-based RIS configuration approach, combined with a data-driven learning model, be designed to improve UE localization accuracy in dynamic RSEs?
- **RQ3:** How can an adaptive, sensing-assisted RIS configuration strategy be devised that dynamically responds to temporal variations in the scattering environment to minimize UE localization error without relying on a fixed codebook?
- **RQ4:** How can the adaptive sensing and RIS configuration approach be extended to jointly estimate UE location and orientation while simultaneously designing BS and UE beamforming vectors, and how does a learning-based design compare with an analytically derived one?

The findings from RQ1 formed the basis for formulating the remaining three interrelated research questions. Research questions RQ1 through RQ4 examine enhancements achieved through procedural, algorithmic, and signal processing techniques applied to data originating from the channel simulator.

1.2 Contributions

To answer the research questions posed in the previous subsection, this thesis makes the following four contributions, each corresponding to one of the four publications on which it is based.

Contribution 1 — Survey of RIS-Assisted Radio Localization (Chapter 2). To address RQ1, a comprehensive survey of RIS-assisted radio localization in 6G networks is presented. It introduces a detailed taxonomy spanning application scenarios, localization measurement modalities, RIS types and deployment configurations, localization algorithms, and performance metrics, and consolidates recent developments across outdoor/far-field, indoor, and near-field scenarios. The survey also identifies open research challenges, including artificial intelligence (AI)-controlled RIS-assisted localization, mobile and multi-user localization, integrated sensing, localization and communication, and hardware standardization. Unlike prior RIS localization surveys, it provides a unified taxonomy that explicitly couples the sensing and localization roles of the RIS and frames open research problems. (Publication I).

Contribution 2 — Codebook-Based RIS Configuration Design in Dynamic RSE (Chapter 3). To address RQ2, a codebook-based approach for optimizing RIS configurations in single-input-single-output (SISO) dynamic RSE is proposed. A data-driven model learns the mapping from the wireless channel, comprising both the UE-side and sensing-element channels, to the optimal RIS configuration and UE location, exploiting a subset of sensing RIS elements to estimate the scattering-object (SO) state and selecting the optimal configuration from a pre-learned codebook at runtime. Experiments show that enlarging the codebook reduces the mean square error (MSE) of UE localization relative to random RIS configurations. Unlike prior codebook methods indexed only by UE geometry, the codebook is conditioned on an estimated scattering state, removing the geometry-only assumption (Publication II).

Contribution 3 — Adaptive RIS Configuration Design with Environmental Sensing (Chapter 4). To address RQ3, an adaptive localization approach is developed that removes the dependence on a fixed codebook by sequentially designing RIS configurations from accumulated measurements and environmental sensing. A data-driven model estimates the dynamic SOs positions, which move along predefined trajectories, from RIS sensing-

element observations, and uses the estimated scattering state to design the next RIS configuration and ultimately estimate the UE position. Evaluated in both SISO and multiple-input-multiple-output (MIMO) configurations, it yields consistent improvements in localization accuracy over codebook-based, random-configuration, and scattering-unaware baselines. Unlike prior RIS sequential configuration designs, scattering is explicitly estimated and fed into sequential design, making the proposed method suitable for environments characterized by rich-scattering (Publication III).

Contribution 4 — Integrated Sensing, Beamforming, and Joint Location and Orientation Estimation (Chapter 5). To address RQ4, the adaptive approach of Contribution 3 is extended to the uplink scenario, where the BS jointly estimates the UE position and orientation while designing RIS configurations and BS and UE beamforming vectors across sequential time frames. The data-driven controller adaptively senses an RSE containing multiple randomly moving SOs and produces the RIS configuration and the BS and UE beamforming vectors, and an analytical design based on the conditional Bayesian Fisher information is derived to provide a benchmark against the learning-based approach. Experiments under varied SO densities, RIS sizes, RIS deployment geometries, and signal-to-noise ratio (SNR) conditions confirm the gains of the proposed approach against all baselines. The main novelty lies in joint sequential co-design of RIS configuration and BS, UE beamforming for location and orientation in dynamic RSE, with theoretical benchmarking (Publication IV).

Table 1 is mapping each RQ onto its corresponding publication and chapter.

Table 1: Mapping of research questions, publications, and corresponding chapters.

Research Question	Publication	Chapter
RQ1	Publication I	Chapter 2
RQ2	Publication II	Chapter 3
RQ3	Publication III	Chapter 4
RQ4	Publication IV	Chapter 5

1.3 Thesis Outline

The remainder of this thesis is organized as follows.

- Chapter 2 presents an overview of the comprehensive survey of RIS-assisted radio localization in 6G networks, covering principles of RIS operation, the localization taxonomy, state of the art in deployment scenarios, and research challenges. It also reviews the closely related literature for subsequent chapters of this thesis, including RIS-assisted localization, codebook-based RIS design for UE localization, and adaptive sensing-assisted UE localization, from the perspective of their application in RSE.
- Chapter 3 describes the codebook-based approach for UE localization in dynamic RSEs, including the system model, the learning approach, and the experimental evaluation.
- Chapter 4 describes the adaptive RIS configuration design using the environmental sensing, learning approach, its training and evaluation in SISO and MIMO settings, and performance evaluation against baselines.
- Chapter 5 addresses the joint location and orientation estimation of the UE with integrated sensing and adaptive beamforming design, including the analytical benchmark.

- Chapter 6 concludes the thesis with a summary of contributions, and directions for future work.

Appendices 1 to 4 reproduce, in full, Publications I to IV on which this thesis is based.

2 Reconfigurable Intelligent Surfaces in 6G Radio Localization

In this chapter, an overview of RIS-assisted radio localization in 6G networks including RIS operation principles, explanation of fundamentals of RIS-assisted localization through a basic system scenario, and brief discussion on comprehensive taxonomy of RIS-assisted localization is presented. It also presents the state-of-the-art in RIS-assisted localization across outdoor/far-field, indoor, and near-field scenarios while identifying the research gaps. Afterwards, it provides an overview of more focused related work relevant to the subsequent chapters of this thesis.

This chapter is primarily based on Publication I:

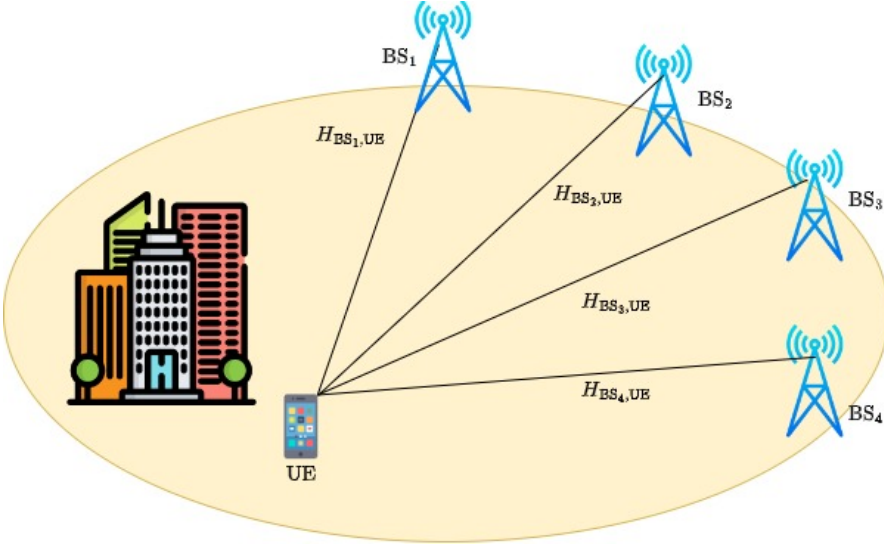
- A. Umer, I. Mürsepp, M. M. Alam, and H. Wymeersch, "Reconfigurable Intelligent Surfaces in 6g Radio Localization: A Survey of Recent Developments, Opportunities, and Challenges," *IEEE Communications Surveys & Tutorials*, vol. 27, no. 6, pp. 3526–3560, 2025

2.1 RIS-assisted Radio Localization

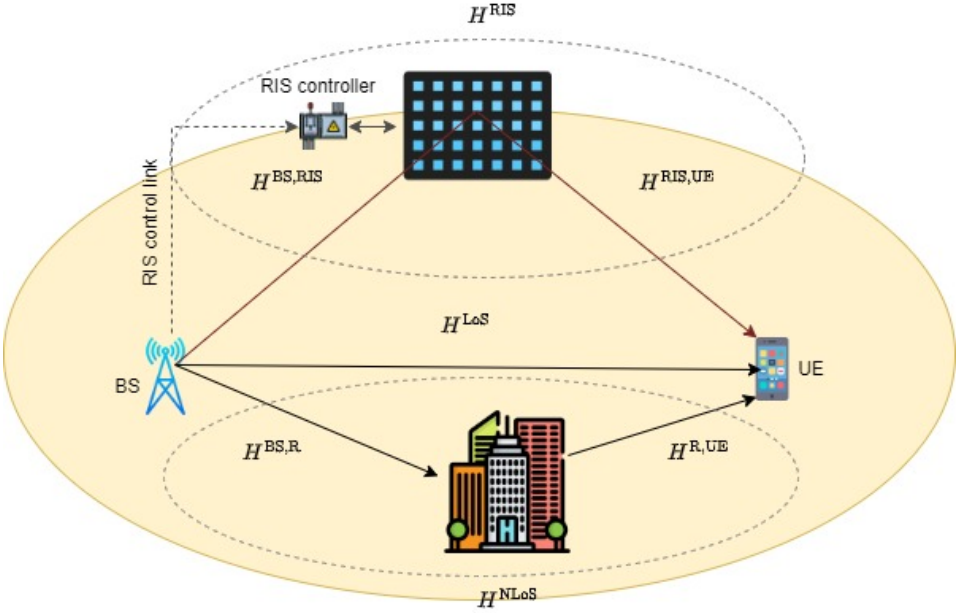
RIS are engineered metasurfaces consisting of a large number of individually controllable electromagnetic elements, each capable of adjusting the phase, amplitude, and polarization of incident radio waves in real time [14, 15]. In contrast to conventional array elements that actively transmit signals, RIS elements are typically passive and require minimal power consumption. Their collective behavior is governed by a central controller, which configures each element according to channel conditions and system objectives [16, 17]. This programmability enables RIS to dynamically manipulate the reflection, transmission, and absorption of electromagnetic waves, offering a high degree of control over the wireless propagation environment [18].

One of the most promising applications of RIS is in radio-signal based localization. Traditional localization systems without RIS typically require at least four synchronized BSs to determine the location of a UE with reduced error, leading to significant infrastructure demands [19, 20]. RIS technology alleviates this requirement by introducing additional controllable propagation paths between a single BS and the UE. Acting as a virtual anchor with a known location, RIS provides additional angular and delay diversity that enhances localization performance [14, 21], as shown in Figure 1. Information embedded in reflected signals, such as time-of-arrival (ToA), angle-of-arrival (AoA), and angle-of-departure (AoD), received signal strength (RSS) and channel state information (CSI) can be extracted and used to estimate the location of the UE by geometric inference [20]. Analytical studies show that the localization root mean squared error (RMSE) decreases as the RIS aperture increases and as multiple RIS units are spatially distributed [22, 23, 24]. RIS improves localization in challenging environments by creating virtual LoS paths in NLoS scenarios at millimeter wave (mmW) and terahertz band (THz) frequencies and enabling iterative accuracy refinement through adaptive configurations, supporting applications such as simultaneous localization and mapping (SLAM), joint communication and localization (JCAL) and integrated sensing and communication (ISAC) [14, 19, 25, 26, 21, 18, 27].

Several review papers address localization fundamentals, though most focus on specific signal types, environments, or localization methods. For example, the topic of indoor localization is surveyed in [28, 29, 30, 31, 32], outdoor localization in [33, 34, 35], and localization in ground-air-space networks in [36]. Regarding signal types, radio-based localization is covered in [29, 37, 32], while visible light positioning (VLP) is reviewed in [38]. Surveys have also examined localization techniques such as SLAM [33, 29], multi-dimensional scaling [39], and machine learning (ML) methods [31, 40]. Application-oriented surveys



(a) Conventional non-RIS-assisted localization network.



(b) RIS-assisted localization network.

Figure 1: Illustration of non-RIS-assisted and RIS-assisted localization networks.

have explored device-free localization (DFL) [35], autonomous driving [33, 34, 41], pedestrian localization [40], emergency response [28], and network localization [29]. More recent works investigate localization use cases in 6G [42], enabling technologies for beyond fifth generation (5G) and 6G such as RIS [14, 18], localization algorithms and signal processing techniques for 6G [43, 44, 45], as well as joint communication, localization, and sensing through ISAC [46, 18] and high-frequency localization [14, 18, 47, 43]. A broad

overview of localization in 6G is presented in [42].

Several studies have investigated the role of RIS in 6G systems, including its use in radio localization and mapping [14, 18], as well as signal processing techniques in RIS-assisted networks [43, 44, 45]. A tutorial on high-frequency radio localization with RIS is provided in [47]. The area of IoT positioning is surveyed in [48]; however, its limited scope does not fully capture the broader research landscape of RIS-assisted localization in 6G, nor does it include the latest developments. Its lack of reproducibility also restricts its utility for validation and future extensions. The concept of RIS-enabled ISAC is introduced in the tutorial in [27]. In addition, [19] studies RIS across different network settings, including SISO, MIMO, multiple-input-single-output (MISO), and single-input, multiple-output (SIMO). Performance gains of RIS over conventional wireless designs in smart environments are further discussed in [49], with emphasis on architecture, deployment, bandwidth, and coverage.

In general, substantial effort is being devoted to advancing RIS for localization. To strengthen understanding of the fundamentals of RIS-assisted radio localization and identify open research directions, a comprehensive survey that, in contrast to existing surveys and tutorials, emphasizes the role of RIS in radio localization by outlining its potential applications and introducing a taxonomy for RIS-assisted localization, presenting an overview of recent studies on the role of RIS in radio localization for 6G networks remains essential. This work brings together and extends existing knowledge to support further progress in RIS-assisted localization within 6G networks.

2.2 Review Method

The survey has been conducted following a systematic methodology to ensure completeness, reproducibility, and relevance. The sub-research questions guiding the review were:

1. How has RIS been used for localization in 6G networks?
2. What are the current trends and developments in RIS technology for 6G radio localization?
3. What are the future directions, technical challenges, and limitations of RIS-assisted radio localization?

The search string was defined by combining two keyword groups. The first group covered RIS terminology, including “intelligent reflecting surface,” “reconfigurable intelligent surface,” “RIS,” “IRS,” “LIS,” and “large intelligent surface.” The second group covered localization terminology, including “localization” and “positioning,” combined with the “6G” qualifier. The resulting combined search string was applied to digital databases such as the IEEE Xplore digital library, covering journal papers, workshop papers, and conference publications. Backward referencing was additionally employed to identify relevant works not captured by the primary search.

Inclusion and exclusion criteria were applied to the collected literature. Duplicate publications, for example where both a preprint and a published version were collected, were resolved in favor of the published version. All remaining studies were assessed for relevance to RIS-assisted localization in 6G, and only those presenting a method, approach, or technique for this purpose were included in the final corpus. Full-text analysis was performed for all included papers to ensure accurate characterization of their contributions, techniques, and performance metrics.

From an initial set of 187 records identified through database searches and backward referencing, 19 were removed during duplication screening, 23 during title/abstract screening, and 12 during full-text assessment, leaving 133 studies that form the basis of this review.

2.3 Overview of RIS Operation

RIS are an advanced electromagnetic surface composed of a large number of tunable elements, each capable of modifying the amplitude, phase, and polarization of incident electromagnetic waves either by reflection, refraction, or absorption [50]. These individual elements are typically small, low-cost, and programmable, enabling the surface to adapt dynamically to varying channel conditions and operational requirements [14, 18]. The key differentiator of RIS from conventional antenna arrays is that RIS elements are predominantly passive, consuming little or no power, and their collective response is coordinated by a central controller that adjusts the configuration of each element [27, 15].

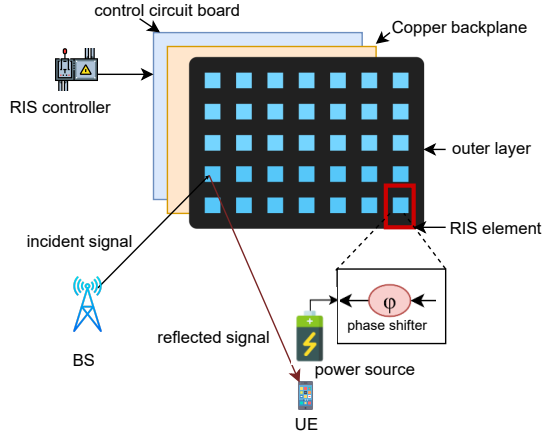
RIS operates through several distinct modes. Passive reflective RIS is the most widely studied variant that alters the phase of incident signals without active amplification, acting as a programmable mirror that shapes and directs radio waves toward desired directions [17]. Each element reflects the incoming signal via a copper backplane, and the overall reflection is described by a diagonal reflection coefficient matrix whose entries encode the amplitude and phase applied by each element, as shown in Figure 2a. Active reflective RIS extends this by incorporating amplification circuitry, as shown in Figure 2b, allowing the reflected signal to be boosted at the cost of additional power consumption [51]. Transmissive RIS, also known as simultaneously transmitting and reflecting (STAR) RIS, allows signals to pass through the surface while modifying their properties, enabling full 360-degree spatial coverage rather than half-space coverage available from conventional reflective designs [17, 52], as shown in Figure 2c. RIS with non-diagonal phase control introduces inter-element signal routing, allowing the signal incident on one element to be reflected from a different element, providing additional degrees of freedom for beam-forming and localization [53]. Hybrid sensing-and-reflecting RIS use meta-atoms that can simultaneously sense and reflect incident waves, enabling the surface to estimate channel parameters and perform localization-relevant measurements alongside its reflective function [9]. This mode of RIS operation is used in the contributions of this thesis.

From a hardware perspective, RIS can be fabricated using low-cost printed circuit board technology and can be mounted on building facades, walls, ceilings, or even unmanned aerial vehicles (UAVs) [18]. Their limited power requirements and passive operation make them attractive for large-scale deployment in 6G networks, where coverage, energy efficiency, and spectral utilization are all critical considerations.

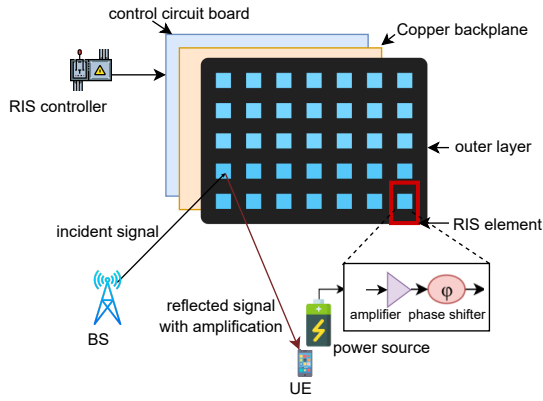
2.4 Fundamentals of RIS-Assisted Localization

The introduction of RIS into the localization network addresses three fundamental limitations of conventional localization infrastructure. First, conventional systems require over-provisioned BS deployments to ensure sufficient geometric diversity for localization, even though a single BS is sufficient for communication [19]. RIS provides additional geometric anchors without requiring active hardware infrastructure, reducing deployment costs substantially [54, 55, 26]. Second, even large-scale MIMO BSs offer limited angular resolution at sub-6 GHz and higher frequencies, restricting localization accuracy in multipath environments. RIS, operating at mmW or THz frequencies where its electrically large aperture provides fine angular resolution, enables centimeter-level localization with a single BS [14]. Third, ToA-based localization at sub-6 GHz requires nanosecond-level synchronization among multiple BSs, a significant engineering challenge. With RIS providing a known, synchronized reflection path, synchronization requirements can be substantially relaxed [19].

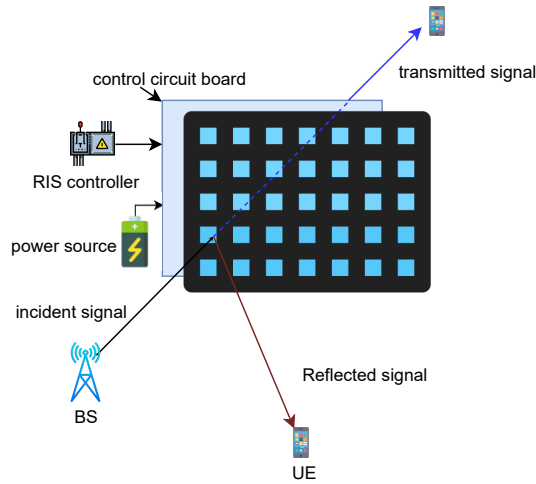
RIS-assisted localization also offers significant benefits in NLoS scenarios, where the



(a) Passive reflective RIS



(b) Active reflective RIS



(c) Transmissive and STAR RIS

Figure 2: Overview of RIS operating modes showing passive reflection, active reflection, and transmissive or STAR operation.

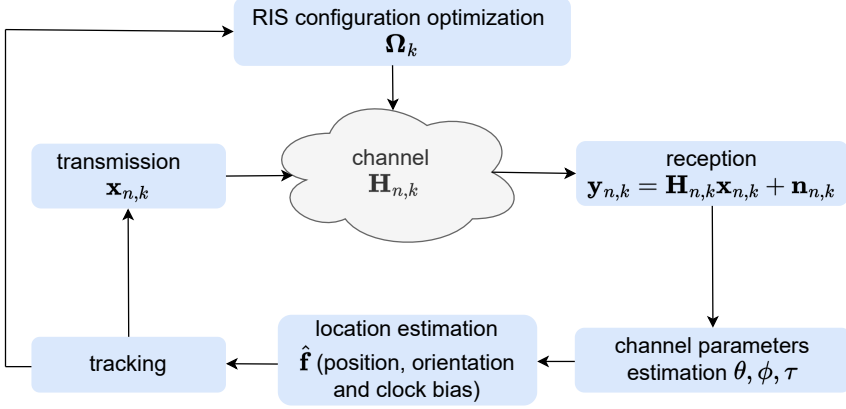


Figure 3: Flowchart demonstrating the typical processing phases in RIS-assisted localization in 6G networks. In the downlink scenario, the transmitted signal received at the UE is used for channel parameters estimation and UE localization. Tracking information is utilized to optimize the RIS configuration.

direct path between the BS and UE is obstructed by walls, furniture, or other objects. In such environments, RIS acts as a programmable reflector that creates a virtual LoS path from the BS to the UE, restoring geometric diversity and enabling localization that would otherwise be infeasible [56]. This property is particularly valuable in indoor environments including industrial facilities, hospitals, and smart homes, where LoS blockages are common.

RIS-assisted localization exploits the controllable electromagnetic properties of RIS to create additional signal paths between the BS and the UE. Single-anchor localization is already attainable without RIS such that a BS with a sufficiently large array can estimate the AoA or AoD and, when the geometry of the surrounding scatterers is known, can exploit deterministic reflections as additional pseudo-anchors. These approaches, however, place the entire burden of geometric diversity on the array aperture and on prior knowledge of the environment, and they degrade when the reflecting geometry is unknown or time varying. In a standard non-RIS localization network operating at sub-6 GHz frequencies and relying on time-difference-of-arrival (TDoA) or ToA measurements, four or more synchronized BSs are typically required to determine the three-dimensional UE position. The contribution of the RIS is that the reflection center is at a known location and its response is programmable, so the additional propagation paths are both identifiable and controllable rather than incidental. A single BS combined with one or more RIS can therefore achieve accurate localization while relaxing the requirement for over-provisioned anchor deployments and for prior knowledge of the passive scattering geometry.

The typical processing phases of the RIS-assisted localization network are shown in Figure 3. The fundamental signal model for RIS-assisted localization considers a multi-antenna BS transmitting known pilot symbols $\mathbf{x}_{n,k}$ on multiple subcarriers n , which propagate to the UE via a direct path (if unobstructed) and via RIS-reflected paths, altered by the channel $\mathbf{H}_{n,k}$ [57]. The received signal at the UE $\mathbf{y}_{n,k} = \mathbf{H}_{n,k}\mathbf{x}_{n,k} + \mathbf{n}_{n,k}$, observed over multiple frequencies and time slots, encodes information about the ToA of each path τ , the AoA at the UE θ , and the AoD ϕ , at the BS. These channel parameters are geometrically related to the positions and orientations of the BS, the RIS, and the UE. By estimating

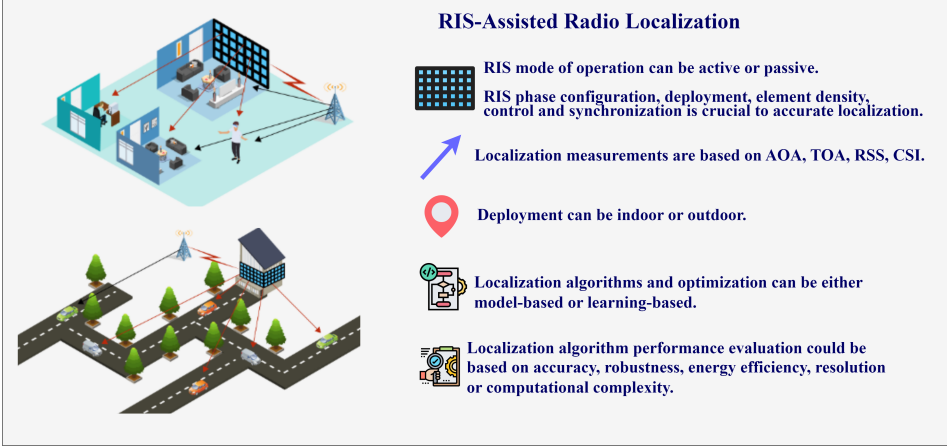


Figure 4: Illustration of RIS-assisted localization taxonomy.

these parameters $\hat{\mathbf{f}}(\cdot)$ from the received pilots and mapping them to the UE state through the known geometric relationships, the UE can be localized with accuracy that scales favorably with signal bandwidth and array aperture [57, 58].

The RIS configuration $\mathbf{\Omega}_k$ directly controls the properties of the RIS-reflected signal, including its strength and direction. Optimizing the RIS phase profile to maximize the Fisher information contained in the received signal about the UE state is therefore a central problem in RIS-assisted localization. This optimization can be performed offline using prior location information, or adaptively using sequential channel measurements, as in the contributions of this thesis.

2.5 RIS-Assisted Localization Taxonomy

RIS-assisted localization systems can be characterized along five dimensions: application scenario, localization measurements, RIS type, RIS configuration and deployment, and localization algorithm and performance evaluation. This taxonomy is illustrated in Figure 4 and provides a structured framework for comparing and positioning the existing literature and approaches.

In terms of application scenario, localization systems can be deployed in indoor or outdoor environments [48]. Indoor environments are characterized by dense multipath, NLoS conditions, and limited propagation range, making RIS particularly valuable for creating controlled reflection paths and enhancing signal diversity [59]. Outdoor environments benefit from larger propagation distances and the ability to leverage mmW and THz bands with large RIS apertures for high angular resolution [60].

The primary localization measurements used in RIS-assisted systems are ToA, AoA, AoD, RSS, and CSI [61]. ToA-based methods extract path delay information with a resolution determined by signal bandwidth [62]. AoA and AoD-based methods exploit spatial information from antenna arrays. RSS-based methods use the signal power attenuation, which depends on the distance and the propagation environment [63]. CSI-based methods use the full channel frequency response, which encodes both delay and spatial information [64].

Localization algorithms can be broadly classified into model-based and learning-based approaches [47]. Model-based approaches, including geometry-based trilateration and



Figure 5: Systematic classification of RIS-assisted localization research.

triangulation, Kalman filtering [65], and CRLB-minimizing optimization, exploit the geometric relationship between the channel parameters and the UE state [57, 58]. These methods are analytically transparent and do not require training data, but they are sensitive to model mismatch and may fail in complex propagation environments. Learning-based approaches, including fingerprinting [37] with deep neural network (DNN) and convolutional neural network (CNN), deep reinforcement learning (RL), and recurrent network-based sequential estimation, can handle nonlinear and non-Gaussian settings and are trained directly on observed data [66, 47, 67], at the cost of requiring representative training datasets.

2.6 State of the Art in RIS-Assisted Radio Localization

The reviewed literature is classified into three deployment scenarios: outdoor and far-field localization, indoor localization, and near-field localization, as shown in Figure 5. Across all categories, there is a clear trend toward high-frequency operation at millimeter wave (mmW) and terahertz band (THz) bands, where RIS provides large aperture gains and fine spatial resolution, and passive reflective RIS is the most commonly studied configuration.

2.6.1 Outdoor and Far-field Localization

Outdoor and far-field RIS-assisted localization studies span both conventional radio frequency (CRF) bands below 24 GHz and high-frequency bands at mmW and THz frequencies. At CRF bands, research has demonstrated that a single RIS combined with one BS can replace multiple BSs in TDOA-based localization, offering centimeter-level positioning accuracy while reducing infrastructure requirements [68]. Studies at these frequencies have explored RSS fingerprinting with RIS for multi-user outdoor positioning, fundamental performance limits through Fisher information analysis, joint communication and localization designs, and RIS configurations optimized for integrated sensing and communication [69, 70, 71, 72].

At mmW and THz frequencies, the high signal bandwidth and large antenna arrays enable sub-centimeter accuracy in RIS-assisted systems. A substantial body of literature has developed CRLB-optimal RIS phase profiles, maximum likelihood estimators for joint localization and synchronization, Bayesian tracking algorithms for mobile users, cooperative localization frameworks, and SLAM systems that use RIS as virtual anchors [23, 73, 24, 74, 64, 75]. Recent studies have also explored active RIS for scenarios where

multiplicative path loss of passive RIS limits performance [76], STAR-RIS for simultaneous indoor and outdoor coverage [77], and RIS-assisted vehicle-to-vehicle localization for intelligent transportation. The trend toward integrated sensing and communication has led to studies optimizing the joint trade-off between localization accuracy and communication rate, with RIS phase design playing a central role [78].

2.6.2 Indoor Localization

Indoor RIS-assisted localization has been studied extensively at WiFi-band frequencies and at higher mmW bands. At 2.4–5 GHz, fingerprinting-based approaches have shown that RIS can substantially enrich the signal fingerprint database by providing a controllable RIS configuration that can be varied to create a large and diverse set of fingerprints for each location [79, 63]. This approach addresses the fundamental limitation of traditional fingerprinting, where the number of fingerprints is determined by the number of observable BSs and is often insufficient for fine-grained localization. Fingerprinting methods enhanced by deep reinforcement learning have demonstrated significant improvement in localization accuracy compared to conventional nearest-neighbor matching [80].

RSS-based indoor localization with RIS has been studied for both single-user and multi-user scenarios, with proposed algorithms for optimizing RIS configurations to maximize the differentiation of RSS signatures between reference locations [81]. Passive localization for determining the position of individuals without requiring them to carry a transmitter has also been demonstrated using WiFi signals reflected from RIS [82], achieving sub-centimeter accuracy by optimizing the RIS phase profile to separate the person-reflected signal from multipath interference. SLAM frameworks incorporating RIS have reduced agent position estimation errors and demonstrated the value of RIS in environments where traditional wireless SLAM suffers from poor signal diversity [83, 84, 85].

2.6.3 Near-field Localization

Near-field localization arises when the UE is within the Rayleigh distance of the RIS, where the spherical wavefront assumption rather than the plane wave assumption of far-field models applies. This regime is increasingly relevant as RIS sizes grow with the operation frequency and aperture requirements of 6G systems, and as indoor deployments at mmW and THz frequencies bring the UE into proximity with large RIS arrays.

Near-field localization offers an important advantage of the wavefront curvature that encodes depth information that is absent in far-field measurements, enabling range estimation from a single RIS without requiring multiple BSs or time synchronization [86]. Studies have derived CRLB expressions for near-field RIS localization accounting for practical effects such as phase-dependent amplitude variations at each RIS element, hardware impairments including pixel failures, asynchronous operation, and beam squint [87]. Localization algorithms designed for the near-field regime have demonstrated feasibility of retaining high localization accuracy even under significant LoS blockage, and near-field sidelink positioning using a single active RIS has been shown to achieve accurate joint position and clock bias estimation [88, 89, 90, 91, 87]. Near-field localization is an area of rapidly growing interest, driven by the anticipated large RIS deployments and high-frequency operation of 6G networks.

2.6.4 RIS Hardware

RIS hardware has moved from single-purpose laboratory samples to surfaces that are fabricated in quantity and tested outside the laboratory. Prototypes are available from both industrial and academic groups and from multi-partner European projects, and cover

bands from sub-6 GHz through mmW to sub-THz [92]. Reported surfaces are predominantly reflective, with one-bit or low-resolution phase control realized with PIN diodes on printed circuit board substrates and driven by an on-board controller [92]. Element counts of the order of a thousand are being used such that a 5.8 GHz surface with 1100 controllable elements has been reported together with an over-the-air configuration procedure [93], and tiled architectures with per-tile addressing and standard control interfaces have been demonstrated to support larger installations [94]. Experimental equipment beyond the surfaces themselves includes dedicated channel sounders, with measurement campaigns providing path loss models at mmW [95] and broadband channel models at sub-6 GHz [96]. Demonstrators have been evaluated with off-the-shelf terminals in commercial 5G networks across indoor, outdoor and mixed scenarios [93, 97], and localization-specific demonstrations have also begun to appear [98]. These trials report the practical limits of present hardware, namely reflection amplitude that varies with the selected phase state and a response that depends on the angle of incidence.

The literature surveyed in this chapter establish their results analytically, through derived error bounds, or numerically, through simulation. Among the reviewed work, [80] supports its claims with measurements from a physical reconfigurable metasurface, showing experimentally that changing the surface configuration alters the received signal strength at a given location and thereby resolves the ambiguity between nearby positions with similar signal strength. A comparison of measured localization accuracy against the analytical prediction derived for the same system, so the agreement between predicted and attainable accuracy in RIS-assisted localization is at present untested. This scarcity follows directly from the state of the hardware, i.e., standardized RIS platforms are not yet available, and the absence of common hardware on which theoretical methods can be exercised is one of the open challenges identified.

2.7 Challenges and Research Gaps

Despite substantial progress in recent studies, a number of challenges remain before RIS-assisted localization can be practically realized in 6G networks. These issues span technical, operational, and standardization aspects.

Accurate localization of mobile users is a major challenge. A large portion of existing work assumes static UEs, whereas it should account for Doppler effects, time-varying channels, continuous UE movement and environment dynamics. Developing methods that adapt RIS configurations and localization algorithms based on present channel conditions, while also handling NLoS dynamics, requires new algorithmic approaches and evaluation frameworks.

Scalable multi-user localization presents another key difficulty. Challenges include mitigating interference among multiple users, efficiently allocating resources in RIS-enabled networks, and designing algorithms that remain computationally feasible as the number of users increases.

The integration of localization, sensing, and communication is a fundamental objective in 6G. Achieving this requires RIS configurations that can jointly optimize communication performance, positioning accuracy, and environmental awareness, often across multiple users and services. This calls for a deeper understanding of trade-offs and the development of unified optimization strategies.

From a deployment standpoint, questions remain regarding the optimal placement, density, and orientation of RIS in various environments such as urban outdoor areas, industrial indoor settings, and vehicular scenarios. Calibration is another significant challenge, as it demands precise knowledge of the response of each RIS element. This be-

comes increasingly complex with larger surfaces and the presence of hardware imperfections such as element variability or failures. Additionally, RIS control for high-mobility scenarios imposes stringent latency requirements on system design.

Artificial intelligence offers a promising avenue to address many of these challenges. Data-driven approaches, particularly deep learning models, can learn direct mappings from observed channel conditions to optimal RIS configurations, reducing reliance on explicit channel models and improving robustness in dynamic environments.

Finally, RIS hardware standardization is still in its infancy. The development of standardized platforms would facilitate experimental validation, enable fair comparisons across studies, and support the establishment of best practices for deployment [99]. Bridging the gap between theoretical predictions and practical performance requires systematic experimental evaluation using real prototypes.

2.8 Related Work for RIS-assisted Localization in Rich-Scattering Environments

This section provides an overview of related works for the upcoming sections of this thesis. Discussion begins with the creation of RIS configuration codebooks for user localization. The design of adaptive RIS configurations, particularly for UE localization and environment sensing is discussed. Throughout this section, we highlight how these concepts impact the design of localization and sensing algorithms for users in indoor RSE.

2.8.1 RIS Configuration Codebooks for Localization

The body of research on RIS-assisted localization has expanded significantly since the early work that demonstrated the feasibility of RIS as programmable reflectors in wireless systems [100]. However, much of this development has relied on assumptions that do not reflect actual deployment scenarios. A large portion of the literature considers quasi-free-space environments, where channels can be analytically modeled and are assumed to be either known or obtainable with minimal overhead. In practice, acquiring accurate CSI incurs considerable overhead [101], which has led to alternative approaches that operate without explicit knowledge about the channel [102]. This trade-off between the need for precise channel information and the difficulty of obtaining it defines a central challenge in codebook-based RIS research.

The problem becomes more complex in environments characterized by rich scattering, such as industrial facilities, public spaces indoors, transportation hubs, and enclosed structures such as aircraft and ships [13, 103]. In such scenarios, signal propagation deviates from simple geometric models, as waves undergo multiple reflections and arrive from diverse directions. This invalidates conventional cascaded channel models and the assumptions underlying them. Additionally, the presence of moving objects introduces rapid temporal variations, causing channel conditions to fluctuate and reducing the reliability of static models [13]. As a result, both spatial complexity and temporal dynamics limit the effectiveness of traditional analytical and model-based approaches.

Initial efforts to address the operation of the RIS in RSEs relied on iterative adjustment of RIS configurations through experimental feedback [103, 104] or based on partial CSI [105]. While these methods improved communication performance, they were not explicitly designed for localization objectives and did not take advantage of temporal correlations in the channel. The introduction of sensing-enabled hybrid RIS architectures marked a shift in this direction [106]. By allocating some RIS elements to sensing rather than reflection, it became possible to infer environmental characteristics directly from received signals without external coordination. This development suggested a new paradigm in

which RIS contributes not only to wave manipulation but also to environmental awareness.

Building on this idea, more recent work has explored data-driven techniques to address the complexity of RSEs [107]. These methods avoid reliance on explicit channel models by learning relationships between observed signals and system parameters, including UE location and RIS configurations. However, many such approaches depend on iterative optimization procedures, which can be computationally intensive and may not meet the latency requirements.

Codebook-based approaches for RIS configuration offer a practical solution to the challenge of environment-aware RIS control by discretizing the configuration space and selecting the optimal configuration from a finite set of pre-designed codewords. In localization applications, codebooks have been employed at mmW frequencies to reduce the overhead of beam scanning and to adapt the RIS configuration to the estimated UE location. For instance, hierarchical codebooks were introduced to enable efficient angular search strategies, reducing measurement requirements for localization tasks, albeit with sensitivity to low signal-to-noise ratios and increased training complexity [108, 109]. In fingerprinting-based localization, the reconfigurability of RIS is exploited to enhance the diversity of observable channel signatures. By cycling through a set of RIS configurations and recording the corresponding RSS patterns, a detailed radio map can be constructed that significantly improves spatial discrimination compared to conventional fingerprinting methods based on static infrastructure [110].

However, existing codebook-based methods are predominantly designed for free space or LoS-dominated channel models and do not account for the impact of dynamic scattering objects on the RIS-to-UE channel. In a RSE, the optimal RIS configuration depends not only on the location of the UE but also on the current state of all SOs in the environment, making a static codebook indexed solely by location insufficient. Moreover, most codebook designs are derived analytically and rely on explicit geometric channel models, which are invalid in environments where signal propagation involves complex, analytically intractable multipath interactions.

2.8.2 Adaptive RIS Configuration Design for Localization

While codebook-based approaches provide a clear improvement over random selection, they inherently suffer from a key limitation: the configuration set is predetermined during the design phase, and no finite codebook can fully represent the continuous and evolving nature of a dynamic RSE. Here on wards, the latest studies are discussed to understand how this limitation has been addressed in the literature.

Model-based approaches have formed the dominant branch of RIS-assisted localization research, primarily because they allow tractable analytical treatment. By constructing the Fisher Information Matrix (FIM) from measurements such as ToA and AoA, these methods derive Cramér-Rao lower bound (CRLB) of location estimation errors, which in turn provide principled guidance for optimization of the RIS phase [24, 86, 23]. Numerous extensions of this framework have been proposed, including joint localization and synchronization for single-antenna receivers under known geometry [111], localization under user mobility and spatial-wideband effects [112], and studies of how the RIS phase design influences the rank of the FIM and therefore the observability of the UE state [23]. Iterative optimization techniques, such as gradient-based adjustment of reflection coefficients of the RIS elements, have been used to minimize the position error bound (PEB) derived from the CRLB [24]. Closed-form expressions for localization performance in near-field scenarios, including position- and orientation estimation, have also been developed [86].

The FIM framework has been widely employed to study how RIS configurations influence estimation accuracy, showing that directing reflected energy toward the UE improves localization performance [23]. Extensions to multi-RIS systems and high-frequency scenarios have incorporated advanced optimization techniques such as particle swarm optimization to further reduce positioning errors [113]. Joint channel estimation and localization strategies have also been proposed for RIS-assisted multi-antenna systems, leveraging structured training designs to improve angular estimation [114]. Overall, this body of work demonstrates that CRLB-based formulations provide valuable theoretical insights.

To address the limitations of deterministic geometric models, Bayesian extensions of the CRLB framework have been developed. Bayesian FIM formulations and robust Bayesian Cramér-Rao lower bound (BCRLB) incorporate prior uncertainty in channel and geometric parameters [115], enabling adaptive RIS beamforming strategies that account for posterior uncertainty when selecting the next measurement configuration [116]. These methods provide a conceptual bridge between purely analytical and fully data-driven designs by recognizing that optimal configuration choices depend on previously acquired information. Nonetheless, they remain rooted in explicit geometric channel models and therefore do not capture the unmodeled scattering phenomena that dominate RSEs. Related model-based efforts have sought to exploit rather than suppress multipath, including Bayesian multi-target tracking methods [117], cooperative three-dimensional positioning schemes with low-complexity estimators [118], and tensor-based ISAC frameworks supporting joint multi-user communication with near-field and far-field localization [119]. Adaptive beamforming strategies that account for location uncertainty have also been explored, though they often overlook the impact of complex scattering [116]. While these contributions advance model-based multipath exploitation, they remain constrained by structured geometric assumptions. These approaches are analytically elegant and require no training data, making them useful benchmarks. Their practical utility, however, decreases substantially in multipath-RSE where reliable path separation and association become infeasible, especially in narrowband indoor scenarios involving unknown and dynamic scatterers.

This perspective has led to the emergence of learning-based sequential optimization methods for RIS-assisted systems. Early work in this area focused on sequential beamforming for initial access in mmW systems, using neural networks to map estimated channel statistics to optimal beamforming decisions [109, 120]. These methods were later extended to multipath environments using recurrent architectures such as long short-term memory (LSTM) and gated recurrent unit (GRU) networks, which capture temporal dependencies across successive measurements [121, 122]. Similar techniques have been applied to beam tracking, enabling dynamic adaptation of RIS configurations to user mobility [123], and sequential joint optimization of RIS and BS beamforming has been explored for localization tasks, with extensions to multi-RIS and multi-antenna systems [124, 125]. Further developments have integrated RIS control with power allocation strategies to simultaneously enhance communication and localization performance [126]. Fingerprinting techniques mapping received signal measurements collected under multiple RIS configurations directly to UE locations [110], offer robustness to model mismatch, and deep reinforcement learning has been investigated as a mechanism for optimizing RIS configurations to improve localization accuracy [127]. However, both fingerprinting and RL-based approaches typically rely on predefined or static configuration sets and therefore underutilize the adaptive reconfigurability of RIS. A more principled framework has emerged through adaptive sensing, which treats measurement acquisition as an active sequential design process: methods developed for initial beam alignment in mmW systems

[121, 122, 128], precoder and combiner optimization in reciprocal MIMO systems [129], RIS-assisted beam tracking [130], and localization in single-path and multipath channels [125, 131, 132] have collectively demonstrated that recurrent neural network architectures can iteratively refine beamforming decisions based on previously observed pilot signals, steering each new measurement toward configurations that maximize information about the unknown UE state. Learned beamforming codebooks for active RIS sensing further show that this sequential decision-making framework is realizable under practical hardware constraints [132]. Despite these collective advances, two critical gaps persist: existing sequential methods do not explicitly incorporate knowledge of the environment's scattering state into RIS configuration decisions, and the underlying propagation assumptions are generally too simplified to transfer directly to complex RSEs. Recent research has begun addressing this transferability challenge through learning-based methods explicitly designed for RSEs. These include joint fingerprinting and feature extraction networks for UE localization [133], and self-adaptive RIS optimization based on learned surrogate scattering models [107].

The progression from static codebooks to adaptive sequential sensing, discussed above, addresses one major source of complexity in RIS-assisted localization: the temporal variability of the propagation environment. A second equally important challenge concerns the estimation objective itself. Jointly estimating the orientation and location of a UE while sensing the SOs expands the parameter space and increases demands on measurement diversity as well as RIS configuration design.

2.9 Summary and Research Gaps

The chapter establishes the conceptual foundation for RIS-assisted radio localization in 6G networks, tracing the development of RIS from its fundamental operating principles to its role as a virtual anchor capable of enabling UE localization with fewer physical BSs. Although substantial progress has been made across a wide range of deployment scenarios and frequency bands, the field required a unified, systematic, and reproducible synthesis spanning conventional radio frequency, mmW and THz systems, while simultaneously addressing indoor, outdoor, and near-field regimes together with emerging paradigms such as ISAC and SLAM, and identifying open research areas. To address this gap, this chapter presented a comprehensive survey of RIS-assisted radio localization in 6G networks, based on Publication I. A structured taxonomy of RIS-assisted localization systems was introduced, and recent advances were synthesized across outdoor and far-field, indoor, and near-field deployment scenarios. The survey highlights several key observations, including the rapid expansion of research at mmW and THz frequencies, the dominant use of passive reflective RIS architectures, the growing adoption of learning-based localization techniques for complex propagation environments, and the increasing focus on integrated sensing, communication, and localization within ISAC-enabled RIS systems. In addition, the chapter outlined open challenges, such as dynamic environment and multi-user localization, AI-driven RIS control, hardware standardization, and near-field operation, which collectively shape the future research landscape.

Building on the identified research gaps, particularly AI-driven RIS control, the absence of adaptive and scattering-aware localization methods for dynamic radio environments, and RIS optimal placement and element density in such scenarios, the subsequent chapters of this thesis develop progressively advanced solutions and this chapter reviews the more closely related work. The review of codebook-based approaches for RIS configuration in RSEs demonstrates that while data-driven codebook selection significantly outperforms random and static configurations, such methods remain constrained by offline dis-

cretization and their inability to continuously adapt to environmental changes. The review of adaptive and model-free approaches for RIS-assisted localization, highlights that although sequential learning, fingerprinting, and reinforcement learning methods improve upon fixed-configuration strategies, they are generally developed under simplified propagation assumptions and do not explicitly incorporate knowledge of the scattering state.

The challenges discussed above expose three research gaps that this thesis directly addresses. The list below summarize each gap and its link to the subsequent chapters.

- **Gap 1 — Lack of scattering-aware, adaptive RIS configuration for dynamic RSE.** Most existing approaches assume static users and a quasi-static channel, and do not account for the continuous movement of scattering objects that characterizes a dynamic RSE. This gap is addressed in two complementary ways: Chapter 3 introduces a codebook-based RIS configuration that captures distinct scattering states (RQ2), and Chapter 4 extends this to an adaptive, sensing-assisted configuration that tracks temporal channel variations (RQ3).
- **Gap 2 — Reliance on fixed codebooks and offline calibration.** Configurations selected during an offline phase quickly become suboptimal as the scattering objects move. Chapter 4 addresses this gap with an adaptive biLSTM-based localization scheme that responds to present channel conditions without offline retraining or exact knowledge of the scattering-object positions (RQ3).
- **Gap 3 — Absence of joint location-orientation estimation with co-designed RIS and BS/UE beamforming, and of theoretical bounds.** Prior work largely treats sequential RIS configuration design for static users and a quasi-static channel for position estimation. Chapter 5 closes this gap by jointly estimating user location and orientation while co-designing the BS and UE beamforming vectors, and by deriving the corresponding theoretical bound in RSE (RQ4).

The following three chapters give an overview of the technical publications of this thesis. Chapter 3 provides an overview of the data-driven codebook selection approach in which the model learns to map joint UE-side and sensing-element channel measurements, together with the estimated SOs state, to the optimal codebook entry. Chapter 4 provides an overview of the codebook-free adaptive approach which sequentially designs RIS configurations using temporal sensing of the dynamic scattering state without relying on offline discretization or geometric channel models. Chapter 5 extends the approach to jointly design RIS configurations, base station, and user beamforming vectors, for simultaneous location and orientation estimation, while deriving an analytical estimator for this extended problem in RSEs. Chapter 6 concludes the thesis and formulates future research directions.

3 RIS Configuration Codebooks for User Localization in Dynamic RSE

3.1 Introduction

In this chapter, a codebook-based approach aimed at identifying the optimal RIS configuration to enhance UE localization accuracy in dynamic RSE is presented. The approach is particularly well suited to structured scenarios such as industrial facilities and indoor spaces, where human, robot and object movement patterns tend to follow predictable trajectories. The proposed approach combines location-related parameters with channel sensing information obtained at sensing RIS elements, together with location-dependent channel features, in order to exploit their underlying relationships.

This chapter is based on Publication II:

- A. Umer, I. Mürsepp, and M. M. Alam, “Reconfigurable Intelligent Surfaces in Dynamic Rich Scattering Environments: BiLSTM-Based Optimization for Accurate User Localization,” in *2024 3rd International Conference on 6g Networking (6gNet)*, pp. 122–126, 2024

3.2 System Model

Consider an enclosed indoor scenario (top view), illustrated in Figure 6, to examine the interactions among system components in a dynamic RSE. It is an indoor scenario with a BS, a UE, and a distributed RIS that partially covers the four walls of the enclosure with its eight elements dedicated to environment sensing. In addition, four SOs moving along the indicated trajectory are also present. The enclosure induces multiple reflections and reverberations as electromagnetic waves repeatedly interact with surrounding walls. At the center of the system model, the BS receives the localization request from the UE located at position U . The SOs moving along predefined trajectories introduce temporal variations in the wireless channel, leading to dynamic fading conditions. These SOs alter signal propagation paths, thereby increasing environmental complexity and producing a rich-scattering scenario [103]. The state of the SOs is represented by the vector P , which aggregates the parameters required to describe their spatial configuration.

A hybrid RIS is strategically deployed along the boundary of the communication environment in a distributed manner. The RIS comprises N_{RIS} reflective elements, each configured according to a predefined state vector $\mathbf{K} \in \mathcal{C}^{N_{\text{RIS}}}$ of dimension $1 \times N_{\text{RIS}}$. Since practical RIS implementations typically support a limited number of discrete states, for example using PIN diode control [14], the configuration set $\mathcal{C}$ is assumed finite and binary. Furthermore, S_{RIS} elements are allocated for channel sensing purposes [13, 9].

It is assumed that channel variations induced by SOs occur sufficiently fast to model the input-output relationship as a discrete-time, fast-fading, frequency-selective channel. In a RSE, the observed field at any location arises from the superposition of multiple reflections, where object-dependent reflections vary with their spatial positions [9]. As a result, sequences of field measurements form distinctive wave fingerprints that enable accurate UE localization.

The wireless channel at the UE depends on both the RIS configuration K and the SO location state P . Let H_{BS-UE} denote the channel impulse response at the UE, incorporating LoS components as well as signals reflected by the RIS, SOs, and enclosure boundaries. The relationship between K and H_{BS-UE} is highly nonlinear and analytically intractable [13]. To capture environmental dynamics, S_{RIS} sensing elements estimate the channel H_{BS-S} between the BS and sensing RIS elements, enabling inference of the SO state P .

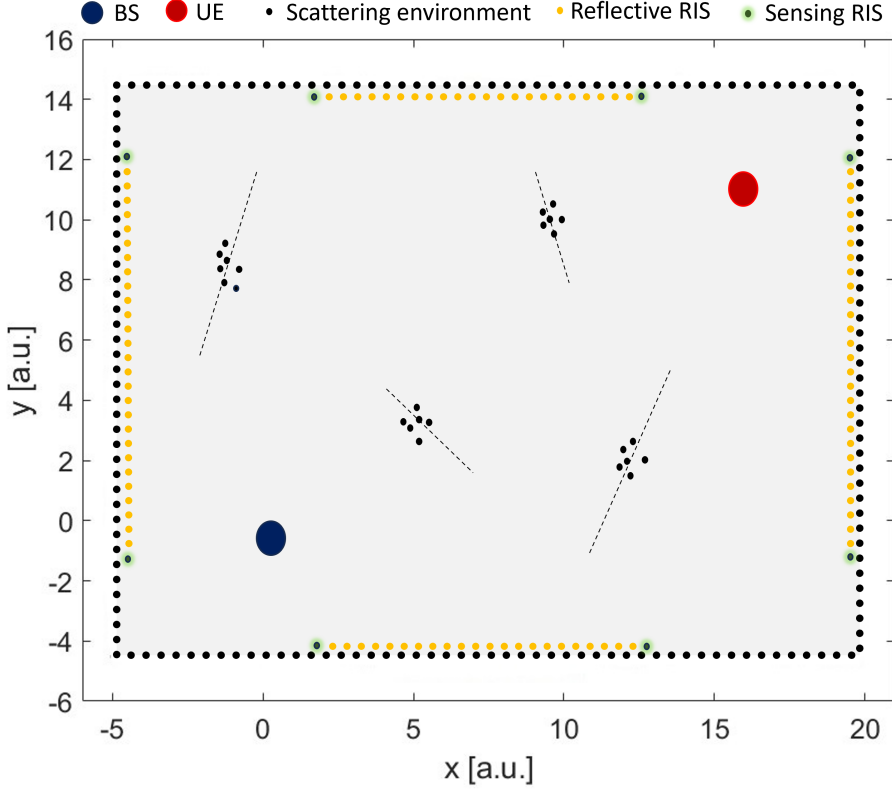


Figure 6: Considered deployment scenario[134] (Top view).

During the offline training phase, the SO state P is the ground-truth SO location produced by the simulator. At inference, P is not observed directly; instead, the S_{RIS} sensing elements measure H_{BS-S} , from which an estimate $\hat{P}$ of the SO state is inferred and used to select the RIS configuration from the codebook. During an offline calibration phase, the system learns optimized RIS configurations for all possible SOs states P using the method described in Section 3.3. At the inference phase, the RIS selects the optimal configuration from a predefined codebook-based on the currently estimated $\hat{P}$.

Conventional cascaded channel models fail to capture the nonlinear RIS parametrization of multipath propagation. Therefore, training data for the proposed learning-based approach is generated using a physics-based end-to-end simulator designed for RIS parametrized wireless environments with controllable fading characteristics [10]. Built on a coupled dipole formulation, it models wireless entities as individual or grouped dipoles defined by physical properties such as resonance frequency and absorption. As shown in Figure 6, scattering surfaces are represented as dipole arrays, while RIS configurations are controlled through dipole resonance tuning [10]. For simplicity, simulations are performed in a two dimensional setting within the x - y plane, with dipole moments oriented along the z axis. The simulator computes both H_{BS-UE} and H_{BS-S} while accounting for wave propagation constraints including causality, dispersion, frequency selectivity, phase amplitude coupling, mutual coupling effects, and long range mesoscopic correlations. Further simulator details are provided in [10].

The environment model contains two classes of scatterer with different roles. The

static dipoles forming the enclosure boundary represent the fixed structure of the room, that is, walls, permanent fixtures and immobile equipment. They are present in every realization and generate the strong, time-invariant multipath component that makes the environment rich scattering in the first place. The SOs represent the mobile part of the environment, such as personnel, autonomous vehicles, forklifts, robotic arms and transported goods in an industrial hall, and it is their motion that makes the optimal RIS configuration time varying. The chosen configuration of four clusters moving along predefined trajectories corresponds to a structured indoor setting in which movement follows repeatable paths determined by the layout of the facility, which is the regime in which an offline-calibrated codebook is meaningful. Because the static and the mobile scatterers are present simultaneously in every realization, the reported results reflect the combined effect of fixed obstacles and SOs; the two are not evaluated as separate scenarios, and the influence of the fixed structure alone therefore corresponds to the limiting case in which the SOs do not move between consecutive localization requests.

3.2.1 Problem Formulation

The objective is to determine the RIS configuration K that enables accurate UE localization. Localization performance is evaluated using the MSE between the estimated coordinates $(\hat{x}, \hat{y})$ and the ground truth location (x, y) , defined as

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N [\mathbf{Y}_i - f(\mathbf{Y}_i)]^2 = \frac{1}{N} \sum_{i=1}^N [(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2] \quad (1)$$

where N denotes the number of measurements, $f(Y_i)$ represents the estimated position, Y_i the true location, and $(\hat{x}_i, \hat{y}_i)$ and (x_i, y_i) correspond to the estimated and actual UE coordinates at the i -th sample. Under fast fading conditions, the goal is to minimize the localization MSE by adapting K according to the stochastic channel behavior induced by RIS configurations.

In free space, the channel H_{BS-UE} is often modeled as a linear cascade between the BS, RIS, and UE. This approximation becomes invalid in RSEs, where signals interact with multiple RIS elements and dynamic SOs along complex propagation paths, leading to analytically intractable channel parametrization. To address this, proposed approach uses a learned biLSTM model. Because the relationships among UE location U , channels H_{BS-UE} and H_{BS-S} , RIS configuration $\mathbf{K}$, and SOs state $\mathbf{P}$ are unknown and highly nonlinear, a training dataset is constructed containing joint samples in format $\{(H_{BS-UE})_l, (H_{BS-S})_l, P_l, K_l, U_l\}_{l=1}^L$. This dataset enables learning an adaptive mapping that optimizes RIS configurations, thereby minimizing localization MSE and improving positioning accuracy under varying channel conditions.

All distances in the coupled-dipole model are expressed in wavelengths, including the enclosure dimensions, the dipole spacings, the RIS element spacing and the grid of UE positions; the localization error is therefore reported in the same unit.

3.3 RIS Configuration Codebook Design Approach

The proposed RIS optimization approach, aligned with the localization objective in (1), employs a biLSTM model trained on historical samples described in 3.2.1. The model learns the mapping between input features $\{H_{BS-UE}, H_{BS-S}, \mathbf{P}\}$ and the corresponding outputs $\{\mathbf{K}, \mathbf{U}\}$.

To jointly estimate the UE position and optimize the RIS configuration, a biLSTM network parameterized by θ is utilized, with architectural details provided in Section 3.4.

The model performs dual tasks: UE localization formulated as a regression problem and RIS configuration selection formulated as a classification problem that minimizes (1). A hybrid loss function is adopted to support both objectives. The regression branch minimizes localization error using MSE, while the classification branch employs categorical cross-entropy for RIS configuration prediction. The combined loss is expressed as

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N (\mathbf{Y}_i - f_{\theta}(\mathbf{Y}_i))^2 + \sum_{i=1}^N \sum_{m=1}^M (-y_m \log(p_m)) + \alpha \|\theta\|^2 \quad (2)$$

where $f_{\theta}(\mathbf{Y}_i)$ denotes the predicted coordinates, $\mathbf{Y}_i$ the ground truth location, y_m and p_m represent true labels and predicted class probabilities, M is the number of RIS configurations, and α is an l_2 regularization coefficient to mitigate overfitting.

The resulting closed-loop approach updates RIS configurations according to environmental variations by selecting optimal settings from a pre-learned codebook, enabling low-latency operation without explicitly modeling nonlinear channel parametrizations. While effective when the SOs parameter space is tractable, performance depends on accurate offline calibration and sufficient discretization resolution of SOs locations. biLSTM networks are particularly suitable due to their bidirectional sequence processing capability, which captures temporal dependencies and contextual correlations essential for reliable prediction in dynamic RSEs [135, 136].

3.4 Performance Evaluation

3.4.1 Simulation Setup

The proposed method is evaluated through numerical simulations of the RSE shown in system model and implemented using a physics-based end-to-end simulator [10]. The setup consists of a single-antenna BS, a mobile-single antenna UE, and a RIS with $N_{\text{RIS}} = (20, 60, 100)$ binary tunable elements. In the simulator, dipole parameters are set in terms of resonance frequency f_{res} , charge term χ and absorptive damping term Γ_L . Dipole parameters for transceivers are set to $\{f_{\text{res}} = 1, \chi = 0.5, \Gamma_L = 0\}$, while scattering objects use $\{f_{\text{res}} = 10, \chi = 50, \Gamma_L = 10^4\}$ with spacing of $\lambda/4$. RIS elements adopt parameters $\{f_{\text{res}} = \{1, 5\}, \chi = 0.2, \Gamma_L = 0.03\}$. The dipole parameters are guided by [107].

Data preparation involves collecting channel response and SOs state across multiple RIS configurations and UE positions as described in Section 3.3. UE locations are sampled on a regular grid with $\lambda/4$ spacing. For each fixed UE position and RIS size, multiple RIS configurations are evaluated, while SO positions are randomly selected at ten points along predefined trajectories. Corresponding channel responses H_{BS-UE} and H_{BS-S} are recorded, and RIS configurations K_l are one-hot encoded for classification.

The resulting dataset $\{(H_{BS-UE})_l, (H_{BS-S})_l, P_l, K_l, U_l\}_{l=1}^L$ is divided into 80% training and 20% testing, with the training portion further split into 80% training and 20% validation for hyperparameter tuning via grid search and overfitting control. Each recorded channel response is a complex value. The dataset is composed of 84,000 samples. The dataset split in this chapter differs from the 70/15/15 partition used in Chapters 4 and 5, which allocates a larger validation set to support Bayesian optimization over a broader hyperparameter space. As the model here is tuned by grid search over a substantially smaller space and requires correspondingly less validation data. Training, validation and test sets contain disjoint SO trajectory realizations, so that no test realization is seen during training or hyperparameter selection.

The implemented biLSTM adopts a dual input architecture. Sequential channel data are processed using a biLSTM layer with 50 units followed by an additional LSTM layer with

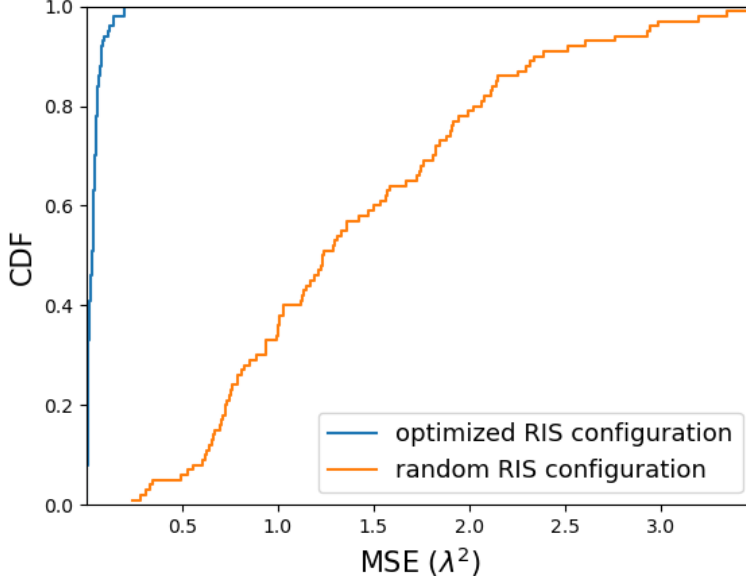


Figure 7: Cumulative distribution function (CDF) of MSE for random and optimized RIS configuration with $K = 500$ and $N_{\text{RIS}} = 20$.

Table 2: Average MSE for random and optimized RIS configuration, standard deviation σ_b of baseline MSE, σ_o of optimized MSE, and percentage error reduction compared to baseline.

N_{RIS}	k	Baseline MSE (λ^2)	Optimized MSE (λ^2)	σ_b	σ_o	% error reduction
20	10	0.87	0.35	0.630	0.271	59.90%
20	100	0.87	0.08	0.630	0.086	90.84%
20	500	0.87	0.04	0.630	0.038	95.42%
60	100	0.59	0.17	0.591	0.166	71.19%
100	100	2.45	0.07	1.484	0.075	97.14%

50 ReLU-activated units for feature refinement. RIS configuration inputs pass through an embedding layer that maps categorical values into a 20-dimensional representation before flattening. Features from both branches are concatenated and fed into two dense outputs: a linear layer for UE coordinate regression and a softmax layer for RIS configuration classification. The model is trained using the Adam optimizer [137] with a learning rate of 0.0001, employing MSE loss for localization and categorical cross entropy for configuration prediction. Training runs for 200 epochs with batch size 32, using checkpointing to retain the model with minimum validation loss for final testing. For baseline comparison, a simple neural network using random RIS configurations is trained under identical dataset splits to establish reference MSE performance. After training, the biLSTM model is evaluated for RIS configuration optimization aimed at minimizing localization MSE. Performance is assessed with test samples with $N_{\text{RIS}} = 20$ and three RIS configuration set sizes $k = \{10, 100, 500\}$.

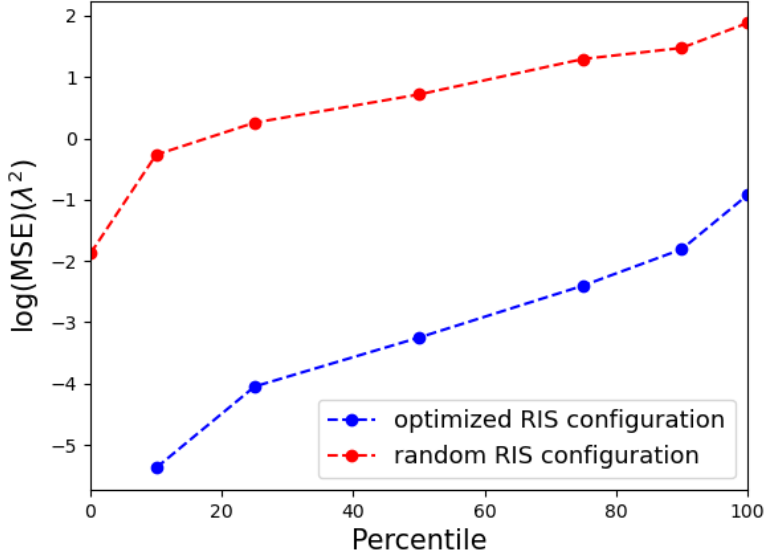


Figure 8: MSE percentile for optimized and random RIS configuration with $K = 100$ and $N_{\text{RIS}} = 100$.

3.4.2 Results

As illustrated in Figure 7 and Figure 8, optimized RIS configurations significantly improve UE localization accuracy compared to random configurations. With $N_{\text{RIS}} = 20$ held fixed, increasing k from 10 to 500 raises the MSE reduction relative to the random-configuration baseline from 59.90% to 95.42%. Over the same range the absolute MSE of the optimized configuration falls from $0.35\lambda^2$ to $0.04\lambda^2$, a reduction of 88.6%. Localization accuracy also benefits from training over a richer configuration space, noting that up to $2^{N_{\text{RIS}}}$ distinct RIS configurations are theoretically available. The random-configuration baseline is independent of the codebook size and is therefore evaluated once per value of N_{RIS} , averaged over the independent runs for N_{RIS} .

The impact of varying the number of RIS elements, $N_{\text{RIS}} = \{20, 60, 100\}$, is also analyzed using the proposed biLSTM model, as shown in Table 2. Although increasing N_{RIS} leads to reduced MSE, the observed improvement remains moderate. This behavior arises because the number of configurations used during training remains fixed despite the exponential growth of the achievable configuration space with larger N_{RIS} . Consequently, the available RIS diversity is not fully exploited. Greater performance gains are expected by incorporating a wider range of RIS configurations, particularly in environments with frequently changing SO positions. Effective selection of N_{RIS} should therefore account for environmental dynamics, including the density, size, and mobility of SOs, to maximize localization performance.

The number of configurations K_l sets the resolution at which the configuration space is sampled. A larger K gives the classifier a finer set to choose from and reduces the loss incurred when no available configuration suits the current SO state. It also increases the number of classes to be separated from a training set of fixed size and the number of simulator evaluations required during calibration, so K in practice is limited by the calibration budget. The available space of $2^{N_{\text{RIS}}}$ configurations remains far larger than any K used here.

The trend observed as k increases indicates the direction in which performance moves as the discretization of the configuration space is refined. The limiting case of an un-

bounded codebook is a design that synthesizes a new configuration for each channel realization instead of selecting a stored entry, which is the adaptive scheme developed in the following chapter. That scheme is evaluated against the codebook-based method of this chapter under the same environment model, and attains lower localization error across the range of RIS sizes and signal-to-noise ratios considered there, which quantifies the residual penalty of the finite codebook used here.

3.5 Summary

This chapter presents an overview of the data-driven RIS configuration approach designed in Publication II, for dynamically evolving RSEs, avoiding reliance on explicit analytical channel modeling. A biLSTM model is employed to learn environment dependent patterns and adapt RIS configurations to improve UE localization accuracy through minimization of the MSE. Performance evaluation validates the effectiveness of the method, demonstrating reliable optimization of RIS settings under complex propagation conditions. Despite these gains, the codebook-based approach has three intrinsic limitations. It depends on an offline calibration phase that must be repeated whenever the environment statistics change; it discretizes the configuration space, so accuracy is bounded by the resolution of the SO-state grid; and it adapts only by re-selecting a pre-stored entry, which limits responsiveness in highly dynamic RSEs. These limitations motivate the codebook-free, adaptive sensing-assisted design developed in following chapter. The following chapter outlines the adaptive RIS configuration by environmental sensing approach for UE localization under rich scattering multipath conditions, based on Publication III. It explores the potential of going beyond static and pre-stored RIS configuration settings in UE localization in RSE.

4 Adaptive RIS Configuration Design by Environmental Sensing for User Localization in RSE

4.1 Introduction

In this chapter, an adaptive RIS configuration approach for UE localization in dynamic RSE using a distributed RIS-assisted network is presented. The BS transmits pilot signals, which are redirected toward the UE by the RIS. A subset of RIS elements actively senses the environment to estimate scattering contributions from SOs, quantized via their location estimates. RIS-assisted sensing leverages predefined sequences of randomized RIS configurations, implemented using hybrid meta-atoms [9] that simultaneously capture and reflect waves, providing sufficient diversity to extract non-cooperative SOs information from a single node pair [107]. Learned sensing further optimizes configuration sequences to enhance UE localization accuracy [138]. Given the highly nonlinear and sequential relationships between RIS configurations, UE measurements, and scattering, scalable, context-aware solutions are necessary. The system dynamically adapts RIS configurations based on accumulated measurements, enabling tracking of evolving multipath conditions and minimizing localization error without relying on static settings or pre-stored mappings.

This chapter is based on Publication III:

- A. Umer, I. Mürsepp, and M. M. Alam, “Adaptive RIS Configuration Design With Environmental Sensing for User Localization in Dynamic Rich Scattering Environment,” *IEEE Transactions on Mobile Computing*, vol. 25, no. 7, pp. 9770–9783, 2026

This chapter presents scalars by italic symbols (for example, b), vectors by bold lower-case symbols (for example, $\mathbf{b}$), and matrices by bold uppercase symbols (for example, $\mathbf{B}$). The notation $|\cdot|$ represents the magnitude, while $\hat{b}$ indicates an estimate of b . The operator $\text{diag}(\mathbf{y})$ forms a diagonal matrix whose diagonal entries are taken from $\mathbf{y}$. The real and imaginary parts of a complex quantity are expressed by $\Re(\cdot)$ and $\Im(\cdot)$, respectively, and the expectation is denoted by $\mathbb{E}(\cdot)$. A complex Gaussian random variable with mean m and variance v is represented as $\mathcal{CN}(m, v)$.

4.2 System Model

Consider a RSE where a user equipment U with N_U antennas estimates its position $\mathbf{u}$ with support from a BS equipped with N_{BS} antennas and a uniform linear array of RIS elements positioned along the enclosure’s periphery, as illustrated in Figure 9. The RSE consists of N_E dipoles whose locations are indicated by a black dipole fence and collections of clusters of colored dipoles at various locations, inside the enclosure, representing SOs. The location of dipoles presented with black color always stays the same, while the location of colored dipoles is varied randomly, in each simulation realization, along their fixed trajectories indicated by the dotted line. The locations of the dynamic dipoles representing SOs are shown in three different colors for first three realizations (plum, orange, cyan corresponding to each realization). The RSE is equipped with N_{BS} antenna BS (blue dipoles), a N_U antenna user equipment U (red dipoles), and a uniform linear array of distributed RIS installation with N_{RIS} elements (yellow dipoles) that partially covers the four walls (black dipole fence) of the enclosure. S_{RIS} denotes the subset of RIS elements (green dipoles) used to estimate the SO location state. The environment contains M SOs, each following a fixed trajectory, with positions updated simultaneously while moving independently along their respective paths, reflecting structured indoor scenarios such as industrial or controlled spaces.

The RIS configuration is managed by a controller receiving commands from the BS.

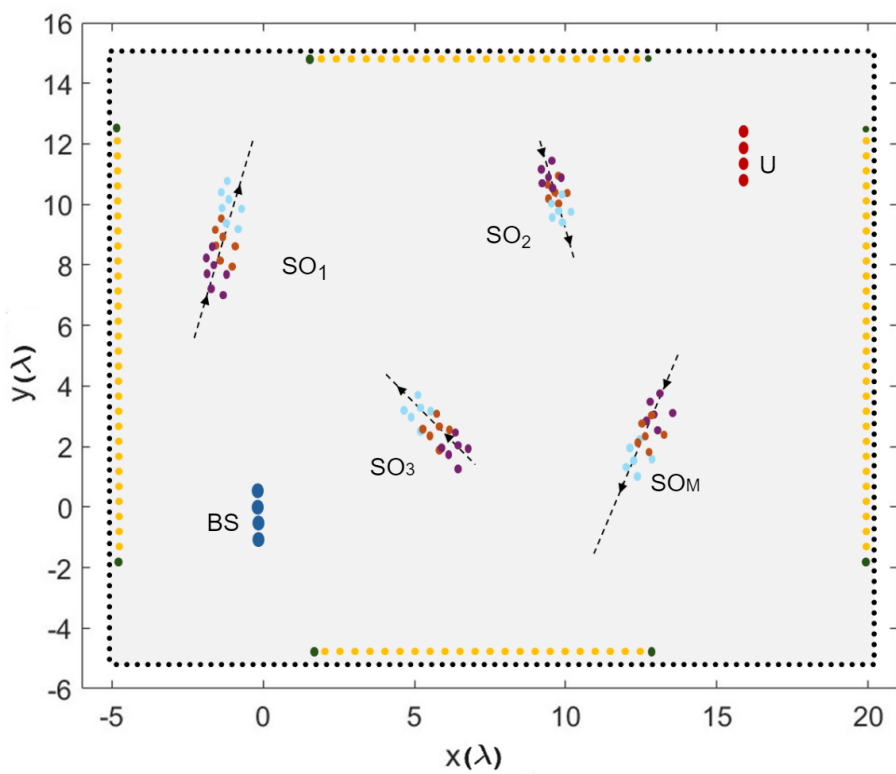


Figure 9: Illustration of considered RSE.

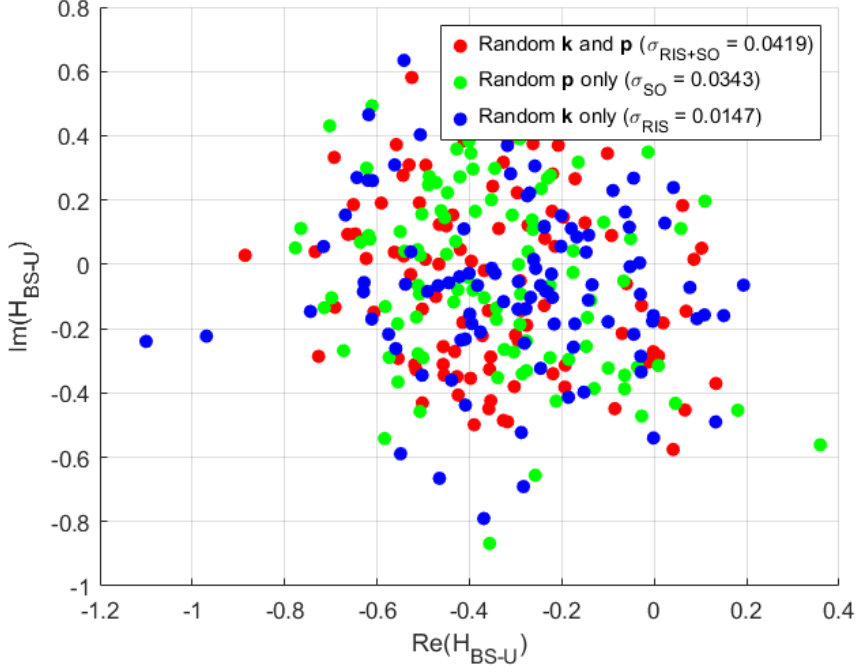


Figure 10: Distribution of $\mathbf{H}_{BS-U}$ in the complex plane for a SISO setup.

Each of the N_{RIS} elements applies a tunable phase shift represented by $\mathbf{k} \in \mathbb{C}^{1 \times N_{RIS}}$ under the unit-modulus constraint $|\mathbf{k}_n| = 1$, ensuring amplitude preservation while adjusting the phase $\delta_n \in [0, 2\pi)$. A subset S_{RIS} of elements is dedicated to channel sensing, with zero power splitting to prevent reflection [9, 13].

Wave propagation in this scenario undergoes multiple reflections and scattering from walls, RIS, and moving SOs, producing a dynamic, complex fading environment [103]. The estimated locations of the M SOs, obtained via S_{RIS} , are represented by the vector $\mathbf{p} \in \mathbb{R}^{2M}$. Figure 10 illustrates the distribution of the wireless channel $\mathbf{H}_{BS-U}$ in the complex plane across 100 random realizations of RIS configurations $\mathbf{k}$ and SOs locations $\mathbf{p}$. Variations in either RIS phases or SO positions highlight the channel's sensitivity to both elements, demonstrating the rich scattering and dynamic nature of the considered environment.

4.2.1 Channel Model

The channel is assumed constant over a coherence period, while subtle, configuration-dependent fluctuations arise in RSE due to slight SOs motion or multipath dynamics. These are modeled as structured fast-fading in discrete time, enabling capture of temporal dependencies across RIS configurations for enhanced scattering and user localization estimation. The stochastic channel frequency response at the user, $\mathbf{H}_{BS-U} \in \mathbb{C}^{N_U \times N_{BS}}$, includes both line-of-sight and multipath components interacting with RIS elements, SOs, and walls.

To model these effects, a physics-based end-to-end channel simulator tailored for RIS-parameterized environments is employed [10]. Using the coupled-dipole formalism, the simulator represents walls, SOs, RIS, and transceivers as dipole assemblies with

configurable properties such as resonance frequency and absorption, ensuring realistic scattering and adherence to electromagnetic principles. The total dipole count is $N = N_{\text{BS}} + N_{\text{U}} + N_{\text{E}} + N_{\text{RIS}}$, where N_{E} and N_{RIS} represent the RSE and RIS elements, respectively.

The user channel response is expressed as

$$\mathbf{H}_{\text{BS-U}} = \mathbf{V}[(N_{\text{BS}} + 1) : (N_{\text{BS}} + N_{\text{U}}), 1 : N_{\text{BS}}], \quad (3)$$

with

$$\mathbf{V} \triangleq \text{diag}([\alpha_1^{-1}, \alpha_2^{-1}, \dots, \alpha_N^{-1}]) \mathbf{W}^{-1}, \quad (4)$$

where α_i^{-1} is the inverse polarizability of the i th dipole. The polarizability is defined as

$$\alpha_i(f) = \frac{\chi_i^2}{4\pi^2 f_{\text{res},i}^2 - 4\pi^2 f^2 + j(\gamma_i^R + 2\pi f \Gamma_i^L)}, \quad (5)$$

with χ_i^2 as a charge-related amplitude factor, $f_{\text{res},i}$ the resonance frequency, γ_i^R the radiation damping, and Γ_i^L the absorptive damping term. Off-diagonal entries in $\mathbf{W}$ are $-G_{ij}(f)$, representing two-dimensional free-space Green's function interactions between dipoles at positions $\mathbf{r}_i$ and $\mathbf{r}_j$:

$$G_{ij}(\mathbf{r}_i, \mathbf{r}_j, f) \triangleq -j \frac{k^2}{4\epsilon\delta} H_0^{(2)}(k|\mathbf{r}_i - \mathbf{r}_j|), \quad (6)$$

where $H_0^{(2)}(\cdot)$ is the Hankel function of the second kind.

The channel model inverts the coupled-dipole matrix $\mathbf{W}$ separately at each frequency, so one frequency point gives a single complex coefficient in which every path is summed with its phase. With one observation per frame the paths stay superposed, and the geometric information comes from how that coefficient varies across frames which is driven both by the designed RIS configurations and by the scatterer motion between frames. This end-to-end modeling accurately captures space-time causality, frequency-selective dispersion, phase-amplitude coupling of RIS elements, mutual coupling, and long-range mesoscopic correlations, providing a realistic representation of wave propagation in complex, dynamic scattering environments.

4.2.2 Signal Transmission and Reception

Assuming a narrowband system, the BS transmits T known pilot symbols $\mathbf{x}^{(t)} \in \mathbb{C}^{N_{\text{BS}} \times 1}$ to the user over T time frames during a localization request. The received signal $\mathbf{y}^{(t)} \in \mathbb{C}^{N_{\text{U}} \times 1}$ comprises contributions from the direct path, if present, and multipath components reflected by the RIS and scattering environment. User responses are fed back to the BS via a low-rate link, enabling centralized RIS configuration and localization. The input-output relation is expressed as

$$\mathbf{y}^{(t)} = \mathbf{H}_{\text{BS-U}}^{(t)} \mathbf{x}^{(t)} + \mathbf{w}^{(t)}, \quad t \in \mathbb{Z}, \quad (7)$$

where $\mathbf{w}^{(t)} \sim \mathcal{CN}(0, \sigma^2)$ represents additive Gaussian noise.

Simultaneously, S_{RIS} RIS elements are dedicated to environmental sensing by measuring the channel $\mathbf{H}_{\text{BS-S}} \in \mathbb{C}^{S_{\text{RIS}} \times N_{\text{BS}}}$ between the BS and sensing elements. Observations follow

$$\mathbf{y}_s^{(t)} = \mathbf{H}_{\text{BS-S}}^{(t)} \mathbf{x}^{(t)} + \mathbf{w}^{(t)}, \quad t \in \mathbb{Z}, \quad (8)$$

enabling inference of the SO location state $\mathbf{p}$ at time t and estimating environmental scattering without requiring user cooperation.

Unlike conventional approaches using random RIS configurations, this method adaptively optimizes $\mathbf{k}$ to enhance user localization in RSE. A centralized architecture is assumed, with the BS coordinating scattering estimation, RIS updates, and user localization.

4.2.3 Problem Formulation

The localization task aims to estimate the unknown user position $\mathbf{u}$ from T received observations $[\mathbf{y}^{(t)}]_{t=0}^{T-1}$, given known BS and RIS positions and estimated SOs locations. The SOs state $\mathbf{p}$ is inferred from RIS sensing signals $[\mathbf{y}_s^{(\tau)}]_{\tau=0}^t$ collected by S_{RIS} elements, capturing environmental scattering in the RSE. In this context, the RIS acts as a set of virtual anchors: it cannot transmit or receive directly, but dynamically adjusting its configuration induces observable variations in received signals to aid localization. RIS operation in RSE involves two stages: sensing to obtain context awareness and identifying optimal configurations for user localization, requiring offline training and online inference. Sensing estimates the SOs state from field measurements, informing RIS configuration design for subsequent localization.

The channel $\mathbf{H}_{\text{BS-U}}$ reflects combined effects of RIS configurations and SOs interactions, while $\mathbf{H}_{\text{BS-S}}$ provides information to infer $\mathbf{p}$. Sequential measurements form a unique wave fingerprint enabling user localization.

The SOs location at time t is estimated from pilot signals sensed at S_{RIS} as

$$\hat{\mathbf{p}}^{(t)} = G^{(t)}([\mathbf{y}_s^{(\tau)}]_{\tau=0}^t), \quad (9)$$

where $G^{(t)}$ maps past sensed pilots to $\hat{\mathbf{p}}^{(t)} \in \mathbb{R}^{2M}$. Based on this estimate and user observations $[\mathbf{y}^{(\tau)}]_{\tau=0}^t$, the next RIS configuration is selected as

$$\mathbf{k}^{(t+1)} = F^{(t)}([\mathbf{y}^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}), \quad (10)$$

where $F^{(t)}$ maps prior signals and estimated SOs state to the next RIS setting. The updated configuration generates the next measurement $\mathbf{y}^{(t+1)}$. At initialization ($t < 0$), a fixed default $\mathbf{k}^{(0)}$ is used.

After collecting all T pilot signals, the user location estimate is obtained as

$$\hat{\mathbf{u}}^{(T)} = Q([\mathbf{y}^{(t)}]_{t=0}^{T-1}, \hat{\mathbf{p}}^{(T-1)}), \quad (11)$$

where Q maps the pilot signals and estimated scattering to the two-dimensional user position.

The overall objective is to minimize the localization error by jointly optimizing $\{G^{(t)}\}_{t=0}^{T-1}$, $\{F^{(t)}\}_{t=0}^{T-1}$, and Q under the constraints

$$\min_{\{G^{(t)}, F^{(t)}\}, Q} \sqrt{\mathbb{E} [\|\hat{\mathbf{u}}^{(T)} - \mathbf{u}\|^2]} \quad (12a)$$

$$\text{s.t. } \hat{\mathbf{p}}^{(t)} = G^{(t)}([\mathbf{y}_s^{(\tau)}]_{\tau=0}^t), \quad (12b)$$

$$\mathbf{k}^{(t+1)} = F^{(t)}([\mathbf{y}^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}), \quad (12c)$$

$$\hat{\mathbf{u}}^{(T)} = Q([\mathbf{y}^{(t)}]_{t=0}^{T-1}, \hat{\mathbf{p}}^{(T-1)}), \quad (12d)$$

$$|[\mathbf{k}^{(t+1)}]_n| = 1, \quad \forall n \in N_{\text{RIS}}, t. \quad (12e)$$

The estimators use both the magnitude and the phase of the received signal at user. The phase carries information about the user position only if the receiver is phase-coherent and time-synchronized with the transmitter, and this is assumed throughout.

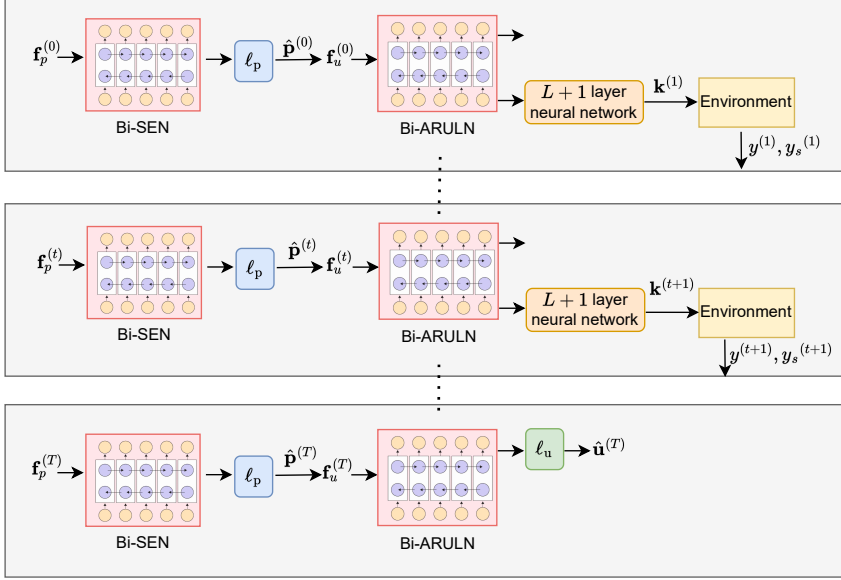


Figure 11: Proposed adaptive localization approach for RIS-assisted RSE.

Carrier frequency offset, phase noise, and timing error would rotate the phase of the received signal and reduce localization accuracy.

Directly solving this problem is challenging due to the joint estimation of scattering, RIS configuration, and user localization. Codebook-based approaches reduce complexity by discretizing RIS settings [108], but limit flexibility and adaptability in dynamic RSE, restricting localization accuracy.

4.3 Adaptive biLSTM-based Localization Approach

A deep learning-based adaptive RIS configuration approach is proposed to solve the localization problem in (12) without relying on predefined geometric channel models or limiting configurations to a fixed codebook. At each time step t , the RIS configuration $\mathbf{k}^{(t+1)}$ is determined from prior user observations $[\mathbf{y}^{(\tau)}]_{\tau=0}^t$ and the estimated SOs state $\mathbf{p}^{(t)}$. A key challenge is the linear growth of measurements over time, which increases computational complexity for large t . To ensure scalability, the network compresses past observations into a fixed-dimensional information vector while retaining relevant features for decision making.

To achieve this, a biLSTM model is employed to encode sequential measurements and capture temporal dependencies. The approach uses a two-stage deep learning structure: first, the Scattering Estimation Network (Bi-SEN) estimates the dynamic SO positions from sensing observations at $\mathcal{S}_{\text{RIS}}$, characterizing the current scattering environment. Second, the Adaptive RIS-Assisted User Localization Network (Bi-ARULN) designs the RIS configurations for the next time slot based on the estimated scattering and user pilot signals, aiming to optimize user localization at the final time T . The bidirectional structure of the network allows it to leverage information from both past and future contexts, enhancing scattering estimation and improving adaptive RIS configuration for accurate localization.

The network architecture, shown in Figure 11, employs a biLSTM-based model com-

posed of two sequential networks, Bi-SEN and Bi-ARULN, each integrating fully connected layers for feature extraction and biLSTM layers for sequential processing over multiple sensing frames.

In the Bi-SEN network, at each time step t , forward and backward hidden states $\mathbf{s}_{p,f}^{(t)}$, $\mathbf{s}_{p,b}^{(t)}$ and corresponding cell states $\mathbf{c}_{p,f}^{(t)}$, $\mathbf{c}_{p,b}^{(t)}$ are updated using the input $\mathbf{f}_p^{(t)} = [|\mathbf{y}_s^{(t)}|, \angle \mathbf{y}_s^{(t)}]$, which concatenates the magnitude and phase of sensed signals. The biLSTM updates and gate activations follow standard formulations with trainable fully connected layers $\mathbf{u}_{cp}(\cdot)$ and $\mathbf{r}_{cp}(\cdot)$ for input, forget, and output gates. The estimated SO positions are produced via a fully connected output layer:

$$\hat{\mathbf{p}}^{(t)} = \ell_p([\mathbf{c}_{p,f}^{(t)}; \mathbf{c}_{p,b}^{(t)}]), \quad (13)$$

representing the inferred scattering environment at time t .

The Bi-ARULN network receives the concatenated vector $\mathbf{f}_u^{(t)} = [|\mathbf{y}^{(t)}|, \angle \mathbf{y}^{(t)}, \hat{\mathbf{p}}^{(t)}]$, combining user pilot measurements and estimated SO positions. Forward and backward hidden and cell states are updated similarly to Bi-SEN, producing a concatenated hidden state $\mathbf{s}_u(t) = [s_{u,f}(t); s_{u,b}(t)]$. This vector passes through a multi-layer fully connected network with ReLU activations to generate an intermediate output $\gamma(t)$, which is mapped via a final linear layer to the real-valued vector $\bar{\mathbf{k}}^{(t+1)} \in \mathbb{R}^{2N_{\text{RIS}}}$ representing the real and imaginary components of the next RIS configuration. The unit-modulus constraint is enforced element-wise to obtain $\mathbf{k}^{(t+1)}$:

$$[\mathbf{k}^{(t+1)}]_n = \frac{[\Re(\bar{\mathbf{k}}^{(t+1)})]_n + j[\Im(\bar{\mathbf{k}}^{(t+1)})]_n}{\sqrt{[\Re(\bar{\mathbf{k}}^{(t+1)})]_n^2 + [\Im(\bar{\mathbf{k}}^{(t+1)})]_n^2}}. \quad (14)$$

The adaptive design in this chapter generates a new configuration at every time frame rather than selecting one from a codebook, so the network must produce the configuration directly. Training by gradient descent requires this output to vary smoothly, which a two-state configuration does not allow, and the phase is therefore treated as continuous. This is an idealization of a practical surface, where the phase is quantized to a small number of bits, and the reflection amplitude varies with the phase state. Quantization and amplitude variation reduce the achievable gain but do not change the structure of the design problem, and the results in this chapter should be read as the performance attainable with a continuously variable surface. The quantization of configurations generated by the network to form a codebook is potential future work.

Finally, the estimated user position at time T is computed by processing the concatenated forward and backward cell states through a fully connected network:

$$\hat{\mathbf{u}}^{(T)} = \ell_u([\mathbf{c}_{u,f}^{(T)}; \mathbf{c}_{u,b}^{(T)}]), \quad (15)$$

yielding the final localization output.

4.3.1 Loss Function

The biLSTM model is trained using the Adam optimizer [137] to minimize the root mean squared error (RMSE) between the true and estimated UE positions. The user localization loss in Bi-ARULN is defined as

$$\sqrt{\mathbb{E} [\|\hat{\mathbf{u}}^{(T)} - \mathbf{u}\|^2]}. \quad (16)$$

For scattering estimation, the cumulative RMSE loss in localizing M SOs at each stage using Bi-SEN is

$$\sqrt{\mathbb{E} [\|\hat{\mathbf{p}}^{(t)} - \mathbf{p}\|^2]}. \quad (17)$$

These losses guide the network to accurately estimate the user position while adapting to environmental dynamics through a sequence of optimized RIS configurations. The loss in (16) focuses on the final time step, allowing the network flexibility to optimize RIS configurations across all T measurement stages. After training, the model generalizes across the deployment area, dynamically generating RIS configurations based on received signals from the user and S_{RIS} elements, independent of the user's location within the coverage region.

4.4 Performance Evaluation

4.4.1 Simulation Setup

The simulation parameters are summarized in Table 3. Two experimental scenarios are considered, namely SISO and MIMO, to evaluate the impact of transceiver antenna arrays alongside RIS operation in RSE. As illustrated in Figure 9, the BS location is fixed, while distributed RIS units are deployed at known positions. The unknown user locations $\mathbf{u}$ are uniformly distributed over the enclosed x - y plane on a regular grid with $\lambda/2$ spacing and fixed orientation. The pilot signal $x^{(t)}$ is deterministic and set to unity.

The trajectories of M SOs are predefined such that each object begins from a known initial position and moves with deterministic steps of maximum length $\lambda/4$, perturbed by Gaussian variations in direction and position, given by $\Delta\theta \sim \mathcal{N}(0, \sigma_\theta^2)$ with $\sigma_\theta = 0.052$ radians and $\Delta p \sim \mathcal{N}(0, \sigma_p^2)$ with $\sigma_p = \lambda/20$. The central dipole position of each SOs cluster is tracked in every realization. Training, validation and test sets contain disjoint SO trajectory realizations, so that no test realization is seen during training. A training sample is therefore a sequence of T frames along a moving trajectory. The number of objects is held at $M = 4$ throughout this chapter, and the environment is not varied in this respect. The sensitivity of the same two-stage design to the number of SOs is examined in Chapter 5, where M is varied over 2, 4, 6 and reported in results.

The tunable dipole parameters for transceivers, environment (including SOs), and RIS, namely the resonance frequency f_{res} , charge term χ , and absorptive damping term Γ_L , follow the configuration specified in Table 3 and are guided by [10]. Each RIS element introduces insertion loss which is configured by Γ_L .

The proposed biLSTM-based adaptive RIS configuration method for sensing-assisted user localization in RSE is implemented using the parameters in Table 3, optimized via Bayesian Optimization (BO). The network is trained for 200 epochs using 1,806,000 samples. Training data for Bi-SEN consists of channel responses measured at S_{RIS} , while Bi-ARULN uses user-side channel responses together with Bi-SEN outputs. Channel measurements are generated by simulating moving SOs across arbitrary user locations to produce received pilot observations. The labels for Bi-SEN correspond to the $2M$ -dimensional ground-truth SO positions, whereas Bi-ARULN is trained using two-dimensional user location labels. The dataset is divided into 70% training, 15% validation, and 15% testing subsets. The network architecture and training hyperparameters were selected by hyperparameter optimization, with each candidate trained from a randomly initialized starting point and evaluated on the validation set. The configuration achieving the lowest validation loss was retained, and evaluated on the held-out test set.

After training, the biLSTM model autonomously generates sequential RIS configurations using recurring scattering estimates and received pilot measurements, enabling localization of users throughout the coverage region. Localization performance is evaluated against the following baseline strategies:

- *Random RIS configuration:* A random configuration baseline selects RIS states independently at each time step and employs a DNN with dimensions [200, 200, 200,

Table 3: Simulation and Network Parameters for Adaptive biLSTM-based Localization Approach

Label	Value
Simulation Parameters	
M	4
N_{BS}	$\{1,4\}$
N_U	$\{1,4\}$
N_{RIS}	20,60,100
Transceivers dipole parameters	$f_{res} = 1, \chi = 0.5, \Gamma_L = 0$
Transceivers dipole spacing	$\lambda/2$
Environment and SOs dipole parameters	$f_{res} = 10, \chi = 50, \Gamma_L = 10^4$
Environment and SOs dipole spacing	$\lambda/4$
RIS dipole parameters	$f_{res} \in \{0.8, 1.2\},$ $\chi = 0.2, \Gamma_L = 0.03$
RIS dipole spacing	$\lambda/2$
Parameters of the biLSTM Network	
Batch size, B	[32,64,128]
BiLSTM Layers, N_L	[2,4,6]
Hidden state dimension, d_s	[25,35,45]
Learning rate, η	[0.001,0.01,0.005,0.05]
Maximum epochs	200
DNN layers, L_n	4

2] to map received pilot magnitude and phase over T frames to user position by minimizing the error in (16).

- *Codebook-based approach*: A codebook-based method learns configuration candidates offline and selects the closest configuration during inference based on estimated environmental conditions, as in [2].
- *DNN-based Scattering Estimation*: A DNN-based scattering estimation baseline replaces sequential Bi-SEN modeling with a feedforward network of size [200, 200, 200, $2M$] while retaining Bi-ARULN for localization.
- *Bi-ARULN only*: This baseline employs Bi-ARULN alone without incorporating environmental scattering estimation. This baseline is based on [125, 124].

All baseline models are evaluated in the MIMO setting, whereas the proposed method is tested under both SISO and MIMO scenarios.

4.4.2 Results

To assess performance relative to benchmark methods, the impact of RIS size N_{RIS} on localization accuracy is analyzed in Figure 12. Increasing N_{RIS} consistently reduces RMSE for all approaches, highlighting the advantage of larger RIS sizes in dynamic RSE due to improved spatial information. The proposed method achieves the lowest RMSE across all configurations, demonstrating effective adaptive optimization of RIS settings for accurate localization. A reduction of 79% in RMSE is observed as N_{RIS} increases from 20 to 100 for the MIMO network, and 76% for the SISO network, while other methods achieve smaller

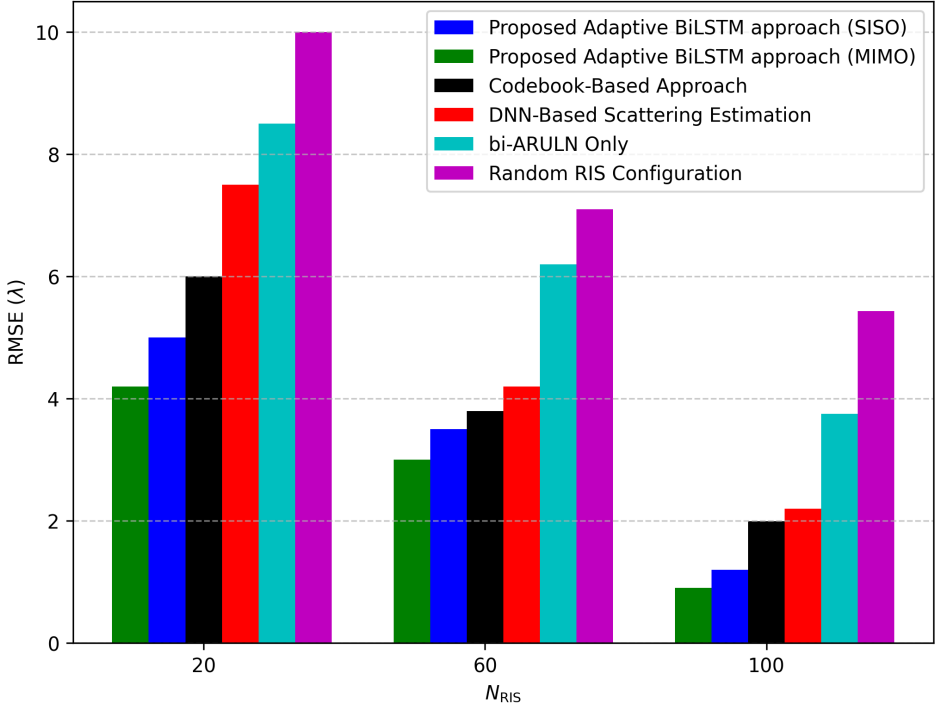


Figure 12: RMSE of user localization versus N_{RIS} , for $T = 21$ and $\text{SNR} = -20$ dB.

improvements below 70%. The MIMO configuration consistently outperforms SISO owing to higher spatial diversity. The proposed biLSTM approach remains scalable across varying RIS sizes, requiring only minor architectural adjustment by modifying the output dimension of the $(L+1)$ layer following the biLSTM cells. Results further indicate that adaptive RIS design and the inclusion of antenna arrays at transceiver nodes significantly enhance localization accuracy in dynamic RSE. The key quantitative takeaway is that enlarging the RIS from $N_{\text{RIS}} = 20$ to 100 reduces localization RMSE by about 79% (MIMO) and 76% (SISO), the largest gain among all methods.

User localization performance versus SNR is defined as $\text{SNR}_{\text{dB}} = 10\log_{10}(P_{\text{BS}}\mathbb{E}[||\mathbf{H}_{\text{BS}-U}||^2]/\sigma^2)$, is evaluated in Figure 13, where P_{BS} denotes the BS transmit power. Localization accuracy increases with SNR for all methods, with different improvement rates. The proposed approach consistently achieves the highest accuracy, demonstrating effective adaptive refinement of RIS configurations using sequential channel observations while accounting for scattering in RSE. Both SISO and MIMO variants improve steadily with increasing SNR, while MIMO outperforms SISO due to greater spatial diversity, most evident in the mid-SNR region. The smaller performance gap at very low and high SNR corresponds to noise-limited and system-limited regimes, respectively, where additional antennas provide limited benefit. The key quantitative takeaway is that across the evaluated SNR range, the proposed method attains the lowest RMSE at every SNR, with the MIMO-SISO gap largest in the mid-SNR region.

The codebook-based method achieves moderate accuracy but lacks adaptability to varying propagation conditions, particularly at low SNR. The DNN-based scattering estimation approach outperforms nonadaptive or scattering-unaware methods but remains

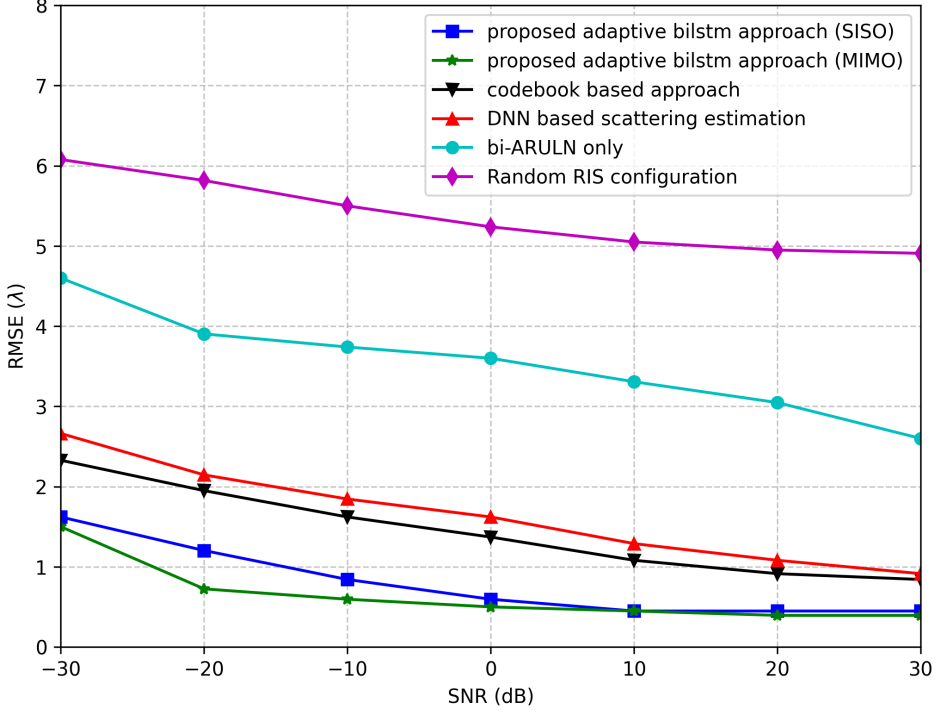


Figure 13: RMSE of user localization versus the SNR for $N_{RIS} = 100$ and $T = 21$.

inferior to sequential modeling, as it captures channel structure without exploiting temporal dependencies. The Bi-ARULN-only method yields the lowest accuracy due to the absence of scattering awareness in dynamic RSE, even at higher SNR.

Figure 14 evaluates scattering estimation error in (17), measured as the cumulative RMSE in estimating M SOs, as a function of the number of time frames used for RIS configuration design and user localization. The proposed Bi-SEN method achieves the lowest error for both MIMO and SISO settings by exploiting sequential modeling for dynamic scattering estimation. Increasing T leads to a consistent RMSE reduction, with MIMO attaining superior performance due to higher spatial diversity and gradual SOs motion, which strengthens temporal correlation learning. The DNN-based estimation approach yields higher RMSE across all T since it lacks temporal modeling and cannot capture long-term scattering dependencies. Although its accuracy improves with larger T , it remains inferior to the biLSTM-based Bi-SEN, highlighting the advantage of recurrent sequence learning for adaptive scattering estimation in dynamic RSE. Key takeaway is that Bi-SEN yields the lowest scattering-estimation RMSE for all T , and the error falls monotonically as T increases, with best performance at MIMO.

Figure 15 analyzes user localization error versus the number of time frames. The proposed approach consistently outperforms benchmark methods, with the MIMO network achieving slightly lower error than SISO. For example, the proposed MIMO configuration reaches a localization error of approximately 2.5λ using 6 time frames, matching or surpassing benchmark performance obtained at 12 or more frames, corresponding to nearly a twofold reduction in required observations. The performance advantage is most significant at small frame counts, indicating efficient extraction of informative features from

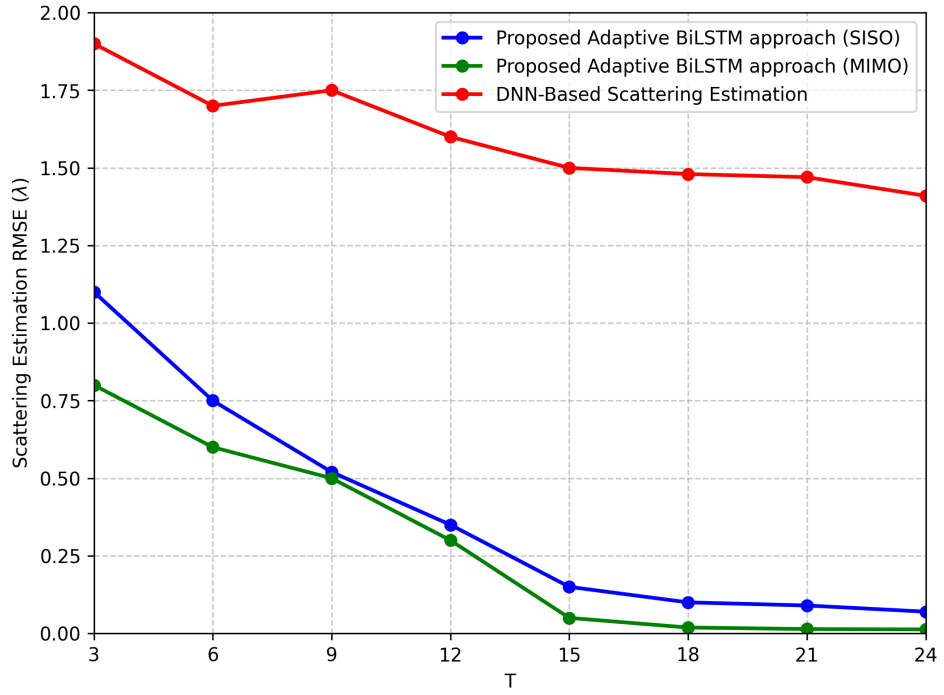


Figure 14: Scattering Estimation RMSE from (17) versus T for SNR = 30 dB.

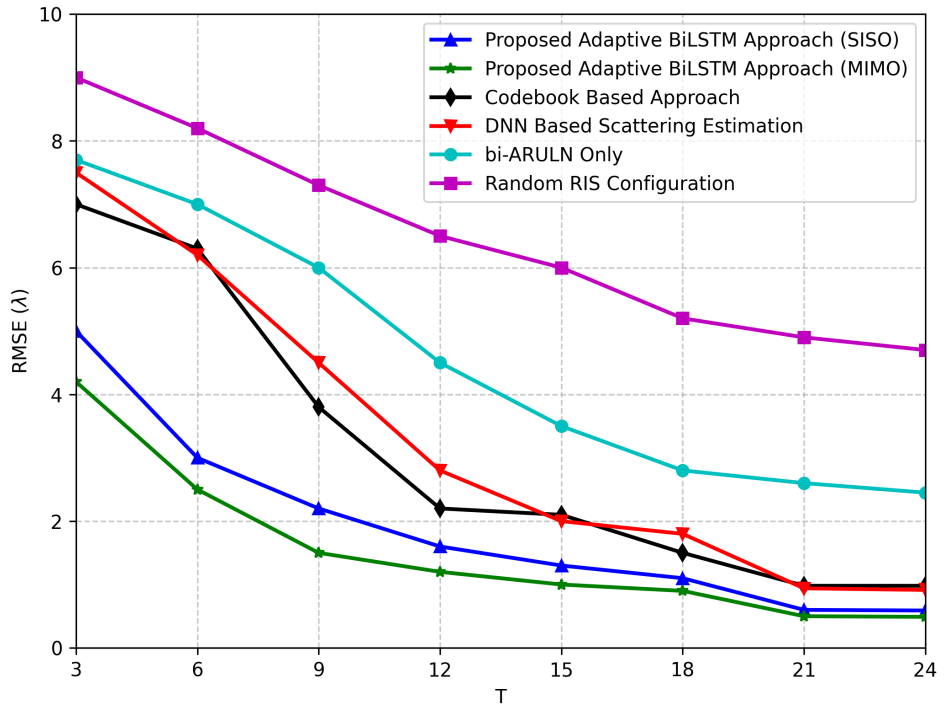


Figure 15: RMSE of user localization versus T for $N_{RIS} = 100$ and SNR = 30 dB.

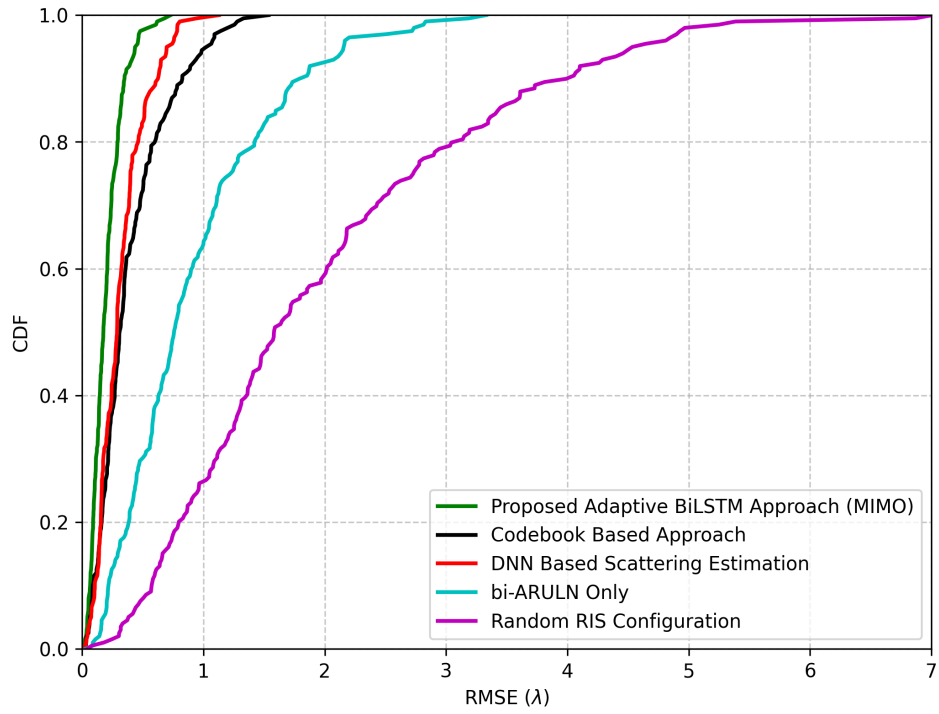


Figure 16: CDF of proposed and baseline approaches versus RMSE of user localization at $T = 21$ for $N_{\text{RIS}} = 100$ and $\text{SNR} = 30$ dB.

limited temporal data and reduced localization latency. Although the gap decreases as the number of frames increases, the proposed method maintains consistent superiority, demonstrating robustness across operating conditions. The improved performance of MIMO further reflects enhanced spatial diversity, enabling faster convergence to low-error regimes. These results indicate that accurate localization can be achieved with fewer observations, reducing latency, energy consumption, and signaling overhead, which is particularly beneficial in bandwidth-constrained or highly dynamic RSE environments. The key takeaway is that the proposed MIMO configuration reaches approximately 2.5λ localization error in 6 frames, matching baselines that need 12+ frames, i.e., a near-twofold reduction in required observations.

Figure 16 shows the underlying error distribution from which average RMSE are formed. Each curve is the CDF of the localization RMSE over the test set. The proposed approach has the steepest rise and the leftmost distribution, indicating that low errors occur consistently. The codebook-based and DNN-based scattering estimation approaches follow, with a wider spread at the upper end. The Bi-ARULN and random configuration approaches rise most gradually, so their errors are both larger and less consistent across the test set. The separation between the distributions is wide which indicates that the relative performance of the methods holds across the test set.

The localization error is the objective minimized during training, but it is not the variable that drives the adaptation at online stage. The true UE position is unavailable during operation, so no error signal can be formed online. The mappings $F^{(t)}$ are instead fixed after training, and at each frame the configuration $\mathbf{k}^{(t+1)}$ is computed from quantities that are directly observable at the BS, namely the magnitude and phase of the received pilots accumulated up to frame t and the scattering estimate $\hat{\mathbf{p}}^{(t)}$ produced by Bi-SEN from the sensing measurements. The dependence on the localization error is therefore embedded in the learned parameters rather than evaluated online. In a practical deployment this corresponds to an offline calibration campaign in the target environment, during which the error can be measured against reference positions, followed by an online phase in which the BS executes a fixed forward pass per frame and issues the resulting configuration to the RIS controller. Recalibration is required only when the statistics of the environment change to the extent that the trained mappings no longer apply.

The baselines considered here all vary the RIS configuration over the T frames, either at random, by selection from a codebook, or adaptively. A further reference point that is not evaluated is a single fixed configuration held constant over all frames, for instance one in which every element is set to a common resonance so that the surface acts as a uniform reflector. Such a baseline would separate the benefit of varying the configuration from the benefit of varying it adaptively, since a constant configuration produces T repetitions of the same channel and the received observations then differ only through noise and through the motion of the SOs. On this basis the fixed-reflector configuration is expected to fall below the random baseline, which supplies some configuration diversity, and the comparison would isolate the contribution of measurement diversity as such.

The computational complexity of the proposed two-stage approach scales as $\mathcal{O}[T(D_i Z_i + 2\Omega + \zeta + 2d_s(\sum_k N_k + M) + D_o Z_o)]$ where Z_i and Z_o are the input- and output-layer dimensions and D_i and D_o are the corresponding feature dimensions, with D_i determined by the concatenated magnitude and phase of the sensed and pilot signals. The term Ω represents the cost of a single biLSTM inference operation over one sensing stage, and the factor of two reflects the two recurrent networks, Bi-SEN and Bi-ARULN, that constitute the model. The term ζ corresponds to the L_n -layer fully connected network that designs the RIS configuration vectors, while the remaining terms

scale with the number of sensing stages T , the number of scattering objects M , and the reflective elements N_k at the k -th RIS. Because past observations are compressed into a fixed-dimensional information vector, this cost remains independent of the configuration space and does not grow with the sensing horizon, in contrast to codebook-based selection. The recurrent and fully connected operations reduce to dense matrix computations, which are efficiently handled by modern graphics processing units, allowing the approach to operate with low overhead during online inference. The recurrent term 2Ω and the design network term ζ dominate the per-stage cost. A single biLSTM pass scales as $\Omega = \mathcal{O}(d_s(d_s + D_i))$ and the design network as $\zeta = \mathcal{O}(L_n d_s^2)$, so both grow quadratically with the hidden dimension d_s , with ζ the larger of the two once several fully connected layers are used. The remaining terms grow only linearly, with the number of reflective elements N_k and the number of scattering objects M .

4.5 Summary

This chapter presents an overview of the data-driven RIS configuration approach designed in Publication III, for RIS-assisted RSE that adaptively designs RIS configurations by explicitly accounting for environmental scattering. A biLSTM-based model leverages RIS-assisted sensing and sequential measurements to dynamically minimize user localization error. The integration of Bi-SEN for scattering estimation and Bi-ARULN for configuration design enables context-aware adaptation of RIS operation throughout the localization process. Simulation results show consistent improvements over fixed-codebook, random, and scattering-unaware adaptive methods across varying RIS sizes and SNR conditions, with reliable generalization to both SISO and MIMO networks. Channel reciprocity allows direct application in uplink settings without modification of the learning scheme. In the following chapter, the proposed approach is expanded to design UE and BS beamforming vectors in addition to RIS configurations and perform UE location and orientation estimation with environmental sensing, based on Publication IV. Various RSE scenarios are explored to study the robustness of the proposed approach and its analytical bounds are derived.

5 Integrated Sensing, User Location and Orientation Estimation in Dynamic RIS-Assisted RSE

5.1 Introduction

This chapter considers uplink localization in RSEs, where a UE repeatedly transmits known pilot signals and the BS estimates the location and orientation of the UE from the received observations. As the wireless channel depends on the UE position, the problem can be formulated as an inverse mapping task that infers location from channel realizations derived from received pilots. The signals received at the BS propagate through multiple paths created by RIS reflections and environmental scattering. Localization accuracy is improved by exploiting multipath diversity, where the BS jointly utilizes received measurements and sensing information from dedicated RIS elements to adaptively update RIS, BS, and UE beamforming vectors across multiple time slots.

This chapter is based on Publication IV:

- A. Umer, I. Mürsepp, and M. M. Alam, "Integrated Sensing, User Location and Orientation Estimation in RIS-Assisted Dynamic Rich Scattering Environment," *IEEE Transactions on Wireless Communications (Under review)*, 2026

This chapter presents scalars by italic symbols (for example, b), vectors by bold lower-case symbols (for example, $\mathbf{b}$), and matrices by bold uppercase symbols (for example, $\mathbf{B}$). The notation $|\cdot|$ represents the magnitude, while $\hat{b}$ indicates an estimate of b . The operator $\text{diag}(\mathbf{y})$ forms a diagonal matrix whose diagonal entries are taken from $\mathbf{y}$. The real and imaginary parts of a complex quantity are expressed by $\Re(\cdot)$ and $\Im(\cdot)$, respectively, and the expectation is denoted by $\mathbb{E}(\cdot)$. A complex Gaussian random variable with mean m and variance v is represented as $\mathcal{CN}(m, v)$.

5.2 System Model

The scenario is illustrated in Figure 17. A multi-antenna UE transmits known pilot symbols to a multi-antenna BS through a distributed RIS installation deployed on the periphery of an indoor enclosure that contains M randomly moving SOs. The BS, at a known location, estimates the UE position $\mathbf{u} = [u_x, u_y]^T \in \mathbb{R}^2$ and the orientation $\alpha \in [0, 2\pi)$, collected in the UE state $\mathbf{u}_e \triangleq [\mathbf{u}^T, \alpha]^T \in \mathbb{R}^3$. The SO positions at frame t are collected in $\mathbf{p}^{(t)} \triangleq [(\mathbf{p}_1^{(t)})^T, \dots, (\mathbf{p}_M^{(t)})^T]^T \in \mathbb{R}^{2M}$, with $\mathbf{p}_m^{(t)} \in \mathbb{R}^2$, and the corresponding estimate is denoted $\hat{\mathbf{p}}^{(t)}$.

The UE and the BS are each equipped with a single RF chain and perform analog beamforming with unit-modulus phase shifters. The UE therefore transmits a single stream through $\mathbf{w}_{\text{UE}} \in \mathbb{C}^{N_{\text{UE}}}$, and the BS combines the outputs of its N_{BS} antennas into a single observation through $\mathbf{w}_{\text{BS}} \in \mathbb{C}^{N_{\text{BS}}}$, with $|[\mathbf{w}_{\text{BS}}]_q| = 1$ for all $q \in \{1, \dots, N_{\text{BS}}\}$ and $|[\mathbf{w}_{\text{UE}}]_{q'}| = 1$ for all $q' \in \{1, \dots, N_{\text{UE}}\}$.

In the adopted end-to-end model, every RIS element is a dipole with a programmable resonance frequency, and the surface is configured by tuning these resonances. The RIS configuration is accordingly the real vector $\mathbf{k} \in \mathbb{R}^{N_{\text{RIS}}}$ whose n -th entry $[\mathbf{k}]_n = f_{\text{res},n}$ is continuously tunable within the admissible range $[\mathbf{k}]_n \in [f_{\min}, f_{\max}]$ for all $n \in \{1, \dots, N_{\text{RIS}}\}$, with $f_{\min}$ and $f_{\max}$ given in Table 4, guided by [10]. This is the physical control variable used in Chapter 3, where each element is switched between two fixed resonance states under PIN diode control, and the two chapters therefore differ in the resolution with which the resonance is set. Chapter 4 abstracts this as a unit-modulus reflection coefficient.

A subset S_{RIS} of elements at fixed positions is dedicated to environment sensing. Following the hybrid reflecting and sensing RIS concept, each such element reflects part of

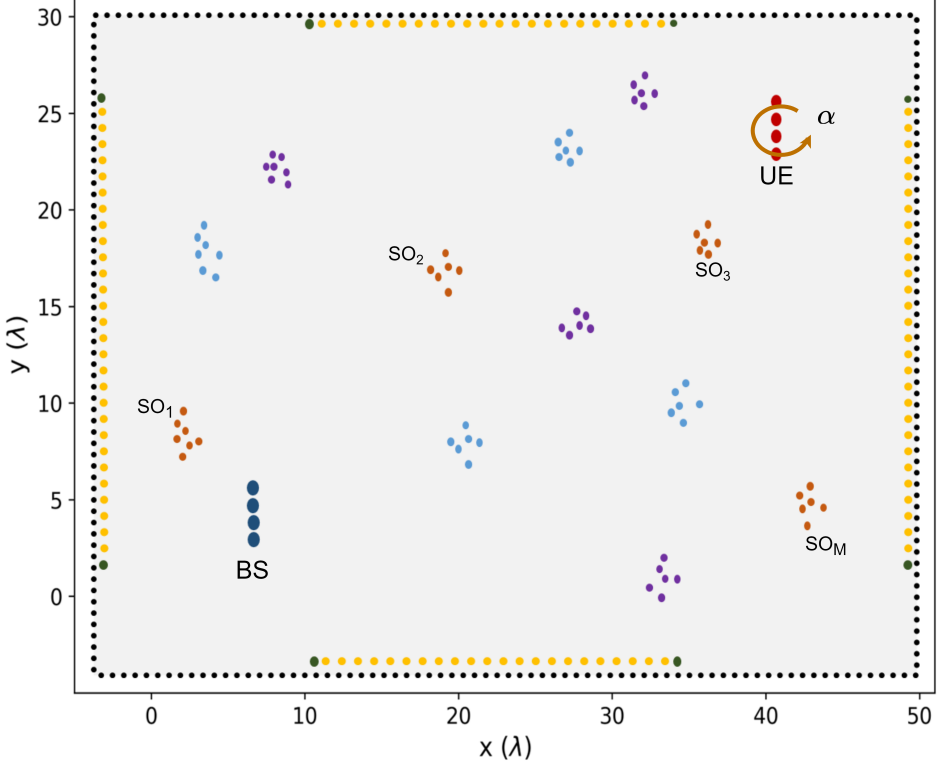


Figure 17: Depiction of the investigated RSE.

the impinging signal and couples the remainder, determined by a non-zero splitting coefficient, to a reception RF chain at the RIS. These measurements are conveyed to the BS over the same control link that carries the configuration commands to the RIS controller, so that the BS processes the received pilots and the sensing measurements jointly to estimate the SOs positions and to design the configuration for the next frame. Updating the configuration at every frame requires this link to deliver a new configuration within the frame duration, which in practice bounds the number of time frames T that can be used within a channel coherence period.

5.2.1 Signal Transmission and Reception

Under a narrowband system model, a localization request triggers the transmission of a sequence of T known uplink pilot symbols from the UE to the BS over T time frames using beamforming vector $\omega_{\text{UE}}^{(t)}$. Let $\mathbf{x}^{(t)} \in \mathbb{C}^{N_U \times 1}$ denote the pilot transmitted at frame t . The BS combines the received signal using beamforming vector $\omega_{\text{BS}}^{(t)}$. The effective received signal $\mathbf{y}^{(t)} \in \mathbb{C}^{N_U \times 1}$ is expressed as

$$\mathbf{y}^{(t)} = (\omega_{\text{UE}}^{(t)})^H \mathbf{H}_{\text{BS-U}}^{(t)}(\mathbf{k}^{(t)}, \mathbf{p}^{(t)}) \omega_{\text{BS}}^{(t)} x^{(t)} + w^{(t)}, \quad t \in \mathbb{Z}, \quad (18)$$

where $w^{(t)} \sim \mathcal{CN}(0, \sigma^2)$ denotes additive Gaussian noise. The received pilot depends on the UE and BS beamforming vectors and the RIS configuration at time t .

A subset S_{RIS} of RIS elements is further used for environment sensing to estimate scattering object locations $\mathbf{p}^{(t)}$ by measuring the channel $\mathbf{H}_{\text{BS-S}} \in \mathbb{C}^{S_{\text{RIS}} \times N_{\text{BS}}}$. The correspond-

ing observations are

$$\mathbf{y}_s^{(t)} = \mathbf{H}_{\text{BS-S}}^{(t)}(\mathbf{k}^{(t)}, \mathbf{p}^{(t)}) \boldsymbol{\omega}_{\text{BS}}^{(t)} x^{(t)} + \mathbf{w}_s^{(t)}, \quad t \in \mathbb{Z}. \quad (19)$$

The carrier observation model and the phase coherence assumption of Chapter 4 apply in this chapter as well, where each time frame produces complex observation at the BS after combining. Since $\boldsymbol{\omega}_{\text{UE}}$ and $\boldsymbol{\omega}_{\text{BS}}$ are applied coherently across the arrays, phase coherence is additionally required between the elements of each array, so that calibration error in the arrays would reduce accuracy in addition to any synchronization error between the transmitter and the receiver.

5.2.2 Problem Formulation

The objective is to estimate the unknown UE location $\mathbf{u}$ and orientation α from T received observations $[\mathbf{y}^{(t)}]_{t=0}^{T-1}$, assuming known BS and RIS positions and a predicted SOs location at each time frame. The SOs state $\mathbf{p}$ is inferred from RIS sensing signals $[\mathbf{y}_s^{(\tau)}]_{\tau=0}^t$ collected over S_{RIS} elements to capture scattering dynamics in the RSE. The RIS acts as a set of virtual anchors, providing directional information through its reflective elements. Accordingly, the RIS configuration, BS beamforming vector, and UE beamforming vector are sequentially designed across t stages to improve final location and orientation estimation at time T .

The field at any point in the RSE results from the superposition of multiple propagation components influenced by dynamic SOs with state $\mathbf{p}^{(t)}$. Let $G^{(t)}(\cdot) : \mathbb{C}^{t+1} \rightarrow \mathbb{R}^{2M}$ denote the mapping from received sensing pilots to the estimated SOs location at time t ,

$$\hat{\mathbf{p}}^{(t)} = G^{(t)}([\mathbf{y}_s^{(\tau)}]_{\tau=0}^t), \quad (20)$$

where τ indexes past observations up to time t . Based on prior pilot signals and the estimated scattering state, define the mapping $F^{(t)} : \mathbb{C}^{t+1} \times \mathbb{R}^{2M} \rightarrow \mathbb{C}^{N_{\text{BS}} \times 1} \times \mathbb{C}^{N_{\text{UE}} \times 1} \times \mathbb{R}^{N_{\text{RIS}}}$ that jointly determines the next RIS configuration and beamforming vectors as

$$[\boldsymbol{\omega}_{\text{BS}}^{(t+1)}, \boldsymbol{\omega}_{\text{UE}}^{(t+1)}, \mathbf{k}^{(t+1)}] = F^{(t)}([\mathbf{y}^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}). \quad (21)$$

The final mapping $Q : \mathbb{C}^T \times \mathbb{R}^{2M} \rightarrow \mathbb{R}^3$ estimates the UE location and orientation from all received pilots and inferred scattering information,

$$[\hat{\mathbf{u}}, \hat{\alpha}] = Q([\mathbf{y}^{(t)}]_{t=0}^{T-1}, \hat{\mathbf{p}}^{(T-1)}). \quad (22)$$

The goal of RIS-aided localization is to minimize estimation error based on received pilot signals. This objective is formulated as

$$\min_{\{\mathcal{G}^{(t)}, \mathcal{F}^{(t)}\}_{t=0}^{T-1}, Q} \sqrt{\mathbb{E}[\|\hat{\mathbf{u}}^{(T)} - \mathbf{u}\|^2]} + \sqrt{\mathbb{E}[d_w(\hat{\alpha}^{(T)}, \alpha)^2]} \quad (23a)$$

$$\text{s.t. } \hat{\mathbf{p}}^{(t)} = \mathcal{G}^{(t)}([\mathbf{y}_s^{(\tau)}]_{\tau=0}^t), \quad (23b)$$

$$[\boldsymbol{\omega}_{\text{BS}}^{(t+1)}, \boldsymbol{\omega}_{\text{UE}}^{(t+1)}, \mathbf{k}^{(t+1)}] = \mathcal{F}^{(t)}([\mathbf{y}^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}), \quad (23c)$$

$$[\hat{\mathbf{u}}, \hat{\alpha}] = Q([\mathbf{y}^{(t)}]_{t=0}^{T-1}, \hat{\mathbf{p}}^{(T-1)}), \quad (23d)$$

$$[\mathbf{k}^{(t+1)}]_n \in [f_{\min}, f_{\max}], \quad \forall n \in \mathcal{N}_{\text{RIS}}, t, \quad (23e)$$

$$|[\boldsymbol{\omega}_{\text{BS}}^{(t+1)}]_n| = 1, \quad \forall n \in \mathcal{N}_{\text{BS}}, t, \quad (23f)$$

$$|[\boldsymbol{\omega}_{\text{UE}}^{(t+1)}]_n| = 1, \quad \forall n \in \mathcal{N}_{\text{UE}}, t, \quad (23g)$$

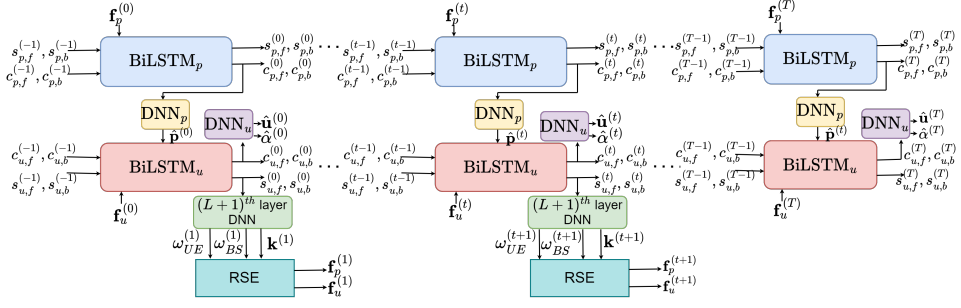


Figure 18: Block diagram of the proposed UE localization approach with adaptive sensing in RIS-assisted RSE.

where $d_w(\hat{\alpha}, \alpha) = \min(|\hat{\alpha} - \alpha|, 2\pi - |\hat{\alpha} - \alpha|)$ accounts for the periodicity of the orientation, so that estimates lying on either side of the boundary between 0 and 2π are penalized by their true angular separation. Constraint (23e) is the tuning range of the RIS elements and the remaining two constraints are the unit-modulus constraints of the analog phase shifters at the BS and the UE.

The number of SOs, M , is assumed known and fixed within a localization request. In a deployment, M would be fixed at calibration from knowledge of the site, for instance the number of vehicles or personnel admitted to a controlled industrial area.

5.3 Joint User Location and Orientation Estimation Approach

UE localization in RSE assisted by RIS integrates environmental sensing with adaptive design of the BS and UE beamforming vectors and the RIS configuration. Environmental sensing extracts the SOs state from field measurements, providing contextual information that guides configuration and beamforming decisions to improve localization accuracy. A learning-based adaptive approach jointly optimizes these parameters to address (23), combining environment-specific offline training with online inference. At time step t , the RIS configuration $\mathbf{k}^{(t+1)}$, BS beamforming $\omega_{BS}^{(t+1)}$, and UE beamforming $\omega_{UE}^{(t+1)}$ are selected using the observation history $[\mathbf{y}^{(\tau)}]_{\tau=0}^t$ and the current scattering estimate $\hat{\mathbf{p}}^{(t)}$. A neural network compresses the growing measurement sequence into a fixed-dimensional representation that preserves relevant temporal information. The proposed neural network architecture is illustrated in Figure 18.

Temporal correlations in sensing and pilot observations are modeled using coupled biLSTM networks. The sensing feature vector $\mathbf{f}_p^{(t)} = [|\mathbf{y}_s^{(t)}|, \angle \mathbf{y}_s^{(t)}]$ is processed to update forward and backward hidden states $\mathbf{s}_{p,f}^{(t)}, \mathbf{s}_{p,b}^{(t)}$ and cell states $\mathbf{c}_{p,f}^{(t)}, \mathbf{c}_{p,b}^{(t)}$ according to

$$(\mathbf{c}_{p,f}^{(t)}, \mathbf{c}_{p,b}^{(t)}, \mathbf{s}_{p,f}^{(t)}, \mathbf{s}_{p,b}^{(t)}) = \text{biLSTM}_p(\mathbf{f}_p^{(t)}, \mathbf{c}_{p,f}^{(t-1)}, \mathbf{c}_{p,b}^{(t-1)}, \mathbf{s}_{p,f}^{(t-1)}, \mathbf{s}_{p,b}^{(t-1)}), \quad (24)$$

where previous states summarize temporal sensing information. The concatenated cell states provide the scattering estimate

$$\hat{\mathbf{p}}^{(t)} = \text{DNN}_p([\mathbf{c}_{p,f}^{(t)}, \mathbf{c}_{p,b}^{(t)}]). \quad (25)$$

Localization decisions incorporate both pilot observations and the estimated scattering state through a second biLSTM. The feature vector $\mathbf{f}_u^{(t)} = [|\mathbf{y}^{(t)}|, \angle \mathbf{y}^{(t)}, \hat{\mathbf{p}}^{(t)}]$ updates

hidden and cell states as

$$(\mathbf{c}_{u,f}^{(t)}, \mathbf{c}_{u,b}^{(t)}, \mathbf{s}_{u,f}^{(t)}, \mathbf{s}_{u,b}^{(t)}) = \text{biLSTM}_u(\mathbf{f}_u^{(t)}, \mathbf{c}_{u,f}^{(t-1)}, \mathbf{c}_{u,b}^{(t-1)}, \mathbf{s}_{u,f}^{(t-1)}, \mathbf{s}_{u,b}^{(t-1)}). \quad (26)$$

The concatenated hidden state $\mathbf{s}_u^{(t)} = [\mathbf{s}_{u,f}^{(t)}; \mathbf{s}_{u,b}^{(t)}]$ is mapped by a fully connected deep neural network (DNN) with L_n layers,

$$\gamma^{(t)} = \beta_{L_n}(\mathbf{W}_{L_n} \beta_{L_n-1}(\dots \beta_1(\mathbf{W}_1 \mathbf{s}_u^{(t)} + \mathbf{b}_1) \dots) + \mathbf{b}_{L_n}), \quad (27)$$

where $\beta_l(x) = \max(0, x)$ and $\mathbf{W}_l, \mathbf{b}_l$ are trainable parameters. Linear output mappings generate intermediate vectors for the RIS configuration and beamforming design,

$$\bar{\mathbf{k}}^{(t+1)} = \dot{\mathbf{W}}_{L_n+1} \gamma^{(t)} + \dot{\mathbf{b}}_{L_n+1}, \quad \bar{\mathbf{k}}^{(t+1)} \in \mathbb{R}^{N_{\text{RIS}}}, \quad (28a)$$

$$\bar{\omega}_{\text{BS}}^{(t+1)} = \ddot{\mathbf{W}}_{L_n+1} \gamma^{(t)} + \ddot{\mathbf{b}}_{L_n+1}, \quad (28b)$$

$$\bar{\omega}_{\text{UE}}^{(t+1)} = \ddot{\mathbf{W}}_{L_n+1} \gamma^{(t)} + \ddot{\mathbf{b}}_{L_n+1}, \quad (28c)$$

whose dimensions match N_{RIS} , N_{BS} , and N_{UE} . Each element is normalized to enforce unit modulus constraints,

$$[\mathbf{k}^{(t+1)}]_n = \min(f_{\max}, \max(f_{\min}, [\bar{\mathbf{k}}^{(t+1)}]_n)), \quad \forall n, \quad (29a)$$

$$[\omega_{\text{BS}}^{(t+1)}]_q = \frac{[\Re(\bar{\omega}_{\text{BS}}^{(t+1)})]_q + j[\Im(\bar{\omega}_{\text{BS}}^{(t+1)})]_q}{\sqrt{[\Re(\bar{\omega}_{\text{BS}}^{(t+1)})]_q^2 + [\Im(\bar{\omega}_{\text{BS}}^{(t+1)})]_q^2}}, \quad \forall q, \quad (29b)$$

$$[\omega_{\text{UE}}^{(t+1)}]_{q'} = \frac{[\Re(\bar{\omega}_{\text{UE}}^{(t+1)})]_{q'} + j[\Im(\bar{\omega}_{\text{UE}}^{(t+1)})]_{q'}}{\sqrt{[\Re(\bar{\omega}_{\text{UE}}^{(t+1)})]_{q'}^2 + [\Im(\bar{\omega}_{\text{UE}}^{(t+1)})]_{q'}^2}}, \quad \forall q'. \quad (29c)$$

This design satisfies the mappings in (23). The final UE location and orientation at time T are estimated from the concatenated bidirectional cell states,

$$\begin{bmatrix} \hat{\mathbf{u}}^{(T)} \\ \hat{\alpha}^{(T)} \end{bmatrix} = \text{DNN}_u([\mathbf{c}_{u,f}^{(T)}; \mathbf{c}_{u,b}^{(T)}]). \quad (30)$$

5.3.1 Loss Function

The overall training objective is defined by a composite loss combining the RMSE of UE position estimation, orientation estimation, and SOs state estimation. The UE localization losses are

$$L_u = \sqrt{\mathbb{E}[\|\hat{\mathbf{u}}^{(T)} - \mathbf{u}\|^2]}, \quad (31a)$$

$$L_\alpha = \sqrt{\mathbb{E}[d_w(\hat{\alpha}^{(T)}, \alpha)^2]}, \quad (31b)$$

where $d_w(\hat{\alpha}, \alpha) = \min(|\hat{\alpha} - \alpha|, 2\pi - |\hat{\alpha} - \alpha|)$ accounts for the periodicity of the orientation. The scattering estimation loss is

$$L_p = \sqrt{\mathbb{E}[\|\hat{\mathbf{p}}^{(T)} - \mathbf{p}\|^2]}. \quad (32)$$

These objectives jointly enforce accurate UE localization and scattering estimation while implicitly guiding adaptive design of the RIS configuration and the BS and UE beamforming vectors under varying propagation conditions. The optimization promotes sequences

of configurations over T stages that minimize the final localization error. After training, the model directly generates the required vectors from received signals for arbitrary UE positions and sensing elements S_{RIS} within the coverage region. Since supervision is applied only at time T , intermediate stages remain unconstrained, enabling exploration of configurations that yield optimal final accuracy.

Two aspects of the recurrent architecture bear on its use in a time-varying environment. The first is timing. The design produces one configuration per frame, so the forward pass of both networks, the transfer of the configuration over the control link, and the settling of the RIS elements must all complete within a frame duration, and the T frames of a localization request must fit within the coherence time of the environment. The second aspect is the bidirectional structure. Within a localization request the T frames are processed as a complete sequence before the location and orientation are read out at frame T , so both directions are available and the backward pass allows the representation at each frame to be informed by later observations, which improves the scattering estimate in the early frames when few measurements have accumulated. The cost is that the readout is not available until the sequence is complete, and that the number of recurrent parameters and the inference cost are approximately doubled with respect to a unidirectional LSTM. A unidirectional LSTM would permit an estimate to be produced at every frame and would suit an application requiring a running estimate, at the price of accuracy in the early frames. A feedforward network over the stacked observations, evaluated as the DNN-based baseline in Chapter 4, avoids the recurrence entirely but does not exploit the temporal correlation of the SO motion and attains higher error.

5.4 Analytical-Modeling-based approach for UE Localization with Environmental Sensing in RSE

Analytical modeling of UE location estimation with scattering estimation in RSE provides an important benchmark for performance evaluation. The learning-based formulation solves (23) by estimating scattering through (20) and jointly optimizing the RIS configuration and the BS and UE beamforming mappings $\{F^{(t)}(\cdot)\}$ in (21) across time frames to reduce localization error. Direct analytical optimization of this multistage design becomes computationally prohibitive as the number of time frames increases [115, 125], requiring a typical greedy sequential design. Since exact RMSE evaluation is intractable, analytical estimation would optimize the lower bound on RMSE. Nevertheless, such an analytical design is an important benchmark. Throughout this thesis, BCRLB based design refers to this idea of designing an analytical approach for user localization in RIS-assisted RSE by minimizing BCRLB using gradient descent in every time step, as discussed below.

The presented model-based analytical approach is similar to the one proposed in [115, 125]. Instead of optimizing the direct mapping of received observations to configurations and beamforming vectors, it decomposes $F^{(t)}(\cdot)$ in (21) into two-step mapping: accumulated observations are first mapped to the conditional BCRLB, which then determines the RIS configuration and beamforming vectors. At each time step, received pilots update the posterior distribution of the UE and SOs location, the conditional BCRLB is subsequently recomputed based on posterior distribution, and then the configuration and beamforming vectors are selected to minimize the bound.

The UE state $\mathbf{u}_e$ and the SO positions $\mathbf{p}$ are modeled as random vectors with known priors $f(\mathbf{u}_e)$ and $f(\mathbf{p})$, and the augmented parameter vector is

$$\boldsymbol{\theta} = [\mathbf{u}_e^T, \mathbf{p}^T]^T \in \mathbb{R}^{3+2M}. \quad (33)$$

Given observations $[\mathbf{y}^{(\tau)}]_{\tau=0}^{t-1}$ and $[\mathbf{y}_s^{(\tau)}]_{\tau=0}^{t-1}$, the objective is to determine the next RIS configuration $\mathbf{k}^{(t+1)}$ such that the conditional RMSE of estimating $\mathbf{u}_e$ is minimized while accounting for environmental scattering. The optimization at time t is formulated as

$$\min_{G^{(t)}(\cdot), F^{(t)}(\cdot), Q(\cdot)} \sqrt{\mathbb{E}[\|\hat{\mathbf{u}}_e^{(t)} - \mathbf{u}_e\|^2 \mid [\mathbf{y}^{(\tau)}]_{\tau=0}^t, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^t]} \quad (34a)$$

$$\text{s.t. } \hat{\mathbf{p}}^{(t)} = G^{(t)}([\mathbf{y}_s^{(\tau)}]_{\tau=0}^t), \quad (34b)$$

$$[\boldsymbol{\omega}_{\text{BS}}^{(t+1)}, \boldsymbol{\omega}_{\text{UE}}^{(t+1)}, \mathbf{k}^{(t+1)}] = \mathcal{F}^{(t)}([\mathbf{y}^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}), \quad (34c)$$

$$\hat{\mathbf{u}}_e^{(t)} = Q([\mathbf{y}^{(\tau)}]_{\tau=0}^t), \quad (34d)$$

$$[\mathbf{k}^{(t+1)}]_n \in [f_{\min}, f_{\max}], \quad \forall n \in N_{\text{RIS}}, \quad (34e)$$

$$|[\boldsymbol{\omega}_{\text{BS}}^{(t+1)}]_n| = 1, \quad \forall n \in \mathcal{N}_{\text{BS}}, t, \quad (34f)$$

$$|[\boldsymbol{\omega}_{\text{UE}}^{(t+1)}]_n| = 1, \quad \forall n \in \mathcal{N}_{\text{UE}}, t. \quad (34g)$$

Let

$$\boldsymbol{\Gamma}^{(t)} = \mathbb{E}[(\hat{\mathbf{u}}_e^{(t)} - \mathbf{u}_e)(\hat{\mathbf{u}}_e^{(t)} - \mathbf{u}_e)^\top \mid [\mathbf{y}^{(\tau)}]_{\tau=0}^t, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^t)] \quad (35)$$

denote the conditional error covariance. Direct evaluation is intractable due to high-dimensional integration; therefore, the conditional BCRLB is adopted as a tractable surrogate objective providing a parameter-independent lower bound on the RMSE while incorporating posterior information.

At time t , the joint Bayesian Fisher Information Matrix (FIM) is

$$\mathbf{J}^{(t)} = \begin{bmatrix} \mathbf{J}_{uu}^{(t)} & \mathbf{J}_{up}^{(t)} \\ \mathbf{J}_{pu}^{(t)} & \mathbf{J}_{pp}^{(t)} \end{bmatrix}, \quad (36)$$

with entries

$$[\mathbf{J}^{(t)}]_{i,j} = -\mathbb{E} \left[\frac{\partial^2 \log f(\mathbf{y}^{(t)}, \mathbf{y}_s^{(t)}, \boldsymbol{\theta} \mid \{\mathbf{y}^{(\tau)}\}_{\tau=0}^{t-1}, \{\mathbf{y}_s^{(\tau)}\}_{\tau=0}^{t-1})}{\partial \theta_i \partial \theta_j} \right], \quad (37)$$

where the expectation is taken with respect to the corresponding conditional distribution. The conditional error satisfies the BCRLB

$$\text{tr}(\boldsymbol{\Gamma}^{(t)}) \geq \text{tr}((\mathbf{J}_{uu}^{(t)} - \mathbf{J}_{up}^{(t)}(\mathbf{J}_{pp}^{(t)})^{-1}\mathbf{J}_{pu}^{(t)})^{-1}). \quad (38)$$

Consequently, the RIS configuration is obtained by minimizing this bound,

$$\min_{F^{(t)}(\cdot)} \text{tr}((\mathbf{J}_{uu}^{(t)} - \mathbf{J}_{up}^{(t)}(\mathbf{J}_{pp}^{(t)})^{-1}\mathbf{J}_{pu}^{(t)})^{-1}) \quad (39a)$$

$$\text{s.t. } [\mathbf{k}^{(t+1)}]_n \in [f_{\min}, f_{\max}], \quad \forall n \in \mathcal{N}_{\text{RIS}}, \quad (39b)$$

$$\mathbf{k}^{(t+1)} = F^{(t)}([\mathbf{y}^{(\tau)}]_{\tau=0}^t). \quad (39c)$$

The procedure is applied sequentially over T time frames to obtain the RIS configurations, after which a maximum a posteriori estimator $Q(\cdot)$ produces the final estimate $\hat{\mathbf{u}}_e^{(T)}$.

5.4.1 BCRLB Calculation

The joint Bayesian FIM in (37) admits a decomposition based on Bayes' theorem [115],

$$[\mathbf{J}^{(t)}]_{i,j} = [\mathbf{J}_D^{(t)}]_{i,j} + [\mathbf{J}_P^{(t-1)}]_{i,j}, \quad (40)$$

where $\mathbf{J}_D^{(t)}$ denotes the information contributed by the current observation and $\mathbf{J}_P^{(t-1)}$ represents the information accumulated from prior measurements. Equation (42) separates the information into what the past frames have already established and what the next frame will add. The prior term $\mathbf{J}_P^{(t-1)}$ carries the former. The data term $\mathbf{J}_D^{(t)}$ carries the latter.

Conditioned on $\boldsymbol{\theta}$ and the past observations, $y^{(t)}$ and $\mathbf{y}_s^{(t)}$ are complex Gaussian with means obtained from the observation model of Section 5.2.1 as,

$$\mu^{(t)}(\boldsymbol{\theta}) = (\boldsymbol{\omega}_{\text{UE}}^{(t)})^H \mathbf{H}_{\text{BS-U}}(\mathbf{k}^{(t)}, \mathbf{p}) \boldsymbol{\omega}_{\text{BS}}^{(t)} x^{(t)}, \quad (41a)$$

$$\boldsymbol{\mu}_s^{(t)}(\boldsymbol{\theta}) = \mathbf{H}_{\text{BS-S}}(\mathbf{k}^{(t)}, \mathbf{p}) \boldsymbol{\omega}_{\text{BS}}^{(t)} x^{(t)}. \quad (41b)$$

$$[\mathbf{J}_D^{(t)}]_{i,j} = \frac{2}{\sigma^2} \mathbb{E} \left[\Re \left\{ \frac{\partial \mu^{(t)}(\boldsymbol{\theta})^*}{\partial \theta_i} \frac{\partial \mu^{(t)}(\boldsymbol{\theta})}{\partial \theta_j} + \frac{\partial \boldsymbol{\mu}_s^{(t)}(\boldsymbol{\theta})^H}{\partial \theta_i} \frac{\partial \boldsymbol{\mu}_s^{(t)}(\boldsymbol{\theta})}{\partial \theta_j} \right\} \right], \quad (42)$$

where the expectation is taken with respect to the posterior distribution of $\boldsymbol{\theta}$ given the past observations, and $y^{(t)}$ and $\mathbf{y}_s^{(t)}$ are conditionally independent given $\boldsymbol{\theta}$ and those observations. From the means above, the required gradients are

$$\frac{\partial \mu^{(t)}(\boldsymbol{\theta})}{\partial \theta_i} = (\boldsymbol{\omega}_{\text{UE}}^{(t)})^H \frac{\partial \mathbf{H}_{\text{BS-U}}(\mathbf{k}^{(t)}, \mathbf{p})}{\partial \theta_i} \boldsymbol{\omega}_{\text{BS}}^{(t)} x^{(t)}, \quad (43a)$$

$$\frac{\partial \boldsymbol{\mu}_s^{(t)}(\boldsymbol{\theta})}{\partial \theta_i} = \frac{\partial \mathbf{H}_{\text{BS-S}}(\mathbf{k}^{(t)}, \mathbf{p})}{\partial \theta_i} \boldsymbol{\omega}_{\text{BS}}^{(t)} x^{(t)}, \quad (43b)$$

so that the Fisher information is determined by the derivatives of the end-to-end channel with respect to the UE position, the UE orientation and the SOs positions. These are obtained in closed form from the coupled dipole model described Section 4.2.1.

The parameters in $\boldsymbol{\theta}$ enter the interaction matrix $\mathbf{W}^{(t)}$ only through the Green's functions in (6), since the inverse polarizabilities in (5) are set by the dipole material parameters and by the RIS resonances, and are therefore independent of $\boldsymbol{\theta}$. Writing $d_{ij} = \|\mathbf{r}_i - \mathbf{r}_j\|$ for the distance between the i -th and j -th dipoles and using $dH_0^{(2)}(z)/dz = -H_1^{(2)}(z)$, the derivative of an off-diagonal entry with respect to any parameter θ_l is

$$\frac{\partial G_{ij}}{\partial \theta_l} = j \frac{\kappa^3}{4\epsilon\delta} H_1^{(2)}(\kappa d_{ij}) \frac{\partial d_{ij}}{\partial \theta_l}, \quad (44)$$

where $H_1^{(2)}(\cdot)$ is the first-order Hankel function of the second kind. Let $\mathcal{U}$ denote the index set of the UE dipoles and $\mathcal{S}_m$ that of the dipoles forming the m -th SO cluster. The UE dipoles have fixed local offsets $\boldsymbol{\delta}_j$ with respect to the UE center, so that the global position of the j -th UE dipole is $\mathbf{r}_j^{\text{UE}} = \mathbf{u} + \mathbf{R}(\alpha) \boldsymbol{\delta}_j$, and the dipoles of an SO cluster translate rigidly with the cluster position. The distance derivatives are therefore

$$\frac{\partial d_{ij}}{\partial \mathbf{u}} = \frac{\mathbf{r}_j^{\text{UE}} - \mathbf{r}_i}{d_{ij}}, \quad j \in \mathcal{U}, \quad (45a)$$

$$\frac{\partial d_{ij}}{\partial \alpha} = \frac{(\mathbf{r}_j^{\text{UE}} - \mathbf{r}_i)^\top \mathbf{R}'(\alpha) \boldsymbol{\delta}_j}{d_{ij}}, \quad j \in \mathcal{U}, \quad (45b)$$

$$\frac{\partial d_{ij}}{\partial \mathbf{p}_m} = \frac{\mathbf{r}_j - \mathbf{r}_i}{d_{ij}}, \quad j \in \mathcal{S}_m, \quad (45c)$$

where $\mathbf{R}'(\alpha)$ is the derivative of the two-dimensional rotation matrix $\mathbf{R}(\alpha) = [\cos(\alpha) \quad -\sin(\alpha); \sin(\alpha) \quad \cos(\alpha)]$. Only those entries of $\mathbf{W}^{(t)}$ that couple a dipole whose position depends on θ_l are non-zero in $\partial \mathbf{W}^{(t)} / \partial \theta_l$. The channel derivatives then follow from the derivative of the matrix inverse,

$$\frac{\partial \mathbf{V}^{(t)}}{\partial \theta_l} = -\text{diag}[a_1^{-1}, \dots, a_N^{-1}] (\mathbf{W}^{(t)})^{-1} \frac{\partial \mathbf{W}^{(t)}}{\partial \theta_l} (\mathbf{W}^{(t)})^{-1}, \quad (46)$$

and $\partial \mathbf{H}_{\text{BS-U}}/\partial \theta_l$ and $\partial \mathbf{H}_{\text{BS-S}}/\partial \theta_l$ are read off as the corresponding sub-blocks, in the same way that $\mathbf{H}_{\text{BS-U}}$ and $\mathbf{H}_{\text{BS-S}}$ are extracted from $\mathbf{V}^{(t)}$. Since $(\mathbf{W}^{(t)})^{-1}$ has already been formed in evaluating the channel, the derivatives with respect to all $3 + 2M$ parameters are obtained without any further matrix inversion.

The Fisher information accumulated from previous observations is

$$[\mathbf{J}_P^{(t-1)}]_{i,j} = -\mathbb{E} \left[\frac{\partial^2 \log f(\boldsymbol{\theta} \mid [\mathbf{y}^{(\tau)}]_{\tau=0}^{t-1})}{\partial \theta_i \partial \theta_j} \right] - \mathbb{E} \left[\frac{\partial^2 \log f(\boldsymbol{\theta} \mid [\mathbf{y}_s^{(\tau)}]_{\tau=0}^{t-1})}{\partial \theta_i \partial \theta_j} \right] \quad (47a)$$

$$= \sum_{t'=1}^{t-1} -\mathbb{E} \left[\frac{\partial^2 \log f(y^{(t')} \mid \boldsymbol{\theta}, [\mathbf{y}^{(\tau)}]_{\tau=0}^{t'-1})}{\partial \theta_i \partial \theta_j} \right] + \sum_{t'=1}^{t-1} -\mathbb{E} \left[\frac{\partial^2 \log f(y_s^{(t')} \mid \boldsymbol{\theta}, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^{t'-1})}{\partial \theta_i \partial \theta_j} \right] - \mathbb{E} \left[\frac{\partial^2 \log f(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \right]. \quad (47b)$$

The summations represent the cumulative information from all past measurements together with the prior distribution of $\boldsymbol{\theta}$.

The conditional FIM in (38) depends on $\mathbf{k}^{(t)}$ only through $\mathbf{J}_D(t)$ [115], leading to the optimization problem

$$\min_{\mathbf{k}^{(t+1)}} \text{tr} \left((\mathbf{J}_{uu}^{(t)} - \mathbf{J}_{up}^{(t)} (\mathbf{J}_{pp}^{(t)})^{-1} \mathbf{J}_{pu}^{(t)})^{-1} \right). \quad (48)$$

This problem is solved using projected gradient descent [139]. The posterior distribution is updated recursively as

$$f(\boldsymbol{\theta} \mid [\mathbf{y}^{(\tau)}]_{\tau=1}^t, [\mathbf{y}_s^{(\tau)}]_{\tau=1}^t, [\mathbf{k}^{(\tau)}]_{\tau=1}^t) = L \cdot f(y^{(t)} \mid \boldsymbol{\theta}, \mathbf{k}^{(t)}) f(\boldsymbol{\theta} \mid [\mathbf{y}^{(\tau)}]_{\tau=0}^{t-1}, [\mathbf{y}_s^{(\tau)}]_{\tau=1}^t, [\mathbf{k}^{(\tau)}]_{\tau=0}^{t-1}), \quad (49)$$

where L is a normalization constant. For the MIMO case, the likelihood becomes vector valued and the Bayesian FIM is obtained from derivatives of the mean vectors with respect to $\boldsymbol{\theta}$ as in [24], while the Schur complement and conditional RMSE expressions remain unchanged.

5.5 Performance Evaluation

5.5.1 Simulation Setup

The simulation parameters are summarized in Table 4. As shown in the system model, the BS and distributed RIS locations are fixed and known. The UE position $\mathbf{u}$ is uniformly generated within the rectangular service region in the x - y plane with spacing $\lambda/2$, while the orientation α is independently sampled from $\alpha \in [0, 2\pi)$. The pilot signal $\mathbf{x}^{(t)}$ is deterministic and equal to unity at all time stages.

The environment contains M SOs that move within the enclosure according to a Gauss-Markov mobility model. Let $\mathbf{p}_m^{(t)}$ and $\mathbf{v}_m^{(t)}$ denote the position and the velocity of the m -th SO at frame t . The velocity is updated as $\mathbf{v}_m^{(t)} = \rho \mathbf{v}_m^{(t-1)} + (1 - \rho) \bar{\mathbf{v}} + \sqrt{1 - \rho^2} \sigma_v \mathbf{w}_m^{(t)}$, $\mathbf{w}_m^{(t)} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_2)$, followed by the position update $\mathbf{p}_m^{(t)} = \mathbf{p}_m^{(t-1)} + \mathbf{v}_m^{(t)}$, with reflection at the enclosure boundaries. Here $\bar{\mathbf{v}}$ is the mean drift, σ_v sets the per-frame step size, and $\rho \in [0, 1]$ controls the temporal correlation of the scattering process, so that values approaching unity produce smooth motion while $\rho = 0$ reduces to independent steps. The initial positions are drawn independently and uniformly over the enclosure in each realization, and all SOs are updated simultaneously and move independently of one another. The central dipole position of each SO cluster is recorded in every realization. The temporal correlation introduced by ρ is what the sequential model of Section 5.3 exploits when estimating the scattering state.

Dipole parameters for transceivers, the environment, and the RIS, including resonance frequency f_{res} , charge term χ , and absorptive damping Γ_L , follow Table 4 and are guided by [10].

The proposed learning-based approach performs joint UE localization, orientation estimation, and environment sensing using the settings in Table 4. Hyperparameters of the biLSTM networks

Table 4: Simulation and Network Parameters for Joint User Location and Orientation Estimation Approach

Label	Value
Simulation Parameters	
M	2, 4, 6
N_{BS}	4
N_{UE}	4
N_{RIS}	20, 60, 100
S_{RIS}	2, 4, 6, 8
Transceivers dipole parameters	$f_{res} = 1, \chi = 0.5, \Gamma_L = 0$
Transceivers dipole spacing	$\lambda/2$
Environment and SOs dipole parameters	$f_{res} = 10, \chi = 50, \Gamma_L = 10^4$
Environment and SOs dipole spacing	$\lambda/4$
RIS dipole parameters	$f_{res} \in [f_{min} = 0.8, f_{max} = 1.2],$ $\chi = 0.2, \Gamma_L = 0.03$
RIS dipole spacing	$\lambda/4$
SOs motion parameters	$\sigma_v = 0.7\lambda, \rho = 0.85, \bar{\mathbf{v}} = \mathbf{0}$
Parameters of the biLSTM Network	
Batch size, B	[32,64,128]
BiLSTM layers, N_L	[2,4,6]
Hidden state dimensions, d_s	[25,35,45]
Learning rate, η	[0.001,0.01,0.005,0.05]
Maximum epochs	200
DNN Layers, L_n	4

are optimized via Bayesian Optimization (BO) [140, 141], selecting the number of layers N_L , hidden dimension d_s , learning rate η , and batch size B to balance accuracy and complexity [3]. Training uses the Adam optimizer [137] on 2,136,000 samples for 200 epochs. The dataset is partitioned into disjoint subsets containing 70% of the samples for training, 15% for validation and 15% for testing. The network architecture and training hyperparameters were selected by hyperparameter optimization, with each candidate trained from a randomly initialized starting point and evaluated on the validation set. The configuration achieving the lowest validation loss was retained, and evaluated on the held-out test set. Scattering estimation labels have dimension $2M$, while localization labels correspond to UE position and orientation. After training, the model sequentially selects RIS configurations and BS/UE beamforming vectors from received pilots and scattering estimates to localize UEs within the coverage region. Performance is compared against the following benchmarks:

- *Beamforming-free biLSTM network*[3]: the RIS configuration is adapted over T time frames while accounting for the scattering in the environment, without any design of the BS or UE beamforming vectors. As the reference design estimates the UE position only, it is extended here to estimate the UE orientation as well, again so that every approach is evaluated on the same estimation task.
- *BCRLB-based design*: the conditional BCRLB is used as the optimization metric at every time frame, as described in Section 5.4. The posterior distributions of the UE state and the SOs positions are refined recursively from the received pilot and sensing measurements, and the RIS configuration and the BS and UE beamforming vectors are designed by projected gradi-

ent descent to minimize the resulting bound. For the posterior evaluation, the $35\lambda \times 55\lambda$ service region in the x - y plane is discretized into 350×550 grid cells and the orientation α is discretized into 180 bins over $[0, 2\pi)$. The SOs positions enter the augmented parameter vector through the prior $f(\mathbf{p})$, which is taken as uniform over the service region.

- *Adaptive design without scattering estimation* [125, 124]: a single recurrent network sequentially designs the beamforming vector and the RIS configuration from the accumulated pilot observations and reads out the UE state from its terminal representation, without a dedicated subset of sensing elements and without an explicit scattering estimate. As the reference design considers a single-antenna UE in a channel dominated by a line-of-sight component, a UE beamforming vector and an orientation output are added here so that every approach is evaluated on the same estimation task over the same channel.

5.5.2 Results

The UE localization performance versus the number of time frames T and SNR is evaluated in Figure 19 and Figure 20. The proposed method achieves consistently lower RMSE in both location and orientation estimation compared with all benchmark approaches across all values of T and SNR. Although performance improves for all methods as T increases, the proposed approach maintains a clear advantage over the adaptive beamforming-free biLSTM and the localization-only biLSTM approaches, the latter neglecting environmental scattering.

The BCRLB-based maximum a posteriori estimator design attains higher RMSE than the learning-based methods. The proposed formulation in (23) jointly estimates scattering and designs configuration vectors over all stages t to minimize the final localization RMSE at T , through $\{G^{(t)}(\cdot), F^{(t)}(\cdot)\}_{t=0}^{T-1}$. In contrast, the BCRLB-based design in (34) optimizes the configuration independently at each time frame. The BCRLB-based scheme selects each RIS configuration to minimize the one-step conditional bound, i.e., it optimizes the information obtained at the current frame without regard to how that choice shapes future measurements. The proposed learning-based controller, in contrast, is trained with supervision applied only at the frame T , so it learns sequences of configurations that maximize cumulative, multi-stage information gathering toward the final estimate. Because the localization objective depends on the joint information collected over all T frames, the multi-stage policy attains lower RMSE than the single-step greedy optimization, particularly as T grows and as scattering dynamics become stronger. The BCRLB optimization is a nonconvex problem, thus the designed beam vectors are suboptimal. The bound based design is retained for reasons independent of the accuracy of the design. It is the tractable analytical design that provides a model-based reference for interpreting the learned design.

Figure 21 shows the effect of RIS deployment and element count on UE localization RMSE. Single-wall deployments produce the highest RMSE due to limited angular diversity. Adding elements improves gain but not directional richness. Two- and three-wall deployments enhance reflections and angular resolution, reducing RMSE, while four-wall deployment achieves the lowest RMSE, with gains saturating at high densities due to noise and channel limits. The proposed method consistently outperforms beamforming-free biLSTM, UE localization biLSTM only, and BCRLB-based baselines. Distributed RIS panels with centralized control improve spatial diversity and measurement identifiability. Both configuration design and panel geometry critically influence UE localization accuracy in RSE.

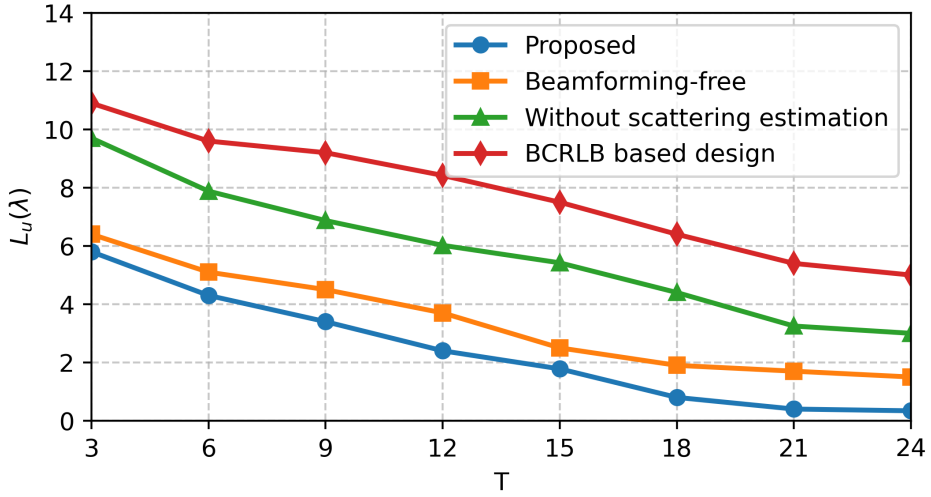
The impact of the number of SOs M on UE and SOs localization is shown in Figure 22. Higher M increases RMSE for UE location, orientation, and SO positions due to denser multipath, inter-path interference, and higher estimation dimensionality, especially at low SNR. Figure 22a shows UE location RMSE rises with M ; higher SNR improves accuracy but cannot fully offset dense scattering. Figure 22b shows orientation errors grow with M from angular ambiguity. Figure 22c shows SOs RMSE increases with M , saturating at moderate-to-high SNR. These results indicate moderate SOs densities balance multipath diversity and estimation complexity, while dense dynamic scattering limits performance. Adaptive RIS configuration and accurate scattering modeling are crucial for reliable UE localization and SOs sensing.

Figure 23 reports the cumulative distribution function (CDF) distribution of the UE localization error over the test set at a fixed operating points. The proposed approach concentrates the majority

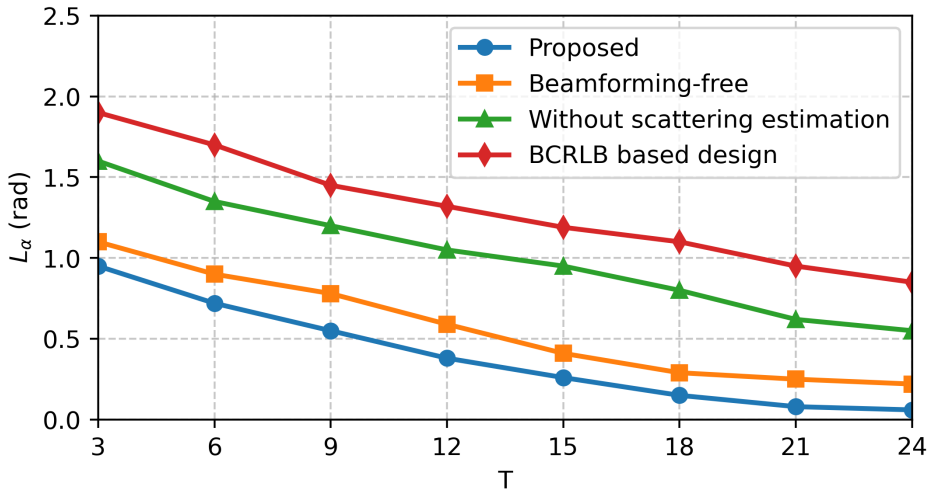
of its errors at low RMSE and rises steeply, so the reported mean is representative of the individual test cases. The beamforming-free and scattering-agnostic designs remain competitive but with visibly wider dispersion.

5.6 Summary

This chapter proposes a learning-based method for UE location and orientation estimation in RIS-assisted networks within RSE. The approach sequentially designs the RIS configuration, BS beamforming, and UE beamforming while estimating scattering from dynamic SOs. Leveraging RIS-assisted sensing and historical measurements at the BS, it models temporal features to adaptively optimize RIS and beamforming vectors, minimizing UE localization error. The following chapter provides concluding remarks and future directions.

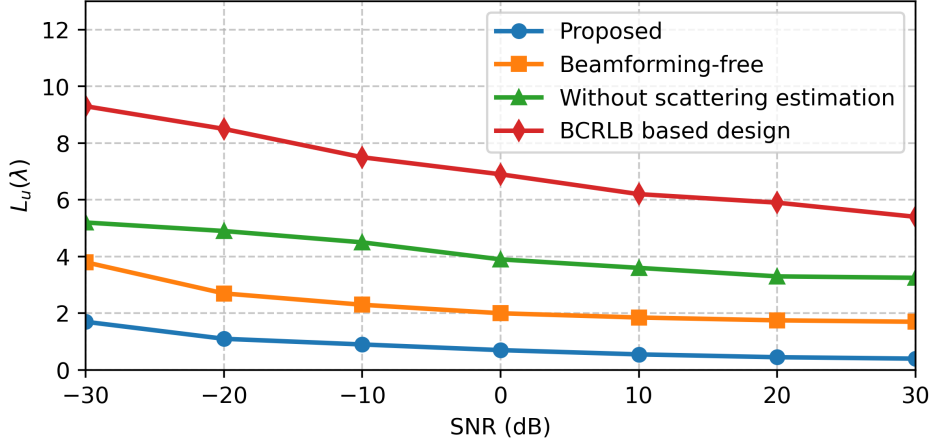


(a) UE location estimation.

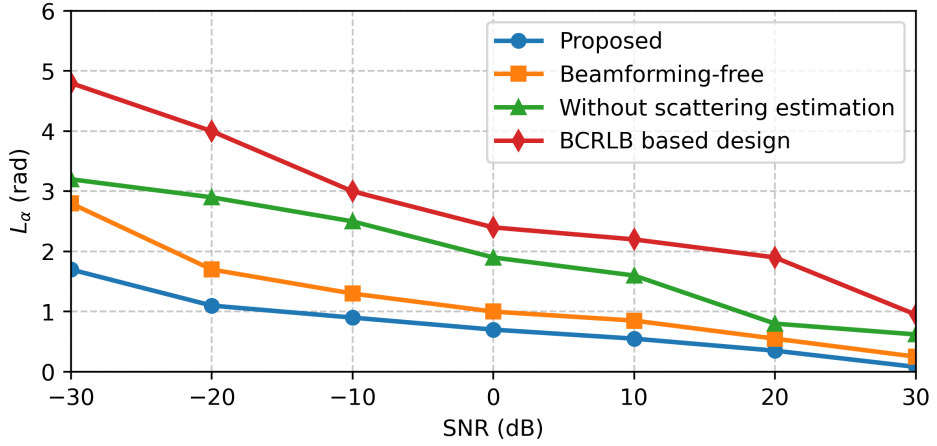


(b) UE orientation estimation.

Figure 19: RMSE of UE localization versus time frames T for $N_{RIS} = 100$, $SNR = 30$ dB and $M = 4$.

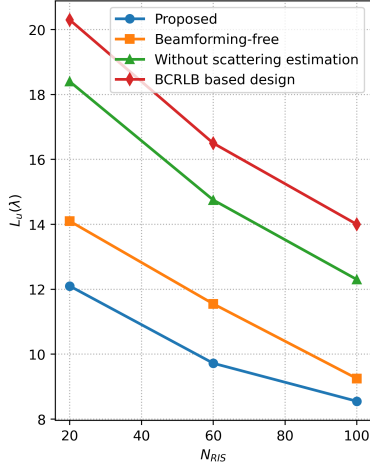


(a) UE location estimation.

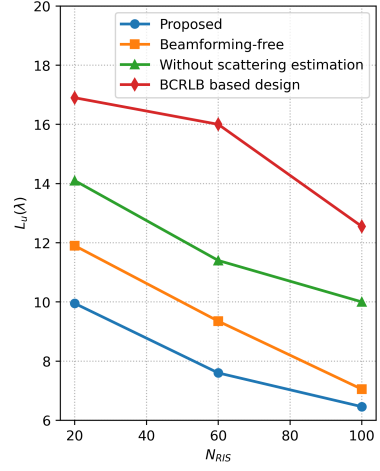


(b) UE orientation estimation.

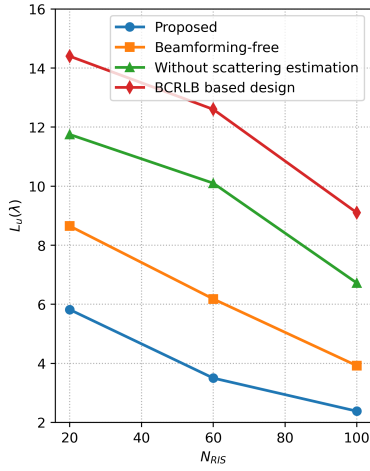
Figure 20: RMSE of UE localization versus SNR for $N_{RIS} = 100$, $T = 21$ and $M = 4$.



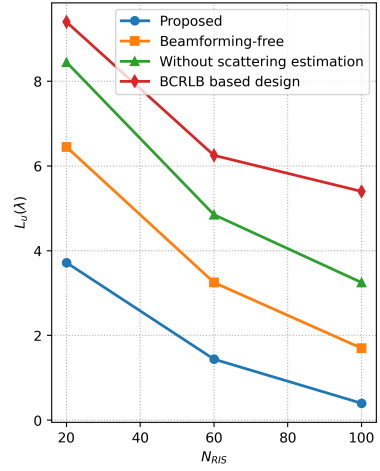
(a) Left wall only.



(b) Left and Right wall.

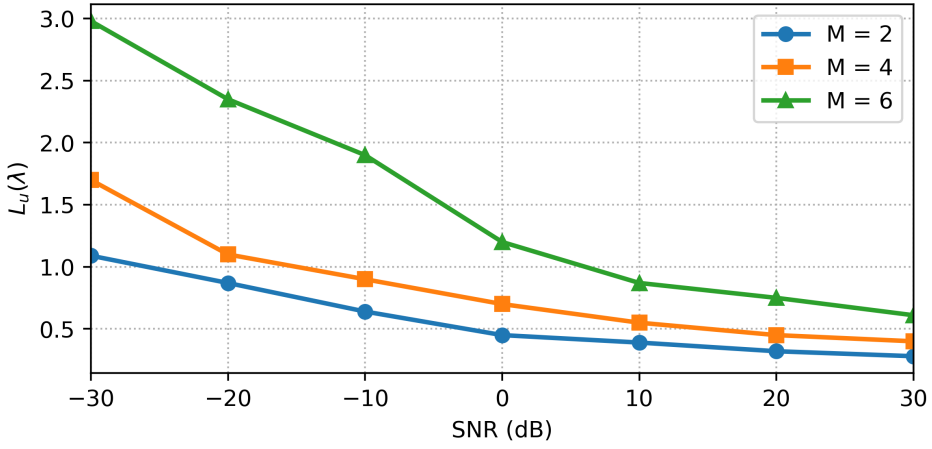


(c) Left, right and top wall.

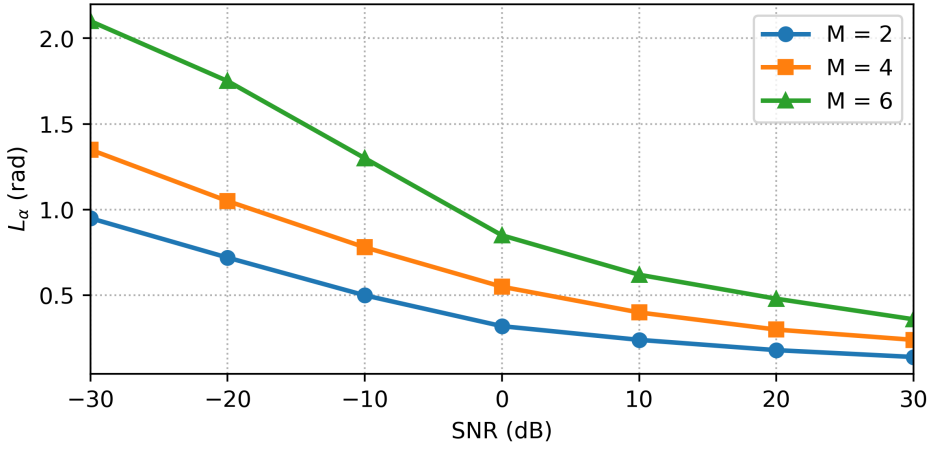


(d) All 4 walls.

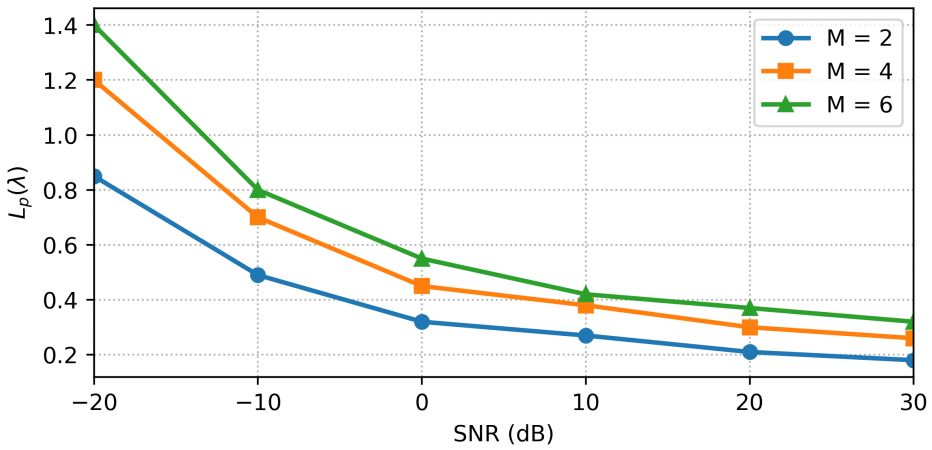
Figure 21: RMSE of UE localization versus N_{RIS} under various distributed RIS installations with SNR = 30 dB, $T = 21$, $M = 4$.



(a) UE location estimation.



(b) UE orientation estimation.



(c) SO location estimation.

Figure 22: RMSE of UE and SOs localization versus SNR for different numbers of SOs with $N_{RIS} = 100$, $T = 21$, $S_{RIS} = 8$.

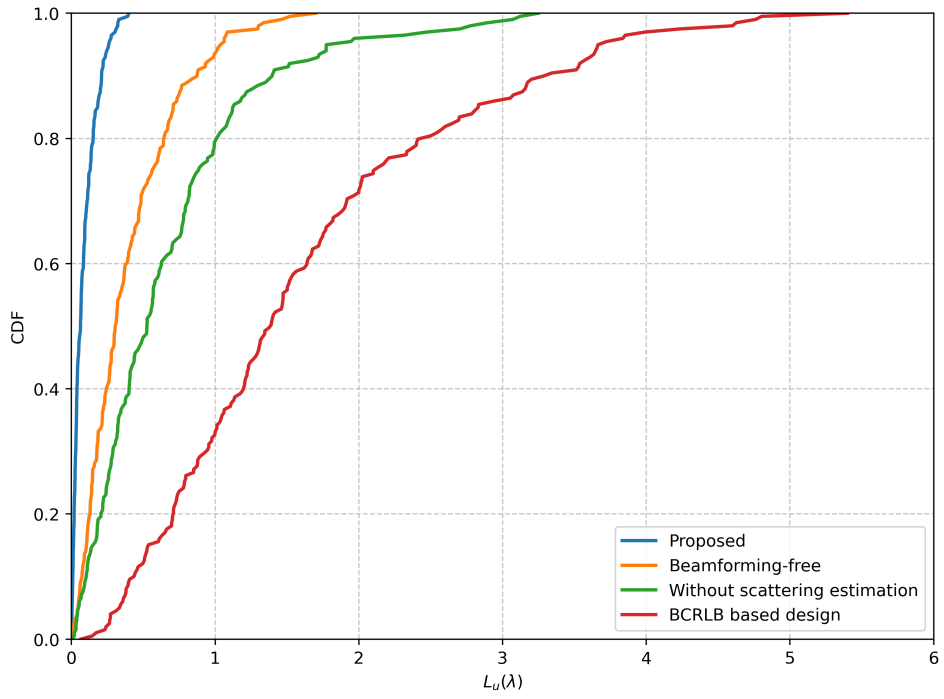


Figure 23: CDF of proposed and baseline approaches versus RMSE of user localization at $T = 21$ for $N_{RIS} = 100$, $SNR = 30$ dB, $M = 4$.

6 Conclusion

This thesis addresses the UE localization and non-cooperative environment sensing problem that arises from the analytical intractability of dynamic RIS-assisted RSEs, where multiple moving SOs jointly influence the wireless channel. Existing methods often assume that the optimal RIS configuration is a stationary function of UE geometry and neglect time-varying scattering effects in sequential measurement design. To address these limitations, this thesis shifts from static geometric optimization to a scattering-aware sequential inference approach, in which the RIS senses the environment, adapts its configuration to maximize measurement information, and enables the joint estimation of UE position and orientation.

The research was guided by four interrelated research questions (RQ1–RQ4). Each question is restated below and answered directly, with reference to the publication in which the corresponding contribution was developed.

RQ1: What is the current state of research on RIS-assisted radio localization in 6G networks, and what are the key developments, opportunities, and challenges in the field?

Despite rapid progress in RIS-assisted localization, the field lacked a unified taxonomic synthesis spanning radio-frequency, millimeter-wave, terahertz, indoor, outdoor, near-field, ISAC, and SLAM paradigms, which hindered the systematic identification of open research problems. This question was answered through the first part of the thesis, which presents a systematic survey of RIS-assisted localization in 6G networks and introduces a comprehensive five-dimensional taxonomy structured by scenario, localization modality, RIS architecture, deployment strategy, and algorithm class. The survey identified the principal structural gaps in the literature, particularly the scarcity of scattering-aware adaptive methods for dynamic indoor environments and the limited development of near-field localization approaches. These findings, reported in Publication I, motivated and shaped the three subsequent research questions.

RQ2: How can a codebook-based RIS configuration approach, combined with a data-driven learning model, be designed to improve UE localization accuracy in dynamic RSEs?

Conventional codebook-based RIS configuration methods assume that the optimal configuration depends only on UE geometry. In dynamic RSEs, however, the optimal configuration depends jointly on the UE state and the evolving SO positions, so static codebook indexing introduces irreducible localization errors. This question was answered through a codebook-based, data-driven approach that maps joint UE-side and sensing-element channel observations, conditioned on estimated scattering states, to optimal RIS configurations. In doing so, codebook selection is re-framed as an environment-aware inference problem rather than a fixed geometric lookup, yielding improved localization accuracy in dynamic scattering conditions. Quantitatively, codebook-based selection reduces localization MSE by up to 97.14% relative to random RIS configurations, while enlarging the codebook from 10 to 500 entries reduces the MSE of the optimized configuration by 88.6%.

RQ3: How can an adaptive, sensing-assisted RIS configuration strategy be devised that dynamically responds to temporal variations in the scattering environment to minimize UE localization error without relying on a fixed codebook?

Existing adaptive sequential methods update RIS configurations from pilot observations without explicitly modeling dynamic scattering effects, which reduces localization accuracy under time-varying environments. This question was answered through an adaptive approach that sequentially estimates the dynamic SO positions and adapts the RIS configuration using explicit scattering awareness, thereby removing the dependence on a fixed codebook. Results showed that the adaptive approach lowers RMSE by up to 79% as the RIS grows from 20 to 100 elements, and the same localization accuracy could be achieved using approximately half the pilot transmissions required by the benchmark methods, demonstrating substantially improved measurement efficiency under temporal channel variation. This contribution is reported in Publication III.

RQ4: How can the adaptive sensing and RIS configuration approach be extended to jointly estimate UE location and orientation while simultaneously designing BS and UE beamforming vectors, and how does a learning-based design compare with an analytically derived one?

Prior to this work, adaptive RIS sensing had not been applied to the joint estimation of UE lo-

cation and orientation in MIMO systems with jointly designed RIS and beamforming vectors, and no analytical design existed against which such a scheme could be compared in RSEs. This question was answered by extending the adaptive framework to the joint sequential design of RIS configurations, BS receive beamforming vectors, and UE transmit beamforming vectors. In parallel, an analytical design was derived, in which the conditional Bayesian Fisher information over UE location, orientation, and SO positions is used to select each configuration and a maximum a posteriori estimator produces the final estimate. Results showed that the learning-based controller attains lower localization and orientation RMSE than the analytical design. The two differ in the information each design rule exploits: the BCRLB-based design optimizes the information collected at the current frame only, whereas the learned controller is supervised at the final frame and therefore selects configuration sequences that maximize the information accumulated across the full sensing horizon. The BCRLB optimization is a nonconvex problem, thus the designed beam vectors are suboptimal.

Taken together, these answers establish scattering-aware sequential adaptive design as a foundational framework for accurate localization in RIS-assisted indoor RSEs. By replacing static geometric optimization with integrated scattering-aware sequential inference, the proposed methods attain performance previously unattainable with scattering-agnostic methods, including reduced pilot overhead and robust joint position and orientation estimation in dense, dynamic RSEs.

6.1 Limitations and Future Work

While this thesis has advanced the state of the art in UE localization and sensing in RIS-assisted RSEs, several scope limitations define the boundaries of the current contribution. The following paragraphs discuss each limitation and outline directions for future work aimed at addressing it.

The dynamic RSE channels were generated using the physics-consistent fading model and the results were obtained through numerical simulation. While the simulator captures the multiple-scattering interactions that motivate this work, the conclusions are inherently conditioned on the fidelity of this model, and results may differ under alternative channel-generation frameworks or measured propagation data. Although the simulated scenarios were designed to reflect representative dynamic indoor conditions, experimental validation on a hardware testbed would be required to confirm performance under real radio-frequency impairments, hardware non-idealities, and measurement noise.

The system geometry, SO motion, and localization were modeled in two dimensions. Extension to full three-dimensional deployments, including elevation-dependent propagation and three-dimensional SO mobility, remains to be studied and may affect both estimation accuracy and the associated bounds. Extending the modeling and estimation framework to three-dimensional geometries, and validating it on an over-the-air testbed, would strengthen the practical relevance of the results and expose effects, such as hardware impairments and elevation-dependent scattering, that cannot be captured in two-dimensional simulation.

The BS and RIS positions were assumed to be known and fixed. In practice, calibration errors or imperfect knowledge of infrastructure placement could degrade performance, and robustness to such uncertainty was not evaluated. An important direction is to develop methods that remain robust to calibration errors and uncertain infrastructure placement, for example through joint self-calibration of RIS and BS parameters alongside UE localization.

The receiver was modeled as ideal and no reconfiguration latency was considered. The RIS elements carry a fixed absorptive damping, so element insertion loss is represented but is not calibrated against a measured device, and its effect on the reported accuracies was not studied. The system is assumed phase-coherent and time-synchronized. The reported accuracies are those attainable when the full complex field is observed without synchronization error, and they would degrade under carrier-frequency offset and phase noise. Moreover, narrowband assumption is taken throughout the thesis due to lower computation time, however, the developed problem statements and approaches can be extended to wideband scenarios, although additional modeling and computational challenges must be addressed. Quantifying the degradations with phase noise and carrier-frequency offset, together with a sensitivity study over element loss and an extension of the design

to wideband pilots, is the most direct route from these results to a hardware demonstration.

The localization problem was formulated for a single UE. Multi-user settings, in which several UEs share the RIS infrastructure and pilot resources, introduce contention and interference effects that fall outside the present scope. Future work may explore federated or cooperative architectures, graph neural networks, and multi-task learning to extend the proposed scattering-aware framework to the multi-user setting, where the joint allocation of sensing and pilot resources across users becomes a central design problem.

The dynamic RSE model considered structured indoor environments with bounded motion. Outdoor and vehicular scenarios introduce faster non-stationary dynamics and shorter coherence times, which challenge the assumptions underlying the present sequential design. Future work should investigate adaptive sensing under Doppler-affected channels, joint localization and velocity estimation, and extensions of the analytical framework to high-mobility settings.

The adaptive approach relied on recurrent biLSTM models. Alternative deep-learning architectures, such as transformer-based sequence models and attention mechanisms, may further improve performance by capturing long-range temporal dependencies and by scaling more favorably to large RIS arrays. Investigating the trade-offs among accuracy, training efficiency, and online inference cost for these architectures is a natural continuation of this work.

Finally, the developed analytical BCRLB based estimation approach provides a foundation for further theoretical investigation of localization in RSEs. Extending the analysis to account for imperfect scattering estimation, correlated SO motion, and distributed RIS deployments could yield tighter and more practically relevant performance bounds, supporting the principled design of future localization systems for complex propagation environments.

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Abstract

Integrated Sensing and User Localization in Reconfigurable Intelligent Surfaces-Assisted Dynamic Rich-Scattering Environments

This thesis considers the problem of radio localization in dynamic reconfigurable intelligent surfaces (RIS)-assisted rich-scattering environment (RSE). This problem is central to autonomous indoor navigation, industrial robotics, smart factory management, and context-aware services in 6G environments where global navigation satellite systems are unavailable. Existing works exhibit three major limitations. First, the lack of a unified and reproducible taxonomic synthesis of RIS-assisted localization spanning conventional radio frequency, millimeter wave (mmW), and terahertz band (THz) systems, and emerging paradigms such as integrated sensing and communication (ISAC) and simultaneous localization and mapping (SLAM) hinders systematic identification of research gaps and unresolved challenges. Second, codebook-based RIS configuration methods discretize the configuration space through offline calibration indexed only by user equipment (UE) geometry, while ignoring dynamic scattering conditions, leading to an irreducible localization error floor that increases with environmental dynamics. Third, adaptive sequential methods reconfigure RIS using accumulated pilot observations without explicitly estimating the effect of dynamic scattering objects (SOs), causing scattering induced variations to be confounded with configuration induced changes and reducing robustness under time-varying propagation.

This thesis addresses these limitations through four main contributions. First, a systematic survey of RIS-assisted radio localization in 6G networks is presented, introducing a five-dimensional taxonomy and consolidating the state of the art across outdoor far-field, indoor, and near-field scenarios. Second, a codebook-based data-driven approach is proposed which learns the mapping from joint UE-side and sensing element channel observations, conditioned on estimated scattering states, to the optimal pre learned RIS configuration. Third, an adaptive codebook free data-driven approach is developed to sequentially estimate dynamic SO positions and adapt RIS configurations for improved UE localization. Fourth, this adaptive framework is extended to the uplink multiple-input-multiple-output (MIMO) setting for joint estimation of UE position and orientation through sequential co-design of RIS configurations, base station (BS) receive beamforming vectors, and UE transmit beamforming vectors, alongside derivation of analytical bounds. Performance is benchmarked against random RIS configurations, static codebook selection, deep neural network based scattering estimation without sequential modeling, scattering agnostic adaptive data-driven designs, and analytical bounds-based greedy optimization. Performance is tested under varying RIS sizes, signal-to-noise ratio (SNR) conditions, SOs densities, and distributed RIS deployment geometries.

Quantitatively, codebook-based RIS configuration selection reduces localization mean square error (MSE) by up to 97.14% relative to random configurations, while enlarging the codebook from 10 to 500 entries reduces the MSE of the optimized configuration by 88.6%. The adaptive codebook-free approach reduces localization root mean squared error (RMSE) by up to 79% as the RIS grows from 20 to 100 elements, while achieving target accuracy using nearly half the pilot transmissions required by benchmark methods, corresponding to a twofold reduction in localization latency. The joint position and orientation estimation approach attains lower RMSE than all learning-based baselines across varying SO densities, RIS element counts, and distributed RIS deployment geometries. It also attains lower RMSE than the Bayesian Cramér-Rao lower bound (BCRLB)-based design, that is, the configuration sequence obtained by minimizing the one-step conditional BCRLB bound at each frame followed by a maximum a posteriori estimator. Overall, the results demonstrate that RIS-assisted localization in RSE can be transformed from a static geometric optimization problem into a scattering-aware sequential inference framework where RIS not only adapts to maximize information from successive measurements, but also enables accurate joint estimation of UE position and orientation under indoor multipath dynamics. For practical RIS deployments in industrial, warehouse, and smart building environments, this provides a principled adaptive framework that avoids explicit geometric channel modeling, path separation, and static offline calibration, while scaling

favorably with RIS aperture, antenna array dimensionality, and temporal observation depth.

Kokkuvõte

Lõimitud tuvastamine ja lokaliseerimine peegeldusterikkas keskkonnas ümberkonfigureeritavate tarkade pindade abil

Käesolevas doktoritöös käsitletakse raadionavigatsiooni probleemi dünaamilises keskkonnas kus eksisteerib ohtralt signaale peegeldavaid ja hajutavaid objekte (Rich-Scattering Environment, RSE) kasutades ümberkonfigureeritavate tarkade pindade (Reconfigurable Intelligent Surfaces, RIS) abi. Probleem on keskse tähtsusega siseruumides positsioneerimises, tööstusrobotikas, nutikate tehaste halduses ning kontekstitudlikes 6G teenustes, kus globaalsed satelliitnavigatsioonisüsteemid ei ole, ühel- või teisel põhjusel, kasutatavad. Olemasolevatel lahendustel on kolm peamist puudust. Esiteks puudub ühtne ja reprodutseeritav RIS-toega lokaliseerimise taksonoomiline käsitlus, mis hõlmaks tavapäraseid raadiosageduslikke süsteeme, millimeeterlainete (mmW) ja terahertssagedusala (THz) süsteeme ning uusi paradigmasid, nagu integreeritud sensor- ja sidevõrgud (Integrated Sensing and Communication, ISAC) ning samaaegne lokaliseerimine ja kaardistamine (Simultaneous Localization and Mapping, SLAM). Koodiraamatu põhised RIS-i häälestusmeetodid kasutavad eelnevalt kalibreeritud konfiguratsioone, mis on indekseeritud üksnes kasutajaseadme (User Equipment, UE) geomeetria alusel, jättes arvestamata dünaamilised levikeskkonna mõjud. Selle tulemusena tekib vältimatu lokaliseerimisviga, mis suureneb keskkonna dünaamilisuse kasvades. Kolmandaks muudavad adaptiivsed järjestikused meetodid RIS-i konfiguratsiooni kogunenud pilootsignaalide vaatluste põhjal, hinnates seejuures dünaamiliste hajumisobjektide (Scattering Objects, SO) mõju kaudselt. Seetõttu segunevad hajumisest tingitud muutused konfiguratsioonist tingitud muutustega, mis vähendab meetodite töökindlust ajas muutuvate levitingimuste korral.

Doktoritöö pakub lahendused ülaltoodud puuduste jaoks järgneva nelja panuse kaudu. Esiteks esitatakse süstemaatiline ülevaade RIS-toega raadiolokaliseerimisest 6G võrkudes, milles tutvustatakse viiemõõtmelist taksonoomiat ning koondatakse senine teadustöö välitingimustes kaugtsoonis, sisetingimustes ja lähitsoonis toimuvate rakenduste kohta. Teiseks pakutakse välja koodiraamatul baseeruv andmepõhine meetod, mis õpib seose kasutajaseadme ja sensorite poolt kogutud kanali hinnangute ning hinnatud hajumisseisundi põhjal optimaalse eelõpitud RIS-i konfiguratsiooniga. Kolmandaks töötatakse välja adaptiivne koodiraamatu vaba andmepõhine meetod, mis hindab järjestikku dünaamiliste, levi mõjutavate, objektide asukohti ning kohandab RIS-i konfiguratsiooni kasutajaseadme lokaliseerimise täpsuse parandamiseks. Neljandaks laiendatakse seda adaptiivset raamistikku üplüüsi mitme sisendi ja mitme väljundiga (Multiple-Input Multiple-Output, MIMO) süsteemile, võimaldades kasutajaseadme asukoha ja orientatsiooni ühist hindamist RIS-i konfiguratsioonide ja mobiilside tugijaama (Base Station, BS) ning kasutajaseadme antennide suunadiagrammi samaaegse modifitseerimise teel. Lisaks tuletatakse ka lahenduse analüütilised jõudluspiirid. Meetodite toimivust võrreldakse erinevate alternatiivsete lahendustega erinevate konfiguratsioonide ja parameetrite väärtuste korral.

Kvantitatiivsed tulemused näitavad, et koodiraamatu mahu suurendamine vähendab lokaliseerimise ruutkeskmist viga kuni 88,6% võrreldes juhuslike konfiguratsioonidega. Adaptiivne koodiraamatuvaba meetod vähendab lokaliseerimise ruutkeskmist viga kuni 79%, kui RIS-i elementide arv suureneb 20-lt 100-ni. Seejuures saavutatakse soovitud lokaliseerimise täpsus ligikaudu poole väiksema pilootsignaalide arvu juures kui võrdlusmeetoditel, mis tähendab ligikaudu kahekordset lokaliseerimisviite vähenemist. Ühise asukoha ja orientatsiooni hindamise meetod ületab järjepidevalt kõigi võrdlusmeetodite tulemusi erineva hajumisobjektide tiheduse, RIS-i elementide arvu ja hajutatud RIS-paigutuste korral. Samuti näidatakse, et analüütilistel piiridel põhinev ahne optimeerimismeetod on oma olemuselt lokaalse otsustushorisondi tõttu mitteoptimaalne. Kokkuvõttes näitavad tulemused, et RIS-toega lokaliseerimist signaale hajutavas keskkonnas saab käsitleda mitte enam staatilise geomeetrilise optimeerimisülesandena, vaid hajumisteadliku järjestike otsuste raamistikuna, milles RIS mitte üksnes kohandub maksimeerimaks järjestikuste mõõtmiste informatiivsust, vaid võimaldab ka kasutajaseadme asukoha ja orientatsiooni täpset ühist hindamist mitmekiirelise levi dünaamilistes tingimustes. Tööstus-, lao- ja nutikate hoonete praktiliste RIS-rakenduste jaoks pakutakse põhimõttelist adaptiivset raamistikku, mis väldib kanalite geomeetria otsest modelleerimist, leviteede eraldamist ja staatilist eelkalibreerimist ning mille skaleeritavus paraneb RIS-i suuru-

se, antennimassiivi mõõtmete ja ajaliste vaatluste arvu kasvades.

Appendix 1

I

A. Umer, I. Mürsepp, M. M. Alam, and H. Wymeersch, "Reconfigurable Intelligent Surfaces in 6g Radio Localization: A Survey of Recent Developments, Opportunities, and Challenges," *IEEE Communications Surveys & Tutorials*, vol. 27, no. 6, pp. 3526–3560, 2025

Reconfigurable Intelligent Surfaces in 6G Radio Localization: A Survey of Recent Developments, Opportunities, and Challenges

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Abstract—In this survey paper, we present an extensive review of the use of reconfigurable intelligent surfaces (RIS) in 6G radio localization, highlighting their pivotal role as a low-cost, energy-efficient technology that reshapes wireless communication and localization landscapes. Investigating the versatile capabilities of RIS, we explore their dynamic control over electromagnetic wave manipulation, including reflection, refraction, and transmission, which opens new horizons in diverse applications ranging from Internet of Things (IoT) connectivity to advanced mobile communication, and various innovative applications in Industry 4.0. Our comprehensive review provides an overview of RIS use in 6G radio localization, highlighting recent progress in RIS technology assisted localization. It focuses on key aspects, including network scenarios, transmission bands, deployment environments, and near-field operations. We discuss studies to examine the state-of-the-art RIS-assisted localization and optimization techniques and their performance evaluation matrices. In addition, we present a detailed taxonomy of RIS-assisted radio localization, emphasizing the rapid evolution and potential of RIS technology in non-line-of-sight scenarios as an alternative to traditional base stations. Based on the careful investigation of the reviewed studies, the survey also sheds light on future research directions, technical challenges, and limitations, offering a clear perspective on the integration and optimization of RIS in 6G networks for enhanced localization capabilities.

Index Terms—6G, localization, reconfigurable intelligent surfaces, RIS.

I. INTRODUCTION

THE reconfigurable intelligent surfaces (RIS) are advanced metasurfaces designed with the remarkable capability of being able to be reprogrammed to alter their electromagnetic

properties and functionalities according to specific requirements [1]. These intelligent surfaces enable dynamic control over the reflection, transmission, and absorption of electromagnetic waves, allowing for unprecedented flexibility and adaptability in manipulating wireless signals and optimizing wireless communication systems. Through their programmability, RIS empower researchers and engineers to explore a wide range of applications, including wireless communication networks, smart environments, Internet of Things (IoT) connectivity, radar systems, and more [2]. By harnessing the potential of RIS technology, we can revolutionize the way we interact with and shape the electromagnetic world around us. They provide the ability to control and program the wireless communication channel, making it a highly versatile tool for wireless communication [3]. This feature makes RIS favorable for radio communication and localization since we can control the illumination of non-line-of-sight (NLoS) areas where direct signaling from the anchor node is not possible. Moreover, radio localization typically requires more than one anchor to function, in contrast, RIS offer a cost-effective and energy-efficient solution to replace additional anchor nodes and relays [4]. This is due to the simpler hardware implementation of RIS, which are easier to deploy and maintain. RIS, with their limited power requirements, can be installed on surfaces like walls, billboards, or even autonomous aerial vehicles for emergency services [5].

Besides reconfigurability, there are other key features that promise to make RIS suitable for use in wireless networks. RIS can be fabricated using low-cost materials such as printed circuit boards, making it affordable for widespread deployment [26]. It can significantly reduce the energy consumption of wireless communication systems. By reflecting and focusing the signal towards the intended receiver, RIS can reduce the need for high-power transmitters and increase the energy efficiency of the whole system [27]. RIS can mitigate interference in wireless communication systems by reflecting and manipulating the signal, it can create nulls in the directions where interference is present, leading to improved signal quality and channel capacity [28], [29].

RIS are, thus, perceived as state-of-the-art technology for the localization of users in sixth generation (6G) mobile communication networks provided the location of the RIS is already known [1]. The research community is actively working on modeling and optimization of various aspects

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TABLE I
TOPIC WISE COMPARISON WITH RECENT LOCALIZATION AND RIS-ASSISTED LOCALIZATION SURVEYS AND TUTORIALS

	Article	Type	Transmission bands			Environment		Applications		
			<30GHz	mmW	THz	Indoor	Outdoor	SLAM	ISAC	JCAL
Localization	[6]	Survey					✓	✓		
	[7]	Survey				✓				
	[8]	Survey					✓			
	[9]	Survey	✓			✓		✓		
	[10]	Survey	✓							
	[11]	Survey				✓				
	[12]	Survey	✓							
	[13]	Survey		✓						
	[14]	Survey				✓				
	[15]	Survey	✓							
	[16]	Survey				✓				
	[17]	Survey	✓	✓						
	[18]	Survey		✓						
RIS-Assisted Localization	[19]	Survey								
	[20]	Survey							✓	
	[21]	Tutorial	✓	✓	✓	✓	✓	✓	✓	✓
	[22]	Survey						✓		
	[23]	Tutorial			✓					
	[24]	Survey		✓		✓				
	[25]	Survey		✓						
	this work	Survey	✓	✓	✓	✓	✓	✓	✓	✓

of RIS-assisted radio localization to enable bigger-impact techniques and applications for 6G networks, such as simultaneous localization and communication (SLAC), simultaneous localization and mapping (SLAM), and numerous inventive applications in the realm of Industry 4.0, as elaborated further in the paper. While research in this area of radio localization is advancing rapidly, it is essential to consolidate the progress made in this field and pinpoint both past accomplishments and future avenues for exploration.

A. Related Work and Motivation

In this subsection, we discuss the related works published in the recent years and highlight the motivation behind current study. Several review studies exist on localization that share the localization basics in common but each of them is primarily focused on either the type of signals used for localization, the localization environment, or the techniques for localization. For instance, indoor localization is discussed in [7], [9], [11], [14], [16], outdoor localization in [6], [8], [30] and localization in ground-air-space networks in [31]. As for the types of signals, radio signals are covered in [9], [10], [16] and visible light positioning (VLP) in [32]. Localization techniques such as SLAM [6], [9], multi-dimensional scaling [12], machine learning (ML) [14], [15] have also been discussed in the dedicated surveys. Several surveys exist on the application of localization such as device-free localization (DFL) [30], autonomous driving [6], [8], [19], pedestrian localization [15], emergency response [7] and network localization [9]. Recent studies focus on envisioned applications and use cases of localization in 6G [21], technological enablers for beyond fifth generation (5G) and 6G localization including RIS [1], [2], surveys on localization signal processing techniques and algorithms for 6G [22], [25], [33], as well as the convergent communication, localization, and sensing including integrated sensing and communication (ISAC) [2], [20], and high-frequency localization [1], [2], [23], [33]. While [21]

provides a holistic overview of localization in 6G networks, our study is focused only on RIS-assisted localization in 6G networks. Several studies explore the potential and applications of RIS in 6G systems. Research has been conducted on the potential of RIS in radio localization and mapping, which are detailed in [1] and [2]. Further studies and surveys discuss signal processing in RIS-assisted networks, as can be found in [22], [25], [33]. A tutorial that gives an overview on radio localization with RIS at higher frequencies is presented in [23]. The domain of IoT positioning has been explored in a contemporary survey presented in [24]. However, the breadth of this study is relatively limited. This constrained scope suggests that it may not fully encapsulate the entire spectrum of research conducted in RIS-assisted radio localization in 6G networks. Furthermore, the survey's content is not up-to-date with the most recent advancements in the field. Additionally, a notable limitation of this survey is its lack of reproducibility, which could be a critical factor for those seeking to validate or build upon its findings. The concept of ISAC with RIS is explained in a tutorial overview in [3]. Lastly, the study in [34] examines the use of RIS in different network scenarios, such as single-input, single-output (SISO), multiple-input, multiple-output (MIMO), multiple-input, single-output (MISO), and single-input, multiple-output (SIMO). The recent study provided an overview of the performance improvements offered by RIS over traditional network designs in smart wireless environments. It specifically focused on the network architecture, deployment scenarios, bandwidth, and area of influence enabled by RIS [35]. Topic wise comparison of recent articles on localization and RIS-assisted radio localization with our work is provided in Table I.

The research community is actively exploring various aspects of RIS in radio localization. These include modeling, analysis, and optimization of various localization scenarios with base station (BS), user equipment (UE), and RIS, determining the number and type of RIS elements, as well as designing phase control and coefficient values for enhanced

TABLE II
RESEARCH QUESTIONS BASED COMPARISON O WITH EXISTING
SURVEYS, TUTORIALS AND REVIEW STUDIES WITH ✓ FOR FULLY
ADDRESSED, ∂ FOR PARTIALLY ADDRESSED AND × OF
NOT ADDRESSED QUESTIONS

Reference	Q1	Q2	Q3	Type of study
[22]	×	×	×	Survey
[23]	∂	∂	∂	Tutorial
[31]	×	×	×	Tutorial
[24]	∂	∂	∂	Review
[21]	∂	∂	∂	Review/ Tutorial
[25]	∂	∂	×	Review/ Tutorial
[66]	×	×	×	Review
[67]	×	×	×	Review
[68]	×	×	×	Review
This work	✓	✓	✓	Survey

localization [26], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [25], [34], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65]. Other factors being studied primarily include the placement of RIS in indoor and outdoor scenarios with variations in the number of antennas on BS and UE, and RIS operation at multiple frequency bands, i.e., frequency range 1 (FR1) (450 MHz to 6 GHz), frequency range 2 (FR2) (between 24.25 GHz and 52.6 GHz), millimeter wave (mmW) (30-300 GHz) and terahertz band (THz) (0.1-10 THz), as well as the near-field and far-field operation of RIS-assisted localization [23], which are the focus of this article. Overall, there is significant interest and effort being dedicated to advancing the use of RIS for localization. To develop the understanding of basics of RIS-assisted radio localization and to determine the unexplored research avenues within this field, it is deemed necessary to carry out a comprehensive survey. We briefly shed light on role of RIS in 6G radio localization and compile the recent developments in terms of state-of-the-art areas of investigation as well as the techniques. In contrast to the existing surveys and tutorials, in this survey, we first highlight the role of RIS in radio localization in terms of its potential applications and by the introduction of RIS-assisted localization taxonomy. Then we provide a comprehensive overview of the recent studies on the role of RIS in radio localization in 6G networks. Our work consolidates and builds upon existing knowledge to promote the advancement of RIS-assisted localization in 6G networks. In this study, we seek answers to the following questions:

- 1) How has RIS been used for localization in 6G networks?
- 2) What are the current trends and developments in the use of RIS technology for 6G radio localization?
- 3) What are the future directions of RIS-assisted radio localization in 6G and what are the associated technical challenges, and limitations?

The comparison of this survey with recent localization surveys, tutorials and review studies on the basis of aforementioned questions is given in Table II.

B. Review Method

After having identified the research questions, we defined our search string and identified the appropriate databases to

find the most relevant literature based on the inclusion and exclusion criteria. For the search string, we selected the keywords from our research questions, based on which two search strings were defined. The first string limits the investigation to the RIS and its synonyms. Similarly, the second string limits the literature to localization and its synonyms. Both search strings were combined using logical operators before being applied to the literature databases. The final search string is: (“*intelligent reflecting surface*” OR “*reconfigurable intelligent surface*” OR “*RIS*” OR “*IRS*” OR “*LIS*” OR “*large intelligent surface*”) AND (“*localization*” OR “*positioning*”) AND (“6G”). The search string was used on digital databases, i.e., IEEE Xplore, to identify the most pertinent papers. We searched for journal, workshop, and conference papers in the databases. As various studies use diverse terms to describe RIS-assisted radio localization, it is possible that our search string might not capture all relevant works. Therefore, we also performed comprehensive backward referencing. To ensure we did not miss pertinent articles, we included full texts in our analysis, even if they did not have our search terms in their titles or abstracts. In short, deliberate effort has been put to include all the works relevant to the topic of our survey.

After having collected all the relevant studies, we passed it through a rigorous inclusion and exclusion criterion to narrow down the database of relevant studies. We excluded all the studies that fulfilled the following exclusion criteria: if multiple versions of the same work are collected, such as a peer-reviewed published version and its pre-print archive version, only the published version shall be kept. The remaining set of studies was evaluated for the following inclusion criteria: the study is relevant to the topic of RIS in radio localization in 6G, and it showcases or illustrates a method, approach, or technique for RIS-assisted radio localization.

The unique aspects of our work are stated below:

- Via the survey, answers to the 3 research questions are provided in the following sections, where Section II answers research question 1, Section III answers research question 2 and Section IV answers research question 3.
- We present the potential applications of RIS-assisted localization from the use case families in RISE-6G project, to motivate the reader towards the topic. We also discuss the RIS-assisted radio localization taxonomy, which has not been comprehensively presented anywhere in literature before.
- We conducted our survey systematically and outlined the review method in Section I-B, ensuring the entire review process is reproducible for validation and further research. Our method for collating, analyzing, and interpreting data is explicitly stated as part of systematic approach. Consequently, our work covers all significant advances in RIS-assisted localization, including the latest studies and their implications.
- Finally, we provide a detailed, updated, and diverse perspective on what are the future research directions in RIS-assisted radio localization in 6G networks, particularly in light of recent advancements.

In the subsequent sections, we present the results of our review. In Section II, we give the comprehensive background

TABLE III
ABBREVIATIONS

2D	two dimensional
3D	three dimensional
5G	fifth generation
6G	sixth generation
AI	artificial intelligence
AOA	angle-of-arrival
AOD	angle-of-departure
BS	base station
CNN	convolutional neural network
CRF	conventional radio frequency
CRB	Cramr-Rao bound
CRLB	Cramr-Rao lower bound
CS	compressive sensing
CSI	channel state information
DFL	device-free localization
DL	downlink
DNN	deep neural network
FIM	Fisher information matrix
GDoP	geometric dilution of precision
GNSS	global navigation satellite systems
IoT	internet of things
ISAC	integrated sensing and communication
JCAL	joint communication and localization
LoS	line-of-sight
mmW	millimeter wave
MIMO	multiple-input, multiple-output
MISO	multiple-input, single-output
MCRB	misspecified Cramr-Rao bound
ML	machine learning
MLE	maximum likelihood estimation
MSE	mean square error
MUSIC	multiple signal classification
NLoS	non-line-of-sight
OEB	orientation error bound
OFDM	orthogonal frequency division multiplexing
OFTS	orthogonal time frequency space
PEB	position error bound
REB	rotation error bound
RIS	reconfigurable intelligent surfaces
RL	reinforcement learning
RSS	received signal strength
RTT	round-trip time
SISO	single-input, single-output
SIMO	single-input, multiple-output
SL	sidelink
SLAC	simultaneous localization and communication
SIM	stacked intelligent metasurfaces
SLAM	simultaneous localization and mapping
STAR	Simultaneously transmitting and reflecting
SNR	signal-to-noise ratio
THz	terahertz band
TOA	time-of-arrival
TDOA	time-difference-of-arrival
UE	user equipment
UL	uplink
UWB	ultra wide band
VLP	visible light positioning

of RIS technology and discuss it from the perspective of its potential for radio localization. In Section III, the developments in RIS-assisted radio localization are consolidated in terms of research in various frequency bands, deployment scenarios, and RIS placement for enhanced localization. In Section IV, we outline the limitations and unexplored research directions of RIS for localization in 6G networks, followed by conclusions in Section V. The sections and main topics of this article are shown in Figure 1. A list

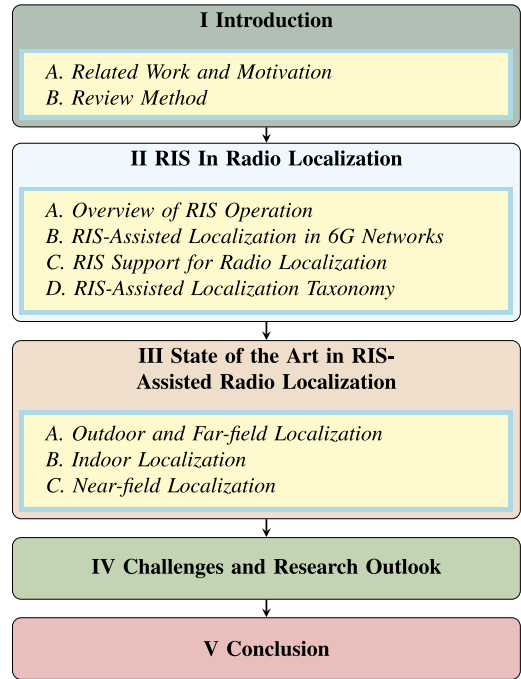


Fig. 1. The overall outline of the article.

of definitions of frequently used abbreviations is given in Table III.

II. RIS IN RADIO LOCALIZATION

In this section, we briefly discuss the RIS and the different types of its working operations. We focus on the reflective RIS signal and channel modeling, as it is the most commonly researched type of RIS operation. We provide the brief overview of the system model and channel model for RIS-assisted radio localization networks to demonstrate how RIS is used in 6G radio localization. Subsequently, we highlight why RIS is an advantageous technology for 6G radio localization, followed by a discussion on the taxonomy of RIS-assisted localization.

A. Overview of RIS Operation

RIS represents a novel electromagnetic surface capable of altering the behavior of wireless channel, paving the way for more efficient and adaptable wireless communication systems. A RIS comprises a multitude of tunable elements designed to regulate the amplitude, phase, and polarization of electromagnetic waves either passing through or reflecting off its surface [45]. These individual elements are generally small, cost-effective, and programmable to accommodate varying channel conditions and modulation methods. The structure of RIS operating across different modes is depicted in Figure 2.

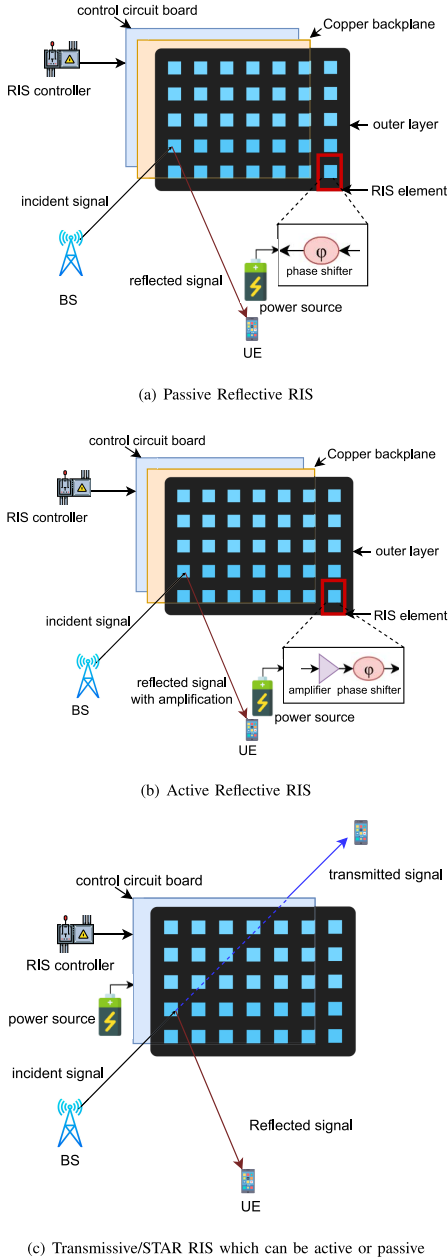


Fig. 2. Comparative structure of RIS under different modes of operation, (a) Passive Reflective RIS can alter the phase of the incident signal only, (b) Active Reflective RIS can amplify and alter the phase of the incident signal, (c) Transmissive RIS passes the signal through while STAR RIS can perform both transmission and reflection simultaneously. The reflection coefficient of each RIS element is reconfigurable in real time via the controller.

The RIS operates by modifying the propagation of electromagnetic waves by reflecting, refracting, or scattering them [1]. Typically, the tunable elements within RIS

are diminutive antennas or resonators that can be electrically manipulated to adjust their electromagnetic properties, including resonant frequency, impedance, and polarization [69]. By altering the impedance of each tunable element, the RIS can govern the amplitude and phase of the reflected or transmitted wavefront, effectively directing the wave towards a desired direction or concentrating it on a specific location [2]. Entrusted with the role of tweaking the electrical parameters of these tunable elements in real-time, the RIS controller uses feedback from the wireless channel conditions, modulation scheme, and performance targets. It employs feedback from the receiver to fine-tune the settings of the tunable elements, optimizing signal quality while curbing interference and noise [3]. Various hardware and software technologies, ranging from analog, digital, or hybrid to software-defined or artificial intelligence (AI)-based solutions, can implement the RIS controllers [69]. The selection of a controller hinges on the RIS's application, complexity, and performance prerequisites [70].

Here, we briefly discuss some of the RIS working operations:

- *Reflective RIS*: This is the most common type, shown in Figure 2(a), where elements of the surface can alter the phase of the incident signal. These essentially act as programmable mirrors that shape and direct the radio waves toward a specific direction [71]. Each RIS element reflects the incoming signal due to the copper backplane [72]. An RIS can reflect electromagnetic signals independently in reflection mode using its N reflection units. The magnitude, $\alpha_n \in [0, 1]$, and phase, $\phi_n \in [0, 2\pi]$, of the reflection coefficient of each reflection unit are reconfigurable via the controller. This leads to a base-band signal model of, $\mathbf{y}_n = \alpha_n e^{j\phi_n} \mathbf{x}_n$, for each unit, where $\mathbf{x}_n$ is the incident signal and $\mathbf{y}_n$ is the reflected signal, respectively. For the entire RIS surface, the relationship between the incident and reflected signals can be represented by a diagonal matrix, as the reflection units are independent, given as, $\mathbf{y} = \text{diag}(\alpha_1 e^{j\phi_1}, \dots, \alpha_1 e^{j\phi_n}, \dots, \alpha_1 e^{j\phi_N}) \mathbf{x} = \mathbf{\Omega} \mathbf{x}$, where $\mathbf{\Omega}$ is the reflection coefficient matrix of RIS. The RIS is designed to reflect incident signals maximally, i.e., ideally $\alpha = 1$. However, α in practice may not be equal to 1. It is usually a constant with a value dependent on the specific circuit [52]. The magnitude and phase, α and ϕ , can be varied within an interval with the limitation on cost and complexity. This leads to three practical reflection coefficient types: constant amplitude with continuous phase shift, optimized amplitude with continuous phase shift, and constant amplitude with discrete phase shift. Continuous phase shift is assumed in some papers, but it is limited by high hardware costs. Thus, a discrete phase shift is often used to increase cost-effectiveness. It is worth mentioning that the amplitude and phase control are not necessarily independent, i.e., when the phase is varied, this also varies the amplitude.
- *Transmissive RIS*: This type allows signals to pass through the surface, modifying their characteristics in the process. This provides an additional degree of flexibility

in controlling the wave propagation. Incident signal penetrates the RIS elements due to the absence of copper backplane as shown in Figure 2(c) [72].

- **Hybrid RIS:** Common RIS designs feature metasurfaces made of passive meta-atoms (building blocks of the meta materials) that can reflect incoming waves in adjustable ways. However, this exclusive reflection method poses considerable coordination challenges in wireless networks. For instance, RIS don't possess the needed data to modify their reflection patterns independently; this data must be gathered by other network components and then relayed to the RIS controller. Moreover, gauging the communication channel, vital for coherent RIS-aided communication, is problematic when using existing RIS models. Hybrid Reflecting and Sensing RIS offer a solution by allowing metasurfaces to not only adjustably reflect the incoming signal but also sense a fraction of it [73]. This sensing ability of hybrid RIS supports many network management tasks, like estimating channel parameters and pinpointing locations, paving the way for potentially self-regulating and self-setting metasurfaces.
- **Simultaneously transmitting and reflecting (STAR) RIS:** This variant allows the RIS to perform both transmission and reflection simultaneously, making it highly efficient and versatile for various communication needs [74]. Conventional RIS, due to their hardware design, are capable of only reflecting incident signals, serving wireless devices situated on the same side. This restricts their deployment adaptability and coverage span [75], [76]. To overcome these limitations, a new type of metamaterial called STAR-RIS has been introduced [77], [78]. It supports both electric-polarization and magnetization currents, enabling it to reflect and/or transmit the incident signals [79]. In contrast to conventional RIS, it can offer full-space service coverage (i.e., 360 degrees), leading to enhanced deployment flexibility.
- **RIS with Non-Diagonal Control:** In conventional RIS structures, it is assumed that a signal hitting a specific element can only be reflected from that same element after the phase shift adjustment. There was no deliberate association between the RIS elements. The phase shift matrix in such designs was diagonal, such that each RIS element is connected to the load disassociated from the other elements on the surface, leaving untapped potential for system performance enhancement through RIS. On the contrary, RIS with non-diagonal control has a design based on non-reciprocal connections, allowing the signal impinging on one element to be reflected from a different element after phase shift adjustment [80]. Consequently, the phase shift matrix can be non-diagonal. This allows for greater adaptability in configuring the RIS structure to optimize system performance. They can increase reflected power, enhance aggregate data rate, and provide versatility in a variety of deployment scenarios.
- **Active RIS :** In the case of passive RIS, the path loss between the transmitter-RIS-receiver connection is determined by multiplying, rather than adding, the path losses

of the transmitter-RIS and RIS-receiver connections. This value is typically many times greater than the direct link's path loss [81]. Consequently, this "multiplicative fading" phenomenon often renders it highly challenging for passive RIS to realize significant capacity gains in numerous wireless settings [82]. It is, thus, a significant performance hindrance to passive RIS operation [83]. Active RIS was introduced as a solution. Like its passive counterpart, it can reflect incident signals with adjustable phase shifts, but it can also amplify these signals, as shown in Figure 2(b). Its hardware architecture is, thus, different from the passive RIS such that its design involves reflection-type amplifiers in addition to the phase shift circuits. Active RIS needs considerably more power to operate [84].

B. RIS-Assisted Localization in 6G Networks

In this subsection, we present a fundamental example for RIS-assisted radio localization, providing a foundational framework upon which more advanced and specialized methods can be developed to address a range of complex problems. The flowchart presenting the typical processing phases is shown in Figure 3. To further illustrate the functioning of RIS in collaboration with BS for UE localization, consider the scenario showing the RIS-assisted radio localization environment in Figure 4(b) where a multiantenna BS equipped with N_{BS} antennas is located at $\mathbf{p}_{BS} = (x_{BS}, y_{BS}, z_{BS})$. RIS has N_{RIS} reflecting elements with its center located at $(x_{RIS}, y_{RIS}, z_{RIS})$ and the UE with N_{UE} antennas is at $\mathbf{p}_{UE} = (x_{UE}, y_{UE}, z_{UE})$. In the context of localization, the UE has an unknown state, i.e., location, orientation and clock bias that needs to be determined based on received downlink signals. The BS, with a known state transmits signals on distinct subcarriers. These signals create observations $\mathbf{y}_{n,k}$ at the UE receiver over the channel $\mathbf{H}_{n,k}$. By analyzing these downlink observations, the UE can estimate its location based on the known location of the BS and the RIS.

1) **Signal Model at UE:** We consider a generic frequency domain representation of the received signal and channel model for N samples spaced Δf apart [85]. The received signal at the UE for frequency $n \in \{0, \dots, N-1\}$ and symbol $k \in \{0, \dots, K-1\}$ can be represented as,

$$\mathbf{y}_{n,k} = \mathbf{H}_{n,k} \mathbf{x}_{n,k} + \mathbf{n}_{n,k}, \quad (1)$$

where $\mathbf{y}_{n,k}$ is the received pilot signal at the UE, $\mathbf{x}_{n,k}$ is the transmitted pilot signal from the BS, and $\mathbf{n}_{n,k}$ is the additive Gaussian noise.

2) **Channel Model:** Two types of propagation paths are available from the BS to the UE in this scenario, i.e., a direct, line-of-sight (LoS), path from the BS to the UE and reflected, NLoS, paths through the RIS or other objects in the environment. In the illustrated downlink scenario, considering a far-field channel with planar wave assumptions (as opposed to the spherical wave structure of near-field channels), the combined channel response, encompassing both the direct and NLOS reflected paths, is given as,

$$\mathbf{H}_{n,k} = \mathbf{H}_{n,k}^{\text{direct}} + \mathbf{H}_{n,k}^{\text{NLoS}}. \quad (2)$$

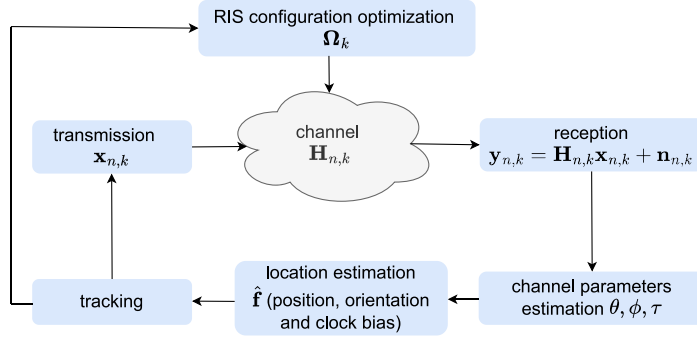


Fig. 3. Flowchart demonstrating the typical processing phases in RIS-assisted localization in 6G networks. In the downlink scenario, the transmitted signal received at the UE is used for channel parameters estimation and UE localization. Tracking information is utilized to optimize the RIS configuration.

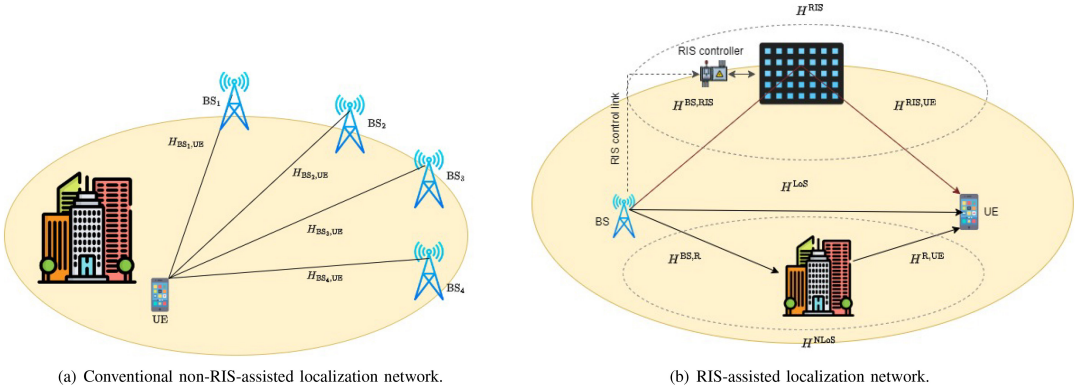


Fig. 4. Illustration of non-RIS-assisted and RIS-assisted localization networks. Localization without RIS requires multiple BSs. The use of RIS makes localization possible with lesser infrastructure with the added advantage of energy efficiency, minimal deployment, and maintenance cost.

Here, $\mathbf{H}_{n,k}^{\text{direct}} \in \mathbb{C}^{N_{\text{BS}} \times N_{\text{UE}}}$ is the channel frequency response of the direct path, given as [85]

$$\mathbf{H}_{n,k}^{\text{direct}} = \sum_{l=1}^L \alpha_l \mathbf{a}_{\text{UE}}(\theta_l) \mathbf{a}_{\text{BS}}(\phi_l) e^{-j2\pi n \Delta f \tau_l}, \quad (3)$$

where

$$|\alpha_l|^2 = \frac{\lambda^2}{(4\pi)^2} \frac{G_{\text{UE}}(\theta_l) G_{\text{BS}}(\phi_l)}{\|d_{\text{BS-UE}}\|^2}, \quad (4)$$

is the complex channel gain with L being the number of direct signal propagation paths, $\mathbf{a}_{\text{UE}}(\theta) \in \mathbb{C}^{N_{\text{UE}}}$ is the UE array response as the function of angle-of-arrival (AOA) $\theta \in \mathbb{R}^2$ in azimuth and elevation, $\mathbf{a}_{\text{BS}}(\phi) \in \mathbb{C}^{N_{\text{BS}}}$ is the BS array response as function of angle-of-departure (AOD) $\phi \in \mathbb{R}^2$ in azimuth and elevation, λ is the carrier wavelength, $G_{\text{BS}}(\cdot)$ and $G_{\text{UE}}(\cdot)$ are the antenna gains at the BS and UE, and τ_l is the time-of-arrival (TOA) given by

$$\tau_l = \frac{d_{\text{BS-UE}}}{c} + K \quad (5)$$

where $d_{\text{BS-UE}}$ is the distance from BS antenna element to the UE antenna element, c is the speed of light and K is the clock synchronization offset.

From (2), $\mathbf{H}_{n,k}^{\text{NLoS}}$ is the combination of reflected signal channel frequency response at the UE from the intended RIS reflectors as well as the random obstacles in the environment. It can, thus, be expressed as,

$$\mathbf{H}_{n,k}^{\text{NLoS}} = \mathbf{H}_{n,k}^{\text{RIS}} + \sum_{i=1}^I \mathbf{H}_{n,k}^{\text{NLoS}(i)}, \quad (6)$$

where I is the number of reflectors between BS and UE, other than RIS. The channel response from such reflectors is defined as [21]

$$\mathbf{H}_{n,k}^{\text{NLoS}} = \sum_{i=1}^I \alpha_i \mathbf{a}_{\text{UE}}(\theta_i) \mathbf{a}_{\text{BS}}(\phi_i) \mathbf{a}_{\text{R}} e^{-j2\pi n \Delta f \tau_i}, \quad (7)$$

such that

$$|\alpha_i|^2 = \frac{\lambda^2}{(4\pi)^2} \frac{\Gamma_{R_i-\text{UE}} G_{\text{UE}}(\theta_i) G_{\text{BS}}(\phi_i)}{(d_{\text{BS-R}_i} + d_{R_i-\text{UE}})^2}, \quad (8)$$

and

$$\tau_i = \frac{d_{\text{BS-R}_i} + d_{R_i-\text{UE}}}{c} + K, \quad (9)$$

where d_{BS-R_i} and d_{R_i-UE} are the distances from BS to reflector R_i and from R_i to UE, $\mathbf{a}_R$ is the steering vector of the reflector R and Γ_{R_i-UE} is the attenuation coefficient. Given the point of incidence of signal on a reflector be $\mathbf{p}_{\text{inc},m} \in \mathbb{R}^3$, the UE array response $\mathbf{a}_{\text{UE}}(\theta_i)$ (similarly for BS array response vector $\mathbf{a}_{\text{BS}}(\phi_i)$) consists of entries given by [86],

$$[\mathbf{a}_{\text{UE}}(\theta_i)]_k = \exp\left(j \frac{2\pi(\mathbf{p}_{\text{UE},k} - \mathbf{p}_{\text{UE}})^\top \mathbf{u}(\theta_i)}{\lambda}\right), \quad (10)$$

where $\mathbf{p}_{\text{UE},k} - \mathbf{p}_{\text{UE}}$ represents the position of the k -th antenna element relative to the reference UE location, and $\mathbf{u}(\theta_i) = \mathbf{p}_{\text{inc},m} - \mathbf{p}_{\text{UE}} / \|\mathbf{p}_{\text{inc},m} - \mathbf{p}_{\text{UE}}\|$, all defined in the UE's frame of reference. These NLoS signals become increasingly important when the LoS between the BS and UE is absent.

The $\mathbf{H}_{n,k}^{\text{RIS}}$ in (6) is the RIS incident and reflected signal channel response such that $\mathbf{H}_{n,k}^{\text{BS,RIS}} \in \mathbb{C}^{N_{\text{BS}} \times N_{\text{RIS}}}$ is the channel response of the path from the BS to the RIS and $\mathbf{H}_{n,k}^{\text{RIS,UE}} \in \mathbb{C}^{N_{\text{RIS}} \times N_{\text{UE}}}$ is the channel response from the RIS to the UE, collectively given as [86],

$$\mathbf{H}_{n,k}^{\text{RIS}} = \mathbf{H}_{n,k}^{\text{BS,RIS}} \mathbf{H}_{n,k}^{\text{RIS,UE}} \quad (11)$$

$$= \alpha_k^{\text{RIS}} \mathbf{a}_{\text{UE}}(\theta_{\text{RIS}}) \mathbf{a}_{\text{BS}}(\phi_{\text{RIS}}) e^{-j2\pi n \Delta f \tau_{\text{RIS}}}, \quad (12)$$

where

$$\alpha_k^{\text{RIS}} = \alpha_{\text{BS-RIS}} \alpha_{\text{RIS-UE}} \mathbf{a}_{\text{RIS}}^\top(\phi_{\text{RIS-UE}}) \mathbf{\Omega}_k \mathbf{a}_{\text{RIS}}(\theta_{\text{BS-RIS}}). \quad (13)$$

Here, α_k^{RIS} is controllable, $\alpha_{\text{BS-RIS}}$ is the complex gain from BS to RIS, $\alpha_{\text{RIS-UE}}$ is the complex gain from RIS to the UE, $\mathbf{a}_{\text{RIS}}(\cdot)$ is the RIS response function as the function of AOA from BS, $\theta_{\text{BS-RIS}}$, and the AOD to the UE, $\phi_{\text{RIS-UE}}$ and $\mathbf{\Omega}_k$ determines the RIS configuration [86]. A RIS with a known location can provide valuable geometric information, such as TOA, an angle at the UE, and an angle at the RIS. Essentially, the RIS operates as an auxiliary, synchronized BS with a phased array, transmitting the same signal as the primary BS [86]. The RIS configurations $\mathbf{\Omega}_k$ can be optimized based on prior location information.

3) *UE Localization*: For the localization of the UE, its position, orientation, and clock bias information are inferred from the received signal $\mathbf{y}_{n,k}$, details of which are well summarized in [85], [86] and discussed briefly below. The process encompasses three steps: first, the channel parameters (TOAs, AOA, AODs) are estimated. Second, if the LoS is available then its parameters, NLoS and RIS path parameters are extracted, and finally, the UE is localized.

a) *Channel parameter estimation*: In wireless communication, channel estimation methods like FFT/Periodograms [87], ESPRIT [88], and orthogonal matching pursuit [89] use principles of sparsity or harmonic retrieval [85]. A common approach is to first obtain a least-squares channel estimate $\hat{\mathbf{H}}_{n,k}$, which can then be vectorized for compressive sensing to estimate path counts and delays. Another way is to arrange least-square estimates of channel parameters in tensor form which allows multi-dimensional harmonic retrieval. Initial path estimates, gains, and geometry can be refined by maximizing the likelihood

function $\log p(\mathbf{y}|\kappa)$, where κ includes parameters like path gains, angles, and delays.

b) *Location estimation*: To estimate the UE's location, the channel parameters $\hat{\boldsymbol{\eta}}$ (e.g., angles, delays), whose estimator uncertainties need to be known, are mapped to the UE state $\mathbf{f}$ through the relationship $\hat{\boldsymbol{\eta}} = \mathbf{h}(\mathbf{f}) + \mathbf{n}$, where $\mathbf{h}(\mathbf{f})$ represents the geometric model linking the UE state to channel parameters (τ, θ, ϕ) and $\mathbf{n}$ represents measurement noise with statistics that depend on the channel parameter estimation. The parameter $\hat{\boldsymbol{\eta}}$ provides estimated angles, and delays with associated noise. We estimate $\mathbf{f}$ by minimizing the cost function [85] given by

$$\hat{\mathbf{f}} = \arg \min_{\mathbf{f}} (\hat{\boldsymbol{\eta}} - \mathbf{h}(\mathbf{f}))^\top \Sigma^{-1}(\hat{\boldsymbol{\eta}}) (\hat{\boldsymbol{\eta}} - \mathbf{h}(\mathbf{f})). \quad (14)$$

After obtaining an initial estimate, local optimization refines $\hat{\mathbf{f}}$. The uncertainty, $\Sigma(\hat{\mathbf{f}})$, is then calculated as

$$\Sigma^{-1}(\hat{\mathbf{f}}) = \left(\frac{\partial \boldsymbol{\eta}}{\partial \mathbf{f}} \right)^\top \Sigma^{-1}(\hat{\boldsymbol{\eta}}) \frac{\partial \boldsymbol{\eta}}{\partial \mathbf{f}} \Big|_{\mathbf{f}=\hat{\mathbf{f}}}. \quad (15)$$

This estimated location and uncertainty, $(\hat{\mathbf{f}}, \Sigma(\hat{\mathbf{f}}))$, can be further integrated into tracking algorithms for more robust localization and RIS configuration optimization.

4) *Extensions*: The aforementioned channel and signal modeling represent the most simple version of the RIS-assisted localization problem, setting the stage for many extensions. For instance, the channel model can be generalized to include wavefront curvature, the RIS model can be generalized to hybrid, STAR, or Non-Diagonal Control RIS, each with their own localization benefits and challenges.

C. RIS Support for Radio Localization

In a standard SISO non-RIS-assisted localization network, shown in Figure 4(a), four synchronized single antenna BSs transmit pilots, generating time-difference-of-arrival (TDOA) or TOA. The UE position is estimated by intersecting hyperboloids (TDOAs) or calculating TOAs for clock bias synchronization [34]. Using round-trip time (RTT) with three BSs allows localization by intersecting spheres centered at the BSs. The UE's velocity is determined from four Doppler shifts. The limitations of such conventional localization include: (i) the need for several BSs for localization, whereas only one is needed for communication, leading to network over-provisioning to support localization systems; (ii) even massive MIMO BSs offer limited angular resolution, making localization constrained by multipath; and (iii) time-based measurements, i.e., TOA and TDOA, which provide the most information for localization, require BSs to be time-synchronized at the sub-nanosecond level. In the following subsection, we show how the inclusion of RIS can address these limitations by reducing reliance on infrastructure, offering high angle resolution, and eliminating extreme synchronization requirements. We delve into the multifaceted role of RIS in enhancing radio localization capabilities, examining how RIS transforms cellular networks into intelligent environments, how it works in tandem with BS for effective UE localization, and exploring applications of RIS-assisted localization in emerging technologies.

1) *RIS-Enhanced Localization in Smart Radio Environments*: Next-generation cellular networks are evolving towards “smart radio environments” enhanced by RIS-covered walls and objects, enabling them to reconstruct and modify radio signal properties like transmission direction and polarization. This innovation leads to an intelligent transmission environment, offering new possibilities in communication, sensing, and localization [69], [90], [91]. The integration of RIS promises improved localization accuracy and extended coverage, contingent upon the development of suitable models and algorithms [1]. Compared to traditional MIMO systems, RIS offers superior localization due to its large surface area, which improves its signal transmitting, receiving, or reflecting capabilities. The Cramér-Rao lower bound (CRLB), a measure of the lower limit of the variance for an unbiased estimator, for UE localization decreases as the RIS area increases, barring certain positions [27], [36]. Distributed RIS deployments are found to enhance CRLB and broaden localization coverage. Further, RIS allows for high-precision radio localization and sensing, significantly estimating UE and device positions [38]. The RIS-aided downlink localization offers better coverage and accuracy than traditional reflecting surfaces and scatter points [39]. These advancements highlight the role of RIS in enhancing radio localization systems.

Accurately quantifying phase and amplitude is essential for effective localization with RIS, but full-resolution measurements can be expensive. Exploring the impact of phase and amplitude quantization on localization is therefore important. The comparison of full-resolution measurements with varying quantization resolutions shows that phase quantization has a more significant effect on the CRLB of localization than amplitude quantization, but both do not greatly differ in CRLB loss [36], [37]. This insight is pivotal for practical RIS-assisted localization, suggesting enhanced phase resolution at the RIS for better accuracy. Utilizing explicit geometric information in wireless channels below 6 GHz is challenging due to limited delay and angle resolution and weak path connectivity to environment geometry. In contrast, frequencies above mmW link more closely to environment geometry and offer better resolution [85], [93]. The high bandwidth and large antenna arrays in mmW and THz bands provide high spatial and temporal resolution, leading to a focus on these higher frequency bands in the majority of the studies in contemporary literature [40], [89], [94], [95], [96]. Moreover, often indoor scenarios are considered due to the limited transmission range of mmW or THz frequencies. While global navigation satellite systems (GNSS) can offer acceptable outdoor localization, its effectiveness is reduced indoors where signal strength is low. In such environments, RIS not only aids in precise localization but also helps alleviate communication congestion caused by obstructions.

When considering algorithms for RIS-assisted localization, it is important to distinguish between far-field and near-field assumptions [1]. In the far-field, energy travels away from the source, and the plane wave assumption is valid, while in the near-field, energy is periodically stored and returned to the source, with radiation patterns varying based on distance from the source, hence the spherical wave model applies. The

near-field region’s extent in RIS-assisted networks is linked to the RIS’s surface area. Near-field propagation, characterized by wavefront curvature, becomes significant at moderate distances to the RIS and must be accurately represented in the communication system. The near-field area of RIS inversely correlates with the wavelength of the incident signal, and its size increases with both operation frequency and surface area, making the UE likely to be in this region. Therefore, particularly in indoor environments at mmW and THz frequencies, far-field models are generally inapplicable [97].

2) *Applications of RIS-Assisted Localization in Emerging Technologies*: RIS-assisted localization offers significant benefits for various applications requiring high accuracy and low latency. It revolutionizes indoor and outdoor localization in IoT networks, smart cities, and automated factories, as shown in Figure 5 [92]. RIS enhances IoT network performance by optimizing signal propagation in different communication scenarios, contributing to advanced multisensory extended reality applications and tele-control technologies by ensuring precise device tracking and location accuracy (Figures 5(d) and 5(g)) [24]. It also plays a crucial role in wireless brain computer interfaces, improving signal quality and reliability for patient tracking and tele-surgery applications (Figure 5(f)) [98], [99]. In smart indoor services, RIS overcomes NLoS challenges and improves privacy protection, crucial for secure and efficient local coverage (Figure 5(c)). It is pivotal in smart transportation, enhancing autonomous driving and vehicle-to-vehicle communications by providing accurate three dimensional (3D) mapping and robust localization in dynamic environments (Figure 5(b)). For automated factories and connected robotics and autonomous systems (CRAS), RIS facilitates cooperative localization, essential for IoT device interaction and efficient production processes (Figure 5(a)) [98], [100]. However, fulfilling these applications in 6G networks presents challenges as outlined in Section IV. The integration of RIS into communication networks can significantly enhance localization and sensing performance. By intelligently manipulating wireless signals, RIS can optimize signal paths, minimize delay, and improve accuracy, thereby enabling intelligent interactions across various applications.

D. RIS-Assisted Localization Taxonomy

RIS-assisted localization works by estimating the location and orientation of a UE with the help of anchor nodes (BS and RIS) provided the location of anchor nodes is already known [1]. To locate itself, UE sends out a known uplink pilot signal to the BS or receives a downlink pilot signal from the BS. The signal’s behavior is influenced by the propagation channel, which depends on the location and orientation of the BS and UE, as well as the environment surrounding them. The level of distortion in the received signal is determined by reflections from the RIS and other objects in the vicinity [86]. The direct unobstructed link from the BS to the UE is called the LoS path, the path of the signal reflected by the RIS is RIS path, and all the other NLoS paths from walls and objects in the environment are classified as the reflected paths and

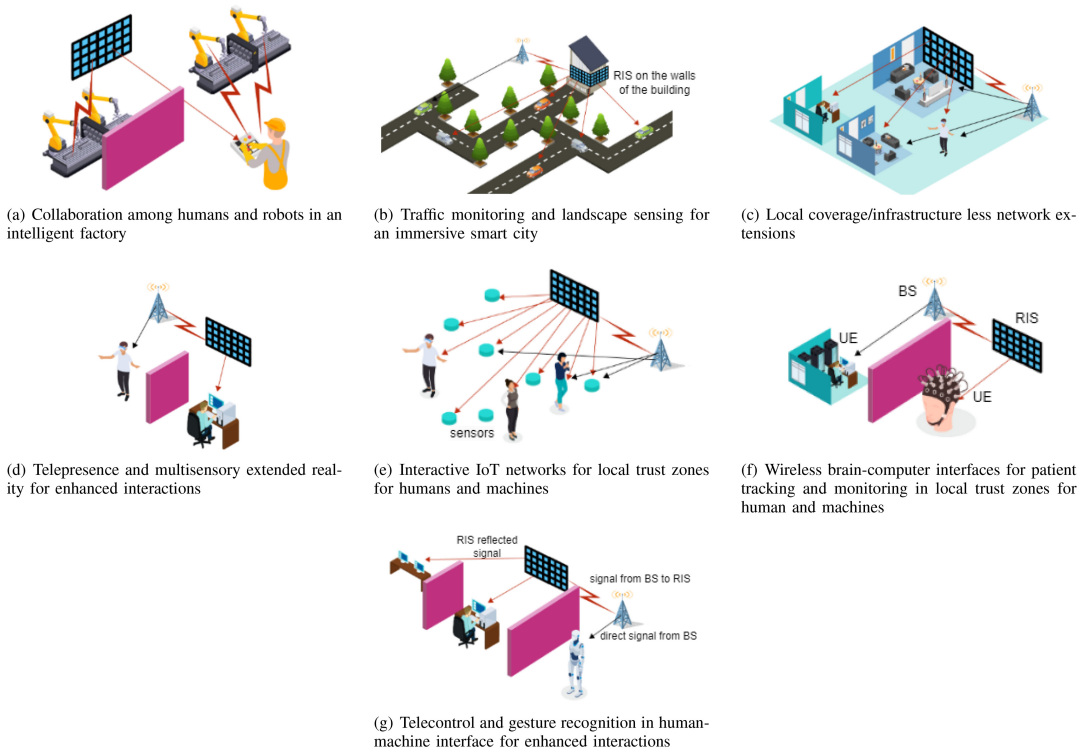


Fig. 5. Illustration of RIS-assisted localization applications in 6G networks from the use case families in [92]. Use cases prominently include sustainable development, massive twinning, telepresence, robots to collaborative robots, and local trust zones.

the scattered paths, respectively. Successful modeling of the pilot signal and the channel allows us to estimate the channel state information (CSI) and identify the parameters for the signal paths [23]. These parameters, which aid in localization, include TOA/delay, AOA, and AOD. UE location can be estimated based on these parameters and their geometrical relationships with the BS and RIS locations [85]. RIS-assisted radio localization scenarios can be either in indoor or outdoor environments, based on which the channel modeling is different.

RIS-assisted localization can also be classified on the basis of the application scenario, localization technique, functionality of RIS employed and its configuration and deployment details, localization method as well the localization performance matrices. A brief taxonomy of RIS-assisted localization systems is shown in Figure 6 and illustrated in Figure 7, respectively.

1) *Localization Measurements*: Geometry-based techniques are widely used for radio localization and typically involve timing-based (TOA) and angle-based (AOA/AOD) methods [17]. The TOA is the time taken by the signal to travel from the BS to the UE. Timing-based localization technique, named trilateration, uses the measured TOA while considering the effects of RIS reflections, to estimate the location. The technique requires at least three BSs to get an unambiguous two dimensional (2D) estimate of the UE

location when RIS are not considered. An alternative is to estimate RTT by recording signal transmission, processing and reception times, providing necessary TOA information. Well-synchronized systems can directly infer TOA from signals, with resolution dependent on signal bandwidth. Angle-based localization technique, named triangulation, estimates the angle from which signals arrive at the receiver, incorporating RIS-assisted reflections, to determine the location [101]. It is typically employed when an antenna array is available at the BS. Some of the other estimation techniques rooted in TOA and AOA include TDOA estimation, AOD-based estimation, angle-difference-of-arrival location and orientation estimation.

The received signal strength (RSS)-based localization techniques utilize the RSS measurements from RIS-assisted reflections to estimate the location of the receiver [38]. It assists with the geometry-based trilateration and fingerprinting localization algorithms [64]. This method capitalizes on the sensitivity of RSS to spatial variations, allowing for accurate localization even in complex indoor or outdoor urban scenarios [102]. The reconfigurability of RIS enables real-time adaptation to changing propagation conditions, enhancing the precision and robustness of the localization system.

The channel state information (CSI)-based localization methods exploit the fine-grained CSI obtained through RIS-assisted reflections for accurate localization. CSI contains valuable insights into the wireless propagation environment,

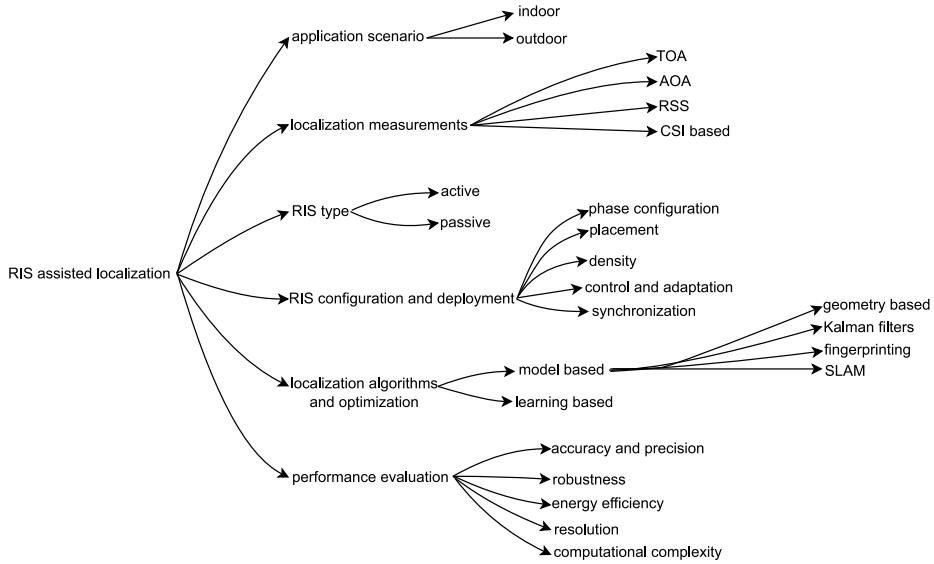


Fig. 6. Taxonomy of RIS-assisted localization. Signal processing involving localization measurements and algorithms could take place at the UE or BS depending on the mode of communication, i.e., uplink or downlink.

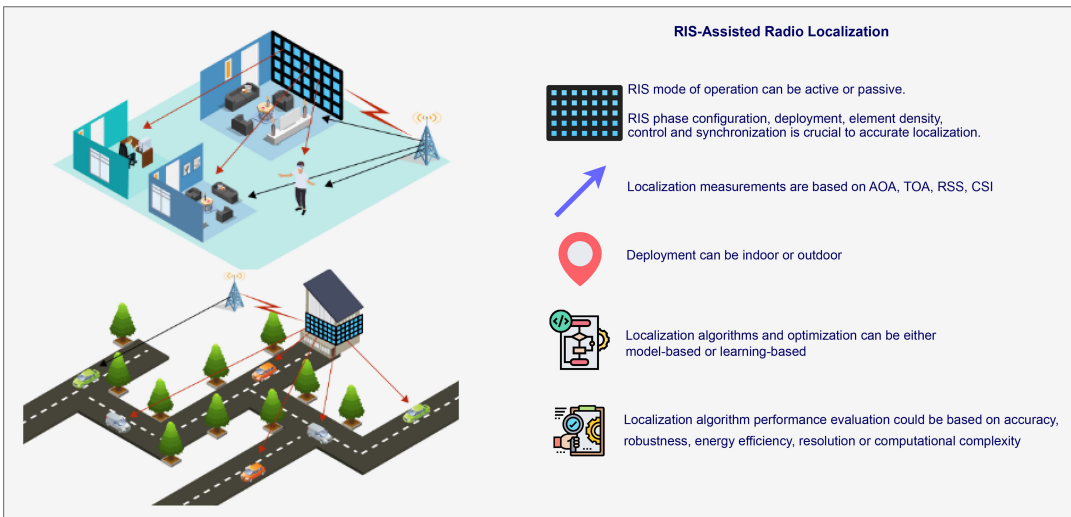


Fig. 7. Illustration of RIS-assisted localization taxonomy. Signal processing involving localization measurements and algorithms could take place at the UE or BS depending on the mode of communication, i.e., uplink or downlink.

including path loss, multipath components, and spatial signatures [59]. Using advanced signal processing and machine learning (ML) algorithms, the collected CSI data can be used to estimate the position of the devices [61]. The integration of RIS with CSI-based localization enables radio localization in dynamic scenarios with changing propagation conditions.

2) *RIS Type*: As discussed in Section II-A, in 6G radio localization, RIS are pivotal, functioning in either passive or active states. Passive RIS, requiring little external power, adjust

only the phase of electromagnetic waves, offering simpler, energy-efficient deployment but limited signal control. In contrast, active RIS, equipped with elements like integrated circuits, can independently manipulate both signal phase and amplitude, enabling more complex functions like dynamic beamforming and interference cancellation [71], [82], [103].

3) *RIS Configuration and Deployment*: The configuration and deployment of RIS play a crucial role in RIS-assisted radio localization. The optimization of the phase configuration

in RIS systems holds immense significance in unlocking its full potential. By precisely fine-tuning the phase shifts of the RIS elements, we can achieve remarkable control over signal propagation, allowing for unprecedented customization and optimization of wireless communication links [1]. The optimization process involves carefully analyzing the channel characteristics, understanding the desired signal characteristics, and employing advanced algorithms to determine the optimal phase shifts for each RIS element [86]. Through this optimization, we can exploit constructive interference, nullify destructive interference, and shape the signal to match specific requirements, such as maximizing coverage, minimizing signal attenuation, or focusing energy in desired directions [23].

The placement and arrangement of RIS in the environment directly impacts the accuracy, coverage, and performance of the localization system [84]. Determining the optimal locations for deploying RIS elements is fundamental to achieving the desired coverage area, signal propagation characteristics, and localization requirements. Proper deployment ensures optimal coverage of the desired area, minimizing low coverage spots and maximizing the availability of RIS reflections for localization purposes [1]. Additionally, the number of RIS elements deployed per unit area or volume affects the granularity of control and the accuracy of localization. The configuration of the RIS elements, including the reflection coefficients, is vital in manipulating the signal propagation and optimizing the received signal at the receiver [104]. The dynamic reconfigurability of RIS further enhances their role, allowing for real-time adaptation to changing propagation conditions and environmental dynamics [105]. Moreover, ensuring proper synchronization among the RIS elements to avoid interference is equally important to configure [106], [107]. By intelligently configuring and deploying RIS, the localization system can achieve improved accuracy, robustness, and scalability, enabling a wide range of location-based applications in various scenarios.

4) *Localization Algorithms and Optimization:* RIS-assisted localization algorithms can be broadly classified as model-based and learning-based [23]. Model-based methods include deductive (physics-based) techniques such as geometry-based location estimation algorithms, Kalman filters, fingerprinting, and SLAM. On the other hand, learning-based techniques are inductive (data-driven) and leverage ML algorithms such as neural networks to learn and model the relationship between RIS-assisted signals and the receiver's location. The advantages of model-based approaches versus data-driven methods are numerous. They are supported by performance constraints that give solid assurances of optimality and dependability, rely on well-established signal processing techniques, and offer typically less complexity than data-driven systems. Some of the model-based approaches that are commonly employed in RIS-assisted localization are briefly discussed below.

- *Geometry-based methods:* Geometry-based methods rely on the TOA and AOA measurements or their combination to determine the 2D or 3D location of the UE [85], [86]. In traditional systems, such methods require a combination of measurements from multiple BSs to determine the UE location. However, the location of the UE can

be estimated with the help of one BS and a RIS [39], more details in [34]. Location estimation typically entails creating an objective function that incorporates geometric information and solving an optimization problem with geometric constraints. Geometry-based localization techniques are characterized by being free from training requirements, easily analyzable from a theoretical standpoint, and scalable across various environments.

- *Kalman filter:* The Kalman filter is a recursive estimation algorithm that optimally fuses noisy measurements with a dynamic model to estimate the state of a system. In the context of localization, the Kalman filter predicts the device's position based on the previous state estimate and motion dynamics and then updates it using RIS-assisted measurements such as RSS or TOA [108]. The Kalman filter-based approach can effectively mitigate the impact of noise, multipath, and other propagation effects on localization accuracy by iteratively updating the state estimate and incorporating RIS-assisted measurements [86]. Despite its widespread use in localization, Kalman filtering has several limitations. Its assumptions of system linearity and Gaussian noise can be inaccurate in complex, real-world scenarios [23]. The initial state, which the filter requires, may not always be accurately known, and any errors in it can propagate, causing inaccuracies in state estimation. Furthermore, Kalman filters assume constant process and measurement noise covariances, an assumption often violated in real-world conditions. For nonlinear challenges, one can utilize an extended Kalman filter [109]. This approach estimates the state distribution by employing a Gaussian random variable and advances it through first-order linearization. Finally, Kalman filters are sensitive to model mismatches and outliers, which can significantly affect their performance [23].
- *Fingerprinting:* In the fingerprinting approach, a database of signal fingerprints is created by collecting and mapping the received signal characteristics at various locations in the environment [10]. The fingerprint database contains information such as RSS, CSI, or signal amplitude patterns specific to each location. RSS has limited precision and CSI demands significant computational resources, spatial beam signal-to-noise ratio (SNR) is chosen as an intermediate channel measurement with moderate granularity [110]. When a device needs to be localized, it measures the RSS or other signal characteristics at multiple RIS-assisted points in the environment. These measurements are then compared with the fingerprint database to find the closest match. The RIS play a crucial role in this process by manipulating the wireless channel to enhance the quality and reliability of the measurements. By adjusting the reflection coefficients of the RIS elements, the received signal can be optimized, leading to more accurate and consistent measurements. However, if the configuration of the RIS changes over time, it would effectively alter the environmental characteristics that the fingerprint is based on, potentially decreasing the accuracy of location estimates. To guarantee the stationarity of the environment when employing RIS

in fingerprinting, the configuration of the RIS should be kept constant during both the fingerprinting process and when using the fingerprint for location estimation. This means that the phase shifts or other manipulations applied to signals by the RIS should be fixed and not vary over time. In practice, this might require careful design and control of the RIS, and thorough testing to ensure its configuration remains stable under different conditions. This issue is resolved by including in the fingerprint the RIS configuration. This provides a richer set of fingerprints. The fingerprint matching process can utilize techniques such as pattern matching or ML algorithms, deep learning methods such as deep neural network (DNN) and convolutional neural network (CNN) to find the best match between the measured signals and the fingerprints in the database [23], [110], [111]. Once the closest match is found, the device's location is estimated based on the known location associated with the matched fingerprint [64]. Fingerprinting can handle complex indoor or outdoor environments where multipath and NLoS conditions pose challenges for traditional localization techniques [14].

- *Simultaneous localization and mapping*: SLAM is a well-established method used to estimate the position of a device while constructing a map of its surroundings [6]. In this approach, RIS are strategically deployed in the environment to manipulate the wireless channel [112]. During the SLAM process, the device measures parameters such as RSS or TOA at multiple RIS-assisted points. These measurements, along with the known positions of the RIS, are used to estimate the UE location and construct a map of the environment [113]. The RIS plays a crucial role in improving the accuracy and reliability of the localization and mapping process by optimizing the quality of the received signals. It offers the advantage of accurate localization in complex environments where multipath propagation and NLoS conditions may exist. Additionally, RIS can adaptively adjust their reflection coefficients, enhancing the performance and robustness of the SLAM-based localization system.

Explicit modeling of geometry information becomes difficult in complicated cases when there are several non-resolvable NLoS paths [17]. Under such conditions the learning-based approaches are recommended [15], [114]. ML-based techniques need offline training, which drastically decreases online calculations, in contrast to the practical algorithms employed in geometry-based localization. To train the models, however, a significant amount of system data must be gathered, and the learned models must be updated on a regular basis to account for changes in the environment. The DNN are used to perform environmental sensing to achieve the best performance in RIS-assisted radio localization [22], [64]. Since the channels are sparse at the higher frequency bands, therefore, most of the studies use geometry-based algorithms [23].

5) *Localization Performance Evaluation*: A radio localization system is designed on the basis of a number of performance objectives that include accuracy, coverage,

latency, robustness, resolution, update rate, stability, scalability, mobility and system complexity, etc [23]. Here we discuss most relevant ones.

Accuracy and precision are metrics to assess the accuracy of the estimated location compared to the ground truth, and the level of precision in determining the location, often represented by the standard deviation or confidence interval. Accuracy is the most widely used localization metric in state-of-the-art studies as it accounts for localization resolution as well as identifiability. CRLB are the commonly used bounds on the achievable accuracy in studies. The deployment geometry, also known as geometric dilution of precision (GDoP) or UE relative position with respect to BSs, determines accuracy in addition to link-level SNR [34].

The separability of completely correlated radio propagation channels in at least one domain is referred to as resolution. Unresolvable signal paths will be treated as a single path, limiting accuracy (regardless of SNR), and producing worse performance than predicted by analytical bounds. The resolution is constrained by the physical resources available, such as antenna array aperture for angle resolution and bandwidth for delay/distance resolution [85]. Despite having a high degree of resolution, radio localization can nevertheless suffer from ambiguity and non-identifiability [34]. This indicates that the localization problem of UE might have many solutions or a continuous space of solutions. This might happen when there are barriers in the way of specific BS signals, or when infrastructure rollout or coverage is insufficient. Ambiguity, which emerges as numerous unique locations, is frequently addressed by prior knowledge or external signals. On the other hand, non-identifiability poses a more significant challenge as there are numerous equally valid solutions to the localization problem, and it is difficult to discard them based on external information.

The robustness of the localization algorithm evaluates its performance under various environmental conditions, such as multipath fading, interference, and mobility. It accounts for availability, latency, and update rate under such conditions [23]. Likewise, assessing the energy consumption of RIS-assisted localization techniques, considering both RIS elements and the receiver device is an important measure in RIS-assisted localization in comparison to the systems without RIS. Energy-efficient techniques aim to minimize energy consumption while achieving accurate localization. Computational complexity quantifies the computational resources needed to perform RIS-assisted localization at the hardware and algorithm level. It includes the processing power, memory requirements, and time complexity of the localization algorithm. Lower computational complexity allows for faster and more efficient localization.

III. STATE OF THE ART IN RIS-ASSISTED RADIO LOCALIZATION

In this section, we discuss the recent literature on RIS-assisted radio localization for 6G networks. The trends in the latest studies are on developing algorithms, optimization, and investigation of RIS-assisted localization systems from the



Fig. 8. State of the art literature breakdown. Studies can be broadly categorized into outdoor, far-field, indoor and near-field RIS-assisted localization. Within these categories, we notice trend towards investigation of systems on mmW and THz frequencies. Further, the passive reflective RIS is the most common type of RIS used in literature for RIS-assisted localization.

perspective of accuracy and availability at various frequency bands, near-field and far-field modeling, and indoor and outdoor scenarios, as summarized in Figure 8.

In the realm of RIS-assisted localization, we classify the frequency bands into two categories: *conventional radio frequency (CRF)*- and *high frequency bands*. CRF bands typically refer to those below 24 GHz, encompassing well-known sub-bands such as FR1. CRF bands are recognized for their longer wavelengths, better penetration capabilities, and widespread application in various wireless services. For outdoor localization, GNSS is predominantly employed, providing meter-level precision with support from long-term evolution (LTE) communication signals. Yet, this method proves ineffective for indoor environments, where intricate surroundings and LoS channel obstructions are common challenges. As alternatives, there are documented localization systems utilizing ultra wide band (UWB) [115], WiFi [116], wireless local-area network (WLAN) [117], and LoRA [11], [118]. By leveraging CRF bands systems in association with the RIS, advantages are gained in location-centric services, including navigation and identification of nearby amenities.

On the other hand, we refer to the localization services in the range of spectrum above 24 GHz as high frequency bands localization. This category consists of FR2 frequencies, mmW and THz band. The range of 100- 300 GHz in mmW band is also referred to as the sub-terahertz (sub-THz) according to the deliverable D2.1 of the European HEXA-X project [119]. These higher frequency bands offer significant advantages in terms of data rate, capacity and localization performance but come with challenges related to limited propagation and penetration. Utilizing antenna arrays at the UE enables to estimation of its orientation [89]. Furthermore, through the use of NLoS paths [120] and RIS [1], [40] localization tasks can be accomplished with only one BS. The THz systems are anticipated to complement mmW systems in diverse environments, and the comparison between the two reveals distinct advantages and challenges in terms of localization [23]. As technology progresses from CRF to 5G and onto 6G, expectations include higher frequencies, increased bandwidths, more compact footprints, and larger array sizes [121]. These changes will affect path loss, delay estimation resolutions, and antenna array design, among other features. Challenges may arise with hardware imperfections and synchronization at THz frequencies. The design of localization algorithms must

also consider the specific properties of THz signals, such as the beam split effect and high path loss [23]. Ultimately, the adaptations and innovations within the THz systems are expected to lead to improved localization performance in 6G networks.

We group the studies as the development of methods for localization of UE in outdoor and far-field, indoor and near-field, respectively. To enhance reader clarity, it is important to emphasize that the first group predominantly encompasses studies centered around far-field and outdoor scenario investigations. Distinct groupings have been established to specifically address indoor scenarios and near-field localization, both of which are considered specialized cases. Studies are presented in comprehensive detail and tabular format in the subsequent subsections.

A. RIS-Assisted Outdoor and Far-Field Localization

In this subsection, we explore the latest advancements and contemporary studies focused on leveraging RIS technology to augment outdoor and far-field localization at CRF and high frequency bands.

1) *RIS-Assisted Conventional Radio Frequency Bands Localization (Below 24 GHz)*: Studies are briefly summarized in Table IV. We attempt to categorize the works into thematic groups based on their core focus as follows.

a) *Foundational studies*: Authors in [126] introduce RIS to enhance RSS fingerprinting-based outdoor localization using just one BS. By adjusting the RIS phase shifts, the approach creates distinct RSS values at the same location, optimizing this through a localization error minimization algorithm. Simulations confirm the scheme's efficacy. Article [63] introduces the concept of continuous intelligent surfaces and investigates the fundamental limits of RIS-aided ISAC systems. The paper proposes a general signal model, derives theoretical limits on localization and communication performance, and performs Fisher information analyses. The numerical results demonstrate that optimized RIS can improve the SNR and spectral efficiency of communication, as well as enhance localization accuracy. Authors in article [60] propose a RIS-assisted positioning method for simultaneously localizing multiple energy-limited IoT devices in location-based IoT services. The proposed method utilizes triangulation-based localization, estimating the propagation delay difference between the direct and reflected paths using cross-correlation. By optimizing the multi-antenna BS and RIS to minimize total transmission power, significant power gain and decimeter-level positioning accuracy are achieved, demonstrating the effectiveness of the proposed optimization approach compared to unoptimized RIS-assisted localization.

b) *Novel techniques and systems*: In [122], the authors propose a new RIS self-sensing system where the RIS controller transmits probing signals and dedicated sensors at the RIS are used for location and angle estimation based on the reflected signals by the target. The multiple signal classification (MUSIC) algorithm is applied to accurately estimate the AOA of the target in the RIS's vicinity, and the RIS passive reflection matrix is optimized to maximize

TABLE IV
SUMMARY OF RIS-ASSISTED OUTDOOR AND FAR-FIELD LOCALIZATION ARTICLES AT CONVENTIONAL RADIO FREQUENCY BAND.
HERE "R" REFERS TO "REFLECTIVE RIS"

RIS	Ref	f_c	Link	System	Purpose	Technique	Performance metric
R	[122]	1.5 GHz	DL	MISO	RIS for sensing/localizing targets in wireless networks	Self-sensing RIS architecture, customized MUSIC algorithm, CRLB	Accuracy
R	[123]	2 GHz	DL	MISO	Localization with obstructed LoS and three RIS	Elimination of destructive effect of the AOD	Accuracy
R	[124]	2.5 GHz	DL	MIMO	Joint active and passive beamforming design for RIS-enabled ISAC system in consideration of the target size	Non-convex optimization	Detection probability, SNR
R	[125]	2 GHz	DL	SISO	UE localization assisted by multiple RIS	Localization algorithm design based on nodes distances	Accuracy
R	[126]	3 GHz	DL	SISO	RSS fingerprinting based multi-user outdoor localization using RIS and single BS	localization error minimization algorithm	Accuracy
R	[60]	3 GHz		SISO	Fundamental limits of RIS-aided localization and communication system with RIS as continuous and discrete intelligent surface	RIS phase design, Fisher information matrix (FIM)	Accuracy, spectral efficiency, SNR
R	[127]	3 GHz	DL	SISO	Wideband localization with RIS	FIM	Accuracy
R	[128]	3 GHz	DL	SISO	JCAL system design	PEB, joint RIS discrete phase shifts design and subcarrier assignment using Lagrange duality and penalty-based optimization	Accuracy and data rate
R	[129]	3 GHz	DL	SISO	Multi-user localization system using modulated RIS	TDOA	Accuracy
R	[130]	3.4/3.5/28 GHz		MIMO	Localization technique that does not require RIS codewords for online location inference	Domain adversarial neural network, fingerprinting	Accuracy
R	[131]	4.9 GHz	UL	MIMO	UE position estimation	Compressed sensing orthogonal simultaneous matching pursuit algorithm, maximum likelihood estimation, discrete Fourier transform, SAGE algorithm, CRLB	Accuracy
R	[132]	5 GHz	DL	MIMO	Lower bounds on the location estimation error for multiple RIS-aided mmW system	CRLB, PEB, REB	Accuracy
R	[133]	10 GHz	DL	MIMO	Bayesian analysis of the information in LoS and RIS reflected signal	Bayesian analysis, FIM	Accuracy
R	[60]	20 GHz	UL	MISO	To localize a large number of energy-limited devices simultaneously and accurately	Triangulation-based localization framework, optimization	Accuracy, energy efficiency
R	[134]	2 GHz	UL, DL	MISO	Environment-adaptive user positioning	Federated learning	Accuracy
R	[135]	3 GHz	UL	MIMO	ISAC for wireless extended reality using RIS	MUSIC, CRLB	Accuracy, capacity
R	[136]	2.45 GHz	DL	SIMO	Theoretical and practical design of RIS-assisted sensing system with localization	Atomic norm minimization direction of arrival estimation network, generative adversarial network	Accuracy
R	[137]	1 GHz	DL	SISO	Method for RIS-assisted fingerprinting localization	Fingerprinting, graph-based radio map interpolation	Accuracy
R	[138]	2.5 GHz	DL	MISO	Joint beamforming and aerial RIS positioning design with multiple access points	Generalized benders decomposition, mixed-integer semidefinite programming	Spectral efficiency
R	[139]	400 MHz		SISO	Positioning, navigation, and timing solution	Game theory	Accuracy

the received signals' power at the RIS sensors, leading to minimized AOA estimation mean square error (MSE). The results demonstrate the benefits of using the RIS controller for probing signals and provide the CRLB for target AOA estimation. In [123], a positioning algorithm is introduced for RIS-assisted networks, focusing on multi-antenna BS and single-antenna UE. Leveraging three RIS and specific phase shifter adjustments, the method effectively overcomes LoS obstructions and minimizes the adverse effects of the AOD, resulting in improved localization accuracy compared to non-AOD estimating algorithms. The study [124] introduces a joint active and passive beamforming design for RIS-enabled

ISAC systems, accounting for target size. Through an alternative optimization method, the paper addresses non-convex problems involving beamforming solutions and RIS phase shifts, with the developed algorithm showcasing superior target detection performance in simulations, especially for practical target sizes, against existing benchmarks. The article [133] presents a Bayesian analysis of the information contained in a signal received by a UE from a BS that includes reflections from RIS. The analysis considers both near and far-field scenarios and incorporates prior information about the UE and the RIS for localization. The results indicate that the orientation offset of the RIS affects the pathloss of the RIS

paths when the RIS elements are spaced half a wavelength apart. In the far-field regime, an unknown phase offset in the received signal prevents the correction of the RIS orientation offset. However, in the near-field regime, the estimation of the RIS orientation offset is possible when the UE has multiple receive antennas. The article also demonstrates that accurate localization with RIS is only possible when there is prior knowledge of their locations. Finally, numerical analysis shows the loss of information when applying a far-field model to signals received in near-field propagation.

Unlike the methods that rely on channel matrices or RIS codewords, the authors in [130] proposed an approach that uses a domain adversarial neural network to extract codeword-independent representations of fingerprints for online location inference in RIS-assisted localization network. The solution is evaluated using the DeepMIMO data set, and the results show that the proposed method performs significantly closer to the theoretical upper bound (oracle case) than the lower bound (baseline case), indicating its effectiveness and robustness. Authors in [131] article investigate the estimation of position and angle of rotation for a UE in a MIMO system with the assistance of a RIS. The RIS creates a virtual LoS link, along with NLoS links from scatterers in the environment, to aid in the estimation process. A two-step positioning scheme is utilized, where channel parameters are acquired first and then position-related parameters are estimated. Coarse estimation is performed using various algorithms, followed by joint refinement using the space-alternating generalized expectation maximization (SAGE) algorithm. The performance of the proposed algorithms is demonstrated to be superior through simulation results, and theoretical quantification is done using the CRLB. The authors in [134] introduced HoloFed, a high-precision, environment-adaptive user positioning system that integrates multi-band reconfigurable holographic surface with federated learning. To enhance positioning accuracy, the system uses a calculated lower bound on error variance to guide multi-band reconfigurable holographic surface beamforming design. An federated learning framework is implemented for collaborative training of a position estimator, utilizing transfer learning to compensate for the lack of user position labels, while a scheduling algorithm optimizes user selection for training based on federated learning convergence and efficiency. Simulation results indicate that HoloFed reduces positioning error variance by 57% compared to traditional beam-scanning methods, demonstrating significant adaptability and precision across diverse environments. A novel RIS-enabled wireless fingerprinting localization method that addresses missing RSS data using a graph-based radio map interpolation technique is proposed in [137]. This approach leverages RIS configuration flexibility and encodes similarities through a multi-layer graph. Numerical results show improved radio map recovery and localization accuracy compared to other methods.

c) *Integrated sensing and communication*: The work presented in [135] explores the use of RIS in future wireless networks for enhanced positioning and communication in extended reality applications. It introduces a positioning algorithm based on MUSIC and optimized RIS configurations.

The joint optimization of UE beamformers and RIS phase shifters maximizes channel capacity under CRLB constraints, solved via alternating optimization. Authors in [136] present a low-cost RIS-assisted sensing system, featuring a novel atomic norm minimization direction of arrival estimation network method for improved localization and communication reliability. The system uses a cost-effective RIS structure and a practical signal model that accounts for RIS phase shifts. The atomic norm minimization direction of arrival estimation network method combines atomic norm minimization for spatial spectra and direction of arrival estimation network for angle estimation, using generative adversarial network to generate a large dataset. Experimental results show that proposed technique effectively localizes sources in the RIS-aided sensing system.

2) *RIS-Assisted High Frequency Bands Localization (24 GHz and Above)*: Studies on RIS-assisted localization in this band of operation are briefly summarized in Table V, VI and VII and discussed as follows.

a) *Foundational studies*: Authors in [39] discussed the use of RIS in 6G radio positioning. The authors propose a two-step optimization scheme that selects the best combination of RIS and controls their constituent elements' phases to improve positioning performance. Preliminary simulation results demonstrate gains in coverage and accuracy compared to natural scattering, but limitations are identified in terms of low SNR and inter-path interference. Assuming the LOS route between the BS and the MS is present, authors in [40] introduced RIS as a reflector into the mmW MIMO positioning system. The CRLB of the positioning as well as the orientation estimation error are obtained by calculating FIM, which reveals that the RIS-aided mmW MIMO positioning system offers better localization accuracy and coverage as compared to the conventional localization system comprising BS nodes only. It has also been demonstrated that one BS with the help of reflection from RIS can also achieve promising positional precision. Nevertheless, nothing is discussed about how to localize the UE in a LOS-obscured environment. To determine the absolute location of the MS under the NLoS scenario, authors in [41] developed the CRLB based on FIM. The study suggests that, in the given setup, the localization can reach the decimeter level of accuracy by refining the reflect beamforming architecture to reduce CRLB. Authors in [56] present localization and synchronization in a wireless system with a single-antenna UE, a single-antenna BS, and a RIS. They calculate the CRLB and develop a low-complexity estimator to determine the AOD from the RIS, as well as the delays of direct and reflected signals. The results indicate that efficient 3D localization and synchronization are achievable in the considered system, showcasing the potential of RIS for enabling radio localization in simple mmW wireless networks.

Authors in [108] investigate the potential of RIS in replacing the function of a remote cell for DL-TDOA measurements in 6G positioning. The study demonstrates that the TDOA between the LoS path and the reflected path through the RIS can effectively replace DL-TDOA measurements, enabling accurate localization within a single cell. Simulation results indicate that RIS-enabled localization achieves positioning

TABLE V

SUMMARY OF RIS-ASSISTED OUTDOOR AND FAR-FIELD LOCALIZATION ARTICLES AT HIGH FREQUENCY BANDS. HERE “R” REFERS TO “REFLECTIVE RIS”, “S” REFERS TO “STAR RIS”, “A” REFERS TO “ACTIVE RIS”

RIS	Ref	f_c	Link	System	Purpose	Technique	Performance metric
R	[108]	24 GHz	DL	MISO	RIS to replace the function of a remote cell in the DL-TDOA measurement	Extended Kalman filter positioning and tracking algorithm	Accuracy
R	[39]	28 GHz	DL	SISO	Analysis of a RIS-aided localization problem	FIM, two step optimization	Accuracy, coverage
R	[43]	28 GHz	UL	MIMO	Beam training designs to estimate optimal beams for BS and UE, RIS reflection pattern and link blockage	maximum likelihood estimation (MLE), positioning algorithm design	Accuracy
R	[59]	28 GHz	DL	SISO	Use of 3D localization technology to achieve the low-complexity channel estimation	Reflecting unit set concept, coplanar maximum likelihood-based based 3D positioning method, CRLB	Accuracy, SNR
R	[62]	28 GHz	UL	MIMO	Localization and channel reconstruction in extra large RIS-assisted MIMO systems	Low-overhead joint localization, channel reconstruction scheme	Accuracy
R	[140]	28 GHz	DL	MISO	Exploiting RIS with suitably designed beamforming strategies for optimized localization and synchronization performance	PEB, MLE	Accuracy
S	[141]	28 GHz	UL	MISO	STAR RIS potential for enhanced concurrent indoor and outdoor localization	CRLB, FIM, optimization	Accuracy
R	[142]	28 GHz	DL	MIMO	Joint beamforming and localization for RIS-aided mmW localization system	Joint localization and beamforming optimization algorithm	Accuracy
R	[143]	28 GHz			Enabling the user to estimate its own position by transmitting orthogonal frequency division multiplexing (OFDM) pilots and processing the signal reflected from the RIS	CRLB, low-complexity position estimation algorithm, temporal coding on RIS phase	Accuracy
R	[144]	28 GHz	UL	MIMO	Channel estimation and user localization	RIS training coefficients designs, array signal processing, atomic norm denoising techniques	Accuracy
R	[145]	28 GHz	DL	SIMO	Joint RIS calibration and user positioning scheme	FIM	Accuracy
R	[146]	28 GHz	DL	MIMO	User localization and tracking	Bayesian user localization and tracking algorithm	Accuracy
R	[147]	28 GHz		SISO	Cooperative localization to improve accuracy in RIS-assisted system	Beam sweeping, optimization, neural network	Accuracy
R	[104]	28 GHz			Cooperative localization with no access point	FIM, CRLB, RIS configuration optimization	Accuracy
Rx	[148]	28 GHz	UL		Localization of UE with partially connected receiving RIS only	Atomic norm minimization, MUSIC, CRLB	Accuracy
A	[103]	28 GHz	UL	SIMO	Joint RIS calibration and user positioning problem with an active RIS	Tensor-ESPRIT estimator, least-squares, 2D search-based algorithm, CRLB	Accuracy
R	[149]	28 GHz	DL	SISO	misspecified Cramér-Rao bound (MCRB) with RIS geometry mismatch	Method for pseudo-true parameter determination for MCRB analysis	Accuracy
R	[150]	28 GHz	UL	MISO	Localization of UE using distributed passive RIS	compressive sensing (CS) approach based on atomic norm minimization, MLE, CRLB	Accuracy
R	[151]	28 GHz		MIMO	Device-free target sensing via joint location and orientation estimation	Target based method for angle estimation, gradient descent method, manifold optimization	Accuracy
A	[152]	28 GHz	UL	MISO	ISAC using sparse active RIS	MUSIC algorithm, optimization	Accuracy
R	[105]	28 GHz	DL	MIMO	JCAL framework	Novel RIS optimization and channel estimation methods	Accuracy, data rate
R	[153]	28 GHz	SL	SISO	UE localization without BS involvement	Two-stage 3D sidelink positioning algorithm, CRLB	Accuracy
R	[56]	30 GHz	DL	SISO	Joint 3D localization and synchronization for a SISO multi-carrier system	CRLB, design of low complexity estimation algorithm	Accuracy
R	[154]	30 GHz	DL	SISO	RIS in a multi-user passive localization scenario	Low complexity TOA based positioning algorithm, CRLB	Accuracy
R	[155]	30 GHz	DL	SISO	Positioning UE by taking into account the its mobility spatial- wideband effects	CRLB, low-complexity estimator design	Accuracy
R	[112]	30 GHz			RIS-enabled radio SLAM without the intervention of BS	RIS phase profile design, marginal Poisson multi-Bernoulli SLAM filter modification, CRLB	Accuracy

accuracy comparable to the traditional two-cell structure, offering a cost-effective solution. Authors present an efficient CSI acquisition method for a RIS-aided communication

system in [59]. They propose a coplanar maximum likelihood-based 3D localization approach and utilize the concept of reflecting unit set to acquire channel information with minimal

TABLE VI

SUMMARY OF RIS-ASSISTED OUTDOOR AND FAR-FIELD LOCALIZATION ARTICLES AT HIGH FREQUENCY BANDS. HERE “R” REFERS TO “REFLECTIVE RIS”, “H” REFERS TO “HYBRID RIS”, “A” REFERS TO “ACTIVE RIS”, “S” REFERS TO “STAR RIS”

RIS Ref	f_c	Link	System	Purpose	Technique	Performance metric
R [156]		DL	MIMO	ISAC with RIS	CS, expectation-maximization algorithm, Bayesian Cramér-Rao bound	Accuracy
H [157]	30 GHz	DL	MISO	Joint localization of a hybrid RIS and a user	CRLB	Accuracy
R [158]	30 GHz	DL	SISO	Cooperative localization in a RIS-aided mmW system	FIM, CRLB, block coordinate descent-based reflect beamforming design algorithm	Accuracy
R [159]	30 GHz		MISO	Location information assisted beamforming design without the requirement of the channel training process	Relaxed alternating optimization process	Data rate
R [41]	50 GHz	DL	MIMO	RIS beamforming under NLoS	CRLB, optimization	Accuracy
R [40]	60 GHz	DL	MIMO	Theoretical bounds for large intelligent surface	CRLB based PEB and OEB	Accuracy
R [26]	60 GHz	DL	MIMO	Improving the positioning accuracy and data rate	Adaptive phase shifter design based on hierarchical codebook and feedback from the UE	Accuracy, data rate
R [44]	60 GHz	UL	MIMO	Localization of UE	Two stage positioning method with dual RIS	Accuracy
R [42]	60 GHz	DL	MIMO	Utilizing RIS in mmW MIMO radar system for multi-target localization	Adaptive localization algorithm utilizing the concept of hierarchical codebook design	Accuracy
R [57]	60 GHz	DL	MISO	Joint localization and synchronization	MLE	Accuracy
R [23]	60 GHz	UL	MIMO	RIS-assisted localization at THz band in comparison with the mmW band	Geometrical modeling and simulations	Accuracy
R [160]	60 GHz	UL	MIMO	Potential of RIS for cooperative localization performance	CRLB, manifold optimization	Accuracy
R [161]	60 GHz	UL	MIMO	To optimize the worst-case localization performance by jointly optimizing beamforming vectors at RIS and UE	Joint array gain and path loss search algorithm, difference of convex-based algorithm	Accuracy
A [83]	60 GHz	DL	MIMO	UE localization with active RIS	Multiple signal transmissions, particle filtering, CRLB	Accuracy
R [34]	60 GHz	DL	SISO	Overview of RIS enabled localization scenarios	Experimental demonstration	Accuracy
R [53]	60 GHz	DL	MIMO	Joint optimal point of the user position/orientation estimation error bound and effective achievable data rate	Worst-case robust beamforming and time allocation optimization approach, majorize-minimization based algorithm	Accuracy, data rate
R [162]	60 GHz	DL	MISO	Investigate the potential of employing RIS in dual-functional radar-communication vehicular networks	Codebook design for optimal phase shift of RIS, position-based CSI design	Accuracy, data rate
R [163]	100 GHz	UL	MISO	Sensing of channel and location under the unique hybrid far-near field effect and the beam squint effect	Location-assisted generalized multiple measurement vector orthogonal matching pursuit algorithm, dictionary-based localization scheme, polar-domain gradient descent algorithm	Accuracy
R [164]	30 GHz		MISO	Enhancing RIS-equipped UAVs' performance	geometry-based simultaneous localization and phase shift method	Accuracy
R [165]	30 GHz			Enhancing 6G user-centric sensing with RIS for improved localization and sensing	geomtry based modeling	Accuracy and sensing performance efficiency
R [166]		DL	MISO	Target localization system utilizing RIS and passive radars to enhance ISAC capabilities	Localization algorithm based on AOA and TOA	Accuracy, detection probability, successful detection probability
R [167]	73 GHz	DL	MISO	Environment aware joint active/ passive beamforming	Channel knowledge map	Energy efficiency, spectrum efficiency
R [168]	30 GHz	DL	MIMO	Fundamental localization bounds in RIS-assisted OFDM systems	FIM	PEB, OEB
R [169]	26 GHz	DL	SISO	RIS-assisted positioning approach	FIM, MSE	Accuracy
S [170]	28 GHz	UL	MISO	STAR-RIS-assisted bilateral user localization	CSI, ML	Accuracy
R [171]	28 GHz	DL	MISO	Joint 3D localization and synchronization using multiple RISs	DL	Accuracy, complexity
R [172]		UL	MISO	Dual-RIS assisted 3D localization and beamforming design in ISAC system	CS, stepwise matching pursuit algorithm	MSE

training resources. Study indicates substantial performance improvements in terms of the SNR of the received signal. Article [62] presents a low-overhead joint localization and channel reconstruction scheme for extra-large RIS-assisted MIMO systems. The proposed scheme accurately identifies the visibility region of each user, achieves centimeter-level

user localization accuracy, and obtains more accurate channel reconstruction results compared to existing works. The results demonstrate the potential of RIS for improving communication and sensing integration.

Authors in [144] focus on the challenges of channel estimation and user localization in a RIS-assisted MIMO-

TABLE VII
SUMMARY OF RIS-ASSISTED OUTDOOR AND FAR-FIELD LOCALIZATION ARTICLES AT HIGH FREQUENCY BANDS.
HERE "R" REFERS TO "REFLECTIVE RIS"

RIS Ref	f_c	Link	System	Purpose	Technique	Performance metric
R [173]	100 GHz	DL	MIMO	User sensing and localization	Tensor, parallel factor method, alternating least squares algorithm	Accuracy
R [174]			SISO	RIS-assisted cooperative localization	Cooperative localization, CRLB, Polyblock-based algorithm, heuristic algorithm	Accuracy
R [175]	30 GHz	DL	SISO	Autonomous receiver localization and tracking	Complex extended Kalman filter	Accuracy
R [176]		UL	MISO	ISAC systems design	Structure-aware sparse Bayesian learning framework, simultaneous communication and localization algorithm for multiple users	Accuracy, spectral efficiency
R [177]		DL	MIMO	Limitation of RIS-assisted localization	FIM, Bayesian FIM	Accuracy
R [178]	28 GHz		MIMO	Joint channel estimation and localization	CS, simultaneous orthogonal matching pursuit	Accuracy
R [179]	300 GHz		MIMO	ISAC	Multi-group Khatri-Rao space-time coding scheme, low-complexity least squares Khatri-Rao factorization algorithm, optimized five linear alternating least squares algorithm	Accuracy, bit error rate
R [180]	70 GHz	DL	MISO	Target-to-user association in ISAC Systems	Mount RIS on the roof of the vehicular UE	Accuracy
R [181]		DL	MISO	ISAC	Modeling based heterogeneous networked sensing architecture	Accuracy
R [182]	28GHz, 5.9GHz	UL	MIMO	Multi-band ISAC	X ² Track framework design, DL	Accuracy
R [183]	28 GHz	UL	MIMO	ISAC	Tensor, DL	Accuracy

OFDM system. The article proposes a unique twin-RIS structure that incorporates spatial rotation to extract the 3D propagation channel. They employ tensor factorization, sparse array processing, and atomic norm denoising techniques to design training patterns and recover the associated parameters. By decoupling the channel's angular and temporal parameters, they achieve precise channel parameter extraction and centimeter-level positioning resolution. A two-stage method is proposed in [150], utilizing the tunable reflection capability of passive RIS and the multi-reflection wireless environment. The first stage employs an off-grid CS approach to estimate the angles of arrival associated with each RIS, followed by a maximum likelihood location estimation in the second stage. The study demonstrates the high accuracy of the proposed 3D localization method, consistent with the theoretical CRLB analysis.

Authors in [168] establish fundamental localization bounds for OFDM systems aided by RIS. It derives Bayesian localization bounds using the Bayesian FIM and the equivalent FIM. The study reveals that constant RIS reflection coefficients across OFDM symbols make angle estimation impossible, necessitating varying coefficients for effective localization. It also decomposes the FIM for RIS-related parameters into contributions from the receiver, transmitter, and RIS components, and concludes that single-antenna UE localization via a single RIS reflection is infeasible in the far-field with constant RIS coefficients. A RIS-assisted positioning method for high-precision user localization, considering the incident planar wavefront on the RIS is proposed in [169]. It derives the MSE to evaluate system accuracy and offers solutions for optimal RIS placement and configuration. Numerical analyses are conducted to assess performance across different scenarios,

focusing on RIS location, element count, and communication bandwidth. Results indicate that RIS significantly enhances positioning accuracy in 6G networks.

b) Advanced techniques and systems: In [141], the authors investigate the potential of STAR-RIS for enhanced indoor and outdoor localization. They study the fundamental limits of 3D localization performance using Fisher information analysis and optimize the power splitting between refraction and reflection at the STAR-RIS, as well as the power allocation between the UE. The results indicate that high-accuracy 3D localization can be achieved for both indoor and outdoor UEs when the system parameters are well optimized, demonstrating the potential of STAR-RIS in concurrent localization. Existing RIS-aided localization approaches assume perfect knowledge of the RIS geometry, which is not realistic due to calibration errors. The authors in [149] derive the MCRB for localization with RIS geometry mismatch and propose a closed-form solution for determining pseudo-true parameters. Numerical results validate the derived parameters and MCRB, demonstrating that RIS geometry mismatch leads to performance saturation in high SNR regions. The article [143] introduces a concept of 3D UE self-localization using a single RIS. The approach involves the UE transmitting multiple OFDM signals and processing the reflected signal from the RIS to estimate its position. The estimation process includes separating the RIS-reflected signal from the undesired multipath, obtaining a coarse position estimate, and refining the estimation through maximum likelihood techniques. The performance of the estimator is evaluated in terms of positioning error and compared to an analytical lower bound. The results demonstrate the potential of RIS as an enabling technology for radio localization, offering improved positioning accuracy.

Authors in [148] introduce the concept of partially-connected receiving RIS that can sense and localize users emitting electromagnetic waveforms. The receiving RIS hardware architecture consists of meta-atom subarrays with waveguides that direct the waveforms to reception RF chains for signal and channel parameter estimation. The focus is on far-field scenarios, and a 3D localization method is presented based on narrowband signaling and AOA estimates using phase configurations of meta-atoms. The results include theoretical CRLBs and extensive simulations, demonstrating the effectiveness of the proposed receiving RIS-empowered 3D localization system, providing cm-level positioning accuracy. The impact of various system parameters on localization performance is also evaluated, such as training overhead, distance between R-RIS and the user, and spacing among R-RIS subarrays and their partitioning patterns. The joint calibration and positioning problem in an uplink system with an active RIS is addressed in [103]. Existing approaches often assume known positions and orientations for RIS, which is not realistic for mobile or uncalibrated RIS. The proposed two-stage method includes a tensor-ESPRIT estimator followed by parameter refinement and a 2D search-based algorithm to estimate user and RIS positions, RIS orientation, and clock bias. The derived CRLBs verify the effectiveness of the algorithms, and simulations show that the active RIS significantly improves localization performance compared to the passive case. Low coverage areas that limit localization performance can be mitigated by providing additional prior information or deploying more BSs.

A novel RIS-enabled SLAM framework is presented in [112] for 6G wireless systems that operates without access points. RIS phase profiles are designed to illuminate the likely location of UE. The modified Poisson multi-Bernoulli SLAM filter estimates UE state and maps the radio environment efficiently. Theoretical CRLB are derived for channel parameters and UE state estimations. Performance evaluations show the method's effectiveness in scenarios with limited transmissions and channel coherence time considerations. This study performed in [170] introduces a high-precision 6G positioning method using ISAC and STAR-RIS. It employs the CsiNet-Former network to extract spatial features from CSI for accurate 3D user localization and trajectory prediction. Simulation results show that in energy splitting mode, the method achieves an average localization error of 0.75 m and a single-side error of 0.034 m, outperforming existing methods and covering a larger area. The authors in [157] present a method for joint localization of a hybrid RIS and a user, using a single radio frequency chain for reflections and sensing. A multi-stage approach estimates hybrid RIS position, orientation, and user location where simulations confirm the method's efficiency and identify an optimal HRIS power splitting ratio.

c) Advanced beamforming and phase shifter designs: The adaptive beamforming of RIS-assisted mmW MIMO placement with obstructed LoS between the BS and the UE is studied in [26]. The authors suggest a hierarchical codebook and receiver feedback-based adaptive phase shifter

architecture to optimize the phase of each of the RIS units and in turn optimize performance in terms of localization accuracy and data rate. Authors in [44] have proposed a two-stage localization technique using dual RIS. The reflecting element's phase shift is first designed for each RIS, and then in the second stage, the location data is calculated and it demonstrates the localization accuracy in the range of 10^{-5} – 10^{-4} meters. Article [160] explores the potential of RIS for improving cooperative localization performance in mmW MIMO systems. The paper presents a study on the fundamental limits of cooperative localization using the CRLB and proposes an optimal phase design at the RIS to enhance position accuracy. The study demonstrates that the proposed optimal passive beamforming algorithm significantly improves localization accuracy, and achieves near-optimal performance with minimal computational complexity. Authors in [43] suggest a simultaneous beam training and placement technique to address the LoS obstruction in mmW MIMO network. The UE estimates its location using the AOD, which is determined via beam training. The location of UE, in turn, helps to improve the beam training. Results demonstrate that the proposed approach can obtain centimeter-level multi-user localization accuracy.

A low-complexity method for joint localization and synchronization in mmW systems using RIS is proposed in [140]. Their approach involves optimizing the beamforming strategies of the BS active precoding and RIS passive phase profiles, considering a single-antenna receiver. The results indicate that the proposed joint BS-RIS beamforming scheme achieves enhanced localization and synchronization performance compared to existing solutions, with the proposed estimator achieving the theoretical bounds even under challenging conditions such as low SNR and uncontrollable multipath propagation. The authors in [142] focused on the successive localization and beamforming design of a RIS-aided mmW communication system. They formulated the problem as a multivariable coupled non-convex problem and proposed an alternating optimization algorithm to solve it. The results showed that their proposed scheme, called joint localization and beamforming optimization, significantly improved the performance compared to existing joint localization and beamforming methods, as demonstrated through simulation results.

The authors in [164] proposed simultaneous localization and phase Shift method for enhancing RIS-equipped autonomous aerial vehicles in 6G networks. It focuses on integrating accurate localization with phase shift adjustments to improve coverage and address blockage issues. The method utilizes geometry-based localization to optimize passive beam-steering, benefiting aerial line-of-sight communication, especially in vehicle-to-vehicle scenarios. Simulation results validate the effectiveness of the method, showing significant improvements in communication performance and safe navigation in complex urban environments. This study [167] explores environment-aware active and passive beamforming for RIS-aided communication using Channel Knowledge Map, which eliminates the need for online training and reduces overhead in mmWave systems while maintaining high energy

efficiency. Simulation results show that CKM significantly enhances beamforming performance compared to traditional training-based methods and remains robust against errors in UE location.

d) Multiuser and joint communication and localization approaches: Authors in [42] examined a multiuser localization method based on an hierarchical codebook design in light of the LoS obstruction scenario. The study results under various SNR situations demonstrate that, with the right hierarchical codebook design, the suggested approach has the ability to provide multiuser localization in mmW MIMO radar systems. In [53], authors present an RIS-aided mmW-MIMO system for JCAL. They derive closed-form expressions of CRLB for position/orientation estimation errors and effective achievable data rate based on RIS phase shifts. They propose a joint optimization algorithm to balance the trade-off between the two metrics, and simulation results demonstrate the effectiveness of the algorithm in terms of estimation accuracy and effective achievable data rate, even in the presence of estimation errors and user mobility. Authors in article [57] address the problem of joint localization and synchronization in a mmW MISO system using a RIS. They formulate the joint maximum likelihood estimation problem in the position domain and propose a reduced-complexity decoupled estimator for position and clock offset. Simulation results demonstrate that their approach achieves high accuracy in localization and synchronization, even in low SNR scenarios, without the need for optimizing transmit beamforming, RIS control matrix, or prior knowledge of the clock offset.

e) Localization in special scenarios: Authors in [155] address the challenge of positioning a single-antenna user in 3D space by considering the received signal from a single-antenna BS and the reflected signal from an RIS. They take into account both user mobility and spatial-wideband effects. Initially, a spatial-wideband channel model is derived under the assumption of far-field conditions, focusing on OFDM signal transmission with a user of constant velocity. CRLB are derived as a benchmark, and a low-complexity estimator is developed to achieve these bounds under high SNR ratios. The proposed estimator compensates for user mobility by estimating radial velocities and iteratively accounting for their effects. The results indicate that spatial-wideband effects can have a detrimental impact on localization accuracy, especially for larger RIS sizes and signal bandwidths deviating from the normal of the RIS. However, the proposed estimator demonstrates resilience against spatial-wideband effects up to a bandwidth of 140 MHz for a 64x64 RIS. Notably, user velocity does not significantly affect the bounds or accuracy of the estimator, indicating that high-speed users can be localized with similar precision as static users.

The potential of 6G THz systems for localization and comparison with mmW localization systems is performed in [23]. They compare various aspects including system properties, channel modeling, localization problem formulation, and system design. Preliminary simulations demonstrate the potential of THz localization in terms of PEB and OEB compared to mmW systems. The article provides recommendations

for efficient localization algorithm design for RIS-assisted adaptive optics-based spatial modulation MIMO systems and highlights the anticipated applications in future communication systems, such as intelligent networks, autonomous transportation, and tactile internet. A framework for RIS-enabled SLAM without the need for access points is proposed in [112]. They design RIS phase profiles based on prior information about the UE, allowing for uniform signal illumination in the UE's probable location. They also modify the Poisson multi-Bernoulli SLAM filter to estimate the UE state and landmarks, facilitating efficient mapping of the radio propagation environment. Theoretical CRLB are derived for the estimators of channel parameters and UE state. The proposed method is evaluated under scenarios with a limited number of transmissions and considering the channel coherence time. Study demonstrates that RIS can solve the radio SLAM problem without the need for access points, and incorporating the Doppler shift improves UE speed estimates.

f) High frequency sensing operations: The authors in [163] perform the sensing of the user's uplink channel and location in THz extra-large RIS systems. The authors propose a joint channel and location sensing scheme that includes a location-assisted generalized multiple measurement vector orthogonal matching pursuit algorithm for channel estimation and a complete dictionary-based localization scheme. They address challenges such as the hybrid far-near field effect and beam squint effect caused by the extra large array aperture and extra large bandwidth. The proposed schemes demonstrate superior performance compared to existing approaches, as indicated by simulation results. They also introduce a partial dictionary-based localization scheme to reduce sensing overhead, where the RIS serves as an anchor for user localization using TDOA. An ISAC scenario using RIS is investigated in [156] where multiple devices communicate with a BS in full-duplex mode while simultaneously sensing their positions. RIS are mounted on each device to enhance reflected echoes, and device information is passively transferred to the BS through reflection modulation. The problem of joint localization and information retrieval is addressed by constructing a grid-based parametric model and formulating it as a CS problem. An expectation-maximization algorithm is applied to tune the grid parameters and mitigate model mismatch. The efficacy of various CS algorithms is analyzed using the Bayesian Cramér-Rao bound. Numerical results demonstrate the feasibility of the proposed scenario and the superior performance of the EM-tuning method.

The challenge of enhancing user-centric sensing capabilities in future 6G networks is studied in [165]. The study explores the use of RIS to support monostatic sensing, improving localization accuracy and sensing performance despite the limited hardware capabilities of user equipment. The proposed method leverages RIS to create a more effective sensing environment, showcasing significant enhancements in sensing precision and efficiency through simulation results. Authors in [166] have introduced a novel target localization system that combines RIS and passive radars for enhanced ISAC. The system leverages the preamble of communication signals to

perform detection and localization tasks. RIS helps passive radar detect targets obscured by obstacles within the propagation channel. The proposed algorithm is designed to uniquely position targets by estimating their AOA and TOA, and it can detect the number of targets present. Simulation results show that the localization method performs effectively across various detection metrics and with increasing RIS sizes.

Authors in [172] address high-frequency fading in 6G ISAC systems using dual-RIS for 3D localization and beamforming. They propose a stepwise matching pursuit algorithm for accurate, low-complexity localization and uses this data for RIS beamforming to maximize system rate with a triangle inequality-based alternating optimization algorithm. Simulations show the proposed method achieves near-optimal rates, confirming its effectiveness. The authors in [179] present a nested tensor-based algorithm for ISAC in RIS-assisted THz MIMO systems. It uses Khatri-Rao space-time coding and RIS phase shifts to model the received signal as nested tensors. The algorithm includes low-complexity factorization for joint channel estimation and symbol detection, and optimized estimation of sensing parameters. Simulations show it outperforms current methods with more relaxed parameter conditions.

g) *Practical localization scenarios and applications*: The authors in [105] focus on leveraging RIS to enhance communication performance when the LoS path between the UE and BS is blocked. The authors propose a novel framework that integrates localization and communications by fixing RIS configurations during location coherence intervals and optimizing BS precoders every channel coherence interval. This approach reduces pilot overhead and the need for frequent RIS reconfiguration. The framework utilizes accurate location information from multiple RIS, along with novel RIS optimization and channel estimation methods. The results indicate improved localization accuracy, reduced channel estimation error, and increased achievable rate, demonstrating the effectiveness of the proposed approach. Authors in [184] focus on the requirements of localization and sensing in the context of smart cities and highlight the limitations of traditional communication infrastructure for meeting localization and sensing demands. The authors argue that RIS and sidelink communications are promising technologies that can address the localization and sensing needs of smart cities. They propose and evaluate anchor point-coordinated and self-coordinated RIS-enabled localization and sensing architectures, considering different application scenarios such as low-complexity beacons, cooperative localization, and full-duplex transceivers. The article also discusses practical issues and research challenges associated with implementing these localization and sensing systems.

Authors in [153] address the importance of localization in intelligent transportation systems and explore the use of reflective RIS to enhance high-precision localization. The authors propose a two-stage 3D sidelink positioning algorithm that utilizes at least two RIS and sidelink communication between UEs to achieve localization without the involvement of BSs. They evaluate the effects of multipath and RIS profile designs on positioning performance, analyze localizability in various scenarios, and propose solutions to eliminate low coverage areas. The study demonstrates the promising accuracy of the proposed BS-free sidelink communication system

in challenging intelligent transportation systems scenarios. A low-complexity, two-stage method for 3D localization and synchronization using multiple RISs in multipath scenarios is proposed in [171]. First, signals are preprocessed and a DL model estimates AOD. An initial user position is then estimated using an asynchronous AOD TOA approach. Finally, an optimization refines the position using estimated delays and clock offset. This method improves accuracy and robustness against multipath effects.

B. RIS-Assisted Indoor Localization

Studies on RIS-assisted indoor localization are briefly summarized in Table VIII and discussed as follows.

1) *Foundational Techniques*: The multipath signal traveling through each RIS may be labeled, which offers a workable concept for processing them, provided each of the RIS elements has a unique phase, i.e., $\phi_1 \neq \phi_2, \dots, \phi_n \in [0, 2\pi)$. Taking advantage of the high multipath resolution of UWB signals and the capability of RIS to identify multipath channels, authors in [47] created a unique indoor RIS-assisted localization technique. The suggested localization scheme's CRLB is calculated, demonstrating how RIS has the ability to provide precise location with just one access point. Also, the suggested system offers a more precise and economical option for indoor placement because it only calls for a single access point and a few inexpensive RIS devices. RIS may be used to complement the RSS-based localization technique in many ways, such as, strengthening the signal received, diminishing co-channel interference, and providing additional propagation paths. As a result, RIS can significantly improve the RSS-based localization algorithms that rely on it. Nevertheless, because it is challenging to tell apart nearby RSS data, the accuracy of such algorithms is constrained. A deep learning method for efficient online wireless configuration of RIS in indoor communication environments is proposed in [38]. They use a database of coordinate fingerprints to train a DNN that maps user location information to the optimal phase configurations of the RIS, maximizing the RSS at the intended location. Simulations in a 3D indoor environment show that the proposed DNN-based configuration method effectively increases the achievable throughput at the target user location in all considered cases.

A RIS-assisted localization scheme utilizing multiple RSS fingerprints and a DNN is presented in [64]. The scheme utilizes RSS values obtained under different RIS configurations as fingerprints and employs an optimization method based on the CRLB to find the optimal RIS configurations. A DNN regression network is trained for localization. The simulation results demonstrate that the proposed scheme achieves robust and accurate location estimation, with an accuracy of approximately 0.5 meters in the NLoS scenario.

2) *Accuracy Improvement With RIS*: By theoretical analysis and practical testing, it has been shown in [102] that RIS can in fact customize the wireless environment. Authors have clearly shown with the help of measurements that RIS configuration changes the RSS at a particular location. Thus, the issue of similar RSS values from nearby sites can be resolved

TABLE VIII
SUMMARY OF RIS-ASSISTED INDOOR LOCALIZATION ARTICLES. HERE “R” REFERS TO “REFLECTIVE RIS,
“T” REFERS TO “TRANSMISSIVE RIS”, “H” REFERS TO “HYBRID RIS”

RIS	Ref	f_c	Link	System	Purpose	Technique	Performance metric
R	[45]	2.4 GHz	UL	SISO	Enhancing the accuracy of RSS based localization	Configuration optimization iterative algorithm	Accuracy
R	[46]	2.4 GHz	DL	SISO	Enhancing the accuracy of RSS based positioning	particle swarm optimization algorithm	Accuracy
R	[47]	2.4 GHz	DL	SIMO	Employment of RIS in indoor localization	UWB technique, CRLB	Accuracy
R	[185]	2.4 GHz	DL	SISO	Fingerprinting localization estimation using RIS	Supervised learning feature selection method, localization heuristics states selection framework	Accuracy
R	[64]	2.4 GHz	UL	MISO	Investigating multiple RSS fingerprint based localization	CRLB, projected gradient descent optimization, DNN	Accuracy
R	[186]	2.4 GHz	DL	SIMO	Passive person localization	Phase control optimization algorithm, side-lobe Cancellation Algorithm	Accuracy
R	[187]	2.4 GHz	DL	SIMO	Passive multi person localization	Phase control optimization algorithm, side-lobe Cancellation Algorithm	Accuracy
R	[38]	2.6 GHz	UL	MISO	Method for efficient online wireless configuration of RIS	DNN	Throughput
R	[188]	3.5 GHz			Radio sensing	ML and computer vision (clustering, template matching and component labeling)	Accuracy
R	[189]	5 GHz	DL	SISO	Fingerprint-based indoor localization system using RIS	RIS configuration design	Accuracy
R	[190]	5 GHz	DL	MISO	RIS-enabled fingerprinting-based localization	Deep RL	Accuracy
R	[191]	5 GHz	UL	MISO	Distributed RIS assisted localization	Two-step positioning approach, CRLB, theoretical analysis	Accuracy
R	[113]	10 GHz	DL	SIMO	Indoor wireless SLAM system assisted by a RIS	RIS-assisted indoor SLAM optimization problem and design of error minimization algorithm	Accuracy
R	[192]	30 GHz			User localization with multiple RIS	MLE, least squares line intersection technique	Accuracy
R	[193]	60 GHz	DL	MIMO	RIS-assisted downlink mmW indoor localization framework	Coarse-to-fine localization algorithm with low-complexity grid design	Accuracy
R	[194]	90 GHz	UL	MIMO	RIS aided UE localization	Space-time channel response vector, residual convolution network regression learning algorithm	Accuracy
R	[195]	150 GHz	DL	SISO	Optimal RIS placement with respect to position and orientation	Analytical modeling	Received power
T	[196]	28 GHz			Improve the accuracy of indoor positioning	Fingerprinting, near-field multi-focal focusing method	Accuracy, throughput
H	[197]		DL	SISO	RIS configuration optimization for localization in dynamic rich scattering environment	Physics based simulator, bi-directional long short term memory	Accuracy
R	[198]		DL		Enhancing indoor localization through RIS-Based RSS optimization	TDOA based static reconfiguration algorithm	Accuracy
R	[199]	30GHz		SISO	Passive localization and tracking of a RIS-equipped object using monostatic sensing	Temporal coding	Accuracy

in smart radio environments enabled by the RIS. Authors in [45] have designed an RIS-assisted localization algorithm that is focused on enhancing localization accuracy. To do so, an iterative configuration optimization algorithm is proposed whose purpose is to select the RIS configuration that improves the localization accuracy. The localization accuracy of the suggested technique is substantially higher than that of the localization method without RIS. The authors also designed a Phase shift optimization technique to address the same issue in [46]. This approach offers a unique solution to the multiuser localization problem and can minimize localization error by at least three times when compared to the conventional RSS-based solution.

Work presented in [198] focuses on improving the accuracy of RSS-based indoor positioning system by addressing the limitations caused by temporal and spatial uncertainties in the indoor wireless environment. An algorithm is introduced that

utilizes RIS technology to optimize RSS values at specific reference points. This is achieved by adjusting the RIS reflection coefficients to enhance the differentiation of RSS values between reference points. Simulation results indicate that this method, even with a relatively small number of RIS elements, significantly boosts the efficiency and accuracy of indoor positioning. Authors in [190] present an RIS-enabled fingerprinting-based localization method enhanced by deep RL. The methodology involves creating a database of RSS lists through periodic RIS configurations, which are then used to estimate receiver positions by comparing them with online-measured RSS data via the nearest neighbor algorithm. Additionally, a deep RL-based RIS configuration selector is developed to optimize RIS configurations and minimize localization error. A communication protocol for the system's operation is also proposed. Extensive simulations demonstrate that the localization accuracy improves with an increasing

number of RIS configurations and is further enhanced by over 40% with the incorporation of deep RL compared to previous methods.

3) *Wireless Indoor Simultaneous Localization and Mapping*: Researchers developed a RIS-assisted wireless indoor SLAM system in [113]. Channel models incorporating RIS are proposed, and a RIS-aided SLAM protocol is introduced to coordinate the RIS and the agent. An optimization problem for SLAM is formulated and solved using a particle filter-based localization and mapping algorithm. The study demonstrates that the RIS significantly enhances channel amplitudes compared to scattered environments. Furthermore, the RIS-assisted SLAM system reduces agent estimation errors by 0.1 meters compared to non-RIS wireless SLAM systems. The article [186] presents a framework for passive human localization using WiFi signals enhanced by RIS. The RIS, consisting of controllable reflective elements, overcomes the limited spatial resolution of WiFi devices to achieve accurate localization. The proposed framework includes a phase control optimization algorithm to maximize the discrepancy between human reflection and multipath interference. Simulation results demonstrate sub-centimeter accuracy in locating moving individuals passively, even in the presence of noise and multipath interference. As an extension, the article [187] addresses the challenge of achieving accurate passive multi-human localization using commodity WiFi devices. A side-lobe cancellation algorithm is introduced to achieve accurate localization iteratively. Results indicate that the proposed framework enables sub-centimeter accurate localization of multiple moving individuals without modifications to existing WiFi infrastructure, even in the presence of multipath interference and random noise.

A new application for RIS-enabled passive localization and tracking is introduced in [199]. It utilizes a single-antenna full duplex transceiver to send multiple OFDM signals and analyze the reflections from a RIS-equipped object in an efficient use of the spectrum. The RIS phase profile is designed to separate desired signal reflections from unwanted multipath signals, allowing for the estimation of the object's location and velocity with low-complexity estimators. Simulations show that this method can achieve centimeter-level location accuracy with just 6 MHz of bandwidth.

4) *Wireless Indoor Integrated Sensing and Communication*: Authors in [196] introduced a RIS-aided method to enhance RSS fingerprinting-based indoor positioning accuracy in 6G networks. By utilizing RIS diversity and requiring RSS from a single access point, it achieves centimeter-level precision. The proposed near-field multi-focal focusing method maintains communication performance while supporting high-precision positioning. Simulations confirm the scheme's effectiveness, offering improved positioning accuracy with only a 10% reduction in average throughput.

C. RIS-Assisted Near-Field Localization

Studies on RIS-assisted near-field localization are briefly summarized in Table IX and discussed as follows.

1) *Foundational Studies*: A two-stage positioning technique for determining the transmitter's location with a RIS, employed as a lens, running at mmW frequency demonstrates the capability of decimeter-level localization accuracy in the near-field region [48]. A generic model of near-field as well as the far-field placement was constructed in [49], and it suggests an SNR-based RIS phase design algorithm for CLRB reduction. The suggested technique can reduce PEB and directional error bounds significantly compared to the conventional system without RIS. Both of these RIS-assisted near-field localization studies disregard the scenario of LoS obstruction, however, it is necessary to take care of to cater for the successful localization in real-world scenarios. Authors in [202] propose a general framework for RIS-assisted regional localization, including RIS phase design and position determination. The results demonstrate the effectiveness of the proposed framework, showing that the designed RIS phase schemes lead to near-optimal localization performance. Authors in article [61] investigate the localization and CSI estimation scheme for a near-field sub-THz system with a RIS. The authors propose a near-field joint channel estimation and localization algorithm, which demonstrates superior performance in terms of localization and CSI estimation root MSE compared to conventional far-field algorithms. The complexity of near-field CSI estimation is influenced by the array steering vector formulation, which takes into account the reflection elements and their coupling effects, leading to higher resolution accuracy. The study highlights the importance of considering the near-field effects and angle separations between UEs for achieving high-precision localization with a single RIS panel. Additionally, it is emphasized that the inclusion of a large RIS panel with more elements must consider the spherical wavefront feature to avoid performance degradation.

A RIS-assisted OFTS system in both near-field and far-field conditions is studied in [215]. It derives signal expressions in the Doppler-delay domain and uses the FIM to find localization error limits. Simulations show that localization error decreases with more antennas and RIS elements. The paper also investigates estimating RIS orientation from UE signals, finding it feasible only in near-field conditions. A major finding is that RIS orientation errors significantly impact localization accuracy. Authors in [217] describe the near-field features of new 6G technologies, such as the spherical wave model, spatial non-stationarity, and beam squint effect, and explores their implications for localization, sensing, and communication.

2) *LoS Blockages*: Researchers in [50] have investigated the SISO system's near-field localization capabilities in the presence of a significant LoS blockage. A two-step localization algorithm based on TOA was presented in [51], and the results supported the feasibility of retaining high localization accuracy even under the situation of significant blockage in the near-field region of RIS. Using the Jacobi-Anger expansion and taking into account the RIS amplitude, a low complexity near-field localization approach, termed approximation mismatched maximum likelihood, has been devised in [52]. It also suggests

TABLE IX
SUMMARY OF RIS-ASSISTED NEAR-FIELD LOCALIZATION ARTICLES. HERE “R” REFERS TO “REFLECTIVE RIS”,
“H” REFERS TO “HYBRID RIS”, “A” REFERS TO “ACTIVE RIS”

RIS	Ref	f_c	Link	System	Purpose	Technique	Performance metric
R	[200]	3 GHz	DL	SISO	RSS based localization algorithms	Weighted least square and alternate iteration methods	Accuracy
R	[201]	3.5/28 GHz	DL	SISO	UE localization under LoS and NLoS conditions	Practical signaling and positioning algorithms design based on an OFDM, RIS time-varying reflection coefficients design	Coverage, accuracy
R	[48]	28 GHz	DL	SISO	Localization of a transmitter using a RIS-based lens	FIM, two stage localization algorithm	Accuracy
R	[49]	28 GHz	UL	MIMO	Localization performance limits in single BS and RIS-assisted UE localization	CRLB, signaling model design applicable for near and far-field localization	Accuracy
R	[50]	28 GHz	DL	SISO	Potential to exploit wavefront curvature in geometric near-field conditions	FIM	Accuracy
R	[51]	28 GHz	DL	SISO	Localization of UE under NLoS	Propose a low complexity algorithm	Accuracy, latency, robustness, coverage
R	[58]	28 GHz	UL	MISO	Performance limits of the RIS-based near-field localization in the asynchronous scenario, impact of cascaded channel on the localization performance	FIM, PEB	Accuracy
R	[202]	28 GHz	DL	SISO	Near-field regional target localization with the RIS-assisted system	Iterative entropy regularization based algorithm for RIS phase design, near-field target localization algorithm	Accuracy
R	[203]	28 GHz	DL	SISO	RIS-assisted near-field localization system under hardware impairment	MCRB, PEB, mismatched maximum likelihood estimator	Accuracy
R	[204]	28 GHz	DL	SISO	Suitable phase profiles design at a reflective RIS to enable NLoS localization	PEB, localization-optimal phase profile design	Accuracy
R	[205]	28 GHz	UL	MIMO	UE localization in near-field	Atomic norm minimization	Accuracy
R	[206]	28 GHz	DL	SISO	Multiuser localization using RIS and cooperative links	CRLB, iterative searching algorithm	Accuracy, power allocation
R	[65]	28 GHz		MISO	Integration of holographic RIS into mmW localization system	FIM, CRLB, iterative entropy regularization based RIS phase optimization	Accuracy
R	[52]	28 GHz	DL	SISO	Near-field localization of a UE under phase-dependent amplitude variations at each RIS element	Low-complexity approximated mismatched maximum likelihood estimator, iterative refinement algorithm to update individual parameters of the RIS amplitude model, MCRB	Accuracy
R	[207]	5.15/28 GHz	DL	SISO	Optimizing the precoders that control RIS under hardware constraints	Low-complexity algorithm design for RIS configuration, FIM, PEB	Accuracy
R	[208]	28 GHz	DL	SISO	RIS-aided Localization under Pixel Failures	MCRB, joint localization and failure diagnosis method	Accuracy
H	[209]	28 GHz	UL	MISO	Hybrid RIS-assisted UE localization	CRLB, automatic differentiation-based gradient descent approach	Accuracy
R	[210]	30 GHz	DL	SIMO/SISO	Design RIS coefficient to convert planar waves into spherical waves and cylindrical wave	MLE, focus scanning method, PEB	Accuracy, energy leakage
R	[211]	30 GHz		SISO	RIS localization	FIM, multistage low-complexity RIS localization algorithm, quasi-Newton method	Accuracy
R	[212]	45 GHz	UL	MISO	Near-field localization	Second-order Fresnel approximation, RIS training phase shifts and pilots design	Accuracy
R	[61]	90 GHz	UL	MISO	Spherical wavefront propagation in the near-field of the subTHz system with the assistance of a RIS	Near-field channel estimation and localization algorithm based on second-order Fresnel approximation of the near-field channel	Accuracy
R	[213]	100 GHz	UL	MIMO	UE localization under beam squint effect	Polar-domain gradient descent algorithm, MUSIC algorithm	Accuracy
R	[61]	320/325/330GHz	UL	MISO	Spherical wavefront propagation in the near-field	Proposed near-field channel estimation and localization algorithm	Accuracy
A	[214]	28 GHz	SL	SISO	SL localization through a single active RIS	Time-orthogonal random codebook, CRLB	Accuracy
R	[215]		DL	MIMO	Fundamental limits of RIS-assisted orthogonal time frequency space (OFTS) systems for localization	FIM	PEB, OEB
R	[216]	28 GHz	DL	SISO	Near-field joint position and velocity estimation under user mobility	Optimization	Accuracy

an iterative refinement approach for joint localization and RIS amplitude model parameter updating, using the result as the initial location estimate. The suggested low-complexity

localization technique performs well in simulations, and the iterative algorithm's localization accuracy is asymptotically approaching CRLB.

3) *Performance and Considerations*: RIS-based asynchronous localization is studied in [58] by examining the PEB and equivalent Fisher information for the intermediate parameters involved. The study considers multi-paths between the BS and the RIS, taking into account amplitude differences. The results indicate that near-field spherical wavefront modeling enables UE localization in the asynchronous scenario, but the equivalent Fisher information decreases as the distance between the UE and RIS increases. The study also highlights the performance difference between spatial gain and power gain in the BS-RIS channel, and cautions against using the SNR-maximizing focusing control scheme for RIS in localization applications. In article [65], the performance of a holographic RIS assisted mmW near-field localization system is investigated. The FIM and CRLB are derived, considering the radiation pattern of antennas. The theoretical analysis demonstrates that the position accuracy improves quadratically with the size of the RIS. An iterative entropy regularization-based method is proposed to minimize the worst-case CRLB by optimizing the holographic RIS phases. Authors in [207] propose a low-complexity approach to optimize the precoders that control the RIS, considering hardware constraints. The method approximates desired beam patterns using pre-characterized reflection coefficients. The evaluation includes beam fidelity for different RIS hardware prototypes and theoretical analysis of the impact on near-field downlink positioning in NLoS conditions. Results demonstrate the effectiveness of the proposed optimization scheme in producing desired RIS beams within hardware limitations, while also highlighting the sensitivity to hardware characteristics and the specific requirements of RIS-aided localization applications.

Authors address the problem of near-field localization using RIS in the presence of phase-dependent amplitude variations at each RIS element in [52]. The authors analyze the performance limitations using a MCRB and demonstrate that performance penalties can occur, particularly at high SNRs, when the UE is unaware of the amplitude variations. They propose a low-complexity approximated mismatched maximum likelihood estimator, leveraging Jacobi-Anger expansion, to mitigate performance loss. The method shows fast convergence and performance close to the CRLB, indicating the effectiveness of the proposed method in recovering performance and calibrating the RIS amplitude model. The issue of RIS pixel failures is studied in [208], which can severely impact localization accuracy. The paper investigates the impact of pixel failures on accuracy and develops two strategies for joint localization and failure diagnosis to detect failing pixels while accurately locating the UE. The proposed algorithms demonstrate significant performance improvements over conventional failure-agnostic approaches, enabling successful localization in the presence of pixel failures. The sidelink positioning in near-field wireless communication using a single active RIS is studied in [214]. It jointly estimates transmitter and receiver positions and clock bias. A time-orthogonal random codebook is used for channel separation, followed by coarse positioning and least-squares refinement. The CRLB validates the algorithm's efficiency. Simulations show that positioning accuracy depends on RIS

size and transmission power, with an optimal power allocation ratio that minimizes CRLB.

IV. CHALLENGES AND RESEARCH OUTLOOK

Based on the review performed in the previous section, in this section, we present a detailed overview of the limitations, open areas of research and challenges in RIS-assisted radio localization that need to be investigated to make it a practical and feasible solution to radio localization in 6G networks. While RIS offers significant benefits for localization, there are some associated limitations, as shown in Figure 9 [71]. Implementing RIS-assisted localization may involve significant costs, including the installation and maintenance of RIS devices throughout the target environment. The deployment of RIS infrastructure can be challenging and require careful planning. Inferring from the reviewed literature, RIS devices typically rely on LoS communication with the devices they assist in localizing. This means that obstacles, such as walls or objects, can obstruct the signal path and potentially degrade the accuracy or reliability of localization. While RIS can optimize signal propagation, there may still be scenarios where NLoS signal paths exist, leading to potential inaccuracies in localization. Overcoming NLoS challenges in complex environments with reflective or obstructive surfaces can be a limitation for RIS-assisted localization. RIS devices require power and connectivity to function effectively. Ensuring an adequate power supply and reliable connectivity to each RIS device can be a logistical challenge, particularly in large-scale deployments or areas with limited infrastructure. RIS-assisted localization may face scalability limitations when applied to larger or more complex environments. As the number of devices and users increases, coordinating and optimizing the RIS network can become more challenging. Additionally, adapting the RIS configuration to accommodate changes in the environment or user requirements may require significant adjustments and maintenance. In situations where multiple RIS devices are deployed in proximity, potential interference and coexistence challenges may arise [106]. Careful planning and coordination are necessary to ensure that RIS devices do not interfere with each other or with other wireless communication systems operating in the same frequency band [107]. These limitations should be carefully considered and addressed during the planning, deployment, and operation of RIS systems to maximize their effectiveness.

Here we discuss the research directions related to the limitations and open areas of research in the path of practical applications of RIS-assisted radio localization in 6G networks that includes the technical as well as the deployment challenges.

- *Availability, Scalability, Privacy and Security*: It is observed in the previous section that the theoretical approaches being developed in the literature are primarily focused on the accuracy of localization. While devising new methods for RIS-assisted localization in 6G networks, it is an important factor to consider also the coverage area and availability of the service [218]. Techniques must be developed in a fashion that it is

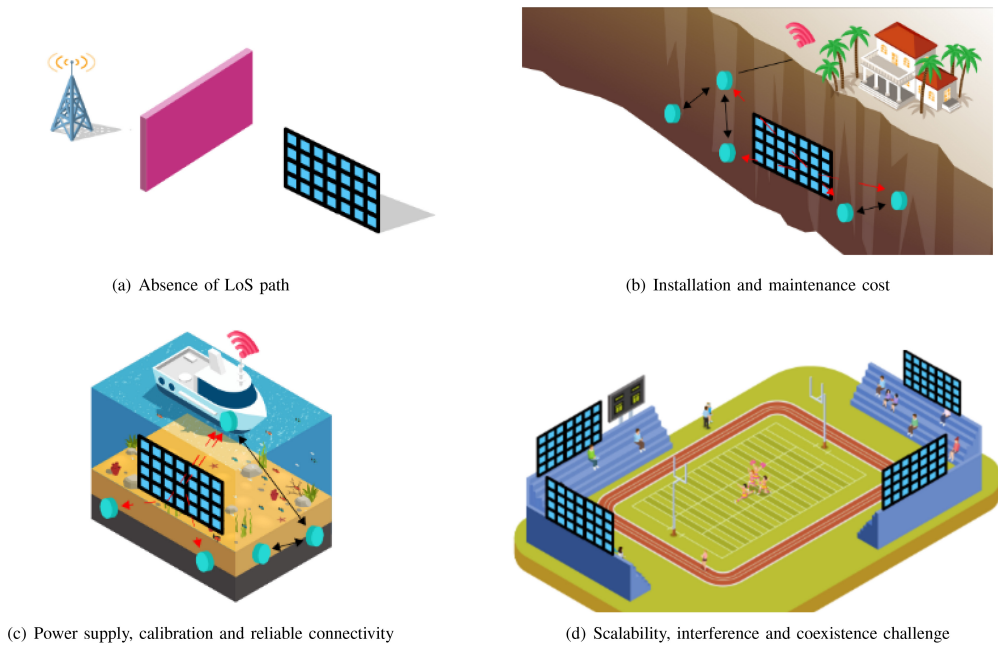


Fig. 9. Illustration of limitations to RIS-assisted radio localization. (a) NLoS challenges in complex environments with reflective or obstructive surfaces can be challenging, (b) The deployment, installation and maintenance of RIS infrastructure can be challenging and require careful planning (c) Ensuring an adequate power supply, RIS calibration and reliable connectivity to each RIS device can be a logistical challenge, (d) when multiple RIS devices are deployed in proximity, potential interference and coexistence challenges may arise.

scalable without any major hardware as well as the software limitations, as shown in Figure 9(a) and 9(d). Lastly, user privacy in such networks is an interesting area of investigation since the transmission and processing of data within RIS systems can be susceptible to eavesdropping, leading to the leakage of sensitive information [34].

- **Mobile User Localization:** Mobility of the UE is an important factor in a real-world scenario that needs to be considered in addition to the 3D position and 3D orientation to localize the user with maximum accuracy [86]. If the Doppler delay effects due to user mobility are ignored, it will negatively impact the location estimates. It is, thus, necessary to account for the velocity of the user and its relative impact on UE position and orientation in a RIS-assisted localization scenario. Continuous monitoring of mobile UEs would gain advantages by incorporating NLoS channel identification to ensure optimal activation of RIS, and the ability to control RIS with low-latency location-based capabilities. Consequently, this necessitates the availability of accurate UE location and uncertainty information at all times. Adapting localization algorithms to changing propagation conditions would be required.
- **Multi-User Localization:** Methods scalable to multi-user localization need to be developed for both LoS and obstructed LoS scenarios for more realistic and holistic

designs for 6G networks [2]. It would require the development of algorithms for managing interference and optimizing resource allocation.

- **Modeling and Analysis of RIS-assisted Localization at Multiple Frequencies:** In practical scenarios, access points operating at different frequency bands, i.e., conventional, mmW and THz, will coexist in future 6G networks. The operation of RIS when interacting with BS operating at different frequency bands needs to be modeled and analyzed. What kind of element configuration is required at RIS to how would the phase and amplitude change of the RIS be modeled to successfully allow multi-band radio localization.
- **Integrated Localization, Sensing and Communication:** Convergence of hardware as well as the technical design of radio localization, sensing and communication is one of the major agenda of 6G network design [219], [220]. In light of this design requirement, it would be an interesting study direction to devise and analyze the methods for RIS-assisted joint localization, sensing and communication such that a unique trade-off is worked out between their performance matrices, thus, they complement one another depending on the scenario at hand. The introduction of these services within a wireless environment enabled by RIS presents new challenges related to optimizing RIS for multiple purposes. These challenges involve striking a suitable balance between configurations

that prioritize localization, communication, and sensing. It entails selecting the appropriate protocols, managing resource sharing among multiple users and operators in complex ecosystems, achieving synchronization between BS and RIS, and seamlessly integrating RIS into open radio access network (RAN) architectures. Such RIS-based solutions also need to be cost-effective for supporting localization and sensing functionalities together with communication. These alternatives include vehicle-mounted reflective RIS, approaches resembling BS-free or multi-static radar systems, and hybrid RIS that can operate in the receiving mode to sense both connected UEs and passive objects.

- *Deployment and Optimization of RIS-Assisted Localization Radio Network:* Most of the contemporary literature quoted in the previous section is based on the development of theoretical approaches where there have been little to no practical campaigns to study the practical design and deployment perspectives of RIS-assisted radio localization. It is, therefore, an important area to explore the practicality of the methods proposed in the literature. The optimization of both the number and positioning of RIS is essential to achieve optimal performance in terms of communication metrics, localization/sensing accuracy, and coverage. Additionally, it is crucial to ensure that the optimized RIS deployment indeed offers advantages, when compared to traditional BS deployments, in terms of overall power consumption and coordination efforts. This optimization process also includes addressing the challenge of accurately calibrating the location and orientation of the RIS and its synchronization with BSs.
- *AI Controlled RIS:* In the age of AI, model-based signal processing is being replaced with data-driven approaches as it leads to more robust algorithms [86]. Based on this, developing AI-driven methods for RIS-assisted radio localization can prove to improve the radio localization performance manifolds. Control of RIS using AI can empower their design manifolds, it is thus an important direction to study.
- *Low Latency Control:* Efficient radio localization with RIS requires low-latency control capabilities. This necessitates real-time knowledge of UE location and uncertainty. Developing location-based RIS control mechanisms that offer low-latency control while maintaining accuracy and reliability is a challenge that must be overcome.
- *RIS Standardization:* In order to analyze the theoretical methods by practical experimentation as well as to develop more suitable methods while considering the practical deployment scenarios, standardization of RIS hardware is necessary. Global standardization of RIS is in very early stages and the process is well summarized in [221]. RIS hardware is not yet available but the efforts for the development of RIS hardware prototypes are underway [222], [223], [224], [225], [226], [227], [228]. Standardized RIS hardware platforms will contribute to the acceleration of development progress. Researchers can build upon existing work, leveraging the availability

of standardized platforms to iterate and refine their ideas. The collective efforts of researchers using standardized platforms can lead to the development of best practices, optimization techniques, and benchmark datasets that drive innovation and efficiency in RIS-related research.

- *Multi-Operator and Multi-RIS Localization:* The coordination and communication between multiple operators can be complex, especially in heterogeneous network environments, potentially leading to increased latency and decreased system efficiency. The synchronization of signals between different operators is another hurdle, as it requires precise timing control to avoid interference and ensure accurate localization. Moreover, the deployment and management of multiple RIS introduces further complexities, from determining optimal placement and density of the RIS to managing their phase configurations, as shown in Figure 9(d) [229]. Additionally, privacy and security concerns may arise with multiple operators, necessitating robust protocols to protect data integrity. Lastly, as the number of operators and RIS increases, so does the computational complexity of localization algorithms, potentially impacting system performance and energy-efficiency.
- *RIS Control and User Mobility:* The process of controlling a RIS typically involves adjusting the electromagnetic properties of the RIS elements to optimize signal reflection and transmission. However, this process can be relatively slow, which poses significant challenges for high-mobility applications. As devices move rapidly across the coverage area, the channel conditions change quickly. By the time the RIS has collected enough information and adjusted its properties for optimal performance, the device may have already moved to a different location with entirely different channel conditions. Thus, the slow control of RIS may lead to outdated or ineffective configurations that fail to improve, or even degrade, the system performance. This lag in RIS control poses a major challenge in realizing the full potential of RIS technology in high-mobility applications such as autonomous vehicles, drones, and high-speed trains.
- *RIS Hardware Limitations and Pixel Failures:* The hardware components of RIS bring about several challenges that can impact their performance and efficacy [71]. RIS are composed of numerous smaller elements or “pixels” that each need to be individually controlled to manipulate the phase and amplitude of incoming electromagnetic waves. However, these pixel-level controls can be limited by hardware constraints such as processing speed, energy consumption, and design complexity. Additionally, the risk of pixel failures is a significant concern. Given the high density of pixels in an RIS, even a small percentage of pixel failures can lead to significant degradation in the overall performance of the RIS. Furthermore, identifying and repairing these failed pixels can be a complex and time-consuming task, especially when the RIS is deployed in hard-to-reach locations, as shown in Figure 9(b). These hardware limitations and pixel failures

pose substantial challenges to the reliable and effective deployment of RIS technology.

- **RIS Calibration:** The calibration of RIS is a challenging phase due to the inherent complexities of these devices [230]. RIS calibration involves adjusting each individual element, or “pixel”, on the surface to manipulate the phase and amplitude of incident signals. Given that a RIS can consist of hundreds or thousands of these elements, this process can be highly complex and time-consuming. In addition, each element may respond differently to adjustments due to manufacturing variances, further complicating the calibration process. Real-world environmental factors, such as temperature and humidity, can also cause drift in the performance of the elements over time, necessitating frequent recalibration. Given that RIS are often deployed in inaccessible or hard-to-reach locations, performing this recalibration can be logistically challenging and costly, as shown in Figure 9(c). Consequently, achieving precise and efficient RIS calibration remains a major hurdle in the wider adoption of RIS technology.
- **New RIS Antenna Technologies:** Developing and integrating RIS antenna technologies into everyday items, such as clothing [71], [230], is an area ripe with potential but also rife with challenges. For instance, creating antennas thin and flexible enough to be woven into fabric without sacrificing performance is a significant technical obstacle. The material used in clothing also presents difficulties as it must be able to withstand regular wear and tear, washing, and various weather conditions while maintaining the antenna’s functionality. Furthermore, it is critical to ensure that these RIS antennas do not negatively affect the wearer’s health, particularly given concerns around prolonged exposure to electromagnetic fields. This necessitates strict control of the emitted power levels. From a design perspective, seamlessly incorporating the antennas in a way that is aesthetically pleasing and unobtrusive is also a major challenge. Given that each piece of clothing may be shaped and sized differently, custom calibration of these antennas could be needed for each garment, presenting further complexities.
- **From RIS to SIM:** The introduction of stacked intelligent metasurfaces (SIM) opens new possibilities in the context of radio localization [231]. Unlike traditional single-layer RIS, SIM consist of multiple reconfigurable metasurface layers, providing enhanced control over electromagnetic wave propagation in 3D. This added dimensionality enables SIM to manipulate complex multi-path environments more effectively, improving the robustness of localization or providing means for replacing digital with analog processing. Additionally, SIM can support multifunctional operations, such as SLAM and ISAC [232], by leveraging their ability to perform spatial filtering, polarization control, and adaptive beamforming across multiple layers. The inter-layer coupling in SIM also allows for greater flexibility in addressing near-field

localization challenges, particularly at higher frequency bands like mmW and THz. These capabilities suggest that SIM could serve as a transformative enabler for high-accuracy and resilient localization in 6G networks, warranting further exploration and experimental validation.

V. CONCLUSION

We presented a comprehensive overview of the utilization of RIS technology for radio localization in 6G networks. We discussed the RIS-assisted localization taxonomy, and recent advancements in theoretical approaches for RIS-assisted localization, identified opportunities, explored challenges, and examined various applications alongside the limitations of RIS-assisted localization. Recent advancements are based primarily on modeling and ML-based techniques where the focus is on improving the accuracy of the user location estimate. RIS can optimize wireless signals for improved localization in smart indoor services, smart transportation, and automated factories. However, there are some limitations to its use that need to be overcome such as the line-of-sight dependency, scalability, and interference. There are technical challenges and open areas of research that need to be addressed such as multi-user and mobile user localization, integrated localization, sensing, and communication algorithms, RIS standardization for practical experimentation as well as the investigation of availability, scalability, and privacy in RIS-assisted localization. Therefore, further research is required to fully realize the potential of RIS technology for localization in 6G.

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Appendix 2

II

A. Umer, I. Mürsepp, and M. M. Alam, "Reconfigurable Intelligent Surfaces in Dynamic Rich Scattering Environments: BiLSTM-Based Optimization for Accurate User Localization," in *2024 3rd International Conference on 6g Networking (6gNet)*, pp. 122–126, 2024

Reconfigurable Intelligent Surfaces in Dynamic Rich Scattering Environments: BiLSTM-Based Optimization for Accurate User Localization

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Abstract—The integration of reconfigurable intelligent surfaces (RIS) in wireless environments offers channel programmability and dynamic control over propagation channels, which is expected to play a crucial role in sixth generation (6G) networks. The majority of RIS-related research has focused on simpler, quasi-free-space conditions, where wireless channels are typically modeled analytically. However, many practical localization scenarios unfold in environments characterized by rich scattering that also change over time. These dynamic and complex conditions pose significant challenges in determining the optimal RIS configuration to maximize localization accuracy. In this paper, we present our approach to overcoming this challenge. This paper introduces a novel approach that leverages a bidirectional long-short term memory (biLSTM) network, trained with a simulator that accurately reflects wave physics, to capture the relationship between wireless channels and the RIS configuration under dynamic, rich-scattering conditions. We use this approach to optimize RIS configurations for enhanced user equipment (UE) localization, measured by mean squared error (MSE). Through extensive simulations, we demonstrate that our approach adapts RIS configurations to significantly improve localization accuracy in such dynamically changing rich scattering environments.

Index Terms—reconfigurable intelligent surface, localization, long-short term learning, sensing, channel estimation, rich scattering, dynamic wireless environment.

I. INTRODUCTION

The reconfigurable intelligent surfaces (RIS) are increasingly recognized for their potential in reshaping wireless communications by converting traditionally unpredictable propagation channels into controllable systems [1]. These dynamic metasurfaces, consisting of numerous low-cost scattering elements, can be tuned almost passively to optimize signal propagation. From a localization and sensing perspective, RIS significantly enhance the accuracy of user equipment (UE) positioning and environment sensing by managing multipath effects and reducing signal degradation [2]. This capability improves signal integrity and strengthens the reliability of localization and sensing techniques essential for applications requiring high spatial accuracy, such as automated navigation and context-aware services [3]. The dynamic nature of RIS technology allows real-time adaptation to environmental changes, enhancing both communication and localization performance, which is crucial for robust, efficient communication

systems in scenarios characterized by rich scattering and dynamic changes typical of emerging network technologies [4]. Understanding the optimal configurations of RIS in such scenarios is critical for realizing the full potential of next-generation communication networks, particularly for enhancing precise localization capabilities of sixth generation (6G) networks.

Recent studies on RIS assisted communication and localization networks have predominantly focused on quasi-free-space contexts with minimal known scatterers, which allow for the application of traditional analytical channel models for wireless propagation. Most algorithmic explorations presume that channel conditions are known, but consistently acquiring this information entails substantial overhead [5], leading to innovative approaches to employ RIS without deterministic channel data [6]. The challenge of accurately estimating channels within RIS-enhanced networks escalates in environments characterized by rich scattering, such as factory settings, indoor settings, metro stations, and inside vehicles like airplanes and ships that present irregularly shaped enclosures leading to significant reverberation [4], [7]. Wave propagation in such environments markedly diverges from the extensively analyzed free-space scenarios. Prior research has focused on optimizing communication metrics in these settings, employing methods such as iterative experimental RIS adjustments [7], [8], or leveraging available channel state information [9]. However, the dynamic nature of these environments, driven by the movement of people and objects, introduces rapid changes and fast fading, which challenges the reliability of channel knowledge and complicates the optimization of RIS configurations [4]. In such rich-scattering environments, wireless channels consist of a superposition of numerous reflected waves arriving from apparently random directions, rendering traditional free-space logic and methods inapplicable. The integration of sensing capabilities into RIS has emerged as a solution [3]. It has initially been explored in simpler free-space scenarios for basic tasks like direction-of-arrival estimation for getting the channel estimate [10], but now increasingly required in more complex, real-world environments that demand advanced data-driven AI approaches to manage rich scattering and unpredictable

propagation conditions [11]. While leveraging RIS sensing capabilities and data-driven approaches, these approaches predominantly utilize iterative algorithms for optimizing the RIS configuration which are typically time-consuming.

In contrast to the existing works, in this paper, we introduce a robust framework designed to effectively determine the optimal RIS configuration to improve UE localization accuracy within dynamically changing, rich-scattering environments using bidirectional long-short term memory (biLSTM) [12]. This design is adeptly suited for environments, including factories and indoor settings, where the movement trajectories of people and objects are generally predictable. Due to the formidable complexity of the rich-scattering environment, an explicit analytical approach is unfeasible. Instead, our proposed method integrates location parameters and channel sensing at RIS elements, along with channel features specific to these locations, to leverage their inherent correlations. We employ the advanced biLSTM model to enhance the network's ability to discern correlations across various signal contexts and establish a link between the RIS configuration and the key statistical channel parameters, i.e., channel impulse response and fading, that significantly impacts UE localization accuracy. The proposed method performs the RIS configuration with lower latency compared to the iterative algorithms. We numerically demonstrate that the proposed BiLSTM-assisted optimization effectively tunes the RIS configuration to minimize MSE in UE localization without needing explicit knowledge of channel statistics or their interactions with the RIS settings.

II. SYSTEM MODEL

We consider an enclosed indoor scenario (top view), shown in Figure 1, to analyse the interactions among various elements in a rich-scattering wireless environment. The environment causes scattering as waves reverberate and reflect multiple times off the walls. At the core of the system model lies the base station (BS) that communicates at a desired frequency with the UE at location U . The scattering objects (SO) moving along a fixed predefined trajectory are present in the environment, resulting in the dynamic nature of the fading wireless channel. The presence of SO introduce complexity into the system by affecting the propagation paths of the signals, resulting in a rich scattering scenario [7]. The status of the SO is presented by the vector P that concatenates all essential parameters required to comprehensively describe the location status of the SO.

The RIS operating in hybrid fashion is strategically placed on the periphery of the communication environment in a distributed manner. It consists of N_{RIS} reflective elements, each capable of adopting states from a predefined vector K of dimensions $1 \times N_{\text{RIS}}$, where $K \in C^{N_{\text{RIS}}}$. Given that RIS systems generally have a limited set of configurations, such as those managed by PIN diodes [2], we assume C to be finite and binary. In addition, we assume that S_{RIS} RIS elements are dedicated to channel sensing [3], [4].

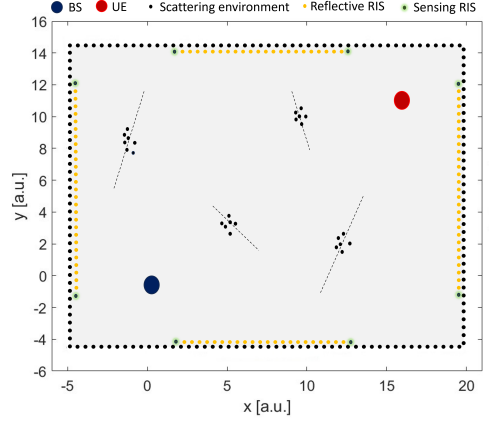


Fig. 1: Considered deployment scenario in PhysFad in arbitrary units [a.u.] [13] (Top view). An indoor scenario with a BS, a UE, and a distributed RIS that partially covers the four walls of the enclosure with its eight elements dedicated to environment sensing. In addition, four SO moving along the indicated trajectory are also present.

A. Channel Model

We assume that channel perturbations owing to SO occur rapidly enough to model the input-output relationship as a fast-fading, frequency-selective channel in discrete time. The field observed at any given point in a rich-scattering environment results from the superposition of all reflections, with reflections off specific objects varying according to their location [3]. Consequently, a sequence of field measurements can serve as a unique wave fingerprint, facilitating the accurate determination of the UE location.

The wireless channel at the UE is influenced by the RIS configuration, K , and SO location status, P . Let, H_{BS-UE} denote the channel impulse response at the UE, which includes line of sight signals, and the signals that interact with the RIS, SO and walls of the enclosure. The influence of the RIS configuration setting K on H_{BS-UE} can be highly complex and potentially intractable [4]. We further employ S_{RIS} RIS elements to sense and learn the channel H_{BS-S} , between the BS and S_{RIS} , to acquire SO status P . It is assumed that in the offline calibration phase, the system model identifies and learns the optimized RIS configurations corresponding to every potential set of SO locations P using the method described in Section III. Then, during the real-time operation, the RIS adopts the best configuration from the codebook based on the currently detected P by the S_{RIS} .

Traditional cascaded models do not adequately represent the nonlinear parametrization of the multipath wireless channel via the RIS. The training data for our biLSTM approach is simulated using a channel simulator, PhysFad, a physics-based, end-to-end communication model tailored for RIS-parametrized wireless environments that accommodates adjustable fading

and accurately reflects the wave physics of the described rich-scattering environment [14]. Developed from first principles through a coupled-dipole formalism, PhysFad strictly adheres to fundamental physical laws by describing wireless entities as either individual dipoles or assemblies, characterized by properties such as resonance frequency and absorption. As illustrated in Figure 1, it models continuous surfaces of scattering objects as arrays of dipole fences, with each RIS element's configuration determined by its dipole's resonance frequency [14]. For the sake of simplicity, we are operating in a two-dimensional space where we examine dipoles positioned within the x - y plane, with their dipole moments aligned vertically along the z -axis. PhysFad computes the wireless channel H_{BS-UE} between designated BS and UE dipoles, and H_{BS-S} between BS and S_{RIS} dipoles, considering both RIS and SO in the environment. It comprehensively covers aspects such as space and causality, dispersion with frequency selectivity, and the interconnection between phase and amplitude responses of RIS elements. The model also accounts for mutual coupling effects and long-range mesoscopic correlations, alongside the nonlinear parametrization of wireless channels influenced by both RIS configurations and environmental SO. PhysFad is constructed using arbitrary units, with the central operating frequency, transmit power and the medium's permittivity and permeability uniformly set to one, further mathematical details can be found in [14].

III. METHODS

In this section, we formulate our problem and present the proposed solution to optimize RIS configuration, minimizing MSE of UE localization in dynamically changing, rich-scattering environments.

A. Problem Formulation

Our objective is to develop a method for optimizing the RIS configuration, K , to localize the UE accurately. The localization performance is quantified by the MSE between the estimated $(\hat{x}, \hat{y})$ and actual (x, y) locations, i.e., ground truth of the UE. This is mathematically expressed as

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (Y_i - f(Y_i))^2 = \frac{1}{N} \sum_{i=1}^N ((\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2) \quad (1)$$

where N is the number of measurement points, $f(Y_i)$ denotes the estimated coordinates, Y_i represents the true coordinates, $(\hat{x}_i, \hat{y}_i)$ represent the estimated coordinates of the UE at the i -th measurement, and (x_i, y_i) are the actual coordinates. As the channel experiences fast-fading, our focus is on minimizing the MSE in UE localization, which involves adjusting K based on understanding of the channel's stochastic behavior influenced by this configuration.

In free-space operations, the wireless channel H_{BS-UE} is typically divided into a straightforward linear cascade: from the BS to the RIS, through the RIS configuration, and from the RIS to the UE. However, this model falls short in rich-scattering environments where each signal path might interact

with various RIS elements along its complex trajectory. Consequently, the parametrization of the channel H_{BS-UE} involving RIS and dynamic SO becomes highly complex and analytically intractable. To tackle this challenge, we use a learned biLSTM. Since the direct correlation between the UE location U , H_{BS-UE} , H_{BS-S} , and K is unknown, highly intricate, and influenced by the status of SO, P , we developed a training dataset comprising H_{BS-UE} , H_{BS-S} , P and, respective configurations K for each user location U . This dataset includes L pairs in the format $\{(H_{BS-UE})_l, (H_{BS-S})_l, P_l, K_l, U_l\}_{l=1}^L$. This dataset enables us to precisely fine-tune the RIS configuration, thereby achieving optimal UE localization with minimal MSE. Through intelligent adaptation of the RIS settings in response to observed channel variations, we systematically minimize the MSE, enhancing localization accuracy.

B. RIS Configuration Optimization

Our proposed approach for optimizing the RIS configuration K , based on the UE localization objective (1), employs a BiLSTM model. This is achieved by training the BiLSTM to recognize patterns from historical data $\{(H_{BS-UE})_l, (H_{BS-S})_l, P_l, K_l, U_l\}_{l=1}^L$, learning the relationships between input features, $\{H_{BS-UE}, H_{BS-S}, P\}$ and their corresponding outcomes $\{K, U\}$.

In order to learn how to optimize K with the estimate of U , we use a biLSTM model, termed as θ , whose exact architecture employed in the experimentation is explained in detail in Section IV. The model is designed to generate two combined outcomes: it predicts the UE location coordinates as a regression problem as well as the RIS configuration as a classification problem that results in the minimum of (1). The model employs a hybrid loss function to cater to the dual objectives of the network. For the regression output, i.e., predicted UE coordinates, $\hat{U}$, we use the MSE, and for the classification output, $\hat{K}$, we use Categorical Crossentropy, such that the combined loss function is given as

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N (Y_i - f_{\theta}(Y_i))^2 + \sum_{i=1}^N \sum_{m=1}^M (-y_m \log(p_m)) + \alpha \|\theta\|^2 \quad (2)$$

here, $f_{\theta}(Y_i)$ denotes the predicted coordinates by the biLSTM parameters θ , Y_i represents the true coordinates, and N is the number of data points. y_m are the true class labels, p_m are the predicted probabilities for each class, and M is the number of classes. We have added α as a l_2 -regularization parameter, which is used to avoid overfitting.

C. Discussion

The proposed closed-loop approach, where the RIS configuration is adjusted based on environmental changes, demonstrates significant advantages in scenarios where the SO parameter space is manageable, streamlining real-time operational decisions by quickly referencing pre-stored configurations from a codebook. This method bypasses the need for learning complex nonlinear channel parametrizations directly, instead utilizing a codebook that matches observed

environmental conditions with optimal configurations, thus minimizing latency and computational overhead. However, it requires precise initial calibration and faces challenges due to the necessary discretization of continuous SO parameters, i.e., location, which can lead to performance losses if the codebook resolution is not sufficiently fine. The degree to which a SO affects the wireless channel further affects the accuracy of the biLSTM to estimate U , even with limited measurement sequences or in noisy conditions [15]. BiLSTM networks are particularly suited for this task over other neural network architectures due to their ability to process sequence data in both forward and backward directions, providing a richer understanding of context and temporal relationships within the data [12]. This capability is critical in dynamic environments where the influence of past and future data points can provide crucial insights for accurate prediction and optimization.

IV. RESULTS

We have implemented our proposed method in a numerical study where a rich-scattering environment, shown in Figure 1, was simulated using [14]. This setup includes a single-antenna BS, a single-antenna UE with changing location, and a RIS equipped with $N_{\text{RIS}} = (20, 60, 100)$, binary-tunable elements. For clarity, the specific parameters of the dipoles, the resonance frequency (f_{res}), charge term (χ), and absorptive damping term (Γ_L), utilized in our PhysFad simulations are set for transceivers as $\{f_{\text{res}} = 1, \chi = 0.5, \Gamma_L = 0\}$. In the scattering environment, these parameters are $\{f_{\text{res}} = 10, \chi = 50, \Gamma_L = 10^4\}$ with dipole spacing of one-fourth of the wavelength, λ . Lastly, for the RIS, the parameters are $\{f_{\text{res}} = \{1, 5\}, \chi = 0.2, \Gamma_L = 0.03\}$.

The data preparation phase includes acquiring frequency response measurements and SO status across various RIS profiles and UE locations, as detailed in Section III-B. The UE locations were taken along a regular grid with $\lambda/4$ spacing. For a fixed UE location and a fixed N_{RIS} , different RIS configuration were considered. For each configuration, the SO was located at 10 randomly chosen locations along their fixed trajectory of motion, from which channel response measurements $H_{\text{BS-UE}}$ and $H_{\text{BS-S}}$ were obtained. RIS configurations K_l are one-hot encoded to facilitate classification tasks within the network architecture. The dataset, represented as $\{(H_{\text{BS-UE}})_l, (H_{\text{BS-S}})_l, P_l, K_l, U_l\}_{l=1}^L$, was divided into 80% for training and 20% for testing. For validation purposes the training set is further divided into 80% training and 20% validation which assists in hyper parameter optimization using grid search to fine tune the model settings and helps prevent overfitting.

The designed biLSTM incorporates a dual-input architecture. It employs a biLSTM layer with 50 units to capture temporal dependencies from sequential channel data, followed by an additional long-short term memory (LSTM) layer with 50 units using ReLU activation to further refine the features. A separate input for RIS configuration features includes an embedding layer that transforms categorical inputs into a 20-dimensional vector, subsequently flattened for processing. The

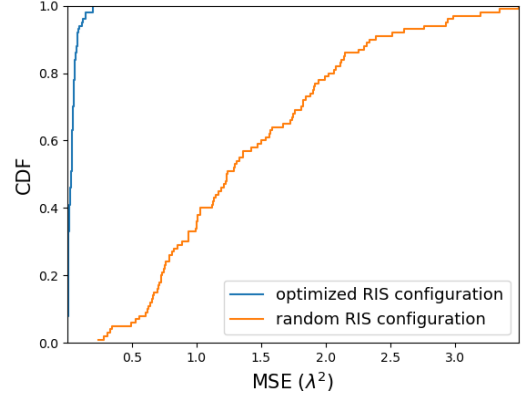


Fig. 2: Cumulative distribution function (CDF) of MSE for random and optimized RIS configuration with $K = 500$ and $N_{\text{RIS}} = 20$.

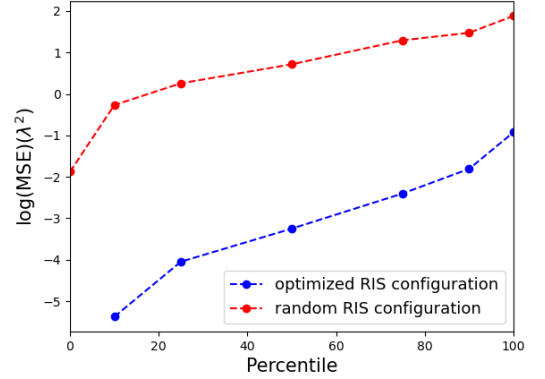


Fig. 3: MSE percentile for optimized and random RIS configuration with $K = 100$ and $N_{\text{RIS}} = 100$.

outputs from both LSTM and embedding layers are concatenated and directed into two dense output layers—one with linear activation for predicting UE coordinates and another with softmax activation for classifying RIS configurations. The model was compiled using the Adam optimizer [16] with a learning rate of 0.0001, applying MSE as the loss function for coordinates and categorical cross-entropy for RIS configuration classification. Training spanned 200 epochs with a batch size of 32, and included a checkpointing mechanism to save only the model iteration with the lowest validation loss, ensuring the highest performance during final evaluations on the test set. Furthermore, for the sake of comparison and to establish a baseline MSE, a simple neural network was trained with random RIS configuration to predict user location given the same dataset splits.

After extensive training of the biLSTM model, we evaluated its efficacy in optimizing RIS configurations for UE

TABLE I: Average MSE for random and optimized RIS configuration, standard deviation σ_b of baseline MSE, σ_o of optimized MSE, and percentage error reduction compared to baseline.

N_{RIS}	K	Baseline MSE (λ^2)	Optimized MSE (λ^2)	σ_b	σ_o	% error reduction
20	10	0.94	0.35	0.771	0.271	62.77%
20	100	0.27	0.08	0.223	0.086	70.37%
20	500	1.41	0.04	0.740	0.038	97.16%
60	100	0.59	0.17	0.591	0.166	71.19%
100	100	2.45	0.07	1.484	0.075	97.14%

localization, aiming to minimize the MSE. This evaluation was conducted using 100 randomly selected test instances. We employed $N_{\text{RIS}} = 20$ and three distinct RIS configurations, $K = \{10, 100, 500\}$, to assess the model's performance. The results, depicted in Figure 2, exhibit a high degree of accuracy in determining the UE location with proposed RIS configuration optimization method compared to the random RIS configuration. Results for varying K are summarized in Table I, where we see that increasing K from 10 to 500 improved the performance by approximately 34.39%. Notably, the accuracy of the localization will improve significantly as the model is trained on data rich in RIS configurations, i.e., in our case $2^{N_{\text{RIS}}}$ distinct configuration are possible.

We further investigated the influence of the varying number of RIS elements, $N_{\text{RIS}} = \{20, 60, 100\}$, on the localization accuracy of system model using proposed biLSTM network, as illustrated in Figure 3 and summarized in Table I. The analysis shows that while the MSE decreases as N_{RIS} increases, the improvement in MSE is relatively modest. This could be attributed to the same number of configurations used in the model, regardless of the significant increase in N_{RIS} , despite the exponential growth in the potential number of configurations, theoretically $2^{N_{\text{RIS}}}$. It suggests that the full potential of increasing N_{RIS} is not being harnessed. Further enhancement in MSE could likely be achieved by utilizing a broader variety of RIS configurations, particularly in scenarios involving frequent changes in the location of the SO. Hence, optimizing the selection and deployment of N_{RIS} is critical, and should consider the environmental dynamics, including the size, number, and mobility of SO, to maximize the system performance.

V. CONCLUSION

In this paper, we address the challenges posed by dynamically changing rich-scattering environments with a novel RIS configuration algorithm that forgoes traditional analytical modeling in favor of learning directly from data. Our method utilizes a biLSTM model to dynamically optimize RIS configurations, for enhancing UE localization accuracy by minimizing the MSE. Numerical evaluations demonstrate the effectiveness of this approach, showcasing its capability to fine-tune RIS settings to improve localization accuracy in complex scattering conditions. Proposed approach holds potential for jointly optimizing communication parameters within a unified framework encompassing communication, sensing, and

localization tasks. The exploration of this integrated approach has been left for future work.

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Appendix 3

III

A. Umer, I. Mürsepp, and M. M. Alam, "Adaptive RIS Configuration Design With Environmental Sensing for User Localization in Dynamic Rich Scattering Environment," *IEEE Transactions on Mobile Computing*, vol. 25, no. 7, pp. 9770–9783, 2026

Adaptive RIS Configuration Design with Environmental Sensing for User Localization in Dynamic Rich Scattering Environment

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Abstract—This paper addresses the problem of adaptive reconfigurable intelligent surfaces (RIS) configuration design for user localization in rich-scattering environment (RSE), where electromagnetic waves undergo multiple interactions with dynamic scatterers and RIS elements. We propose an adaptive learning-based localization approach for a distributed RIS-assisted network in a RSE using a bidirectional long-short term memory (biLSTM) model that captures temporal correlations between observations. The proposed approach actively senses the environment using sequential pilot transmissions from the base station (BS), accounting for scattering effects, and adaptively updates the RIS configuration based on prior measurements to eventually accurately estimate and minimize the user localization error. The proposed model comprises two neural sub-networks: Scattering Estimation Network (Bi-SEN), for estimation of scattering in the environment, and Adaptive RIS-Assisted User Localization Network (Bi-ARULN), for RIS configuration and localization. Bayesian optimization is used for hyperparameter tuning of the model. The simulation results demonstrate the effectiveness of the proposed approach, achieving significantly lower localization root mean squared error (RMSE) compared to random configuration, prestored codebook look-ups, and adaptive baselines in both single-input-single-output (SISO) and multiple-input-multiple-output (MIMO) RIS-assisted networks in RSE. The design is generalized across configurations and scales with RIS size and network dimensions. The results highlight the strong potential of RIS deployment and of the proposed approach to enable reliable location services in RSE.

Index Terms—reconfigurable intelligent surface, localization, long-short term memory, sensing, channel estimation, rich scattering, dynamic wireless environment.

I. INTRODUCTION

Traditional localization techniques often fail in rich multipath or rapidly changing environments—herein referred to as rich-scattering environments (RSEs)—and face infrastructure limitations, particularly indoors [1], [2]. The programmable nature of reconfigurable intelligent surfaces (RIS) offers a transformative solution by enabling fine-grained control over the wireless propagation environment with minimal power consumption [3]–[5]. Composed of numerous passive elements that manipulate the phase of reflected electromagnetic waves, RIS can act as intelligent anchors or improve existing infrastructure to overcome challenges such as synchronization,

interference, and directional ambiguity [1], [2], [6]. These capabilities make RIS especially valuable for precise, sustainable, and adaptive localization—critical for applications such as autonomous vehicles, robotics, virtual reality, smart factories, and traffic systems [2], [7], [8]. With 6G's all-spectrum integration—from microwave to terahertz and optical bands—indoor environments like offices and industrial settings are particularly prone to such rich scattering effects [9].

Dynamic RSE introduces complex propagation conditions, where electromagnetic waves experience multiple interactions with surrounding objects and RIS elements, resulting in a superposition of reflected signals with varying angle-of-arrival (AOA) and polarizations [10]–[12]. Unlike free space, where wave propagation is predictable and RIS parameterization is typically linear (via base station (BS)–RIS–receiver cascades), or quasi-free space, where RIS serves as an alternative relay due to blocked line-of-sight (LoS) paths, RSE conditions lead to highly nonlinear and dynamic RIS behavior [8]. Here, RIS act as controlled perturbations, while the environment contributes uncontrolled, time-varying disturbances such as moving objects or humans—herein referred to as scattering objects (SOs), resulting in a nonlinear double-parameterized system influenced by both RIS configurations and environmental factors [13]. Addressing these challenges requires advanced RIS configuration algorithms that transcend free-space assumptions and leverage environmental context to minimize localization errors and meet the precision and robustness demands of next-generation localization, sensing, and communication systems [8], [11], [14]. This requires context-aware adaptation of RIS, achieved through sensing and estimating the evolving state of SOs. Although incorporating sensing capabilities into RIS offers a promising direction [14], the optimal design of RIS configurations guided by such environmental awareness in dynamic RSE remains an open research challenge.

This work considers the problem of accurate user localization in a dynamic RSE using a distributed RIS-assisted network deployed in a reverberant enclosure. In the considered scenario, simulated with a physics-based end-to-end channel [10], a BS, a user, and multiple non-cooperative SOs, each following their own fixed trajectory, are present. The BS transmits pilot signals, while the RIS assists in redirecting them toward the user. A subset of RIS elements is dedicated to actively sensing the environment to estimate the scattering contributed by SOs and quantized by their location estimate. Estimation of SOs location at any instant can leverage RIS-assisted sensing by utilizing a predefined sequence of ran-

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domized RIS configurations. This is achieved using hybrid meta-atoms [14], which simultaneously capture and reflect electromagnetic waves, providing sufficient configurational diversity to enable the extraction of noncooperative SOs information from transmission measurements between a single node pair [15]. Learned sensing further enhances this capability by optimizing RIS configuration sequences to improve the accuracy of user localization [16]. However, the underlying relationships between RIS configurations, user measurements, and scattering are highly nonlinear and sequential in nature. As measurements accumulate, the need for scalable, context-aware solutions becomes essential. We address this by sequentially configuring the RIS using an adaptive, data-driven model based on prior and current measurements. This dynamic sensing and configuration mechanism enables the system to track evolving multipath conditions and minimize localization error without relying on static configurations or pre-stored mappings.

To address the challenges of user localization in dynamic RSE, we propose a deep learning (DL)-based approach that jointly performs RIS configuration design and user position estimation. Leveraging prior measurements and real-time sensing of SOs, the RIS is adaptively configured to improve localization accuracy. At the core of our approach is a recurrent neural network with bidirectional long-short term memory (biLSTM) units, which capture long-term dependencies and temporal patterns in sequential observations by processing data in both forward and backward directions [17]. This enables the dynamic construction of compact information vectors for guiding RIS updates and refining user location estimates without relying on complex real-time computations or static pre-stored mappings. The biLSTM architecture is particularly suited for RSE environments due to its adaptability to diverse data types, efficient training through parallelization, and superior performance over traditional machine learning (ML) models that rely on manual feature extraction [18], [19]. By integrating DL with RIS-assisted RSE, the system continuously learns to extract key signal characteristics and environmental features, yielding accurate and robust localization in complex propagation scenarios [20]. The numerical results demonstrate superior localization performance in single-input-single-output (SISO) and multiple-input-multiple-output (MIMO) RSE scenarios, highlighting the generalizability and effectiveness of the proposed approach.

A. Related Work

Numerous recent studies have explored RIS-assisted localization, focusing on fingerprinting-based methods, optimization and error-bound driven approaches, and more recent learning-based solutions, all aiming to enhance localization accuracy by exploiting RIS reconfigurability [6], [21]–[32]. The authors in [6] enhance diversity in fingerprint-based localization by leveraging the RIS ability to reconfigure its electromagnetic response by selecting optimal configurations from a large codebook to generate distinct radio maps. This variation in configurations improves the discriminability of received signal strength (RSS) fingerprints, enriching the feature space and

improving localization accuracy without requiring multiple access points. In [21] a hierarchical RIS codebook is proposed to facilitate adaptive bisection search across the angular space for enhanced 2D localization, although such codebooks may be suboptimal in low signal-to-noise ratio (SNR) conditions and training overhead can be substantial [33]. In [24], the authors categorize RIS profiles into three distinct classes and analyze their effects on the 3D positioning error bound of the user. Two classes are designed heuristically to generate narrow or broad beams, while the third class comprises randomly generated RIS profiles. The authors in [26] and [27] improve indoor localization by optimizing RIS profiles to maximize received signal strength (RSS) variations between nearby locations, using local and global search techniques. Their proposed scheme achieves a threefold reduction in localization error compared to traditional RSS based methods. Analytically derived profiles, as in [28], jointly optimize communication throughput and localization performance based on geometric models, but often rely on idealized channel assumptions that may not hold in practice for RSEs.

Other studies focus on channel-aware optimization and theoretical error bounds. A codebook-based RIS configuration method for user localization in RIS-assisted SISO networks under RSE is proposed in [34], leveraging historical and real-time channel data to jointly predict optimal RIS settings and user position. The approach achieves up to 97.16% reduction in localization error compared to random RIS configurations. In [22] a gradient descent method is used to iteratively adjust RIS reflection coefficients to minimize the Cramér-Rao lower bound (CRLB) of the user location. In [31], the CRLB is derived for near-field localization and orientation in RIS-assisted systems using synchronous and asynchronous signaling, and a closed-form RIS phase profile is proposed to maximize SNR at the BS while accounting for spherical wavefronts. Similarly, [35] investigates RIS-aided downlink positioning by optimizing RIS elements to improve the Fisher Information Matrix (FIM) rank, emphasizing the importance of directing the reflected energy toward the user. In [36], a multi-RIS-assisted millimeter positioning system is examined, where RIS phase shifts are optimized using particle swarm optimization to minimize the position and rotation error bounds. Channel estimation and user positioning in RIS-assisted MIMO-frequency division multiplexing (OFDM) systems are studied in [25], which proposes four RIS training coefficient designs—random, structured, grouping, and sparse—for improved estimation followed by AOA-based positioning. These studies demonstrate that CRLB-based formulations can provide strong theoretical guidance. Extensions such as Bayesian FIM and robust Bayesian Cramér-Rao lower bound (BCRLB) allow uncertainty in prior knowledge to be formally integrated, for example, through prior distributions on channel or geometry parameters [37]. Adaptive RIS beamforming strategies that exploit the estimated location of the user and associated uncertainty have been proposed in [38], although these designs neglect scattering effects, which may limit their applicability in dynamic RSEs.

Learning-based approaches for sequential beamforming and RIS optimization have also been investigated. In [33] and

[39], sequential beamforming for initial access in single-path millimeter channels is addressed using a Deep Neural Network (DNN) that maps the estimated AOA posterior distribution to the next beamforming vector. This is extended in [40] to multipath channel models settings using an LSTM model, while [41] employs Gated Recurrent Units for the same task. The LSTM in [40] is also applied to beam tracking, where RIS is dynamically adjusted to follow user movement over time [42]. A sequential RIS and BS beamforming design is proposed in [43] for RIS-assisted localization in a SISO network using LSTM, and extended to a multi-RIS multiple-input-single-output (MISO) network in [29]. An LSTM-based approach is also proposed in [30] to optimize user positioning through adaptive RIS control and power allocation, enhancing channel capacity. These methods highlight the potential of data-driven solutions to exploit temporal correlation in user mobility. However, these works do not address adaptive RIS configuration design for user localization as a function of previous measurements while accounting for the impact of scattering in RSEs.

B. Main Contributions

In this study, we introduce a learning-based user localization approach for a RIS-assisted RSE that dynamically adjusts the RIS configuration based on sensing of scattering in the environment, contributed by dynamic SOs, as well as historical environmental measurements to improve accuracy. Unlike free-space localization [44], which relies on ray-tracing techniques and AOA estimation, rich-scattering conditions involve multiple reflections from various angles, rendering conventional methods ineffective [13]. Instead, we extract information about object location and movement from scattered wave patterns by learning the correlation between SOs positions and received field measurements. Our approach leverages a data-driven optimization strategy to refine the mapping from prior observations to future RIS configurations, enabling accurate localization. In such environments, signal propagation exhibits long-range dependencies due to scattering, which biLSTM effectively models through sequential data processing. This enables the model to adapt to dynamic channel and RIS conditions while mitigating gradient vanishing or explosion, ensuring robust performance [17]. At each time step, a biLSTM cell processes current and past measurements to update a hidden state that represents the environment. This hidden state undergoes successive updates through multiple layers until it effectively encodes the necessary information for designing the next RIS configuration. After accumulating sufficient measurements, the final cell state is passed through a fully connected neural network, which generates the estimated position of the user. The approach supports both moving SOs and user scenarios, with RIS configurational diversity enabling efficient sensing at a single frequency with minimal sensing nodes. The main contributions of this work are as follows.

- 1) We propose an adaptive sensing-based localization approach for a distributed RIS-assisted SISO network in RSE, where RIS configurations are dynamically designed using prior measurements and sensed scattering in the

environment. The designed RIS configuration is used to enable better user location estimates in terms of accuracy.

- 2) We employ a biLSTM model to map pilot signal responses, from user and RIS elements dedicated to environment sensing, to RIS configurations. The model consists of two sequential networks: Bi-SEN (*Scattering Estimation Network*) for scattering estimation, feeding context into Bi-ARULN (*Adaptive RIS-Assisted User Localization Network*) for RIS configuration design and user localization. Additionally, Bayesian Optimization (BO) is integrated for hyperparameter tuning [45]–[47] to improve prediction accuracy by efficiently identifying optimal model settings.
- 3) We extend the proposed approach to a MIMO network to evaluate the impact of antenna array size at transceiver nodes in dynamic RSE scenarios.

The proposed approach produces interpretable results, demonstrating that the sequential design of the RIS configuration progressively enhances the SNR of received pilots and improves localization accuracy. Simulation results confirm that the adaptive RIS configuration design in RSE via the devised approach achieves lower localization errors than conventional random configuration, non-adaptive pre-stored configuration lookup based RIS designs, or adaptive designs not taking scattering into account. When extended to a MIMO network, the proposed learning-based adaptive approach delivers a higher localization accuracy compared to the SISO network, demonstrating the advantages of having multiple antenna nodes in addition to RIS in RSEs.

C. Paper Organization and Notations

The remainder of the paper is organized as follows. The system model and the formulation of the problem are presented in Section II. Section III presents the architecture of the devised approach. The results are presented in Section IV. Conclusions are derived in Section V.

Notations: Scalars, vectors, and matrices are represented in italic (e.g. a), lowercase bold letters (e.g. $\mathbf{a}$), and capital boldface letters (e.g. $\mathbf{A}$), respectively. Furthermore, $|\cdot|$ denotes the modulus, $\hat{a}$ denotes an estimate of a , $\text{diag}(\mathbf{x})$ presents a diagonal matrix with entries of $\mathbf{x}$ on diagonal. The real and imaginary components of a complex number are represented by $\Re(\cdot)$ and $\Im(\cdot)$, respectively. The expectation of a random variable is denoted by $\mathbb{E}(\cdot)$. The complex Gaussian distribution with mean m and variance v is presented by $\mathcal{CN}(m, v)$.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

This paper considers the problem of localization in a distributed RIS-assisted enclosed indoor scenario, presenting a RSE, where a user equipment U with N_U antennas aims to estimate its location $\mathbf{u}$ with the help of a BS equipped with N_{BS} antennas and uniform linear array of RIS strategically placed on the periphery of the communication environment as in Figure 1 (top view). To maintain tractability and relevance to structured RSEs such as industrial or controlled indoor

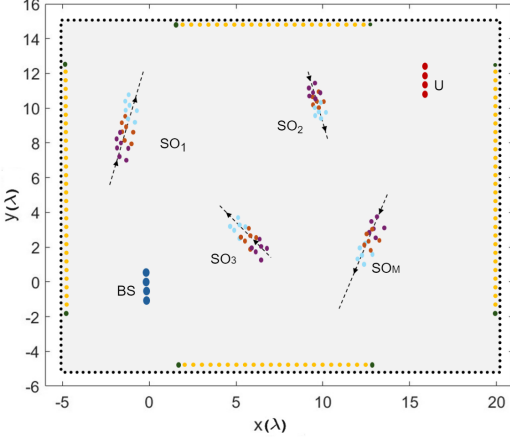


Fig. 1: Illustration of considered RSE, modeled in physics-based end-to-end channel [10] as a many-wavelengths large regularly shaped room (described by wavelength λ scale). The RSE consists of N_E dipoles whose locations are indicated by black dipole fence and collections of clusters of colored dipoles at various locations, inside the enclosure, presenting SOs. The location of dipoles presented with black color always stays the same, while the location of colored dipoles is varied randomly, in each simulation realization, along their fixed trajectories indicated by the dotted line. The locations of the dynamic dipoles presenting SOs is shown in three different colors for first three realizations (plum, orange, cyan corresponding to each realization). The RSE is equipped with N_{BS} antenna BS (blue dipoles), a N_U antenna user equipment U (red dipoles), and a uniform linear array of distributed RIS installation with N_{RIS} elements (yellow dipoles) that partially covers the four walls (black dipole fence) of the enclosure. S_{RIS} donates the subset of RIS elements (green dipoles) used by the BS to estimate the SOs location status based on the measurement of the wireless channel from S_{RIS} .

settings, we assume that there are M SOs present in the environment and each of them moves along its fixed trajectory. For simplicity, the SOs positions are updated simultaneously, while their movements remain independent along their respective paths.

The distributed RIS installation configuration design is managed by a RIS controller, which operates based on control signals received from BS. It comprises of N_{RIS} reflective elements, each applying a tunable phase shift to the incident signal. The configuration of these elements is represented by the vector $\mathbf{k} \in \mathbb{C}^{1 \times N_{RIS}}$, where each entry satisfies the unit-modulus constraint, i.e., $|\mathbf{k}_n| = 1, \forall n \in \{1, \dots, N_{RIS}\}$. This ensures that each element reflects the incoming wave with a controllable phase shift $\delta_n \in [0, 2\pi)$ while preserving its amplitude. In addition, S_{RIS} , a subset of RIS elements placed at fixed locations, is specifically allocated for channel sensing where the power splitting ratio is set to zero, resulting in no

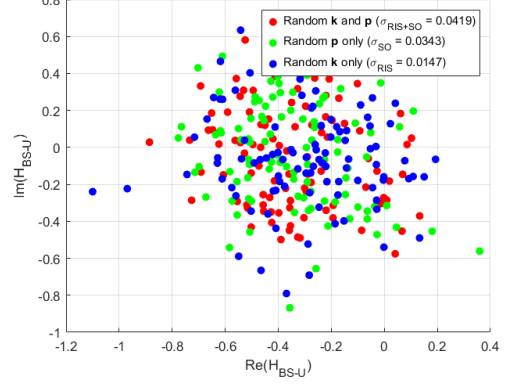


Fig. 2: Distribution of $\mathbf{H}_{BS-U}$ in the complex plane for a SISO setup, shown over 100 random realizations of RIS configurations $\mathbf{k}$ and SOs locations $\mathbf{p}$ (red), of $\mathbf{p}$ with fixed $\mathbf{k}$ (green), and of $\mathbf{k}$ with fixed $\mathbf{p}$ (blue), simulated with [10]. The SO positions are sampled uniformly along their predefined trajectories (as shown in Figure 1), and RIS phase configurations are sampled independently and uniformly from the range $[0, 2\pi)$. Here, σ is the standard deviation of the complex-valued $\mathbf{H}_{BS-U}$.

signal reflection [13], [14].

Electromagnetic waves undergo multiple reflections and scatter off from walls. RIS and SOs, causing significant signal scattering, while the movement of SOs further alters propagation paths, creating a dynamic and complex fading wireless communication environment [48]. The estimated location status of M SOs, via S_{RIS} , is represented by the vector $\mathbf{p} \in \mathbb{R}^{2M}$.

B. End-to-End Channel Modeling

We assume that the channel is constant within a coherence period. In RSE, subtle, configuration-dependent fluctuations in observed signal responses may occur due to fine-grained environmental perturbations, e.g., slight SOs motion or multipath dynamics. These fluctuations are modeled as structured fast-fading behavior in discrete time. This allows our model to capture temporal dependencies across RIS configurations for improved scattering and user location estimation. Let $\mathbf{H}_{BS-U} \in \mathbb{C}^{N_U \times N_{BS}}$ represent the stochastic channel frequency response at the user, encompassing both the LoS signals and multipath components that interact with the RIS elements, SOs, and the walls.

The influence of RIS configuration $\mathbf{k}$ and moving SOs location $\mathbf{p}$ on statistical properties of the channel response at the user, $\mathbf{H}_{BS-U}$, simulated with the physics-based end-to-end channel model [10], is illustrated in Figure 2. It shows the standard deviation σ of the complex-valued $\mathbf{H}_{BS-U}$ distribution when $\mathbf{k}$, $\mathbf{p}$, or both are varied independently. As expected, when $\mathbf{k}$ and $\mathbf{p}$ are changed simultaneously, the standard deviation increases. These observations underscore

the significant parametric dependence of $\mathbf{H}_{\text{BS-U}}$ on both $\mathbf{k}$ and $\mathbf{p}$. This renders simplified analytical models, typically used in free-space scenarios, inadequate for RSE. In free-space conditions, the channel $\mathbf{H}_{\text{BS-U}}$ is typically modeled as a linear cascade from the BS to the RIS and then to the user. In contrast, RSE introduces complex multipath interactions involving multiple RIS elements and dynamic SOs, making the channel highly nonlinear and analytically intractable [48].

To address this, we simulate the RSE using a physics-based end-to-end channel simulator specifically designed for RIS-parameterized environments [10]. Based on the coupled-dipole formalism, end-to-end channel models wireless entities as dipole assemblies with configurable properties such as resonance and absorption, enabling realistic simulation of scattering effects and ensuring compliance with fundamental electromagnetic principles.

As shown in Figure 1, end-to-end channel models SOs, walls, RIS and transceiver surfaces as dipole arrays. Note that $N \triangleq N_{\text{BS}} + N_{\text{U}} + N_{\text{E}} + N_{\text{RIS}}$ gives the total count of dipoles within the system where N_{E} dipoles constitute the RSE and N_{RIS} dipoles constitute the RIS. To simplify the analysis, the model operates in a two-dimensional space, with dipoles positioned in the x - y plane with their moments aligned along the z -axis.

The channel frequency response at the user is given by

$$\mathbf{H}_{\text{BS-U}} = \mathbf{V}[(N_{\text{BS}} + 1) : (N_{\text{BS}} + N_{\text{U}}), 1 : N_{\text{BS}}], \quad (1)$$

where

$$\mathbf{V} \triangleq \text{diag}([\alpha_1^{-1}, \alpha_2^{-1}, \dots, \alpha_N^{-1}]) \mathbf{W}^{-1}, \quad (2)$$

and α_i^{-1} is the inverse frequency-dependent polarizability of the i^{th} dipole. The i^{th} diagonal element of $N \times N$ complex-valued matrix $\mathbf{W}$ represents the inverse polarizability $\alpha_i^{-1}(f)$ of the i^{th} dipole. The polarizability $\alpha_i(f)$ of the i^{th} dipole is given by

$$\alpha_i(f) = \frac{\chi_i^2}{4\pi^2 f_{\text{res},i}^2 - 4\pi^2 f^2 + j(\gamma_i^{\text{R}} + 2\pi f \Gamma_i^{\text{L}})}, \quad (3)$$

where χ_i^2 represents a charge-related term functioning as an amplitude factor for $\alpha_i(f)$. The parameter $f_{\text{res},i}$ denotes the resonance frequency, while γ_i^{R} accounts for intrinsic radiation damping. Additionally, $\Gamma_i^{\text{L}} \geq 0$ corresponds to the absorptive damping term.

The off-diagonal entry in $\mathbf{W}$ at position (i, j) is given by $-G_{ij}(f)$, which corresponds to the negative of the two-dimensional free-space Green's function describing the interaction between the i^{th} and j^{th} dipoles at the positions $\mathbf{r}_i$ and $\mathbf{r}_j$, given by

$$G_{ij}(\mathbf{r}_i, \mathbf{r}_j, f) \triangleq -j \frac{k^2}{4\pi\epsilon_0} H_0^{(2)}(k|\mathbf{r}_i - \mathbf{r}_j|). \quad (4)$$

where $H_0^{(2)}(\cdot)$ denotes a Hankel function of the second kind.

The channel response from the end-to-end channel modeling accurately incorporates aspects such as space-time causality, frequency-selective dispersion, phase-amplitude coupling of RIS elements, mutual coupling effects, and long-range mesoscopic correlations, providing a realistic depiction of wave propagation in complex scattering environments.

C. Signal Transmission and Reception

Assuming a narrowband system model, the BS transmits a sequence of T known pilot symbols $\mathbf{x}^{(t)} \in \mathbb{C}^{N_{\text{BS}} \times 1}$ to the user over T time frames when a localization request is initiated. The received signal $\mathbf{y}^{(t)} \in \mathbb{C}^{N_{\text{U}} \times 1}$ at the user includes contributions from the direct path, if available, and multipath components reflected by the RIS and scattering environment. We assume that the BS receives the user's responses through a low-rate feedback link, enabling centralized inference for RIS configuration and localization. The input-output relationship is given by:

$$\mathbf{y}^{(t)} = \mathbf{H}_{\text{BS-U}}^{(t)} \mathbf{x}^{(t)} + \mathbf{w}^{(t)}, \quad t \in \mathbb{Z} \quad (5)$$

where $\mathbf{w}^{(t)} \sim \mathcal{CN}(0, \sigma^2)$ is additive Gaussian noise.

In parallel, the BS uses S_{RIS} dedicated RIS elements set to sense the environment by observing the channel $\mathbf{H}_{\text{BS-S}} \in \mathbb{C}^{S_{\text{RIS}} \times N_{\text{BS}}}$, between BS and S_{RIS} with observations $\mathbf{y}_s^{(t)} = \mathbf{H}_{\text{BS-S}}^{(t)} \mathbf{x}^{(t)} + \mathbf{w}^{(t)}$, $t \in \mathbb{Z}$. This sensing enables inference of the scattering object (SO) location status $\mathbf{p}$ at an instant t , providing an estimate of the scattering in RSE without requiring cooperation from the user.

Unlike conventional methods that rely on random RIS configurations, this paper aims to adaptively optimize the RIS configuration $\mathbf{k}$ to improve user localization accuracy in RSE. The proposed approach assumes a centralized architecture in which the BS coordinates the scattering estimation, RIS configuration updates and user localization.

D. Localization in RSE

The goal of the localization task is to estimate the unknown position of the user $\mathbf{u}$ from T received observations $[\mathbf{y}^{(t)}]_{t=0}^{T-1}$, given the known positions of the BS and RIS and predicted SOs location. The SOs location status $\mathbf{p}$ is inferred from RIS sensing signals $[\mathbf{y}_s^{(t)}]_{t=0}^T$ collected by S_{RIS} elements, to account for environmental scattering in the RSE. In this setting, RIS serves as a cost-effective source of directional information, acting as a set of virtual anchors through its dense and distributed reflective elements. Although RIS cannot transmit or receive directly, it aids in localization by dynamically adjusting its configuration to induce observable variations in the received signal.

Previous studies suggest that strategically selecting RIS configurations in RSE can improve the localization accuracy by shaping the received signal distribution to make nearby spatial samples yield more distinguishable observations [15], [34], [49]. However, most studies rely on fixed configurations that remain unchanged during operation, using predetermined beams to scan the search area at set angles. In contrast, this paper introduces an adaptive sensing-based approach that sequentially refines the search space by dynamically updating RIS configurations based on received pilot signals and sensed environmental changes, thus improving the accuracy of localization.

RIS operation in RSE involves two key stages: sensing the environment to gain context awareness and identifying the optimal configurations to support user localization. This process requires offline training tailored to the specific RSE

and online inference during deployment. Sensing focuses on estimating the SOs state from field measurements, enabling informed configuration design for the subsequent localization process.

In a RSE, the observed field at any point results from the superposition of multipath signals, with variations introduced by dynamic SOs depending on their location $\mathbf{p}$. The channel response $\mathbf{H}_{\text{BS-U}}$ reflects the combined effects of the RIS configurations and SOs interactions on the transmitted pilot signal, while $\mathbf{H}_{\text{BS-S}}$ captures information used to infer $\mathbf{p}$. A sequence of such measurements forms a unique wave fingerprint that enables user localization.

To adapt to temporal variations in scattering, the SOs location $\hat{\mathbf{p}}^{(t)}$ at time t is estimated as a function of the pilot signals sensed at $\mathcal{S}_{\text{RIS}}$,

$$\hat{\mathbf{p}}^{(t)} = G^{(t)}([\mathbf{y}_s^{(\tau)}]_{\tau=0}^t), \quad (6)$$

where $G^{(t)}(\cdot) : \mathbb{C}^{t+1} \rightarrow \mathbb{R}^{2M}$ represents mapping from previously sensed pilots to the estimated SOs location. Here, τ accounts for previous time steps up to the current time t .

Using the estimate in (6) and the user's prior received observations, i.e., $[\mathbf{y}^{(\tau)}]_{\tau=0}^t$, the BS determines the next set of $\mathbf{k}$ RIS configurations, denoted as $\mathbf{k}^{(t+1)}$, at time t . The RIS configuration vector at the $(t+1)$ -th stage is expressed as

$$\mathbf{k}^{(t+1)} = F^{(t)}([\mathbf{y}^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}), \quad (7)$$

where $F^{(t)} : \mathbb{C}^{t+1} \times \mathbb{R}^{2M} \rightarrow \mathbb{C}^{1 \times N_{\text{RIS}}}$ defines the mapping from the previously received pilot signals and estimated SOs location to the next RIS configuration. The updated RIS configuration is then used to generate the next measurement $\mathbf{y}^{(t+1)}$ in time frame $(t+1)$. For initialization at $t < 0$, there are no prior observations. Here, the function $F^{(-1)}(\emptyset)$ takes an empty input set and provides a fixed default initial RIS configurations $\mathbf{k}^{(0)}$.

After collecting all T pilot signals, the estimated user location $\hat{\mathbf{u}}^{(T)}$ is obtained as a function of all past observations at the user and environment sensing:

$$\hat{\mathbf{u}}^{(T)} = Q([\mathbf{y}^{(\tau)}]_{\tau=0}^{T-1}, \hat{\mathbf{p}}^{(T)}), \quad (8)$$

where $Q : \mathbb{C}^T \times \mathbb{R}^{2M} \rightarrow \mathbb{R}^2$ maps the collected pilot signals and the estimated scattering to the estimated two-dimensional user location.

The general objective is to minimize localization error by jointly optimizing $\{G^{(t)}\}_{t=0}^{T-1}$ in (6), $\{F^{(t)}\}_{t=0}^{T-1}$ in (7) and Q in (8), under the following constraints:

$$\min_{\{G^{(t)}(\cdot), F^{(t)}(\cdot)\}_{t=0}^{T-1}, Q(\cdot)} \sqrt{\mathbb{E}[\|\hat{\mathbf{u}}^{(T)} - \mathbf{u}\|^2]} \quad (9a)$$

$$\text{subject to } \hat{\mathbf{p}}^{(t)} = G^{(t)}([\mathbf{y}_s^{(\tau)}]_{\tau=0}^t) \quad (9b)$$

$$\mathbf{k}^{(t+1)} = F^{(t)}([\mathbf{y}^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}), \quad (9c)$$

$$\hat{\mathbf{u}}^{(T)} = Q([\mathbf{y}^{(\tau)}]_{\tau=0}^{T-1}, \hat{\mathbf{p}}^{(T)}). \quad (9d)$$

$$\left\| [\mathbf{k}^{(t+1)}]_n \right\| = 1, \quad \forall n \in N_{\text{RIS}}, t. \quad (9e)$$

The solution of the optimization problem in (9) is challenging due to the joint estimation of scattering $\{G^{(t)}\}_{t=0}^{T-1}$, the

RIS configuration design $\{F^{(t)}(\cdot)\}_{t=0}^{T-1}$ and user localization $Q(\cdot)$. To simplify the problem, a common approach is to use codebooks to select RIS configurations heuristically. For example, [21] addresses RIS-aided localization in free space by employing a hierarchical codebook to adaptively scan the space. While codebooks are appealing due to their low control overhead and hardware feasibility, such strategies inherently limit design flexibility by restricting RIS configurations to a discrete predefined set, which cannot fully adapt to the dynamic nature of RSE, thereby constraining localization accuracy.

In this paper, we directly optimize (9) using a neural network to parameterize the functions $G^{(t)}(\cdot)$, $F^{(t)}(\cdot)$ and $Q(\cdot)$. This enables scalable adaptation to rich scattering conditions while maintaining localization accuracy and computational efficiency. As demonstrated in Section IV, our learning-based strategy significantly outperforms codebook-based designs in dynamic RSE environments.

III. PROPOSED ADAPTIVE BiLSTM BASED LOCALIZATION APPROACH

We present a deep learning-based adaptive RIS configuration approach to address the localization problem in (9), without relying on a predefined geometric channel model or restricting the design space to a fixed codebook. At each time step t , the RIS configuration $\mathbf{k}^{(t+1)}$ is determined based on prior user observations $[\mathbf{y}^{(\tau)}]_{\tau=0}^t$ and the estimated SO status $\hat{\mathbf{p}}^{(t)}$. A core challenge is the linear accumulation of measurements over time, making it computationally expensive to process them when optimizing RIS configurations for large t . To maintain scalability, the neural network must condense past observations into a compact fixed-dimensional information vector.

To this end, we employ a BiLSTM model that captures temporal dependencies and efficiently encodes sequential measurements. Unlike conventional approaches that adapt RIS configurations solely based on user pilot signals, the proposed method introduces a two-stage deep learning model:

- 1) *Scattering Estimation Network (Bi-SEN)*: Estimates dynamic SOs positions at time t using sensing observations at $\mathcal{S}_{\text{RIS}}$, characterizing the current scattering in RSE.
- 2) *Adaptive RIS-Assisted User Localization Network (Bi-ARULN)*: Designs the RIS configurations for the time slot $(t+1)$ based on the estimated scattering via Bi-SEN and pilot received at the user at t , with the objective of localizing the user at final time T .

By leveraging a bidirectional recurrent neural network, the proposed approach captures dependencies from both past and future contexts, improving scattering estimation and RIS adaptation for user localization.

A. Bayesian Optimization Based Hyperparameter Tuning

We employ BO to fine-tune the hyperparameters of the Bi-SEN and Bi-ARULN models prior to training, efficiently identifying optimal settings for the number of BiLSTM layers N_L , hidden state dimension d_s , learning rate η and batch size B . This optimally balances computational efficiency and

localization accuracy. BO models the relationship between hyperparameters and validation loss using a Gaussian Process (GP) regression model,

$$L_{\text{val}}(N_L, d_s, \eta, B) \sim GP(\mu(\Theta), k(\Theta, \Theta')) \quad (10)$$

where L_{val} is the validation loss, $\mu(\Theta)$ is the mean function and $k(\Theta, \Theta')$ is the covariance kernel function measuring the similarity between hyperparameter sets $\Theta = (N_L, d_s, \eta, B)$.

To explore promising hyperparameter configurations, BO uses the Expected Improvement (EI) acquisition function,

$$\alpha_{\text{EI}}(\Theta) = \mathbb{E}[\max(0, L_{\text{min}} - L_{\text{val}}(\Theta))]. \quad (11)$$

where, L_{min} denotes the best validation loss observed among all previously evaluated hyperparameter configurations. The next set of hyperparameters is selected as

$$\Theta^* = \arg \max_{\Theta} \alpha_{\text{EI}}(\Theta). \quad (12)$$

This process enables effective hyperparameter tuning of both models while minimizing overall computational overhead.

B. Neural Network Architecture

The network architecture is illustrated in Figure 3. The proposed BiLSTM-based localization model comprises two sequential networks—a Bi-SEN and Bi-ARULN. Both networks incorporate fully connected layers for feature extraction and BiLSTM layers for processing sequential data across multiple sensing frames.

1) *Bi-SEN Network*: At each time step t , a biLSTM cell updates its forward- and backward hidden states, $s_{p,f}^{(t)}$ and $s_{p,b}^{(t)}$, and forward- and backward cell states $c_{p,f}^{(t)}$ and $c_{p,b}^{(t)}$, based on the newly received input $\mathbf{f}_p^{(t)}$. The input vector is formed by concatenating the magnitude and phase of the sensed signal, i.e., $\mathbf{f}_p^{(t)} = [\|\mathbf{y}_s^{(t)}\|, \angle \mathbf{y}_s^{(t)}]$.

The updates for the forward and backward cell states and hidden states are given by

$$c_{p,f}^{(t)} = \mathbf{f}_{p,f}^{(t)} \circ c_{p,f}^{(t-1)} + \mathbf{i}_{p,f}^{(t)} \circ \tanh(\mathbf{u}_{cp}(\mathbf{f}_p^{(t)}) + \mathbf{r}_{cp}(s_{p,f}^{(t-1)}, s_{p,b}^{(t+1)})), \quad (13a)$$

$$s_{p,f}^{(t)} = \mathbf{o}_{p,f}^{(t)} \circ \tanh(c_{p,f}^{(t)}), \quad (13b)$$

$$c_{p,b}^{(t)} = \mathbf{f}_{p,b}^{(t)} \circ c_{p,b}^{(t+1)} + \mathbf{i}_{p,b}^{(t)} \circ \tanh(\mathbf{u}_{cp}(\mathbf{f}_p^{(t)}) + \mathbf{r}_{cp}(s_{p,f}^{(t-1)}, s_{p,b}^{(t+1)})), \quad (13c)$$

$$s_{p,b}^{(t)} = \mathbf{o}_{p,b}^{(t)} \circ \tanh(c_{p,b}^{(t)}), \quad (13d)$$

where $\mathbf{u}_{cp}(\cdot)$ and $\mathbf{r}_{cp}(\cdot)$ are fully connected linear layers, and $\mathbf{f}_{p,\cdot}^{(t)}$, $\mathbf{i}_{p,\cdot}^{(t)}$, and $\mathbf{o}_{p,\cdot}^{(t)}$ represent the forget, input, and output gate activation vectors, respectively. The element-wise updates for these gates are defined as

$$\mathbf{f}_{p,f}^{(t)} = \sigma_s(\mathbf{u}_{p,f}(\mathbf{f}_p^{(t)}) + \mathbf{r}_{p,f}(s_{p,f}^{(t-1)})), \quad (14a)$$

$$\mathbf{i}_{p,f}^{(t)} = \sigma_s(\mathbf{u}_{p,i}(\mathbf{f}_p^{(t)}) + \mathbf{r}_{p,i}(s_{p,f}^{(t-1)})), \quad (14b)$$

$$\mathbf{o}_{p,f}^{(t)} = \sigma_s(\mathbf{u}_{p,o}(\mathbf{f}_p^{(t)}) + \mathbf{r}_{p,o}(s_{p,f}^{(t-1)})), \quad (14c)$$

where the element-wise sigmoid function is $\sigma(x) = \frac{1}{1+e^{-x}}$. The parameters $\mathbf{u}_{p,f}, \mathbf{u}_{p,i}, \mathbf{u}_{p,o}, \mathbf{r}_{p,f}, \mathbf{r}_{p,i}, \mathbf{r}_{p,o}$ are trainable linear

layers in the network. The backward states update follows the similar structure to ensure bidirectional processing.

The final estimated SOs positions are computed via a fully connected network output layer

$$\hat{\mathbf{p}}^{(t)} = \ell_p([\mathbf{c}_{p,f}^{(t)}; \mathbf{c}_{p,b}^{(t)}]), \quad (15)$$

where $\ell_p(\cdot)$ is a trainable fully connected network. The estimate in (15) corresponds to the criterion in (9b).

2) *Bi-ARULN Network*: A biLSTM cell processes newly received input to update its forward and backward hidden states, denoted as $s_{u,f}^{(t)}$ and $s_{u,b}^{(t)}$, along with the corresponding cell states $c_{u,f}^{(t)}$ and $c_{u,b}^{(t)}$. The input vector at time t , $\mathbf{f}_u^{(t)}$, consists of the magnitude and phase of the pilots received at the user, and the estimated $\hat{\mathbf{p}}^{(t)}$, given by $\mathbf{f}_u^{(t)} = [\|\mathbf{y}^{(t)}\|, \angle \mathbf{y}^{(t)}, \hat{\mathbf{p}}^{(t)}]$. The update equations for the forward and backward cells, hidden states, and their respective gates are as in (13) and (14).

The final hidden state at time t is obtained by concatenating the forward and backward hidden states,

$$s_u(t) = [s_{u,f}(t); s_{u,b}(t)]. \quad (16)$$

The hidden state vector $s_u(t)$ is used as input to a fully connected neural network with L_n layers to derive the next RIS configurations at an instant $t+1$. The transformation is performed as

$$\gamma(t) = \beta_{L_n}(\mathbf{W}_{L_n} \beta_{L_n-1}(\dots \beta_1(\mathbf{W}_1 s_u(t) + \mathbf{b}_1) \dots) + \mathbf{b}_{L_n}), \quad (17)$$

where β_l is the activation function for the l -th layer, set as $\text{ReLU}(x) = \max(0, x)$ where $l \in \{1, \dots, L_n\}$. The parameters $\mathbf{W}_l$ and $\mathbf{b}_l$ are trainable weights and biases.

The $(L_n + 1)$ -th layer outputs the real-valued vector

$$\bar{\mathbf{k}}^{(t+1)} = \mathbf{W}_{L_n+1} \gamma(t) + \mathbf{b}_{L_n+1}. \quad (18)$$

Here, $\bar{\mathbf{k}}^{(t+1)}$ represents the sequence of real and imaginary components of the RIS configuration vector. The trainable weight and bias matrices, $\mathbf{W}_{L_n+1}$, $\mathbf{b}_{L_n+1}$, are structured to maintain the appropriate output dimensions such that $\bar{\mathbf{k}}^{(t+1)} \in \mathbb{R}^{2N_{\text{RIS}}}$, producing N_{RIS} complex-valued entries. To ensure that each element of the RIS configuration vector satisfies the unit-modulus constraint, it undergoes element-wise normalization:

$$[\mathbf{k}^{(t+1)}]_n = \frac{[\Re(\bar{\mathbf{k}}^{(t+1)})]_n}{\sqrt{[\Re(\bar{\mathbf{k}}^{(t+1)})]_n^2 + [\Im(\bar{\mathbf{k}}^{(t+1)})]_n^2}} + j \frac{[\Im(\bar{\mathbf{k}}^{(t+1)})]_n}{\sqrt{[\Re(\bar{\mathbf{k}}^{(t+1)})]_n^2 + [\Im(\bar{\mathbf{k}}^{(t+1)})]_n^2}}, \quad (19)$$

Design in (19) corresponds to the criterion in (9c) and (9e), respectively.

The final estimated UE position is obtained in the time frame T as

$$\hat{\mathbf{u}}^{(T)} = \ell_u([\mathbf{c}_{u,f}^{(T)}; \mathbf{c}_{u,b}^{(T)}]), \quad (20)$$

where $\ell_u(\cdot)$ is a fully connected network that processes the concatenated forward and backward cell states to obtain the final position estimate as in (9d).

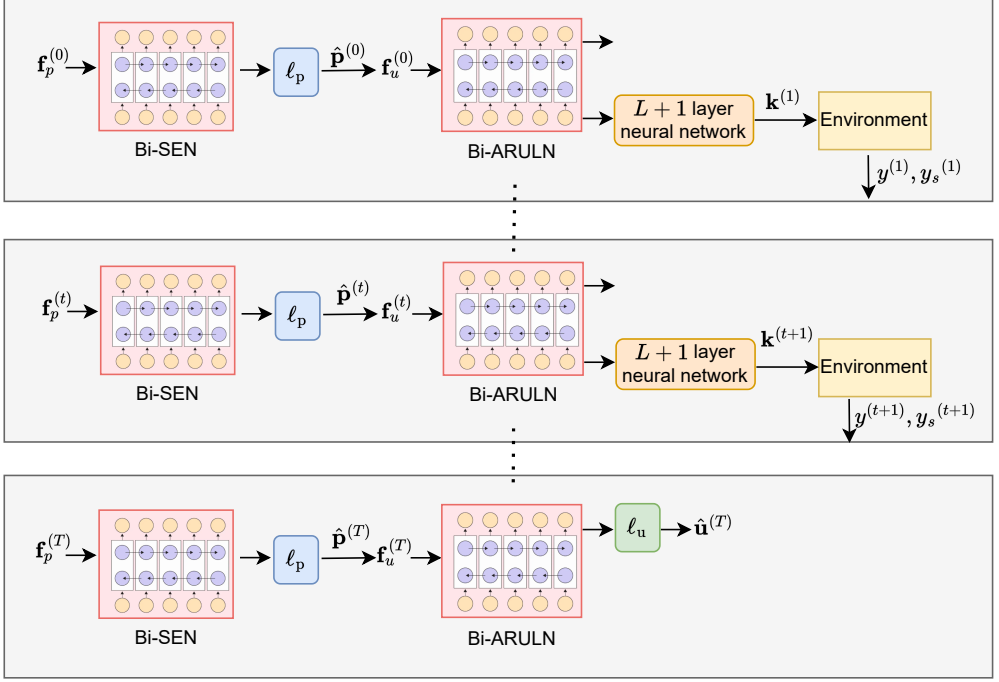


Fig. 3: Proposed adaptive localization approach for RIS-assisted RSE. At each time step $t \in [0, T-1]$, sensed signals from $\mathcal{S}_{\text{RIS}}$ is fed as input feature set $\mathbf{f}_p^{(t)} = [\mathbf{y}_s^{(t)}, \angle \mathbf{y}_s^{(t)}]$ to Bi-SEN to estimate SOs locations $\hat{\mathbf{p}}^{(t)}$, corresponding to (9b). The feature set $\mathbf{f}_u^{(t)} = [\mathbf{y}^{(t)}, \angle \mathbf{y}^{(t)}, \hat{\mathbf{p}}^{(t)}]$ is input to Bi-ARULN, which predicts the next RIS configuration $\mathbf{k}^{(t+1)}$, corresponding to (9c) and (9e). The designed configuration $\mathbf{k}^{(t+1)}$ is used to make next received pilot measurements $\mathbf{y}_s^{(t+1)}$ and $\mathbf{y}^{(t+1)}$ in $(t+1)$ -th time frame. After all the pilot measurements have been received, user location $\hat{\mathbf{u}}^{(T)}$ is estimated at the T -th time frame via a feedforward prediction layer, as a function of all T historical measurements, corresponding to (9d).

C. Loss Function

The overall BiLSTM model is trained using the Adam optimizer [50] to minimize the root mean squared error (RMSE) loss between the true and estimated user location. The loss for user localization in Bi-ARULN, corresponding to (9a), is defined as

$$\sqrt{\mathbb{E} [\|\hat{\mathbf{u}}^{(T)} - \mathbf{u}\|^2]}. \quad (21)$$

To account for scattering estimation loss, the cumulative RMSE loss in localizing M SOs with Bi-SEN at each stage is given by

$$\sqrt{\mathbb{E} [\|\hat{\mathbf{p}}^{(t)} - \mathbf{p}\|^2]}. \quad (22)$$

These losses guide the model to accurately estimate location of the user and adapt to environmental changes by learning a sequence of optimal RIS configurations. The loss function in (21) encourages the model to design a sequence of T RIS configurations that minimize the localization error in the final stage. After training, the network generalizes across the deployment area and dynamically generates RIS configuration

vectors based on the recurring received signals for any user and $\mathcal{S}_{\text{RIS}}$, regardless of the location of the user within the coverage area. Notably, the loss function for the location of the user focuses solely on the estimation error in the final stage T . This is good since it gives the network the freedom to design the RIS configuration strategy at all T measurement stages.

IV. NUMERICAL RESULTS

A. Simulation Setup

The simulation parameters are summarized in Table I. We consider two scenarios in the experiments, SISO and MIMO to account for the impact of the antenna array at transceiver nodes in addition to RIS in RSE. As shown in Figure 1, the location of BS is fixed and the distributed RIS is installed at known locations. The unknown user locations $\mathbf{u}$ are uniformly distributed on the x - y plane within the simulated enclosed area, arranged on a regular grid with $\lambda/2$ spacing and a known, fixed orientation. The pilot signal $x^{(t)}$ is a known deterministic scalar fixed to unity. The M SOs trajectories

TABLE I: Numerical Results Parameters

Label	Dimension
Simulation Parameters	
M	4
N_{BS}	$\{1, 4\}$
N_U	$\{1, 4\}$
N_{RIS}	20,60,100
Transceivers dipole parameters	$f_{res} = 1, \chi = 0.5, \Gamma_L = 0$
Transceivers dipole spacing	$\lambda/2$
Environment and SOs dipole parameters	$f_{res} = 10, \chi = 50, \Gamma_L = 10^4$
Environment and SOs dipole spacing	$\lambda/4$
RIS dipole parameters	$f_{res} \in \{0.8, 1.2\}, \chi = 0.2, \Gamma_L = 0.03$
RIS dipole spacing	$\lambda/2$
Parameters of the biLSTM Network	
B	[32,64,128]
N_L	[2,4,6]
d_s	[25,35,45]
η	[0.001,0.01,0.005,0.05]
Maximum epochs	200
L_n	4

are predefined a priori such that each SOs starts at a known initial position and moves along a path with deterministic steps of maximum size $\lambda/4$, with random Gaussian offset in direction, $\Delta\theta \sim \mathcal{N}(0, \sigma_\theta^2)$, $\sigma_\theta = 0.052$ radians, and position, $\Delta p \sim \mathcal{N}(0, \sigma_p^2)$, $\sigma_p = \lambda/20$, at each step. The positions of the central dipoles in each SOs cluster are tracked in each simulation realization. The same base trajectories are used in training and testing, with independently sampled perturbations producing different realized paths. The tunable dipole parameters for transceivers, environment (including SOs), and RIS namely the resonance frequency (f_{res}), the charge term (χ) and the absorptive damping term (Γ_L), are configured as in Table I [10].

B. Proposed Approach and Baseline Approaches

The proposed biLSTM approach for adaptive RIS configuration design via sensing of RSE for user localization is implemented using the parameters described in Table I, which are optimized using BO. For training, the network is trained on 1,806,000 samples over 200 epochs. The training data for Bi-SEN comprises of channel response measurements at S_{RIS} and for Bi-ARULN channel response measurements at the user alongside the outputs of Bi-SEN. We need channel responses to generate the received pilots. These measurements are generated by moving SOs across arbitrary user locations in the simulation. The training labels for Bi-SEN are of dimension $2M$ which includes the two-dimensional true SOs locations, whereas the labels for Bi-ARULN correspond to the two-dimensional true user locations. We partitioned the dataset into 70% for training, 15% for validation, and 15% for testing. Once the BiLSTM model is trained, it autonomously determines a sequence of RIS configurations utilizing recurring sequential scattering estimation and user received pilot measurements, enabling accurate localization of any user within the coverage area. We evaluated the localization accuracy of our proposed approach in comparison with the following baseline approaches.

- 1) *Random RIS Configurations*: The sequence of RIS configurations at each time instant are randomly chosen and do

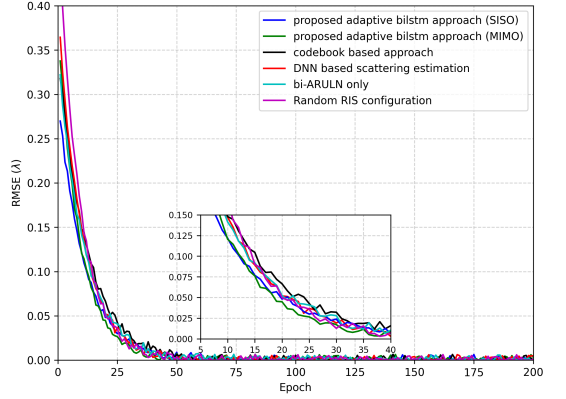


Fig. 4: RMSE loss curves for proposed and baseline approaches for 200 evaluation epochs.

not adapt dynamically based on sensing of the scattering in RSE. Randomness in configurations introduces diversity in the observed signals, which is leveraged during training. A DNN with dimensions [200, 200, 200, 2] is used to map the magnitude and phase of the user response received over T time frames, $[\mathbf{y}^{(t)}]_{t=0}^{T-1}$ to predict the location of the user by minimizing the loss in (21).

- 2) *Codebook based Approach*: This employs a codebook-based RIS configuration design such that a BiLSTM model is trained to learn optimal RIS configurations corresponding to various SOs states, as in [34]. During inference, the BS estimates the current environment and selects the closest RIS configuration from the precomputed codebook to optimize the accuracy of the user localization quantized by the loss in (21).
- 3) *DNN based Scattering Estimation*: Here, we use Bi-ARULN for user localization, but replace the sequential modeling of Bi-SEN with a DNN with dimensions [200, 200, 200, $2M$] to estimate SOs location from the sensed signals $[\mathbf{y}_s^{(t)}]_{t=0}^{T-1}$ at S_{RIS} .
- 4) *Bi-ARULN only*: This model uses Bi-ARULN for user localization and RIS configuration design, but does not take into account scattering in the environment, according to [29], [43].

All baseline models have been evaluated for the MIMO setting, while the proposed approach is tested in both SISO and MIMO scenarios.

C. Results

The results in Figure 4 show the user localization RMSE loss curves for various approaches, demonstrating fast convergence across all methods. The loss function exhibits a rapid decline within the first 25 epochs, indicating efficient learning and adaptation of model parameters. The loss stabilizes near zero after epoch 50, indicating effective training with no signs of overfitting or divergence. Smooth convergence confirms that the models generalize well and that the training process was efficiently optimized.

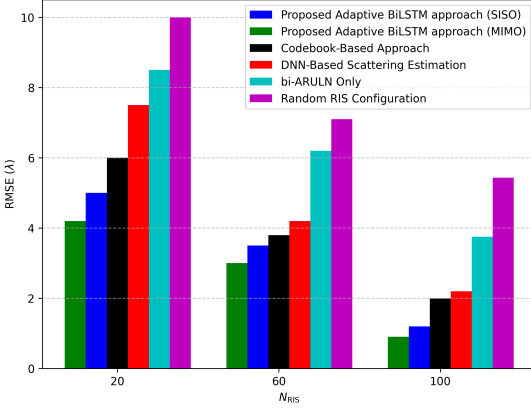


Fig. 5: RMSE of user localization versus N_{RIS} , for $T = 21$ and $\text{SNR} = -20$ dB.

To evaluate the performance of the developed approach against the benchmarks, we first examine the effect of RIS size N_{RIS} on localization accuracy, as shown in Figure 5. The results show that increasing N_{RIS} , consistently reduces RMSE across all approaches, confirming the benefit of large RIS sizes on localization performance in dynamic RSE. This performance gain is expected, as a larger RIS provides more spatial information. The proposed approach achieves the lowest RMSE across all RIS sizes, indicating its effectiveness in adaptively optimizing RIS configurations for accurate localization compared to the baseline approaches. In particular, there is a 79% reduction in RMSE as N_{RIS} increases from 20 to 100 for the MIMO network, and a 76% reduction for the SISO network. The MIMO network consistently outperforms SISO due to its greater spatial diversity. All other methods show meaningful but relatively smaller drops, that is, below 70%, in error. The proposed biLSTM approach remains scalable across various RIS sizes. Adapting the localization process for different RIS dimensions requires only a minor modification in the architecture of the neural network, specifically, by modifying the output size of the neural network in the $(L+1)$ layer following the biLSTM cells. The findings emphasize the importance of the adaptive RIS design in RIS-assisted and dynamic RSE. It is also observed that incorporating antenna array at the transceiver nodes further enhances the localization accuracy due to increased spatial diversity.

Next, we examine cumulative distribution function (CDF) of the user localization error from (21) for the proposed and benchmark approaches, as shown in Figure 6. The proposed adaptive BiLSTM approach exhibits the most favorable distribution, with most localization errors concentrated at lower RMSE values, indicating high accuracy and reliability. The codebook-based approach and DNN-based scattering estimation follow closely, demonstrating relatively good performance but with slightly higher RMSE variability. In contrast, the bi-ARULN method and random RIS configuration show notably poorer performance. Their CDF curves rising more gradually

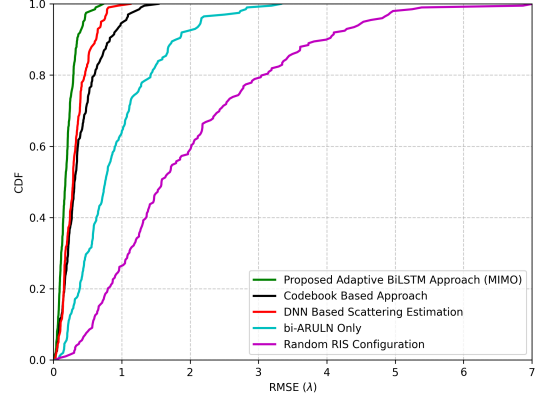


Fig. 6: CDF of proposed and baseline approaches versus RMSE of user localization for $N_{\text{RIS}} = 100$, $T = 21$ and $\text{SNR} = 30$ dB.

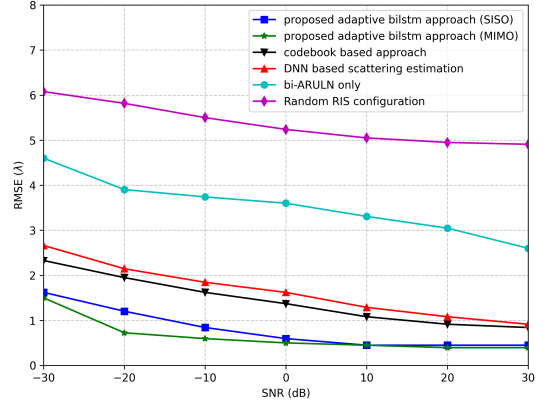


Fig. 7: RMSE of user localization versus the SNR for $N_{\text{RIS}} = 100$ and $T = 21$.

indicate higher and more variable errors. The random RIS configuration, in particular, exhibits the worst performance, with a large fraction of instances experiencing high RMSE values. These results confirm that adaptive, learning-based RIS configuration approaches offer substantial improvements in localization accuracy, while non-adaptive approaches or adaptive approaches not taking scattering into account suffer from greater uncertainty in dynamic RSE.

We now examine the user localization performance against the SNR, i.e., $\text{SNR}_{\text{dB}} = 10 \log_{10} (P_{\text{BS}} \mathbb{E} [||\mathbf{H}_{\text{BS}-U}|^2] / \sigma^2)$ in Figure 7, which plots the accuracy of the user localization versus SNR, where P_{BS} is BS transmit power. The results indicate that increasing SNR significantly improves the accuracy of the localization in all approaches, with varying degrees of effectiveness. The proposed approach consistently outperforms other benchmark approaches with nonadaptive designs or ones that do not take into account the scattering in RSE. This

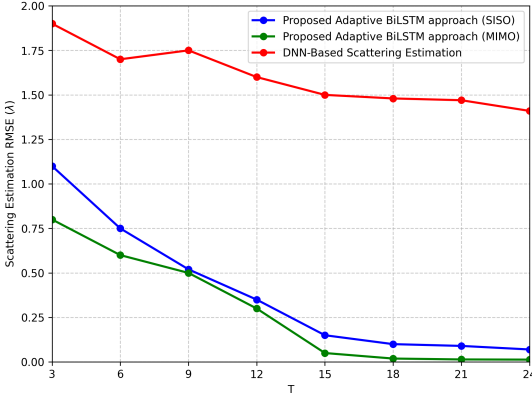


Fig. 8: Scattering Estimation RMSE from (22) versus T for SNR = 30dB.

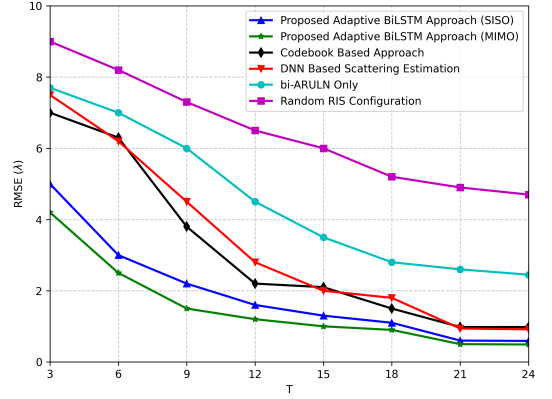


Fig. 9: RMSE of user localization versus T for $N_{\text{RIS}} = 100$ and SNR = 30 dB.

demonstrates its superior ability to refine RIS configurations using historical and current channel observations, ensuring its adaptive nature against other approaches. Both the SISO and MIMO networks in the proposed approach exhibit a consistent improvement with increasing SNR. MIMO generally outperforms SISO due to spatial diversity, particularly evident at low SNRs where robustness is critical. The narrow gap between SISO and MIMO performance at the lowest and highest SNR values likely reflects regimes where the estimator is dominated by noise at low SNR or by model and system limitations at high SNR. In both extremes, additional antennas provide little exploitable spatial information, and the benefits of MIMO become visible mainly in the mid-SNR range where spatial features can be effectively resolved.

The codebook-based approach, which utilizes pre-learned RIS configurations, shows moderate performance since it has limited adaptability to varying propagation environments, especially at lower SNR. The DNN based scattering estimation approach performs worse than the codebook based and proposed approach, but better than a method not taking scattering into account or with random RIS configuration. It shows a consistent drop with increasing SNR. This is because DNNs can effectively model complex channel behaviors and compensate for non-ideal conditions in RSE. However, it does not fully capture sequential dependencies as efficiently as the biLSTM-based method. The Bi-ARULN only approach performs worse than deep learning-based approaches, mainly because it cannot effectively handle the scattering effects introduced by dynamic SOs in RSE, even at higher SNR.

The random RIS configuration is not optimized for system requirements, leading to ineffective signal enhancement and poor localization accuracy such that its performance is largely insensitive to SNR changes. This underscores the necessity of accurate scattering estimation and well-designed adaptive RIS settings for improved localization. In general, the results highlight the superiority of adaptive learning-based approaches and the pivotal role of optimized RIS configurations in achieving high-precision user localization in RIS-assisted RSE.

In Figure 8 we study the scattering estimation error in (22), accounting for cumulative RMSE in estimating M SOs, as a function of the number of time frames that is used for designing RIS configuration and estimating user location, highlighting the performance of different estimation techniques. The proposed Bi-SEN approach, for both MIMO and SISO networks, outperforms the baseline by effectively leveraging sequential modeling for scattering estimation. As T increases, both the MIMO and SISO networks exhibit a significant reduction in RMSE, with MIMO achieving the lowest error due to enhanced spatial diversity and limited movement of SOs along their trajectories, which allows the Bi-SEN to leverage temporal correlations effectively. In contrast, the DNN-based scattering estimation approach, shows consistently higher RMSE across all values of T , as it lacks temporal modeling and thus fails to capture long-term scattering dependencies. Although its performance improves as T increases, it remains inferior to the biLSTM-based Bi-SEN approach. In general, the performance gap between BiLSTM and DNN-based approaches highlights the importance of leveraging recurrent architectures for dynamic scattering estimation, reinforcing the benefit of adaptive, sequence-based learning in RIS-assisted localization in dynamic RSE.

Next, we examine the user localization error against varying time frames in Figure 9. We observe that the devised approach performs consistently better than the benchmark approaches with the MIMO network giving slightly better performance than the SISO network. To demonstrate, observe that the devised approach with MIMO network at 6 time frames achieves a localization error of approximately 2.5λ , which is comparable to or better than the error achieved by benchmark approaches at or after 12 time frames. This demonstrates a twofold reduction in the number of observations required to reach the same accuracy level. The performance gap is most pronounced at lower frame counts, highlighting the efficiency of the proposed method in rapidly extracting useful features from limited temporal information. In particular, the advan-

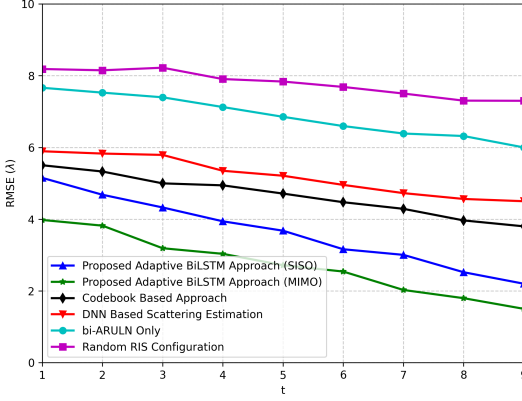


Fig. 10: RMSE of user localization versus time frames t up to the last time frame $T = 9$ for $N_{\text{RIS}} = 100$ and $\text{SNR} = 30$ dB.

tage of requiring fewer time frames translates into reduced localization latency. Although the gap narrows somewhat as the number of frames increases, the devised approach consistently maintains a margin over all benchmarks, indicating robustness across different operating conditions. The role of MIMO is also evident, as the richer spatial diversity in the MIMO network allows more reliable feature extraction, thus accelerating convergence to low-error regimes. This suggests that combining the proposed method with multi-antenna network configurations can further reduce latency and improve performance in practical deployments. From an application standpoint, these results imply that high localization accuracy can be achieved with fewer observations, which may lead to reduced latency, lower energy consumption, and diminished signaling overhead in comparison to the baselines. Such characteristics are particularly advantageous in power-limited or bandwidth-constrained scenarios, as well as in highly dynamic RSEs where long observation windows are impractical due to user or environmental mobility.

We next plot the user localization RMSE as a function of the time stages $t \leq T$ in Figure 10. To observe the RMSE at $t < T$, the localization process must be terminated before reaching the final stage T . In this case, the BiLSTM network should still provide reliable position estimates at earlier stages of RIS configuration design and environment sensing. However, the loss function in (21) does not explicitly account for this requirement. To address this issue, we employ a weighted RMSE loss, defined as $\sqrt{\mathbb{E}[\sum_{t=1}^T \alpha_t \|\hat{\mathbf{u}}^{(t)} - \mathbf{u}\|^2]}$, where $\hat{\mathbf{u}}^{(t)} = \ell_u([c_{u,f}^{(t)}, c_{u,b}^{(t)}])$, and the weights satisfy $\sum_{t=1}^T \alpha_t = 1$. By assigning higher weights to earlier stages, the network is encouraged to reduce localization error even when early termination occurs.

The results in Figure 10 illustrate that RMSE consistently decreases as t increases, showing that each method progressively refines the RIS configuration with additional pilot observations. The proposed adaptive BiLSTM approach achieves the most significant improvements, consistent with the ability of

recurrent models to capture and exploit temporal dependencies in the scattering environment. The use of multiple transceiver antennas provides richer information on the scattering geometry, thereby accelerating error reduction. In contrast, the DNN-based scattering estimator lacks explicit temporal memory and treats each frame independently, limiting its ability to exploit correlations over time. This explains its inferior performance relative to the BiLSTM-based methods, which effectively integrate information over multiple stages.

The codebook-based approach performs moderately well, but is constrained by quantized RIS states. While it benefits from improved selections as the environment estimate stabilizes, its performance ceiling is ultimately dictated by the codebook resolution. Thus, although codebook-based methods are attractive for their simplicity, they cannot match the continuous adaptivity and robustness of recurrent approaches in RSE. The adaptive Bi-ARULN-only method relies solely on user-side signals without modeling scattering in the RSE, thus limiting its ability to design configurations suitable for environmental conditions. The random configuration strategy provides measurement diversity, but lacks directed adaptation, resulting in slow convergence and the highest error.

A general trend across all methods is that performance gaps widen with t . The early stages capture only coarse information, whereas the later stages refine both the environment representation and the RIS design. This allows adaptive methods to accelerate improvements, while non-adaptive methods provide only limited gains. In the final stage, the proposed adaptive BiLSTM with MIMO converges to the lowest error, demonstrating stable tracking of the SOs and robust RIS configuration design in the considered RSE.

From a practical standpoint, if the system is subject to stringent latency or pilot constraints, the proposed BiLSTM with MIMO should be prioritized where hardware resources allow, while the SISO variant offers an alternative with lower complexity. For applications requiring early termination, training with a weighted early-stage loss is particularly valuable, as it drives the network to place the RIS in informative states earlier, reducing RMSE even at small t .

V. CONCLUSION

This paper presents a learning-based localization approach for RIS-assisted RSE to adaptively design the RIS configuration for accurate user localization by taking into account scattering in the environment. By leveraging RIS-assisted sensing and sequential measurement history, our proposed BiLSTM-based model adaptively configures RIS elements to minimize user localization error. The integration of Bi-SEN for scattering estimation and Bi-ARULN for RIS configuration design allows the system to maintain context awareness and adaptively design RIS configuration for user localization. Simulation results validate that the proposed approach outperforms fixed-codebook, random, and adaptive designs that do not take scattering into account across varying RIS sizes and SNR conditions. The proposed approach also generalizes well to both SISO and MIMO networks. Given the reciprocity of the underlying channel model, the proposed approach can

also be applied in an uplink configuration without modifying the core learning method. Future work may explore analytical benchmarking of the proposed solution, and quantizing the adaptive configuration space to enable deployment under practical bandwidth and storage constraints. Moreover, the extension of the proposed approach to the estimation of user orientation in addition to location and unstructured RSEs with unknown or varying numbers of SOs and their mobility and different RIS deployment strategies may also be investigated.

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Appendix 4

IV

A. Umer, I. Mürsepp, and M. M. Alam, "Integrated Sensing, User Location and Orientation Estimation in RIS-Assisted Dynamic Rich Scattering Environment," *IEEE Transactions on Wireless Communications (Under review)*, 2026

Integrated Sensing, User Location and Orientation Estimation in RIS-Assisted Dynamic Rich Scattering Environment

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Abstract—This paper investigates uplink user equipment (UE) location and orientation estimation in an indoor rich-scattering environment (RSE) for a multiple-input multiple-output (MIMO), reconfigurable intelligent surface (RIS)-assisted system, where the uplink pilot undergoes repeated interactions with the RIS and with non-cooperative, dynamic scattering objects (SOs). We propose an adaptive design in which the base station (BS) senses the environment through a dedicated subset of RIS elements and sequentially designs the RIS configuration and the BS and UE beamforming vectors over the pilot sequence. A two-stage bidirectional long short-term memory (biLSTM) network realizes this design, first estimating the SOs positions and then, conditioned on this estimate, the UE position and orientation. As an analytical benchmark, we derive a conditional Bayesian Cramér-Rao lower bound (BCRLB) based design that treats the SOs positions as nuisance parameters. The approach is evaluated under diverse RSE conditions against this benchmark, a beamforming-free baseline, and an adaptive design without scattering estimation. Simulation results show that the proposed approach consistently attains lower localization and orientation error than the considered baselines across the evaluated SNR range, number of time frames, and RIS deployment configurations, and that the localization error decreases significantly relative to the beamforming-free design, confirming the benefit of sensing the scattering for accurate localization in dynamic RSEs.

Index Terms—reconfigurable intelligent surfaces (RIS), localization, long-short term memory, sensing, channel estimation, rich scattering, dynamic wireless environment.

I. INTRODUCTION

Achieving reliable localization in rich-scattering environments (RSEs) dominated by dense multipath and rapid changes has become increasingly important as many modern applications depend on precise and resilient positioning [1], [2]. Conventional approaches often fail in such settings, especially indoors, where infrastructure constraints and rich scattering further complicate signal behavior. The need is amplified in emerging 6G networks that span microwave through terahertz and optical bands, where indoor environments exhibit strong scattering [3]. The user equipment (UE) localization is particularly challenging in narrowband indoor RSEs, where

the UE pilot signal is reflected by discrete, mobile, non-cooperative objects and reaches the base station (BS) through multiple paths after several reflections. Thus, the overlapping propagation components, with different amplitudes and phases, are hard to distinguish from one another.

This paper explores the role of reconfigurable intelligent surfaces (RIS) as an affordable substitute for large antenna arrays for localizing the UE in RSEs. RIS use numerous passive low power elements to tune reflected wave phases and regulate the propagation environment [4]–[6]. These characteristics enable them to act as intelligent anchors or to enhance existing systems by mitigating interference and directional issues, supporting the localization requirements of autonomous platforms, robotics, immersive applications, smart manufacturing, and traffic management [1], [2], [7]–[9]. They are viewed as a key enabler for 6G localization because they maintain a dependable reflected link when the direct path is weak or obstructed, and introduce additional anchor points without extra Radio Frequency (RF) chains [2], [9]. Under dynamic RSE conditions, repeated interactions with objects and RIS elements create composite reflections with diverse angle-of-arrival (AoA) and polarizations [10]–[12], leading to nonlinear behavior far from free or quasi free space models [9]. In these settings, RIS supply controlled perturbations, whereas moving objects or humans, referred to as scattering objects (SOs), introduce uncontrolled, time varying effects, yielding a nonlinear system shaped jointly by RIS configurations and environmental evolution [13]. It is shown in [14] that adaptive sensing enables accurate UE localization in RSEs, with the RIS acting as a virtual anchor.

In this work we consider the uplink localization problem in RSEs, in which the UE transmits known pilot signals and the BS determines the UE location and orientation from the received pilots. Since the wireless channel depends on the UE location, the considered scenario can be viewed as an inverse mapping problem, where the goal is to infer the UE location from the channel realizations. The main idea is to exploit the multiple paths, such that the BS senses the environment via a dedicated subset of RIS elements and adaptively reconfigures the RIS, BS and UE beamforming vectors over multiple time slots, with the objective of localizing the UE with accuracy.

A. Related Work

Prior studies on RIS-assisted UE localization can be broadly grouped into model based and learning based approaches [9].

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Model based methods design the RIS configuration through analytical formulations, most commonly by minimizing the Cramér-Rao lower bound (CRLB) of the UE position [15]–[19]. Such formulations rely on an explicit relationship between the UE location and geometric measurements, such as time-of-arrival (ToA) or AoA, to construct the Fisher Information Matrix (FIM). However, they become impractical in multipath dominated RSEs, where reliable path separation and association are difficult, particularly in narrowband indoor scenarios with unknown SOs. Extensions based on the Bayesian FIM and the robust Bayesian Cramér-Rao lower bound (BCRLB) incorporate prior uncertainty in the channel or geometric parameters [20], and have enabled adaptive RIS beamforming that exploits location uncertainty [21]. These methods, however, typically neglect scattering effects and therefore degrade in dynamic environments. More recent model based works instead exploit multipath structure for improved estimation, including Bayesian multi target trajectory tracking [22], cooperative RIS-assisted 3D positioning with a low complexity estimator [23], and a tensor based integrated sensing and communication framework supporting joint multi user communication and near and far field localization [24]. While effective, these approaches still assume resolvable propagation paths and do not address the dense, dynamic scattering that characterizes indoor RSEs.

In contrast, learning based localization has gained attention with advances in machine learning. Fingerprinting methods map received signal measurements under multiple RIS configurations to UE locations [7], and deep reinforcement learning has been used to optimize RIS configurations for improved accuracy [25]. These techniques, however, generally rely on fixed or predefined configurations and therefore do not fully exploit adaptive RIS reconfiguration. Adaptive sensing has recently emerged as a powerful paradigm across wireless applications, including initial beam alignment in millimeter wave systems [26]–[28], precoder and combiner design for reciprocal MIMO channels [29], RIS assisted beam tracking [30], and localization in single path and multipath environments as well as with adaptive RIS codebooks [31]–[33]. These works commonly employ recurrent neural network (RNN) based architectures that sequentially adapt the sensing vectors from previously observed pilots, progressively refining the design toward a target objective. In particular, the active sensing framework of [31] sequentially designs the BS beamforming vector and the RIS reflection coefficients for a single antenna UE; however, it assumes a Rician fading channel in which the line-of-sight (LoS) component carries the geometric information, and it estimates the UE position only. Such models are generally not directly transferable to rich scattering conditions, where propagation is dominated by dense multipath [14]. Recent studies address this gap with learning driven designs tailored to RSEs, including joint fingerprinting and feature extraction networks for 3D localization [34], self adaptive RIS optimization via learned surrogate models [35], and RNN based codebook driven joint RIS phase design and position estimation [36]. Closest to the present work, our earlier study [14] introduces an adaptive, beamforming-free scheme that sequentially designs only the RIS configuration in a downlink

RSE, employing a dedicated subset of sensing RIS elements to estimate the scattering contributed by non-cooperative SOs that follow fixed trajectories, and estimates the UE position.

This paper addresses joint UE location and orientation estimation in an uplink, MIMO RIS-assisted RSE with randomly moving SOs. It differs from [14] and from the aforementioned active sensing frameworks, such as [31], in four essential respects. The first is the propagation regime, as in [31] a dominant specular component carries the geometric information, the scattered field is a weak diffuse term that is never estimated, and higher-order reflections are neglected. In the considered RSE no single path dominates, the narrowband pilot cannot resolve the constituent paths, and the geometry must be recovered through the scattering itself, which we sense explicitly using a dedicated subset of RIS elements. The second is the design space, as [14] is beamforming-free and configures only the RIS, and [31] considers a single antenna UE for which no receive beamformer exists, we jointly design the RIS configuration and the BS and UE beamforming vectors over the sequence of uplink pilots. The third is the environment dynamics, as [31] assumes block fading with a static environment, and [14] confines the SOs to fixed trajectories, whereas this work considers SOs moving randomly within the enclosure. The fourth is the analytical benchmark as the analytical approach in [31] is formulated over the UE position alone, we augment the parameter vector with the SOs positions and marginalize them as nuisance parameters, yielding a bound on the joint UE position and orientation error under unknown scattering. We further evaluate the approach under scenarios not considered in [14] or [31], including distributed RIS deployments across one to four enclosure walls, and varying numbers of randomly moving SOs and sensing RIS elements.

B. Main Contributions

In this paper we develop an adaptive learning based localization approach for distributed RIS assisted MIMO networks operating in RSEs, where both the propagation medium and the network geometry are dynamic due to randomly moving SOs. Since the localization information is embedded in dense, spatio temporally coupled scattering patterns rather than in resolvable geometric paths, we exploit sequential learning to capture the long range dependencies in the received pilot and environmental sensing measurements, and to learn the evolving relationship between the scattering dynamics, the designed configurations, and the resulting localization accuracy. The main contributions of this work are summarized as follows.

- 1) In a distributed RIS assisted uplink MIMO network operating in a dynamic RSE, we formulate an adaptive sensing based approach that jointly designs the RIS configuration, BS beamforming and UE beamforming vectors from the past measurements at the BS and the sensed environmental scattering, with the objective of simultaneously estimating the UE position and orientation.
- 2) We propose a biLSTM based network that realizes this design. A dedicated subset of RIS elements senses the environment and BS estimates the positions of the non-cooperative SOs, and this estimate conditions the sequen-

tial design of BS, RIS and UE beams as the pilot sequence proceeds.

- 3) We derive an analytical approach for UE localization in RSE. The conditional BCRLB that augments the parameter vector with the SOs positions and marginalizes them as nuisance parameters is used to construct a greedy analytical estimator.
- 4) We conduct a comprehensive performance evaluation under a variety of RSE conditions, including different deployment configurations of distributed RIS arrays, and varying numbers of randomly moving SOs and sensing RIS elements, providing insight into the impact of the environmental complexity and the sensing capability on the scattering estimation, the localization and orientation accuracy, and the robustness of the proposed approach.

The joint sequential design progressively reduces the terminal localization and orientation error of UE as the pilot sequence proceeds, and the achievable accuracy improves with the density and the spatial diversity of the distributed RIS deployment.

The rest of the paper is organized as follows. The system model, end-to-end channel modeling, pilot transmission and observation protocol and the problem formulation are presented in Section II. Section III presents the devised neural network architecture. The analytical modeling approach is derived in Section IV. The simulation results are presented in Section V and conclusions are drawn in Section VI.

Notations: Scalars, vectors, and matrices are represented in italic (e.g. b), lowercase bold letters (e.g. $\mathbf{b}$), and capital boldface letters (e.g. $\mathbf{B}$), respectively. Furthermore, $|\cdot|$ denotes the modulus, $\hat{b}$ denotes an estimate of b , $\text{diag}(\mathbf{y})$ presents a diagonal matrix with entries of $\mathbf{y}$ on diagonal. The real and imaginary components of a complex value are given by $\Re(\cdot)$ and $\Im(\cdot)$, respectively. The expectation of a random variable is denoted by $\mathbb{E}(\cdot)$. The complex Gaussian distribution with mean m and variance v is presented by $\mathcal{CN}(m, v)$.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

The considered scenario is illustrated in Figure 1. A multi-antenna UE transmits known pilot symbols to a multi-antenna BS through a distributed RIS installation deployed on the periphery of an indoor enclosure containing M randomly moving SOs. The BS, at a known location, estimates the UE position $\mathbf{u} = [u_x, u_y]^T \in \mathbb{R}^2$ and orientation $\alpha \in [0, 2\pi)$, collected in the UE state $\mathbf{u}_e \triangleq [\mathbf{u}^T, \alpha]^T \in \mathbb{R}^3$.

The UE and the BS are each equipped with a single RF chain and perform analog beamforming with unit-modulus phase shifters. The UE therefore transmits a single stream through $\omega_{\text{UE}} \in \mathbb{C}^{N_{\text{UE}}}$, and the BS combines its N_{BS} antenna outputs into a single observation through $\omega_{\text{BS}} \in \mathbb{C}^{N_{\text{BS}}}$, where $|\omega_{\text{BS}}[q]| = 1$, $\forall q \in \{1, \dots, N_{\text{BS}}\}$, and $|\omega_{\text{UE}}[q']| = 1$, $\forall q' \in \{1, \dots, N_{\text{UE}}\}$.

In the adopted end-to-end model [10], each RIS element is a dipole whose resonance frequency is programmable, and the RIS is configured by tuning these resonance frequencies. Accordingly, the RIS configuration is $\mathbf{k} \in \mathbb{R}^{N_{\text{RIS}}}$ whose n -th

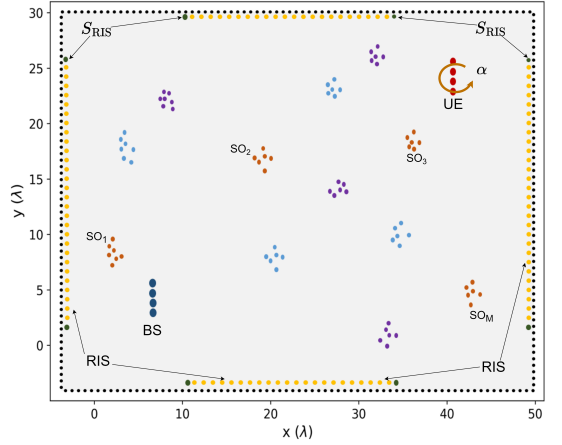


Fig. 1. Top view of the investigated RSE, modeled as a two-dimensional assembly of dipoles. The environment is represented by N_E dipoles: a stationary black dipole fence forms the enclosure boundary, and clusters of colored dipoles represent the M SOs, whose positions are drawn randomly in each realization; plum, orange, and cyan show the SOs positions for three such realizations. The BS, with N_{BS} antennas, is shown as blue dipoles, and the UE, with N_{UE} antennas, as red dipoles. The distributed uniform linear RIS installation, comprising N_{RIS} elements, is shown as yellow dipoles partially covering the four enclosure walls. Green dipoles indicate the subset of N_{RIS} hybrid reflecting-and-sensing elements used for environment sensing.

entry $[\mathbf{k}]_n = f_{\text{res},n}$ is continuously tunable, within the admissible range $[\mathbf{k}]_n \in [f_{\min}, f_{\max}]$, $\forall n \in \{1, \dots, N_{\text{RIS}}\}$, with $f_{\min}$ and $f_{\max}$ given in Table I.

A subset of S_{RIS} RIS elements at fixed positions is used for environment sensing [13], [37]. Following the hybrid reflecting and sensing RIS concept [13], each such element simultaneously reflects a portion of the impinging signal and couples the remaining portion, set by a non-zero splitting coefficient, to a reception RF chain at the RIS. The resulting measurements are conveyed to the BS over the same control link through which the RIS controller receives the configuration, so that the BS jointly processes the received pilots and the sensing measurements to estimate the SOs positions and to design the configuration for the next frame. The SOs positions at frame t are given by $\mathbf{p}^{(t)} \triangleq [(\mathbf{p}_1^{(t)})^T, \dots, (\mathbf{p}_M^{(t)})^T]^T \in \mathbb{R}^{2M}$, where $\mathbf{p}_m^{(t)} \in \mathbb{R}^2$, and the corresponding estimate is denoted $\hat{\mathbf{p}}^{(t)}$.

B. End-to-End Channel Modeling

As the rays in an RSE interact with the RIS elements repeatedly, the channel cannot be represented by a linear BS–RIS–UE cascade [12], [38]. We therefore adopt the physics based end-to-end model of [10], which represents each entity as a dipole assembly and captures mutual coupling, the amplitude-phase coupling of the RIS elements, and the long-range correlations induced by reverberation. Only the elements of [10] relevant to our study are summarized here.

The enclosure walls, the SOs, the RIS and the transceivers are modeled as dipole arrays. Let N_E be the number of dipoles representing the enclosure fence and the SOs, so that the total number of dipoles is $N = N_{\text{BS}} + N_{\text{UE}} + N_E + N_{\text{RIS}}$. The coupled

dipole system is governed by the $N \times N$ interaction matrix $\mathbf{W}$, whose i -th diagonal entry is the inverse polarizability $a_i^{-1}(f)$ of the i -th dipole and whose (i, j) -th off-diagonal entry is $-G_{ij}$, the negative of the two-dimensional free-space Green's function between the dipole positions $\mathbf{r}_i$ and $\mathbf{r}_j$, with

$$a_i(f) = \frac{\chi_i^2}{4\pi^2 f_{\text{res},i}^2 - 4\pi^2 f^2 + j(\gamma_i^R + 2\pi f \Gamma_i^L)}, \quad (1)$$

$$G_{ij}(\mathbf{r}_i, \mathbf{r}_j, f) = -j \frac{\kappa^2}{4\epsilon\delta} H_0^{(2)}(\kappa \|\mathbf{r}_i - \mathbf{r}_j\|), \quad (2)$$

where χ_i^2 scales the amplitude of $a_i(f)$, γ_i^R captures radiation damping, $\Gamma_i^L \geq 0$ is the absorptive damping term, $H_0^{(2)}(\cdot)$ is the zeroth-order Hankel function of the second kind, κ is the wavenumber, ϵ is the permittivity and δ is the dipole length.

The quantities of interest enter $\mathbf{W}$ through distinct mechanisms. By (1), the RIS configuration $\mathbf{k}^{(t)}$ sets the resonance frequencies, and hence the inverse polarizabilities $a_i^{-1}(f)$, of the RIS dipoles, which occupy the diagonal of $\mathbf{W}$. By (2), the SOs positions $\mathbf{p}^{(t)}$ determine the Green's functions, and hence the off-diagonal entries of $\mathbf{W}$. The UE is an array of N_{UE} dipoles whose local offsets $\{\delta_j\}_{j=1}^{N_{\text{UE}}}$ are fixed with respect to the UE center. For UE position $\mathbf{u}$ and orientation α , the global coordinate of the j -th UE dipole is $\mathbf{r}_j^{\text{UE}} = \mathbf{u} + \mathbf{R}(\alpha)\delta_j$, where $\mathbf{R}(\alpha) = [\cos \alpha \quad -\sin \alpha; \sin \alpha \quad \cos \alpha]$. Both $\mathbf{u}$ and α therefore enter $\mathbf{W}^{(t)}$ through the Green's functions in (2) that couple the UE dipoles to the BS and RIS dipoles, so that $\mathbf{H}_{\text{BS-UE}}^{(t)}$ depends on the full UE state $\mathbf{u}_e = [\mathbf{u}^\top, \alpha]^\top$. This dependence renders the UE position and orientation recoverable from the received pilots.

We therefore write $\mathbf{W}^{(t)} \triangleq \mathbf{W}(\mathbf{k}^{(t)}, \mathbf{p}^{(t)})$, where the arguments make explicit only the variables the BS actively designs, $\mathbf{k}^{(t)}$, and estimates online, $\mathbf{p}^{(t)}$, the UE position and orientation being the fixed unknown to be inferred, and define

$$\mathbf{V}^{(t)} \triangleq \text{diag}([a_1^{-1}, \dots, a_N^{-1}]) (\mathbf{W}^{(t)})^{-1}, \quad (3)$$

where the diagonal prefactor converts the solved dipole moments into the received fields [10]. Ordering the dipole indices as BS, UE, environment and RIS, the BS-UE channel is the corresponding sub-block of $\mathbf{V}^{(t)}$,

$$\mathbf{H}_{\text{BS-UE}}^{(t)}(\mathbf{k}^{(t)}, \mathbf{p}^{(t)}) = \mathbf{V}^{(t)}[(N_{\text{BS}} + 1) : (N_{\text{BS}} + N_{\text{UE}}), 1 : N_{\text{BS}}], \quad (4)$$

with $\mathbf{H}_{\text{BS-UE}}^{(t)} \in \mathbb{C}^{N_{\text{UE}} \times N_{\text{BS}}}$. Similarly, denoting by $\mathcal{S}$ the row index set of the S_{RIS} sensing dipoles, the channel between the BS and the sensing elements is given by,

$$\mathbf{H}_{\text{BS-S}}^{(t)}(\mathbf{k}^{(t)}, \mathbf{p}^{(t)}) = \mathbf{V}^{(t)}[\mathcal{S}, 1 : N_{\text{BS}}] \in \mathbb{C}^{S_{\text{RIS}} \times N_{\text{BS}}}. \quad (5)$$

The enclosure, the BS and the RIS remain static over the T frames of a localization request, whereas the SOs positions are updated at each frame. The M SOs move within the enclosure according to a Gauss-Markov mobility model. Let $\mathbf{p}_m^{(t)} \in \mathbb{R}^2$ and $\mathbf{v}_m^{(t)} \in \mathbb{R}^2$ denote the position and velocity of the m -th SO at frame t . The velocity evolves as $\mathbf{v}_m^{(t)} = \rho \mathbf{v}_m^{(t-1)} + (1 - \rho) \bar{\mathbf{v}} + \sqrt{1 - \rho^2} \sigma_v \mathbf{w}_m^{(t)}$, $\mathbf{w}_m^{(t)} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_2)$, followed by the position update $\mathbf{p}_m^{(t)} = \mathbf{p}_m^{(t-1)} + \mathbf{v}_m^{(t)}$, with reflection at the boundaries of the enclosure. Randomness of the channel stems from

the random SOs positions $\mathbf{p}_m^{(t)}$ as for the fixed geometry the channel is deterministic. The variation of $\mathbf{H}_{\text{BS-UE}}^{(t)}$ across frames is, therefore, structured and temporally correlated, which is exploited by the sequential design in Section III. The UE position and orientation are constant within a localization request.

C. Pilot Transmission and Reception

Assuming a narrowband system, upon a localization request the UE transmits a sequence of T known pilot symbols over T frames. Let $x^{(t)} \in \mathbb{C}$ be the pilot symbol at frame t . Since the UE and the BS each employ a single RF chain, the transmit beamformer $\omega_{\text{UE}}^{(t)}$ and the combiner $\omega_{\text{BS}}^{(t)}$ reduce each frame to a scalar observation at the BS given by,

$$y^{(t)} = (\omega_{\text{UE}}^{(t)})^H \mathbf{H}_{\text{BS-UE}}^{(t)}(\mathbf{k}^{(t)}, \mathbf{p}^{(t)}) \omega_{\text{BS}}^{(t)} x^{(t)} + w^{(t)}, \quad t \in \mathbb{Z}, \quad (6)$$

where $y^{(t)} \in \mathbb{C}$ and $w^{(t)} \sim \mathcal{CN}(0, \sigma^2)$. The observation therefore depends jointly on the UE and BS beamforming vectors and, through $\mathbf{H}_{\text{BS-UE}}^{(t)}$, on the RIS configuration.

In parallel, the BS senses the environment through the S_{RIS} sensing elements. As these are read individually at their reception RF chains, the sensing observation is given by,

$$\mathbf{y}_s^{(t)} = \mathbf{H}_{\text{BS-S}}^{(t)}(\mathbf{k}^{(t)}, \mathbf{p}^{(t)}) \omega_{\text{BS}}^{(t)} x^{(t)} + \mathbf{w}_s^{(t)}, \quad t \in \mathbb{Z}, \quad (7)$$

with $\mathbf{y}_s^{(t)} \in \mathbb{C}^{S_{\text{RIS}} \times 1}$ and $\mathbf{w}_s^{(t)} \sim \mathcal{CN}(\mathbf{0}, \sigma^2 \mathbf{I})$.

D. Problem Formulation

Our objective is to estimate the unknown UE position $\mathbf{u}$ and orientation α from the T received observations $[y^{(t)}]_{t=0}^{T-1}$, given the known BS and RIS locations, while the SOs positions are estimated online from the sensing measurements $[\mathbf{y}_s^{(\tau)}]_{\tau=0}^t$ collected at the S_{RIS} elements, so as to account for the scattering in the RSE. To this end, the BS designs the RIS configuration and the BS and UE beamforming vectors over the T frames to improve the terminal UE state estimate, through the mappings defined below.

The BS estimates the SOs positions at frame t from the accumulated sensing observations through the mapping $G^{(t)}(\cdot) : (\mathbb{C}^{S_{\text{RIS}}})^{t+1} \rightarrow \mathbb{R}^{2M}$,

$$\hat{\mathbf{p}}^{(t)} = G^{(t)}([y_s^{(\tau)}]_{\tau=0}^t), \quad (8)$$

where τ indexes the frames up to the current frame t .

Using the past pilot observations together with this estimate, the BS designs the configuration and beamforming vectors for the next frame through the mapping $F^{(t)} : \mathbb{C}^{t+1} \times \mathbb{R}^{2M} \rightarrow \mathbb{R}^{N_{\text{RIS}}} \times \mathbb{C}^{N_{\text{BS}}} \times \mathbb{C}^{N_{\text{UE}}}$,

$$(\mathbf{k}^{(t+1)}, \omega_{\text{BS}}^{(t+1)}, \omega_{\text{UE}}^{(t+1)}) = F^{(t)}([y^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}). \quad (9)$$

After T frames, the UE state is estimated through the mapping $Q : \mathbb{C}^T \times \mathbb{R}^{2M} \rightarrow \mathbb{R}^3$,

$$\hat{\mathbf{u}}_e^{(T)} = Q([y^{(t)}]_{t=0}^{T-1}, \hat{\mathbf{p}}^{(T-1)}). \quad (10)$$

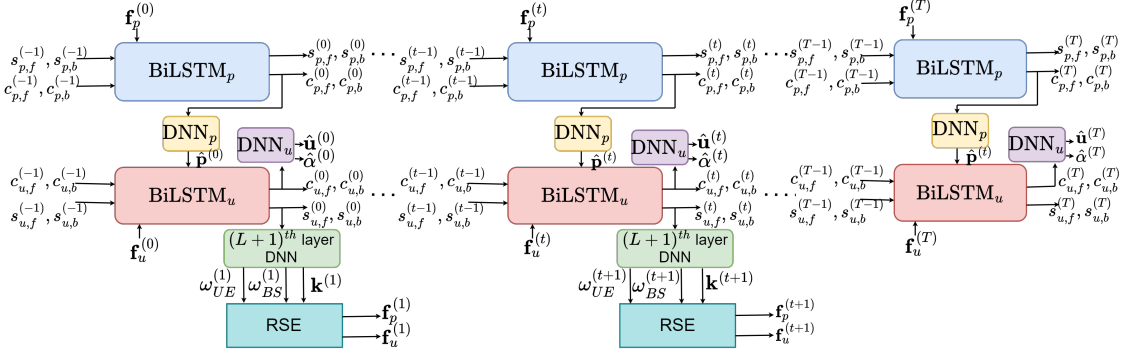


Fig. 2. Block diagram of the proposed UE localization approach with adaptive sensing in RIS-assisted RSE.

The design and estimation mappings are optimized to minimize the combination of the terminal UE position and orientation errors,

$$\min_{\{G^{(t)}, F^{(t)}\}_{t=0}^{T-1}, Q} \sqrt{\mathbb{E}[\|\hat{\mathbf{u}}^{(T)} - \mathbf{u}\|^2]} + \sqrt{\mathbb{E}[d_w(\hat{\alpha}^{(T)}, \alpha)^2]} \quad (11a)$$

$$\text{s.t.} \quad (8), (9), (10), \quad (11b)$$

$$[\mathbf{k}^{(t+1)}]_n \in [f_{\min}, f_{\max}], \quad \forall n, t, \quad (11c)$$

$$|[\omega_{\text{BS}}^{(t+1)}]_q| = 1, |[\omega_{\text{UE}}^{(t+1)}]_{q'}| = 1, \quad \forall q, q', t \quad (11d)$$

where $d_w(\hat{\alpha}, \alpha) = \min(|\hat{\alpha} - \alpha|, 2\pi - |\hat{\alpha} - \alpha|)$ accounts for the periodicity of the orientation. Constraint (11c) is the tuning range of the RIS elements, and (11d) the unit-modulus constraint of the analog phase shifters at the BS and the UE.

The analytical solution to (11) is difficult, as it involves the joint estimation of the UE location and orientation and the scattering, together with the joint design of the three vectors. Evaluating the exact objective requires a high-dimensional integration that is difficult to compute numerically. A common approach instead minimizes a surrogate metric at each frame, and the BCRLB has been suggested for this purpose [20]. We adopt a design driven by the conditional BCRLB, described in Section IV to treat the SOs as nuisance parameters, as an analytical benchmark, and solve (11) with the biLSTM based approach of Section III.

III. PROPOSED JOINT USER LOCATION AND ORIENTATION ESTIMATION WITH ENVIRONMENT SENSING SOLUTION

We propose a learning based adaptive approach that jointly designs the RIS configuration together with the BS and UE beamforming vectors to solve (11), comprising offline training specific to the RSE and online inference during deployment. At each frame t , the configuration $\mathbf{k}^{(t+1)}$ and the beamformers $\omega_{\text{BS}}^{(t+1)}, \omega_{\text{UE}}^{(t+1)}$ are designed from the measurement history $[\mathbf{y}^{(\tau)}]_{\tau=0}^t$ and the current SOs estimate $\hat{\mathbf{p}}^{(t)}$. As the number of measurements grows with t , a neural network compresses the past observations into a fixed dimensional representation.

The proposed two stage approach comprises a *scattering estimation* biLSTM, which estimates the time varying SOs positions from the S_{RIS} sensing measurements to characterize the RSE, and a *UE localization* biLSTM, which designs the configuration and beamforming vectors for frame $(t+1)$ from the estimated scattering and the UE pilot at frame t , so as to enable accurate localization at the final frame T . The architecture is shown in Figure 2.

A. Scattering Estimation BiLSTM

At each frame t , a biLSTM processes the sensing feature vector $\mathbf{f}_p^{(t)} = [|\mathbf{y}_s^{(t)}|, \angle \mathbf{y}_s^{(t)}] \in \mathbb{R}^{2S_{\text{RIS}}}$, formed by the magnitude and phase of the sensing observation, and updates its forward and backward hidden states $\mathbf{s}_{p,f}^{(t)}, \mathbf{s}_{p,b}^{(t)}$ and cell states $\mathbf{c}_{p,f}^{(t)}, \mathbf{c}_{p,b}^{(t)}$,

$$(\mathbf{c}_{p,f}^{(t)}, \mathbf{c}_{p,b}^{(t)}, \mathbf{s}_{p,f}^{(t)}, \mathbf{s}_{p,b}^{(t)}) = \text{BiLSTM}_p(\mathbf{f}_p^{(t)}, \mathbf{c}_{p,f}^{(t-1)}, \mathbf{c}_{p,b}^{(t-1)}, \mathbf{s}_{p,f}^{(t-1)}, \mathbf{s}_{p,b}^{(t-1)}), \quad (12)$$

where the superscript $(t-1)$ denotes the states carrying the information of the measurements before frame t . The biLSTM update rules follow [14].

The concatenated cell states are passed to a fully connected layer to estimate the SOs positions,

$$\hat{\mathbf{p}}^{(t)} = \text{DNN}_p([\mathbf{c}_{p,f}^{(t)}, \mathbf{c}_{p,b}^{(t)}]), \quad (13)$$

where $\text{DNN}_p(\cdot)$ is a trainable network. This realizes the mapping $G^{(t)}(\cdot)$ in (8).

B. UE Localization BiLSTM

At each frame t , a second biLSTM updates its forward and backward hidden states $\mathbf{s}_{u,f}^{(t)}, \mathbf{s}_{u,b}^{(t)}$ and cell states $\mathbf{c}_{u,f}^{(t)}, \mathbf{c}_{u,b}^{(t)}$ from the input $\mathbf{f}_u^{(t)} = [|\mathbf{y}^{(t)}|, \angle \mathbf{y}^{(t)}, \hat{\mathbf{p}}^{(t)}]$,

$$(\mathbf{c}_{u,f}^{(t)}, \mathbf{c}_{u,b}^{(t)}, \mathbf{s}_{u,f}^{(t)}, \mathbf{s}_{u,b}^{(t)}) = \text{BiLSTM}_u(\mathbf{f}_u^{(t)}, \mathbf{c}_{u,f}^{(t-1)}, \mathbf{c}_{u,b}^{(t-1)}, \mathbf{s}_{u,f}^{(t-1)}, \mathbf{s}_{u,b}^{(t-1)}), \quad (14)$$

with the state update rules as in [14].

The per-frame configuration and beamforming vectors for frame $(t+1)$ are designed from the states that summarize the measurements up to frame t only. The backward recursion of the biLSTM is evaluated only at the terminal frame T , where

Algorithm 1: Joint UE Location and Orientation Estimation with Environmental Sensing in RSE Algorithm

Input: Initial configuration $\mathbf{k}^{(0)}$, BS beamformer $\omega_{\text{BS}}^{(0)}$,
 UE beamformer $\omega_{\text{UE}}^{(0)}$.
Output: $\mathbf{k}^{(t+1)}, \omega_{\text{BS}}^{(t+1)}, \omega_{\text{UE}}^{(t+1)}, \hat{\mathbf{u}}^{(T)}, \hat{\alpha}^{(T)}$, trained
 $\text{BiLSTM}_p, \text{BiLSTM}_u, \text{DNN}_p, \text{DNN}_u$.

```

1 for  $t = 0$  to  $T - 1$  do
2   UE transmits pilot  $x^{(t)}$ ;
3   BS receives  $y^{(t)}$  and the  $S_{\text{RIS}}$  elements receive  $\mathbf{y}_s^{(t)}$ ;
4   Update  $\mathbf{s}_{p,\cdot}^{(t)}, \mathbf{c}_{p,\cdot}^{(t)}$  using (12);
5   Estimate  $\hat{\mathbf{p}}^{(t)}$  using (13);
6   Update  $\mathbf{s}_{u,\cdot}^{(t)}, \mathbf{c}_{u,\cdot}^{(t)}$  using (14);
7   Design  $\bar{\mathbf{k}}^{(t+1)}, \bar{\omega}_{\text{BS}}^{(t+1)}, \bar{\omega}_{\text{UE}}^{(t+1)}$  using (15);
8   Project onto feasible sets using (16);
9 Estimate  $\hat{\mathbf{u}}^{(T)}, \hat{\alpha}^{(T)}$  using (17);
10 return
     $\mathbf{k}^{(t+1)}, \omega_{\text{BS}}^{(t+1)}, \omega_{\text{UE}}^{(t+1)}, \hat{\mathbf{u}}^{(T)}, \hat{\alpha}^{(T)}, \text{BiLSTM}_p, \text{BiLSTM}_u,$ 
     $\text{DNN}_p, \text{DNN}_u;$ 

```

all T measurements are available, and is used to refine the terminal UE state estimate. The forward hidden state is passed through a fully connected Deep Neural Network (DNN) with L_n layers to produce an intermediate representation

$$\gamma^{(t)} = \beta_{L_n}(\mathbf{W}_{L_n} \beta_{L_n-1}(\dots \beta_1(\mathbf{W}_1 \mathbf{s}_{u,f}^{(t)} + \mathbf{b}_1) \dots) + \mathbf{b}_{L_n}), \quad (15)$$

where $\beta_l(x) = \max(0, x)$ is the ReLU activation and $\mathbf{W}_l, \mathbf{b}_l$ are trainable parameters.

Three output layers map $\gamma^{(t)}$ into the real RIS configuration and the complex BS and UE beamforming vectors,

$$\bar{\mathbf{k}}^{(t+1)} = \mathbf{W}_{L_n+1} \gamma^{(t)} + \mathbf{b}_{L_n+1}, \quad (15a)$$

$$\bar{\omega}_{\text{BS}}^{(t+1)} = \mathbf{W}_{L_n+1} \gamma^{(t)} + \mathbf{b}_{L_n+1}, \quad (15b)$$

$$\bar{\omega}_{\text{UE}}^{(t+1)} = \mathbf{W}_{L_n+1} \gamma^{(t)} + \mathbf{b}_{L_n+1}, \quad (15c)$$

where $\bar{\mathbf{k}}^{(t+1)} \in \mathbb{R}^{N_{\text{RIS}}}$ contains the RIS configuration, and $\bar{\omega}_{\text{BS}}^{(t+1)} \in \mathbb{R}^{2N_{\text{BS}}}, \bar{\omega}_{\text{UE}}^{(t+1)} \in \mathbb{R}^{2N_{\text{UE}}}$ contain the real and imaginary parts of the BS and UE beamforming vectors.

The outputs are projected onto their feasible range such that the RIS configuration entries are clipped to the tuning range, while the beamforming entries are normalized to unit modulus,

$$[\bar{\mathbf{k}}^{(t+1)}]_n = \min(f_{\text{max}}, \max(f_{\text{min}}, [\bar{\mathbf{k}}^{(t+1)}]_n)), \quad \forall n, \quad (16a)$$

$$[\omega_{\text{BS}}^{(t+1)}]_q = \frac{[\Re(\bar{\omega}_{\text{BS}}^{(t+1)})]_q + j[\Im(\bar{\omega}_{\text{BS}}^{(t+1)})]_q}{\sqrt{[\Re(\bar{\omega}_{\text{BS}}^{(t+1)})]_q^2 + [\Im(\bar{\omega}_{\text{BS}}^{(t+1)})]_q^2}}, \quad \forall q, \quad (16b)$$

$$[\omega_{\text{UE}}^{(t+1)}]_{q'} = \frac{[\Re(\bar{\omega}_{\text{UE}}^{(t+1)})]_{q'} + j[\Im(\bar{\omega}_{\text{UE}}^{(t+1)})]_{q'}}{\sqrt{[\Re(\bar{\omega}_{\text{UE}}^{(t+1)})]_{q'}^2 + [\Im(\bar{\omega}_{\text{UE}}^{(t+1)})]_{q'}^2}}, \quad \forall q'. \quad (16c)$$

This realizes the mapping $F^{(t)}(\cdot)$ in (9) and satisfies the constraints (11c) and (11d).

Finally, the UE state at frame T is estimated as

$$\hat{\mathbf{u}}_e^{(T)} = \begin{bmatrix} \hat{\mathbf{u}}^{(T)} \\ \hat{\alpha}^{(T)} \end{bmatrix} = \text{DNN}_u([\mathbf{c}_{u,f}^{(T)}; \mathbf{c}_{u,b}^{(T)}]), \quad (17)$$

where $\text{DNN}_u(\cdot)$ maps the concatenated terminal cell states to the UE position $\hat{\mathbf{u}}^{(T)}$ and orientation $\hat{\alpha}^{(T)}$, realizing the mapping Q in (10).

C. Loss Function

The composite loss combines root mean squared error (RMSE) for the terminal UE position and orientation with the SOs estimation RMSE. The position, orientation and the scattering estimation losses are

$$L_u = \sqrt{\mathbb{E}[\|\hat{\mathbf{u}}^{(T)} - \mathbf{u}\|^2]}, \quad (18a)$$

$$L_\alpha = \sqrt{\mathbb{E}[d_w(\hat{\alpha}^{(T)}, \alpha)^2]}, \quad (18b)$$

$$L_p = \sqrt{\mathbb{E}[\|\hat{\mathbf{p}}^{(T)} - \mathbf{p}\|^2]}. \quad (19)$$

Since only the terminal estimate at frame T is penalized, the network is free to explore different designs at earlier frames to minimize the final error. After training, the network produces the configuration and beamforming vectors directly from the received signals for any UE and S_{RIS} across the coverage region. The procedure is summarized in Algorithm 1.

IV. ANALYTICAL APPROACH FOR UE LOCALIZATION WITH ENVIRONMENT SENSING IN RSE

Analytical modeling of the UE localization problem with scattering estimation in RSE provides a benchmark for the proposed learning driven approach. The proposed learning driven approach addresses UE location and orientation estimation problem in (11) by estimating scattering in RSE in (8) and jointly optimizing the RIS configuration, BS and UE beamforming vectors mapping $\{F^{(t)}(\cdot)\}$ in (9) over t time frames, with the goal of reducing localization error. The computational cost of an exact multistage design grows with the number of time frames, and the exact conditional MSE is analytically intractable. Such modeling, therefore, requires a stage design that optimizes a tractable bound instead.

In this section we outline an analytical modeling approach devised on similar lines as [20], [31]. Rather than learning a direct mapping from the observations to the design variables, the mapping $F^{(t)}(\cdot)$ in (9) is decomposed into two consecutive mappings: from the accumulated observations to the conditional BCRLB, and from that bound to the RIS configuration and the beamforming vectors. At every time frame, the posterior distribution of the parameters is refined using the previously received pilots and sensing measurements, the conditional BCRLB is recomputed, and the design variables are selected so as to minimize it.

A. Problem Formulation

We assume that $\mathbf{u}_e$ and $\mathbf{p}$ are random vectors with known priors $f(\mathbf{u}_e)$ and $f(\mathbf{p})$, and define the augmented parameter vector

$$\boldsymbol{\theta} = [\mathbf{u}_e^\top \quad \mathbf{p}^\top]^\top \in \mathbb{R}^{3+2M}. \quad (20)$$

Using the observations $[\mathbf{y}^{(\tau)}]_{\tau=0}^t$ and $[\mathbf{y}_s^{(\tau)}]_{\tau=0}^t$, the goal is to design the next RIS configuration $\mathbf{k}^{(t+1)}$ and beamforming vectors $\boldsymbol{\omega}_{\text{BS}}^{(t+1)}$, $\boldsymbol{\omega}_{\text{UE}}^{(t+1)}$ while accounting for the scattering in the environment, so that the conditional mean square error (MSE) of the estimate of $\mathbf{u}_e$ is reduced. To this end, the optimization task in (11) is reformulated to be solved at each frame t as

$$\min_{G^{(t)}, F^{(t)}, Q} \quad \text{tr}(\boldsymbol{\Gamma}^{(t)}), \quad (21a)$$

$$\text{subject to} \quad \hat{\mathbf{p}}^{(t)} = G^{(t)}([\mathbf{y}_s^{(\tau)}]_{\tau=0}^t), \quad (21b)$$

$$(\mathbf{k}^{(t+1)}, \boldsymbol{\omega}_{\text{BS}}^{(t+1)}, \boldsymbol{\omega}_{\text{UE}}^{(t+1)}) = F^{(t)}([\mathbf{y}^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}), \quad (21c)$$

$$\hat{\mathbf{u}}_e^{(t)} = Q([\mathbf{y}^{(\tau)}]_{\tau=0}^t, \hat{\mathbf{p}}^{(t)}), \quad (21d)$$

$$[\mathbf{k}^{(t+1)}]_n \in [f_{\min}, f_{\max}], \quad \forall n, t, \quad (21e)$$

$$|[\boldsymbol{\omega}_{\text{BS}}^{(t+1)}]_q| = 1, \quad |[\boldsymbol{\omega}_{\text{UE}}^{(t+1)}]_{q'}| = 1, \quad \forall q, q', t, \quad (21f)$$

where

$$\boldsymbol{\Gamma}^{(t)} = \mathbb{E}[(\hat{\mathbf{u}}_e^{(t)} - \mathbf{u}_e)(\hat{\mathbf{u}}_e^{(t)} - \mathbf{u}_e)^\top | [\mathbf{y}^{(\tau)}]_{\tau=0}^t, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^t] \quad (22)$$

is the conditional error covariance matrix of $\mathbf{u}_e$, and $\hat{\mathbf{p}}^{(t)}$, $\hat{\mathbf{u}}_e^{(t)}$ denote the estimates of the SOs positions and the UE state at frame t .

Although the formulations in (11) and (21) are both adaptive, the latter designs a single time frame such that $F^{(t)}(\cdot)$ is optimized independently at each instant to minimize the conditional MSE at the immediately following stage, whereas (11) optimizes the sequence $\{F^{(t)}(\cdot)\}_{t=0}^{T-1}$ jointly over T frames. Computing $\boldsymbol{\Gamma}^{(t)}$ requires a high dimensional integration. We therefore adopt the conditional BCRLB as the design criterion, as it provides a parameter independent lower bound on the conditional MSE while incorporating the posterior information from prior measurements [39].

At the t -th frame, the joint Bayesian FIM is partitioned according to $\mathbf{u}_e$ and $\mathbf{p}$ as

$$\mathbf{J}^{(t)} = \begin{bmatrix} \mathbf{J}_{uu}^{(t)} & \mathbf{J}_{up}^{(t)} \\ \mathbf{J}_{pu}^{(t)} & \mathbf{J}_{pp}^{(t)} \end{bmatrix}, \quad (23)$$

with entries

$$[\mathbf{J}^{(t)}]_{i,j} = -\mathbb{E} \left[\frac{\partial^2 \log f(\mathbf{y}^{(t)}, \mathbf{y}_s^{(t)}, \boldsymbol{\theta} | [\mathbf{y}^{(\tau)}]_{\tau=0}^{t-1}, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^{t-1})}{\partial \theta_i \partial \theta_j} \right], \quad (24)$$

where θ_i and θ_j are any two components of $\boldsymbol{\theta}$ in (20), encompassing both the UE state and the SOs positions. The joint density factors by Bayes' rule into the posterior $f(\boldsymbol{\theta} | \cdot)$ and the conditional likelihoods of $\mathbf{y}^{(\tau)}$ and $\mathbf{y}_s^{(\tau)}$, and the expectation is taken with respect to this conditional distribution.

Since the SOs positions are unknown, they are treated as nuisance parameters and marginalized through the Schur

complement of (23), so that the conditional MSE of $\mathbf{u}_e$ is lower bounded by

$$\text{tr}(\boldsymbol{\Gamma}^{(t)}) \geq \text{tr} \left((\mathbf{J}_{uu}^{(t)} - \mathbf{J}_{up}^{(t)}(\mathbf{J}_{pp}^{(t)})^{-1} \mathbf{J}_{pu}^{(t)})^{-1} \right). \quad (25)$$

The design problem is therefore formulated as

$$\min_{F^{(t)}} \quad \text{tr} \left((\mathbf{J}_{uu}^{(t)} - \mathbf{J}_{up}^{(t)}(\mathbf{J}_{pp}^{(t)})^{-1} \mathbf{J}_{pu}^{(t)})^{-1} \right) \quad (26a)$$

$$\text{subject to} \quad (21c), (21e), (21f). \quad (26b)$$

The problem in (21) is addressed sequentially by repeatedly solving (26) across the T frames. Once all stages are completed, the mapping $Q(\cdot)$ in (21d) is realized by a maximum a posteriori estimator to produce the final estimate $\hat{\mathbf{u}}_e^{(T)}$.

B. BCRLB Calculation

The block partitioning in (23) and the Schur complement in (25), which marginalize the SOs positions as nuisance parameters, together with the formulation for MIMO end-to-end channel, are specific to the considered problem.

The joint Bayesian FIM in (24) is decomposed using Bayes' theorem as [20], [31]

$$[\mathbf{J}^{(t)}]_{i,j} = [\mathbf{J}_D^{(t)}]_{i,j} + [\mathbf{J}_P^{(t-1)}]_{i,j}, \quad (27)$$

where $\mathbf{J}_D^{(t)}$ is the incremental Bayesian information from the latest observation and $\mathbf{J}_P^{(t-1)}$ the information accumulated from prior observations and the prior of $\boldsymbol{\theta}$.

Conditioned on $\boldsymbol{\theta}$ and the past observations, the distributions of $\mathbf{y}^{(t)}$ and $\mathbf{y}_s^{(t)}$ are complex Gaussian, $\mathcal{CN}(\boldsymbol{\mu}^{(t)}(\boldsymbol{\theta}), \sigma^2)$ and $\mathcal{CN}(\boldsymbol{\mu}_s^{(t)}(\boldsymbol{\theta}), \sigma^2 \mathbf{I})$, with means given by (6) and (7) as

$$\boldsymbol{\mu}^{(t)}(\boldsymbol{\theta}) = (\boldsymbol{\omega}_{\text{UE}}^{(t)})^H \mathbf{H}_{\text{BS-U}}(\mathbf{k}^{(t)}, \mathbf{p}) \boldsymbol{\omega}_{\text{BS}}^{(t)} x^{(t)}, \quad (28a)$$

$$\boldsymbol{\mu}_s^{(t)}(\boldsymbol{\theta}) = \mathbf{H}_{\text{BS-S}}(\mathbf{k}^{(t)}, \mathbf{p}) \boldsymbol{\omega}_{\text{BS}}^{(t)} x^{(t)}. \quad (28b)$$

The entries of the incremental Bayesian FIM are obtained from the gradients of the means as

$$[\mathbf{J}_D^{(t)}]_{i,j} = \frac{2}{\sigma^2} \mathbb{E} \left[\Re \left\{ \frac{\partial \boldsymbol{\mu}^{(t)}(\boldsymbol{\theta})^*}{\partial \theta_i} \frac{\partial \boldsymbol{\mu}^{(t)}(\boldsymbol{\theta})}{\partial \theta_j} + \frac{\partial \boldsymbol{\mu}_s^{(t)}(\boldsymbol{\theta})^*}{\partial \theta_i} \frac{\partial \boldsymbol{\mu}_s^{(t)}(\boldsymbol{\theta})}{\partial \theta_j} \right\} \right], \quad (29)$$

where the expectation is taken with respect to the posterior $f(\boldsymbol{\theta} | [\mathbf{y}^{(\tau)}]_{\tau=0}^{t-1}, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^{t-1})$, and $\mathbf{y}^{(t)}$ and $\mathbf{y}_s^{(t)}$ are conditionally independent given $\boldsymbol{\theta}$ and the past observations. From (28), the gradients follow as

$$\frac{\partial \boldsymbol{\mu}^{(t)}(\boldsymbol{\theta})}{\partial \theta_i} = (\boldsymbol{\omega}_{\text{UE}}^{(t)})^H \frac{\partial \mathbf{H}_{\text{BS-U}}(\mathbf{k}^{(t)}, \mathbf{p})}{\partial \theta_i} \boldsymbol{\omega}_{\text{BS}}^{(t)} x^{(t)}, \quad (30a)$$

$$\frac{\partial \boldsymbol{\mu}_s^{(t)}(\boldsymbol{\theta})}{\partial \theta_i} = \frac{\partial \mathbf{H}_{\text{BS-S}}(\mathbf{k}^{(t)}, \mathbf{p})}{\partial \theta_i} \boldsymbol{\omega}_{\text{BS}}^{(t)} x^{(t)}. \quad (30b)$$

Since only the Green's functions in (2) depend on $\boldsymbol{\theta}$, the derivative of the interaction matrix $\partial \mathbf{W}^{(t)} / \partial \theta_i$ is available in closed form, with

$$\frac{\partial G_{ij}}{\partial \theta_i} = j \frac{\kappa^3}{4\pi\delta} H_1^{(2)}(\kappa d_{ij}) \frac{\partial d_{ij}}{\partial \theta_i}, \quad d_{ij} = \|\mathbf{r}_i - \mathbf{r}_j\|, \quad (31)$$

where $H_1^{(2)}(\cdot)$ is the first-order Hankel function of the second kind. Let U and S_m denote the index sets of the UE dipoles

and of the dipoles of the m -th SO cluster, respectively. The distance derivatives with respect to the estimated parameters are

$$\frac{\partial d_{ij}}{\partial \mathbf{u}} = \frac{\mathbf{r}_j^{\text{UE}} - \mathbf{r}_i}{d_{ij}}, \quad j \in U, \quad (32)$$

$$\frac{\partial d_{ij}}{\partial \alpha} = \frac{(\mathbf{r}_j^{\text{UE}} - \mathbf{r}_i)^\top \mathbf{R}'(\alpha) \delta_j}{d_{ij}}, \quad j \in U, \quad (33)$$

$$\frac{\partial d_{ij}}{\partial \mathbf{p}_m} = \frac{\mathbf{r}_j - \mathbf{r}_i}{d_{ij}}, \quad j \in S_m. \quad (34)$$

The channel derivatives then follow from the derivative of the matrix inverse,

$$\frac{\partial \mathbf{W}^{(t)}}{\partial \theta_i} = -\text{diag}[a_1^{-1}, \dots, a_N^{-1}] (\mathbf{W}^{(t)})^{-1} \frac{\partial \mathbf{W}^{(t)}}{\partial \theta_i} (\mathbf{W}^{(t)})^{-1}, \quad (35)$$

and $\partial \mathbf{H}_{\text{BS-U}} / \partial \theta_i$ and $\partial \mathbf{H}_{\text{BS-S}} / \partial \theta_i$ are obtained by extracting the corresponding sub-blocks of (35), as in (4) and (5). The prefactor $\text{diag}[a_1^{-1}, \dots, a_N^{-1}]$ depends on the dipole resonances, and hence on the design $\mathbf{k}^{(t)}$, not on θ ; only $\mathbf{W}^{(t)}$ is therefore differentiated in (35). Since $(\mathbf{W}^{(t)})^{-1}$ is already available from the channel evaluation, the gradients for all $3 + 2M$ parameters are obtained without any additional matrix inversion.

The elements of the FIM accumulated from the historical observations are

$$\begin{aligned} [\mathbf{J}_p^{(t-1)}]_{i,j} &= \sum_{t'=0}^{t-1} -\mathbb{E} \left[\frac{\partial^2 \log f(\mathbf{y}^{(t')} | \boldsymbol{\theta}, [\mathbf{y}^{(\tau)}]_{\tau=0}^{t'-1})}{\partial \theta_i \partial \theta_j} \right] \\ &+ \sum_{t'=0}^{t-1} -\mathbb{E} \left[\frac{\partial^2 \log f(\mathbf{y}_s^{(t')} | \boldsymbol{\theta}, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^{t'-1})}{\partial \theta_i \partial \theta_j} \right] \\ &- \mathbb{E} \left[\frac{\partial^2 \log f(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \right], \end{aligned} \quad (36)$$

where the summations over t' accumulate the information contributed by all measurements up to frame $(t-1)$, and the last term is the contribution of the prior.

By (27), only $\mathbf{J}_D^{(t)}$ depends on the design variables, through the means in (28). The design problem (26) is solved with the projected gradient descent method of [40], where each iterate is projected onto the feasible set, i.e., the RIS entries are clipped to $[f_{\min}, f_{\max}]$ as per the constraint in (21e), and the beamforming entries are normalized to unit modulus as per (21f). The posterior is updated recursively as

$$\begin{aligned} f(\boldsymbol{\theta} | [\mathbf{y}^{(\tau)}]_{\tau=0}^t, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^t, [\mathbf{k}^{(\tau)}]_{\tau=0}^t) = \\ L \cdot f(\mathbf{y}^{(t)}, \mathbf{y}_s^{(t)} | \boldsymbol{\theta}, \mathbf{k}^{(t)}) f(\boldsymbol{\theta} | [\mathbf{y}^{(\tau)}]_{\tau=0}^{t-1}, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^{t-1}, [\mathbf{k}^{(\tau)}]_{\tau=0}^{t-1}), \end{aligned} \quad (37)$$

where L is a normalization constant. The BCRLB based design is summarized in Algorithm 2.

V. PERFORMANCE EVALUATION

A. Simulation Setup

The simulation parameters are summarized in Table I. As in Figure 1, in the system model considered, the location of BS and the various distributed RIS installations are known and fixed. The UE locations $\mathbf{u}$ are generated uniformly within the

Algorithm 2: Greedy BCRLB based design for UE localization in RSE

Input : Priors $f(\mathbf{u}_e)$, $f(\mathbf{p})$; initial $\mathbf{k}^{(0)}$, $\omega_{\text{BS}}^{(0)}$, $\omega_{\text{UE}}^{(0)}$.

Output: Estimated UE state $\hat{\mathbf{u}}_e^{(T)}$.

- 1 **for** $t = 0$ to $T - 1$ **do**
- 2 Draw samples from the posterior
 $f(\boldsymbol{\theta} | [\mathbf{y}^{(\tau)}]_{\tau=0}^t, [\mathbf{y}_s^{(\tau)}]_{\tau=0}^t, [\mathbf{k}^{(\tau)}]_{\tau=0}^t)$ using (37);
- 3 Compute the mean gradients (30) via (31) and (35);
- 4 Compute $\mathbf{J}_D^{(t)}$ in (29) and $\mathbf{J}_P^{(t-1)}$ in (36);
- 5 Solve (26) by projected gradient descent to obtain
 $\mathbf{k}^{(t+1)}$, $\omega_{\text{BS}}^{(t+1)}$, $\omega_{\text{UE}}^{(t+1)}$;
- 6 **return** $\hat{\mathbf{u}}_e^{(T)}$ from the posterior via the Maximum a Posteriori (MAP) estimator in (21d);

TABLE I
NUMERICAL RESULTS PARAMETERS

Label	Dimension
Simulation Parameters	
M	2, 4, 6
N_{BS}	4
N_{UE}	4
N_{RIS}	20, 60, 100
S_{RIS}	2, 4, 6, 8
Transceivers dipole parameters	$f_{\text{res}} = 1$, $\chi = 0.5$, $\Gamma_L = 0$
Transceivers dipole spacing	$\lambda/2$
Environment and SOs dipole parameters	$f_{\text{res}} = 10$, $\chi = 50$, $\Gamma_L = 10^4$
Environment and SOs dipole spacing	$\lambda/4$
RIS dipole parameters	$f_{\text{res}} \in [f_{\min} = 0.8, f_{\max} = 1.2]$, $\chi = 0.2, \Gamma_L = 0.03$
RIS dipole spacing	$\lambda/4$
SOs motion parameters	$\sigma_v = 0.7\lambda$, $\rho = 0.85$, $\bar{\mathbf{v}} = \mathbf{0}$
Parameters of the biLSTM Network	
B	[32,64,128]
N_L	[2,4,6]
d_s	[25,35,45]
η	[0.001,0.01,0.005,0.05]
Maximum epochs	200
L_m	4

rectangular periphery in the x - y plane with spacing $\lambda/2$. The unknown orientation α of the UE is independently drawn from a uniform distribution over the interval $\alpha \in [0, 2\pi)$. The pilot signal $\mathbf{x}^{(t)}$ is a deterministic scalar set to unity for all time stages.

The initial positions $\{\mathbf{p}_m^{(0)}\}_{m=1}^M$ of SOs are drawn independently and uniformly over the enclosure in each simulation realization, and all SOs are updated simultaneously with mutually independent motion. Here $\bar{\mathbf{v}}$ is the mean drift, σ_v sets the per-frame step size, and $\rho \in [0, 1]$ is a persistence parameter that controls the temporal correlation of the scattering process such that $\rho \rightarrow 1$ yields smooth motion, whereas $\rho = 0$ reduces to independent continuous steps. The positions of the central dipoles in each SOs cluster are recorded in each simulation realization. The adjustable dipole parameters for transceivers, the environment including the SOs, and the RIS such as the resonance frequency (f_{res}), the charge term (χ) and the absorptive damping term (Γ_L), are set as in Table I [10].

B. Proposed and Baseline Approaches

The proposed approach for UE location and orientation estimation with environment sensing is implemented with the parameters settings given in Table I. Bayesian Optimization (BO) [41], [42] is used to tune the hyperparameters of the biLSTM networks before training by selecting the number of BiLSTM layers N_L , the hidden dimension d_s , the learning rate η , and the batch size B to balance localization accuracy and computational cost [14]. The dataset of 2,136,000 samples is partitioned into disjoint sets with 70% for training, 15% for validation, and 15% for test. The network is trained on the training set using the Adam optimizer [43] for 200 epochs. The training labels for scattering estimation biLSTM are of dimension $2M$ and for UE localization biLSTM are UE location and orientation. Network training is offline on simulated data of the target enclosure and online operation is one forward pass per frame. After training, the model autonomously selects a sequence of RIS configurations, BS and UE beamforming vectors using sequential scattering estimates and received pilot measurements at BS to accurately localize UEs within the coverage area.

The performance of the proposed approach is evaluated against the following benchmarks.

- *Adaptive design without scattering estimation* [31], [44]: A single recurrent network sequentially designs the BS beamforming vector and the RIS reflection coefficients from the accumulated pilot observations and reads out the UE state from its terminal representation, without a dedicated subset of sensing RIS elements and without an explicit scattering estimate. As [31], [44] considers a single-antenna UE in a LoS-dominated Rician channel, a UE beamforming vector and an orientation output are added so that all approaches are compared on the same estimation task over the same channel. The design principle, however, is as of approach in [31], [44].
- *Beamforming-free biLSTM network* [14]: The adaptive RIS configuration is designed over T time frames while accounting for scattering in the environment, without any BS or UE beamforming design. As [14] estimates the UE position only, it is extended here to also estimate the UE orientation, so that all approaches are compared on the same estimation task. The performance of the approach is quantified with the RMSE loss in location and orientation estimation as in (18) and scattering estimation as in (19).
- *BCRLB based design*: An analytical model is constructed using the conditional BCRLB as the optimization metric at every time frame, as derived in Section IV. At each frame t , the posterior distribution of the unknown UE state and SOs positions is refined using the previously received pilot and sensing measurements, which yields an updated conditional BCRLB. The RIS configuration $\mathbf{k}^{(t+1)}$ and the BS and UE beamforming vectors $\omega_{\text{BS}}^{(t+1)}$, $\omega_{\text{UE}}^{(t+1)}$ are then designed by projected gradient descent to minimize this bound. To determine the posterior distributions, the $30\lambda \times 50\lambda$ service region in the x - y plane is discretized into 300×500 grid cells, and the orientation α is discretized into 180 bins over $[0, 2\pi)$. The M SO

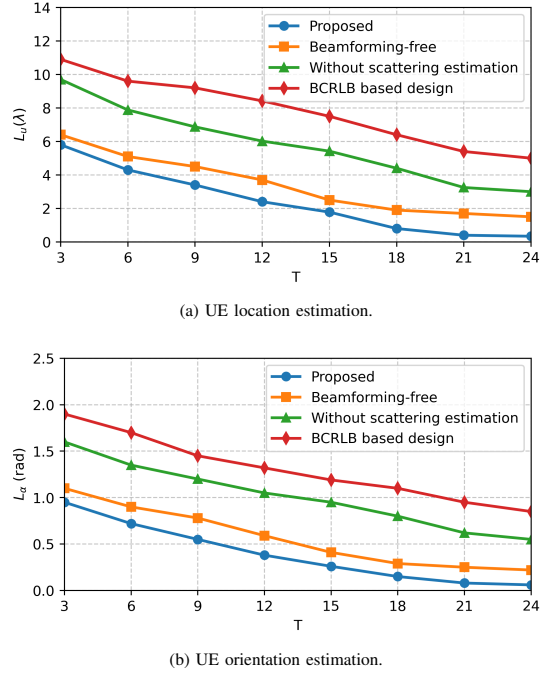


Fig. 3. RMSE of UE localization versus time frames T for $N_{\text{RIS}} = 100$, SNR = 30 dB and $M = 4$.

positions $\mathbf{p} = [\mathbf{p}_1^T, \dots, \mathbf{p}_M^T]^T$ enter the augmented parameter vector through their prior $f(\mathbf{p})$, taken as uniform over the service region. The performance is shown with the RMSE loss of location estimate obtained with the MAP estimation.

C. Results

We first study the UE localization performance against the number of time frames T in Figure 3. It is observed that the proposed approach has a consistently lower RMSE for UE location and orientation estimation against all benchmark approaches for all T . The performance of all approaches improves with T but the proposed approach outperforms both the beamforming-free design and the without scattering estimation design, which does not take into account the scattering in the environment.

It is also observed that the BCRLB based design is suboptimal relative to the learning-based approach in the RSE. This gap follows from the two design strategies. The proposed approach in (11) learns the adaptive policy $\{G^{(t)}(\cdot), F^{(t)}(\cdot)\}_{t=0}^{T-1}$, which estimates the scattering in the RSE and shapes the configuration vector across all t to minimize the RMSE of UE localization evaluated at the terminal frame T . In contrast, the BCRLB based design in (21) designs $G^{(t)}(\cdot), F^{(t)}(\cdot)$ greedily at each frame t , optimizing the per-frame BCRLB in isolation. The bound optimization is a nonconvex problem, thus, the designed beam vectors are suboptimal.

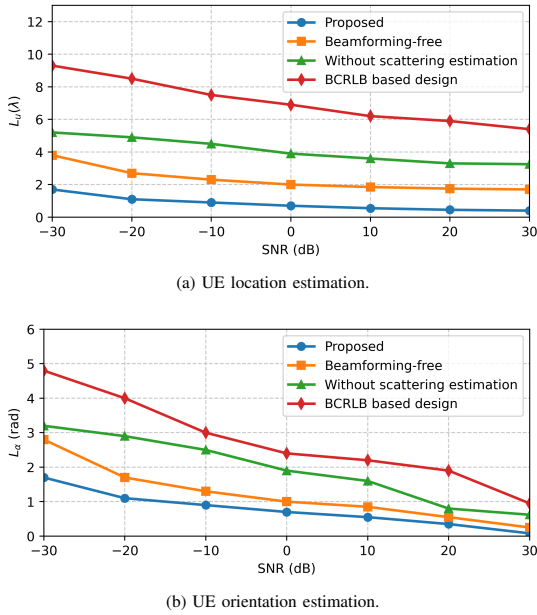


Fig. 4. RMSE of UE localization versus SNR for $N_{\text{RIS}} = 100$, $T = 21$ and $M = 4$.

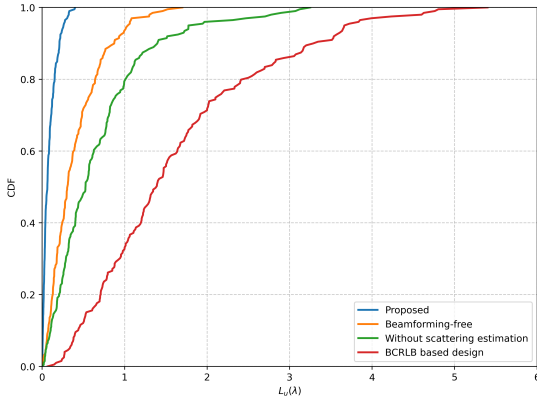


Fig. 5. CDF of the proposed and baseline approaches versus RMSE of UE localization for $N_{\text{RIS}} = 100$, $T = 21$, $\text{SNR} = 30\text{dB}$ and $M = 4$.

We examine the UE localization performance, quantified with (18), against SNR in Figure 4. The receive SNR is defined as $\text{SNR} = \mathbb{E}[|(\omega_{\text{UE}}^{(t)})^H \mathbf{H}_{\text{BS-UE}} \omega_{\text{BS}} x^{(t)}|^2] / \sigma^2$, i.e., the average received pilot power after combining relative to the noise power σ^2 . The proposed approach exhibits the lowest RMSE in the range of SNR compared to the other learning based and analytical benchmarks. This demonstrates the benefit of using the past measurements and the estimated scattering contribution of the RSE to design the UE and BS beamforming vectors and the RIS configuration for the next time frame.

Next, we analyze CDF of the UE localization error for

the proposed method and the baselines, as illustrated in Figure 5. The proposed approach achieves the most favorable distribution, with the majority of localization errors clustered at low RMSE values, reflecting strong accuracy and robustness. The beamforming-free and without scattering estimation designs also deliver competitive performance, though with slightly wider error dispersion. In comparison, the BCRLB based design performs significantly worse. Its more gradually increasing CDF curve reveals larger and more inconsistent localization errors. In general, these findings demonstrate that adaptive learning driven design approaches markedly improve localization accuracy, whereas non adaptive methods or adaptive solutions that neglect scattering effects lead to increased uncertainty in dynamic RSE scenarios.

We study the impact of distributed RIS deployment and the number of RIS elements on UE localization RMSE in Fig. 6, varying the RIS deployment across the walls of the system model in Fig. 1. The single-wall deployment in Fig. 6a yields the highest RMSE: the RIS illuminates the UE from a single direction, so the observations are spatially redundant and the UE is weakly observable despite the multipath propagation. Increasing the number of RIS elements raises the received signal power, but the single illumination direction limits the achievable accuracy. Mounting RIS panels on two walls, Fig. 6b, reduces the RMSE markedly, as illumination from independent directions supplies the BS with less redundant spatial information about the UE. Extending the deployment to three walls, Fig. 6c, provides near-surround coverage and a more pronounced RMSE reduction as RIS density increases. The four-wall deployment, Fig. 6d, attains the lowest RMSE overall through maximal spatial diversity. At large RIS densities the gains diminish, as the additional elements provide progressively less independent spatial information under the prevailing noise and scattering conditions.

We investigate the influence of the number of sensing RIS elements S_{RIS} on scattering estimation using the scattering-estimation biLSTM, with the SOs localization RMSE given by (19), in Fig. 7. The RMSE decreases consistently as S_{RIS} increases, across all considered time-frame lengths T . A larger S_{RIS} provides more independent sensing measurements per frame, improving the spatial sampling of the field and the observability of the SOs positions, which the network exploits to infer the underlying scattering. The RMSE also decreases with T for all S_{RIS} , as longer observation windows let the biLSTM exploit temporal correlations in the scattering process. For small S_{RIS} the reduction with T is gradual, as limited spatial sampling constrains the benefit of temporal averaging; for large S_{RIS} the combination of rich spatial measurements and extended temporal information produces a steeper RMSE decay and a lower overall error.

The impact of the number of SOs M on both UE and SOs localization is shown in Fig. 8. Increasing M raises the estimation RMSE across all considered SNR values for UE location, orientation, and SOs localization. As M grows, the number of coupled dipoles increases, which enlarges the set of jointly estimated parameters and strengthens the coupling in the interaction matrix $\mathbf{W}$. This reduces the separability of individual scattering contributions and elevates the uncertainty

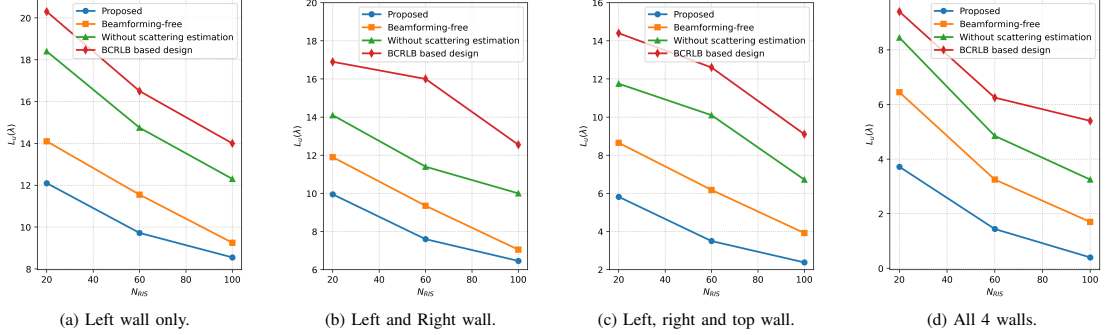


Fig. 6. RMSE of UE localization versus N_{RIS} under various distributed RIS installations with $\text{SNR}=30\text{dB}$, $T=21$, $M=4$.

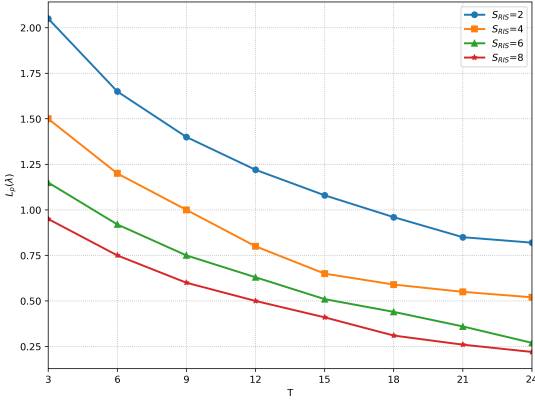


Fig. 7. RMSE of SOs localization versus time frames T for different number of S_{RIS} for $\text{SNR}=30\text{dB}$, $N_{\text{RIS}}=100$, $M=4$.

of the learning-based scattering estimation, and the resulting errors propagate to the subsequent UE localization. The effect is most pronounced at low SNR, where noise further obscures the scattering structure. For UE localization in Fig. 8a, the location RMSE increases with M . Higher SNR improves accuracy for all M , but the gap between scattering densities remains largely unchanged, so increased SNR alone does not compensate for the loss of spatial information under dense scattering. UE orientation in Fig. 8b follows the same trend, with additional SOs making the orientation harder to estimate. For SOs localization in Fig. 8c, the RMSE likewise increases with M , as stronger dipole coupling reduces the identifiability of individual SOs. Increasing SNR mitigates this degradation, with the rate of improvement decreasing at high SNR.

Overall, these results show that the proposed approach remains robust across the considered RSE conditions, with the localization and SOs sensing RMSE degrading gradually as the SOs density M increases. The degradation reflects the higher-dimensional, more strongly coupled estimation problem that dense scattering induces, and it is mitigated but not removed by higher SNR. These trends underline the role of adaptive RIS

configuration and explicit scattering estimation in sustaining reliable UE localization and SOs sensing under dense and dynamic RSE.

D. Complexity and Scaling

The online cost of the proposed approach is one forward pass of the biLSTM networks per frame, and is therefore linear in the number of frames. For a fixed hidden dimension, the per-frame cost grows only with the input and output widths, i.e., the observation dimension scales with the number of sensing elements S_{RIS} , and the design output with $N_{\text{RIS}} + N_{\text{BS}} + N_{\text{UE}}$. Enlarging the array or the surface, thus, widens the first and last layers of the controllers but leaves the recurrent structure, the training procedure, and the number of frames unchanged. Generating each observation requires one evaluation of the end-to-end channel, whose dominant cost is the $N \times N$ solve implied by $(\mathbf{W}^{(t)})^{-1}$ in (3) with $N = N_{\text{BS}} + N_{\text{UE}} + N_{\text{E}} + N_{\text{RIS}}$. This cost is intrinsic to the channel model rather than to the proposed design. Larger antenna arrays, surfaces, and number of SOs, therefore, affect the proposed approach only through the layer widths and this shared channel evaluation, indicating how it extends to larger-scale regimes and identifying the channel evaluation as the principal target for acceleration.

VI. CONCLUSION

This paper presents a learning-based approach for joint UE location and orientation estimation in a distributed RIS-assisted MIMO network operating in a dynamic RSE. A two-stage biLSTM controller senses the environment through a dedicated subset of RIS elements to estimate the positions of the non-cooperative SOs, and uses this estimate to sequentially design the RIS configuration and the BS and UE beamforming vectors, progressively focusing them onto the UE over the pilot sequence. As an analytical reference, a conditional BCRLB that marginalizes the SOs positions is derived. Simulation results across the considered SNR range, number of time frames, and distributed RIS deployment configurations show that the proposed approach consistently attains lower UE localization and orientation error than the beamforming-free design, the design without scattering estimation, and the BCRLB based

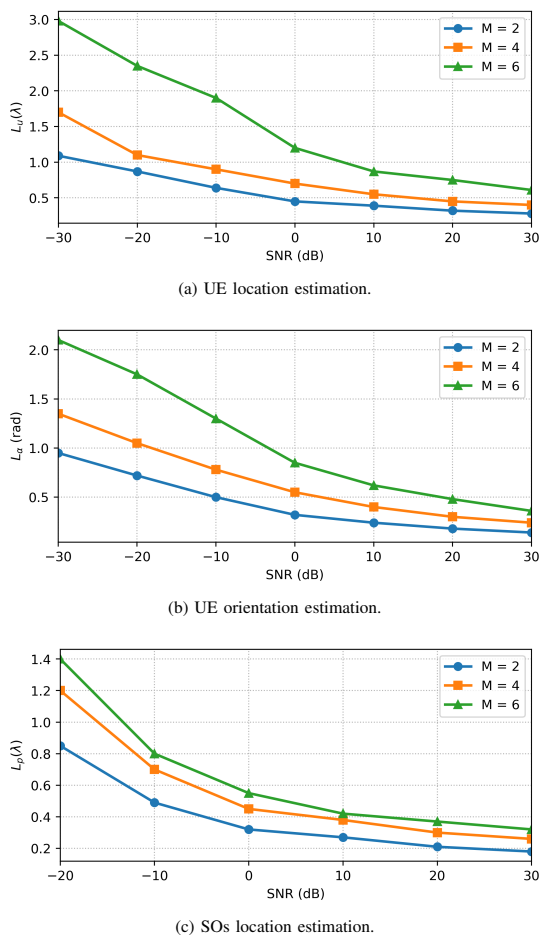


Fig. 8. RMSE of UE and SOs localization versus SNR for different number of SOs for $N_{\text{RIS}} = 100$, $T = 21$, $S_{\text{RIS}} = 8$.

design, and that this gain grows with the number and spatial diversity of the deployed RIS elements, confirming the benefit of explicit environmental sensing for accurate UE localization in dynamic RSEs. The approach is developed for a two-dimensional RSE and extension to three dimensions follows by replacing the two-dimensional Green's function with its three-dimensional counterpart, which enlarges the parameter and feature dimensions but leaves the coupled-dipole channel structure and the learning pipeline unchanged, and is left for future work.

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Curriculum Vitae

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2019–2022	National University of Sciences and Technology, Research Associate
2016–2018	National University of Sciences and Technology, Graduate Student Researcher

6. Computer skills

- Operating systems: Linux, Windows
- Document preparation: MS Office, LaTeX
- Programming languages: C++, Python,
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7. Defended theses

- 2017, Stochastic modeling and performance analysis of multi-tier HetNets, MS, supervisor Prof. Ali Hassan, National University of Sciences and Technology.

8. Field of research

- Wireless communications

9. Scientific work

Papers

1. A. Umer, I. Mürsepp, and M. M. Alam, "Integrated Sensing, User Location and Orientation Estimation in RIS-Assisted Dynamic Rich Scattering Environment," *IEEE Transactions on Wireless Communications (Under review)*, 2026
2. A. Umer, I. Mürsepp, and M. M. Alam, "Adaptive RIS Configuration Design With Environmental Sensing for User Localization in Dynamic Rich Scattering Environment," *IEEE Transactions on Mobile Computing*, vol. 25, no. 7, pp. 9770–9783, 2026
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Conference presentations

1. A. Umer, I. Mürsepp, and M. M. Alam, "Reconfigurable Intelligent Surfaces in Dynamic Rich Scattering Environments: BiLSTM-Based Optimization for Accurate User Localization," in *2024 3rd International Conference on 6g Networking (6gNet)*, pp. 122–126, 2024, Paris

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