DOCTORAL THESIS

Urban Traffic: Data Fusion and Vehicle Flow Prediction in Smart Cities

Chahinez Ounoughi

TALLINNA TEHNIKAÜLIKOOL
TALLINN UNIVERSITY OF TECHNOLOGY
TALLINN 2024

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DOCTORAL THESIS
8/2024

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TALTECH PRESS

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The dissertation was accepted for the defense of the Doctor of Philosophy (Computer Science) degree on 19 February 2024

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Defence of the thesis: 12 March 2024, Tallinn

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 any academic degree elsewhere.

Chahinez Ounoughi ______________________
signature

ISSN 2585-6898 (publication)
ISBN 978-9916-80-115-4 (publication)
ISSN 2585-6901 (PDF)
ISBN 978-9916-80-116-1 (PDF)
DOI https://doi.org/10.23658/taltech.8/2024
Printed by Koopia Niini & Rauam

Ounoughi, C. (2024). *Urban Traffic: Data Fusion and Vehicle Flow Prediction in Smart Cities* [TalTech Press]. https://doi.org/10.23658/taltech.8/2024

TALLINNA TEHNIKAÜLIKOOL
DOKTORITÖÖ
8/2024

Linnaliiklus: andmete ühtesulamine ja sõidukite voo prognoosimine nutikates linnades

CHAHINEZ OUNOUGHI

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List of Publications

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

I C. Ounoughi and S. Ben Yahia. Sequence to sequence hybrid bi-lstm model for traffic speed prediction. *Expert Systems with Applications*, 236:121325, 2024

II C. Ounoughi, G. Touibi, and S. B. Yahia. Ecolight: Eco-friendly traffic signal control driven by urban noise prediction. In C. Strauss, A. Cuzzocrea, G. Kotsis, A. M. Tjoa, and I. Khalil, editors, *Database and Expert Systems Applications*, pages 205–219, Cham, 2022. Springer International Publishing

III C. Ounoughi and S. Ben Yahia. Data fusion for its: A systematic literature review. *Information Fusion*, 89:267–291, 2023

IV C. Ounoughi, D. Ounoughi, and S. B. Yahia. Ecolight+: a novel multi-modal data fusion for enhanced eco-friendly traffic signal control driven by urban traffic noise prediction. *Knowledge and Information Systems*, July 2023

Author’s Contributions to the Publications

Contribution to the papers in this thesis are:

I The author of this thesis is the lead author of this article (first author and corresponding author), responsible for the majority of the article content, including data collection, data analysis, implementation and evaluation of the approach, and manuscript writing.

II The author of this thesis is the lead author of this article (first author and corresponding author), responsible for the majority of the article content, including data collection, data analysis, implementation and evaluation of the approach, and manuscript writing.

III The author of this thesis is the lead author of this article (first author and corresponding author), responsible for the majority of the article content, including reviewing all the articles, evaluating their relevance, methodology, findings, and manuscript writing.

IV The author of this thesis is the lead author of this article (first author and corresponding author), responsible for the majority of the article content, including data collection, data analysis, implementation and evaluation of the approach, and manuscript writing.

Other Publications

The author has contributed to other publications during her studies at Tallinn University of Technology.

V K. Katsarou, C. Ounoughi, A. Mouakher, and C. Nicolle. Stcms: A smart thermal comfort monitor for senior people. In *2020 IEEE 29th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE)*, pages 187–192, 2020

VI C. Ounoughi, T. Yeferny, and S. Ben Yahia. Zed-tte: Zone embedding and deep neural network based travel time estimation approach. In *2021 International Joint Conference on Neural Networks (IJCNN)*, pages 1–10, 2021

VII C. Ounoughi, A. Mouakher, M. I. Sherzad, and S. Ben Yahia. A scalable knowledge graph embedding model for next point-of-interest recommendation in tallinn city. In S. Cherfi, A. Perini, and S. Nurcan, editors, *Research Challenges in Information Science*, pages 435–451, Cham, 2021. Springer International Publishing

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1 Introduction

Traffic congestion is a widespread problem that extends beyond geographical boundaries, impacting communities globally and significantly influencing society. The 2021 Urban Mobility Report conducted by the Texas A&M Transportation Institute unveils the alarming repercussions of congestion within the United States, exposing significant time wastage and the depletion of billions of gallons of fuel, which inflict substantial economic losses on the nation [48]. Similarly, the INRIX Global Traffic Scorecard offers a glimpse into the economic toll of congestion in Europe, revealing an estimated cost of 166 billion euros in 2019. This staggering figure underscores the magnitude of the problem [45]. However, the detrimental consequences of traffic congestion extend well beyond their financial implications. One of the most concerning effects is the degradation of air quality, which poses a significant risk to public health and the environment. According to the World Health Organization, outdoor air pollution, primarily driven by congested roadways, contributed to an alarming 4.2 million premature deaths globally in 2016 [57]. Such harmful impacts on human well-being highlight the urgent need to tackle traffic congestion as a critical public health concern.

The increased congestion on the road networks also compromises safety, which makes it a leading cause of accidents and injuries. The congestion-induced delays, frustration, and impatience experienced by drivers often lead to risky behaviors such as speeding, reckless maneuvering, and impaired decision-making, increasing the likelihood of accidents. Shockingly, statistics from the World Health Organization reveal that approximately 1.35 million lives are tragically lost on roads globally each year, with traffic accidents emerging as a pressing public safety issue [57]. These multifaceted consequences of traffic congestion underline the imperative to develop comprehensive strategies and innovative solutions to alleviate this global challenge. Efforts to mitigate congestion not only hold the potential to enhance mobility and alleviate economic losses but also address critical issues such as air pollution, public health, and road safety. By addressing congestion, we can forge a path toward sustainable cities that prioritize the well-being of their inhabitants and safeguard the environment for future generations.

In addressing the urgent problem of traffic congestion, the advent of traffic management systems has offered a promising solution, utilizing state-of-the-art technologies to usher in a fresh era of smart and effective traffic control. While these traditional systems have made notable contributions, they need to be improved due to their inherent limitations in capturing the dynamic nature of real-time traffic conditions, primarily due to their heavy reliance on historical data and rigid traffic models. Recognizing the need for more accurate and responsive solutions, recent research endeavors have focused on integrating intelligence within traffic management systems to outperform traditional methodologies' boundaries and unlock traffic congestion mitigation and management's full potential. By embracing the power of machine learning algorithms, deep learning-based approaches can revolutionize traffic management by leveraging vast amounts of historical data and additional information sources. This integration empowers the system to discern intricate patterns and hidden relationships, making more informed and precise predictions about future traffic conditions [59]. Unlike their traditional counterparts, these innovative approaches can adapt to and learn from evolving traffic dynamics, offering a dynamic and responsive framework for intelligent traffic management.

Integrating deep learning-based approaches into intelligent transportation systems (ITS) represents a major shift in traffic management, offering the potential to overcome traditional limitations. These approaches utilize neural networks to uncover intricate traffic patterns, adapt to changing conditions, capture temporal dependencies, and reveal non-linear relationships that were previously elusive [50]. Incorporating real-time data sources like live traffic feeds, weather updates, and social media trends, along with data fusion techniques that seamlessly blend diverse data types from different sources and capture a broader range of factors influencing traffic patterns, leads to more accurate and robust predictions [30, 37]. This holistic approach empowers authorities to make informed decisions, optimize traffic flow, and proactively address congestion. These advancements in deep learning promise a future with reduced congestion, improved travel efficiency, and an enhanced quality of life.

The effectiveness of deep learning models in addressing traffic congestion has been extensively validated through various empirical studies. For instance, a study published in the IEEE Transactions on Intelligent Transportation Systems investigated the performance of deep learning models in traffic flow prediction and found that they surpassed traditional models, exhibiting superior accuracy and precision [33]. Another study highlighted the remarkable advantages of a deep learning-based approach to traffic signal control. This approach reduced travel time and mitigated delays, enhancing efficiency and improving traffic conditions [20]. These empirical findings underscore the immense potential of deep learning models for tackling traffic congestion and optimizing traffic management strategies. As the field continues to evolve, further research and development efforts are needed to refine and enhance these models, address potential challenges, and explore innovative applications.

The practical application of deep learning models in traffic management introduces substantial technical challenges that warrant meticulous examination [51]. At the forefront of these challenges lies the intricate issue of data privacy. Integrating diverse data sources necessitates handling sensitive information, compelling us to strike an intricate balance between data utilization for enhanced traffic management and robust privacy protection mechanisms. Achieving this equilibrium is vital for building public trust and ensuring compliance with stringent data protection regulations such as GDPR, which demand meticulous data handling. Another significant challenge is the substantial amount of data required to train and fine-tune deep learning models effectively. Collecting and curating large-scale datasets can be resource-intensive and time-consuming [35]. Moreover, maintaining the quality and representativeness of the data is crucial to preventing biases and inaccuracies during the training process, which can lead to skewed or unreliable results. Furthermore, the complexity inherent in deep learning models poses another obstacle, particularly regarding understanding and interpretability. These models often feature numerous parameters and intricate architectures, making it difficult to comprehend their decision-making processes. Addressing this complexity is essential to fostering trust among stakeholders, enabling transparency in the system's functioning, and facilitating the seamless integration of deep learning models into existing traffic management systems. In addition to the technical challenges mentioned earlier, implementing zero-touch systems in traffic management introduces additional complexity. One notable challenge is system robustness and adaptability without human intervention [16]. Designing and deploying algorithms and models capable of making autonomous decisions in real-time traffic scenarios while ensuring the system's reliability is a challenging task. The challenge lies in developing AI-driven systems that can effectively handle unforeseen and dynamic situations. These systems should be able to self-monitor, detect anomalies, and make informed decisions to optimize traffic flow, mitigate congestion, and respond to emergencies without human intervention.

Future research in traffic management should focus on developing advanced deep-learning models that prioritize privacy, can work effectively with smaller datasets, and incorporate mechanisms for transparency. Additionally, seamless integration with existing traffic management systems is essential for practical implementation and the transition to more efficient and sustainable transportation networks. These efforts aim to create robust, adaptable, and privacy-conscious deep learning solutions that enhance traffic management and reduce the need for human intervention.

In summary, combating worldwide traffic congestion necessitates exploring and deploying inventive strategies. Leveraging the capabilities of deep learning-based approaches and data fusion techniques within ITS holds the promise of revolutionizing traffic management. The rewards include enhanced traffic flow, decreased congestion, and improved overall mobility. Nevertheless, sustained investment in research and development is indispensable to surmount hurdles related to data privacy, data prerequisites, and model intricacies. This commitment will enable us to unleash the complete potential of these cutting-edge methodologies and cultivate transportation networks that remain efficient and sustainable over the long term.

The thesis is thoughtfully arranged with a well-structured framework that includes several key chapters:

- **Chapter 2:** "Focus and Aim": This chapter introduces the research questions and presents the various publications that address these questions.
- **Chapter 3:** "Research Methodology": This chapter outlines the applied research methodology consistently employed throughout the study.
- **Chapter 4:** "Related Research": This chapter gives an overview of the related work regarding traffic prediction approaches and the data fusion techniques used in the field of ITS.
- **Chapter 5:** "Publication-specific Contributions": This chapter thoroughly explores the contributions conducted in each publication.
- **Chapter 6:** "Discussion of Challenges": This chapter comprehensively examines the challenges encountered during the research journey.
- **Chapter 7:** "Conclusion": The final chapter provides a concise summary of the thesis's key findings and contributions.

2 Focus and Aim

This Ph.D. thesis strives to tackle the prevalent and growing issue of traffic congestion in urban areas. Acknowledging the negative impact of congestion on various aspects of urban life, the main aim of this research is to enhance prediction accuracy and alleviate congestion by integrating diverse information from different sources. By utilizing advanced deep-learning architecture and data fusion techniques, this research seeks to transform the field of traffic management, contributing to more efficient and sustainable urban transportation systems. The various adverse effects of congestion on society, including extended travel times, increased fuel consumption, elevated environmental pollution, compromised public health, and financial losses, emphasize the pressing need to address the issue. To fill existing research gaps and address these challenges, this thesis seeks to answer two primary research questions as outlined in Section 2.1.

2.1 Research Questions

- **RQ.1**: Which are the suitable models, in terms of scalability, to improve traffic prediction accuracy?
  The first research question focuses on identifying models that can notably improve the accuracy of traffic predictions. Scalability is considered important due to the significant amount of real-time data produced in urban areas, which requires efficient processing. This research explores different scalable models to reveal strategies for handling traffic data's increasing volume and speed while ensuring high prediction accuracy. Finding models that achieve a balance between computational efficiency and prediction performance is seen as crucial for effective traffic congestion management.

- **RQ.2**: How can multimodal data fusion techniques aggregate heterogeneous information collected from different sources to improve prediction models accurately?
  The second research question dives into the domain of data fusion methodologies. With numerous data sources available, including traffic sensors, GPS data, weather reports, and social media updates, the seamless integration of diverse information becomes crucial for building accurate prediction models. This investigation aims to investigate and develop techniques capable of harmonizing data from various sources to improve the accuracy of traffic forecasting and management models. The primary goal of this research is to enhance the overall effectiveness and reliability of prediction models by leveraging the capabilities of diverse data sources.

The research questions have been addressed in four articles to accomplish the objectives of this thesis. These articles aim to comprehensively understand the latest approaches in traffic prediction and data fusion techniques. Each article contributes to the overall research goals by exploring different aspects of traffic congestion management and proposing innovative solutions.

Publication I, **"Sequence to Sequence Hybrid Bi-LSTM Model for Traffic Speed Prediction"**, directly addresses the first research question by proposing the "Grizzly" hybrid approach. An advanced sequence-to-sequence bidirectional long-short-term memory (Bi-LSTM) neural network model is combined with data preprocessing techniques in this method to improve the accuracy of traffic speed predictions. This publication provides valuable insights into improving traffic prediction accuracy by offering a scalable model capable of handling substantial data volumes efficiently. It shows how adding sequence-to-sequence architectures, data preprocessing methods (like normalization and embeddings), and bidirectional LSTM neural networks to ITS can be helpful. The approach effectively addresses non-linearity and large-scale time-series traffic data challenges.

Publication II, **"EcoLight: Eco-friendly Traffic Signal Control Driven By Urban Noise Prediction"**, addresses the first research question by focusing on scalability and efficient traffic control. This approach prioritizes scalability and efficient traffic control by optimizing cycle timing at road intersections to alleviate congestion and promote eco-friendliness. With real-time traffic data streams and a sequence-to-sequence long-short-term memory (SeqtoSeq-LSTM) prediction model combined with deep reinforcement learning, the study aims to improve the accuracy of traffic predictions. This research represents a comprehensive effort to advance traffic management systems' predictive capabilities and sustainability.

Publication III, **"Data Fusion for ITS: A Systematic Literature Review"**, partially addresses the second research question by conducting a systematic literature review on data fusion methods applied in ITS. This review explores the potential of data fusion for enhancing prediction models by aggregating varied information from different sources in traffic management applications. While not presenting a specific technique, the publication provides valuable insights, identifies research gaps, and outlines challenges in this field.

Publication IV, **"EcoLight+: A Novel Multi-Modal Data Fusion for Enhanced Eco-friendly Traffic Signal Control Driven by Urban Traffic Noise Prediction"**, builds upon previous research (Publications I, II, and III) and introduces innovative methodologies to extend the knowledge of traffic congestion management. It directly addresses the second research question by presenting the "EcoLight+" approach, which combines future noise predictions with a deep dueling Q-Network Reinforcement Learning algorithm. Additionally, it introduces a novel data fusion approach to enhance the LSTM-based noise prediction model by integrating heterogeneous data from multiple sources.

The four publications in this thesis align with the research questions and significantly contribute to the field. They introduce innovative models, such as the "Grizzly" hybrid approach and the "EcoLight" approach, specifically designed to enhance traffic prediction and control accuracy. Furthermore, these publications delve into data fusion techniques, combining diverse information from multiple sources. The systematic literature review provides a comprehensive overview of different data fusion methods in Intelligent Transportation Systems (ITS). Simultaneously, another publication introduces a novel data fusion approach to enhance the accuracy of the Long Short-Term Memory (LSTM)-based noise prediction model, thereby improving the overall accuracy of the EcoLight approach. These advancements in data fusion contribute to a better understanding of how different data sources can be effectively integrated to enhance prediction accuracy in the context of traffic management.

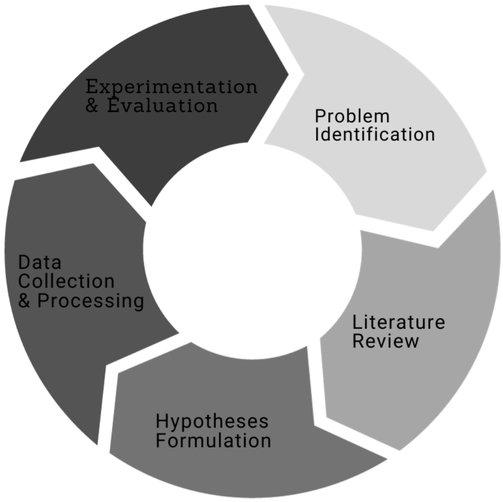

Figure 1: Applied Research Cycle.

3 Research Methodology

This thesis adopts the applied research methodology based on its effectiveness in addressing complex and practical issues, as supported by [14]. The selection of this methodology is driven by its capacity to systematically tackle the multifaceted challenges associated with predicting and managing urban traffic congestion, focusing on developing practical solutions for real-world problems [21]. Applied research follows a systematic cycle that involves problem identification, hypothesis formulation, experimentation, and the application of findings. By embracing this methodology, the study aims to derive actionable insights to enhance traffic flow, alleviate congestion, and contribute to the sustainable development of urban transportation systems [36]. Figure 1 provides an illustration of the applied research cycle used in this thesis.

This applied research methodology, widely employed in diverse fields, proves pertinent to ITS [24]. In the realm of traffic management, outcomes from applied research may manifest in diverse forms, including the development of predictive models, the formulation of traffic management strategies, or the implementation of data-driven techniques to alleviate congestion. This research methodology provides a robust framework for crafting and enhancing practical solutions to confront the persistent and complex issue of urban traffic congestion. Through this approach, the author aims to extract insights from existing traffic management practices, peer-reviewed studies, and other pertinent sources to formulate effective strategies for congestion mitigation.

To address the multifaceted challenges of urban traffic congestion, this thesis has undertaken three iterations of the applied research methodology cycle through four publications. Notably, publications [I, III] are published in high-impact Q1 journals, reflecting their substantial impact and rigorous evaluation. The inclusion of these respected journals underscores the importance of the presented research. Additionally, publication IV appears in a well-regarded Q2 journal. Publication II is presented as a notable feature in a prestigious international conference, accentuating the research's broad recognition and scholarly value. Cumulatively, these publications form a robust foundation for the findings and insights presented in this thesis, underscoring a dedication to academic excellence and real-world applicability.

Applied research encompasses various methods and techniques that can be used to investigate and address practical problems or questions in real-world contexts. Each selected publication in this thesis followed an applied research method tailored to the research questions and objectives. These methods were carefully designed to tackle the unique challenges and explore innovative traffic congestion prediction and management solutions. Table 1 presents the publications included in this thesis and their related research questions and methods employed.

Table 1: Publications, Research Questions, Research Cycle and Methodology

RQ.	Publication	Cycle	Methodology
RQ.1	I	1	**Experimental Research:** Development and evaluation of advanced deep learning algorithms for traffic speed prediction using real-world data.
	II	2	**Simulation and Modeling Research:** Implementation and evaluation of advanced deep reinforcement learning algorithms for traffic signal control management, utilizing real-world data in a simulated environment.
RQ.2	III	3	**Secondary Research:** Comprehensive analysis of existing literature through systematic review methods, focusing on ITS, to extract insights into data fusion techniques.
	IV	3	**Simulation and Modeling Research:** Integration of a Data Fusion approach and the Deep Dueling Q-Network Reinforcement Learning algorithm, followed by empirical evaluations using real-world data to address traffic congestion challenges.

The development of a novel AI model for predicting road segment speed in Publication I, utilizing real-world datasets, aligns with the principles of experimental research within applied science. This method involves creating, testing, and validating a model to address real-world problems, aiming to establish causal relationships and produce practical applications. Specifically, the methodology employs Python as the central programming language, with TensorFlow-Keras [1] serving as the primary deep learning framework. This strategic integration enables the construction and fine-tuning of prediction models. Simultaneously, the research in [II, IV] involving the proposal of a new traffic signal management system and experiments conducted using a simulation tool and real-world datasets fall within the realm of simulation and modeling in applied research. This approach allows for creating and analyzing models to study complex systems, providing a controlled environment to test and optimize the system's performance before potential real-world implementation. This research leverages tools like the SUMO (Simulation of Urban MObility) traffic simulator [31] to establish a controlled environment for testing and refining the proposed smart traffic signal models. Python and TensorFlow-Keras play a central role in constructing and fine-tuning models, ensuring compatibility with advanced neural network architectures. Lastly, the secondary research method was applied to synthesize and analyze existing data, research, and literature on data fusion techniques used in ITS. Operating within the category of secondary research, a systematic literature review contributes to understanding the current state of knowledge and informing practical solutions, policies, or interventions in the context of applied research. Each method contributes uniquely to the overarching goal of providing evidence-based insights and recommendations, ensuring a robust exploration of the congestion mitigation topic.

4 Related Research

This section provides an overview of related knowledge extracted from existing literature, establishing a foundation by synthesizing and summarizing the current state of knowledge in the field. It also emphasizes gaps and limitations in the existing literature relevant to the research questions introduced in Section 2. By identifying these gaps, the thesis aims to make a meaningful contribution to the knowledge base. The intention is to address these research gaps through original research, offering novel insights and solutions.

4.1 Traffic Prediction and ITS Management

A crucial research challenge is pursuing precise and efficient short- and long-term traffic prediction within ITS. This challenge is inherently tied to the issue of traffic congestion, a problem with widespread societal, governmental, and economic implications. To alleviate these challenges, researchers have dedicated efforts to developing traffic prediction methods utilizing extensive data on vehicle behavior, often collected through various technologies like loop detectors and radar systems. Despite advancements, existing models in this domain encounter a critical issue — the struggle to provide highly accurate predictions, especially when confronted with non-linear, multi-feature, and high-frequency traffic data at a large scale. The dynamic and ever-changing nature of traffic data, influenced by diverse factors such as road conditions, further complicates the accuracy of predictions. The research landscape reveals a pronounced gap concerning the limitations of current traffic prediction models, including parametric and non-parametric approaches. Parametric models like the Auto-Regressive Integrated Moving Average (ARIMA) exhibit historical significance but falter in handling non-linear traffic data and real-world traffic patterns due to their reliance on linear conditions [6]. On the other hand, non-parametric models, notably deep neural network architectures, offer flexibility in dealing with non-linear traffic data [50]. However, their effectiveness is hindered by inadequate analysis and pre-processing of dynamically changing traffic data patterns.

Accurately predicting traffic conditions within a road network is undoubtedly valuable, but the ultimate goal extends beyond forecasting. It entails taking timely and meaningful actions to shape traffic flow effectively and prevent congestion. Transitioning from prediction and detection to proactive management is the key to ITS and urban traffic control. Therefore, it is crucial to stress the significance of moving from foresight to action. To address this problem, urban planners and policymakers seek ways to enhance existing infrastructure since building new infrastructure is often slow and costly. One hypothesis presented is that improving the traffic light system can lead to better traffic management and, consequently, more peaceful urban areas [2]. Optimizing cycle timing at intersections can alleviate congestion and improve environmental quality. Real-time traffic signal control reduces congestion by responding to constantly changing traffic network dynamics. Moreover, the rapid growth in transportation needs poses challenges to sustainable development, including emissions and energy consumption caused by traffic. Noise pollution from road traffic significantly contributes to environmental and health problems, affecting around 100 million people in Europe. The World Health Organization (WHO) [57] has linked exposure to loud noise with health issues such as high blood pressure, hearing loss, heart disease, sleep disturbances, and stress.

Various traffic signal control strategies have been explored and categorized into fixed-time and traffic-responsive approaches. Fixed-time strategies rely on predetermined signal plans periodically adjusted based on historical traffic data, yet their effectiveness diminishes in the face of sudden traffic surges or disruptions. On the other hand, traffic-responsive strategies, incorporating real-time traffic information, have shown promise, especially with the integration of reinforcement learning techniques [26, 7, 56, 54, 55]. However, a noticeable research gap emerges — the lack of consideration for sustainability and proactivity in traffic signal control. These methods often prioritize current traffic conditions, neglecting long-term environmental impact and predictive capabilities. The identified research gap underscores the need for innovative solutions that integrate sustainable practices, addressing challenges such as noise pollution and CO2 emissions. Proactively anticipating future traffic congestion patterns becomes crucial, leading to developing more effective and environmentally conscious traffic signal control methods.

4.2 Data Fusion Techniques for ITS

The increasing need for reliable transportation networks has driven rapid advancements in ITS. The widespread deployment of communication technologies, including IP, Bluetooth, surveillance cameras, GPS, smartphones, loop detectors, magnetometers, radars, social media, and Vehicle to X (V2X), enables the continuous monitoring of traffic attributes, resulting in extensive databases of diverse traffic data [59, 8, 47, 53, 19, 15, 9]. These varied data sources offer insights into different traffic conditions and statistics, catering to various ITS applications such as vehicle navigation, incident detection, and traffic prediction, all aimed at enhancing safety and efficiency on the roads [10, 12, 27, 64, 3]. Nevertheless, challenges persist, particularly regarding real-time heterogeneous data and sensor reliability. Continuous data generation in inconsistent formats and diverse storage settings poses obstacles to direct usability [18]. Additionally, issues with sensor reliability, arising from technical and operational issues like locations or damages, introduce gaps and missing information, impacting decision-making for stakeholders. Addressing these challenges is crucial to enhancing the robustness and accuracy of ITS applications [59].

Multi-source Data Fusion (MDF) models have gained significant interest in response to these challenges. As an advanced technique, MDF combines information from multiple sources to yield more accurate results than individual sources can provide separately [4]. Bachmann et al. [5] investigated the efficiency of several data fusion algorithms (simple convex combination and Kalman filter) for fusing data from loop detectors and probe vehicles to gauge freeway traffic speeds accurately. Essien et al. [13] stated an improved traffic speed prediction model involving traffic-related variables and weather data fusion with the deep learning LSTM architecture. Lin et al. [29] —presented a unified probabilistic framework for traffic speed prediction based on fusing multi-source data, including location, textual traffic descriptions, and heterogeneous traffic-related data. Yang et al. [60] propose a hybrid deep learning structure for short-term traffic speed prediction involving external factors such as weather conditions and the air quality feature fusion to measure the impact of environmental factors. Shan et al. [49] used the multiple linear regression fusion models (MLR) to estimate missing traffic data by extracting the inherent spatio-temporal correlations from road segments to improve the performance of traffic speed prediction.

The challenges associated with data fusion techniques in ITS are diverse and complex. The accumulation of communication technologies has led to the extensive collection of traffic-related data to address transportation issues. Challenges include the difficulty in evaluating the effectiveness of methodologies due to the lack of standardized metrics and the non-uniform application of fusion methods across different ITS domains. The integration of traffic and environmental features, along with the need for comprehensive studies combining various methods, emerges as a key area for prospective research.

5 Publication-specific Contributions

The thesis presents conceptual and practical solutions, addressing the two primary research questions and concluding with four significant contributions.

5.1 Traffic Speed Prediction [I]

In this study, the author aims to tackle the challenge of achieving precise and efficient long-term traffic prediction within the framework of ITS. The need for advanced traffic prediction models is highlighted by challenges such as non-linearity, complex data, and high-frequency fluctuations in traffic dynamics. Current traffic prediction models face limitations (as mentioned in Section 4), as parametric models struggle with non-linear patterns, and non-parametric models, like deep neural networks, may lack accuracy due to inadequate analysis of dynamic traffic data. Bridging these gaps is essential for developing effective models that account for the complexity of real-world traffic conditions.

This research gap emphasizes a compelling need for holistic solutions to surmount parametric models' limitations and non-parametric models' challenges. These solutions should provide accurate predictions for large-scale, dynamic traffic data, enabling informed decision-making in ITS.

The core hypothesis of the study in Publication I posits that deep learning algorithms, renowned for their ability to model intricate traffic patterns, can further enhance their predictive performance through integration with complementary techniques such as recurrent neural networks (RNNs) and advanced data preprocessing methods. This integration is anticipated to improve traffic forecasting algorithms' accuracy and reliability significantly. By combining the pattern recognition capabilities of deep learning with RNNs' handling of temporal dependencies and advanced data preprocessing techniques, the resulting model is expected to empower stakeholders with accurate traffic predictions, ultimately benefiting traffic management and urban planning.

In response, the author introduces the Grizzly hybrid model, which uses sequence-to-sequence bi-directional long-short-term memory neural networks to predict traffic speed. The model incorporates advanced techniques to enhance traffic prediction accuracy, including data preprocessing, normalization, and embeddings. Figure 2 illustrates the architecture of the Grizzly approach, which consists of two main phases:

Figure 2 provides a high-level abstraction of the framework, while a more detailed overview is illustrated in Figure 2 in [40], involving three main phases:

- **Data preprocessing phase**: This phase involves encoding the input sequences for categorical and continuous features and applying normalization techniques to the continuous features.
- **Model training phase**: In this phase, the model learns the embedding of each categorical feature and integrates the resulting embeddings with the normalized continuous features. These combined features are then fed into a deep-stacked bi-directional LSTM architecture to predict future traffic sequences accurately.
- Prediction and Evaluation phase: Following the training, the model utilizes the learned parameters to make predictions on new data, and its accuracy is evaluated using different metrics.

The methodology involved experimenting with large-scale real-world datasets, namely PEMS-BAY and METR-LA [1], and comparing the performance of Grizzly against other time-

[1]PEMS-BAY and METR-LA datasets available at: `https://github.com/liyaguang/DCRNN`

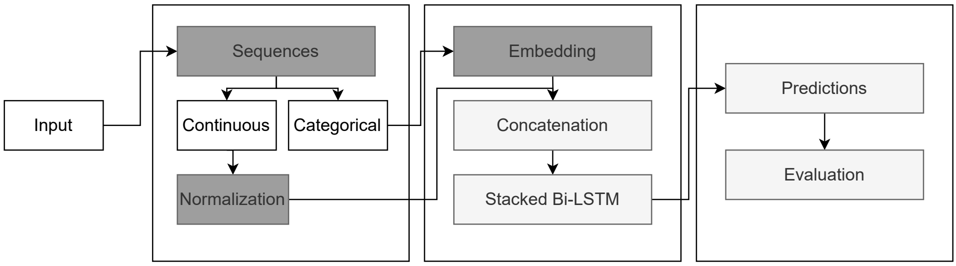

Figure 2: A high-level abstraction of the Grizzly framework.

series-based and hybrid neural network-based baselines (ARIMA, STGCN [62], DCRNN [28], GWNet [58], SLCNN [63]) using regression evaluation metrics such as mean absolute error (MAE) and root mean square error (RMSE). This rigorous evaluation allowed for a comprehensive assessment of the Grizzly hybrid approach and demonstrated its prediction and computation time accuracy.

The study's results highlight Grizzly's effectiveness in traffic speed prediction, consistently outperforming competitors. It substantially improves, with approximately 10.76% to 18.58% lower MAE and 2.92% to 15.40% lower RMSE, depending on the prediction task. Traditional models like ARIMA$_{\text{kal}}$ exhibit the poorest performance. Graph-based models, GWNet and SLCNN, offer practical alternatives, with performance dependent on dataset characteristics. With its embedded temporal features, Grizzly enhances its ability to capture temporal dependencies, particularly for smaller sequence sizes. Importantly, it proves efficient regarding training times, approximately three times faster than SLCNN. In summary, Grizzly presents a substantial improvement in traffic speed prediction, with superior prediction accuracy and impressive computational efficiency, offering a valuable asset for ITS. Through this publication, the author concludes the initial iteration of the applied research methodology cycle adopted in this thesis, spanning the entire process from problem identification to evaluation.

5.2 Eco-friendly Traffic Signal Control driven by Urban Noise Prediction [II]

The author introduces the invaluable task of accurately predicting traffic conditions in [Publication I]. However, the true objective surpasses mere forecasting, aiming to transition from prediction to proactive traffic management—a cornerstone for ITS and effective urban traffic control. In pursuit of this shift, Publication II posits a hypothesis of incorporating sustainable and proactive aspects into traffic signal control strategies. The system is proposed to reduce traffic congestion while effectively addressing environmental concerns. The "sustainable" aspect involves considering the environmental impact of transportation systems, such as noise pollution and CO2 emissions, and optimizing traffic signals to minimize these negative effects. The "proactive" aspect is achieved by implementing predictive models that anticipate future traffic congestion patterns. These models use real-time data and historical trends to forecast traffic conditions, enabling traffic signals to make informed and timely adjustments to manage traffic more efficiently and reduce congestion before it becomes a significant issue.

In response, the author delves into integrating Grizzly's (Publication I) predictive capabilities with dynamic traffic signal control. This integration facilitates real-time interventions, effectively alleviating congestion and enhancing urban traffic flow, thereby minimizing the impact of environmental emissions. The EcoLight approach represents a refinement in traffic signal control, utilizing deep reinforcement learning (RL) and innovative techniques to enhance the sustainability and efficiency of urban traffic management. This integration aimed to enhance the decision-making capabilities of the model and increase the environmental consciousness of the city's stakeholders by optimizing traffic signal control based on predictions of future noise levels. The proposed methodology aimed to go beyond traditional approaches and promote environmentally friendly practices. EcoLight focuses on predicting traffic noise levels using Grizzly's architecture. This prediction model significantly outperforms the traditional ARIMA model in forecasting future noise levels, demonstrating its effectiveness in enhancing predictive accuracy. Figure 3 shows a high-level representation of the EcoLight framework. This figure illustrates the process steps involved in one iteration, integrating the noise prediction model, deep reinforcement learning, and their application in optimizing traffic signal control. Figures 1 and 3 provide a more in-depth framework in [43].

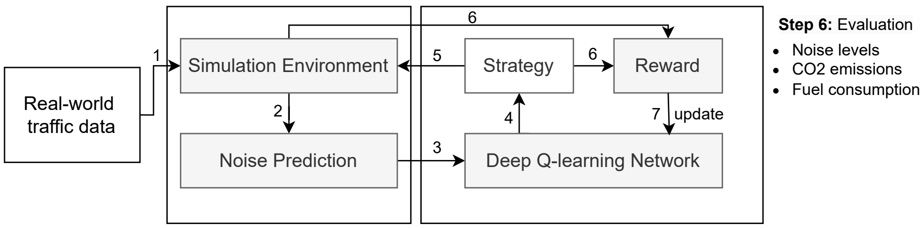

Figure 3: A high-level abstraction of the EcoLight framework.

The methodology involved experimenting with real-world data from Helsinki, Finland, ensuring a realistic assessment of its performance and comparing the performance of EcoLight against other baseline methods such as BASIC [31] (fixed-timing control), PETSSA [17], and IntelliLight [56] (Deep RL-based approach). The empirical evaluations demonstrated the effectiveness of EcoLight. In terms of noise prediction, it significantly outperforms the ARIMA model, substantially reducing Mean Absolute Error (MAE) from 65.89 to 1.15 and Mean Squared Error (MSE) from 4439.42 to 6.94 for the morning period. MAE drops from 2.31 to 1.07 for the evening period, and MSE decreases from 11.24 to 6.39. During the night, MAE is reduced from 72.94 to 1.62, and MSE is reduced from 5537.93 to 10.27. Regarding reducing traffic noise pollution, EcoLight outperforms the traditional BASIC and the advanced models PETSSA and IntelliLight. Moreover, the proposed approach showcases remarkable reductions in CO_2 emissions, with the BASIC model emitting 74,579,545.10 kg of CO_2, while EcoLight lowers this to 62,053,611.60 kg. It also significantly reduces fuel consumption, with the BASIC model consuming 32,925.02 liters and EcoLight lowering this to 26,675.58 liters. These results underscore the potential of the EcoLight approach to create more sustainable and eco-friendly urban transportation systems. While Publication II does not extensively discuss scalability, it offers valuable insights for developing scalable models. By leveraging real-time traffic data streams and reinforcement learning, the EcoLight system aims to address scalability challenges and efficiently manage traffic on a larger scale. Through this publication, the author concludes the second iteration of the applied research methodology cycle adopted in this thesis, spanning the entire process from problem identification to evaluation.

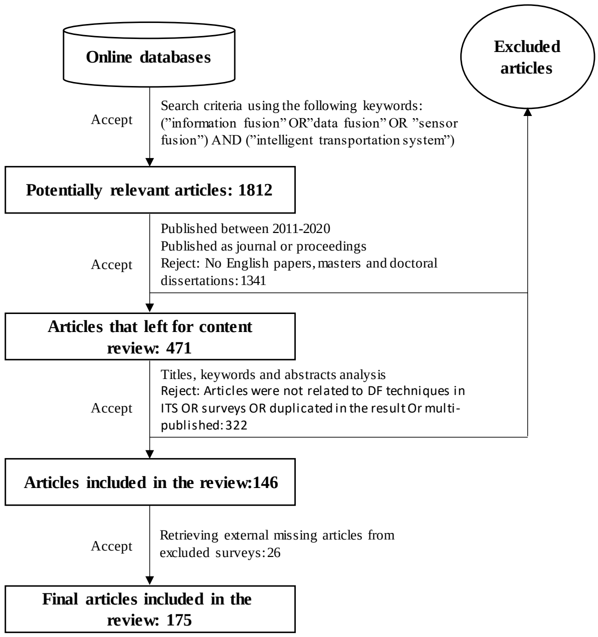

Figure 4: Research methodology of the review.

5.3 Data fusion for ITS [III]

Expanding on the groundwork established by the EcoLight approach (Publication II) for effective urban traffic management, the author conducted an investigation into the pivotal role of data fusion techniques in optimizing traffic management strategies. This systematic review aims to show how integrating diverse data sources can enhance traffic systems, mitigate congestion, promote sustainability, and elevate the overall quality of urban life. Addressing a critical gap in ITS, this research responds to the absence of a comprehensive study systematically exploring the landscape of data fusion techniques in the context of ITS applications. Conducting the review per established guidelines by Kitchenham [23], the author comprehensively searched and analyzed scholarly literature, focusing on multi-sensor data sources and their properties in various traffic domains.

Figure 4 illustrates this review's detailed secondary research method. This figure outlines the systematic approach taken during the review process, including the stages of literature search, selection criteria for articles, data extraction methods, quality assessment techniques, and the overall systematic review protocol. The study scrutinizes 175 articles utilizing data fusion in ITS applications, categorizing methods into probabilistic-based, evidence-reasoning-based, and knowledge-based approaches. Notably, the author observes a shift toward data-driven and knowledge-based methods. The review highlights the increasing interest in data fusion techniques incorporating relationships between traffic and environmental features. Assessing the effectiveness of these methodologies is challenging due to the varied evaluation methods, with real-world scenarios and simulation-based evaluations playing roles. With certain domains extensively investigated and others receiving comparatively less attention, exploring data fusion methods in ITS is unevenly distributed. As a noticeable outcome, the author presents a taxonomy of ITS applications in Figure 5, categorizing them into seven types based on their characteristics,

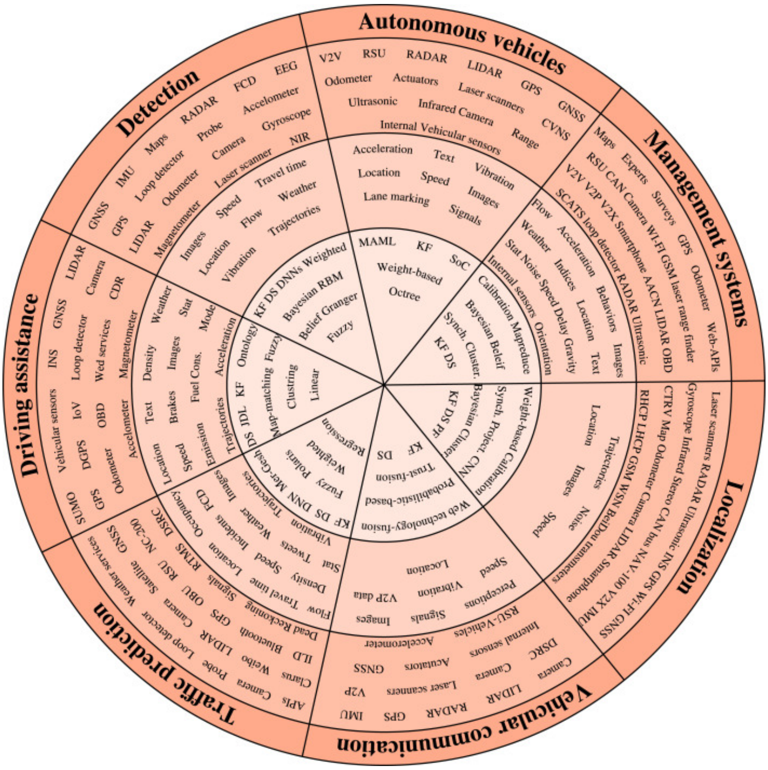

Figure 5: Taxonomy of Data Fusion for ITS applications.

data sources, features, and fusion models, offering a comprehensive overview within the realm of data fusion in ITS.

This comprehensive review adds significant insights into the current trends, challenges, and empirical discoveries within the realm of data fusion in ITS. The author not only identifies crucial methodological and empirical gaps but also proposes avenues for future research, emphasizing the exploration of secure and privacy-preserving data fusion in ITS applications. Furthermore, the review underscores the need for research that combines different data fusion methods, as existing publications predominantly focus on individual approaches. By consolidating these findings, the author highlights the escalating importance of data fusion in urban traffic management, connecting the innovative EcoLight approach to the broader landscape of data-driven solutions addressing urban mobility challenges. Through this publication, the author advances into the third iteration of the applied research methodology, specifically focusing on the literature review stage within the cycle.

5.4 Multi-modal data fusion for enhanced eco-friendly traffic signal control [IV]

Building on the insights from the findings in Publication III, the author undertook decisive action to enhance the system in Publication II. This improvement is manifested in EcoLight+, an advanced iteration of EcoLight that integrates a data fusion technique. EcoLight+ adopts a methodology that combines a Deep Dueling Q-Network Reinforcement

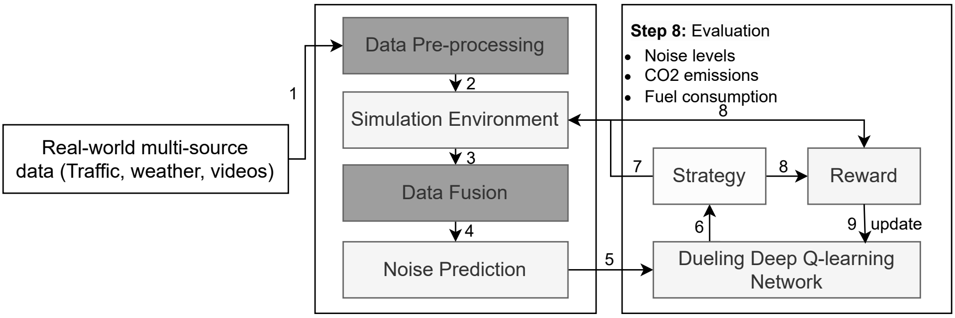

Figure 6: A high-level abstraction of the EcoLight+ framework.

Learning algorithm with a data fusion embedding-based approach. The goal is to enhance noise prediction and traffic signal control by integrating heterogeneous data from different sources. The approach is shown in Figure 6, which is a high-level diagram that shows how the approach's sustainable and proactive parts are added to the deep dueling Q-network for noise-driven traffic signal control along with the data fusion part.

In the empirical evaluations of EcoLight+, real-world data collected from various sources, including noise sensors, video cameras, weather data, and traffic-related features, was used to assess the efficiency of EcoLight+ against pioneering baselines. The experiments focused on the Tammsaare tee-Sõprus intersection in Tallinn, Estonia, and spanned various prediction intervals from 1 minute to 60 minutes. The methodology involves two critical data preprocessing steps (step 1 in Figure 6) to address reliability issues in the collected data. Firstly, the data exhibited gaps and missing information due to sensor reliability issues from technical and operational factors. To mitigate this concern, the KNN-imputation technique was employed to fill in the missing values in the dataset. Secondly, the YOLOv4 algorithm was utilized to detect and determine the number of each vehicle type (motorbike, car, bus, and truck) passing through the intersection in each video frame.

EcoLight+ demonstrated remarkable improvements in noise prediction, outperforming baseline models with a reduction in Mean Squared Error (MSE) of approximately 80% when compared to the absence of fusion techniques. This improvement signifies a substantial enhancement in the accuracy of predicting future noise levels in congested intersections. Regarding traffic signal control, EcoLight+ exhibited benefits over existing strategies. In particular, it reduced noise levels by over 74% and significantly decreased CO_2 emissions, up to 46.18% less compared to baseline models. Moreover, the approach led to an impressive reduction in fuel consumption, with vehicles consuming up to 69% less fuel, demonstrating its potential to create more eco-friendly and cost-efficient urban transportation systems. The potential annual savings, amounting to approximately 14.8 million U.S. dollars for a single intersection in Estonia, underscore the far-reaching implications of this research in addressing urban traffic challenges.

The publication acknowledges the need to extend the applicability of the EcoLight+ approach to real-world scenarios. While the current research focuses on a simplified case of a single intersection, the author highlights the complexity of real-world network design. Furthermore, future work is proposed to address multiple intersections by combining reinforcement learning agents. Additionally, with the growing popularity of electric vehicles, which are environmentally friendly and produce less noise, the authors suggest exploring a hybrid approach that incorporates traffic-related features to reduce delay times further and mitigate congestion levels. With this publication, the author brings the thesis research to a close, finalizing the third iteration of the applied research methodology cycle, covering the stages from the literature review, as conducted in Publication 3, to the evaluation phase.

The thesis encompasses a collection of publications, each employing tailored methods to address specific research questions and objectives. These methods span a scope of advanced techniques, including neural network models, reinforcement learning algorithms, systematic literature reviews, and data fusion methods. By embracing these approaches, the research aims to explore innovative solutions, subjecting them to rigorous empirical evaluations and thereby contributing valuable insights and problem-solving strategies in traffic congestion prediction and management.

By utilizing advanced neural network models, the publications harness the capabilities of deep learning to capture intricate traffic data patterns and relationships. Incorporating reinforcement learning algorithms enhances decision-making processes and optimizes traffic signal control systems. Systematic literature reviews systematically gather, synthesize, and analyze existing knowledge, identifying research gaps and unveiling emerging trends and challenges in ITS. Data fusion techniques play a pivotal role by integrating data from multiple sources, affording a comprehensive understanding of traffic conditions, and enabling precise predictions.

The application of these methodologies allows for the exploration of new avenues in traffic congestion prediction and management. The rigorous empirical evaluations conducted in each publication offer practical insights and serve as validation for the proposed methodologies. Consequently, this research pushes the field's boundaries, providing innovative solutions, addressing real-world challenges, and fostering the development of more efficient and sustainable transportation systems.

6 Discussion of Challenges

The publications discussed in this study have significantly contributed to traffic prediction and management. However, it is essential to acknowledge and address the limitations and challenges identified in these works. By understanding these limitations, future research can focus on overcoming these challenges and improving the proposed approaches.

One standard limitation observed across the publications is the difficulty in detecting outliers or trending events. Outliers, whether from gross errors or genuine anomalies in the data, pose a significant hurdle affecting the performance of prediction methodologies. Due to their infrequent occurrence within the training dataset, machine learning models often struggle to recognize and learn from these exceptional data points. Consequently, this limitation has a cascading effect on the accuracy and reliability of the predictions generated by these models. Simultaneously, addressing data drift is equally essential. Data drift involves changes in the statistical properties of the data used to train models over time [34]. In traffic prediction and management, data drift can result from various factors, including seasonal variations, infrastructure changes, behavioral shifts, and variability in data sources. Neglecting data drift can make models less accurate and relevant to evolving traffic conditions.

Recent research has proposed utilizing the Matrix Profile algorithm [61] to tackle this limitation effectively. This algorithm has shown immense promise in time series data analysis, particularly in identifying intricate patterns and anomalies that might otherwise go unnoticed [25]. By integrating automated outlier detection algorithms like the Matrix Profile into their methodologies, future studies stand to greatly enhance their models' ability to detect outliers across extensive and complex datasets. Effectively addressing outliers and data drift in traffic prediction and management requires a multifaceted approach. This includes using strict data preprocessing methods to find and deal with outliers, keeping an eye on model predictions and data patterns all the time, adaptive learning algorithms to make changes to the model on the fly, ensemble techniques to lessen the effect of outliers, retraining the model with data that includes outliers regularly, and using informed feature engineering to take into account both outliers and data drift. This comprehensive strategy ensures the resilience and precision of traffic management systems in urban environments, enabling them to handle unexpected events and evolving data patterns effectively. Incorporating such algorithms and techniques allows predictive models to adapt to both temporary and permanent alterations in the behavior of traffic features. This adaptability is crucial for ensuring the models remain accurate and reliable even when faced with unexpected events or irregular patterns.

Another limitation highlighted in publications II and IV on the simplified experimental setup underscores a notable challenge within traffic prediction and management. These publications, while valuable, have a narrow focus on a single intersection in a specific location, which does not comprehensively capture the intricacies of real-world urban traffic networks. In urban environments, traffic systems involve a multitude of intersections, each presenting unique characteristics and complexities. Future research endeavors must prioritize scalability and adaptability across more extensive and diverse urban networks to overcome this limitation. This entails extending the methodologies and models developed in these publications to manage multiple intersections effectively. One promising avenue involves the combination of several reinforcement learning agents capable of concurrently optimizing traffic signal control strategies for various intersections. Also, looking into hybrid approaches that combine the best parts of different algorithms and techniques can help the models better handle the many problems that come up in complicated traffic situations in cities.

Furthermore, it is imperative to address concerns related to hardware deployment and real-time performance in the context of traffic prediction and management systems. While the proposed models show promise in software-based simulations and implementations, it is very important to test how well and accurately they work when used on specialized hardware platforms like Field-Programmable Gate Arrays (FPGAs) or Ti-developed kits [11]. Uncertainties persist regarding the adaptability of these models to hardware-accelerated environments. Deploying these models on such platforms necessitates a comprehensive assessment of their computational efficiency, energy consumption, and real-time responsiveness. Future research endeavors should thus investigate the feasibility of migrating these models to hardware accelerators, measuring their performance against software-based implementations, and identifying potential advantages, such as improved computational speed and scalability. This exploration holds the potential to offer valuable insights into the practicality and viability of utilizing hardware-accelerated solutions in real-time traffic prediction and management scenarios. By bridging the gap between software simulations and hardware deployment, researchers can ascertain the true benefits of these models in terms of efficiency, responsiveness, and scalability, ultimately paving the way for more effective and robust traffic management solutions in dynamic urban environments.

Another significant limitation that warrants careful consideration is the generality of the proposed traffic signal control approaches. This limitation stems from the inherent requirement for a more extensive and varied dataset, encompassing diverse traffic scenarios and environments, to effectively deploy and assess the methodology. The approach's efficacy is intricately tied to the availability of comprehensive data from many sources in real-time [32]. However, gathering such heterogeneous data and ensuring timely transfer to the cloud is no small feat, often entailing substantial time and effort investments. The true power of the proposed approach lies in its adaptability across a spectrum of traffic conditions, each demanding unique insights and responses. Consequently, acquiring this breadth of data sources is essential for evaluating and fine-tuning the approach to diverse real-world scenarios.

Addressing this limitation calls for concerted efforts in several directions. Firstly, enhancing data collection infrastructure is imperative, encompassing the development of advanced sensors, data acquisition systems, and data storage solutions. Secondly, promoting collaborative data-sharing initiatives among various stakeholders, including traffic authorities, research institutions, and technology companies, can facilitate the accumulation of a more diverse dataset. Moreover, establishing standardized protocols for integrating heterogeneous data and sensors is pivotal. These protocols should streamline data harmonization, ensuring that information from various sources can be effectively combined and utilized. By addressing these challenges, the generalization of the traffic signal control approach can be substantially improved, rendering it more applicable and robust in real-world urban settings with their diverse and dynamic traffic conditions.

In conclusion, while the publications reviewed in this thesis have undeniably contributed to advancing traffic congestion prediction and management, they also bring to light several critical challenges. These challenges encompass the identification of outliers, scalability issues in complex urban networks, hardware deployment uncertainties, data source diversification, and the need for generalizing traffic signal control methods. To address these limitations and propel the field forward, future research endeavors should be directed towards the enhancement of outlier detection through advanced algorithms, the adaptation of solutions to handle intricate urban networks, the exploration of hardware deployment options for real-time performance, the integration of a wider array of data sources through data fusion techniques, and the establishment of robust data collection infrastructure. Such endeavors will undoubtedly lead to the development of more accurate, efficient, and sustainable traffic prediction and management systems, thereby improving urban transportation in the years to come.

7 Conclusion

The findings and contributions of this thesis have far-reaching implications for addressing the complex problem of traffic congestion in urban areas. By employing cutting-edge deep learning architecture and data fusion techniques, this research offers the potential to revolutionize urban transportation systems, making them more efficient and sustainable. The division of the study into two primary parts, focusing on traffic congestion detection and prediction as well as traffic light management, ensures a comprehensive approach to tackling congestion. The innovative approach for traffic speed prediction in road segments, utilizing advanced deep learning algorithms, enables real-time detection and proactive management of traffic congestion. Integrating heterogeneous data sources through data fusion techniques further enhances the accuracy and reliability of the prediction models, enabling more informed decision-making in traffic management. The systematic literature review in the field of ITS also gives useful information about the best ways to make predictions more accurate and proactive. This improves the methodology used in this thesis and helps us understand how to manage traffic congestion better overall.

Future research in this domain should focus on developing scalable models capable of handling traffic data's increasing volume and velocity in urban areas. Striking a balance between computational efficiency and prediction performance will be crucial in achieving real-time and effective traffic congestion management. Additionally, further advancements in data fusion techniques and exploring new approaches for integrating heterogeneous data sources will enhance the accuracy and reliability of prediction models, enabling more comprehensive and proactive traffic management strategies. The emergence of technologies such as the Internet of Things (IoT), edge computing, and artificial intelligence (AI) presents exciting opportunities for improving traffic congestion management. Leveraging real-time data from connected devices and utilizing AI algorithms for data processing and decision-making can significantly enhance prediction accuracy and enable dynamic and adaptive traffic control systems.

In conclusion, this Ph.D. thesis has made substantial progress in addressing the challenge of traffic congestion in urban areas. By incorporating advanced deep learning architecture, data fusion techniques, and a systematic literature review, a comprehensive and practical solution for traffic congestion management has been developed. The insights and findings from this research provide a solid foundation for future advancements in scalable models, data fusion techniques, and the integration of emerging technologies. By continuing to innovate in these areas, the work can achieve more efficient, sustainable, and livable urban environments.

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Acknowledgements

I am profoundly honored and sincerely grateful to express my heartfelt appreciation to all those who have played a significant role in my journey toward my Ph.D. This milestone was not without its challenges, especially considering the unprecedented circumstances imposed by the COVID-19 pandemic. Navigating uncharted territories and enduring prolonged periods away from home demanded resilience and adaptability. However, I am immensely grateful for the unwavering support, guidance, and encouragement that I have received from my supervisor, colleagues, friends, and family, who have been instrumental in overcoming these difficulties and succeeding in my studies.

First and foremost, I would like to extend my deepest gratitude to my supervisor, Sadok Ben Yahia, whose exceptional support, patience, and mentorship have been invaluable throughout my Ph.D. journey. Their expertise, dedication, and unwavering belief in my abilities have shaped my research and fostered my personal growth. Their consistent commitment to my success has been a constant source of motivation, pushing me to surpass my expectations.

I would also like to express my sincere appreciation to my colleagues and friends, who have been an indispensable source of camaraderie and support throughout this arduous journey. Their presence, friendship, and engaging intellectual discussions have motivated me to overcome challenges and persevere during the most demanding times. I am profoundly grateful for our collaborative environment, where we could exchange ideas, offer feedback, and mutually strive to reach new heights. To my beloved family, I owe an immeasurable debt of gratitude. Their unwavering love, encouragement, and belief in my abilities have been my rock throughout my academic pursuit. Despite the physical distance that separated us, their constant support, understanding, and sacrifices have allowed me to pursue my dreams. Even during the most challenging times, their enduring presence has given me the strength to persist and overcome obstacles.

I would also like to acknowledge the profound impact of the COVID-19 pandemic on my Ph.D. journey. The unprecedented circumstances presented significant challenges, including remote learning, limited resource access, and isolation from my academic community. However, the support and understanding of my supervisor and colleagues have helped me adapt to this new reality, enabling me to continue my studies and research despite the obstacles. Furthermore, I am deeply grateful to the university and its esteemed faculty members for providing me with a stimulating and conducive environment for learning and research. The institution's unwavering commitment to academic excellence and the availability of resources and state-of-the-art facilities have nurtured my intellectual growth and facilitated my research endeavors. I am genuinely thankful for the opportunities I have been granted and the platform provided to showcase and contribute to urban traffic management.

In conclusion, I extend my heartfelt thanks to everyone who has played a role in my success in achieving my Ph.D. Your unwavering support, guidance, and encouragement have been truly invaluable. I am profoundly grateful for the privilege of working with such exceptional individuals who have contributed to my academic growth and enriched my personal and professional journey. This significant accomplishment would not have been possible without your collective belief in me.

Abstract

Urban Traffic: Data Fusion and Vehicle Flow Prediction in Smart Cities

This Ph.D. thesis proposes a comprehensive solution to tackle the problem of traffic congestion in urban areas. By leveraging advanced deep-learning architecture and data fusion techniques, the research aims to integrate heterogeneous features from various sources and enhance the accuracy and efficiency of traffic prediction and management. The study unfolds in two key phases.

In the initial phase, the author focuses on effectively preempting and addressing traffic congestion. The author introduces an innovative method for predicting traffic speeds within road segments, harnessing the potential of advanced deep-learning algorithms. This approach empowers us to pinpoint congestion accurately, enabling proactive traffic management. The methodology involves training deep neural network models with historical traffic data and multifaceted contextual factors such as weather conditions, road topology, and time of day. These models proficiently forecast traffic speeds across various road segments, enabling timely intervention in congestion-prone areas. Moreover, the author pioneered a novel approach that combines a sequence-to-sequence LSTM prediction model with deep reinforcement learning (RL) for optimizing traffic signal control. Diverging from the traditional focus on current traffic conditions, the proposed approach incorporates sustainability and proactivity into a deep RL Q-network. This elevation in decision-making capabilities enhances traffic flow and promotes environmental consciousness by optimizing traffic signals based on future noise level predictions. The approach aspires to transcend conventional methods, championing eco-friendly practices through informed decisions that ameliorate traffic flow while mitigating noise, CO2 emissions, and fuel consumption.

The second phase of the thesis pivots toward a comprehensive systematic literature review of data fusion techniques applied in Intelligent Transportation Systems (ITS). This review identifies the most fitting data fusion techniques utilized by domain experts. These methodologies combine data from diverse sources, including traffic sensors, GPS devices, and social media feeds, to create a comprehensive, precise snapshot of traffic conditions. This fusion-based solution ensures the robustness and reliability of the traffic prediction framework. The author integrates data fusion methodologies, adhering to established best practices and procedures. Moreover, the author employs the predictions derived from the initial phase to refine traffic light management and enhance traffic flow. The author introduces an innovative data fusion technique that merges heterogeneous features from traffic and environmental sensors. This integration augments the precision of traffic prediction and empowers precise traffic light management decisions. The proposed methodology dynamically adjusts traffic signal timing to alleviate congestion and optimize traffic flow by considering real-time traffic conditions, including predicted congestion levels. The author evaluates the effectiveness of this approach through simulations and empirical assessments utilizing real-world traffic data.

The proposed solution provides a pragmatic and effective approach to tackling urban traffic congestion, ultimately leading to a more sustainable and efficient urban transportation system. By harnessing deep learning architecture and data fusion techniques, this research contributes to creating a livable and sustainable urban environment, offering a potential solution to one of the most substantial challenges modern cities face. The insights and findings from this thesis hold significant implications for transportation planning and policymaking, offering valuable guidance to optimize traffic management strategies and

enhance the overall efficiency of urban transportation systems.

In conclusion, this thesis unveils a comprehensive solution that leverages innovative methodologies and cutting-edge technologies to elevate the precision and efficiency of traffic prediction and management. Built upon a thorough literature review and incorporating state-of-the-art data fusion techniques, the proposal promises to significantly alleviate urban traffic congestion, ultimately enhancing the quality of life for urban citizens and the operational efficiency of urban transportation systems. Future research endeavors may involve refining prediction models, exploring additional data sources for fusion, and integrating emerging technologies such as connected and autonomous vehicles.

Kokkuvõte
Linnaliiklus: andmete ühtesulamine ja sõidukite voo prognoosimine nutikates linnades

Käesolev doktoritöö pakub terviklikku lahendust linnaalade liiklusummikute probleemi lahendamiseks. Töö eesmärk on kasutada kaasaegseid sügava õppimise arhitektuure ja andmete sulandumise tehnikaid, et integreerida mitmekesiseid omadusi erinevatest allikatest ning suurendada liikluse prognoosimise ja juhtimise täpsust ja efektiivsust. Uuring koosneb kahest peamisest osast.

Esimeses osas keskendub autor liiklusummikute tõhusale ennetamisele ja lahendamisele. Autor tutvustab uuenduslikku meetodit liikluskiiruste ennustamiseks teepiirkondades, kasutades sügava õppimise algoritmide potentsiaali. See lähenemine võimaldab meil ummikuid täpselt tuvastada, võimaldades proaktiivset liikluse juhtimist. Meie metoodika hõlmab sügavaid tehisnärvivõrgu mudeleid, mis on treenitud ajalooliste liiklusandmete ja mitmekülgsete kontekstuaalsete teguritega, nagu ilmastikutingimused, tee topoloogia ja päeva aeg. Need mudelid ennustavad tõhusalt liikluskiirusi erinevates teepiirkondades, võimaldades õigeaegset sekkumist ummikualadel. Lisaks on autor välja töötanud uudse lähenemise, mis ühendab järjestikuste LSTM ennustusmudelite sügava tugevdusõppega (RL) liiklusmärgaliikluse optimeerimiseks. Eristudes traditsioonilisest keskendumisest praegustele liiklusoludele, hõlmab meie lähenemine jätkusuutlikkust ja proaktiivsust sügavas RL Q-võrgus. See otsustusvõime tõstmine suurendab liikluse voolavust ja soodustab keskkonnateadlikkust, optimeerides liiklusmärke tulevaste müratasemete prognooside põhjal. Meie lähenemise eesmärk on ületada tavapäraseid meetodeid, propageerides keskkonnasõbralikke tavasid teadliku otsustamise kaudu, mis parandavad liikluse voolavust, vähendavad müra, CO2 heitmeid ja kütusekulu.

Uuringu teine osa keskendub põhjalikule süstemaatilisele kirjanduse ülevaatele andmete sulandumise tehnikatest, mis on rakendatud intelligentsetes transpordisüsteemides (ITS). See ülevaade tuvastab kõige sobivamad andmete sulandumise tehnikad, mida valdkonna eksperdid kasutavad. Need metoodikad kombineerivad andmeid mitmesugustest allikatest, sealhulgas liiklussensoritest, GPS-seadmetest ja sotsiaalmeedia voogudest, et luua põhjalik, täpne pilt liiklusoludest. See sulandpõhine lahendus tagab meie liiklusprognooside raamistiku tugevuse ja usaldusväärsuse. Autor integreerib andmete sulandumise metoodikad, järgides kehtestatud parimaid tavasid ja protseduure. Lisaks kasutab autor algfaasis saadud ennustusi liiklusvalguse juhtimise täiustamiseks ja liiklusvoolu parendamiseks. Autor tutvustab innovaatilist andmete sulandumise tehnikat, mis ühendab liikluse ja keskkonnaandurite mitmekesiseid omadusi. See integreerimine suurendab liiklusprognooside täpsust ja võimaldab täpsemaid liiklusvalguse juhtimisotsuseid. Autor hindab selle lähenemise tõhusust simulatsioonide ja empiiriliste hindamiste abil, kasutades reaalmaailma liiklusandmeid.

Meie pakutud lahendus pakub praktilist ja tõhusat lahendust linnaliikluse ummikute vähendamiseks, mis viib lõpuks jätkusuutlikuma ja tõhusama linna transpordisüsteemi poole. Sügava õppimise arhitektuuri ja andmete sulandumise tehnikate kasutamisega aitab see uuring kaasa elamiskõlbliku ja jätkusuutliku linna keskkonna loomisele, pakkudes potentsiaalset lahendust ühele kaasaegsete linnade suurimale väljakutsele. Sellest doktoritööst saadud teadmised ja leiud on olulised transpordiplaneerimisele ja poliitikakujundamisele, pakkudes väärtuslikku juhendit liikluse juhtimisstrateegiate optimeerimiseks ja linna transpordisüsteemi üldise tõhususe suurendamiseks.

Kokkuvõttes avab see doktoritöö tervikliku lahenduse, mis kasutab uuenduslikke metoodikaid ja tipptasemel tehnoloogiaid liikluse prognoosimise ja juhtimise täpsuse ja efek-

tiivsuse tõstmiseks. Põhjaliku kirjanduse ülevaate põhjal ja kasutades kaasaegseid andmete sulandumise tehnikaid lubab meie ettepanek märkimisväärselt leevendada linnaliikluse ummikuid, parandades linnakodanike elukvaliteeti ja linnatranspordisüsteemide operatiivset efektiivsust. Tulevased uurimisprojektid võivad hõlmata ennustusmudelite täiustamist, täiendavate andmeallikate uurimist sulandumiseks ja uute tehnoloogiate, näiteks ühendatud ja autonoomsete sõidukite integreerimist.

Publications (Article I - IV)

Publication I

C. Ounoughi and S. Ben Yahia. Sequence to sequence hybrid bi-lstm model for traffic speed prediction. *Expert Systems with Applications*, 236:121325, 2024

Expert Systems With Applications 236 (2024) 121325

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Sequence to sequence hybrid Bi-LSTM model for traffic speed prediction

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ARTICLE INFO

Keywords:
Embedding
Hybrid Bi-directional LSTM neural network
Intelligent transportation system (ITS)
Normalization
Sequence to Sequence
Time-series
Traffic speed prediction

ABSTRACT

Congestion is a bane of urban life that affects a large share of the population on a daily basis. Thus, congestion gets tremendous attention from city stakeholders, residents, and researchers. The key challenge to preventing congestion is to accurately predict the traffic status (e.g., speed) of a particular road segment which is greatly affected by many factors, such as spatial, temporal, and road conditions. Although several research studies have focused on preventing congestion, most prediction-based literature came short of accurate predictions regarding precision and time efficiency regarding large-scale datasets. This paper proposes a new hybrid approach called Grizzly. This approach utilizes an improved Sequence to Sequence Bi-directional Long Short Term Memory Neural Network model that integrates data pre-processing techniques such as normalization and embeddings to improve traffic prediction accuracy. Carried out experiments on two large-scale real-world datasets, namely PEMS-BAY and METR-LA, pinpointing that the proposed approach outperformed the pioneering competitors from time-series-based and hybrid neural network-based baselines in terms of the agreed-on evaluation criteria (precision and computation time).

1. Introduction

An intelligent transportation system (ITS) is integral to any smart city. Traffic congestion is ITS and individuals' primary concern because of its adverse effects on governments, society, and the economy. According to the Urban Mobility Report of 2019 published by the Texas A&M Transportation Institute (Schrank et al., 2019), the 8- to 10-year growing economy has brought traffic congestion to the highest measured levels in most U.S. cities. In 2017, congestion forced urban Americans to travel an extra 8.8 billion hours and purchase an additional 3.3 billion gallons of fuel for a congestion cost of 166 billion dollars. The average commuter wastes 54 h and 21 gallons of fuel due to congestion, totaling 1080 dollars.

Researchers have devised solutions to congestion problems through traffic prediction approaches using vast data on vehicle behavior around routes. With the progressive deployment of low-cost sensors that continuously measure traffic attributes (such as loop detectors, radars, etc.), various authorities provide public transport management and priority, traffic control in urban areas, and real-time traffic light management systems.

Prediction results allow ITS stakeholders to ascertain and identify the levels of congestion based on future forecasts to reduce congestion, allocate resources, and increase safety and sustainability. For example, they could offer new routes or services (Zhang, Li, et al., 2021), maintain a dynamic pricing system (Qian & Rajagopal, 2015), automate lane openings and closings using an adaptive traffic light system (de Gier et al., 2011; Zhang, Ishikawa, et al., 2021), etc. Furthermore, traffic predictions are paramount for the marketing industry, which helps marketers dynamically adapt their digital billboard advertisements or shop owners to invest and open new branches in more frequented congested locations (Nagy & Simon, 2018). Thus, the main research question addressed in this paper is:

> How can ITS applications provide accurate and efficient long-term traffic prediction (flow, speed, etc.) from this massive amount of high-frequency and non-linear traffic data?

This research question is particularly challenging due to the dynamic nature of the data and the number of road conditions factors that need to be considered. A burgeoning research background elaborated time-series prediction and analysis, relying on enormous algorithmic variants and processing enrichment to tackle the above challenge. Those approaches aim at standing by stakeholders' sidekicks for proactive decision-making. However, prediction models of the early days have failed to provide evidence for high accuracy on non-linear, multi-feature, and high-frequency large-scale traffic data.

Using recurrent architectures, neural network models outperform parametric statistical models. Moreover, the former architectures confirmed their potential to extract the temporal dependencies and learn

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https://doi.org/10.1016/j.eswa.2023.121325
Received 31 May 2022; Received in revised form 14 August 2023; Accepted 24 August 2023
Available online 26 August 2023

more abstract representations in the non-linear traffic data (Shao & Soong, 2017). Nevertheless, most traffic prediction models proposed so far fail to consider the analysis and pre-processing feature engineering phases of the dynamically changing large-scale traffic patterns, resulting in inaccuracies and longer computation time. This paper introduces an improved LSTM-based recurrent architecture called Grizzly, a Sequence-to-Sequence Bi-directional Long Short Term Memory Neural Network hybrid model (SeqtoSeq-Bi-LSTM) aiming to address the above crucial accuracy and time efficiency issues. Our new architecture strives to predict future traffic sequences based on previous ones. Furthermore, the Grizzly approach ushers in improving prediction accuracy and cost by incorporating data pre-processing techniques (Normalization and Embeddings) to better unveil the hidden temporal dependencies by the Bi-LSTM stacked layers proposed sequence to sequence architecture. The novelty of this approach is combining multiple techniques and carefully treating each part of the dataset with the most appropriate method to improve accuracy. The more valuable our results are the more effective stakeholders' proactive decision-making to overcome the congestion issue will be.

By and large, the main contributions of Grizzly hybrid approach are as follows:

- We adopt the sequence-to-sequence architecture and propose splitting the time-series traffic data into a fixed size s for each sequence, where s is determined after analyzing the different road network traffic behaviors. Through this architecture, patterns can be effectively identified from every data sequence in the time-series input.
- We use a Normalization technique for the continuous features. This technique improves the model's performance by decreasing the high cost of both time and resources.
- We build the Embeddings for the temporal categorical features. Thus, we reduce the high dimensionality of the input data and help extract the hidden dependencies between the inputs and the target value to be predicted (speed). Furthermore, it speeds up the learning process of the regression model.
- To efficiently unveil the inherent temporal dependencies from the data, we build bi-directional LSTM-based stacked layers with improved architecture with more sophisticated activation functions that help to achieve better accuracy at a lower cost. The latter receives inputs, both normalized and embedded sequences of past traffic status. In the output, we harvest predictions of future traffic sequences.
- We ran extensive experiments on two large-scale public traffic datasets collected in Los Angeles County highways and California freeway bay areas. Outcomes from the agreed-on evaluation criteria (precision and computation time) indicate that we outperform pioneering attempts in the literature. The code of our approach is released to facilitate further reproduction of our models in this link.[1]

The remainder of this paper is organized as follows. In Section 2, we present an overview of the related work about traffic prediction models. In Section 3, we discuss the methodological contribution of our work compared to the related work and their practical applications in a real-life scenario. Before proposing our approach, we briefly describe, in Section 4, preliminary information about the LSTM neural networks and their variant structures. Then, Section 5 presents the main proposed steps of our approach. We thoroughly discuss the harvest of the experimental evaluation and compare our results to those of the pioneering literature in Section 6. Finally, the conclusion and issues of future works are stated in Section 7.

[1] https://github.com/Ounoughi-Chahinez/Grizzly

2. Scrutiny of the related work

In the dedicated literature, we usually categorize traffic prediction approaches as parametric and non-parametric ones (Kong et al., 2019).

2.1. Parametric-based approaches

They require determining specific mathematical and statistical parameters according to data conditions. One such model is the Auto-Regressive Moving Average Integrated (ARIMA) model, which was proposed in the 1970s and is still widely used (Box & Pierce, 1970). Other models include the Hidden Markov Model (HMM), which uses GPS data to assess road congestion (Lwin & Naing, 2015), and a method that uses particle swarm optimization and fuzzy division to classify congestion status (Kong et al., 2016). Additionally, a recent study proposed an adaptive time series prediction approach that selects the best prediction model's error among five algorithms, including ARIMA, Linear Regression, Polynomial Regression, Moving Average, and K-Nearest Neighbors (Nadeem & Fowdur, 2018). Lastly, the Kalman filter-based models estimate traffic measurements for dynamic systems with slowly changing parameters (Byon et al., 2018).

Parametric-based approaches flog out a worthy-of-mention advantage, which could also be a con since they do not require large datasets for the training step, as do non-parametric-based approaches. Notwithstanding, this makes them unable to leverage additional information found in large datasets. Furthermore, parametric methods are limited only to specific linear traffic data conditions. Thus, even any pointless change in external conditions badly affected their prediction accuracy (Kong et al., 2019; Nagy & Simon, 2018).

2.2. Non-parametric-based approaches

Non-parametric methods are generally more reliable because they attempt to find the best fit for the data. However, this requires numerous observations to estimate the function f accurately. They are highly flexible and produce better results because they make no assumptions about the underlying objective.

2.2.1. Feed forward neural networks (FFNN)

Recently, we have witnessed a focus shift from traditional statistical models to non-parametric neural network-based models, particularly for handling large amounts of non-linear traffic data. This has led to a focus on deep neural network (DNN) architectures, which have more layers than a simple neural network and aim to discover abstract data representations. DNNs have lower computational complexity, enabling better feature extraction (Shao & Soong, 2017). Various authors (Albertengo & Hassan, 2018; Kong et al., 2019; Qu et al., 2019; Wang et al., 2017; Zhang et al., 2018) have suggested using different types of neural network architectures like Restricted Boltzmann Machine (RBM), convolutional neural network (CNN), and deep neural network to forecast traffic congestion in their respective studies. Neural networks can extract knowledge and patterns without relying on the events' order. For instance, if we want to classify events in a movie sequence, neural networks can use their understanding of past events to predict future events, even with uncertainty.

2.2.2. Recurrent neural networks (RNN)

Recurrent neural networks (RNNs) are a type of deep neural network model that addresses the issue of sequential dependencies in artificial neural networks (ANNs). RNNs are specifically designed to analyze traffic time-series data and have inner loops that allow information to persist and be passed from one step to the next. They have successfully solved various time-series problems like speech recognition, language modeling, translation, and image captioning. However, a fundamental problem with RNNs is called the Vanishing Gradient problem (Bengio et al., 1994; Hochreiter, 1991), which makes it challenging to deal with long-term dependencies. An improved model called recurrent long-short-term memory (LSTM) has emerged to overcome this issue.

Several new LSTM architectures have been proposed in the literature to address issues such as long-term dependencies, missing data, and trends in traffic prediction. These include an LSTM-based encoder–decoder model introduced by Shao and Soong (2017), a greedy layer-wise unsupervised learning algorithm proposed by Zhao et al. (2017) to tune LSTM units applied to an Origin-Destination Correlation (ODC) matrix, an improved version of LSTM called LSTM-M presented by Tian et al. (2018) that can infer traffic flow even with missing values, and a pre-processing technique using an attention mechanism layer to assign weights to inputs before using them in the LSTM layer, proposed by Yang et al. (2019) for their improved LSTM+ model.

2.2.3. Hybrid neural networks

Hybrid neural network schemes combine one or more neural network models that have recently become relevant approved approaches. Furthermore, modeling complex correlations can be enhanced by combining different methods, as the models can utilize the capabilities of multiple techniques concurrently (Do et al., 2019).

Several approaches have been proposed for traffic prediction, including the Spatiotemporal hybrid model, which combines convolutional and recurrent neural networks, proposed by Du et al. (2020), Guo et al. (2021), Lv et al. (2018), Ma et al. (2021). Another approach is using temporal clustering analysis and a deep convolutional neural network to predict traffic speed, proposed by Shen et al. (2018). The authors used the wavelet transform technique and multi-dimensional Taylor network in Zhu et al. (2021) to effectively learn the temporal features' periodicity. Additionally, Zhang et al. (2019) proposed a layerwise structure that uses LSTM neural networks to predict short, medium, and long-term traffic flow. In Luo et al. (2019), a Spatiotemporal traffic flow prediction method based on KNN and LSTM was proposed. The road was divided into stations, and KNN assessed the spatial correlation between these stations and other trained ones. Two LSTM layers were used for prediction. Xiao and Yin (2019) used a complex LSTM architecture with multi-neural network layers divided into input, intermediate, and output to predict traffic vehicle flow. Non-parametric neural network models are scalable and robust to abnormal conditions. They can train different types of information, such as weather conditions, incidents, or special events, to enhance model performance (Do et al., 2019). In a recent study by Modi et al. (2022), they connected two pre-trained deep auto-encoders using latent space mapping. They selected nearby road sensors based on the similarity of traffic and distance for predicting traffic speed. However, if the analysis and pre-processing of dynamically changing traffic data patterns are ignored, most deep neural network-based traffic prediction models fail to provide accurate predictions.

Graph-based deep neural networks improve traffic prediction by learning correlations between data features. DCRNN, introduced in Li et al. (2018), models traffic flow as a diffusion process on a directed graph using bidirectional random walks and an encoder–decoder architecture. STGCN, introduced in Yu et al. (2018), formulates the model as a graph and uses complete convolutional structures for faster training with fewer parameters than regular convolutional and recurrent units. GWNet is another graph-based prediction model that uses an adjacency matrix to represent the road network with on-road distances between sensors to predict traffic speeds, which has been improved recently in Wu et al. (2019). SLCNN (Zhang, Chang, et al., 2020) is an extended version of traditional convolutional neural networks that captures dynamic spatial and temporal feature dependencies in time series data. DHSTNet (Ali et al., 2022) is a unified dynamic deep Spatiotemporal neural network model that combines convolutional neural networks and long short-term memory. In their recent work, the authors used a convolutional graph network (GCN) based on their previous research in Ali et al. (2021) to capture short-term patterns and successfully predict traffic crowd flows. The authors in Zheng et al. (2022) introduced a self-attention graph convolutional network that captures spatial, sub-spatial, and temporal dynamics of traffic speed. To improve long-term dependency extraction, they implemented a sequence-to-sequence model in an encoder–decoder architecture.

Traffic prediction is a problem of capturing Spatiotemporal dimensionality and correlations in the data. Nonetheless, convolutional neural networks can only extract local features from standard grid data. On the other hand, graph convolution can automatically mine the spatial patterns of traffic data by extracting features from graph-structured data. Therefore, convolution operation along the time axis can reveal the temporal patterns of traffic data. However, graph convolution and attention-based methods produce satisfactory results but rely heavily on adjacency matrix coefficients computed based on spatial or contextual information. In some cases, these coefficients are unavailable or cannot represent genuine dependency relationships. In addition, fixed coefficients may fail to capture dynamic dependencies and produce inaccurate results.

3. Methodological and practical contributions

This section makes the article gainful for both researchers and practitioners by comparing the above approaches and illustrating how to apply our method in a real-life scenario. Table 2 summarizes the surveyed approaches related to the traffic prediction area considering the following criteria:

- **Category:** the family of the used model.
- **Model:** the model used to generate the predictions.
- **Prediction interval:** the predicted time interval by the used model.
- **Area:** the type of road networks used to evaluate the model.
- **I-O:** the shape of the input and output the generated model handles. One and Multi refer to univariate and multivariate, respectively.
- **Structure:** the architecture and the hyper-parameters used to build the model.
- **pre-processing:** the technique of preparing the model's inputs.
- **Evaluation:** the metrics used to gauge the model's performance.
- **Pros/Cons:** outlines the benefits and drawbacks of using such a category.

A list of the abbreviations used in this in Table 2 is provided in Table 1.

Traffic dynamics are complex and stochastic, making it challenging to use a single model to capture traffic characteristics across a city's wide area. Hybrid approaches have been proposed to extract spatial dependencies and temporal correlations between groups of sensors in different locations or corridors. Recurrent-based deep learning structures such as LSTM or GRU are commonly used for temporal correlations, while convolutional neural network-based architectures are primarily used for spatial dependencies. As expressed in Table 2, many traffic prediction solutions have integrated pre-processing techniques to improve their prediction quality. Mainly they have been focusing on using several normalization techniques to manipulate the continuous features and interpolating missing data if it existed. Only the authors in Ali et al. (2021) have considered a pre-processing for the categorical features using one-hot encoding. However, this technique maps each label to a binary static vector. It is worth mentioning that any surveyed approaches do not use embedding as another powerful technique for categorical features. It provides a learned distributed representation for each distinct label. This technique has proved to be a game-changer for improving deep-learning prediction models' performances (Ounoughi et al., 2021). To the best of the author's knowledge, no previous research has studied the importance of combining dynamic embedding pre-processing for categorical features with the normalization of continuous ones and their effect on the prediction results.

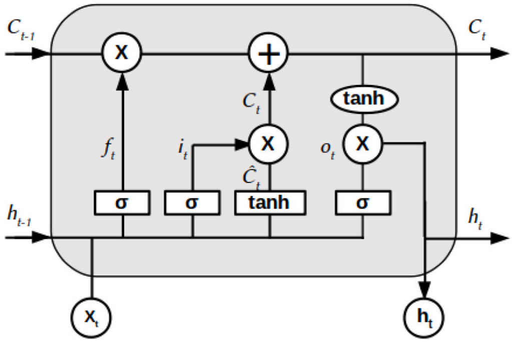


Fig. 1. LSTM general structure.

Based on the above studies and considering the differences between periodic data and the changing dependencies of traffic patterns, a novel network structure named Grizzly, a Sequence to Sequence Bi-Directional Long-Short-Term Memory Neural Network model, is proposed to predict traffic speed. Due to the high performance of LSTM-based neural network prediction models and their ability to capture long-term dependence in sequential data, they are an ideal choice for traffic prediction. The selection of Bidirectional LSTM in our proposed model was based on several factors, including its ability to capture both past and future context in the data sequence, which is vital for accurate traffic prediction. Additionally, the Bidirectional LSTM architecture has been shown to perform well on time-series sequence forecasting problems, which makes it a suitable candidate for traffic prediction. The main methodological contribution of this paper is the combination and application of pre-processing (Normalization, Embedding, and sequence-to-sequence structure) concepts and recurrent deep learning architecture to extract the temporal correlations and spatial dependencies within the road network to predict traffic speed. A thorough description of the LSTM-based structures and our proposed approach is given in Sections 4 and 5, respectively.

It is worthy of mention that our new proposed method can be applied in different real-life scenarios. For example, it can be integrated into an intelligent traffic signal control agent. Thanks to a responsive strategy, it can adapt and update its phases according to the predicted traffic speed to deal with congestion issues. Recent responsive studies, e.g., Chen et al. (2020), Zang et al. (2020) and Zhang, Liu, et al. (2020), to cite but a few, have shown promising results when using reinforcement learning techniques for traffic signal control. However, these techniques rely only on the current traffic conditions. Therefore, through our approach, we contribute to this line of research with a novel proactive aspect. In particular, these reinforcement learning-based models can be invoked with the pre-knowledge of the traffic status predicted using our approach.

4. Preliminaries

In this section, we first recall preliminaries about the elemental components of the LSTM model architecture and its variation. Then, we state the explanations for using the activation layers in neural networks.

4.1. Long-short term memory neural network (LSTM)

Long-short term memory neural network (LSTM) is a specific architecture of RNNs, whose design is capable of learning long-term dependencies using the concept of memory. Firstly introduced by Hochreiter and Schmidhuber (1997), then they have been varied and popularized

Table 1
List of abbreviations.

AC	Average Correlation
ACC	Accuracy
AHP	Analytic Hierarchy Process
APE	Absolute Percentage Error
CNN	Convolutional Neural Network
DAE	Deep Auto-Encoder
DNN	Deep Neural Network
F	Filter
FFNN	Feed Forward Neural Network
GRU	Gated Recurrent Unit
HMM	Hidden Markov Machine
I/O	Input/Output
KF	Kalman Filter
KNN	K-Nearest Neighbors
l_c	Sequence length of the current flow
l_d	Sequence length of the daily flow
l_r	Sequence length of the weekly flow
LSTM	Long-Short Term Memory
M	Time window
MA	Moving Average
MAE	Mean Absolute Error
MARE	Mean Absolute Relative Error
ME	Mean Error
MRE	Mean Relative Error
MSE	Mean Squared Error
MTM	Markov transition matrix
MTN	Multi-Dimensional Taylor Network
NN	Neural Networks
PSO	Particle Swarm Optimization
RB	Residual Block
RBM	Restricted Boltzmann Machine
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Networks
SCAAT	Single Constraint At A Time
Self-AGCN	Self Attention Graph Convolutional Network
SVM	Support Vector Machines
SVR	Support Vector Regression

later in solving numerous issues. Fig. 1 shows the basic three-gates-LSTM structure is also called the *forward-pass LSTM network*. A forget gate f and an input gate i are both made for the cell state's update C_t. The third and output gate, o, decides how much information about the current input x_t should remain for the current output cell h_t. The equations of the different gates are as follows:

$$f_t = \sigma(W_f \times [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\hat{C}_t = tanh(W_c \times [h_{t-1}, x_t] + b_c) \tag{3}$$

$$C_t = f_t \times C_{t-1} + i_t \times \hat{C}_t \tag{4}$$

$$o_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \times tanh(C_t) \tag{6}$$

We compute the different outputs as follows; first, the forget gate (Eq. (1)) uses a sigmoid layer that takes as inputs h_{t-1} and x_t to compute the percentage of information to be conserved of the previous cell state C_{t-1}. The next step is to define which values to be updated using the input gate' sigmoid layer (Eq. (2)); and a tanh layer (Eq. (3)) to create a vector of new candidate values $\hat{C}_t$. The combination of both resulting information creates an update to the cell state C_t (Eq. (4)). Next, a sigmoid layer (Eq. (5)) that decides the parts of the cell state to be output is applied. At last, to get the h_t (Eq. (6)), first, pass the cell state C_t through the tanh function and multiply it by the output of o_t.

Table 2
Summary of traffic prediction proposed approaches.

Category	Model	Reference	Prediction interval	Area	I-O	Structure	Pre-processing	Evaluation	Pros/Cons
Parametric	Hidden Markov	Lwin and Naing (2015)	1 min	Urban	One-One	Hidden Markov	Map matching	ACC	HMM is efficient learning algorithm can take place directly from raw sequence data. However, it cannot express dependencies between hidden stats.
	SVM	Kong et al. (2016)	5 min	Urban	Multi-One	SVM + PSO	Eliminate noise	ACC, Instantaneity, Stability	SVR has greater generalization ability, but it is more easily affected by training data.
	Kalman filters	Byon et al. (2018)	10, 30 sec (simulation)	Urban	Multi-One	SCAAT Kalman filters	Data fusion	ME, MAE, MRE, MARE, MSE, RMSE	KF is fast to converge to a valid state. However, it needs a larger computational complexity to get better results.
Non-Parametric	FFNN	Wang et al. (2017)	5 min	Urban	Multi-One	AHP + Multilevel Fuzzy set theory	Information fusion	Score (%)	NN can explore nonlinear relations among the traffic data, resulting in better predictions than parametric methods. However, NN requires more parameters to be determined in the training step.
		Nadeem and Fowdur (2018)	5 min	Urban	Multi-One	NN (2,7,1)	None	MSE, RMSE	
		Zhang et al. (2018)	10 min	Urban	One-One	NN (16, 16, 1)	None	MAE, RMSE	
		Albertengo and Hassan (2018)	5 min	Urban	One-One	NN (50, 50)	Linear interpolation Smoothing MA	RMSE, RME RMSE, RME	
		Qu et al. (2019)	5, 10, 15, 30, 60 min	Freeway	One-One	DNN (15, 18, 22, 9, 5)	None	APE, MAPE	
		Kong et al. (2019)	5 min	Expressway	One-One	RBM	Normalization	MRE, RMSE	
	RNN	Shao and Soong (2017)	5 min	Freeway	Multi-One	LSTM + Linear Regression	None	MAPE, RMSE	RNN model structure is more complex than the NN methods, so it performs best for sequential traffic data. However, it requires large-scale training data and plenty of training parameters.
		Zhao et al. (2017)	15, 30, 45 and 60 min	Urban	One-One	LSTM (Units = 500)	None	MAE, MSE, MRE	
		Yang et al. (2019)	15 min	Freeway	One-One	Attention layer + LSTM	Smoothing noisy data	MAE, MRE, RMSE	
	Hybrid-NN	Li et al. (2018)	15, 30, 60 min	Freeway	One-One	Stacked Diffusion ConvRecurrent Layer (Units = 64, F = 3)	Z-Score normalization	MAE, RMSE, MAPE	Hybrid model captures dependencies between heterogeneous features (temporal/spatial). It is scalable and adaptable to a variety of circumstances. However, it is computationally extensive and needs large-data for the training.
		Yu et al. (2018)	15, 30, 45 min	Urban	One-One	Graph-CNN + Gated-CNN (M = 12, F = [64, 16, 64])	Linear interpolation + Z-score normalization	MAE, RMSE, MAPE	
		Lv et al. (2018)	–	Urban	Multi-One	Look-up ConvLSTM + Fusion (F = [32,16], M = 5)	Normalization	RMSE	
		Shen et al. (2018)	5 min	Urban	Multi-One	Fusion + Spatio-temporal regression + Evidence theory	Temporal Clustering	MAE, APE	
		Zhang et al. (2019)	15, 30, 60 min	Urban	Multi-One	Fusion + Layerwise structure+ MTM (NN neurons = 70)	Min-Max Normalization	MAE, RMSE	
		Luo et al. (2019)	5 min	Freeway	Multi-One	KNN (K = [10, 6]) + LSTM	None	ACC, RMSE	
		Xiao and Yin (2019)	5 min	Urban	One-One	Stacked-LSTM (Units = 8, Dropout = 0.5)		None RMSE	
		Wu et al. (2019)	15, 30, 60 min	Highway	One-One	8 Graph-WaveNet + Graph-CNN (F = 2)	Z-score normalization	MAE, RMSE, MAPE	
		Shleifer et al. (2019)	15, 30, 60 min	Highway	One-One	Gated-TCN + Graph-CNN (F = 40)	None	MAE	
		Du et al. (2020)	15 min	Urban	Multi-One	1D-CNN + GRU + Attention (128, 128, 128)	None	RMSE	
		Guo et al. (2021)	15, 30 min	Urban/Highway	Multi-Multi	Graph-CNN + GRU (M = 3, F = 64)	None	MAE, MAPE, MSE	
		Zhang, Chang, et al. (2020)	15, 30, 60, 90 min	Urban/Highway	One-One	Global SLC (F = 6) + Local SLC (F = 8) + 3 P3D (depth = 32)	None	MAE, RMSE	
		Ma et al. (2021)	5, 10, 15, 30, 60 min and 24 h	Highway	One-One	ConvLSTM (F = 8, M = 28)	Abnormal data adjustment	APE, MAPE	
		Zhu et al. (2021)	10 min	Urban	One-One	MTN + Wavelet transform technique	None	MAE, MAPE, RMSE, AC	
		Ali et al. (2021)	30, 60 min	Urban	Multi-One	Attention + ConvLSTM (l_c = 4, l_d = 4, l_r = 4/l_c = 6, l_d = 4, l_r = 4)	Min–Max Normalization + One-hot Encoding	MAPE, RMSE	
		Ali et al. (2022)	30, 60 min	Urban	Multi-One	LSTM + Graph-CNN(l_c = 4, l_d = 4, l_r = 4/l_c = 6, l_d = 4, l_r = 4) + Residual units	Min–Max Normalization	MAPE, RMSE	
		Modi et al. (2022)	15, 30, 60 min	Freeway	One-One	2 DAEs with 3 2D-CNN (F =3, stride=2, padding=1) + batch normalization + tanh + 3 RBs with 2 2D-CNN (F=3, stride=1, padding=1) + batch normalization and ReLU	Min-Max normalization	MAE, RMSE, MAPE	
		Zheng et al. (2022)	5, 15, 30, 45, 60 min	Freeway	Multi-Multi	m Graph-CNN + FFNN + Self-AGCN + GRU (m=[1-6])	None	MAE, RMSE, MAPE	

4.2. Bi-directional LSTM

The forward-pass LSTM takes the inputs following a direction from past to future. However, backward-pass LSTM is another variation of LSTM networks that works in the opposite direction. The bi-directional LSTM network, introduced by Schuster and Paliwal (1997), extracts both past and future temporal patterns. This latter attached both forward-pass and backward-pass LSTM networks to the same output layer. Thus, both hidden states (forward and backward) enable us to capture past and future information. The bi-directional LSTM is relatively handy regardless of tasks and contexts since it leverages the sequential information in both directions (Ma & Hovy, 2016).

4.3. Activation layer

The activation layer is typically applied to enhance the training model's learning ability. The activation output layer can use specific activation functions, i.e., mathematical formulas for computing a neural network's output. It can essentially function like a step function that depends on a particular rule, or threshold, to turn a neuron output on and off. There are three categories of functions: binary step, linear, and non-linear. First, a binary step function is a threshold-based activation function. If the input value is greater than or equal to a threshold, the neuron is activated and sends the same value to the next layer. However, it does not support multi-value outputs. Second, the linear function (Eq. (7)) multiplies the inputs by the weights for each neuron to produce proportional outputs. We use this function for regression problems very often.

$$f(x) = ax \tag{7}$$

Finally, recent neural network models use non-linear activation functions. Doing so allows the creation of complex modeling between the network's inputs and outputs. These latter are essential for learning and modeling complex data, e.g., images, video, audio, and high-dimensional datasets. The most used activation that better suits the classification problem is the sigmoid function called the logistic function. We computed it using Eq. (8).

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{8}$$

Many advanced activations have been developed to enhance the training of deep, complex neural networks. The most popular and successful, especially for regression problems, are the Rectified Linear Unit (ReLU), Exponential Linear Unit (ELU), and Leaky Rectified Linear Unit (Leaky ReLU) cf. Eqs. (9) and (10).

$$ELU(x) = \begin{cases} x, & \text{if } x > 0 \\ \alpha(e^x - 1), & \text{if } x < 0 \end{cases} \tag{9}$$

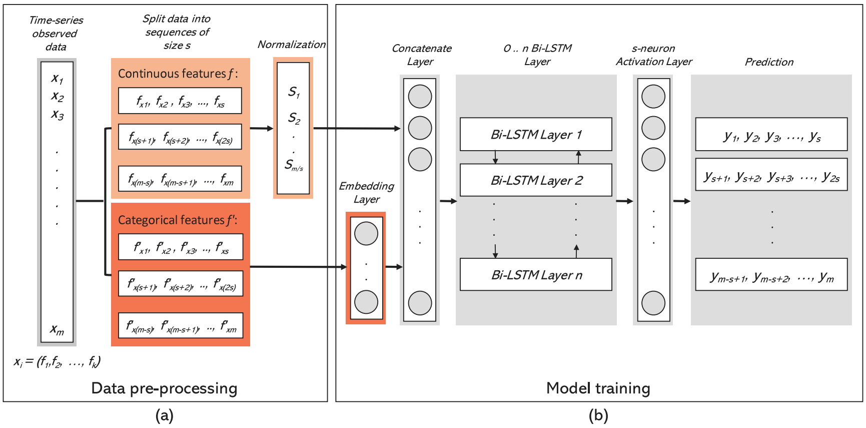


Fig. 2. Grizzly hybrid approach.

$$LReLU(x) = \begin{cases} x, & \text{if } x > 0 \\ \alpha x, & \text{if } x \le 0 \end{cases} \tag{10}$$

Based on the presented LSTM neural network and activation layers variants, we introduce, in the remainder, our new Sequence-to-Sequence Bi-directional LSTM neural network (SeqtoSeq-Bi-LSTM) hybrid approach for traffic speed prediction.

5. Proposed approach

Traffic prediction refers to predicting the next or future status of the road. The traffic status can be volume, speed, density, or behavior (Nagy & Simon, 2018). We introduce in the remainder Grizzly a Sequence-to-Sequence Bi-directional LSTM neural network approach. The sought-after goal is to predict traffic of predefined fixed future periods, e.g., daily, weekly, etc. Grizzly is a hybrid approach aiming to improve prediction performance in terms of time and resources. It combines different pre-processing techniques to efficiently encode spatial and temporal features within a sequence-to-sequence representation of traffic time series. First, it splits the traffic time series into fixed-sized sequences. Then, it fits them through an improved Bi-directional LSTM architecture to accurately capture the temporal dependencies between sequences in both directions (forward and backward). Fig. 2 depicts the general architecture of our approach, which operates through two main phases:

1. A data pre-processing phase (Fig. 2a) that encodes the input sequences for both categorical and continuous features and applies a Normalization technique for the continuous ones.
2. A model training phase (Fig. 2b) that learns the Embeddings of each categorical feature. Then, it feeds them into the deep-stacked Bi-directional LSTM architecture alongside the normalized continuous features to accurately predict future traffic sequences.

5.1. Phase 1: Data pre-processing

5.1.1. Sequence generation

A time series is a sequence of numerical data points collected and stored in time order at regular intervals. We characterize this data type by its '*Frequency*' (the time interval separating two consecutive data points). For example, if the flow is recorded once per day from January the 1st, 2011 to January the 1st, 2021, a single interval would be a day, while the entire period would be a decade (10 years). The frequency must be equal and clearly defined. It could range from a few milliseconds to several years. However, the most common ones for traffic flow data are 5 min., 10 min., and 1 h. According to our proposed approach, if we aim to predict daily traffic, then the form of the input and output data would be presented with s observations as follows:

$$\text{Past day} \xrightarrow{topredict} \text{Future day}$$
$$[x_{(1,1)}, x_{(1,2)}, \dots, x_{(1,s)}] \xrightarrow{topredict} [y_{(2,1)}, y_{(2,2)}, \dots, y_{(2,s)}]$$
$$[x_{(2,1)}, x_{(2,2)}, \dots, x_{(2,s)}] \xrightarrow{topredict} [y_{(3,1)}, y_{(3,2)}, \dots, y_{(3,s)}]$$
$$\dots \xrightarrow{topredict} \dots$$

Where $y_{(day,observation)}$ denotes the traffic status, and each $x_{(day,observation)}$ is presented with a k value of different features as $x_{(i,j)} = (f_{(i,j,1)}, f_{(i,j,2)}, \dots, f_{(i,j,k)})$.

$$[(f_{(1,1,1)}, \dots, f_{(1,1,k)}), \dots, (f_{(1,s,1)}, \dots, f_{(1,s,k)})] \xrightarrow{topredict} [y_{(2,1)}, y_{(2,2)}, \dots, y_{(2,s)}]$$
$$[(f_{(2,1,1)}, \dots, f_{(2,1,k)}), \dots, (f_{(2,s,1)}, \dots, f_{(2,s,k)})] \xrightarrow{topredict} [y_{(3,1)}, y_{(3,2)}, \dots, y_{(3,s)}]$$
$$\dots \xrightarrow{topredict} \dots$$

We separate the continuous features from the categorical ones from these output sequences and apply a normalization technique to the continuous ones.

5.1.2. Normalization

Normalization is the pre-processing stage that takes an important role in manipulating large and sparse datasets. This approach aims to equalize the contribution of each feature by scaling or transforming the data before it becomes used for further stages (Singh & Singh, 2020). The performance of data-driven approaches depends upon the data quality to obtain a generalized predictive model for a specific task. Therefore, many normalization techniques improve the performance of neural network-based architectures, namely Min–max, Z-score, and Decimal scaling. Min–max normalization, the widely used one, performs a linear transformation on the original data. Suppose that min_f and max_f are the minimum and maximum values for the feature F. Min–max normalization maps a value v of F to $v\prime$ in the range $[min_f\prime, max_f\prime]$ by computing:

$$v\prime = \frac{v - min_f}{max_f - min_f} \times (max_f\prime - min_f\prime) + min_f\prime \tag{11}$$

The final output of this phase is then a group of normalized continuous features (using Eq. (11)) and categorical feature sequences of a fixed size s to be used in the next step of our approach. Instead of using time as a continuous feature, we propose to extract meaningful temporal information related to traffic dynamics, e.g., the hour of the day on which day of the week. Therefore, we automatically benefit from detailed information about each observation.

5.2. Phase 2: Model training

The success of LSTM-based neural networks with time-series data is owing to their ability to capture long-term temporal dependencies. We introduce an improved version of the Bi-directional LSTM neural network architecture in the following. Furthermore, we adopt the categorical feature embedding representation as a powerful technique to improve the efficiency of the proposed approach.

5.2.1. Embedding

Embedding is a data representation technique (Grohe, 2020) that has been extensively used recently because of data on a large scale provided by road networks. This technique produces low-dimensional continuous vector representations of the high-dimensional categorical inputs that improve the performance quality and speed up the training process for the model (Ounoughi et al., 2021). For example, the Hour_of_ the_day is a high cardinality categorical feature, which is crucial in accurately ascertaining the variation in road traffic behavior during the day to predict future traffic patterns.

Fig. 2 shows how we concatenate these embeddings with the rest of the normalized continuous features in one layer to feed them all together into the training process of a $(0 \dots n)$ stacked Bi-directional LSTM layer. We designed these latter to take past and future information by combining both the forward-pass and backward-pass of the LSTM network.

5.2.2. Bi-directional LSTM

We propose to replace the default *tanh* activation in Eqs. (3) and (6) of the Bi-LSTM layer with two more sophisticated activation functions (detailed in Section 6). We claim that using ELU and Leaky ReLU instead of other non-linear activations, e.g., tanh, ReLU, would help us to enhance precision in extracting sequential patterns from time-series input data with better efficiency. Due to the simple definition of ReLU as $max(0, x)$, it suffers from a "dying problem during the training step". A dead ReLU will not perform any learning on the layers below it since 0 will be multiplied by the accumulated gradient when the weights are updated. Thus, it results in dead neurons. Leaky ReLU and ELU will always have a slope to allow the gradients to pass. The ELU activation function can produce negative outputs, which could aid the recurrent network in establishing weights and biases in the right direction. Thus, it allows a swifter model's convergence and increases its accuracy by allowing activation values to be returned instead of letting them equal 0 when computing the gradient (Ounoughi et al., 2021). Leaky ReLU is advantageous since it reduces the concern about initializing the neural network. Since we seek to improve our Bi-LSTM's time efficiency, Leaky ReLU can speed up training. Which can be accelerated by having 'mean activation' close to 0.

Later, we attach the output of the stacked Bi-directional LSTM layers to an s-sized output activation layer. Then, to evaluate the model, we train and update the model using a back-propagation algorithm as an optimizer and a loss function to minimize the prediction error. Finally, we evaluate the model's predicted sequences and compare them with the actual traffic sequences using two constantly used evaluation metrics.

Algorithm 1 summarizes all the steps of Grizzly traffic prediction approach. First, we identify the sequence size Seq_size and prepare the sequences for the pre-processing step (line 1–2), i.e., Normalization for the continuous features. Once the dataset has been split into train and test sets, we separate the categorical (S_{cat}) and continuous (S_{cont}) sequences from each other (lines 3–7). After that, we feed each categorical feature x to the Embedding layer with its embedding dimension v_size, which is the size of the weights vector for each discrete category of x (lines 8–11). Afterward, we concatenate the output of the embedded features with the remainder of the values of the normalized continuous features (line 12). Finally, we train the fully connected layers of our Bi_LSTM stacked layers architecture given the concatenated inputs followed by an Seq_size-neuron activation layer (line 21). To assess the performance (line 18), we can compare the ground-truth speeds of the test set versus the predicted ones yielded by Grizzly (lines 23–26) using several evaluation metrics.

Algorithm 1: Grizzly: traffic prediction

Require: D: a Time series multi-features dataset;
Where $D = \{x_1, x_2, \dots, x_m\}$ and each observation $x_{observation}$ is collected each I time
interval (e.g. 5 min.).
Ensure: $\hat{Y}$: the prediction of future traffic values;
Where $\hat{Y} = \{\hat{y}_1, \hat{y}_2, \dots, \hat{y}_m\}$ and each y_i is the traffic sequence to be predicted.
1: Seq_size ← $24 * 60/I$
2: Sequences ← $Split$(D, Seq_size)
3: Fix the normalization $range$
4: S_{cont} ← $MinMax\_Normalize$($Sequences_{cont}$, $range$)
5: S_{cat} ← $Sequences_{cat}$
6: $Train_{cat}$, $Test_{cat}$ ← $SplitTrainTest$(S_{cat})
7: $Train_{cont}$, $Test_{cont}$ ← $SplitTrainTest$(S_{cont})
8: **for all** x **in** $Train_{cat}$.F **do**
9: Fix the Embedding vector size v_size
10: Emb[x] ← $Embedding\_layer$(x, v_size)
11: **end for**
12: Concat ← $Concatenate\_layer$([Emb, $Train_{cont}$])
13: Model.add(Concat)
14: $i \leftarrow 1$
15: Fix the LSTM output activation $output\_act$
16: Fix the layers number of Bi-LSTMs bi_layers_number
17: **while** $i \le bi\_layers\_number$ **do**
18: Model.add($Bi\_LSTM\_layer(output\_act)$)
19: $i \leftarrow i + 1$
20: **end while**
21: Model.add($Activation\_layer(Seq\_size)$)
22: Model.Train($Optimizer, loss\_function$)
23: **for all** sequence **in** [$Test_{cat}$,$Test_{cont}$] **do**
24: $\hat{y}$ ← Model.predict(sequence)
25: $\hat{Y}$.append($\hat{y}$)
26: **end for**
27: **return** $\hat{Y}$

6. Experimental evaluation

Here we evaluate the performance of Grizzly versus the pioneering time-series traffic prediction methods. The performance evaluation is based on the prediction errors of each model on two large-scale real-world sensor datasets. In the following, we usher by describing the considered datasets.

6.1. Datasets description

Grizzly is designed to handle large-scale high-frequency traffic time-series datasets that contain an enormous variety of previous observations of the status of the road network. Table 3 summarizes the datasets used for the evaluation process. Both datasets are publicly available released by previous works (Li et al., 2018; Zhang, Chang, et al., 2020).[2]

[2] Datasets available at: https://github.com/liyaguang/DCRNN.

Table 3
Description of datasets used during the experimental evaluation.

Dataset	PEMS-BAY	METR-LA
Time window	5 min	5 min
Time span	6 months	4 months
Features	Speed, timestamp	Speed, timestamp
Speed unit	mph	km/h
#sensors	325	207
#training_set	36,465	23,974
#validation_set	5,209	3,425
#testing_set	10,419	6,850

- **PEMS-BAY (Caltrans Performance Measurement System**[3]**)**: provides a consolidated database of real-time traffic data from over 39,000 individual detectors like inductive loop sensors, magnetic sensors, or microwave radar sensors by Caltrans on California freeways, as well as other partner agency datasets. In our experiments, we look at 325 specific loop detector data in the Bay Area collected each 5-min time interval during 6 months from January 1st, 2017 to May 31st, 2017.
- **METR-LA**: is a traffic information dataset collected from loop detectors on the highway of Los Angeles County. Our experiments look at 207 particular loop detector data collected with a 5-min time window during 4 months from March 11st, 2012 to June 31th, 2012.

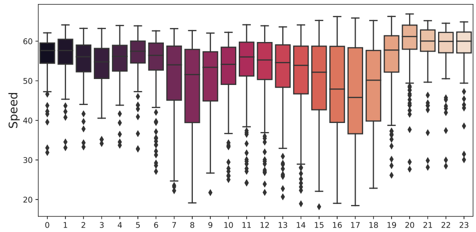
For both considered datasets, two other temporal categorical features (the Hour of the Day and Day of the week) are collected alongside the traffic speed feature to extract better the temporal dependencies patterns. For example, Fig. 3 depicts the decrease in traffic speed during morning and evening rush hours, e.g., between 4 pm to 6 pm, the mean speed decreases to less than 50 km/h for the METR-LA dataset, c.f., Fig. 3(a). Fig. 4, on the other hand, sheds light on how the traffic slows down around weekdays more than on weekends, e.g., most of the observations during the weekends have a mean speed of more than 65 km/h for the PEMS-BAY dataset, c.f., Fig. 4(b). Therefore, according to the applied analysis, each Hour_of_the_day and Day_of_the_week are of utmost importance to determine the variation between road traffic behaviors during different weekdays and times of the day, which would efficiently enhance the prediction accuracy of the future status.

6.2. Experimental setup

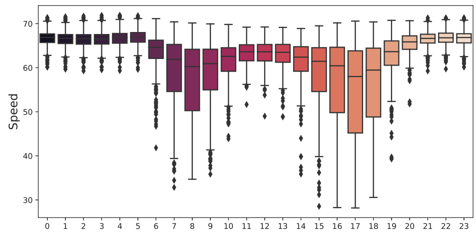
Our experiments were performed using Ubuntu 18.04.3 LTS (CPU: Intel Xeon Processor (Skylake) × 8, RAM: 16 GB), with Python (Version 3.7) and Keras (Version 2.3.1) installed.

To efficiently gauge the performance of the proposed Grizzly approach, we predicted the future road segments' speed for the next 15 min, 30 min, and 60 min. We determine the size of the time-series sequence after analyzing the different road networks. More specifically, the time-series sequence's size is determined based on the temporal characteristic of the speed data. For example, the size of the time-series sequence may depend on the time interval between speed data samples and the specific time of the day of the type of the day itself (Figs. 3 and 4).

As long as both datasets' speed information is collected within a 5-min time window, the sequence-to-sequence architecture would have the respective sequence sizes (3, 6, 12). In both considered datasets, we apply a Min–max normalization technique implemented by the *Scikitlearn* python library (Pedregosa et al., 2011) with a range between 0 and 1 on the speed feature values. We aggregate 70% of data training,

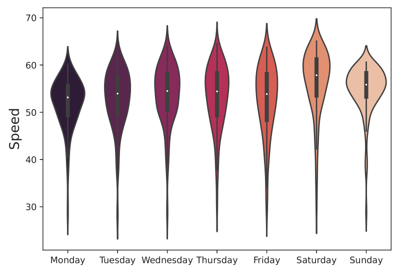


(a) METR-LA

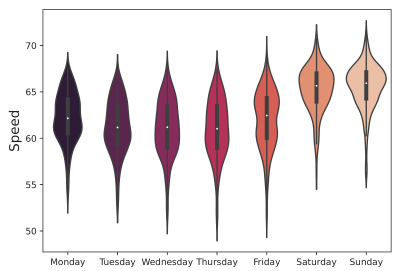


(b) PEMS-BAY

Fig. 3. Speed vs. Hour of the day across all sensors.



(a) METR-LA



(b) PEMS-BAY

Fig. 4. Speed vs. Day of the week across all sensors.

20% for testing, and the remaining 10% for validation, where we adopt the same data split ratio as in Li et al. (2018).

Before proceeding to the model training process phase, we extract the embeddings for the set of categorical features. We fit the

[3] http://pems.dot.ca.gov

Table 4
Trainable Parameters for Grizzly Model Complexity.

Dataset	Task	Trainable params
METR-LA	60 min	148,525
	30 min	103,335
	15 min	101,604
PEMS-BAY	60 min	148,525
	30 min	140,839
	15 min	136,996

Hour_of_the_day, Day_of_the_week and Sensor_ID into $\mathbb{R}^1$, $\mathbb{R}^1$ and $\mathbb{R}^1$ respectively, for both considered datasets. The embedding outputs with the remainder of the normalized continuous speed values are concatenated at a single Concatenate layer (Fig. 2). Output data from the latter is fed to the learning architecture for the training process.

For the PEMS-BAY dataset, we adopt the use of a fully connected network of one Bi-LSTM ELU activation layer. To do so, we replace the *tanh* in Eqs. (3) and (6) with ELU Eq. (9). We set the number of units equal to 128 and the output layer of the sequence sizes (3, 6, 12) neurons. We also use the Leaky ReLU activation function (cf. Eq. (10)) for the three prediction tasks. For the METR-LA dataset, we adopt the use of a fully connected network of three Bi-LSTM sigmoid activation layers. We also replace the tanh in Eqs. (3) and (6) by sigmoid Eq. (8). These stacked layers are with the respective sizes of (64, 32, 32) units connected to an output layer of the dimensions of the sequence (3, 6, 12) neurons with the Linear activation function Eq. (7) for the three prediction tasks. The Adam optimizer (Kingma & Ba, 2014), as well as Mean Absolute Error (MAE) Eq. (12) as the loss function are used to fine-tune the training model within 60 epochs for both datasets.

Moreover, the model complexity of Grizzly is inherently associated with the number of trainable parameters, which plays a crucial role in shaping its behavior. This aspect is captured in Table 4, which presents the relationship between the model's complexity and the varying number of trainable parameters across different prediction tasks and datasets. These numbers exemplify the intricate relationship between model complexity and the number of trainable parameters, further emphasizing the underlying mathematical and logical operations required to implement the Grizzly model successfully. The careful consideration of these complexities contributes to the robustness and efficiency of the proposed approach.

6.3. Baseline methods for comparison

To assess the performance of our proposed Grizzly approach, we carried out a comparison with the pioneering time-series traffic prediction baseline methods scrutinized in Section 2. The baseline methods are the following:

- **ARIMA$_{\mathbf{kal}}$**: an Auto-Regressive Integrated Moving Average model with Kalman filter, which is the classical baseline method for time-series prediction (implemented by Li et al., 2018)
- **STGCN** (Yu et al., 2018): a convolutional structure built using graphs, enabling rapid training with fewer parameters.
- **DCRNN** (Li et al., 2018): a graph-based deep learning architecture using an encoder–decoder architecture to extract temporal dependencies and bidirectional random walks to capture spatial correlations.
- **GWNet** (Wu et al., 2019): an adjacency matrix-based representation of the road network that uses the on-road distance between sensors to predict future traffic speeds.
- **SLCNN** (Zhang, Chang, et al., 2020): a graph-structured CNN architecture that captures the dynamic spatial features and temporal dependencies in time-series data.

6.4. Evaluation metrics

The performance of our model versus the baseline models is evaluated using two regression metrics: the mean absolute error (MAE) and the root mean squared error (RMSE), which are defined respectively in Eqs. (12) and (13).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{12}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

Where y_i stands for the real observed traffic value and $\hat{y}_i$ for the predicted traffic value by the model. Smaller values indicate better prediction performance for both metrics. Both metrics gauge the absolute deviation between predicted values and actual values.

6.5. Results and discussion

Table 5 shows the obtained values for both MAE and RMSE metrics by the Grizzly approach compared to its competitors. In addition, we analyze the models' performance under different prediction tasks of 60 min., 30 min., and 15 min., representing another degree of efficiency in the long run. Grizzly outperforms all the pioneering baseline methods using the PEMS-BAY dataset. However, for the METR-LA dataset, Grizzly performances are not outperforming those of SLCNN in terms of MAE. Nevertheless, Grizzly surpasses all the other four competitors. An in-depth analysis can reveal exceptionally gainful insights:

1. Among all the baselines, ARIMA$_{\mathrm{kal}}$ has the worst performance. Compared to the Non-parametric-based approaches, traditional statistical parametric-based methods cannot handle complex or large-scale Spatiotemporal traffic data.
2. GWNet method achieves better results than convolutional graph-based methods on the PEMS-BAY dataset, while the SLCNN outperforms it on the METR-LA dataset. Thus, we can conclude that GWNet and SLCNN methods are more practical for graph-structured data since they capture spatial information better.
3. The results of GWNet and SLCNN methods, respectively, outperform the results of STGCN and DCRNN, which extract Spatiotemporal features simultaneously. This is generally because both methods avoid exploiting the graph structure and use only the pre-defined available graph structures.
4. Different speed units (km/h and mph for METR-LA and PEMS-BAY, respectively) are responsible for the difference in error results between both datasets.
5. Better improvements are achieved by our proposed Grizzly. It underscores that embedded temporal features contributed to better capturing the inherent temporal dependencies. In doing so, we helped the Grizzly architecture better manage the time series of traffic data.

Figs. 5 and 6 compare the performance of Grizzly when varying sequence sizes (3, 6, and 12) of 20 random roads sensors from both considered datasets. It depicts that whenever the size of the sequences goes bigger, the MAE and RMSE values increase. Although the average values are not large, the variation between the different model performances is evident. Accordingly, the Grizzly approach performs better when considering smaller sequences. In addition, the model performs differently for different sensors. Yet, simultaneously, the range of errors is not remarkably high, which may be due to the unusual behavior of the sensors, their locations, or different traffic factors, as illustrated in Fig. 7. This can explain the presence of outliers that affect the prediction but may not be predictable or detectable.

Table 5
Performance comparison of different approaches for traffic speed prediction.

Models Evaluation	PEMS-BAY						METR-LA					
	MAE			*RMSE*			*MAE*			*RMSE*		
	60 min	30 min	15 min	60 min	30 min	15 min	60 min	30 min	15 min	60 min	30 min	15 min
$ARIMA_{kal}$	3.38	2.33	1.62	6.50	4.76	3.30	6.90	5.15	3.99	13.23	10.45	8.21
STGCN	2.49	1.81	1.36	5.69	4.27	2.96	4.59	3.47	2.88	9.40	7.24	5.74
DCRNN	2.07	1.74	1.38	4.74	3.97	2.95	3.60	3.15	2.77	7.59	6.45	5.38
SLCNN	2.03	1.72	1.44	4.53	3.81	2.90	**3.30**	**2.88**	2.53	7.20	6.15	5.18
GWNet	1.95	1.63	1.30	4.52	3.70	2.74	3.53	3.07	2.69	7.37	6.22	5.15
Grizzly	**1.74**	**1.46**	**1.20**	**3.68**	**3.13**	**2.45**	3.43	2.98	**2.38**	**6.29**	**5.97**	**4.88**
Improvement (%)	**−10.76**	**−10.42**	**−7.69**	**−18.58**	**−15.40**	**−10.58**	+3.79	+3.35	**−5.92**	**−12.63**	**−2.92**	**−5.24**

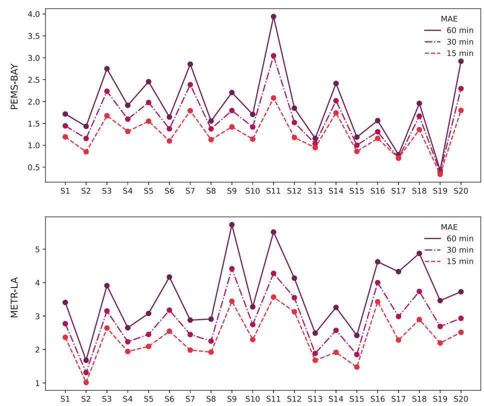


Fig. 5. Grizzly performance evaluation of 20 random sensors with different sequence sizes (MAE).

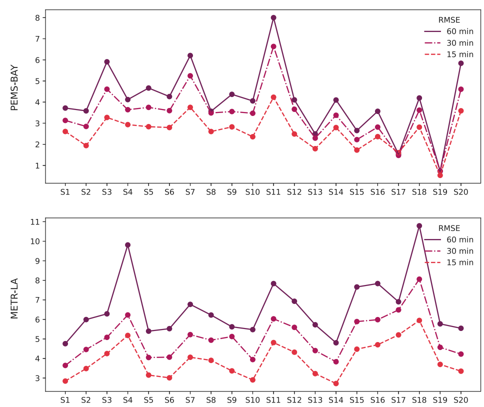


Fig. 6. Grizzly performance evaluation of 20 random sensors with different sequence sizes (RMSE).

Fig. 7 shows the predicted speed values using Grizzly approach versus the actual speed of a random sensor from both PEMS-BAY and METR-LA datasets with a 5 min frequency pad. It is visible that both actual and predicted curves are almost overlapping. However, by analyzing the figure, our proposed approach is less accurate with detecting some *outliers*. Nevertheless, the comparative analysis puts forward that the Grizzly model is more effective with the non-linear large-scale traffic data and contributes to improving ITS performances.

Table 6
The computation time comparison of different approaches for the traffic speed prediction.

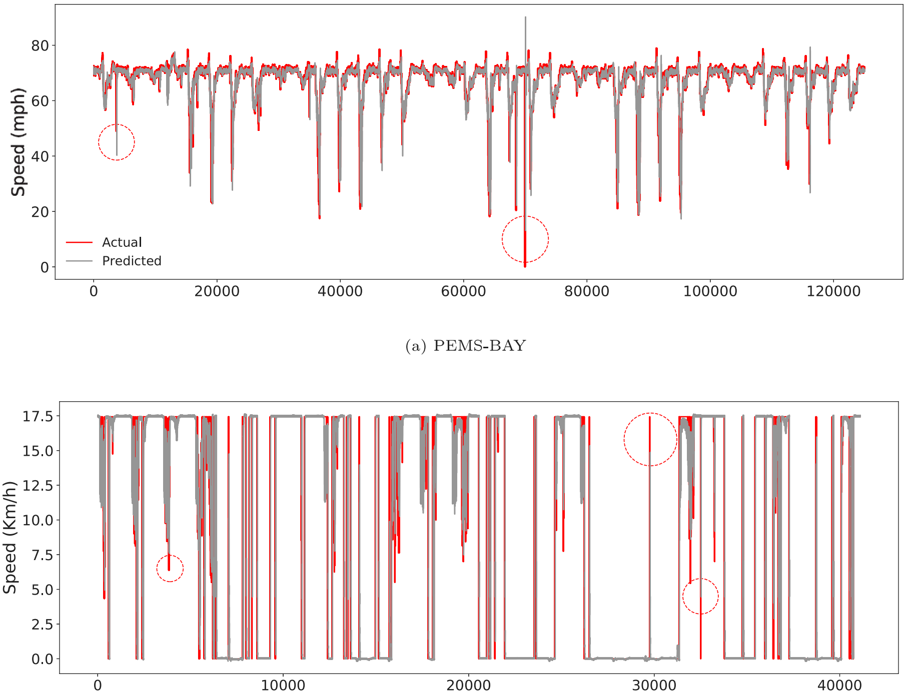
Dataset	Model	Training (s/epoch)
PEMS-BAY	STGCN	51.35 s
	DCRNN	650.64 s
	SLCNN	21.55 s
	GWNet	182.21 s
	Grizzly-15 min	**6 s** (178 μs/step)
	Grizzly-30 min	**6 s** (169 μs/step)
	Grizzly-60 min	**5 s** (126 μs/step)
METR-LA	STGCN	19.10 s
	DCRNN	249.31 s
	SLCNN	9.30 s
	GWNet	53.68 s
	Grizzly-15 min	**8 s** (337 μs/step)
	Grizzly-30 min	**1 s** (5 ms/step)
	Grizzly-60 min	**3 s** (4 ms/step)

6.6. Computation time

Table 6 shows the computation times of Grizzly with its variant architectures (15, 30, and 60 min) as well as those of its competitors on both PEMS-BAY and METR-LA datasets. Note that the average time consumption of our architectures is about 5 s per epoch. Compared with the pioneering models, Grizzly's training time was better. The results reveal that Grizzly is three times faster than SLCNN using PEMS-BAY and two times faster using METR-LA, while it shows less prediction performance (Table 5). DCRNN is more sluggish than other methods because of its intensive sequence learning in recurrent networks. In contrast to the second-best model, GWNet, shown in Table 5, Grizzly performs favorably compared to GWNet for the training of long-term traffic, e.g., 60 min ahead (Table 6). Grizzly is an appropriate option if time consumption minimization is favored, as it yields superior performance and maintains high efficiency. It is worth noting that once the model is trained, predicting speed values for all segments in the network is a straightforward task that requires very little computation time. Even for larger road networks, the prediction time is typically only a few seconds. A faster training process can also result in faster prediction or inference times.

7. Conclusion and future work

This paper highlighted the benefits of integrating sequence-to-sequence architectures and data pre-processing techniques (Normalization and Embeddings) with bi-directional LSTM neural networks to provide traffic predictions for ITS. Non-linearity and large-scale time-series traffic data problems were mainly addressed. In addition, we thoroughly investigated the performance of the developed approach compared with the traditional time series prediction model ARIMA and the Deep learning graph-based most performing models in the



(a) PEMS-BAY

(b) METR-LA

Fig. 7. Actual vs. predicted 5 min frequency test values of a random sensor.

literature STGCN, DCRNN, GWNet, and SLCNN in terms of MAE and RMSE values. Experiments on two real-world, large-scale datasets with three different time interval regression tasks showed that our proposed approach outperforms the baseline models regarding precision and computation time.

Limitations and future research direction

Even though this work is worth highlighting, it can still be improved. Upon analysis of the predictions of our proposed approach, we discovered that it is not capable of detecting outliers (or trend events). The primary reason for this failure is that these events do not frequently occur in the training dataset. Thus, the model was unable to learn much about them. These outliers often pose problems and influence the performance of the prediction methods. They can generally be identified as gross errors or true outliers. Gross errors are faulty observations, such as measurement, recording, or typing errors. Hampel et al. (2011) estimated that the frequency of gross errors in "row-data" varies from 1% to as high as 10%, whereas in "highly reliable data", there are hardly any. However, if the observation is not a gross error, it must be considered a true outlier. In other words, it is an accurate observation that was unexpected.

One of the problems with outliers is that they can be difficult to detect within time-series data. The Matrix profile (Yeh et al., 2016) is a method that can be used to identify patterns and anomalies within time series. It is a vector that stores the z-normalized Euclidean distance between any sub-sequence within a time series and its nearest neighbor. This algorithm is agnostic to domains, fast, supplies an exact solution, and only requires one parameter (window size). Future work will integrate tuning an automated detection algorithm (i.e., Matrix Profile) into our approach to identify outliers across thousands to billions of observations. If abnormal behavior is determined, the model will be updated accordingly. This algorithm would give the new outlier a much smaller weight than a standard data point and gradually increase it the longer it persists until it has equal weight with non-anomalous data. In that way, the system can adapt to permanent, substantial changes in a feature's normal behavior while also alerting the model of the change at the moment it occurs.

A promising area for future research is implementing the Grizzly model on FPGA or Ti-developed kits. Although our model's complexity is not a barrier to deployment on such platforms, there are still uncertainties regarding its real-time performance and accuracy on these devices. As a next step, we intend to explore the feasibility of creating a TinyML version of the Grizzly model that can be deployed on FPGA or Ti-developed kits. Our objective will be to compare the performance and accuracy of this hardware-based implementation to its software-based counterpart. We anticipate this study will offer valuable insights into the viability of deploying our model in hardware and its potential benefits.

Furthermore, we aim to explore *data fusion* techniques to aggregate heterogeneous information, e.g., audio, images, and videos collected from distinct sources (microwave sensors, radars, cameras, etc.). Doing so would increase the accuracy of the long-term prediction with a bigger sequence size and exploit the enormous variety of features available in each data source to identify better any outliers that may affect our results.

CRediT authorship contribution statement

Chahinez Ounoughi: Conceptualization, Methodology, Software, Validation, Visualization, Writing – review & editing. **Sadok Ben Yahia:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors have provided access to the datasets and code repositories by including their respective links in the manuscript.

Acknowledgment

This work was supported by grants to TalTech – TalTech Industrial (H2020, Grant No 952410) and Estonian Research Council, Estonia (PRG1573).

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Publication II

C. Ounoughi, G. Touibi, and S. B. Yahia. Ecolight: Eco-friendly traffic signal control driven by urban noise prediction. In C. Strauss, A. Cuzzocrea, G. Kotsis, A. M. Tjoa, and I. Khalil, editors, *Database and Expert Systems Applications*, pages 205–219, Cham, 2022. Springer International Publishing

EcoLight: Eco-friendly Traffic Signal Control Driven by Urban Noise Prediction

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Abstract. Traffic congestion is of utmost importance for modern societies due to population and economic growth. Thus, it contributes to environmental problems like increasing greenhouse gas emissions and noise pollution. Traffic signal control plays a vital role in improving traffic flow in urban networks. Hence, optimizing cycle timing at many intersections is paramount to reducing congestion and increasing sustainability. In this paper, we introduce an alternative to conventional traffic signal control, namely *EcoLight*, that provides significant improvements in noise levels, CO2 emissions, and fuel consumption, resulting from the incorporation of future noise predictions. A *Sequence to Sequence Long Short Term Memory (SeqtoSeq-LSTM)* prediction model, combined with a deep reinforcement learning algorithm, allows the system to achieve higher efficiency than its competitors based on real-world data from Helsinki, Finland.

Keywords: CO2 emissions · Congestion · Fuel consumption · Reinforcement learning · SUMO Simulation · Traffic signal control · Urban noise

1 Introduction

Traffic congestion levels have been rising precipitously in the last few years due to an imbalance between the rise in travel demand and the availability of transportation services. According to [18], the cost of congestion in cities such as Stuttgart and Paris is around 2% of their GDP. The general rule is that cities should develop strategies based on their visions and goals to reduce congestion. Implementation of new infrastructure is often slow and costly. Therefore, urban planners and policymakers are interested in making existing infrastructure more efficient [16]. One of the proposed hypotheses is that *"An improved traffic light system will lead to better traffic management and, therefore, more peaceful urban areas"* [1]. Hence, optimizing cycle timing at intersections can potentially contribute significantly to reducing congestion and improving environmental quality at the same time. Real-time control of traffic signals plays a vital role in

C. Strauss et al. (Eds.): DEXA 2022, LNCS 13426, pp. 205–219, 2022.
https://doi.org/10.1007/978-3-031-12423-5_16

reducing congestion by responding in real-time to several factors, including constantly changing traffic network dynamics. Moreover, the rapid increase in transport requirements has brought challenges to the sustainable development of our society concerning emissions and energy consumption induced by traffic. The European Environment Agency (EEA) reports that road traffic noise continues to be the primary contributor to noise pollution. Around 100 million people are exposed to road traffic noise above 55 decibels (dB) in the 33 member countries of the EEA. Among them, 32 million (about one-third) are subjected to extremely high levels of noise exceeding 65 dB [8]. Furthermore, according to the World Health Organization (WHO), exposure to loud noise causes high blood pressure, hearing loss, heart disease, sleep disturbances, and stress. Hence, measuring road traffic noise is a good indicator of traffic congestion intensity.

Numerous traffic signal control solutions have been used and proposed to overcome the traffic congestion issue. Worthy of mentioning, integrated Arduino in cameras with machine learning (e.g., object detection deep learning algorithms), and genetic algorithms for traffic signal timing optimization to help experts manage congestion. Recently, researchers have begun investigating reinforcement learning (RL) techniques for controlling traffic signals. These techniques appear to be more effective than traditional transportation methods. Its main advantage is that it learns how to take real-time action by observing the environment's reaction to previous actions.

One major issue of most RL-based traffic signal control approaches is that the setting considers, in each phase, only *mobility* and *current* traffic conditions when designing the next control strategy. We elaborate on these two characteristics by integrating two novel aspects into the RL techniques: *(i) Sustainability*: is achieved by incorporating noise as an environmental input feature; and *(ii) Proactivity*: is achieved by predicting future levels of noise so that the model is better prepared to make decisions based on current observations as well as future noise predictions. Therefore, in this paper, we propose a new eco-friendly RL-based traffic signal control model driven by urban noise traffic prediction, namely *EcoLight*. Our proposed approach reduces traffic congestion by reducing noise levels, CO2 emissions, and fuel consumption. By and large, the main contributions of *EcoLight* are as follows:

- At the noise prediction stage, we take advantage of the sequence to sequence architecture and propose splitting the time-series noise traffic data into fixed-sized sequences, where the size is determined based on an analysis of road network traffic behavior. Our method includes building a stacked layers architecture based on LSTM to extract temporal dependencies from noise data. Then, by using the past noise sequences as input, we would return a future traffic noise sequence.
- At the traffic signal control stage, we heavily rely on a deep reinforcement learning control model that takes as an input traffic-related information, i.e., the queue length, average waiting time, the phase, number of vehicles, and the vehicles' position at an intersection, besides the traffic noise estimation to predict the upcoming traffic signal action.

– We run our simulation experiments on a publicly available dataset of a road intersection collected in Helsinki, Finland. The harvested evaluation criteria (noise levels, CO2 emissions, and fuel consumption) outperform those obtained by the pioneering ones in the literature.

The rest of this paper proceeds as follows. In Sect. 2, we scrutinize the related work that paid attention to both traffic noise prediction and traffic signal control approaches. As an introduction to traffic signal control, Sect. 3 introduces key notions that will simplify the understanding of our research goal. Section 4 thoroughly describes the proposed *EcoLight* approach. In the penultimate section, we present the experimental evaluation and discuss the proposed model's performance against its competitors. The final section includes a conclusion and recommendations for future research.

2 Related Work

Modern societies nowadays are characterized by a great deal of noise. In addition to being a nuisance, it can also negatively impact the environment and human health. While evidence of noise's harmful effects is increasing, spatial understanding of its distribution is limited. This section introduces, first, brief overview noise prediction methods for traffic congestion enhancement, followed by methods for traffic signal control.

2.1 Noise Prediction

Noise pollution from road traffic is the most prevalent source of outdoor ambient noise in Europe. Different prediction models may produce different noise levels depending on traffic noise's location and emission sources. At present, very little research focuses on developing models that help determine the effects of traffic noise on society. Worth mentioning, Staab et al. [20] used a land-use regression (LUR) model and context-aware feature engineering to construct a geostatistical model mapping approach to represent the arrangement of sources and the surrounding environment. In this article, the authors deal with small communities that have not been adequately mapped in Europe. To improve traffic noise modeling, another solution was proposed by Ahmed et al. [2] that developed a deep neural network-based optimization approach that integrated the wrapper for the feature-subset selection (WFS) method. Using this method, weekday noise maps are created for different times of the day, such as mornings, afternoons, evenings, and nights. Khan et al. [10] conducted a comparison study between three different noise estimation models used throughout Europe. In this study, the main focus was to explore potential patterns in the performance of the models for specific configuration types. Based on vehicular traffic volume, percentage of heavy vehicles, and vehicles' average speed, a neuro-fuzzy inference system that identifies at what noise level the traffic (Leq dBA) will be detected has been proposed by Singh et al. [19]. Comparing it with conventional soft-computing techniques validates its suitability for planning mitigation measures for both new and existing roads. Finally, Zhang et al. [29] examined the accuracy of different machine learning recurrent architectures for predicting traffic noise using real-life traffic data with multiple variables. According to the study, using a multivariate bidirectional GRU model (Gated Recurrent Unit) with a many-to-many architecture achieved the best computation efficiency and accuracy.

The noise generated by traffic is a complex phenomenon. In modeling traffic noise, large and high-dimensional data are gathered. In this case, deep recurrent learning architectures are the best tools for analyzing large datasets and discovering nonlinear relationships.

2.2 Traffic Signal Control

Traffic signal control is an integral part of an intelligent transportation system that improves traffic efficiency. However, some challenges accompany these systems, such as protecting against high roadside cameras, keeping malicious vehicles from getting in, and preventing single points of failure. Literature has examined several traffic signal control systems to cope with those challenges. Two different approaches have been developed: a fixed-time (rule-based) strategy and a traffic-responsive strategy [13].

As part of a fixed-time strategy, several signal plans (e.g., from 8:00 to 10:00 am) are predetermined based on historical traffic flow data. Thus, a traffic signal is periodically changed per the predetermined signal plans. Worth mentioning, Le et al. [12] proposed a decentralized traffic signal control using a Back-pressure scheme for urban roads networks, which has received widespread recognition as a method for achieving an optimal throughput control policy in data networks. They concluded that the proposed scheme of fixed cycle times and cyclic phases stabilizes the traffic for any possible transportation demand. However, since such traditional transportation systems do not work in real-time, they can only be used when the demand is relatively stable within each time interval.

By using current traffic information, the traffic-responsive strategy overcomes the above limitation. In this strategy, the major challenge is forecasting incoming vehicles or traffic status. Bravo et al. [5] proposed a city-wide traffic control management program that assists traffic managers in making decisions, namely HITUL. Utilizing meta-heuristic algorithms and nature-inspired techniques, the HITUL system uses different technologies to gather data and optimize traffic signal priorities using existing traffic information. Various reinforcement-learning methods have recently been proposed to improve the traffic signal control and achieved better results than traditional transportation methods. Worth mentioning, *IntelliLight* [24], an RL-based method with an extended phase-sensitive gate that provides an overall measure of traffic signal control performance based on factors such as the waiting time and the number of vehicles at intersections. *Presslight* [22] is another RL-based method that uses the current phase, the number of vehicles on outgoing lanes, and the number of vehicles on incoming lanes as the state, and uses the Max-pressure (MP) as the reward for achieving coordination between neighbors. *Colight* [23] utilizes graph attentional networks to facilitate communication. In this case, it uses the attention mechanism to represent neighboring information to achieve the goal of cooperative traffic signal control.

Table 1. Representative traffic signal control methods.

Citation	Method	Simulator	Road net. (# inters.)	Evaluation
[12]	Back-pressure scheme	SUMO	Real (2)	Avg. travel time
[5]	Meta-heuristic algorithm	SUMO	Real (961)	Emissions, Waiting time
[24]	RL with extended phase-sensitive gate	SUMO	Synthetic (1), Real (24)	Reward, Queue Length, Delay, Duration
[22]	RL with MP-based reward	CityFlow	Sythetic (1), Real (3, 5, 16)	Avg. travel time
[23]	RL with graph attentional networks	CityFlow	Real (196)	Avg. travel time
[25]	RL trained with Demonstrations	CityFlow	Real (1)	Travel time
[15]	RL with object detection	Pygame	Synthetic (1)	Avg. waiting time
[3]	Queue-length responsive	Real env	Real (1)	Avg. waiting time
[7]	RL-FRAP with MP coordination	CityFlow	Real (2510)	Avg. travel time, Throughput
[26]	RL-FRAP with MAML	CityFlow	Real (1)	Travel time
[28]	MUMOMAML with clustering for Parameter initialization	CityFlow	Real (1, 5, 16)	Avg. travel time

DemoLight [25] learns a stochastic policy (demonstrations) that maps states to an action probability distribution based on a generated analogy between agents and humans. *FRAP* [30] is a reinforcement learning-based method designed to learn the inherent logic of the traffic signal control problem, called phase competition. The advantage of this method is that it combines similar transactions irrespective of the intersection structure or local traffic conditions.

ThousandLight [7] is one of the most recent works that has been tested on the real-road network with 2510 traffic signals. By leveraging the *'pressure'* concept, they developed RL-FRAP-based agents capable of signal coordination at a regional level. Furthermore, the authors demonstrated that individual agents can achieve implicit coordination through reward design, thereby decreasing dimensionality. Another RL-FRAP with model-agnostic meta-learning (MAML) is proposed in [26]. This model is able to transfer knowledge between different intersections by focusing on action spaces and state spaces instead of traffic flow, for example, training an agent at a four-way intersection and testing it at a five-way intersection. To improve the generalization ability of traffic signal control models, [28] proposed a meta-RL framework called *GeneraLight*. *GeneraLight* enhances generalization performance by combining flow clustering parameters initialization with multi-modal MAML (MUMOMAML). Table 1 summarizes the comparison of factors that influence the evaluation of traffic signal control strategies: method, simulation environment, road network, and evaluation metrics. Recent studies have shown promising results when using reinforcement learning techniques for traffic signal control. However, the use of these techniques relies only on the *current* traffic conditions. Therefore, through our approach, we contribute several novel *sustainable* and *proactive* aspects to this line of research.

3 Formalization of the Problem

This section introduces the fundamental notions used to formalize the traffic signal control problem.

A road network consists of several junctions indexed by J. Each junction $j \in J$ consists of a number of in-roads, R_j. Note that the R_j are mutually disjoint, and denote $R = \cup_{j \in J} R_j$. Multi-lane roads with different turns, such as left- or right-turn-only lanes, are represented by multiple in-roads. Therefore, in-roads may model one or more lanes of traffic flow. A junction may serve different combinations of in-roads at the same time. It refers to service *phases* when several in-roads are maintained simultaneously. For a junction j, a service phase can be represented as a vector $\sigma = (\sigma_r, r \in j)$, where σ_r is the rate at which cars at j can be serviced by the in-road r. Specifically, $\sigma_r > 0$ if the in-road r is green during phase σ, or $\sigma_r = 0$ otherwise. Accordingly, at each time step t, the system has to determine how much time it will spend serving each phase in S_j over the next interval, with the constraint that each phase must last for some non-zero length of time. Where S_j denotes the set of phases at junction j.

4 EcoLight Approach

Deep reinforcement learning has proven to be a promising method for controlling traffic signal. By extending the previously proposed reinforcement learning solutions, we improve the robustness of the traffic signal control system by using future traffic noise predictions. Our proposed traffic signal control driven by noise prediction, namely *EcoLight*, takes advantage of all traffic features along with the predicted amount of future generated noise. Integrating these *sustainable* and *proactive* aspects into our deep RL Q-network will enhance its decision-making capabilities and raise the green awareness of the city's stakeholders. Figure 1 illustrates the final approach framework.

4.1 Traffic Noise Prediction

A time series is an ordered sequence of numerical observations collected and stored at regular intervals over time. It characterizes by its *"Frequency"* (the time separating two consecutive data points). Time-series data must be defined clearly and with equal frequency. The time intervals we most often deal with for traffic-related data are 1, 5, 10 to 60 min. According to the sequence-to-sequence

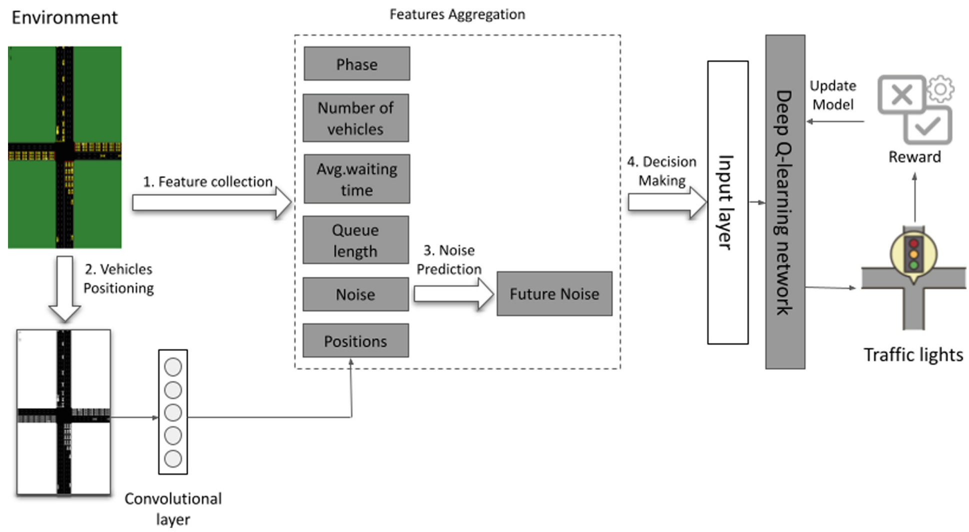


Fig. 1. EcoLight general framework.

architecture that we adopt in our algorithm, predicting hourly traffic noise would grant the input and output data as follows:

$$\begin{array}{ccc}
\text{Past hour} & \xrightarrow{topredict} & \text{Future hour} \\
[x_{(1,1)}, x_{(1,2)}, \ldots, x_{(1,s)}] & \xrightarrow{topredict} & [y_{(2,1)}, y_{(2,2)}, \ldots, y_{(2,s)}] \\
[x_{(2,1)}, x_{(2,2)}, \ldots, x_{(2,s)}] & \xrightarrow{topredict} & [y_{(3,1)}, y_{(3,2)}, \ldots, y_{(3,s)}] \\
\ldots & \xrightarrow{topredict} & \ldots
\end{array}$$

where $x_{(hour,observation)}$ and $y_{(hour,observation)}$ denote the past and future noise, respectively. And s represents the number of noise observations in one hour. Our approach embraces the Sequence to Sequence architecture to pre-process the time-series noise data. After splitting the time-series traffic data into fixed-sized sequences, we leverage an LSTM-based architecture to predict traffic noise of a future specific period (e.g., hourly, daily, etc.). Effectively it pinpoints long-term temporal dependencies accurately. We train and update the model using the back-propagation algorithm as an optimizer and a loss function to minimize the prediction error. Finally, we evaluate the model's predicted sequences, comparing them with the actual traffic noise ones using the prevalent evaluation metrics.

4.2 Traffic Signal Control

A reinforcement learning model consists of online and offline stages. A traffic state can be defined as a combination of five features: queue length, waiting time, number of vehicles, the vehicles' positions, and the phase. As soon as the prediction algorithm has been executed, the noise prediction will be explored as a state input to the model. Then, we use the reward to describe how much that action a has improved the traffic. In summary, the *EcoLight* approach is described as follows:

1. **Offline stage:** the traffic was allowed to flow through the system according to a fixed timetable to train the model and collect data samples.
2. **Online stage:** at every time interval Δ_t, the traffic signal agent will observe the state s from the environment and take action a according to ϵ-greedy strategy combining exploration (random action with probability ϵ) and exploitation (the estimation of the potential reward of doing this action given the state s).
3. **Memorization:** the agent will observe the environment and get the reward r from it. Then, the tuple (state, action, reward) will be stored in memory.
4. **Network update:** after several timestamps, the network will be updated according to the logs in the memory.

Algorithm 1 summarizes the steps of the reinforcement learning approach.

Algorithm 1. EcoLight: Traffic signal control

Require: predicted_roads_noise: predictions output; Simulation.
Ensure: CO2, Noise, Fuel_consumption

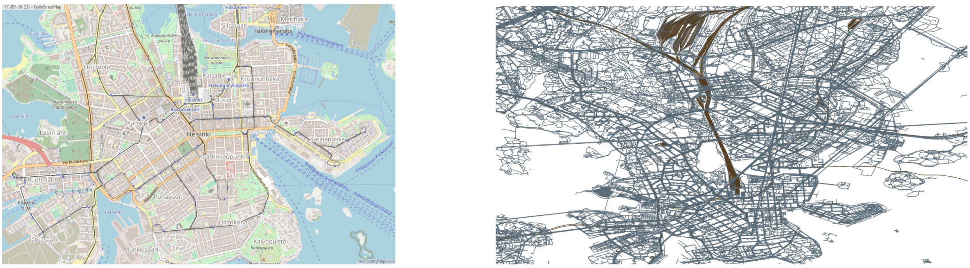
Initialize action-value function Q
Initialize updated Q'
$Prnoise$ extracted from predicted_roads_noise
Initialize experience memory M
Initialize the Agent to interact with the environment
$\epsilon \leftarrow$ setting new Epsilon
for (i=0; i < N; i++) **do**
  while simulation not terminated **do**
    Observe state s
    $s \leftarrow (Q\_leng, W\_time, N\_Veh, Pos\_veh, Prnoise)$
    With probability ϵ select action a_t
    Choose $QValues(M)$, action a
    Observe reward r, next state s_+
    Store transition(s,a,r,s_+) in M
  end while
  if UpdateTime **then**
    Update(network)
    Reset $Q' \leftarrow Q$
  end if
end for
Noise, CO2, Fuel_consumption $\leftarrow$ Evaluation(Simulation)
return Noise, CO2, Fuel_consumption

5 Experimental Evaluation

This section describes our experimental setup and evaluation process for comparing our *EcoLight* approach to pioneering baselines using real-world data.

5.1 Dataset

Experiments on real-world data are needed to determine *EcoLight*'s efficiency against the pioneering baselines. The Helsinki Region InfoShare [9] provided us with a complete database of urban traffic noise in Helsinki. The provided dataset is composed of several shapefiles [14], which present a storage format for geographic data between November 2011 and January 2012. These files can contain lines, points, polylines, and polygons representing different map features. Therefore, we performed a data transformation process to extract the complete traffic information, such as road names and noise values. The applied process can be resumed in these four steps: *(i)* convert the Helsinki OpenStreet map to shapefile (Fig. 2); *(ii)* project the noise file on the shapefile; *(iii)* using *QGIS3*, run the intersection tool to extract the full dataset noise and roads details; and finally *(iv)* export the intersection results to *.csv* file to be used for the noise prediction model.



(a) OpenStreetMap (b) Shapefile

Fig. 2. Conversion of the Helsinki OpenStreet map to shapefile.

5.2 Experimental Setups

Our experiments carried out under the configuration of *Ubuntu 18.04.3 LTS* (CPU: *Intel Xeon Processor (Skylake)* × 8, RAM: 16Go), in which *Python* (3.7) and *Keras* (2.3.1) with the simulator *SUMO* [21] have been installed.

Prediction Settings. We adopt the use of a fully connected network of an *LSTM Tanh* activation layer with the size of 40 units and output layer *Sigmoid* activation layer for the prediction task. The *Adam* optimizer [11], as well as *mean squared error (MSE)* as the loss function, are used to fine tune the training model within 100 epochs for the three considered dataset splits according to the period of the day (Morning, Evening, and Night).

Simulation Settings. *"Lonnrotinkatu"* is the intersection in Helsinki that is chosen to create a network in *SUMO*. First, the simulation presents the environment, including the state. Then the **EcoLight** model, according to that state, will predict the action of the lights then get its reward (as depicted in Fig. 3). Table 2 presents the parameters setting of the model and reward coefficient hence the simulation. We found out that the action time interval Δ_t has minimal influence on the performance of our model as long as Δ_t is between 5 to 25 s.

5.3 Baseline Methods for Comparison

To accurately validate the performance of our proposed **EcoLight** approach, we led a comparison with the existing traffic signal control baseline methods; the Deep RL-based **IntelliLight** [24], a Max-green-based algorithm Priority-driven Enhanced Traffic Signal Scheduling Algorithm **PETSSA** [17], and the defaults fixed-time-based traffic signal control model in the *SUMO* simulator with no intervention **BASIC**. For the sake of a fair comparison, we tested all the baseline methods using the same datasets.

5.4 Evaluation

Noise Prediction: The prediction performance of our model compared to a time-series forecasting baseline are evaluated using the *mean squared error (MSE)* and the *mean absolute error (MAE)* defined respectively by (1) and (2).

Table 2. Simulation settings.

Parameter	Value
Model update interval	300 s
Action time interval Δ_t	5 s
γ for future reward	0.80
ϵ for exploration	0.05
Sample size	300
Memory length	1000

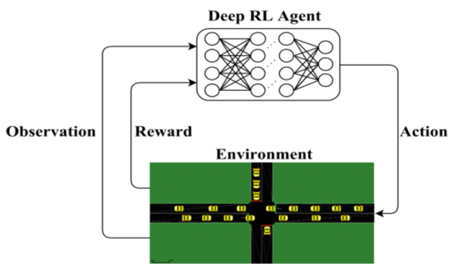


Fig. 3. Simulation process.

$$MSE = \frac{1}{J}\sum_{j=1}^{J}(n_j - \hat{n}_j)^2 \qquad (1) \qquad\qquad MAE = \frac{1}{J}\sum_{j=1}^{J}|n_j - \hat{n}_j| \qquad (2)$$

where J is the size of the tested junctions, n_j is the ground-truth junction's noise, and $\hat{n}_j$ is the predicted noise level yield by the model of the j-th junction.

Traffic Signal Control: Traffic poses a significant burden on society through its environmental impact, including air and noise pollution and the consumption of nonrenewable materials. With the use of *SUMO*, we can measure the generated pollution and the fuel consumption by using different models and interfaces. Among the information that can be obtained are: *(i) Trip information:* sum of pollutants emitted/fuel consumed by a single vehicle; *(ii) Lane emissions*: pollutants emitted and fuel consumed at a lane, aggregated over time; and *(iii) Lane noise*: noise generated along a lane, accumulated over a period of time.

Therefore, the traffic signal control performance evaluation of our approach against the pioneering ones is based on the emitted *noise*, *CO2 emissions*, and *fuel consumption* of each model on the considered dataset.

5.5 Results and Discussion

Table 3 glances the noise prediction performance of our **SeqtoSeq-LSTM** approach versus the **AutoRegressive Integrated Moving Average (ARIMA)** [4] non-parametric model using both mentioned evaluation metrics for each period of the day. This baseline combines the advantages of both autoregressive and moving average models in stationary random sequence analysis. In practice, most time-series aren't stationary. **ARIMA** overcomes this limitation by introducing a differencing process [27]. A good look at our results underscores that our model sharply outperforms **ARIMA** in predicting future noise with high improvement percentages for both morning and night periods of the day. Notwithstanding, the **ARIMA** model gives a slightly similar performance to our proposed model for the evening period of the day. In the sequel, we evaluate the effectiveness of our **EcoLight** traffic signal control in response to several environmental and economic factors.

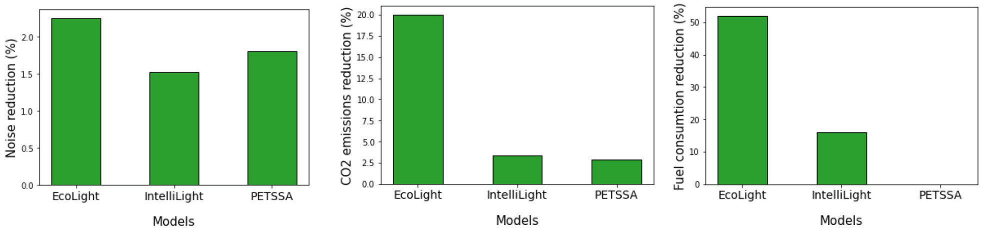
Table 3. Noise prediction performance.

Model	MAE			MSE		
Evaluation	Morning	Evening	Night	Morning	Evening	Night
ARIMA	65.89	2.31	72.94	4439.42	11.24	5537.93
SeqtoSeq-LSTM	**1.15**	**1.07**	**1.62**	**6.94**	**6.39**	**10.27**

Effectiveness over Traffic Noise. From the achieved results (Table 4), the **BASIC** shows the worst performance on the considered intersection as it is based on a fixed-timing strategy that does not adapt according to current and potential future situation of the traffic. The results underscore that the **PETSSA** model reduces better the noise level for both lanes of the fourth in-road of the intersection. Figure 4(a) depicts the improvement percentages of **IntelliLight**, **PETSSA**, and **EcoLight** models compared to the **BASIC** logic strategy. Overall, our proposed approach outperforms all the baselines for the produced noise at the considered intersection.

Table 4. Produced noise performance.

Model	Lane11	Lane12	Lane21	Lane22	Lane31	Lane32	Lane41	Lane42
Basic	70.38	69.38	72.86	69.54	68.91	71.57	70.25	70.55
PETSSA	70.20	67.99	72.80	68.28	67.88	70.38	**67.24**	**68.50**
IntelliLight	70.09	67.95	72.94	67.92	68.53	70.37	68.02	69.00
EcoLight	**68.77**	**67.90**	**72.62**	**67.08**	**67.52**	**68.09**	69.82	68.92



(a) Noise level. (b) CO2 emissions level. (c) Fuel consumption.

Fig. 4. Reduction vs. BASIC.

Effectiveness over CO2 Emission. According to our approach, significant reductions in CO2 are recorded for the majority of lanes compared to the other baselines (Fig. 4(b)). Although **EcoLight** isn't the best for some lanes, its performance is barely worse than the best achieved by the **IntelliLight** (Table 5). As depicted in Fig. 4(b), the improve rates of **IntelliLight**, **PETSSA**, and **EcoLight** models are comparable to those of the **BASIC**.

Table 5. Produced CO2 emission performance.

Model	Lane11	Lane12	Lane21	Lane22	Lane31	Lane32	Lane41	Lane42
BASIC	74, 579, 545.10	19, 333, 168.50	145, 881, 252.44	16, 540, 482.62	49, 821, 628.05	78, 431, 824.14	18, 681, 756.18	26, 546, 180.90
PETSSA	73, 854, 895.81	**18,137,521.04**	143, 853, 266.32	15, 721, 922.60	48, 154, 074.55	75, 249, 215.03	17, 950, 045.97	24, 612, 349.73
IntelliLight	73, 954, 895.81	**18,137,521.04**	142, 853, 266.32	**15,521,922.60**	49, 254, 074.55	75, 249, 215.03	**17,850,045.97**	**22,712,349.73**
EcoLight	**62,053,611.60**	18, 692, 031.10	**106,341,550.52**	15, 628, 314.04	**41,154,824.82**	**58,907,941.13**	18, 167, 102.88	22, 801, 416.51

Effectiveness over Fuel Consumption. A comparison of the improvement percentages of fuel consumption by **IntelliLight**, **PETSSA**, and **EcoLight** models to that of **BASIC** logic is shown in Fig. 4(c). **PETSSA** performs the same as **BASIC** with no improvement in terms of fuel consumption. We notice that the **IntelliLight** model gives a significant power reduction in two different lanes on the considered intersection (as shown in Table 6). While operating **EcoLight**, vehicular fuel consumption can be reduced by more than 50%.

Table 6. Produced fuel consumption performance.

Model	Lane11	Lane12	Lane21	Lane22	Lane31	Lane32	Lane41	Lane42
BASIC	32, 925.02	9, 759.01	105, 496.35	3, 357.92	20, 427.88	55, 544.55	5, 723.92	74, 821.11
PETSSA	32, 925.02	9, 759.01	105, 496.35	3, 357.92	20, 427.88	55, 544.55	5, 723.92	74, 821.11
IntelliLight	32, 157.82	10, 171.84	90, 043.45	**3,303.29**	20, 325.73	38, 920.39	**5,498.10**	58, 134.54
EcoLight	**26,675.58**	**8,034.87**	**45,713.41**	6, 717.90	**17,691.55**	**25,323.00**	7, 809.22	**9,801.32**

6 Conclusion

In this paper, we introduced an eco-friendly traffic signal control driven by urban noise prediction, namely *EcoLight*. We address the traffic signal control problem using a well-designed deep reinforcement learning approach that integrates future noise predictions. We conduct our experiments on Helsinki's geographical data. The yielded results provide evidence for the reliability and sustainability of the use of future noise predictions. Indeed, carried out experiments underscore the incapacity of the baselines to perform better in terms of noise, CO2 emissions, and fuel consumption compared to our *EcoLight* approach.

We point out a critical future direction to make *EcoLight* more relevant to the real world. The *EcoLight* is designed and tested to consider a simplified case of one intersection in Helsinki, whereas real-world network design is significantly more complex. Multiple intersections have been addressed by combining several reinforcement learning agents at a limited number of intersections. Meanwhile, sales of electric cars jumped 43% to more than 3.2 million of 370 different car models in 2020 [6]. This type of vehicles tend to be environmentally friendly and provide less noise. Future work will seek to improve the reduction by proposing a hybrid approach that enhances our *EcoLight* with traffic-related features prediction other than noise, combined with the *PETSSA* method to benefit from the Max-green strategy to reduce delay times, thereby limiting congestion levels.

Acknowledgment. This work was supported by grants to TalTech - TalTech Industrial (H2020, grant No 952410) and Estonian Research Council (PRG1573).

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Publication III

C. Ounoughi and S. Ben Yahia. Data fusion for its: A systematic literature review. *Information Fusion*, 89:267–291, 2023

Information Fusion 89 (2023) 267–291

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

Data fusion for ITS: A systematic literature review

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ARTICLE INFO

Keywords:
Intelligent transportation system (ITS)
Data fusion
Information fusion
Sensor fusion
Systematic literature review

ABSTRACT

In recent years, the development of intelligent transportation systems (ITS) has involved the input of various kinds of heterogeneous data in real time and from multiple sources, which presents several additional challenges. Studies on Data Fusion (DF) have delivered significant enhancements in ITS and demonstrated a substantial impact on its evolution. This paper introduces a systematic literature review on recent data fusion methods and extracts the main issues and challenges of using these techniques in intelligent transportation systems (ITS). It endeavors to identify and discuss the multi-sensor data sources and properties used for various traffic domains, including autonomous vehicles, detection models, driving assistance, traffic prediction, Vehicular communication, Localization, and management systems. Moreover, it attempts to associate abstractions of observation-level fusion, feature-level fusion, and decision-level fusion with different methods to better understand how DF is used in ITS applications. Consequently, the main objective of this paper is to review DF methods used for ITS studies to extract its trendy challenges. The review outcomes are (i) a description of the current Data fusion methods that adopt multi-sensor sources of heterogeneous data under different evaluation strategies, (ii) identifying several research gaps, current challenges, and new research trends.

1. Introduction

Accelerated evolution in intelligent transportation systems is obtained in response to the increased demand for reliable transportation networks. Thanks to the deployment of ubiquitous communication technologies that can continuously measure traffic attributes, *e.g.,* IP, Bluetooth, surveillance video camera, GPS, smartphones, loop detectors, magnetometers, R- ADARs, social media, and Vehicle to X (V2X), massive databases of various traffic data have been so far collected [1]. Such sensors measure traffic conditions with different methods and technologies, resulting in varying degrees of accuracy in their output [2]. E.g., While loop detectors collect frequent traffic information at a limited set of fixed points along a given road section [3–5], probe vehicles can provide continuous traffic measurements using GPS sensors along the same section of the road [6–8].

These heterogeneous sources of data provide different traffic conditions and statistics (quantitative and qualitative [2]) to different ITS applications (*e.g.* vehicle navigation [9,10], incident detection [11–13], traffic prediction [14–16]) to the aim of ease traffic problems by maximizing their safety and efficiency. However, they still suffer from many issues worth mentioning *(i)* real-time heterogeneous data and *(ii)* and sensor reliability. First, data are continuously generated with inconsistent formats and managed in different storage settings, which render the data unusable directly [17]. Second, sensors are not continuously reliable because of technical and operation-related issues (geometry locations or damages [7]), which cause gaps and missing information that affects stakeholders' decision-making. Therefore, a major challenge is to reduce the data missing, redundancy, delay, and anomalies phenomenon to improve the robustness and accuracy of the intelligent transportation systems applications [1].

Multi-source data fusion (MDF) models have grasped an extensive interest in an attempt to deal with these issues. Data fusion is an advanced technique to combine information coming from several sources to get more accurate results in an execution of an application in a way that is hardly performed by the use of individual sources separately [18]. Some existing papers have tried to summarize the efforts in data fusion. Table 1 summaries the characteristics of each data fusion previously conducted survey. We can see that the latest specific systematic review that covers the data fusion techniques applied in intelligent transportation systems was proposed in 2011 by Faouzi et al. [19]. The remaining surveys cover the general application of the data fusion techniques in different domains such as the internet of things (IoT) and smart cities. Both [20,21] are very recent and updated surveys that focus only on the machine and deep learning data fusion techniques used for different IoT applications that may also concern the ITS.

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https://doi.org/10.1016/j.inffus.2022.08.016
Received 2 August 2021; Received in revised form 12 August 2022; Accepted 14 August 2022
Available online 24 August 2022

Table 1
Characteristics of the reviewed literature reviews.

Article	Year	Coverage	Objectives and topics
Faouzi et al. [22]	2011	DF in ITS	Data fusion techniques, Challenges, Applications
Alam et al. [23]	2017	DF in IoT	IoT applications (Methods and Environment)
Lau et al. [24]	2019	DF general applications	Multi-perspectives classification of the data fusion
Ding et al. [25]	2019	DF in IoT	DF techniques in smart city applications
Liu et al. [26]	2020	Urban big data	Deep Learning data fusion techniques
Meng et al. [21]	2020	DF general applications	Machine learning data fusion techniques

This paper performs a thorough systematic literature review on recent data fusion techniques, applications to extract issues, and challenges of using these techniques in intelligent transportation systems (ITS).

By and large, the main contributions of this systematic literature review are as follows:

- We review a wide range of existing data fusion technologies in ITS literature, including their primary methods, data properties, evaluations, and applications.
- We discuss the important insights gleaned from data fusion techniques gathered from the raised research questions using a multi-perspectives classification methodology.
- We list several significant open issues and future research directions, which are useful for researchers and practitioners based on the completed review and in-depth analysis.

We organize the remainder of this paper as follows. First, we searched articles in multiple databases using a search strategy described in Section 2. Then, once we collected the articles, they were reviewed and organized in Section 3, which discusses the significant insights gathered from the raised research questions. Finally, we provide the conclusion and suggestions for future research on data fusion techniques within the context of intelligent transportation applications in Section 4.

2. Methodology and research protocol

This systematic literature review aims to summarize the recent state-of-the-art data fusion techniques applied to intelligent transportation systems (ITS) by performing an exhaustive search of papers since 2011 and reporting our main results and findings following the protocol recommended in the Kitchenham report [27].

2.1. Research questions

The primary research question in this systematic review is: "What are the challenges and future directions of data fusion for ITS applications?". To seek to answer this question, we split it into the following sub-questions:

1. What are the methods and techniques of data fusion used in ITS?
2. What are the different data properties used in data fusion for the further ITS applications?
3. What are the different methods of evaluation of these techniques?
4. What are the other systems' architectures and applications that use the Data Fusion?

2.2. Search strategy

In this section, we identify the potential range of published articles in the field by an electronic search from **ACM digital library**, **IEEE Xplore**, **ScienceDirect**, **Scopus**, and **SpringerLink** online databases. Fig. 1 depicts the research methodology steps that were applied to collect the potential articles. We have considered manifold and distinct search keys in titles, keywords, abstracts, and the text of articles. The main search keys were **"data fusion, information fusion, sensor fusion, and Intelligent transportation system"** using the following query (10.11.2020): *("information fusion" OR "data fusion" OR "sensor fusion") AND "intelligent transportation system"*. The obtained number of potentially relevant articles was **1,812** articles. Table 2 glances at the collected articles from each database.

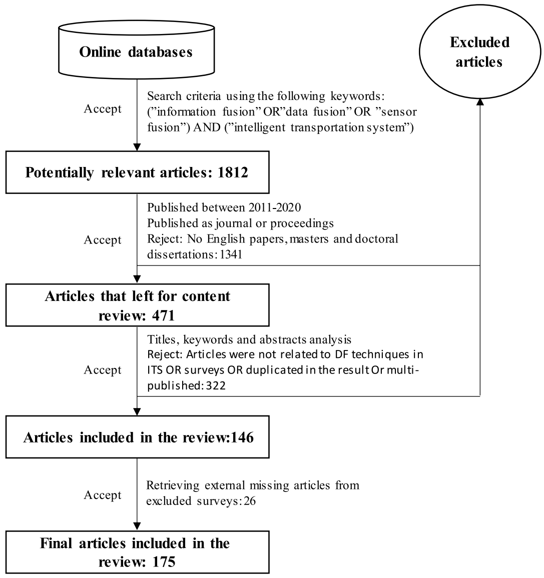

Fig. 1. Research methodology of the review.

Table 2
Databases search results.

Database	Number of articles
ACM digital library	20
IEEE Xplore	85
ScienceDirect	625
Scopus	287
SpringerLink	795
Total	1,812

2.3. Inclusion and exclusion criteria

The scope of this systematic review was restricted to the following criteria to select the potentially relevant papers: *(i)* because the latest specific systematic review that covers the data fusion techniques applied in intelligent transportation systems was proposed in 2011 by Fouzi et al. [19], only papers published since **2011** are included in this study; *(ii)* only conference proceedings and journal manuscripts in the English language were evaluated. Neither ScienceDirect nor SpringerLink provides information about the type of research paper. The number of potentially relevant articles, resulting after applying the inclusion and exclusion criteria, is equal to **471** articles, as shown in Table 3.

Table 3
Distribution of database's search results by type of the research article.

Database	Journals	Proceedings	Total
ACM digital library	2	12	14
IEEE Xplore	21	27	48
ScienceDirect	–	–	199
Scopus	60	64	124
SpringerLink	–	–	86

Table 4
Quality assessment criteria.

Criteria	Number of excluded articles
Not related articles	215
Surveys	50
Duplicates	54
Multi-published	3
Total	322

2.4. Quality assessment

According to their study design, each of the identified articles was chosen according to the following quality assessment criteria: (*i*) only papers that apply data fusion techniques in intelligent transportation systems applications are selected. So, we eliminated surveys from our study; (*ii*) excluded duplicated articles from different data sources; and (*iii*) excluded multi-published articles in various conferences or journals. Thus, the number of total excluded articles after applying the quality assessment criteria is **322** articles (as shown in Table 4).

We systematically reviewed the lists of references from the **50** excluded survey articles and added those research articles that met the inclusion criteria under the **149** articles. Finally, we selected **26** more data fusion techniques articles that will be included in our review, *i.e.*, **175** scientific studies.

2.5. Data extraction

As for the analysis of the selected literature studies, we have extracted the following data from each: *(i)* the complete reference; *(ii)* classification of the study of application domain; and *(iii)* the classification of the data fusion techniques level. Finally, in the sequel subsections, we usher by tabulating the extracted data to state a general overview of the scientifically reviewed studies.

2.5.1. Distribution by years of publication

The distribution of the retained studies per publication year shows that the period after 2015 presents a significant expansion of data fusion research works (see Fig. 2). Indeed, the number of retained papers in data fusion has increased remarkably from 15, before 2015, to 120 between 2016 and 2021. This evolution of articles is a natural result of integrating big sensor data in roads and vehicles. Table 5 shows the yearly percentages of the retained articles.

2.5.2. Distribution by data sources

We show the classification of the retrieved articles by data sources in Fig. 3. Our statistics indicate Scopus contains 86 articles with 49.14% of the reviewed studies.

2.5.3. Distribution by fusion level

Independent of the type of sensors, data fusion techniques can be categorized into three main types: *(i)* observation-level fusion (low-Level); *(ii)* feature-level fusion; and *(iii)* decision-level fusion (high-Level) [28]. The first level of fusion means that raw sensor data are combined directly. The second level underscores a preliminary extraction of representative features from the original sensor data. Finally, decision-level fusion is used only after a first determination of the target's attributes of interest [29]. As described in Table 6, almost all the kept articles use the feature-level fusion techniques (164 papers or 93.44%). This high percentage could be explained by the need to refine and pre-process the huge number of the collected raw data before using it.

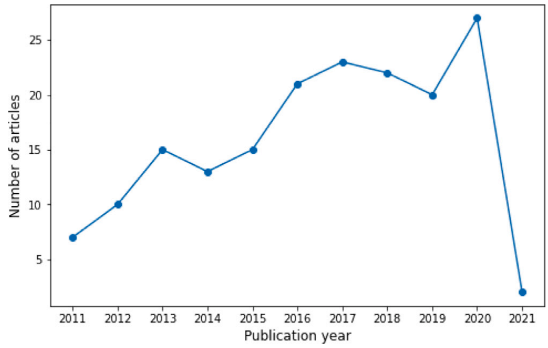

Fig. 2. Distribution by year of publication.

Table 5
Percentage distribution by years of publication.

Years	Number of articles	Percentage (%)
2011	7	4.00
2012	10	5.71
2013	15	8.57
2014	13	7.18
2015	15	7.43
2016	21	12.00
2017	23	12.57
2018	22	13.14
2019	20	11.43
2020	27	15.43
2021	2	1.14
Total	**175**	**100**

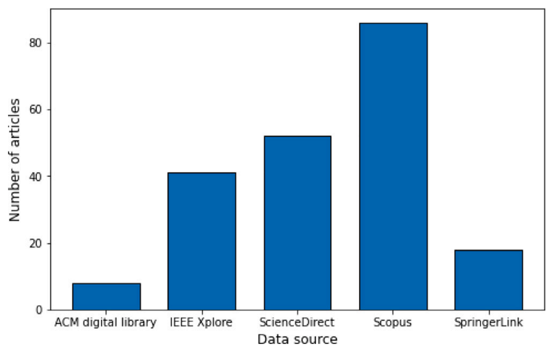

Fig. 3. Distribution by data sources.

Table 6
Distribution by fusion level.

Level	Number of articles	Percentage (%)
Observation-level	5	3.28
Feature-level	164	93.44
Decision-level	6	3.28
Total	**175**	100

Table 7
Distribution by application domains.

Domain	Number of articles	Percentage (%)
Autonomous vehicles	14	8.00
Detection	16	9.14
Driving assistance	17	9.71
Traffic prediction	38	21.71
Vehicular communication	8	4.57
Localization	48	27.42
Management systems	34	19.42

Table 8
List of abbreviations.

Abbreviation	Description
CAN	Controlled Area Network
CDR	Call Detail Records
CNN	Convolutional Neural Network
CVNS	Continuous Visual Navigation System
CTRV	Constant Turn Rate and Velocity
DGPS	Differential Global Positioning System
DSRC	Dedicated Short Range Communications
EEG	ElectroEncephaloGraphy
FBN-PSD	Functional Brain Network-Power Spectrum Density
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GSM	Global System for Mobile communications
ILDs	Inductive Loop Detectors
IMU	Inertial Measurement Units
INS	Inertial Navigation System
IoV	Internet of Vehicles
ITS	Intelligent Transportation System
JDL	Joint Directors of Laboratory
LHCP	Light-Hand Circular Polarized
LIDAR	Light Detection And Ranging
LSSVM-NARX/KF	Least-Squares Support Vector Machine Nonlinear Autoregressive with eXogenous input/Kalman filter
MEC	Mobile Edge Computing
Mer-Gesh	Merges multiple data sources in a similar manner to transmission Gears meshing
OBU	On Board Units
RHCP	Right-Hand Circular Polarized
RTMS	Remote Transportation Microwave Sensors
RSU	Road Side Units
SCATS	Sydney Coordinated Adaptive Traffic System
SNR	Signal to Noise Ratio
SVM	Support Vector Machine
UWB	Ultra-WideBand
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
V2X	Vehicle to All
VANET	Vehicular Ad Hoc Network
VLC	Visible Light Communication
WSN	Wireless Sensors Network

2.5.4. Distribution by application domains

In this distribution, we classify papers by the different purposes of the data fusion using: autonomous vehicles, Detection (incident, fatigue, traffic signs, lanes, and types of vehicles), driving assistance (navigation systems, parking assistance, and trip planning), traffic prediction (speed, flow, stat, and travel time), vehicular communication (Vehicle-2-Vehicle, vehicle2X, and Vehicle-2-Pedestrian), localization (positioning and tracking applications), management systems (coverage and quality of the collected traffic information, decision making, automatic emergency decision, driving behavior extraction, and taxi demand). As sketched by Table 7, most reviewed articles are related to localization (48 papers or 27.42%) and traffic prediction (38 papers or 21.71%). The popularity of localization applications in intelligent transportation systems is explained by the need to accurately determine the position of vehicles and different road stats to provide better services.

Table 9
Fusion methods classification.

Method	Number of articles	Percentage (%)
Probabilistic-based	81	46.29
Evidence reasoning	14	8.00
Knowledge-based methods	52	29.71
Others	28	16.00
Total	**175**	**100**

3. Harvest scrutiny

Following the search strategy, we identified 175 articles published between January 2011 and November 2020. We critically reviewed all of the 175 articles to shed light on the issues raised in Section 2. At a glance, Tables 16–24 sketch the studied articles based on the raised researches questions using the following criteria:

- **Fusion approach:** refers to the used data fusion methods/techniques (to answer the first question of this review).
- **Data properties**: presents the nature of the information used for the fusion process.
- **Source**: presents different hardware/software used to collect data.
- **Evaluation**: indicates whether the proposed approach was evaluated using a real-life collected dataset (Real-life environment) or a synthetic dataset (Simulation).
- **Domain of application**: classifies the research study into one of the application fields depicted in Fig. 4.

All the abbreviated terms are explained in Table 8.

3.1. What are the methods and techniques of data fusion used in ITS?

The first issue of this review is about choosing the technique/method to adopt the selected application in ITS. These techniques are mentioned in Tables 16–24 respectively. We can notice that according to Khaleghi et al. [30] and Pires et al. [31], these approaches could be categorized in four groups: *Probabilistic-based* methods, *Evidence reasoning-based* methods, and *Knowledge-based* methods. The final distribution of the approaches according to the classification is presented in Table 9.

3.1.1. Probabilistic-based methods

The results of this review showed that most of the studies had used probabilistic-based fusion methods since 2011 with a percentage of 46.29%. Worthy of mentioning the Kalman filter algorithm and its variations (42 articles), *e.g.*, *Extended Kalman filtring* [9,32–38], *Unscented Kalman filter* [39–43], *Sequential Kalman filtering* [44], Cubature Kalman filtering [26,45,46], *Federated Kalman filter* [47]. Kalman filters require little processing power in their simplest form and are typically used to fuse raw (low-level) nonlinear data. The modified Kalman filter known as the extended Kalman filter (EKF) is ideal for implementing nonlinear recursive filters. Nevertheless, it is time-consuming when it comes to computing the Jacobians. Therefore, linearization has been applied to reduce the computational cost. Yet this introduces errors in the filter, which leads to instability of the filter. The unscented Kalman filter (UKF) has gained popularity since it eliminates the linearization step and associated errors of the EKF. The UKF uses deterministic sampling to determine the minimum set of points around the mean. By doing so, it captures the true mean and covariance. Using nonlinear functions, these points are propagated, and the covariance of the estimations can be recovered. The UKF also provides the advantage of being used in parallel implementations.

Contrary to the Kalman filter, *Particle filter* is rarely used for fusion in ITS applications (5 articles). Despite that in dynamic models with nonlinearities and non-Gaussian densities, particle filters provide

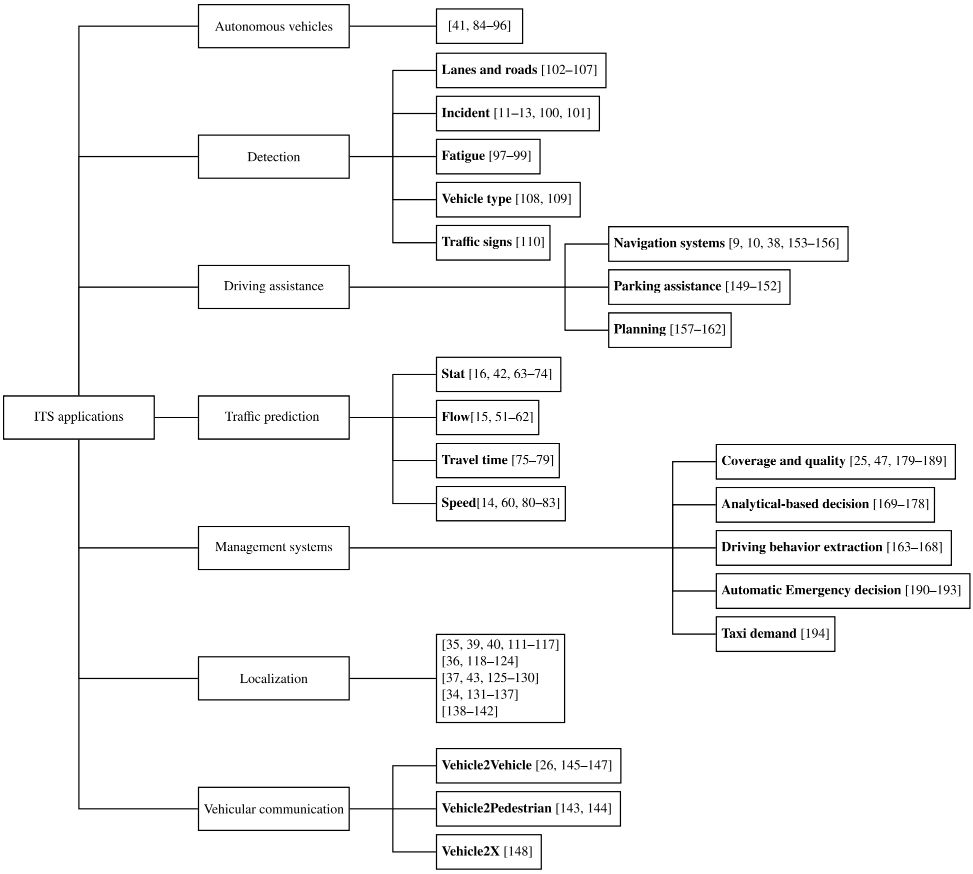

Fig. 4. Distribution by application domains.

more flexibility than Kalman filters. They do, however, come with certain disadvantages. Obtaining low variance in the estimator requires many particles. Moreover, it is tricky to determine the optimal number of particles in advance; this affects the computational cost significantly [48]. Furthermore, a fair number of approaches based on probabilistic (e.g., fuzzy theory, Bayesian networks, stochastic process, etc.) and statistical formulas (e.g., average, majority, maximum, co-variance, etc.) were proposed for the fusion of information from different sources (12, 22 articles respectively).

3.1.2. Evidence reasoning-based methods

Evidence reasoning-based is the most minor used category with a percentage of 8%. Nevertheless, the Dempster Shafer theory is one of its most known methods for data fusion (12 articles). The basic idea behind this theory is that one has to combine all the evidence and come up with a conclusion or degree of belief in light of all the considered ones. A significant benefit of an evidence-based approach lies in its ability to quantify ignorance, which makes it sound like a framework for dealing with missing values [49]. Furthermore, the Dempster–Shafer theory transforms the data by adjusting the granularity and reallocating the masses. In other words, a rule that holds at a lower level of granularity may only be valid when generalized to a higher level of aggregation. Furthermore, Dempster–Shafer's combination law (the orthogonal sum) allows us to combine data from independent sources. Having the same frame of discernment for two mass functions derived independently from different data, we may assign a unified mass. Nevertheless, it has some disadvantages, *e.g.*, in some cases, an overestimation of the final assessment can occur; small changes in input can cause essential changes in output; high efficiency with bodies of evidence in pseudo-agreement; lower efficiency with bodies of evidence in conflict [50]. In addition to the Dempster Shafer theory, two more evidence reasoning-based studies used the belief-multi-level fusion process.

3.1.3. Knowledge-based methods

Recently, knowledge-based methods have grasped attention from both academic and industrial fields. These methods are mainly capable of processing many non-linear heterogeneous traffic data. In this respect, and with the development of the automatic learning-based techniques, more data fusion research is using the machine/deep learning models (27 articles - 51.92%) and linear weight-based (11 articles - 21.15%). Classical ML-based fusion (abductive reasoning) infers the most accurate explanation of observation by choosing a hypothesis under the assumption that explains it most accurately. By all means, when a set of observed data are fused, the approach attempts to determine the best explanation. However, the complexity of machine learning algorithms used to solve these problems increases as the size and complexity of data increase. ML approaches are becoming increasingly complex, *i.e.* deep learning architectures, making it challenging to understand what they have learned or why a given fusion was made, representing a barrier to its adoption. Other researchers have focused on using data mining techniques, *e.g.*, clustering (6 articles - 11.53%).

In general, there is no guarantee that clustering algorithms will find the optimum number of clusters or of cluster centers. Furthermore, these algorithms assume that the dataset has already been normalized or that its co-variance is irrelevant. Other data pre-processing-based techniques, *e.g.*, such as time/spatial synchronization (6 articles), and knowledge-based methods are proposed using semantic web technology and ontology (2 articles - 3.84%).

The idea of semantic fusion is to integrate sensor data and translate it into formal languages. So the resulting language is compared with similar languages stored in the database based on the observations of the environment. The transmission cost is reduced in this type of method since the nodes only need to transmit the language structure rather than the raw data. However, a set of known behaviors must be stored in a database beforehand, which can be challenging in some cases.

3.1.4. Other

The remaining approaches, called 'Other' (28 articles), are distributed between the physical fusion at the sensors level. Hybrid methods that use combinations of the ones mentioned above, *e.g.*, Extended Kalman filter and SVM [33], CNN-Kalman filter algorithm [51], and LSSVM-NARX/KF [52]. Hybrid methods combine one or more algorithms that have recently become relevant favored ones. These methods can rely on the capabilities of different techniques simultaneously and expand the ability to model complex correlations.

3.2. What are the different data properties used in data fusion for further ITS applications?

Over the last decade, tremendous amounts of transportation-related data have been collected owing to the availability of sensors. Sensors are deployed in a real-world environment to collect and forward data about particular physical behavior to support the design and development of a wide range of applications to increase drivers' and passengers' satisfaction, improve road safety and reduce traffic congestion. Fleming [53], in his review, classified sensors based on the place of deployment: *(i)* **In-vehicle** which many companies install (*e.g.*, Taxi companies) or manufacturers to control the performance and status of the vehicle; and *(ii)* **In-roads** that are located along the roadside to offer smart parking services (*e.g.*, corresponding drivers with free parking spots), provide information about congestion levels on the road, or collect environmental data which can be processed to improve the flexibility of traffic networks. Table 10 summarizes the data collection technologies used by the reviewed data fusion literature articles. The GPS and video camera are the most commonly used technologies to collect transportation-related data, followed by the V2X, LIDAR, Loop detector, IMU, RADAR, and GNSS. From the analysis, the remaining technologies are used according to the context of the application (*e.g.*, Weather data) or not used because they are not affordable (cost) or the size of the device disables its integration in cars, etc. More specific used technologies that are clustered as 'Others' in Table 10 are classified as follows:

- **Frameworks:** RESTful,[1] 4K Stogram software[2], Web crawlers, and traffic light signals.
- **APIs:** Bing maps routes API,[3] Here Maps API,[4] and social media content.
- **Simulators:** SUMO simulator.[5]

Table 10
Data collection technologies used by the literature approaches.

Source	Number of articles
GPS	53
Camera/video/RGB	38
V2X	17
LIDAR	16
Loop detector	16
IMU	12
RADAR	12
GNSS	11
Laser scanners	9
Odometers	8
Internal sensors vehicular sensors	6
INS	5
CAN (message protocol)	5
Gyroscope	5
Accelerometer	5
Twitter API	5
Ultrasonic	4
DSRC	4
RSU	4
Infrared	4
Smartphones	4
Probe vehicle	4
OBU or OBD	4
WI-FI	3
Magnetometer	3
Inductive loop	3
GSM	2
RTMS	2
Bluetooth	2
Others	48

- **Maps:** HD Map,[6] OD analyzer,[7] Google earth,[8] and digital compass.[9]
- **Human based data:** surveys, human experts reports, data service providers, and driver's behaviors.
- **Environmental sensors:** Weather sensors.
- **Systems:** ITS subsystems, Clarus footnotehttps://www.its.dot.gov/research_archives/clarus, highway information safety, MEC server, wireless sensor networks, traffic sensors, CDR, and Cellular network.
- **Algorithms:** CTRV, DGPS, Dead Reckoning, stereo vision systems, obtained from a camera, and Floating Car Data.
- **Other types of sensors:** Spatial NAV100, NC-200 sensors, wireless geomagnetic sensors, SNR transmitters, laser rangefinder, gravity sensors, AACN, acoustic sensors, EEG, RHCP, and LHCP antennas.

In the sequel, we will discuss some of the most commonly used data features for fusion in ITS.

3.2.1. Geographical data

The decisive role of a sensor network is to collect and forward data to a destination. Therefore, it is crucial to determine the location of the collected data. The localization process is absolute to find the position of an object as data is useless without its geographical position. This data is obtained with the help of specialized algorithms deployed into different sensor technologies. For example, GPS (global positioning system) is the simplest method for detecting sensors. However, it becomes expensive if many sensors exist in a given network. From the review articles, many algorithms have been proposed to solve the issue of localization, 27.42%, dedicated to using such sensors to determine the

[1] https://restfulapi.net
[2] https://4k-stogram.en.softonic.com
[3] https://www.microsoft.com/en-us/maps
[4] https://developer.here.com/develop/rest-apis
[5] https://sumo.dlr.de

[6] https://www.tomtom.com/products/hd-map
[7] https://developer.tomtom.com/od-analysis
[8] https://earth.google.com
[9] https://www.digitalcompass.org

position or the series of trajectories maps grids, worth mentioning: laser scanners, RADAR, INS, Cellular network, WI-FI, GNSS, IMU, Bluetooth, Loop detector, Video camera, LIDAR, Odometers, RSU, RHCP and LHCP antennas, OBU, DSRC, GSM, smartphones GPS, VANET, DGPS, RTMS, CDR, and google earth application. The number of papers uses the location as an input feature: 89 articles, to wit 50.85%.

3.2.2. Temporal data

Despite the rapid development of geographical positioning tools, spatial information can only be analyzed for a fixed time point or period for which it is assumed to remain unchanged. However, human behaviors, transportation facilities, traffic conditions, to name a few, all change with time. Hence, all sensors are developed to record temporal data alongside the targeted data collected, which is the key to transportation decision-making. Thus, the default time is primarily used in most articles as input features for any application.

3.2.3. Visual data

As the transportation field seeks new and inventive methods to transition to a "smart city", video surveillance solutions have become essential for analyzing and managing traffic flow, safety, and security. Rapid technological development of surveillance cameras and sensors (Ultrasonic sensors, LIDAR, infrared camera, and laser scanner) allows the sector to get vital information. Exceptionally that utilization enables the stakeholders to capture a wealthy amount of knowledge, e.g., traffic patterns, congestion levels, the distance between vehicles, vehicles detection across several lanes and can classify vehicles by their length or type, to name but a few. The major limitation of the visual devices/sensors is that environmental conditions can cause reliability issues in detecting objects in varying lighting conditions. Therefore, to overcome the above problems, the latest management systems tend to use image sensors (such as Laser scanners, LIDAR) with the fusion of multiple sensor information (such as RADAR) to improve the precision of measuring for Advanced applications. For example, positioning, traffic prediction, object detection/tracking, autonomous car driving safety, road condition classification, V2X communication, noise detection, travel time estimation, routing system, quality enrichment of the data, and journey planning [9,34,35,39,41,42,54–68].

For the visual feature collection, from Tables 10 and Tables 16–24, we notice that right after the use of the simple camera/video sensors comes the use of the LIDAR technology. LIDAR is a novel system in the industry that measures distances to both fixed and moving objects. LIDAR uses specialized processes to create three-dimensional images of the detected objects. The primary limitations of LIDAR are its expense, limited performance in adverse weather (e.g., fog, rain, snow, etc.), and no color or contrast detection, which yields poor optical recognition because it makes use only of light spectrum waves [69]. Nevertheless, companies such as Google are using an advanced LIDAR in the *Waymo* self-driving car project note Waymo. An Ultrasonic sensor calculates the distance between the sensor and the object by measuring the time it takes for the transmitter emitting sound to contact the receiver. The main drawback of this kind of sensor is its high sensitivity to environmental effects. The infrared sensor measures the radiation in its surrounding environment (vehicles, roads, or other objects). This type of sensor is used for object tracking/detection that emits heat (has a temperature > 5 degrees Kelvin) resulting from infrared radiation.

3.2.4. Traffic data

Table 11 glances at the various use of traffic-related data (speed, flow, travel time, occupancy, congestion stat, and construction works) by the reviewed research articles. The mentioned traffic data are broadly applied for various traffic applications. First, the historically recorded information supports predictions [15,16,55,57,67,70–91], planning [92–94], behavior reporting and analysis [95–99]. Second, streaming or (near) real-time traffic data can be useful for automated driving cars [56,100], incident detection [11–13], advanced travel information systems (ATIS) (*e.g.*, V2X communication [101], positioning/tracking [102–105], parking assistance [106]), and traffic signal priorities [107], which require the most up-to-date data so that applications can take the best decision. There are two sorts of traffic sensor issues in producing precise traffic data indicators. First, the internal problems connected to the accuracy of the devices in collecting data are referred to as a technical restrictions (*e.g.*, scanner inaccuracy, which provides erroneously detected speed). Second, the external issues are related to the data's limitations in portraying the actual traffic situation. For example, in speed data collection, loops detect the instantaneous speed at one point on the lane, not necessarily reflecting the full lane speed. We should consider these internal and external issues when using traffic data; as a result, traffic data can correctly depict the actual traffic situation.

Table 11
Traffic data properties used by the literature.

Source	Number of articles
Speed	47
Flow	24
Trajectories	16
Travel time	4
Occupancy	3
Density	4
Congestion stat	5
Construction works	1

Table 12
Internal vehicle data properties used by the literature.

Source	Number of articles
Acceleration	7
Vibration	4
Brake	3
steering wheel	4
Turns behavior	2
Horn	1

3.2.5. Internal vehicle's data

Recently, the automobile sector is being transformed by digitization. Connectivity and in-vehicle data are the primary driving forces behind the development of new and innovative mobility services. Vehicle manufacturers are controlling and exploiting the in-vehicle data commercially using in-vehicle sensors to collect information related to driving controls. Table 12 presents a variety of uses of in-vehicle data in the literature. The primary usage of in-vehicle data was dedicated to extracting the driving behavior in roads [95,108–111] and for autonomous driving applications [41,56,112]. Some other articles utilized this type of data to classify the road conditions [42,58], to detect drivers fatigue [113,114], to localize vehicles [104], and as a parking assistance information [115].

3.2.6. Environmental data

Many studies have shown that environmental factors such as weather (*e.g.*, temperature) and noise in residential zones and touristic locations influence the traffic on roads [70]. 7.42% of the reviewed articles used the weather conditions data to predict traffic congestion [70,74,77,79,88,116–118], future planning [92], emergency and accident detection [13,107,119,120], taxi demand [121], and driving assistance [122]. 1.71% of the articles exploit the noise information for driver fatigue detection [113], emergency response [107], and for vehicle localization [123]. And finally, just one article mentioned the employment of vehicle emissions data driving assistance [122] (see Table 13).

Table 13
Environmental data properties used by the literature.

Source	Number of articles
Weather	13
Noise	3
Emissions	1

Table 14
Textual/social media data properties used by the literature.

Source	Number of articles
Tweets	6
Instagram images	1

Table 15
Textual/social media data properties used by the literature approaches.

Source	Number of articles
Real-life environment	110
Simulation	65

3.2.7. Textual/social media data

People can publish and distribute information/opinions instantly with the help of smartphones and social media applications (*e.g.*, Twitter). Therefore, it makes every user an instant social sensor. Because of this, social media has emerged as a valuable source of real-time traffic content (as shown in Table 14). Furthermore, this information is used as input to traffic prediction approaches [16,70,71,80,117,124] for a host of transportation services by the traffic management agencies, such as signal control, transit scheduling, traveler information, etc.

3.3. What are the different methods of evaluation of these techniques?

As a result of reviewing the strategies for evaluating applications (as shown in Table 15), 62.85% of the articles used real-life evaluation, which validated the real-world scenarios and proved the adaptability of the solutions. However, according to the reviewed articles, 37.14% use simulations due to the continuous change in methodologies. Therefore, it is necessary to conduct simulations as an evaluation process to reduce the cost of evaluating strategies under different scenarios, conditions, and parameters.

3.4. What are the different systems' architectures and applications that use data fusion?

Fig. 5 summarizes a taxonomy for ITS applications. The taxonomy defines seven categories based on the type/aim of the application for ITS.

3.4.1. Autonomous vehicles

Vehicles manufacturers are towards the innovation of enhancing vehicles' ability to be more autonomous without human intervention. Therefore, they focus on improving the safety of travelers by reducing the number of accidents, injuries, and fatalities [68]. The autonomous driving control decision is obtained by collecting massive traffic events and intensive knowledge fusion processing. Worth mentioning in the literature, Cao et al. [100] proposed an intelligent distributed collaborative decision scheme using a multi-dimensional data fusion mechanism that thoroughly considered the spatial and temporal characteristics of IoV services for autonomous driving. Chitnis et al. in [56] introduced a distributed multi-sensor fusion architecture to ensure the no-failure that could cause hazardous situations for humans. Dominic et al. [125] proposed a risk assessment framework for autonomous and cooperative automated driving. Fukatsu et al. [126] analyzed and fused the considerable amount of dynamic (real-time) information received from the cooperative perception exchange to enable a new level of safety and reliability in autonomous vehicles. Hong et al. [127] designed an accurate 3D-object detector that takes both LIDAR point clouds and RGB images as inputs to the CrossFusion Net. This proposed fusion model exploits features from both sources through a hierarchical fusion structure. Laghmara et al. [128] tackled the issue of 3D object detection in the Belief Function framework for autonomous vehicles. The approach adopts the evidence theory for multi-feature fusion to include two heterogeneous sources defined by the position and size besides the direction of motion in the scene of the dynamic objects. Marin-Plaza et al. in [41] proposed a ROS-based approach by fusing data and knowledge to adapt and alter overall vehicle parameters in different platforms. This fusion strategy aids the vehicles' embedded systems increase their powerfulness, flexibility, and modularity. Zanchin et al. [68] presented a discussion about sensors use in autonomous vehicles. The latter is recently switching from unidimensional to multi-dimensional sensor fusion. The authors demonstrated the importance and the necessity of fusion strategies to provide an expansive vision of the environment in which the vehicle is inserted to hold decisions per driveability conditions that aspire to attain. Martín et al. [61] relied on the fusion of different sources of data (inertial measurement units and differential GPS) to ensure vehicles' robustness and safety in case of a large variety of lighting conditions and complex perception tasks such as shadows, low lighting conditions, and night vision. Raouf et al. [129] proposed an analytical approach for fault detection of an automated Octree fusion-based system for a low-speed autonomous vehicle. This system was tested on three different scenarios with different sensors. The results showed that the sensor fusion system proves its efficiency in decision making, especially when a sensor sends incorrect data to the system. Shen et al. [130] integrated the time-varying information into an adaptive federated Kalman filter (FKF) fusion model based on the criteria of the degree of observability. This model enhances the accuracy, robustness, and fault-tolerance ability of the navigation systems for unmanned ground vehicles in a highly dynamic environment. Wang et al. [111] designed a lower-level controller to ensure that all the vehicle's tires work using a novel data fusion technique to generate the estimation value of the tire-road friction coefficient of both through the integrated longitudinal force and lateral force. To reduce the system delays caused by the extensive data downloading strategies of vehicles, Yu et al. in [131] established an optimization indicator based on mathematical programming with equilibrium constraints (MPEC) to control and assess fusion computing services. Daniel et al. [132] have incorporated the use of Kalman Filter (KF) fusion techniques into an efficient architecture for real-time big data analysis in an autonomous vehicle. Therefore, it augments the data processing competence and removes noise from the obtained sensor information. To strengthen the safety and trustworthiness in autonomous vehicles, it is pivotal to adopt the data fusion algorithms from different sources to enable drivers' notifications and determine expeditious automated reactions and decisions to reduce the potential of road accidents.

3.4.2. Detection

ITS applications in this category relieve the traffic flow and ease the driving in roads and urban zones. Detection applications can be divided into five sub-categories as follows:

Lanes and roads detection: Cheng et al. [142] proposed a novel road centerline detection based on a multiscale collaborative representation of VHR remote sensing images fusion of multiple features and spatial information. Garg et al. [58] proposed a dual-modality decision-level fusion with a belief revision approach including a particular emphasis on robust road hazard detection. Gu et al. [151] introduced a road detection framework based on fusing 3-D LiDAR and a monocular camera. The proposed method projects the 3-D point cloud of LiDAR onto the camera's image for the escapade of range and color information. Finally, Li et al. [162] proposed a real-time feature-level fusion

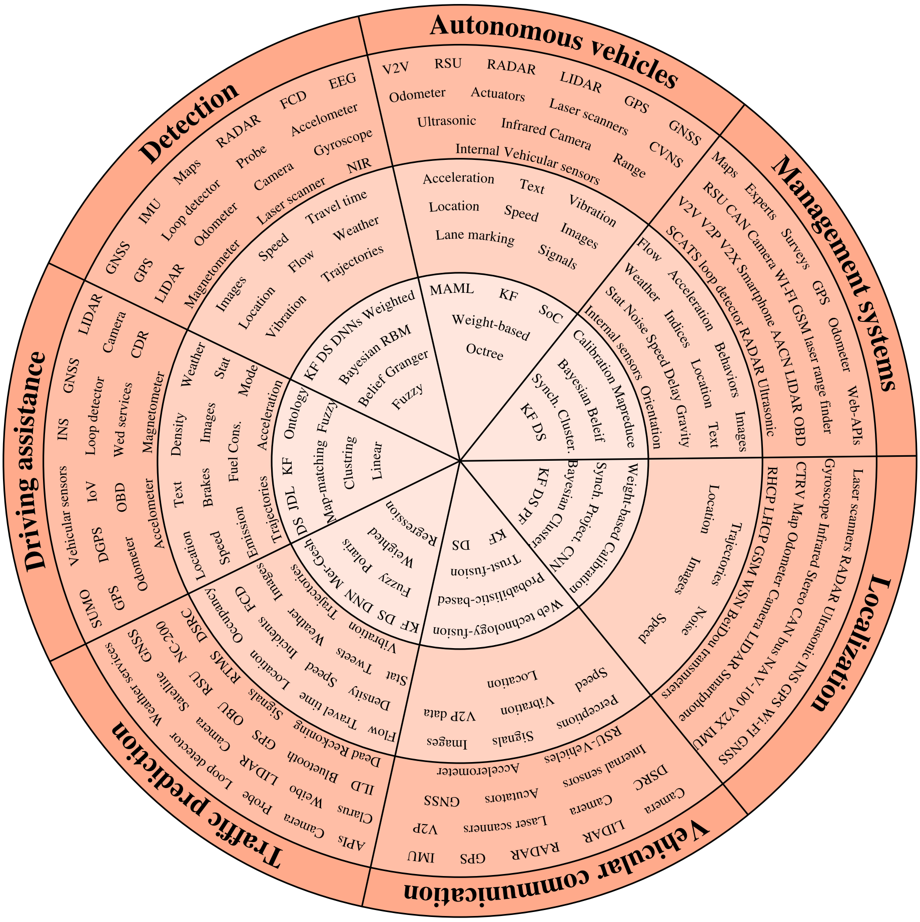

Fig. 5. Taxonomy of Data Fusion for ITS applications.

method for both LIDAR and vision data using an optimal selection strategy for detecting the best drivable region in front of a vehicle. Moreover, a conditional lane detection algorithm is selectively executed depending on the system's fusion output. Finally, Atia et al. [136] provided a low-cost real-time lane-determination model based on high-resolution estimation of the vehicle's position, speed, and orientation using an extended Kalman filter data fusion model on several sources (accelerometers, gyroscopes, GNSS, and roads network maps). Bosi et al. [140] proposed an in-vehicle IoT object for real-time pothole detection to evaluate the road condition. The proposed design is based on implementing sensor fusion techniques to provide enhanced services combining raw data coming from onboard devices.

Fatigue detection: Chen et al. [113] implemented a feature fusion model for automated fatigue detection. The fusion is based on the output features of the functional brain network, which characterizes the relationship between brain network organization and fatigue, and the output features of the power spectrum density, which marks the relationship between power variation and fatigue. Daza et al. [114] presented a non-intrusive approach for detecting driver drowsiness based on the fusion of the driver's Percentage of Eye Closure information captured in real-time by a stereo vision system, and its driving behavior gathered from the CAN bus (lateral position and steering wheel angle). Finally, Kartsch et al. [155] proposed an energy-aware solution for drowsiness detection based on the fusion of the driver's physiological (single-channel EEG signal) and behavioral (IMU sensor) data.

Incident detection: Dia et al. [11] conducted a comparative study to assess the performance of using different data fusion neural network-based architectures for incidents detection using various probe vehicle penetration rates and loop detector configurations. Fernandes et al. [12] developed an Android OS application, namely HDy Copilot, for automatic crash detection. The offered solution applies a data fusion mechanism to information collected from the vehicular communications and driver/passenger's smartphone sensors (accelerometer, magnetometer, and gyroscope). Smartphone applications ensure a low-cost mobile solution compared to built-in commercial systems. In [13], a deep fusion model is proposed to determine the traffic accident duration based on traffic accident data and spatial–temporal correlations of traffic flow reports. The authors adopted different types of RBMs to handle both categorical and continuous variables separately; furthermore, the extracted features from each model are fused for the final estimated output. Rapant et al. [81] proposed a data fusion solution that avails from the advantages and disadvantages of two different traffic data sources (floating card data and ASIM sensors) based on Granger causality analysis to manage and successfully control traffic incident situations. Yu et al. [120] used a deep learning graph-based Spatio-temporal architecture with an embedding layer for traffic accident prediction. The model fused different heterogeneous inputs

Table 16
Data fusion for ITS approaches (part 1).

Article	Fusion approach	Data properties	Source	Evaluation	Domain of application
Aeberhard et al. [54]	Track-to-Track fusion	Location, images	Laserscanner, RADAR, Ultrasonic sensors	Real-life environment (BMW 5 Series)	Positioning
Akbar et al. [70]	Time synchronization (organize according to time)	Congestion(0,1), tweets, weather conditions	RESTful, Twitter API, Weather Underground	Simulation	Congestion prediction
Aliedani et al. [133]	Vehicles signals-fusion	Location	SUMO simulator	Simulation	Parking assistance
Alkouz et al. [16]		Tweets: English and Arabic, Instagram images, traffic stat, time, location	Twitter API 4K Stogram software Bing maps routes API	Real-life environment	Congestion prediction
Alomari et al. [71]	Text Fusion	Tweets: Arabic	Twitter API	Real-life environment	Congestion prediction
Anand et al. [72]	Kalman filtering algorithm	Flow, travel time	Video recorder, probe vehicle	Simulation	Density prediction
Ardakani et al. [134]	Weight-based fusion	Location	INS, GPS, Cellular Network, and Wi-Fi	Real-life environment	Position tracking
Arribas et al. [135]	Kalman filtering algorithm	Location	GNSS, INS and odometers	Simulation Real-life environment	Positioning
Atia et al. [136]	Kalman filtering algorithm	Location	GNSS and IMU	Real-life environment	Lane detection
Awasthi et al. [137]	Dempster Shafer theory	Transportation measures	Human experts, sensors, Models and survey	Real-life environment	Sustainability evaluation of solutions
Bachmann et al. [14]	Simple Convex Bar-Shalom/Campo Kalman filtering-based Ordered Weighted Averaging Fuzzy Integral Artificial Neural Network	Location	Bluetooth (probe vehicle), Loop detector	Real-life environment	Speed prediction
Bauer et al. [138]	Weight-based fusion	Location	GNSS, CTRV, HD Map	Real-life environment	Positioning
Behere et al. [101]	–	Location, speed	Video, RADAR, LIDAR	Real-life scenarios	Vehicle2Vehicle communication
Belhajem et al. [32]	Hybrid approach (Extended Kalman filtering and Neural networks)	Location	GPS, Odometers	Simulation	Positioning
Belhajem et al. [33]	Hybrid approach (Extended Kalman filtering and SVM)	Location	GPS, Odometers	Simulation	Positioning
Benalla et al. [92]	Dempster Shafer theory	Traffic density, weather, age	Sensors	Simulation	Planning

from Taxi's GPS, historical traffic accident data, POI distributions, and weather observations at various road networks.

Vehicle type detection: Yao et al. [197] adopt a multi-stage information fusion to improve the performance of the conventional Adaboost vehicle's license plate detector. Li et al. [163]adopt a multistage information fusion to enhance the performance of the traditional Adaboost vehicle's license plate detector. Their multi-stage fusion system detects, first, the existence of the license plate using the fusion of a color checking module with an SVM classifier. Furthermore, the latter output gets through the enhanced Adaboost for the final license plate detection.

Traffic signs detection: Lauffenburger et al. [159] examined multi-object detection algorithms based on a transferable belief approach dedicated to Traffic Sign Recognition. The associated targets are pursued over time and space using the Kalman Filtering algorithm.

3.4.3. *Traffic prediction*

Traffic prediction is a crucial part of intelligent transportation systems. Accurate traffic forecasting can be used to improve routing, dispatching, and congestion management. Recent research has focused on this area and has provided efficient solutions for predicting traffic flow, stats, travel time, and speed.

Flow prediction: Anand et al. [72] presented a study using a Kalman filter to fuse spatial and location-based data to predict traffic density. Chen [55] proposed a new hybrid fusion approach based on fuzzy rough set theory and evidence theory. Cui et al. [143] introduced a new fusion approach named Polaris. Polaris is based on a sparsity analysis of the traffic volume and the different correlations between the spatial–temporal features. Essien et al. [117] fused the social information that is publicly available by Tweets with traffic and weather conditions to improve their deep learning model for traffic flow prediction task. Finally, Hong et al. [76] introduced a new fusion model that avoids noisy and error-prone manual feature engineering. Furthermore, it seizes the intrinsic characteristics of complex traffic flow patterns in high-dimensional data using a hybrid multi-metric based k-nearest neighbor method for traffic flow prediction. Koesdwiady et al. [77] focused on extracting the correlation between traffic information and weather and proposed a decision-level data fusion scheme to improve the prediction accuracy using weather conditions. Li et al. [79] developed a real-time transportation flow prediction system named VTraffic, which integrated data from heterogeneous sources using a data fusion strategy to maximize the quality of the prediction. Pu et al. [174] proposed a novel hybrid prediction model based on the fusion of traffic images' features using an attention CNN with an encoder–decoder framework. Sun et al. [84] introduced a conditional fusion method to enhance the data anomaly detection accuracy of ensemble traffic prediction models. Finally, the purpose of Zheng et al. mention Zheng2020 was to predict the traffic flow based on the LASSO coefficient fusion of Spatio-temporal factors dictionary.

Stats: Akbar et al. [70] introduced a two-layer architecture for analyzing the heterogeneous (traffic, weather, and social media) IoT data streams. The first layer ingests, stores, and analyzes data from multiple interfaces in real-time to extract and detect complex events. At the same time, the second layer fuses the removed events using a probabilistic-based model. Alkouz et al. [16] proposed a new Linguistic-based model for traffic jam events prediction named SNSJam using cross-lingual data fusion collected from multiple social media platforms. Alomari et al. [71] focused on analyzing tweets about traffic to detect congested areas. The authors fused tweets in the Arabic language collected from the Twitter REST API with other traffic data in the SAP HANA

Table 17
Data fusion for ITS approaches (part 2).

Article	Fusion approach	Data properties	Source	Evaluation	Domain of application
Birek et al. [139]	MapReduce framework	Text data, location	Web crawlers, user mobile device, vehicle	Real-life environment	Driver's behavior extraction
Bosi et al. [140]	–	Location, vehicle vibrations	GPS, IMU, accelerometer (smartphone, internal sensors)	Real-life environment	Patholes detection
Bresson et al. [34]	Extended Kalman filtering	Location, images	Odometer, camera	Simulation	Positioning
Cao et al. [100]	MAML (multi-dimensional information fusion)	Location, speed, road constraints	V2V, RSU	Simulation	Automated Driving
Chen [55]	Evidence theory and Fuzzy rough set	Flow, travel time, speed, lane occupancy	Loop detectors, video detectors, OD analyzer	Real-life environment	Flow prediction
Chen et al. [108]	Adaboost	Steering wheel, brake throttle, road conditions	Internal sensors	Simulation	Driving behavior
Chen et al. [141]	Message-fusion	warning messages	V2V	Simulation	Decision-making
Chen et al. [113]	FBN-PSD (feature fusion)	Steering wheel, a horn, brake pedal, noise, an accelerator, the chair and turn signals, speed	Internal sensors	Simulation	Fatigue detection
Cheng et al. [142]	Multi-scale information fusion	VHR images (spectral, structural and contextual road characteristics)	Google Earth	Real-life environment	Road segments detection
Chhabra et al. [109]	Dynamic Bayesian Network	Time of day, hours of driving, temperature, acceleration, turns behavior	Smartphone sensors (accelerometer, gyroscope)	Real-life environment	Driver's behavior classification
Chiang et al. [112]	Constraint fusion	speed, distance, brake	Internal sensors	Real-life environment	Decision making
Chiang et al. [9]	Extended Kalman filter with motion constraints	Location, images	POS (INS/GNSS), LIDAR	Real-life environment	Navigation
Chitnis et al. [56]	SoC multi-sensor fusion	Images, location, speed, acceleration, etc.	Camera, RADAR, LIDAR, Ultrasonic, infrared camera, IMU, GPS, odometry sensors, actuators	Real-life environment	Autonomous cars safety
Cho et al. [35]	Extended Kalman filter	Images, shapes, location	Camera, LIDAR, RADAR	Real-life environment	Tracking
Clairais et al. [73]	Multi-component Kalman gain	Flow	Loop detectors	Real-life environment	Flow prediction
Cong et al. [102]	Time synchronization	Speed, location	Smartphone accelerometer and gyroscope	Real-life environment	Positioning
Cui et al. [143]	Polaris data fusion	Flow, location	Loop detector, signaling	Real-life environment	Flow prediction
Daniel et al. [132]	Kalman filtering	Images and texts	Camera, laser scanners	Real-life environment	Autonomous cars

database in the city of Jeddah. Finally, Fulari et al. [57] presented a study for real-time speed estimation based on a dynamical Kalman filtering technique for location-based and spatial traffic variables data fusion. Mai-Tan et al. [167] advanced novel mobile crowd-sourcing fusion-based approaches for traffic prediction. The proposed framework integrates and analyzes the traffic-related data shared by mobile crowds in real-time and incorporates the missing data by applying data mining techniques to the historical data. Osman et al. [42] acquainted an online adaptive covariance estimation algorithm for drift suffering proprioceptive sensors used on exteroceptive sensors with known uncertainty. It proves the high ability to estimate the true covariance and its adaptiveness to different driving situations. Saadeddin et al. [181] developed a low-cost system for congestion avoidance based on the fusion of IMU with GPS using an extended Kalman filter approach. Shi et al. [82] exploited multi-modal data fusion through graph and hypergraph modeling based on a neural network learning process for traffic stat classification. Xia et al. [87] proposed a formal representation of heterogeneous traffic-related data by determining their mutual features and fusing the spatiotemporal data. Using GPS and SCATS loop detectors, this formal representation is sketched according to different granularity levels of the collected traffic data. Wang et al. [86] adapted the theory of cognitive psychology to learn the driving behaviors in the road network using a simulation method. They applied a visual-filtering model and a perceptual-information fusion model to describe drivers' heterogeneous cognitive processes. Based on a computational domain theory for data understanding, Xia et al. [194] proposed a new approach to formally represent heterogeneous extensive traffic data. The authors used the data-centric and operations-centric transfer functions to assess the computational intensity of different aspects of traffic data fusion and analysis. Xia et al. [204] proposed a cooperative neural fusion approach for fast image restoration that defeats the difficulty of estimating the noise error based on a novel L2-norm. Yao et al. [89] introduced a new approach for traffic stat prediction that fuses after handling the missing data attaining from multiple sensor data streams using Spatio-temporal correlations with the historical data.

Travel time estimation: A novel notion of intersection-to-intersection real-time travel time estimation and route recommendation model was proposed by Lee et al. [160] based on the fusion of vehicular ad-hoc network extracted data. Rahmani et al. [64] introduced a non-parametric travel time estimation method that fuses data from two traffic data sources (automated number plate recognition system and floating car data). Zhang et al. [90] advanced a data fusion structure, called Mer-Gesh, that fuses data from multiple sources to transmission Gears meshing in a uniform Spatio-temporal context. This gear framework can add new heterogeneous sensor features at different locations dynamically. A new data fusion algorithm was stated by Zhang et al. [91], based on the cosine theorem, to gauge the degree of mutual support between beliefs and the conflicts between pieces of evidence. Finally, Zhao et al. [201] adopted the use of recurrent deep learning architecture, Gated Recurrent Unit, for the travel time estimation by the fusion of both dedicated short-range communications (DSRC) and remote transportation microwave sensors RTMS data.

Table 18
Data fusion for ITS approaches (part 3).

Article	Fusion approach	Data properties	Source	Evaluation	Domain of application
Datta et al. [144]	Semantic web technologies	–	Vehicular sensors and smartphone actuators	Real-life environment	Vehicle2Vehicle communication
Dawood et al. [39]	Interacting Multiple Model Unscented Kalman filter	Location, 3D environment images	GPS, odometer and gyroscope, laser scanner, camera	Real-life environment	Positioning
Daza et al. [114]	Artificial neural network	Steering wheel angle, lateral position, heading error, percentage of eye closure	Internal sensors, NIR stereo rig	Simulation	Fatigue detection
Deng et al. [145]	Weight-based fusion	Images	RGB sensors, Infrared depth sensors	Simulation	Positioning
Dheekonda et al. [146]	Deep learning (CNN)	Images, distance	LIDAR, digital camera, Ultrasonic distance transducer	Simulation	Moving object positioning
Dia et al. [11]	Neural network fusion	Speed, travel time	Loop detector, probe vehicle	Simulation	Incident detection
Ding et al. [25]	Mining algorithm	Video, text, speed, location, etc.	ITS subsystems	Real-life environment	Multi-media information sharing
Dominic et al. [125]	Weight-based fusion	Location, road/lane markings	Inertial and Odometric, GPS, range sensors	Real-life environment	Automated driving safety
Du et al. [106]	City Traffic Data-as-a-Service Ontology-based fusion	Traffic congestion, location	GPS, data processing service, data service providers	Simulation	Parking assistance
Eciolaza et al. [10]	Computational theory of perceptions	Text, signals	Drivers	Simulation	Driving behavior reporting
Essein et al. [74]	Data in-data out technique	Flow, average speed, density weather	Inductive loop sensors	Real-life environment	Speed prediction
Essain et al. [117]	Data in-data out technique	Flow, average speed, density, weather, tweets	Inductive loop sensors, Twitter API	Real-life environment	Flow prediction
Fernandes et al. [12]	High/low filtering	Speed, location	Accelerometer, magnetometer, gyroscope	Real-life environment	Accident detection
Flores et al. [103]	Multi-track Kalman filter	Images, location	LIDAR, V2P communication	Real-life environment	Emergency Braking
Flórez et al. [147]	Calibration	Images, speed, location	LIDAR, Stereo vision systems, proprioceptive sensors	Real-life environment	Positioning
Fukatsu et al. [126]	–	Images, signals	LIDAR, V2V communication	Simulation	Automated Driving

Speed prediction: Bachmann et al. [14] investigated the efficiency of several data fusion algorithms (simple convex combination, the Bar-Shalom/Campo combination, and the Kalman filter) for fusing data from loop detectors and probe vehicles to gauge freeway traffic speeds accurately. Essien et al. [74] stated an improved traffic speed prediction model involving traffic-related variables and weather data fusion with the deep learning LSTM architecture. Lan et al. [78] impersonated a speed prediction method based on the space-matching fusion model between loop vehicle detector data and probe vehicle data according to each road segment. This fusion technique uses the Newton method as a training method to adjust the weights. Lin et al. [80] —presented a unified probabilistic framework for traffic speed prediction based on fusing multi-source data, including location, textual traffic descriptions, and heterogeneous traffic-related data. Yang et al. [88] propose a hybrid deep learning structure for short-term traffic speed prediction involving external factors such as weather conditions and the air quality feature fusion to measure the impact of environmental factors. Shan et al. [97] used the multiple linear regression fusion models (MLR) to estimate traffic missing data by extracting the inherent spatiotemporal correlations from road segments to improve the performance of traffic speed prediction.

3.4.4. Vehicular communication

Communication among vehicles and roadside infrastructure is an area of growing importance. The development of wireless communications has made it possible to share information between vehicles and infrastructure in real-time. As a result, applications are now available to boost vehicle safety and connect passengers with the Internet. Additionally, efforts are underway to standardize vehicular communication to make vehicular transportation safer, greener, and more convenient.

Vehicle2Pedestrian: Based on a probabilistic association between perception and V2P communication, Merdrignac et al. [62] developed an integrated cooperative system for vulnerable road users' safety. Salmane et al. [182] investigated the use of video data from crossing scenes to detect and evaluate potential dangerous situations caused by users (pedestrians, vehicles, unattended objects). The authors first used the Hidden Markov Model to predict the ideal trajectories of the detected objects. A Dempster–Shafer-based fusing is then applied for each identified hazard scenario to consider different sources of danger.

Vehicle2Vehicle: Behere et al. [101] implemented a cooperative driving architecture that shares knowledge in real-world scenarios. The system possesses a flexible data fusion component that maintains invariance through system changes. Finally, Datta et al. [144] outlined several leading research and engineering challenges for integrating connected vehicles into IoT ecosystems. The main difficulties are collecting data uniformly from vehicle sensors and integrating heterogeneous features into a standard IoT architecture for connected vehicles using data fusion. With the help of cameras on connected cars, Liu et al. [26] devised a unified probabilistic tracking and localization data fusion approach to allow safe decision-making in V2V communication. In addition, Liu et al. [164] developed a hybrid integrity monitoring method that moves beyond the limitations of conventional satellite visibility-based techniques by creating measurements from virtual satellites via ground-based V2V range-rate measurements and a priori road geometry.

Vehicle2X: Qui et al. [177] implemented a trust architecture to integrate data from multiple sources and formats in heterogeneous networks with various levels of trust.

3.4.5. Localization

Many Intelligent Transport System (ITS) applications, including the position and heading information of vehicles and Vulnerable Road

Table 19
Data fusion for ITS approaches (part 4).

Article	Fusion approach	Data properties	Source	Evaluation	Domain of application
Fulari et al. [57]	Kalman filtering algorithm	Flow, speed, density, travel time	Camera, Bluetooth	Real-life environment	Congestion prediction
Gao et al. [104]	Interacting multiple model and Kalman filtering	location, velocity, acceleration, heading	GPS, CAN bus, Spatial NAV100	Simulation	Positioning
García et al. [40]	Unscented Kalman filter, Kalman filter, Particle filter	Images	Laser scanner, camera	Real-life environment	Tracking
Garg et al. [58]	Decision-level fusion and Belief revision	Images, vibrations	Camera, internal sensors	Simulation and Real-life environment	Road conditions classification
Geetla et al. [107]	–	Location, time of crash, weather, congestion, road noise	AACN and acoustic sensors	Simulation	Emergency response
Geng et al. [59]	Weight assignment fusion	Location, images	GPS, visual odometer,LIDAR	Simulation	Path tracking
Ghaleb et al. [123]	innovation-based adaptive estimation Kalman filter	Trajectories, environmental noise	GNSS	Simulation	Positioning
Golestan et al. [36]	Extended Kalman filtering	Location	GPS, V2V communication	Simulation	Positioning
Golestan et al. [37]	Extended Kalman filtering	Location	V, V2V, V2I communication	Simulation	Positioning
Goli et al. [148]	Bayesian filter	Location, distance	GPS, V2V communication	Simulation	Positioning
Gorrieri et al. [149]	Cluster Probabilistic-based fusion	Location, road condition	V2V communication	Simulation	Positioning
Guermah et al. [150]	–	Location (C/N0-R-L, satellite elevation)	RHCP and LHCP antennas	Simulation	Positioning
Gu et al. [151]	Inverse-depth CNN	RGB image, inverse LIDAR map	3D-LIDAR, monocular camera	Real-life environment	Road detection
Gua et al. [110]	Weight based fusion	Location, longitudinal and lateral accelerations	GPS, INS	Simulation	Side-slip angle definition
Hoang et al. [152]	Particle filter	Location	GPS, V2V communication	Simulation	Positioning
Hong et al. [76]	Multi-metric weights assignment	Traffic toll (flow)	Road sensors	Real-life environment	Flow prediction
Hong et al. [127]	Deep Cross fusion (NN)	RGB images, point clouds	Camera, LIDAR	Real-life environment	Autonomous driving
Hu et al. [153]	CNN fusion	Images	Camera	Real-life environment	Driver's behavior extraction
Jayarajah et al. [154]	Deep-learning based	Mode, location	Traffic sensors	–	Anomalous events detection

Users (VRUs), cannot rely on the performance of the Global Navigation Satellite System (GNSS) as a standalone technology. Therefore, numerous research articles have studied the localization problem that includes both object positioning and tracking in roads network [135].

Aeberhard et al. [54] outlined a high-level architecture for combining sensor data for highly automated driver assistance functions. An adaptive hybrid approach was developed by Ardakani et al. [134] that takes into account data from various sources (INS, GPS, WiFi, and cellular network). Using the proposed approach, all four major tracking technologies are integrated to increase tracking accuracy. Bauer et al. [138] proposed a method for pinpointing the location of mobile objects using HD maps in urban environments. They incorporated lane marking detection into their fusion algorithm input to improve accuracy. A new sensor fusion configuration (RADAR, LIDAR, and vision) was developed by Cho et al. [35] to seamlessly incorporate measurements from various angles to improve tracking and movement classification of nearby moving objects. Dawood et al. [39] demonstrated the utility of virtual 3D models in in-vehicle localization systems using unscented Kalman Filtring data fusion algorithms. Deng et al. [145] developed an image fusion positioning scheme to mitigate the effects of flexible sampling periods and data loss on the control algorithm of automated guided vehicles. Dheekonda et al. [146] aimed to examine the impact of the fusion of multi-sensor data on the robustness and accuracy of moving object detection. This study included preliminary findings on a deep learning-fusion model for object detection, comparing it with those based on just image sensor data. By fusing data from vehicle sensors with stereo vision perception, RodriguezFlorez et al. [147] examined a multimodal approach for improving vehicle localization and tracking dynamic objects. Gao et al. [104] presented a multi-source information fusion algorithm for vehicle navigation that is based on a hybrid model of both multiple interacting models (IMM) and Kalman filtering algorithms. Garcia et al. [40] used both Unscented Kalman Filter and Joint Probabilistic Data Association algorithms to fuse data from vision-based systems, laser sensors, and global positioning systems to provide augmented environment information and knowledge to intelligent vehicles. Ghaleb et al. [123] developed an innovation-based Adaptive Estimation Kalman Filter fusion model based on vehicle kinematics and positioning measurements. The proposed algorithm improves positioning accuracy in dynamic and unstable measurement conditions. By integrating different techniques of localization along with data fusion and vehicle-to-vehicle communication, Golestan et al. [36] proposed a scheme for improving the accuracy of the localization information of the vehicles by integrating available data and cooperatively improving it. Gorrieri et al. [149] designed a novel scheme for clustered VSNs in which the vehicle carries out a spatially constant process of decentralized detection by combining several clustered algorithms with fusion rules. Guermah et al. [150] devised a novel GNSS signal classifier based on information provided by a fusion of RHCP and LHCP antennas and a machine learning method. The proposed classifier exploits the characteristics and potential of the RHCP and LHCP antennas to process the GNSS signal. To maintain the level of positioning precision under severe correlation environments, Hoang et al. [152] developed an innovative framework for both GPS and V2V received data fusion capable of mitigating the effects of measurement noise. Krishnamurthy et al. [157] used a Bayesian estimation algorithm to perform a non-overlapping fusion of video surveillance data for person tracking applications. Laghmara et al. [128] described Dempster–Shafer as a new method for real-time tracking of objects using a robust Dempster–Shafer approach. Laghmara et al. [60] proposed a method for dynamic object detection that uses Evidential 2.5D Occupancy Grids as well as the Belief Theory to perform a grid fusion over time to keep track of moving objects in the grid. Description of dynamic behavior is based on the issue of the temporal conflict after the fusion. Golestan et al. [37] proposed a new scheme that involves different techniques of localization along

Table 20
Data fusion for ITS approaches (part 5).

Article	Fusion approach	Data properties	Source	Evaluation	Domain of application
Kartsch et al. [155]	Decision fusion technique	brain cells electrical activity, blink duration, gestures	EEG and IMU signals	Simulation	Fatigue detection
Koesdwiady et al. [77]	Decision In Decision Out technique Out technique	Flow, weather	Loop detectors, weather service network	Real-life environment	Flow prediction
Kong et al. [156]	Cluster Probabilistic-based fusion	Traffic data packets	Wireless sensor networks	Simulation	Bandwidth allocation
Krishnamurthy et al. [157]	Probabilistic-based fusion	Images	Cameras network	Simulation	Tracking
Laghmara et al. [128]	Dempster-Shafer theory	Images	Camera	Real-life environment	Pedestrian tracking
Laghmara et al. [60]	Dempster-Shafer belief theory	2.5 Grid maps, location	GPS/IMU, LIDAR, laser scans	Real-life environment	3D object detection
Laghmara et al. [158]	Multiple feature fusion	Location, Images	Camera, LIDAR	Real-life environment	3D object detection
Lan et al. [78]	Newton weight-based fusion	Speed, location	Loop detector, probe vehicle	Simulation	Speed prediction
Lassoued et [44]	Sequential Kalman filtering	Location	GPS, CAN-bus	Real-life environment	Positioning
Lauffenburger et al. [159]	Kalman filtering	Images	Camera	Real-life environment	Traffic sign recognition
Lee et al. [160]	Weight-based fusion	Location	GPS, OBU, RSU	Simulation	Travel time estimation
Li et al. [79]	Time synchronization	Flow, speed, occupancy, weather	NC-200 sensors, Clarus		Flow prediction
Li et al. [161]	Split co-variance intersection filter	Location	–	Simulation	Positioning
Li et al. [162]	Multi-layer feature fusion	Images	laser scanners, camera	Real-life environment	Lane detection
Li et al. [163]	Probabilistic feature fusion	waveforms	wireless geomagnetic sensors	Real-life environment	Vehicle type recognition
Li et al. [13]	Restricted Boltzmann machines	Flow, accident Information, weather, personal information	Loop detector, highway safety information system	Real-life environment	Traffic accident prediction
Lin et al. [80]	Topic-Enhanced Gaussian Process Aggregation Model	Speed, trajectories, tweets	Sensors, Twitter API	Real-life environment	Speed prediction
Liu [164]	Inference-based fusion	Videos, trajectories	Camera	Real-life environment	Positioning
Liu et al. [165]	Map matching	Location	GPS	Simulation	Positioning
Liu et al. [45]	Cubature Kalman filtering	Location	GNSS, DSRC	Simulation	Positioning
Liu et al. [166]	Particle Filtering	Location, range	IMU, UWB	Simulation	Positioning
Liu et al. [26]	Cubature Kalman filtering	Location	GPS, GNSS, DSRC	Simulation	V2V communication
Lu et al. [118]	Regression models	Weather, text posts, Traffic Incidents	Weibo, social media	Real-life environment	Congestion prediction

with data fusion and vehicle-to-vehicle communication to integrate the available data and improve the accuracy of the localization information of the vehicles. Goli et al. [148] developed a cooperative multi-sensor multi-vehicle localization algorithm with high accuracy for terrestrial vehicles based on the fusion of heterogeneous observations in the form of GPS coordinates of nearby vehicles as well as inter-vehicle distance measurements. Arribas et al. [135] designed a multi-sensor positioning Bayesian fusion algorithm that uses GNSS, IMU, and Odometric signals for ground ITS applications. The algorithm was improved by looking at dynamic noise covariance matrices with non-holonomic constraints on vehicle movement and calibrating for zero velocity using the vehicle's speedometer measurements. Novak et al. [170] presented a new approach to enhancing the detection of LEDs for Visible Light Communication by fusing their outputs. Based on the use of multimodal sensor fusion, Oliveira et al. [171] presented a robust solution to overcome the significant limitation in inverse perspective mapping for road obstacle detection. As a result of fusing laser range finding data with the camera images, the maps are not computed in areas where obstacles exist. Peixoto et al. [173] presented a framework for representing and processing spatiotemporal data that is suitable for handling a variety of mobility data as well as supporting multiple approaches to data visualization and processing. For this, the authors described how actual data from heterogeneous sources is integrated into the proposed framework by defining a set of concepts. Schwarzbach et al. [184] provided GNSS pseudo ranges fusion based on spatial data given in the form of a digital elevation model. To detect various types of abnormal driving, Sun et al. [43] integrated data from multiple sources (GPS, BeiDou, and IMU) using an Unscented Particle Filter. By using Kalman filters to combine information from radar, GPS, and DSRC V2V communications equipment, a tracking system that increases target tracking accuracy is proposed by Tian et al. [190]. Qin et al. [175] adopted the use of the Particle Filter (PF) data fusion algorithm to exploit GNSS, Dead Reckoning, and road segment information for vehicle location estimation. A probabilistic Bayesian algorithm is applied by Verentsov et al. [192] to combine global coordinates from GPS and relative coordinates from IMU to generate a vehicle's trajectory in an unknown environment. Verentsov et al. [193] presented a Bayesian approach for sensor fusion that improves vehicle localization using crowdsourced data on traffic sign positions. Compared to using only GNSS and IMU, this method offers noticeable improvements and uses precise traffic sign positions. Li et al. [205] proposed a multi-sensor fusion approach based on enhanced Kalman filters (KF) that fuses information from a low-cost GPS, MEMS IMU, and digital compass to provide reliable and low-cost navigation solutions in different scenarios. Bresson et al. [34] proposed a new approach to solve the decentralized Simultaneous Localization And Mapping issue using Extended Kalman Filter fusion architecture designed for low-density maps built with low-cost sensors. Zhu et al. [203] developed an expectation–maximization algorithm that performs a joint data association and fusion simultaneously for distributed tracking. Cong et al. [102] proposed a smart and eco-friendly tracking approach that uses the smartphone as a sensing platform to obtain and fuse real-time data about vehicle acceleration, velocity, and location. Through the use of a novel federal Kalman filtering approach with a two-state chi-square detector and residual chi-square detector, Geng et al. [59] developed a robust fault-tolerant path tracking control algorithm that detects and identifies sensor faults in autonomous vehicles. Pi et al. [63] created a framework for the detection and removal of bogus mobility information that involves a fusion model. Additionally, the authors integrated the proposed algorithms with previous data fusion algorithms to achieve joint mobility tracking in autonomous vehicles. Qin et al. [176] developed a measurement framework for a large-scale data-driven tracking study that fuses two different sensing approaches: vehicular tracking using crowdsourcing and cellular tracking using the infrastructure. Smaili et al. [187] proposed an approach

Table 21
Data fusion for ITS approaches (part 6).

Article	Fusion approach	Data properties	Source	Evaluation	Domain of application
Mai-Tan et al. [167]	Quality validation	Traffic-related crowd-sources data	APIs	Real-life environment	Congestion prediction
Marin-Plaza et al. [41]	Unscented Kalman filter	Images, location, vibration	LIDAR, GPS, Wheel odometer	Real-life environment	Automated Driving
Martín et al. [61]	Context-aided Unscented Kalman filter	Images, location	Laser scanner, LIDAR, digital camera, GNSS, IMU	Real-life environment	Automated Driving
Merdrignac et al. [62]	Probabilistic-based fusion	Perception (obstacles detection data), V2Pedestrian data	Camera, laser scanner, GPS, V2P communication	Real-life environment	V2Pedestrian communication
Moghaddasi et al. [168]	Time synchronization	Velocity, delay	RADAR and radio signals	Real-life environment	Sensor data quality
Müller et al. [105]	Probabilistic-based fusion	Speed, location	RADAR, GPS	Real-life environment	Positioning
Müller et al. [169]	Belief-based fusion	Location, speed	RSU, V2X communication	Simulation	Trust management and misbehavior Detection
Narayanan et al. [95]	GRU fusion	Images, speed, accelerator, braking pedal positions, yaw rate, turns, steering wheel angle	Video stream, CAN signals	Simulation	Driver's behavior extraction
Novák et al. [170]	Weighted-based fusion	Images colors, shape, time	VLC, LED, and SNR transmitters	Real-life environment	Positioning
Oliveira et al. [171]	Inverse projection fusion	Images, location, range	Laser range finder, camera	Simulation	Positioning
Osman et al. [42]	Unscented Kalman Filter	Images, location, vibrations	LIDAR, camera, optical encoders, digital magnetometer, GPS	Real-life environment	Noise detection
Pang et al. [172]	Kalman filtering algorithm	Location	IoV communication	Simulation	Distance prediction
Peixoto et al. [96]	Clustering based fusion	Location, speed, orientation	GPS, Wi-Fi, GSM	Real-life environment	Urban dynamics analysis
Peixoto et al. [173]	Spatial synchronization	Location	GPS, Wi-Fi, GSM	Real-life environment	Human movement analysis
Pi et al. [63]	Kalman filtering algorithm	Location, images, trajectories	GPS, IMU, camera, V2X communication	Simulation	Tracking
Pu et al. [174]	CNN	2D and 3D Images	Satellite	Real-life environment	Human flow prediction
Qin et al. [175]	Particle Filter	Location, road segment information	GNSS, Dead Reckoning,	Simulation and Real-life environment	Flow prediction
Qin et al. [176]	Average-based fusion	Location	GPS, cellphone	Real-life environment	Positioning
Qiu et al. [177]	Trust-level fusion	Signals	RSU-Vehicle communication	Simulation	V2X communication

based on hybrid dynamic bayesian networks: linear Kalman filters and Hidden Markov Models. These two models, when combined, offer the ability to manage and manipulate multi-hypotheses and multi-modality of observations characteristic of Map Matching problems and improve integrity approaches. Thomaidis et al. [188] presented an algorithm for fusing and associating tracking data from an onboard radar sensor with position and motion data received from the VANET. The algorithm is based on a track-oriented multiple hypothesis tracker, modified to incorporate information from VANET messages. Tian et al. [189] developed a cooperative vehicle infrastructure system based on the concept of multi-source data fusion (machine vision, including vehicular subsystem, the roadside subsystem, and the parking lot subsystem) to detect road channelization, pedestrians, and vehicle.

3.4.6. Management systems

Transport management systems play a crucial role in supply chains, from planning and procurement to logistics and lifecycle management. In turn, this means better transportation planning and execution, which leads to a higher level of customers satisfaction. Not only these systems are beneficial with reliable and robust solutions, but they also enable you to anticipate future needs of the industry while providing visibility and complete control over your entire execution process.

Driving behavior extraction: Chen et al. [108] introduced an innovative algorithm of driving behavior analysis based on AdaBoost, fusing a variety of driving operations (steering wheel angle, brake force, and throttle position) and traffic information. Chhabra et al. [109] presented a context-aware system for driver behavior classification as a safe, or fatigue or unsafe driver that considers the fusion of vehicle, driver, and the environment information using a Dynamic Bayesian Network. Birek et al. [139] examined the numerous data sources available within the car and the surrounding environment, both of which can be analyzed with different conceptual and contextual representations for predicting the drivers' intent and behavior. Inspired by the gating mechanisms in LSTM units, Narayanan et al. [95] proposed a novel Gated Recurrent Fusion Units (GRFU) that learns fusion weighting and temporal weighting simultaneously from multimodal signals, including video, LiDAR, and CAN signal data streams. Singh et al. [185] used DTW-based event detection techniques to detect sudden braking and aggressive driving behaviors using smartphone-based sensory data fusion. Finally, Hu et al. [153] presented a CNN approach for combining the multi-scale information and generating the final decision in behavior recognition by filtering images with different fusion strategies.

Analytical-based decision: Aiming to assess the impact of green transport measures on city sustainability, Awasthi et al. [137] presented a hybrid approach based on the Analytical Hierarchy Process and Dempster Shafer's theory. This theory combines information from multiple sources (human experts, questionnaires, sensors, etc.). Chen et a. [141] investigated the information security of a vehicular Ad hoc network whose messages were susceptible to abuse before they were transmitted. This framework analyzes message dissemination using a fusion mechanism in a malicious vehicles network. Yang et al. [196] proposed a pairwise inconsistency-based algorithm to address the security problems of Cyber–Physical Systems that use multiple sensors to measure the same physical variables. This approach uses fusion intervals and historical measurements of the sensor to identify attacks using virtual sensor inconsistencies in pairs. An analysis of correlations among urban traffic multi-sensors was conducted by Kong et al. [156]

Table 22
Data fusion for ITS approaches (part 7).

Article	Fusion approach	Data properties	Source	Evaluation	Domain of application
Rahmani et al. [64]	Weight-based fusion	Automatic vehicle identification data, floating car data	Camera, GPS, loop detector	Real-life environment	Travel time estimation
Raouf et al. [129]	Octree fusion	Location	LIDAR	Real-life environment	Fault detection in Autonomous driving cars
Rapant et al. [81]	Granger causality fusion	Location, speed, travel direction, speed	Infrared detectors, RADARs, floating car data	Real-life environment	Incident detection
Raposo et al. [178]	Calibration of a color	Images	Color camera, laser-range finder, depth camera	Real-life environment	Detection quality
Ren et al. [65]	Map-matching	Location, direction, speed, images images	GPS, loop detector, camera	Real-life environment	Routing system
Rettore et al. [179]	Artificial neural network	Location, speed, flow, trajectories	Vehicle's OBD, CAN, smartphones	Real-life environment	Quality enrichment
Rettore et al. [124]	Weighted mapping fusion	Tweets, location, speed, flow, trajectories	Twitter API, vehicle's OBD, CAN, smartphones	Real-life environment	Quality enrichment
Rodrigues et al. [121]	Neural network	Flow, text, weather, event data	Sensors, Web, APIs	Real-life environment	Taxi demand
Rodriguez-Castaño et al. [180]	Fuzzy logic fusion	Location	GPS, odometric sensors	Real-life environment	High-speed navigation
Ruta et al. [122]		Location, road type, weather, Emissions, fuel consumption	Smartphone-GPS, Web services, vehicle's OBD	Real-life environment	Driving assistance
Saadeddin et al. [181]	Neuro-Fuzzy Inference	Location	GPS, INS	Real-life environment	Congestion prediction
Salmane et al. [182]	Demptster-Shafer theory	Images	Camera	Real-life environment	Detecting hazard situations
Salpietro et al. [183]	Probabilistic-based fusion	Location	Sensors, GPS	Simulation	Parking assistance
Schwarzbach et al. [184]	Probabilistic-based fusion	Location, ranges	GNSS, WSN	Simulation	Positioning
Shan et al. [97]	Dempster-Shafer theory	Speed	Traffic microwave sensors, GPS	Real-life environment	Speed prediction
Shen et al. [66]	Evidence theory	Location, images	GPS, camera	Real-life environment	Quality enrichment
Shen et al. [116]	Time synchronization	Flow, weather, Construction works, holidays	Here Maps API	Real-life environment	Important crossroads
Shen et al. [130]	Federated Kalman filter	Location, images	GNSS, odometer, and CVNS	Simulation	Automated driving
Shi et al. [82]	CNN	Trajectories	GPS	Simulation	Congestion prediction

to fuse the monitoring information within the coverage area of the sensing system. Therefore, improving the vehicle type recognition system's resolution and accuracy. Muller et al. [169] suggested the fusion of information from multiple agents reporting the same event, based on a subjective logic-based mechanism that adds reliability information to the shared data. Peixoto et al. [96] investigated a set of basic concepts for representing and processing spatiotemporal urban mobility data using a learning algorithm. Their geometric and symbolic data fusion demonstrates the adequacy of the proposed concepts and uncovers new possibilities for fusing heterogeneous datasets. Zhang et al. [198] fused local feature descriptors based on different scales and image features to enhance the detection of objects in traffic scenes. Zhang et al. [199] created a visibility monitoring system using video camera facilities distributed along highway roadsides that provided services such as data transmission, data fusion, monitoring alert, and data publish/subscribe mechanism. This system can be integrated with other ITS systems using a data-sharing bus. Zhou et al. [202] presented a novel coupled tensors model incorporating multi-source traffic data fusion for missing data imputation and proposed a new tensor completion algorithm using a modified associated matrix and tensor factorization weighted optimization algorithm. Finally, Xia et al. [99] proposed a parallelized fusion approach to overcome data heterogeneity and high computation intensity for processing massive transportation data.

Coverage and quality: Ding et al. [25] investigated the properties of IoT data to propose many IoT data fusion requirements. These requirements are used as a metric to evaluate and compare methods for data fusion. Jayarajah et al. [154] explored sociophysical analytics of multimodal informatics data that fuses social media analytics to identify anomalous events, localize, and explain them. Van wyk et al. [51] applied a nonlinear car-following model based on an adaptive extended Kalman filter model to smooth sensor readings from a connected and automated vehicle to detect anomalies. In support of joint radar-communication functions, Moghaddasi et al. [168] proposed a multifunctional transceiver. Using a multiport interferometer, the system can determine the target's range, angle, velocity, and direction of motion in radar mode. Raposo et al. [178] provided an accurate and practical solution for the extrinsic calibration of mixtures of color cameras, LRFs, and depth cameras whose fields of view are not overlapping with each other using calibration software based on mirror reflections. Rettore et al. [124] outlined a framework for data enrichment that fuses heterogeneous data to enhance Intelligent Transportation System (ITS) services, such as vehicle routing. Sinha et al. [186] presented a novel architecture of multi-channel cognitive radio based on a dynamic Bayesian network for decision and data fusion. Xia et al. [98] designed a hierarchical evidential parallelized fusion model based on the Dempster Shafer Evidence theory to implement the feature-level fusion. Xia et al. [47] proposed a novel theoretical framework to assess the computational demand and computing resources of ITS services based on federated Kalman filters and Dempster Shafer evidence theories for the multi-sensor data fusion. The authors transformed this framework into a generic methodology applied for Cyber-ITS, mainly consisting of region-based ITS data divisions and tasks scheduling for processing, to support the efficient use of cyber-infrastructure in Xia et al. [206]. Xiong et al. [195] designed a cloud computing platform based on multi-source massive data fusion to provide different transportation data services for different traffic enterprises and business users. Shen et al. [116] proposed a novel adaptive federated Kalman filter based on the criteria for the degree of observability with time-varying information sharing factors. Shen et al. [66] have built a multi-source traffic data analysis method based on a Spatio-temporal regression model and an evidence theory data fusion method that relies on the confidence tensor for different ITS services. Geetla et al. [107] conducted analysis-based research to determine where to place accident-detecting omnidirectional sensors to maximize detection capabilities for crash characterization using data fusion techniques. Titouna et al. [191] develop a new approach based on clustering and graphical possibilistic

Table 23
Data fusion for ITS approaches (part 8).

Article	Fusion approach	Data properties	Source	Evaluation	Domain of application
Shi et al. [83]	JDL fusion model	Location	Automatic Dependent Surveillance-Broadcast	Simulation	Trajectory prediction
Singh et al. [185]	Normalization	Gyroscope, gravity	Gyroscope, gravity sensors	Real-life environment	Driver's behavior extraction
Sinha et al. [186]	Dynamic Bayesian network	Location, speed,	GPS, local RADAR and gyroscopic	Simulation	Quality enrichment
Smaili et al. [187]	Hybrid Dynamic Bayesian Networks	Location, speed	GPS, trajectory data	Real-life environment	Positioning
Sun et al. [43]	Unscented Particle Filter	Location	BeiDou, GPS, IMU	Real-life environment	Positioning
Sun et al. [84]	Conditional Information Fusion	Flow, speed	Road sensors	Real-life environment	Flow prediction
Tak et al. [85]	Average fusion	Speed	ILDs and DSRC	Real-life environment	Travel time estimation
Terroso-Sáenz et al. [93]	Density-based clustering fusion	Location, trajectory	GPS	Simulation	Planning
Thomaidis et al. [188]	Interacting Multiple Mode filtering	Location, speed	VANET, RADAR	Simulation	Positioning
Tian et al. [189]	–	images	Camera	Real-life environment	Moving object detection
Tian et al. [190]	Kalman Tracking Model	Location, speed	RADAR, V2V (GPS)	Real-life environment	Tracking
Titouna et al. [191]	Clustering and graphical possibilistic fusion	Emergency case	road sensor signal	Simulation	Emergency decision
Verentsov et al. [192]	Probabilistic Bayesian fusion	Trajectories	GPS, IMU	Simulation	Positioning
Verentsov et al. [193]	Probabilistic Bayesian fusion	Trajectories	GPS, IMU	Simulation	Positioning
Vu et al. [38]	Extended Kalman filter	Location, images	Computer vision, DGPS	Real-life environment	Positioning
Wang et al. [119]	Bayesian reasoning	Flow, weather, location	Sensors	Real-life environment	Emergency decision
Wang et al. [111]	Weight-based fusion	Speed, acceleration	Internal sensors	Simulation	Automated wheels control
Wang et al. [86]	Fuzzy-Logic Model of Perception	Traffic environmental information	Traffic light signals, sensors	Simulation	Congestion prediction
Wyk et al. [51]	CNN-Kalman filtering algorithm	Speed, acceleration, location	Internal sensors, GPS	Real-life environment	Quality enrichment
Xia et al. [87]	Dempster–Shafer theory	Location, speed, flow	GPS, SCATS loop detectors	Real-life environment	Congestion prediction
Xia et al. [47]	Federated Kalman filter and Dempster–Shafer theory	Traffic data, Location	traffic sensors, GPS	Real-life environment	Data coverage
Xia et al. [98]	Hierarchical Dempster–Shafer theory	Speed, flow	GPS, SCATS loop detector	Real-life environment	Parallelized analysis

fusion modeling to proactively change traffic lights during emergencies. The proposed system decomposes the environment into clusters, performs a local fusion mechanism inside each cluster, then applies a global fusion at the level of head clusters. Flores et al. [103] proposed a cooperative approach using the fusion of LIDAR sensing V2V and V2P communication signals for unexpected car-following situations. Finally, Wang et al. [119] proposed a Perceptual Control Architecture of Traffic Incident Management systems by fusing heterogeneous information processing and varying environmental interactions.

Taxi demand: Rodrigues et al. [121] proposed two deep learning architectures that rely on word embeddings, convolutional layers, and attention mechanisms for fusing text information with time-series data for taxi demand forecasting in event areas.

3.4.7. Driving assistance

Systems of advanced driver assistance help drivers with driving and parking tasks. These systems play a crucial role in increasing road and vehicle safety by utilizing a safe human–machine interface. Cameras and sensors use automated technology to identify nearby obstacles or driver errors and act accordingly.

Parking assistance: Aliedani et al. [133] investigated the deception behavior of malicious vehicles looking to park by sending false information in decentralized vehicle cooperation using a deception detection fusion-based mechanism. Based on a sensor feature-fusion model called the Orthogonality Error Estimate, a new method for detecting vehicle parking activity to reduce vacant parking space search times is presented by Yeh et al. [115]. With this model, parking activity can be detected with high accuracy and low power consumption. Salpietro et al. [183] developed an urban parking spot search mobile application designed to reduce the overhead of parking operations. This application performs the automatic detection of parking actions algorithm by analyzing smartphone fused sensors' (accelerometer and gyroscope) and the Bluetooth connectivity. Du et al.. [106] developed a novel City Traffic Data-as-a-Service that identifies associations and relationships among data resources to fuse data from distributed providers.

Navigation systems: Chiang et al. [9] proposed a semi-tightly coupled integration scheme based on Extended Kalman Filter (EKF) with motion constraints that fuse INS/GNSS with grid-based Simultaneous Localization and Mapping for robust and stable navigation information. Eciolaza et al. [10] developed an application for driving behaviors reporting to ensure safe driving practices Based on Fuzzy Logic and the computational theory of Perceptions. Based on the fusion of GPS and odometric sensors using fuzzy logic, Rodriguez-Castano et al. [180] developed a GPS-based autonomous navigation method for heavy vehicles at high speeds. Yu et al. [67] created a multi-modal journey planner that combines comprehensive traffic network data with real-time traffic speed data to provide commuters with more accurate and practical recommendations. As an alternative to travel diaries, Zilske et al. [94] considered integrating call details with link volume counts as inputs for an agent-based traffic simulation to reduce spatiotemporal uncertainty and correct underrepresented traffic segments. Ren et al. [65] presented an information fusion model based on a dynamic traffic routing system multi-resource heterogeneous data sources. In addition to providing comprehensive traffic information to the system and traveler, the fusion results will help optimize operations. Finally, Vu et al. [38] described a sensor fusion technique that can assist an INS in challenging environments with limited or unreliable GPS reception, using computer vision and differential pseudo-range GPS measurements.

Table 24
Data fusion for ITS approaches (part 9).

Article	Fusion approach	Data properties	Source	Evaluation	Domain of application
Xia et al. [99]	Rough Dempster–Shafer theory	Speed, flow	GPS, SCATS loop detector	Real-life environment	Parallelized analysis
Xia et al. [194]	Dempster–Shafer theory	Speed, flow	GPS, SCATS loop detector	Real-life environment	Big-data management
Xiong et al. [195]	Time synchronization	Human, road, vehicle data	Sensors technologies	Real-life environment	Big-data management
Xu et al. [52]	LSSVM-NARX/KF	Location,	GPS, IMU, digital compass	Real-life environment	Positioning
Yang et al. [196]	Pairwise fusion	Speed	Ultrasonic sensor	Real-life environment	Sensors security
Yang et al. [88]	Neural network	Speed, Weather, road data, date	Floating car data, environmental sensors	Real-life environment	Speed prediction
Yao et al. [197]	Adaboost and SVM	Images	Camera	Real-life environment	License Plate detection
Yao et al. [89]	Dempster–Shafer theory	Speed	GPS, RTMS	Real-life environment	Speed prediction
Yeh et al. [115]	Orthogonality Error Estimate	Location, speed, acceleration	Accelerometer, magnetometer	Real-life environment	Parking assistance
Yu et al. [67]	Linear fusion	Speed, trajectories	GPS, camera	Real-life environment	Planning
Yu et al. [131]	Hierarchical game	Traffic data	MEC server, V2X	Simulation	Time optimization
Yu et al. [120]	Deep neural network	Location, weather, trajectories	GPS, environmental sensors	Real-life environment	Incident detection
Zanchin et al. [68]	–	Speed, location, images	RADAR, camera, scanner, LIDAR	Real-life environment	Automated driving
Zhang et al. [198]	Boosting fusion	Images	video sensors	Real-life environment	Surveillance
Zhang et al. [90]	Mer-Gesh	Trajectories	GPS	Real-life environment	Travel time estimation
Zhang et al. [91]	Uncertainty feedback fusion	Speed, Trajectories	GPS	Real-life environment	Travel time estimation
Zhang et al. [199]	–	Images	Video sensors	Real-life environment	Roads management
Zhang et al. [200]	R-CNN and Kalman filter	Images, speed	Video sensors	Real-life environment	Tracking
Zao et al. [201]	Gated Recurrent Unit	flow, speed, location, time occupancy	DSRC, RTMS	Real-life environment	Travel time estimation
Zheng et al. [15]	Time synchronization dictionary	Flow	Loop detector	Real-life environment	Flow prediction
Zhou et al. [202]	Coupled tensors model	Flow, Speed	Loop detector	Simulation	Quality enrichment
Zhu et al. [203]	Maximum likelihood function	Speed	Sensors	Simulation	Tracking
Zilske et al. [94]	–	Location, transport mode, trajectory	CDR technology	Simulation	Planning

Planning: Benalla et al. [92] proposed a novel agent-based evidential reasoning system that deals jointly with the driving behavior and driving environment conditions. Chiang et al. [112] developed a data fusion stage based on a collision warning algorithm which is integrated into a driver-assistance system that uses a low-cost embedded digital signal processor based on driving information supplied by multiple sensors to avoid collisions. Pang et al. [172] proposed a method for determining the vehicle-to-vehicle distance utilizing a Kalman filter to ensure better accuracy. This method enables the Double DQN algorithm to compute the optimal scheduling strategy to minimize the navigation system's total consumption cost. Ruta et al. [122] developed a driving assistance application that makes use of the on-board diagnostics protocol, the vehicle's diagnostic information, smartphone embedded micro-device data, and web information is collected and fused consistently. Finally, Terroso-Saenz et al. [93] implemented an on-board context-aware application that processes the typical routes of the Ego Vehicle according to its context. The application detects vehicular occupancy and the meaningful points of the frequent itineraries using a density-based cluster fusion algorithm.

3.5. What are the challenges and future directions of data fusion for ITS applications?

This article aims to highlight the challenges of using data fusion in ITS applications that must be addressed in the future when trying to improve transportation systems, increase mobility, and reduce accidents for both drivers and travelers. Based on a computational vision, stakeholders in traffic management are steadily deploying sensors on the roads and within vehicles. Despite this, physical infrastructure deployment cannot resolve mobility challenges due to the large scale of heterogeneous information generated by these different sources. Consequently, it is necessary to integrate other technologies such as data fusion and analytics, automated operation tools, decision-making tools, and social and mobile networks to capture, analyze and share in real-time, with the relevant parties, all the information generated by all the different sources. Data fusion techniques have been widely applied in multi-sensory environments to combine and aggregate data from various sensors according to specific criteria, such as complementing or redundant data, data type, centralized, decentralized, or distributed architecture.

3.5.1. Hybrid data fusion models

Multiple levels of transportation-related information can be fused into a single decision-making process, which leads to the improvement of the application domain. Sources of this heterogeneous information differ in what they convey conceptually, contextually, and graphically. The uncertainty and complex data handling process are tedious while using their content in the fusion process. Thus, the ancient approaches have the limitation to retail each fusion results of each group of similar features with a different one. The challenge here is the combination of efficient algorithms that detect and fuse traffic patterns from the collected heterogeneous features that increase the performance of transportation systems. Data samples are gathered from different sources (such as cameras and sensors) and transmitted by other methods (through wires/wireless links). Thus, it is tricky to analyze the data first to remove some redundancy and preserve relevant features; then compare and fuse the data collected from different sources using different algorithms; finally, provide a single output from all the fusion process to the system.

3.5.2. Explainable Deep Neural Network data fusion

A recent increase in the sophistication of ML-based models used in different ITS applications has made their design and deployment almost utterly automated. As such systems can ultimately affect human lives (*e.g.*, self-driving vehicles), it will become necessary to understand the processes through which such decisions are generated. In contrast to the early machine learning systems that were easily interpretative, advanced decision systems such as Deep Neural Networks (DNN's) have recently been developed. The effectiveness of DNNs is linked to their wide parametric space and effective learning algorithms. Consequently, DNNs are considered complex black-box models due to the large number of layers they contain and the millions of parameters they contain. The eXplainable AI (XAI) [207] proposes creating a suite of ML techniques that will produce more explainable models while retaining a high level of learning performance. Therefore, it enables humans to better understand, respect, and trust the next generation of artificially intelligent partners.

3.5.3. Adaptative sensor selection

In the context of ITS data fusion, sensor selection and flexible data fusion are both sought-after research topics. A significant issue in the fusion of multi-sensor data is the selection, evaluation, and characterization of sensor performance and the establishment of confidence factors for each sensor as part of the interpretation and multi-target tracking. In other words, a methodology, that adaptively determines sensor confidence for any given tracking or positioning system, must be devised under a practical research question, namely *"how to adaptively select suitable sensors, and then perform flexible data fusion relying on the selection*".

3.5.4. Privacy-preserving

Data fusion with privacy-preserving features remains a hot topic. Privacy-sensitive sensors may not provide enough information for application design. Security and privacy for users are still open issues that require more research. Data analytics and machine learning can be performed using Homomorphic encryption, but they cannot be employed in real-time applications because of their high computation cost. Despite recent information fusion trends, there are significant limitations with real-time data fusion to solve the security issues for both low-level and high-level fusion. Secret sharing schemes, which combine data in clusters with reduced communication costs, may be a solution in a highly distributed system to tackle this issue. Yet a literature review suggests that more advanced solutions can be widely implemented in practice. Privacy-preserving data fusion is a fascinating and challenging field of research.

3.5.5. Sensor data quality

The quality of sensor data produced by an ITS application may suffer due to errors, as poor sensor data quality could lead to incorrect decision-making. Even if an ITS application contains hundreds of sensors that produce vast amounts of data, the latter is rendered useless if it is riddled with errors. Furthermore, the term error refers to the soft faults found in sensor data, such as outliers, missing/incorrect values, and uncertainty, which should be identified or quantified and removed or corrected to improve sensor data quality [208]. Therefore, sensor data fusion raises the following fundamental challenges:

- **Outliers and spurious collected records:** uncertainty does not arise only from the absence of details and noise but also from the environment's obscurity and unpredictable behavior.
- **Data imperfection:** information gathered from sensors is affected by some degree of incompleteness (missing values) and ambiguity (incorrect values).
- **Data correlation:** this problem is primarily critical and not unusual in distributed fusion settings, e.g., wireless sensor networks. For example, sensors can be uncovered to an equal outer sound which biases their readings. Fusion procedures, in such cases, are not based on information reliance and may be impacted by over/under command effects.
- **Data association:** this problem occurs when it is hard to determine from which sensor the information is gathered. Measurement-to-track or track-to-track are two possible solutions.
- **Data adjustment:** Sensor data should be merged into one record before being fused. The problem is referred to as *data registration* because it involves calibration errors caused by different sensor nodes.
- **Data dimensionality:** data need to be compressed to lower dimensionality either locally or globally. In addition to speeding up the transmission process, this would reduce the transmission range and the amount of capacity needed to transfer the records.

It is crucial to treat highly conflicting data problems carefully. Data fusion procedures require showing such imperfections successfully and making use of the records excessively to minimize their effects.

3.5.6. Real-time acquisition

As transportation systems generate many data and requests that need to be handled quickly, fog computing is a powerful complement to the cloud since it can significantly improve transportation services. A task scheduling policy is applied by fog computing to the incoming task to ensure that the service runs at its optimal performance. For determining the correct handling of incoming tasks, Louail et al. [209] proposed a real-time dynamic task scheduler that considers schedule deadlines and frequency constraints at the fog level. As a result of edge computing-based video pre-processing, another solution was proposed by Wan et al. [210] to eliminate redundant frames, reducing the computing, storage, and network bandwidth requirements of the cloud center based on video segmentation for real-time traffic monitoring on the internet of vehicles. Through the exploration of short-term traffic predictions, Chen et al. [211] proposed a novel data dissemination scheme for Industry 4.0 applications enabled by the Internet of Vehicles. This paper presents a three-tiered network architecture aiming to simplify network management and reduce communication overhead. Furthermore, Chen et al. in [212] addressed this issue by proposing a traffic flow detection scheme based on deep learning deployed on an edge node. The authors claimed that this solution solves storage, communication, and processing problems associated with traditional transportation systems.

4. Conclusion

Intelligent transportation refers to a set of applications that requires knowledge to ensure reliable and safe movement of passengers and freight in various environments. However, because of the ubiquitous deployment of communication technologies, tremendous amounts of traffic-related data have been collected to ease traffic issues. As a result, multi-source data fusion models have grasped an extensive interest in an attempt to deal with these issues. The present paper systematically reviews a broad range of data fusion technologies in ITS literature (175 publications) regarding extraction of their primary methods, data properties, evaluations, and applications. The key findings and conclusions of the review are as follows:

- Data fusion methods can be conventionally divided into three main categories (*Probabilistic-based* methods, *Evidence reasoning-based* methods, and *Knowledge-based* methods). We analyzed the dynamics of method applications from different categories in intelligent transportation. We concluded that the general trend has recently shifted from probabilistic and Evidence reasoning-based methods to various data-driven or knowledge-based methods.

- Data fusion methods that utilize both traffic and environmental features relationships are gaining scientific interest in the field of different ITS applications in which the number of related publications has increased during the past decade and is expected to continue to grow.
- The effectiveness of data fusion methodologies is challenging to compare based on the existing literature. Studies are typically evaluated using real-world scenarios; however, simulation can provide a safer evaluation method in some instances (applications).
- The coverage of using data fusion methods in ITS applications is not uniform. For example, several application domains (i.e., Localization) have been intensively examined using different data fusion methods with heterogeneous data properties. On the other hand, several others (i.e., Vehicular communication) have not been widely analyzed. In addition, most publications are limited to applying a single data fusion method, and there is a lack of studies based on combining different methods. This may loom to a broad direction for future research.

The added value of this review includes the trends and challenges discovered in the methodology of using data fusion and empirical insights into applied ITS problems. The list of 175 studies, classified by the applied methods, the handled data properties, evaluation processes, and application domains, is a self-contained contribution to assist further literature analyses in this field. Following a systematic review of the scientific literature, we identified several methodological and empirical gaps and provided suggestions for future research. The systematic review discussion leads to the identification of several methodological and empirical gaps related to the characteristics and the quality of sensor data (*e.g.*, the voluminous size, heterogeneity, real-time processing, and scalability). Further, it suggests promising directions for research towards secure and privacy-preserving data fusion in ITS applications.

CRediT authorship contribution statement

Chahinez Ounoughi: Conceptualization, Methodology, Validation, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Sadok Ben Yahia:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgments

This work was supported by grants to TalTech – TalTech Industrial (H2020, grant No 952410) and Estonian Research Council (PRG1573).

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Publication IV

C. Ounoughi, D. Ounoughi, and S. B. Yahia. Ecolight+: a novel multi-modal data fusion for enhanced eco-friendly traffic signal control driven by urban traffic noise prediction. *Knowledge and Information Systems*, July 2023

Knowledge and Information Systems
https://doi.org/10.1007/s10115-023-01938-y

REGULAR PAPER

EcoLight+: a novel multi-modal data fusion for enhanced eco-friendly traffic signal control driven by urban traffic noise prediction

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Received: 20 January 2023 / Revised: 30 May 2023 / Accepted: 10 July 2023

Abstract
Urban traffic congestion is of utmost importance for modern societies due to population and economic growth. Thus, it contributes to environmental problems like increasing greenhouse gas emissions and noise pollution. Improved traffic flow in urban networks relies heavily on traffic signal control. Hence, optimizing cycle timing at many intersections is paramount to reducing congestion and increasing sustainability. This paper introduces an alternative to conventional traffic signal control, EcoLight+, which incorporates future noise predictions with the deep dueling Q-network reinforcement Learning algorithm to reduce noise levels, CO_2 emissions, and fuel consumption. An innovative data fusion approach is also proposed to improve our LSTM-based noise prediction model by integrating heterogeneous data from different sources. Our proposed solution allows the system to achieve higher efficiency than its competitors based on real-world data from Tallinn, Estonia.

Keywords CO_2 emissions · Congestion · Fuel consumption · Data Fusion · Dueling DQN · SUMO Simulation · Traffic signal control · Urban noise

1 Introduction

Traffic congestion levels have been rising precipitously in the last few years due to an imbalance between the rise in travel demand and the availability of transportation services. According to [1], congestion cost in cities such as Stuttgart and Paris is around 2% of their

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Published online: 25 July 2023

GDP. Moreover, in 2021, New York City drivers lost an average of 102 hours in congestion which before the pandemic it was even worse.[1] The general rule is that cities should develop strategies to reduce congestion based on their visions and goals. Implementation of new infrastructure is often slow and costly. Therefore, urban planners and policymakers are interested in making existing infrastructure more efficient [2]. One of the proposed hypotheses is that *"An improved traffic light system will lead to better traffic management and, therefore, more peaceful urban areas"* [3]. Hence, optimizing cycle timing at intersections can significantly reduce congestion and improve environmental quality.

Furthermore, the rapid increase in transport requirements has brought challenges to the sustainable development of our society concerning emissions and energy consumption induced by traffic. The European Environment Agency (EEA) reports that road traffic noise continues to be the primary contributor to noise pollution. Around 100 million people are exposed to road traffic noise above 55 decibels (dB) in the 33 member countries of the EEA. Among them, 32 million (about one-third) are subjected to extremely high noise levels exceeding 65 dB [4]. Furthermore, according to the World Health Organization (WHO), exposure to loud noise causes high blood pressure, hearing loss, heart disease, sleep disturbances, and stress. Hence, measuring traffic noise is a good indicator of traffic congestion intensity.

Numerous traffic signal control solutions have been used and proposed to overcome the traffic congestion issue. Worth mentioning is the integration of Arduino in cameras with machine learning (e.g., object detection deep learning algorithms) and genetic algorithms for traffic signal timing optimization to help experts manage congestion. Recently, researchers have begun investigating reinforcement learning (RL) techniques for controlling traffic signals. These techniques appear to be more effective than traditional transportation methods. Its main advantage is that it learns how to take real-time action by observing the environment's reaction to previous actions. One major issue with most RL-based traffic signal control approaches is that their setting considers, in each phase, only *mobility* and *current* traffic conditions when designing the next control strategy. In our previous EcoLight solution [5], we elaborated on these two characteristics by integrating two novel aspects into the RL techniques. First, sustainability is achieved by incorporating noise as an environmental input feature. The second aspect is the proactivity achieved by predicting future noise levels so that the model is better prepared to make decisions based on current observations alongside future noise predictions. The EcoLight solution proved its efficiency in reducing noise levels, CO_2 emissions, and fuel consumption.

Data fusion is a sophisticated technique for combining information from multiple sources to obtain more accurate results in the execution of an application in a way that is barely possible by using individual sources separately. Due to the deployment of ubiquitous communication technologies, e.g., surveillance video cameras, loop detectors, and radars, multi-source data fusion models have captured great interest. The sought-after goal is to process knowledge from these enormously collected databases of heterogeneous traffic data [6]. To this end, as an enhancement to EcoLight, we leverage the heterogeneous traffic data available and propose a novel data fusion technique to improve the accuracy of our noise prediction model. Moreover, we use a deep dueling Q-network reinforcement learning-based architecture as an improved alternative to the deep Q-network to learn the best strategies for traffic signal control. By and large, the main contributions of *EcoLight+* are as follows:

- At the data fusion stage, we want to leverage knowledge from different available sources with varied structures by integrating data from on-road sensors, cameras, and weather stations. Furthermore, we propose a new embedding-based multi-modal data fusion module

[1] https://inrix.com/scorecard/.

that uses different embedding techniques for each data type. Our module uses a neural network-based embedding to generate the categorical feature vectors and feature2vec to learn the continuous ones.

- At the noise prediction stage, we take advantage of the sequence-to-sequence architecture and propose splitting the time-series noise traffic data into fixed-sized sequences, where the size is determined based on an analysis of road network traffic behavior. Our method includes building a stacked layer architecture based on LSTM to extract temporal dependencies behavior from the fused data. Using the current state as input, the model will return a future traffic noise sequence.
- At the traffic signal control stage, we heavily rely on a deep dueling Q-network reinforcement learning-based model that inputs the current state traffic-related information alongside the traffic noise estimation to predict the upcoming traffic signal phase.
- We run our simulation experiments on a real-world dataset of a road intersection collected in Tallinn, Estonia. The harvested evaluation criteria (noise levels, CO_2 emissions, and fuel consumption) outperform those obtained by the pioneering ones in the literature. We designed this solution to function as stakeholders' accurate sidekick for proactive decision-making at a lower cost. Indeed, our approach has wide practical use in real-life scenarios.

We organize the remainder of this paper as follows: In Sect. 2, we scrutinize the related work that paid attention to both data fusion for traffic prediction and traffic signal control approaches. In Sect. 3, key notions for traffic signal control are introduced to simplify the understanding of our research goal. Section 4 thoroughly describes the proposed *EcoLight+* approach. A comparative analysis of the proposed model's performance against the competition is presented in the penultimate section. The final section wraps up our findings and sketches avenues for future work.

2 Related work

Modern societies are characterized by a great deal of urban noise. In addition to being a nuisance, it can negatively impact the environment and human health. While evidence of noise's harmful effects is increasing, spatial understanding of its distribution is limited. A brief overview of noise prediction methods is given in this section, followed by a discussion of data fusion for enhancing traffic prediction methods, followed by a discussion of traffic signal control methods.

2.1 Noise prediction

Noise pollution from road traffic is Europe's most prevalent source of outdoor ambient noise. Different prediction models may produce different noise levels depending on traffic noise's location and emission sources. At present, very little research focuses on developing models that help determine the effects of traffic noise on society. Staab et al. [7] used a land-use regression (LUR) model and context-aware feature engineering to construct a geostatistical model mapping approach to represent the arrangement of sources and the surrounding environment. In this article, the authors deal with small communities that have not been adequately mapped in Europe. To improve traffic noise modeling, another solution was proposed by Ahmed et al. [8] that developed a deep neural network-based optimization approach that integrated the wrapper for the feature-subset selection (WFS) method. This method creates weekday noise maps for different times, such as mornings, afternoons, evenings, and nights. Khan et al. [9] compared three different noise estimation models used throughout Europe. This study mainly explored potential models' performance patterns for specific configuration types. Based on vehicular traffic volume, percentage of heavy vehicles, and vehicles' average speed, a neuro-fuzzy inference system that identifies at what noise level the traffic will be detected has been proposed by Singh et al. [10]. Comparing it with conventional soft-computing techniques validates its suitability for planning mitigation measures for new and existing roads. Finally, Zhang et al. [11] examined the accuracy of different machine learning recurrent architectures for predicting traffic noise using real-life traffic data with multiple variables. According to the study, using a multivariate bidirectional GRU model (Gated Recurrent Unit) with a many-to-many architecture achieved the best computation efficiency and accuracy. Recently, Ounoughi et al. [5] introduced a sequence-to-sequence LSTM-based architecture to predict urban noise. Using a real-life dataset, the model underscores high performance at different times of the day (morning, evening, and night). The noise generated by traffic is a complex phenomenon. In modeling traffic noise, large and high-dimensional data are gathered. In this case, deep recurrent learning architectures are the best tools for analyzing large datasets and discovering nonlinear relationships.

2.2 Multi-modal data fusion

Current intelligent transportation systems (ITS) incorporate heterogeneous multi-modal input data from multiple sources in real time. Multimodality involves extracting and combining relevant information from individual sensors to solve a given problem. Therefore, the expected output will have a richer representation and performance than the individual modalities. In a single-domain dataset, deep learning-based prediction models have proven successful. In recent years, studies on data fusion (DF) have contributed significantly to the development of ITS and contributed significantly to its improvement. Recently, Ounoughi and Ben Yahia [6] categorized data fusion techniques into three primary levels. This categorization is driven by the stage where the fusion process takes place:

1. Observation-level: raw sensor data are combined directly;
2. Feature-level: emphasizes a preliminary extraction of representative features from the original sensor data; and
3. Decision-level: is used only after a first assessment of the target's attributes of interest.

The techniques applied to solve and improve different applications are Bayesian inference, Dempster–Shafer evidential reasoning, artificial neural networks, fuzzy logic, and Kalman filters. It is worth mentioning that Mai-Tan et al. [12] introduced a mobile crowd-sourcing fusion-based approach for traffic prediction. In the proposed framework, the mobile crowd-shared data are analyzed in real time, and the missing data are incorporated using data mining techniques and historical data. Using a simulation method, Wang et al. [13] applied cognitive psychology to learning driving behaviors on the road network. They used visual-filtering and perceptual-information fusion models to describe drivers' heterogeneous cognitive processes. Yeferny and Ben Yahia [14] introduced the Markov Chain-based data Dissemination Protocol (MCDP), an adaptive geocast protocol designed specifically for vehicular ad hoc networks (VANETs). MCDP dynamically determines the Zone of Relevance (ZOR) for events by considering the probability of receiving vehicles' information encountering them within VANETs. Alkouz et al. [15] proposed a cross-lingual data fusion model named SNSJam that predicts traffic jam events using cross-lingual data collected from multiple social media platforms. Many traffic prediction research works have involved external environmental factors such as weather conditions and air quality in measuring environmental factors. Worth citing, Essien et al. [16] stated an improved traffic speed prediction model fusing traffic-related variables with weather into a deep learning LSTM architecture. Moreover, Essien et al. in [17] fused public tweets with traffic and weather conditions to improve their deep learning model for traffic flow prediction tasks. Yang et al. [18] presented a hybrid deep learning structure for short-term traffic speed prediction using weather conditions and an air quality fusion model. Furthermore, Pu et al. [19] introduced a novel hybrid prediction model based on the fusion of traffic images' features using an attention CNN with an encoder–decoder framework. Real-world fusion-based applications have to deal with several data-related challenges. Their input data might be imperfect, correlated, inconsistent, or in various forms or modalities. Regardless of how different inputs to the data fusion module are managed, the underlying fusion algorithms must ultimately fuse the input data. As a result, we proposed to explore multi-modal data fusion according to our novel module based on the data embedding aspect.

2.3 Traffic signal control

Traffic signal control is integral to an intelligent transportation system that improves traffic efficiency. However, some challenges accompany these systems, such as protecting against high roadside cameras, keeping malicious vehicles from getting in, and preventing single points of failure. The literature has examined several traffic signal control systems to cope with those challenges. Two approaches have been developed so far: a fixed-time (rule-based) strategy and a traffic-responsive strategy [20].

Several signal plans (e.g., from 8:00 to 10:00 am) are predetermined based on historical traffic flow data as part of a fixed-time strategy. Thus, a traffic signal is periodically changed per the predetermined signal plans. Le et al. [21] proposed a decentralized traffic signal control scheme using a back-pressure scheme for urban road networks, which has received widespread recognition for achieving an optimal throughput control policy in data networks. They concluded that the proposed scheme of fixed cycle times and cyclic phases stabilizes the traffic for any possible transportation demand. However, since such traditional transportation systems do not work in real time, they can only be used when the demand is relatively stable within each time interval.

By using current traffic information, the traffic-responsive strategy overcomes the above limitation. In this strategy, the major challenge is forecasting incoming vehicles or traffic status. Bravo et al. [22] proposed a city-wide traffic control management program that assists traffic managers in making decisions, namely HITUL. Relying on a conjunction of meta-heuristic algorithms and nature-inspired techniques, the HITUL system uses different technologies to gather data and optimize traffic signal priorities using existing traffic information. Various reinforcement learning methods have recently been proposed to improve traffic signal control and achieve better results than traditional transportation methods. Worth mentioning, *IntelliLight* [23] is an RL-based approach that incorporates an extended phase-sensitive gate. It comprehensively evaluates traffic signal control performance, considering variables like waiting time and vehicle count at intersections. *Presslight* [24] is another RL-based method that uses the current phase, the number of vehicles on outgoing lanes, and the number of vehicles on incoming lanes as the state and uses the Max-pressure (MP) as the reward for achieving coordination between neighbors. *Colight* [25] utilizes graph attentional networks to facilitate communication. In this case, it uses the attention mechanism to represent neighboring information to achieve the goal of cooperative traffic signal control.

DemoLight [26] learns a stochastic policy (demonstrations) that maps states to an action probability distribution based on a generated analogy between agents and humans. *FRAP* [27] is a reinforcement learning-based method designed to learn the inherent logic of the traffic signal control problem, called phase competition. The advantage of this method is that it combines similar transactions, irrespective of the intersection structure or local traffic conditions. *ThousandLight* [28] is one of the most recent works that has been tested on the real-road network with 2510 traffic signals. By leveraging the *'pressure'* concept, they developed RL-FRAP-based agents capable of signal coordination at a regional level. Furthermore, the authors demonstrated that individual agents could achieve implicit coordination through reward design, thereby decreasing dimensionality. Another RL-FRAP with model-agnostic meta-learning (MAML) is proposed in [29]. This model can transfer knowledge between different intersections by focusing on action spaces and state spaces instead of traffic flow. For example, it can train an agent at a four-way intersection and test it at a five-way intersection. To improve the generalization ability of traffic signal control models, the authors in [30] proposed a meta-RL framework called *GeneraLight*. *GeneraLight* enhances generalization performance by combining flow clustering parameter initialization with multi-modal MAML (MUMOMAML). Our previously proposed approach is designed to manage traffic signal control by considering both sustainability and proactivity aspects. This solution adapts the traffic lights to reduce noise levels, CO_2 emissions, and vehicle fuel consumption.

Table 1 summarizes the factors influencing the evaluation of traffic signal control strategies: method, simulation environment, road network, and evaluation metrics. Recent studies have shown promising results when using reinforcement learning techniques for traffic signal control. However, these techniques rely only on the *current* traffic conditions. Therefore, through our improved approach, we accurately contribute several novel *sustainable* and *proactive* aspects to this line of research.

3 Formalization of the problem

This section introduces the fundamental notions formalizing the traffic signal control problem.

A road network consists of several junctions indexed by J. Each junction $j \in J$ consists of several in-roads R_j. Note that the R_j are mutually disjoint and denote $R = \cup_{j \in J} R_j$. Multi-lane roads with different turns, such as left- or right-turn-only lanes, are represented by multiple in-roads. Therefore, in-roads may model one or more lanes of traffic flow. A junction may serve different combinations of in-roads at the same time. It refers to service *phases* whenever several in-roads are maintained simultaneously. For a junction j, a service phase is represented as a vector $\sigma = (\sigma_r, r \in j)$, where σ_r is the rate at which cars at j can be serviced by the in-road r. Specifically, $\sigma_r > 0$ if the in-road r is green during phase σ, or $\sigma_r = 0$ otherwise. Accordingly, at each time step t, the system has to determine how much time it will spend serving each phase in S_j over the next interval, with the constraint that each phase must last for some nonzero length of time. Here, S_j denotes the set of phases at junction j.

4 The EcoLight+ approach

Deep reinforcement learning has proven to be a promising method for controlling traffic signals. By extending the previously proposed reinforcement learning solutions, we improve

Table 1 Representative traffic signal control methods

Citation	Method	Simulator	Road net. (# inters.)	Evaluation
[21]	Back-pressure scheme	SUMO	Real (2)	Avg. travel time
[22]	Meta-heuristic algorithm	SUMO	Real (961)	Emissions, Waiting time
[23]	RL with extended phase-sensitive gate	SUMO	Synthetic (1), Real (24)	Reward, Queue Length, Delay, Duration
[24]	RL with MP-based reward	CityFlow	Synthetic (1), Real (3, 5, 16)	Avg. travel time
[25]	RL with Graph Attentional Networks	CityFlow	Real (196)	Avg. travel time
[26]	RL trained with Demonstrations	CityFlow	Real (1)	Travel time
[31]	RL with Object Detection	Pygame	Synthetic (1)	Avg. waiting time
[32]	Queue-length responsive	Real env.	Real (1)	Avg. waiting time
[28]	RL-FRAP with MP coordination	CityFlow	Real (2510)	Avg. travel time, Throughput
[29]	RL-FRAP with MAML	CityFlow	Real (1)	Travel time
[30]	MUMOMAML with Clustering for parameter initialization	CityFlow	Real (1, 5, 16)	Avg. travel time
[5]	DQN with noise prediction	SUMO	Real (1)	Noise, CO_2, Fuel consumption

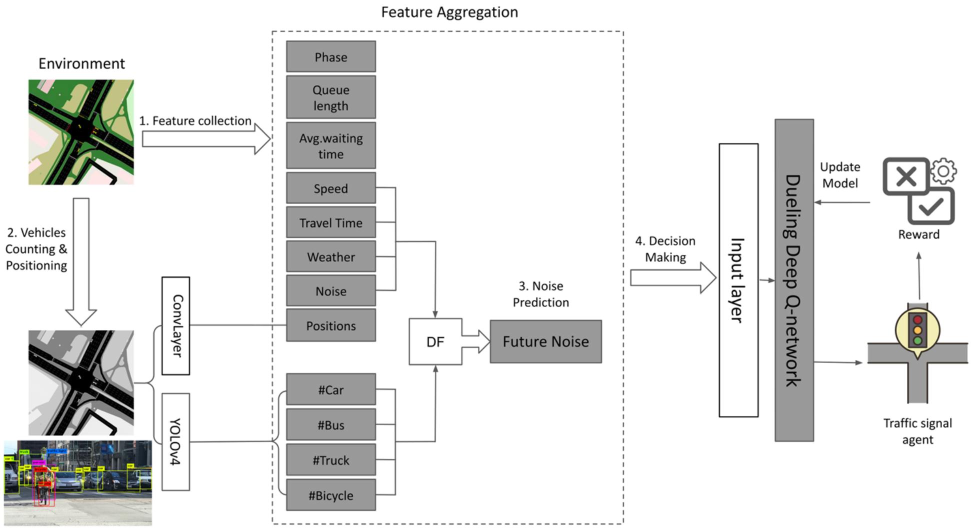


Fig. 1 EcoLight+ general framework

the robustness of the traffic signal control system by using future traffic noise predictions. Our enhanced proposed traffic signal control driven by noise prediction, namely *EcoLight*+, takes advantage of all traffic features along with the predicted amount of future generated noise. Integrating these sustainable and proactive aspects into our deep dueling Q-network will enhance its decision-making capabilities and raise the green awareness of the city's stakeholders. Figure 1 illustrates the final approach framework.

4.1 Data fusion for traffic noise prediction

In the last two decades, many cities have adopted intelligent transportation systems (ITS) that support urban transportation network planning and traffic management. These systems use current traffic information and generate predictions to improve transport efficiency and safety by informing users of current road conditions and adjusting road infrastructure (traffic lights). Traffic prediction aims to estimate the volume and density of traffic flow, generally to reduce congestion and generate optimal decisions with the least time or energy consumption. Traffic is influenced by many factors that should all be considered to make accurate predictions. Thus, we introduce a new embedding-based feature data fusion module that presents heterogeneous modalities into homogeneous learned numerical vectors. Figure 2 illustrates an overview of the proposed embedding-based feature data fusion module for urban noise prediction.

4.1.1 NN-Embeddings

The neural network embeds categorical values with similar output values into an N-dimensional space [33]. This spatial representation allows us to extract intrinsic properties from each categorical value, which generalize and replace our old high-dimensional dummy encoded features. NN-embedding weights act as a lookup table, leading to reduced memory usage and speeding up the training compared with one-hot encoding [2]. Moreover, this technique reduces the dimensionality of feature space, which should reduce overfitting in prediction problems. The embedding size defines the dimensionality with which we map the

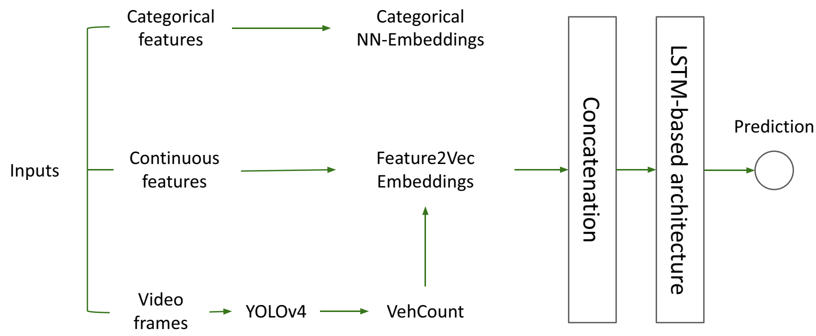


Fig. 2 Data fusion for prediction

categorical features. Howard et al. [34] provided a general rule of thumb about the number of embedding dimensions (shown in Eq. 1).

$$\mathrm{Emb}_{\mathrm{size}} = \min(50, (|\mathrm{feature}| + 1)/2) \tag{1}$$

where |feature| is the number of distinct values of the categorical feature.

4.1.2 Feature2Vec embeddings

Kazemi et al. in [35], proposed a new method, called Time2vec, that generates embeddings for the time feature. In our case, we adopt their Time2Vec and adjust it to generate embedding representations of our continuous input features. The latter captures three main properties (periodicity, invariance to time rescaling, and simplicity). For a given scalar notion of feature f, Feature2Vec of f denoted as $F2v(x)$ is vectors of size $k+1$ defined as follows:

$$F2v(x)[i] = \begin{cases} w_i x + \varphi_i, & \text{if } i = 0 \\ \mathcal{F}(w_i x + \varphi_i), & \text{if } 1 \leq i \leq k \end{cases} \tag{2}$$

where $\mathcal{F}$ is a periodic activation function and w_i and φ_i are the learnable parameters. This vector representation of feature x allows it to be ingested in any architecture. We used $\mathcal{F}$ as the *cosine* function in our implementation.

4.1.3 Prediction

Our approach embraces the sequence-to-sequence architecture for the input fused embedding vectors and the noise prediction output. After generating our fixed-sized sequences, we leverage an LSTM-based architecture to predict traffic noise for a specific future period (e.g., hourly, daily). Effectively, it pinpoints long-term temporal dependencies accurately. We train and update the model using the back-propagation algorithm as an optimizer and a loss function to minimize the prediction error. Finally, we evaluate the model's predicted sequences, comparing them with the actual traffic noise ones using the prevalent evaluation metrics.

4.2 Traffic signal control

Reinforcement learning involves learning through reward and error to make decisions. It can take significant inputs to decide what actions to take to maximize the reward (advantage A).

With deep RL, agents can learn from unstructured data and make decisions without manually engineering their state space. Among the types of RL Q-networks, dueling network has two streams to estimate the state value according to each action separately. Both state value $V(s)$ and advantage $A(s, a)$ streams share a standard convolutional feature learning module. The two streams are combined via a particular aggregating layer to produce an estimate of the state-action value function $Q(s, a)$ denoted as follows:

$$Q(s, a, \theta, \alpha, \beta) = V(s, \theta, \beta) + A(s, a, \theta, \alpha) \quad (3)$$

where θ denotes the parameters of the convolutional layers. The parameters α and β are for fine-tuning two streams of fully connected layers.

A traffic state can be defined as a combination of various features such as queue length, waiting time, and the vehicles' positions. Once the prediction algorithm has been executed, the noise prediction will be explored as a state input. Then, we use the reward to describe how much that action a has improved traffic. In summary, the *EcoLight+* dueling-based approach is described as follows:

- The offline stage allows traffic to flow through the system according to a fixed schedule to train the model and collect data samples.
- At every time interval Δ_t, the traffic signal agent observes the state s of the environment. It takes actions a based on a greedy ϵ-based strategy combining exploration (random action with probability ϵ) and exploitation (estimating the reward of taking this action given the current state s).
- The agent observes the environment and receives the reward r. Then, the tuple (state, action, reward) will be stored in memory.
- The network will be updated based on the logs in memory after several timestamps.

Figure 3 sketches the steps of the dueling deep Q-network approach.

5 Experimental evaluation

This section describes our experimental setup and evaluation process for comparing our *EcoLight+* approach to pioneering baselines using real-world data. The source code for our project is publicly available and can be accessed through the following link.[2]

5.1 Dataset

Experiments on real-world data are needed to determine *EcoLight+*'s efficiency against the pioneering baselines. We collected data from noise sensors, video cameras[3], weather [4] data, and TomTom [5] traffic-related features in one of the most congested intersections in Tallinn, Estonia, the Tammsaare tee-Sõpruse between 2022-02-15 and 2022-04-06 with a one-minute frequency. The applied preprocessing can be depicted in the following two steps:

- According to the applied analysis, the collected time-series data suffer from sensor reliability issues. Sensors are not continuously reliable because of technical and

[2] Link to the source code: https://github.com/doua-ounoughi/EcoLightPlus.

[3] https://ristmikud.tallinn.ee/index.php/cams.

[4] https://ristmikud.tallinn.ee/index.php/temperature.

[5] https://www.tomtom.com.

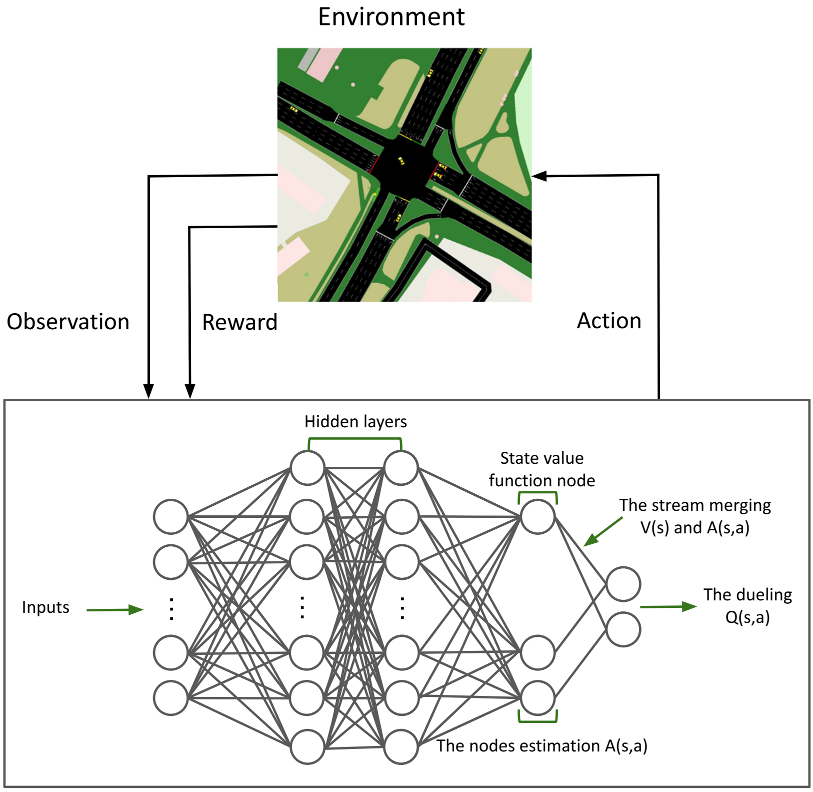


Fig. 3 Dueling deep Q-network process

operation-related issues, which cause gaps and missing information that could affect the accuracy of the prediction model. Therefore, to tackle this issue, we used the KNN-imputation technique with $k = 5$ to fill in the missing value in our dataset.
- Using YOLOv4 [36], we have been able to detect the number of each type of vehicle (motorbike, car, bus, and truck) that passed through the intersection in each single video frame.

The final input features we get after the preprocessing procedure are as follows: timestamp, noise, temperature, air pressure, air humidity, wind speed, rain, current speed, wind direction, cloudiness, sunrise hour, speed, travel time, minute, the hour of the day, the day of the week, the day of the month, road type, road closed, number of cars, number of motorbikes, number of buses, and number of trucks.

5.2 Experimental setups

Our experiments carried out under the configuration of *Ubuntu 18.04.3 LTS* (CPU: *Intel Xeon Processor (Skylake)* × 8, RAM: 16Go), in which *Python* (3.7) and *Keras* (2.3.1) with the simulator *SUMO* [37] have been installed.

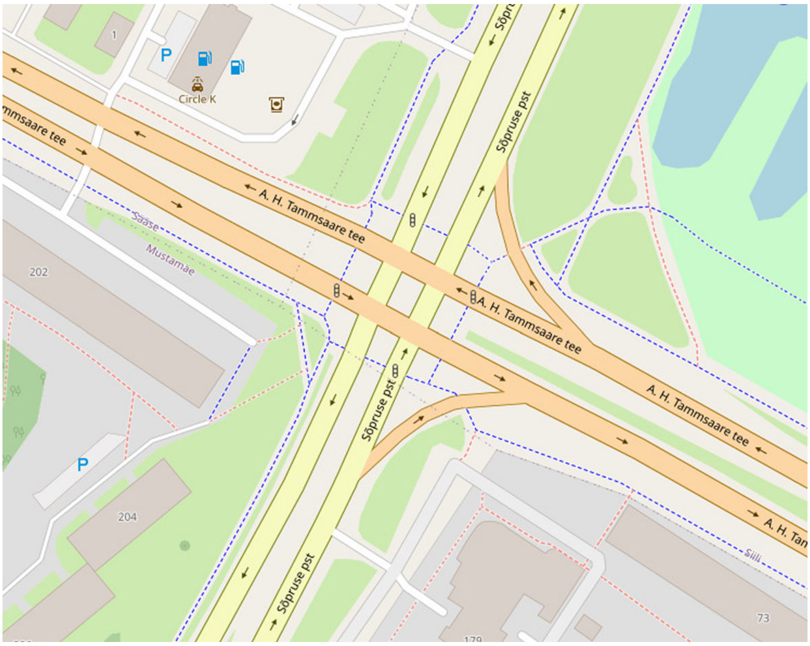


Fig. 4 Tammsaare tee-Sõpruse intersection, Tallinn, Estonia

Table 2 Simulation settings

Parameter	Value
Model update interval	400,000 s
Action time interval Δ_t	5 s
γ for future reward	0.80
ϵ for exploration	0.05
Sample size	300
Memory length	1000

5.2.1 Prediction settings

To efficiently reckon the performance of the proposed approach, we predicted the future noise levels for the next 1 min, 5 min, 10 min, 15 min, 30 min, and 60 min. We apply a min–max normalization technique implemented by the *Scikit-learn* python library [38] with a range between 0 and 1 on all the continuous feature values. We aggregate 80% of data training and 20% for testing. After preprocessing our inputs and generating our fixed-sized sequences, we adopt the use of a fully connected network of a bidirectional *LSTM ReLU* activation layer connected to seven *ELU* activation dense layers with the sizes of 256, 256, 256, 256, 256, 128, and 128 units, respectively, and an output layer *linear* activation layer for the prediction task. The *Adam* optimizer [39], as well as *mean squared error (MSE)* as the loss function, is used to fine-tune the training model within 40 epochs and a batch size of 128 for the considered dataset.

5.2.2 Simulation settings

We have used the Open Street Map WebWizard to generate the *"Tammsaare tee-Sõprus"* intersection network and configuration files to be used in the *SUMO* simulator. We obtained 43 lanes at this intersection after considering all the types of lanes (car, bus, bicycle, pedestrian). First, the simulation presents the environment, including the state (current phase, queue length, waiting time, vehicles' positions, and noise prediction). Then, the **EcoLight+** model, according to that state, will predict the action of the lights and then get its reward (as depicted in Fig. 3). Table 2 presents the parameter settings of the model and reward coefficient, hence the simulation. We found out that the action time interval Δ_t has minimal influence on the performance of our model as long as Δ_t is between 5 and 25 s. For a fair comparison, we kept the same configuration for all the deep Q-network-based baselines. For the simulation of the fixed-time BASIC strategy, we had the default green phases generated by the WebWizard network with the following time intervals: {7, 3, 7, 7, 7, 7, 7, 3, 7}.

5.3 Baseline methods for comparison

To accurately validate the performance of our proposed **EcoLight+** approach, we carried out a comparison versus the existing traffic signal control baseline methods: the deep RL-based **IntelliLight** [23], our previously proposed solution **EcoLight** enhanced with the embedding fusion [5], and the default fixed-time-based traffic signal control model in the *SUMO* simulator with no intervention **BASIC**. In addition, we conducted an ablation study to test different reinforcement learning models, i.e., double deep Q-network (**DDQN**) with and without using our embedding-based fusion model and dueling deep Q-network (**DDDQN**). All baseline methods are tested with the same network data and simulation configuration to ensure a fair comparison.

5.4 Evaluation

5.4.1 Noise prediction

The prediction performance of our model compared to the baselines is evaluated using the mean squared error (MSE), the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) defined, respectively, by (4), (5), (6), and (7).

$$\mathrm{MSE} = \frac{1}{J}\sum_{j=1}^{J}(n_j - \hat{n}_j)^2 \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{J}\sum_{i=1}^{J}(y_i - \hat{y}_i)^2} \tag{5}$$

$$\mathrm{MAE} = \frac{1}{J}\sum_{j=1}^{J}|n_j - \hat{n}_j| \tag{6}$$

$$\mathrm{MAPE} = \frac{1}{J}\sum_{j=1}^{J}\frac{|n_i - \hat{n}_i|}{n_i} \tag{7}$$

Table 3 Noise prediction performance (MSE)

Prediction Model	MSE 1 min	5 min	10 min	15 min	30 min	60 min
No fusion	13.04	19.85	24.22	27.76	27.12	17.59
UKF fusion	39.74	39.94	39.70	39.80	39.83	39.79
KF fusion	5.02	9.06	11.40	11.72	12.36	9.19
SKF fusion	3.38	8.23	10.96	11.23	11.69	8.65
Embeddings	**2.89**	**7.37**	**9.95**	**10.52**	**11.55**	**8.61**
-based fusion	**−14.49%**	**−32.75%**	**−9.21%**	**−6.32%**	**−1.19%**	**−0.45%**

The bold font indicates the best results

where J is the size of the tested junctions, n_j is the ground-truth junction's noise, and $\hat{n}_j$ is the predicted noise level yielded by the model of the j-th junction.

5.4.2 Traffic signal control

Traffic poses a significant burden on society through its environmental impact, including air and noise pollution and the consumption of nonrenewable materials. Using *SUMO*, we can measure the generated pollution and fuel consumption using different models and interfaces. Among the information that can be obtained are:

- *Trip information* sum of pollutants emitted/fuel consumed by a single vehicle.
- *Lane emissions* Pollutants emitted and fuel consumed at a lane aggregated over time.
- *Lane noise* Noise generated along a lane accumulated over a period of time.

Therefore, our approach's traffic signal control performance evaluation against the pioneering ones is based on each model's emitted noise, CO_2 emissions, and fuel consumption on the considered dataset.

5.5 Results and discussion

Tables 3, 4, 5, and 6 glance at the noise prediction performance of our **Bidirectional SeqtoSeq-LSTM** with embedding fusion approach against the baselines. We use the mentioned evaluation metrics to compare our approach with the same architecture without fusion and with different Kalman filter fusion variations (simple KF, unscented KF, and smooth KF). Our results underscore that our model sharply outperforms the baselines in predicting future noise with high improvement percentages. Notwithstanding, the **SKF** fusion model performs slightly similarly to our proposed model.

In the sequel, we evaluate the effectiveness of our **EcoLight+** traffic signal control in response to several environmental and economic factors. The tested simulation ran for $960,243$ seconds (approximately 266 hours). After each phase change, the evaluation results between all the models were compared to the model's hourly average emitted noise, CO_2, and consumed fuel.

5.5.1 Effectiveness over traffic noise

From the achieved results (c.f., Table 7), the DDQN model and **BASIC** show similar and the worst performance on the considered intersection, respectively. Indeed, they use a fixed-

Table 4 Noise prediction performance (RMSE)

Prediction	RMSE					
Model	1 min	5 min	10 min	15 min	30 min	60 min
No fusion	3.61	4.45	4.92	5.26	5.20	4.19
UKF fusion	6.30	6.32	6.30	6.30	6.31	6.30
KF fusion	2.24	3.01	3.37	3.42	3.51	3.03
SKF fusion	1.84	2.87	3.31	3.35	3.42	2.94
Embeddings	**1.70**	**2.71**	**3.15**	**3.24**	**3.39**	**2.93**
-based fusion	**−7.60%**	**−5.57%**	**−16.00%**	**−3.28%**	**−0.87%**	**−0.34%**

The bold font indicates the best results

Table 5 Noise prediction performance (MAE)

Prediction	MAE					
Model	1 min	5 min	10 min	15 min	30 min	60 min
No fusion	2.62	3.29	3.63	3.86	3.85	3.14
UKF fusion	5.12	5.14	5.13	5.13	5.13	5.13
KF fusion	1.58	2.23	2.54	2.57	2.68	2.27
SKF fusion	1.35	2.12	2.46	2.49	**2.58**	2.17
Embeddings	**1.20**	**2.02**	**2.38**	**2.45**	2.60	2.17
-based fusion	**−11.11%**	**−4.71%**	**−3.35%**	**−1.60%**	+0.77%	0%

The bold font indicates the best results

Table 6 Noise prediction performance (MAPE)

Prediction	MAPE					
Model	1 min	5 min	10 min	15 min	30 min	60 min
No fusion	4.41	5.57	6.19	6.61	6.56	5.31
UKF fusion	8.99	9.04	9.01	8.99	8.99	9.01
KF fusion	2.67	3.80	4.34	4.39	4.57	3.85
SKF fusion	2.30	3.61	4.19	4.24	**4.38**	**3.68**
Embeddings	**2.05**	**3.45**	**4.07**	**4.19**	4.46	3.71
-based fusion	**−10.86%**	**−4.43%**	**−2.86%**	**−1.17%**	+1.82%	+0.81%

The bold font indicates the best results

timing strategy that does not adapt to current and potential future traffic situations. The results underscore that the **DDQN** alongside the noise prediction model performs slightly the same as the **IntelliLight** model. Additionally, **EcoLight+** shows a better performance than its former counterpart, **EcoLight**, with an improvement of 18.77%, which proves that using dueling DQN yields better strategies for traffic signal control. Figure 5a depicts the sharp improvement percentages of **EcoLight+** model compared to the **BASIC** logic strategy with more than 74% and outperforms all the baselines for the produced noise at the considered intersection (Fig. 4).

Table 7 Average hourly performance evaluation

Model	Noise (dB)	CO_2 (kg)	Fuel consumption (L)
BASIC	69,938.82	0.1811	1272.85
DDQN	71,417.23	0.1972	1282.97
DDQN with EF	52,604.22	0.1715	1027.28
IntelliLight	52,036.50	0.1742	1060.82
DDDQN	34,984.01	0.1331	732.20
EcoLight with EF	22,335.80	0.1219	689.97
EcoLight+	**18,141.59**	**0.0656**	**385.78**
Improvement	**−18.77%**	**−46.18%**	**−43.50%**

The bold font indicates the best results

5.5.2 Effectiveness over CO_2 emission

Our approach shows a significant reduction in CO_2 for the considered intersection compared to other baselines, more specifically the **EcoLight** with a 46.18%. We notice that the dueling deep Q-network performs better than the different reinforcement learning model variations. Furthermore, with our multi-modal data fusion noise prediction enhancement, it performs even better. The improvement rates of most models are comparable to those of **BASIC**, as shown in Figure 5b.

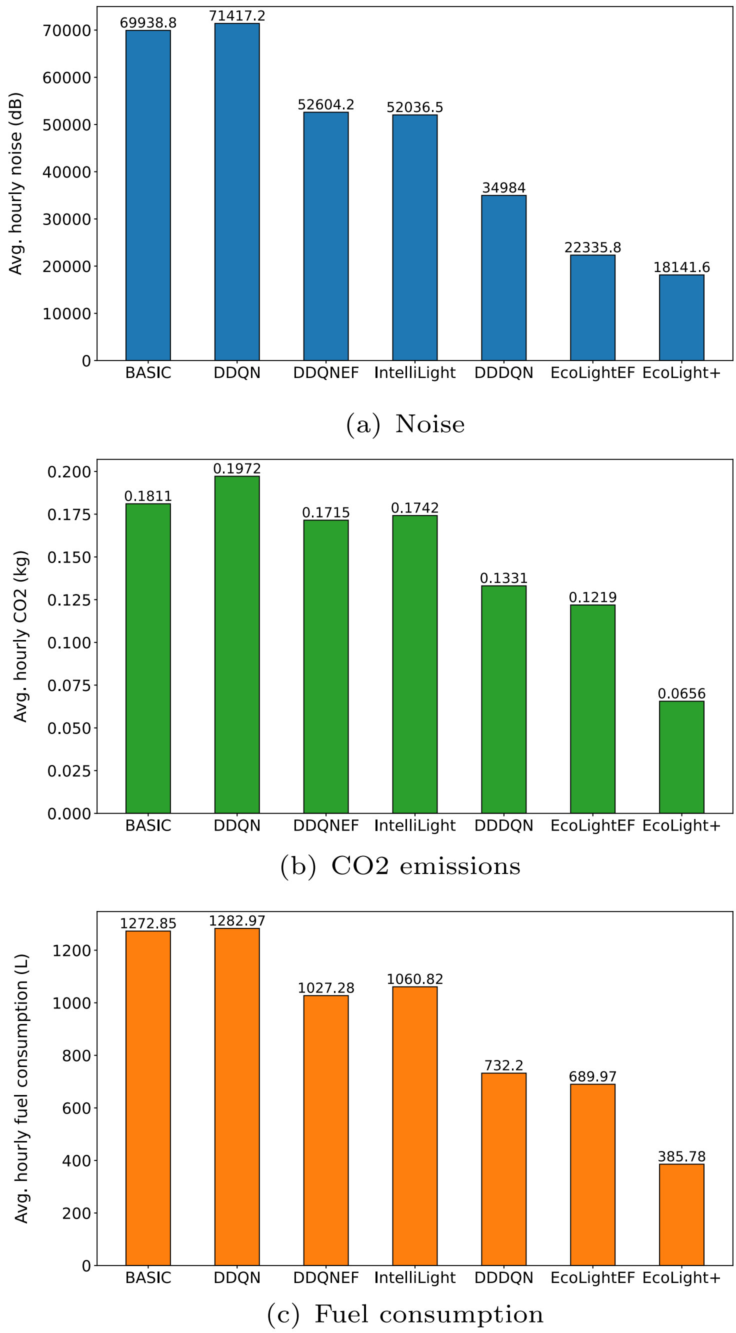
5.5.3 Effectiveness over fuel consumption

A comparison of the improvement percentages of fuel consumption by all the models to that of **BASIC** logic is shown in Figure 5b. **DDQN** performs the same as **BASIC** with no significant improvement in fuel consumption. We notice that the DDQN with noise prediction outperforms the **IntelliLight** model. While operating **EcoLight+**, vehicular fuel consumption can be reduced by more than 69% compared to the **BASIC**. According to the **EcoLight+** approach, if we assume that Estonia's current average fuel price is 1.905 US dollars, we will save up to 1,689.86 US dollars per hour, which works out to approximately 14.8 million dollars annually only this intersection.

6 Conclusion

In this paper, we introduced an advanced eco-friendly traffic signal control driven by urban noise prediction, namely *EcoLight+*. We address the traffic signal control problem using a well-designed deep dueling reinforcement learning-based approach that integrates future noise predictions. We conduct our experiments on Tallinn's multi-modal data from different sources. The yielded results provide evidence for the reliability and sustainability of the use of future noise predictions. Indeed, experiments underscore the baselines' inability to perform better in terms of noise, CO_2 emissions, and fuel consumption compared to our *EcoLight+* approach.

We point out a critical future direction to make *EcoLight+* more relevant to the real world. The *EcoLight+* is designed and tested to consider a simplified case of one intersection in Tallinn, whereas real-world network design is significantly more complex. Multiple inter-



(a) Noise

(b) CO2 emissions

(c) Fuel consumption

Fig. 5 Average hourly performance

sections have been addressed by combining several reinforcement learning agents at limited intersections. Meanwhile, sales of electric cars jumped 43% to more than 3.2 millions of the 370 different car models in 2020 [40]. This type of vehicle tends to be environmentally friendly and makes less noise. Future work will improve emissions reduction by proposing a hybrid approach that enhances our *EcoLight+* with traffic-related features other than noise to reduce delay times, thereby limiting congestion levels.

Acknowledgements This work was supported by grants to TalTech - TalTech Industrial (H2020, grant No 952410), Estonian Research Council (PRG1573), and EU-Astra - TUT Development Plan for 2016-2022 (ASTRA) reg no. 2014-2020.4.1.16-0032.

Author Contributions CO: Conceptualization, Methodology, Software, Validation, Visualization, Writing - Review & Editing. DO: Methodology, Software. SBY: Review & Editing.

Declarations

Conflict of interest The authors declare no coflict of interest.

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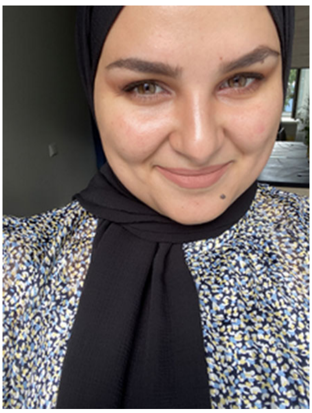
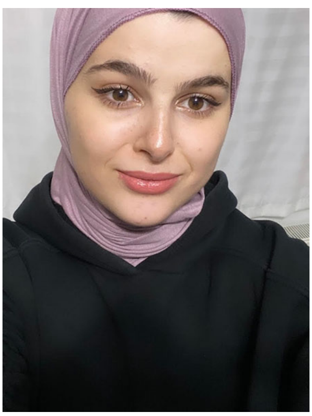


Chahinez Ounoughi received her B.Sc. degree in computer science in 2016 and her M.Sc. in Data Engineering and Web Technology in 2018 from Ferhat Abbas Setif-1 University, Algeria. She is pursuing a Ph.D. in 'Urban traffic: Data fusion and vehicle flow prediction in smart cities' at Tallinn University of Technology (TalTech), Estonia. Her research focuses on providing accurate predictions to improve intelligent mobility management systems, integrating advanced deep learning architectures and data fusion techniques to reduce traffic congestion, urban noise, and CO_2 emissions. Additionally, she has worked on the recommendation topic using the notion of Knowledge Graph Embedding. Her methodological interests include deep learning architectures, data fusion, analysis, and pre-processing methods.



Doua Ounoughi is currently pursuing a 4th-year bachelor's degree in computer engineering at Çanakkale Onsekiz Mart University (ÇOMÜ), Turkey. As part of the data science research group at TalTech, she worked as an Erasmus+ trainee in 2022. Her research is focused on Smart Traffic Signal Control Management, Reinforcement Learning, and Urban Mobility Simulations.

Sadok Ben Yahia has been a Full Professor at the Technology University of Tallinn (TalTech) since January 2019. He obtained his HDR in Computer Sciences from the University of Montpellier (France) in April 2009 and has taught since then. He leads the Data Science Group in the IT School, focusing on data-driven approaches for near-real-time big data analytics, including urban mobility in smart cities (e.g., information aggregation and dissemination, traffic congestion prediction), and Ontology engineering (Matching and merging).

Curriculum Vitae

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Education

2020–2024	Tallinn University of Technology, School of Information Technologies, Computer Science, PhD studies
2016–2018	Ferhat Abbas University Setif-1, Algeria Computer Science, MSc
2013–2016	Ferhat Abbas University Setif-1, Algeria Computer Science, BSc

Language competence

Arabic	native
English	fluent
Frensh	fluent

Professional employment

2023	GaiaHub, Co-Founder and CTO

Computer skills

- Programming languages: Python, R, Java, C, Pascal
- Database management system: Oracle, MySql
- Design and modeling language: UML, Merise
- Operating system: Linux, Windows
- Artificial Intelligence: Machine Learning, Deep Learning Statistical Analysis

Supervision (Defended)

- 2023, Andres Suislepp, Data Fusion for Traffic Prediction, MSc, supervisor Prof. Sadok Ben Yahia, **Chahinez Ounoughi**, Tallinn University of Technology.
- 2021, Muhammad Ibraheem Sherzad, Next Point of Interest Recommendation, MSc, supervisor Prof. Sadok Ben Yahia, **Chahinez Ounoughi**, Tallinn University of Technology.
- 2021, Ghofrane Touaibi, A urban noise pollution reduction system, MSc, supervisor Prof. Sadok Ben Yahia, **Chahinez Ounoughi**, Tunis El Manar University.

Publications

1. C. Ounoughi and S. Ben Yahia. Sequence to sequence hybrid bi-lstm model for traffic speed prediction. *Expert Systems with Applications*, 236:121325, 2024
2. C. Ounoughi, G. Touibi, and S. B. Yahia. Ecolight: Eco-friendly traffic signal control driven by urban noise prediction. In C. Strauss, A. Cuzzocrea, G. Kotsis, A. M. Tjoa, and I. Khalil, editors, *Database and Expert Systems Applications*, pages 205–219, Cham, 2022. Springer International Publishing
3. C. Ounoughi and S. Ben Yahia. Data fusion for its: A systematic literature review. *Information Fusion*, 89:267–291, 2023
4. C. Ounoughi, D. Ounoughi, and S. B. Yahia. Ecolight+: a novel multi-modal data fusion for enhanced eco-friendly traffic signal control driven by urban traffic noise prediction. *Knowledge and Information Systems*, July 2023
5. K. Katsarou, C. Ounoughi, A. Mouakher, and C. Nicolle. Stcms: A smart thermal comfort monitor for senior people. In *2020 IEEE 29th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE)*, pages 187–192, 2020
6. A. Mouakher, W. Inoubli, C. Ounoughi, and A. Ko. Expect: Explainable prediction model for energy consumption. *Mathematics*, 10(2), 2022
7. C. Ounoughi, T. Yeferny, and S. Ben Yahia. Zed-tte: Zone embedding and deep neural network based travel time estimation approach. In *2021 International Joint Conference on Neural Networks (IJCNN)*, pages 1–10, 2021
8. C. Ounoughi, A. Mouakher, M. I. Sherzad, and S. Ben Yahia. A scalable knowledge graph embedding model for next point-of-interest recommendation in tallinn city. In S. Cherfi, A. Perini, and S. Nurcan, editors, *Research Challenges in Information Science*, pages 435–451, Cham, 2021. Springer International Publishing
9. A. Torim, I. Liiv, C. Ounoughi, and S. B. Yahia. Pattern based software architecture for predictive maintenance. In E. Zouganeli, A. Yazidi, G. B. M. Mello, and P. Lind, editors, *Nordic Artificial Intelligence Research and Development - 4th Symposium of the Norwegian AI Society, NAIS 2022, Oslo, Norway, May 31 - June 1, 2022, Revised Selected Papers*, volume 1650 of *Communications in Computer and Information Science*, pages 26–38. Springer, 2022

10. D. Rincon-Yanez, C. Ounoughi, B. Sellami, T. Kalvet, M. Tiits, S. Senatore, and S. B. Yahia. Accurate prediction of international trade flows: Leveraging knowledge graphs and their embeddings. *Journal of King Saud University - Computer and Information Sciences*, page 101789, 2023

Project participation

2020–2021	Eurora Project. The STACC and Tallinn University of Technology. Data scientist, Models generation for HS-Code classification.
2022–...	Economic Complexity, Machine Learning and Economic Policy. Tallinn University of Technology. Data scientist, Data analysis, trades prediction, decision making.
2022	Integrated Monitoring and Diagnosis Solution For Predictive Maintenance of Expansion Joints. Pentamet Campany. Data scientist, Model generation for predictive maintenance.

Conference presentations

1. C. Ounoughi, G. Touaibi, and S. Ben Yahia. Ecolight: Eco-friendly traffic signal control driven by urban noise prediction. DEXA: August 2022, Vienna, Austria.

2. C. Ounoughi. Zone Embedding and Deep Neural Network based Travel Time Estimation Approach. NGGS: September 2021, Online.

3. C. Ounoughi, T. Yeferny, S. Ben Yahia. ZED-TTE: Zone Embedding and Deep Neural Network based Travel Time Estimation Approach. IJCNN: July 2021, Online.

4. C. Ounoughi, A. Mouakher, M. I. Sherzad, S. Ben Yahia. A Scalable Knowledge Graph Embedding Model for Next Point-of-Interest Recommendation in Tallinn City. RCIS: May 2021, Online.

5. K. Katsarou, C. Ounoughi, A. Mouakher, C. Nicolle. STCMS: A Smart Thermal Comfort Monitor For Senior People. WETICE: October 2020, Online.

Honors and awards

- In 2022, I participated in the EuroTeQaThon International Competition hosted by the Technical University of Munich in Germany, alongside prestigious universities. The challenge was centered around the theme "Leave no Waste Behind." I had the honor of representing Tallinn University of Technology and presenting our innovative solution, the Urban Mobility Hub, which was recognized as the winning project in the Cities category.

- In February 2023, I was recognized as a team member at Tallinn University of Technology for developing a solution that uses artificial intelligence to monitor the status of industrial equipment. Our solutions were considered the best development work of the year, and I am proud to have received recognition for my skills.

Elulookirjeldus

Isikuandmed

Nimi	Chahinez Ounoughi
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Rahvus	Alžeeria

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Haridus

2020–2024	Tallinna Tehnikaülikool, Infotehnoloogia teaduskond, Arvutiteaduse doktoriõpingud
2016–2018	Ferhat Abbasi Ülikool Setif-1, Alžeeria Arvutiteaduse magister
2013–2016	Ferhat Abbasi Ülikool Setif-1, Alžeeria Arvutiteaduse bakalaureus

Keeleoskus

Araabia	emakeel
Inglise	vabalt valdav
Prantsuse	vabalt valdav

Töökogemus

2023	GaiaHub, kaasasutaja ja tehnoloogiadirektor

Arvutioskused

- Programmeerimiskeeled: Python, R, Java, C, Pascal
- Andmebaasisüsteemid: Oracle, MySQL
- Disaini- ja modelleerimiskeel: UML, Merise
- Operatsioonisüsteemid: Linux, Windows
- Tehisintellekt: Masinõpe, Süvaõpe, Statistiline analüüs

Juhendamine (kaitsmised)

- 2023, Andres Suislepp, Liikluse ennustamiseks andmefusioon, magister, juhendaja prof. Sadok Ben Yahia, **Chahinez Ounoughi**, Tallinna Tehnikaülikool.
- 2021, Muhammad Ibraheem Sherzad, Järgmise huvipunkti soovitamine, magister, juhendaja prof. Sadok Ben Yahia, **Chahinez Ounoughi**, Tallinna Tehnikaülikool.
- 2021, Ghofrane Touaibi, Linnamüra vähendamise süsteem, magister, juhendaja prof. Sadok Ben Yahia, **Chahinez Ounoughi**, Tunis El Manar Ülikool.

Publikatsioonid

1. C. Ounoughi and S. Ben Yahia. Sequence to sequence hybrid bi-lstm model for traffic speed prediction. *Expert Systems with Applications*, 236:121325, 2024
2. C. Ounoughi, G. Touibi, and S. B. Yahia. Ecolight: Eco-friendly traffic signal control driven by urban noise prediction. In C. Strauss, A. Cuzzocrea, G. Kotsis, A. M. Tjoa, and I. Khalil, editors, *Database and Expert Systems Applications*, pages 205–219, Cham, 2022. Springer International Publishing
3. C. Ounoughi and S. Ben Yahia. Data fusion for its: A systematic literature review. *Information Fusion*, 89:267–291, 2023
4. C. Ounoughi, D. Ounoughi, and S. B. Yahia. Ecolight+: a novel multi-modal data fusion for enhanced eco-friendly traffic signal control driven by urban traffic noise prediction. *Knowledge and Information Systems*, July 2023
5. K. Katsarou, C. Ounoughi, A. Mouakher, and C. Nicolle. Stcms: A smart thermal comfort monitor for senior people. In *2020 IEEE 29th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE)*, pages 187–192, 2020
6. A. Mouakher, W. Inoubli, C. Ounoughi, and A. Ko. Expect: Explainable prediction model for energy consumption. *Mathematics*, 10(2), 2022
7. C. Ounoughi, T. Yeferny, and S. Ben Yahia. Zed-tte: Zone embedding and deep neural network based travel time estimation approach. In *2021 International Joint Conference on Neural Networks (IJCNN)*, pages 1–10, 2021
8. C. Ounoughi, A. Mouakher, M. I. Sherzad, and S. Ben Yahia. A scalable knowledge graph embedding model for next point-of-interest recommendation in tallinn city. In S. Cherfi, A. Perini, and S. Nurcan, editors, *Research Challenges in Information Science*, pages 435–451, Cham, 2021. Springer International Publishing
9. A. Torim, I. Liiv, C. Ounoughi, and S. B. Yahia. Pattern based software architecture for predictive maintenance. In E. Zouganeli, A. Yazidi, G. B. M. Mello, and P. Lind, editors, *Nordic Artificial Intelligence Research and Development - 4th Symposium of the Norwegian AI Society, NAIS 2022, Oslo, Norway, May 31 - June 1, 2022, Revised Selected Papers*, volume 1650 of *Communications in Computer and Information Science*, pages 26–38. Springer, 2022
10. D. Rincon-Yanez, C. Ounoughi, B. Sellami, T. Kalvet, M. Tiits, S. Senatore, and S. B. Yahia. Accurate prediction of international trade flows: Leveraging knowledge graphs and their embeddings. *Journal of King Saud University - Computer and Information Sciences*, page 101789, 2023

Projektides osalemine

2020–2021	Eurora projekt. STACC ja Tallinna Tehnikaülikool. Andmeanalüütik, mudelite genereerimine HS-koodide klassifitseerimiseks.
2022–...	Majanduslik keerukus, masinõpe ja majanduspoliitika. Tallinna Tehnikaülikool. Andmeanalüütik, andmeanalüüs, kauplemise ennustamine, otsuste tegemine.
2022	Integreeritud jälgimis- ja diagnoosilahendus eeltelliste hoolduseks. Pentamet Campany. Andmeanalüütik, mudelite genereerimine eeltelliste hoolduse jaoks.

Konverentsiettekanded

1. C. Ounoughi, G. Touaibi, and S. Ben Yahia. Ecolight: Eco-friendly traffic signal control driven by urban noise prediction. DEXA: August 2022, Vienna, Austria.

2. C. Ounoughi. Zone Embedding and Deep Neural Network based Travel Time Estimation Approach. NGGS: September 2021, Online.

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5. K. Katsarou, C. Ounoughi, A. Mouakher, C. Nicolle. STCMS: A Smart Thermal Comfort Monitor For Senior People. WETICE: October 2020, Online.

Autasud ja auhinnad

- 2022. aastal osalesin EuroTeQaThon rahvusvahelisel võistlusel, mida korraldas Tehniline Ülikool Münchenis Saksamaal, koos mainekate ülikoolidega. Väljakutse keskendus teemale "Leave no Waste Behind". Mul oli au esindada Tallinna Tehnikaülikooli ja tutvustada meie innovaatilist lahendust, Urban Mobility Hub'i, mis tunnistati võiduprojektiks linnade kategoorias.

- 2023. aasta veebruaris tunnustati mind Tallinna Tehnikaülikooli meeskonnaliikmena, kes arendas lahendust, mis kasutab tehisintellekti tööstusseadmete seisundi jälgimiseks. Meie lahendusi peeti aasta parimateks arendustöödeks ning olen uhke, et minu oskusi tunnustati.

ISSN 2585-6901 (PDF)
ISBN 978-9916-80-116-1 (PDF)