DOCTORAL THESIS

Residential Energy Management System to Support Increased Renewable Penetration

Noman Shabbir

TALLINNA TEHNIKAÜLIKOOL
TALLINN UNIVERSITY OF TECHNOLOGY
TALLINN 2022

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37/2022

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TALTECH PRESS

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This dissertation was accepted for the defence of the degree on 28/05/2022

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Declaration:

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

Noman Shabbir

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ISSN 2585-6898 (publication)
ISBN 978-9949-83-857-8 (publication)
ISSN 2585-6901 (PDF)
ISBN 978-9949-83-858-5 (PDF)
Printed by Koopia Niini & Rauam

TALLINNA TEHNIKAÜLIKOOL
DOKTORITÖÖ
37/2022

Taastuvenergiaallikate kasutustihedust toetav energiahaldussüsteem

NOMAN SHABBIR

TALTECH KIRJASTUS

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List of Publications

The list of author's publications, on the basis of which the thesis has been prepared:

I **Shabbir, N**.; Kütt, L.; Astapov, V.; Husev, O.; Ahmadiahanagr, R.; Kull, K.; Wen, F. (2022). Congestion Control Strategies for Increased Renewable Penetration of Photovoltaic in LV Distribution Networks, Energy Reports [Accepted for Publication]

II **Shabbir, N**.; Kütt, L.; Astapov, V.; Jawad, M.; Allik, A; Husev, O. (2022). Battery Size Optimization with Customer PV Installations and Domestic Load Profile. IEEE Access, 10, 13012–13025.

III **Shabbir, N**.; Kütt, L.; Daniel, K.; Astapov, V.; Raja, H.A.; Iqbal, M.N.; Husev, O. (2022). Feasibility Investigation of Residential Battery Sizing Considering EV Charging Demand. Sustainability, 14(3), 1079.

IV **Shabbir, N**.; Kütt, L.; Raja, H.A.; Jawad, M.; Allik, A; Husev, O. (2022). Techno-Economic Analysis and Energy Forecasting Study of Domestic and Commercial Photovoltaic System Installations in Estonia. Energy, 253, 124156.

V **Shabbir, N.;** Kütt, L.; Jawad, M.; Husev, O.; Rehman, A.U. et al. (2022). Short-Term Wind Energy Forecasting Using Deep Learning-Based Predictive Analytics. CMC-Computers, Materials & Continua, 72(1), 1017–1033.

VI **Shabbir, N**.; Kütt, L.; Raja, H.A.; Ahmadiahangar, R.; Rosin, A.; Husev, O. (2021). Machine Learning and Deep Learning Techniques for Residential Load Forecasting: A Comparative Analysis. 2021 IEEE 62nd International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON): Riga, Latvia. IEEE. DOI: 10.1109/RTUCON53541.2021.9711741.

Other Publications:

VII **Shabbir, N**.; Kütt, L.; Asad, B.; Jawad, M., Iqbal, M.N.; Daniel, K. (2021). Spectrum Analysis for Condition Monitoring and Fault Diagnosis of Ventilation Motor: A Case study. Energies, 14 (7), 1−16.

VIII **Shabbir, N**.; Kütt, L.; Alam, M.M.; Rossipuu, P.; Jawad, M.; Qureshi, M.B.; Ansari, A.R.; Nawaz, R. (2021). Vision Towards 5G: Comparison of Radio Propagation Models for Licensed and Unlicensed 5G Indoor Femtocells Sensor Networks. Physical Communication. DOI: 10.1016/j.phycom.2021.101371.

IX **Shabbir, N**.; Kütt, L.; Jarkovoi, M.; Iqbal, M.N.; Rassõlkin, A.; Daniel, K. (2021). An Overview of Measurement Standards for Power Quality. Agronomy Research, 19. DOI: 10.15159/AR.21.074.

X **Shabbir, N**. (2021). Residential Load Forecasting Using Machine Learning Techniques: A Comparative Analysis, 20TH International Symposium TOPICAL PROBLEMS IN THE FIELD OF ELECTRICAL AND POWER ENGINEERING: 20th International Symposium TOPICAL PROBLEMS IN THE FIELD OF ELECTRICAL AND POWER ENGINEERING. Tallinn, Estonia, TalTech, 73−74.

XI **Shabbir, N**.; Usman, M.; Jawad, M.; Zafar, M.H.; Iqbal, M.N.; Kütt, L. (2020). Economic Analysis and Impact on National Grid by Domestic Photovoltaic System Installations in Pakistan. Elsevier Renewable Energy.10.1016 / j.renene.2020.01.114.

XII **Shabbir, N**.; Kütt, L.; Jawad, M.; Iqbal, M.N.; Ghahfaroki, P.S. (2020). FORECASTING OF ENERGY CONSUMPTION AND PRODUCTION USING RECURRENT NEURAL NETWORKS. Advances in Electrical and Electronic Engineering, 18 (3), 190−197. DOI: 10.15598/aeee.v18i3.3597.

XIII Ahmadiahangar, R.; **Shabbir, N**.; Rosin, A.; Kütt, L.; Palu, I.; Fushuan, W. (2020). Flexibility Enhancement for a Power System through Machine-learning based Electricity Demand Prediction. Electric Power Construction, (S), 38−44.

XIV **Shabbir, N**.; Ahmadiahangar, R.; Raja, H.A.; Kütt, L.; Rosin, A. (2020). Residential Load Forecasting using Recurrent Neural Networks. IEEE 14th International Conference on Compatibility, Power Electronics and Power Engineering (CPE - POWERENG 2020). Portugal.

XV **Shabbir, N.** (2020). Machine Learning and Deep Learning Techniques for wind Energy Forecasting. Proceedings of the 19th International Symposium “Topical Problems in the Field of Electrical and Power Engineering” and “Doctoral School of Energy and Geotechnology III”: 19th International Symposium “Topical Problems in the Field of Electrical and Power Engineering” and “Doctoral School of Energy and Geotechnology III”, Tartu, January 14 - 17, 2020. TalTech.

XVI **Shabbir, N**.; Ahmadiahangar, R.; Kütt, L.; Rosin, A. (2019). Comparison of Machine Learning Based Methods for Residential Load Forecasting. 2019 Electric Power Quality and Supply Reliability Conference (PQ) & 2019 Symposium on Electrical Engineering and Mechatronics (SEEM), Hiiumaa, Estonia, June 12 - 15, 2019. IEEE, .10.1109 / PQ.2019.8818267.

XVII **Shabbir, N**.; Ahmadiahangar, R.; Kütt, L.; Iqbal, M.N.; Rosin, A. (2019). Forecasting Short Term Wind Energy Generation using Machine Learning. IEEE 60th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON). Riga, Latvia.

XVIII **Shabbir, N**.; Ahmadiahangar, R.; Kütt, L.; Iqbal, M.N.; Rosin, A. (2019). Wind Energy Forecasting using Recurrent Neural Networks. IEEE International Conference “Big Data, Knowledge and Control Systems Engineering” (BdKCSE’2019). Sofia, Bulgaria.

XIX **Shabbir, N**; Hassan, S.R.; Iqbal, M.N.; Kütt, L.; Unbreen A. (2019). Comparative analysis of ZigBee based wireless sensor networks (WSNs). International Journal of Recent Technology and Engineering, 7 (6s), 980−984.

XX **Shabbir, N**. (2019). Advanced Sensors and On-line Measurements for Power Lines in Smart Grids. 18th International Symposium “TOPICAL PROBLEMS IN THE FIELD OF ELECTRICAL AND POWER ENGINEERING” and “Doctoral School of Energy and Geotechnology III. Toila, TalTech, 205−206.

Author’s Contribution to the Publications

Contribution to the papers in this thesis are:

I Noman Shabbir is the primary author of this article. He generated the battery profiles, designed, and implemented the congestion control strategies and wrote the initial draft of the paper.

II Noman Shabbir is the primary author of the article. He designed and implemented the BESS optimization algorithm for minimizing cost and conducted simulations. He also wrote the initial draft of the paper.

III Noman Shabbir is the primary author of this article. He collected all the data, ran the simulation for PV-BESS-EV system and wrote the initial draft of the paper.

IV Noman Shabbir is the primary author of the article. He gathered the data and designed the machine learning algorithms for PV energy forecasting and wrote the initial draft of the paper.

V Noman Shabbir is the primary author of the article. He implemented machine learning and deep learning algorithms for wind energy forecasting and carried out a comparative analysis. He also wrote the initial draft of the article.

VI Noman Shabbir is the primary author of the article. He implemented the machine learning and deep learning algorithms for residential load forecasting and carried out the comparative analysis. He also wrote the initial draft of the article.

Abbreviations

ANFIS	Auto-neuro fuzzy integrated systems
ANN	Artificial neural networks
AR	Autoregressive neural networks
BESS	Battery energy storage systems
BPNN	Backpropagation neural networks
CoE	Cost of energy
CNN	Convolutional neural networks
DL	Deep learning
DoD	Depth of discharge
DR	Demand response
DSM	Demand-side management
EMS	Energy management system
ER	Energy router
EU	European union
EVs	Electric vehicles
ET	Extremely randomized trees
GBM	Gradient boosting algorithm
HC	Hosting capacity
HMC	Hosting capacity motivated battery control
ICT	Information & communication technologies
IT	Information Technology
KNN	K-nearest neighbour
Li-Ion	Lithium-ion
LR	Linear regression
Li-Po	Lithium polymer
LP	Linear programming
LSTM	Long short-term memory
LV	Low voltage
MAPE	Mean absolute percentage error
ML	Machine learning
MILP	Mixed-integer linear programming
MLP	Multilayer perceptron
MV	Medium voltage
NAR	Non-autoregressive neural networks
NMC	Nickel manganese cobalt oxide
NPC	Net present cost
nZEBs	Nearly zero-energy buildings
OLTCs	On-load tap changer
OE	Output error

PDF	Probability density function
PI	Profitability index
PV	Photovoltaic
RBFNN	Radial basis function neural network
RES	Renewable energy sources
RF	Random forest
RNN	Recurrent neural networks
RMSE	Root mean square error
RPC	Reactive power control
SVM	Support vector machine
SoC	State of charge
TBC	Trivial battery control
TR	Tree regression
TSO	Transmission system operator
TDCNN	Two-stream deep convolutional neural networks

Symbols

$C_{bat}^{ch,u}$	Battery charging cost per unit
$C_{bat}^{dis,u}$	Battery discharging cost per unit
$C_{grid}^{sell,u}$	Per-unit energy selling cost
C_{PV}^{u}	Per-unit energy selling cost
C_{Bat}	Cost of battery
$C_{Inv./Unit}$	Per-unit inverter cost
C_{PV}	Cost of PV
DOD	Depth of discharge
E_{BC}	Battery capacity
E_{Day}	Average daily energy consumption
E_{bat}^{ch}	Energy received from the battery
E_{bat}^{dis}	Energy supplied from the battery
E_{grid}^{sell}	Energy sold to the grid
E_{grid}^{pur}	Energy purchased from the grid
E_{L}	Electrical energy consumption
E_{bat}^{max}	Max. energy from the battery
E_{PV}	PV generated energy
E_{PV}^{max}	Max. energy from PV
INV_{rated}	Rated inverter power
K_{p}	Status of the BESS
P_{rated}	Rated PV power
P_{z}	Maximum charging power
st	Time interval
η	BESS efficiency
β	Solar panel tilt angle

1 Introduction

1.1 Background

The rapidly growing population and developing economies around the world are driving energy utilization and demand growth. Especially the role of electric energy is growing. Electric energy production though is one of the main contributing factors to global greenhouse gas emissions. To reduce carbon dioxide emissions and provide additional electric energy production, the world has witnessed a paradigm shift toward renewable energy sources (RES) during the last recent decades. At the same time, advances in technology now offer a variety of methods to achieve the same functions with lower losses in the process. As the global warming and environmental impact leveraging have been stated as a top priority by the leading global parties, both shift towards greener and emission-free production of electrical energy is mandated by governments' policies, similarly, turn towards more efficient technologies is enforced. For example, the EU has pressed for the Fit for 55 policy and many more energy efficiency directives imposed through the European Commission (EC) [1].

Of the commercial energy consumption, one of the greatest increases is expected to be in the global energy market where buildings share a huge 40% of the share of total consumption [2]. According to recent research [2], [3], most of these buildings are more than 50 years old and are quite energy inefficient. Therefore, an EC mandate for nearly zero energy buildings (nZEBs) has been issued for more efficient energy utilization and the inclusion of renewable energy sources (RES) in both private and public buildings. These nZEBs would include smart energy management solutions to lower the dependency on the energy supply from district grids and minimize the cost of energy utilization.

In recent times, the advancement of photovoltaic (PV) technology, their decreasing costs, and the simple installation method have increased their usage [4], especially in residential areas. Connected to a low-voltage AC grid, PV systems' output power ratings can range from kW in case of domestic usage and to MW in case of large-scale commercial deployment [5]. Taking into account the average household energy demand, these PV-based systems are quite efficient and useful for domestic energy supply. However, it has been seen that the integration of these PV systems into the distribution networks creates challenges [6].

The integration of large-scale photovoltaics into the distribution network may lead to voltage stability issues and overloading of the distribution lines. Therefore, the hosting capacity (HC) evaluation of the grid becomes very important. HC is usually defined as the amount of PV power that can be added to the network without needing to upgrade the network while the network can operate safely and reliably. The HC depends on many indices and their corresponding limits, such as the installed throughput capacity of the lines and supply transformed, PV installed power and control options, other electrical loads on the line, local storage availability, etc. Increasing the HC of PV would most easily be done through network reinforcement, this is a costly replacement of components. Investment in network infrastructure on the other hand means more operating service costs attached to the customer energy bill.

It is thus reasonable to consider options to increase the HC through the network efficient localized control of PV, storage, load, and other equipment at the customer end. Automated systems would be able to do this and take into account a high number of variables, such as in-house power demand, hourly energy market price, estimated renewable production availability, etc. It can be seen that much potential would be available in more dynamic and self-adjusting control. Especially artificial intelligence and machine learning-based forecasting tools for load and energy generation can also be useful in this regard as they can help in improved energy management.

1.2 Smart Grids Technologies

A classic electric power system has been an AC power grid (having a frequency of 50 or 60 Hz) built to operate relying on large-scale power plants. Large AC networks incorporate main substations interconnected with longer extremely high voltage transmission lines and short delivery spans at low voltages at distribution levels [7]. To ensure operating characteristics such as voltage level stability the control of the transmission grid levels responsible for delivery of greater energy amounts has been sophisticated and included very expensive equipment. On the other hand, the distribution networks have been mostly low-controlled as implementing similar options using equipment associated with transmission system control is unfeasible.

A series of improvements have been implemented to the methodology of AC network management commonly known as Smart Grid (SG) technologies to increase efficiency and operating capability. These methods are found at all levels of electrical networks, and many have been proposed for distribution levels. The ideology behind SG is to construct a power network along with information and communication technology (ICT) services-enabled features (framework is shown in Figure 1.1 [8]). More efficient and economical use of grid resources is available through keywords such as continuous monitoring, demand-side management (DSM), forecasting of energy generation, consumption, electrical grid self-awareness and self-healing, and many more [9], [10].

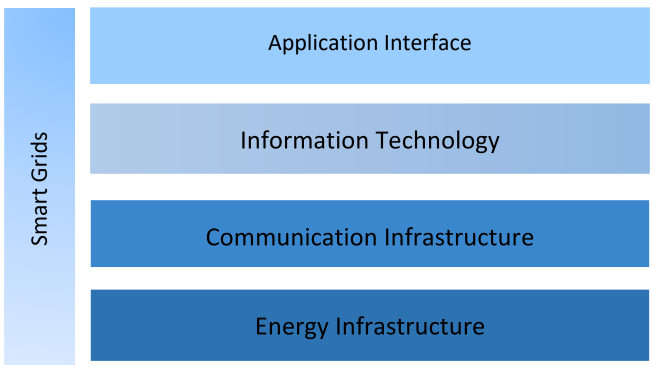

Figure 1.1. The framework of smart grids with energy infrastructure and ICT

Even for the distribution and low-voltage levels, the SG methods offer benefits of two-way fast communication, power flow information, advanced RES integration, storage technologies, and online computing for smooth operation and preventing failure or service unavailability in the grid. With the goal of making the energy infrastructure more reliable and flexible, it also helps to decrease the maintenance costs of the utility network and the energy consumption costs of the customers.

The currently designed local distribution networks are traditionally uncontrolled and without a proper monitoring solution. SGs have been proposed for some time now, but they have not been realized yet, in full spirit. DSM is usually looked at as a possible solution, however, still everyday PV energy production can cause congestion in the distribution network. The problem cannot be solved using only DSM methods. More localized but wider-looking control of networks is required to solve these problems. This means for example a domestic system with capabilities to include wider incentives from the grid. This presents though a wider range of variables to consider. The advances in the information technology (IT) interconnections enabled in SG and flexible algorithms to handle the required data capacity bring more capabilities. Machine learning (ML) is making its progress in network control and can be seen as a viable perspective tool for these advanced systems.

1.3 Localized Energy Management System

There are several developments that basically require advanced energy management functions to fulfil the operating goals. The EU-led Green Deal policies and energy efficiency targets are well known. For example, efficiency targets the residential sector [11] require all newly constructed buildings must be nZEBs [12]. These buildings should be able to generate their energy and, therefore, have a very low dependency on the electrical grid [13]. The sum of energy utilized on-site, and locally produced energy accumulated for nZEBs should be zero or near zero at the end of the year. Buildings can buy energy from the grid, but they have to generate energy in commercial form themselves and sell it back to the grid. Looking into it in more detail, this outline greatly reveals many challenges as well as opportunities on a household level to utilize the more advanced energy management systems.

In the northern latitudes, meeting the nZEBs goals will require the deployment of RES such as PV or small-power wind, battery energy storage systems (BESS), flexible power electronic converters and control techniques to use these resources in an appropriate, efficient and economical manner [14]–[16]. The winters can be extremely dark and without sunlight for many days and indoor heating requirements will make the energy consumption at its peak values. In summer, the weather can be sunny, and the photovoltaic systems will be generating energy around their maximum potential; however, summer load requirements are usually the lowest. This can create challenges for the network operators to accommodate that high energy generation with minimum self-utilization. The PV peak power curtailment can be a solution but with this, however, the customers would lose a lot of money [Paper I]. If not limited, the high PV injection in the distribution grid may cause overloading and voltage fluctuation in the grid, which is problematic for both operator and customers.

The energy management systems (EMS) for nZEBs have received great interest targeting reduction in energy costs while matching the household demand and supply of RES [17]. Demand repose (DR) and DSM are mainly discussed to solve the challenges [18]. However, they alone cannot solve the problem of customer load shifting and neither the congestion in networks caused by the RES installations [19]. Therefore, a robust real-time algorithm [20], [21] is required to dynamically charge/discharge BESS while keeping the economic numbers steady, increasing the hosting capacity (HC) of the network, and also avoiding the congestion of the distribution network [22]–[24].

Moreover, machine learning-based (ML) residential load and PV energy generation forecasting techniques incorporated in the EMS will provide additional functionality. These forecasts could provide efficient control and scheduling for BESS charging/discharging to provide users with added economic benefits and decreased service costs from the grid. Forecasting is an especially demanding task toward the proper energy management goals, as it refers to massive data processing. Taking into account the number of variables and scenarios needed for the complete EMS tasks range, the forecasting thorough the ML, artificial intelligence (AI) and other flexible adaptive algorithms provide an advantage

1.4 Research Problem and Scope of Thesis

The combination of PV-BESS is the most potent solution for residential houses and nZEBs [25]. For the house owner, the target is to build these systems economically viable, this is making the costs or payback periods as low as possible. The lowest cost to a homeowner could be available through:

- The optimal installation cost of the local energy management system.
- Lowest cost of energy bought from the utility grid.
- Highest benefit from the energy sold to the grid.
- Lowest service cost for using the grid.

A standalone local system that offers the same comfort as the power grid would have an unmotivating cost. Even if the case of nZEBs, the energy management system will still be connected to the local grid, the initial cost of PV and particularly BESS is still remarkable even if further price decrease is expected [26]. Even only to meet the domestic yearly energy usage, rather large PV units need to be installed. For the utility grid, high PV system produced energy infeed can mean problems if all customers want to supply the grid with PV produced energy at the same time. This could lead the utility to costly upgrades and reinforcement of the components and lines to guarantee the throughput. If not reinforced, the customer could not sell the PV-produced energy to the grid, decreasing the income from PV energy production. On the other hand, grid reinforcement investments effectively raise the utility service prices for customers. Therefore, this raises a multivariate challenge on how to build up the local EMS to meet the conditions of having the lowest cost to the homeowner.

Options are available then to include the BESS for more operations, such as storage of low-cost energy from the grid during excess PV generation or low market price, for financial profit. In turn, this would provide the benefit to the utility, as local energy load point is added, and network load decreased. Further options could include EV charging control, as, in the near future, the penetration of electric vehicles (EVs) is going to increase rapidly.

EVs are environmentally friendly if power to these vehicles is provided through RES such as locally PV-produced energy, which also is comparatively much cheaper [27]–[30] than buying charging energy from the grid. The EVs can potentially impose diverse impacts on the distribution grid but also the local energy management system. The integration of EV loads means that larger PV systems will be required to power their local fully renewable charging. These higher rated PV installations can cause hosting capacity issues in the grid as the electrical lines have a limited capacity and replacing these lines with new higher capacity lines is not an easy task in terms of financial and physical deployment. So having a high amount of PV to support charging EVs could cause overloading of the lines and overvoltage problems [6], [31]–[33]. On the other hand, the presence of a high number of loads of electric vehicles can increase the maximum loads on the lines and the undervoltage in the electrical network [34], [35]. The problems mentioned above can be eliminated to a large extent by the optimal design of the PV-BESS system according to the limits and parameters of the network [36], [37].

The inclusion of the BESS can make sure that the excessive PV energy is stored in it and not injected into the grid thus limiting congestion and overloading the network. The BESS stored energy can then be used for residential loads or charging EVs. This method will not only decrease the dependency on the grid but also reduce the cost of electric energy purchased from the utility. The goal of photovoltaic system-based energy is to make users self-sufficient and decrease the costs of energy. However, by optimally using these resources with smart control strategies, several targets can be achieved, including limiting the PV power injected into the grid to minimize overloading and congestion, increasing self-sufficiency, better DSM, and reduction in peak loads. This in turn can decrease the grid service costs, as the utility would not need to make investments to provide a good level of service. Therefore, one of the main targets in this thesis is to provide EMS viewpoint grid utilization with the improvement of overall energy service availability capabilities as much as possible and to guarantee an equally high quality of service to the users. Therefore, this solution can be quite useful as it makes this system economically viable by reducing the energy costs for the residential user and at the same time making sure that the capability of the grid is increased, and the quality of service is not affected.

Additionally, the EMS can benefit from the knowledge of imminent upcoming RES availability. This way more information will be available on the selection of best strategies for BESS charging and discharging. There is a strong potential to estimate and forecast the future capabilities and characteristics of the network operation. Within this thesis, several pilot investigations have been presented to reflect the capabilities of the tools. The use of ICT can be beneficial here and machine learning (ML) techniques make a good tool for such purpose forecasting. Targets usable for the local EMS are considered and analysis is done to determine the appropriate ML method to implement. It has been shown that ML based forecasting methods are ready for the tasks of the EMS, considering the capabilities in forecasting.

1.5 Hypotheses & Research Tasks

The main aim of this research work is to design and develop an EMS that will be capable of reducing the electricity cost for the residential users and decreasing their dependency on the electrical grid. At the same time, the EMS will be responsible for increasing the PV penetration in the grid and ensuring reliable operation by minimizing the problems like congestion and voltage fluctuation in the network. Moreover, the machine learning-based residential load and PV energy generation techniques can add extra features and functions in the EMS for better management of energy and cost reduction. Following are the hypotheses and research tasks of this work:

Hypotheses:

- The EMS can help in increasing the PV penetration in the local grid without reinforcements to the grid.
- EMS incorporating PV-BESS can help reduce energy purchase costs.
- The payback periods can be shorter than the expected component failure time periods.
- Machine learning techniques could add extra functionalities and capabilities to the EMS.

Research Tasks:

- Development of optimal EMS usage strategy.
- Energy cost minimization using optimization techniques.
- Localized congestion control strategies for increased hosting capacity.
- Additional capabilities using machine learning techniques

1.6 Scientific Contributions and Novelty

The thesis provides the results of an investigation to build and operate a local electrical energy management system in a least-cost configuration. The discussion includes novel aspects of the burden of customer operation to the utility, such as impacting the utility grid service and installation costs, but also the potentially imposed limitations on the grid capacity availability can make up a critical portion of the costs to the property owner. The novelty and scientific contribution of the thesis can be listed as follows:

1) Planning of domestic energy management system installation, given its potential contribution to both domestic targets (nZEBs) but also utility support to the renewable power sources high infeed. To provide the best possible quality of service and increased throughput in the local distribution networks, a localized congestion control strategy has been proposed. Different PV installation scenarios have been considered and different control strategies have been discussed and evaluated. The focus is to increase the penetration of RES in distribution networks while limiting network congestion and minimizing the economic impact on consumers. (Publication I)
2) Estimation of the control capability of a domestic energy management system, considering the usability of BESS for more flexible service. A heuristic algorithm based on linear programming (LP) for the chagrining/discharging of BESS has been developed. The algorithm incorporates the real-time values of domestic electrical load, energy generation from RES, the status of BESS, and the market electricity prices. The payback periods and economic benefits are calculated using the proposed algorithm. (Publications II & III)
3) More capable service proposals for further optimized and efficient implementation of the local energy system are available through more detailed data available on the expected energy production and loading. The forecasting of the RES feed is discussed here as a prerequisite for more optimal sizing and management of the BESS capabilities. Machine learning-based forecasting algorithms have been studied to estimate the energy generation and availability from PV (Publication IV), wind (Publication V), and the forecasting of residential load. (Publication VI)

1.7 Outline of the Thesis

The thesis is structured as follows. Chapter 2 is related to the survey of related work. This survey covers the energy management system components, battery optimization and efficient control, and congestion control techniques in power distribution networks and machine learning techniques for PV and wind energy forecasting. Chapter 3 is about the BESS sizing and its optimal use for domestic users. The energy-cost reduction and BESS control algorithms have been elaborated in detail here. The economic analysis using the proposed algorithm has also been described here for the residential PV-BESS-EV system. Chapter 4 gives an overview to increase the hosting capacity and decrease the congestion in the local distribution networks. Control strategies are described here in detail. Chapter 5 gives an in-depth overview of the renewable energy cases of solar PV, wind, and residential load. The development of forecasting algorithms along with the results are discussed here Finally, Chapter 6 presents the conclusions and future work of this study.

2 In-Depth Literature Analysis

2.1 Local Energy Management System Components

The optimal design of EMS for nZEBs requires efficient control algorithms along with the required PV system design and BESS. The design of PV-BESS is a critical component as it will significantly impact the payback period. The EMS also includes a net metering system and smart control algorithm to gain monetary benefits by selling energy to the grid when the market energy prices are higher and vice versa. During the last few years, many studies have been conducted in different countries regarding the design of PV systems, its feasibility and risk analysis, net metering solution and payback periods have been calculated [15], [21], [38], [39]. Table 2.1 presents a detailed overview and comparison of different studies conducted in recent years. Most of the studies are on the on-grid and off-grid implementation of PV systems. The key indicators for the selection of these studies are PV system designing, payback periods, bill reductions, net metering solutions, energy forecasting and optimal PV angle calculations. The installation of PV systems is highly dependent on the location of installation; therefore, this table presents a thorough analysis of the variations of PV systems in different countries. Most studies have incorporated many of these factors, but none have considered all of them together with energy forecasting. A comparison of previous studies has also been presented.

Table 2.1. Comparison of previous studies

Survey	Country	System design	Optimal angle for max. power output	Payback time	Bill reduction	Bill reduction with net metering
[40]	Cyprus	√	×	×	×	√
[41]	Netherlands	√	×	√	×	√
[42]	USA	√	×	×	×	√
[43]	Brazil	√	×	×	×	√
[44]	Chile	√	×	×	×	√
[45]	Pakistan	×	×	×	×	√
[46]	India	×	×	√	√	√
[47]	Palestine	√	√	√	×	×
[48]	Italy	√	×	×	×	√
[49]	China	×	×	√	√	√
[50]	Egypt	√	×	×	×	×
[51]	Australia	√	×	√	×	√
[52]	Iran	√	√	×	×	×
[53]	Brazil	√	×	×	×	×
[54]	Finland	√	×	√	√	√
[55]	Turkey	√	×	×	×	×
[56]	Jordan	√	×	√	×	×

The PV system installation requires certain criteria and standards to be fulfilled while utilizing the full potential of the technology. The PV systems design and requirements in Estonia are different from many other parts of the world. It needs continuous monitoring for the efficient use of the system. The PV system is able to generate power for 16-18 hours a day in summer, while around 5-6 hours a day in winter. The system also requires protective devices to be installed on the AC/DC interfaces, such as energy routers and inverters. According to Eesti Energia, the payback period for an around 10 kW PV-only system is around 18 years [57].

One of the important criteria for conducting feasibility analysis and site selection for the installation of a solar photovoltaic system is the solar radiation pattern of the area. The parameters that need to be observed during the study of solar radiation patterns are solar irradiance, and solar panel angles for elevation, declination, and incidence [4], [13]. The solar irradiance patterns are different parts of Estonia are almost similar and the irradiance is high in the summertime lasts from April to August and is low in winter from November to March [58]. The angle of incidence for the PV system can be calculated using the methods described in [59]–[62]. The solar panel tilt angle β for Estonia is computed to be 38^{o} to 40^{o} for fixed PV installations [63].

2.2 Residential Operation Optimization

The PV-BESS systems are convenient and easy to deploy but their initial cost and payback periods are still high [64], [65]. The initial cost of especially BESS is comparatively high and the usual operation of a residential BESS has limited operation cycles and its usual life is around 5 years [66]. Therefore, the optimal sizing and operation of BESS are critical as they will directly impact the initial and operational costs of the PV-BESS system. Moreover, BESS needs to be utilized economically and efficiently to fully exploit its potential. Numerous research studies have been conducted on the BESS size optimization, BESS efficient control, increasing the life cycle of BESS and reducing the overall energy cost using PV-BESS systems. The comparative analysis of the previous studies on this topic is given in Table 2.2. These studies have tried to explore the possibility of cost reduction, BESS size optimization, minimizing the peak load and energy scheduling using BESS.

In the near future, the usage of electric vehicles will also increase, as the goal is to have 50% of the vehicles on the road being electric vehicles by 2050 [67]. Most of these electric vehicles will be charged at home as the number of charging stations is limited. Therefore, the integration of PV-BESS-EV is very important, as it can reduce the energy cost for use if it is designed properly. The successful use of PV-BESS can provide users with clear economic benefits. Several studies have been conducted to optimize BESS energy utilization taking into account PV energy generation and load. Numerous research studies related to the integration of PV-BESS-EV are available. The impact of charging from the PVs and the corresponding reduction of emissions are discussed in [68]. In these studies, the impact of PV installation [69]–[71] and electric vehicles [72]–[75] on the grid has been presented. The EV modeling [28], [76]–[78], EV charging on power quality [79] and the control algorithm together with the economic analysis are given in [27], [80]–[83]. Meanwhile, the possibility of using batteries from electric vehicles for household loads is presented in [84].

Table 2.2. Literature survey of PV-BESS optimization studies

Survey	Year	Location	Main Feature	Algorithm
[85]	2013	US	Minimize peak load	LP
[86]	2016	US	Minimize peak load	Genetic Algorithm
[87]	2013	US	Energy Cost reduction	LP
[88]	2016	Switzerland	Energy Cost reduction	LP
[89]	2020	Iran	Energy Cost reduction	Teaching-Learning-Based Optimization
[90]	2015	Korea	Energy Cost reduction	Markov decision process
[91]	2019	Switzerland	Energy scheduling	lithium-ion battery model
[92]	2010	Turkey	PV/BESS size optimization	Simulated Annealing
[93]	2020	US	PV/BESS size optimization	Monte Carlo
[94]	2018	Germany	Energy Cost reduction	LP
[95]	2017	China	BESS size optimization	Convex programming

2.3 Congestion Control & Hosting Capacity

The hosting capacity (HC) has been gaining importance for some time now, as it plays an important role in delivering quality service to customers defined by the standards [96]. The level of HC depends on the risks that customers and network operators are willing to take. Therefore, it depends on a variety of parameters, and it has been defined as the maximum PV energy generation and a peak load of the feeder ratio [97], yearly PV energy production and consumption [98], or then transformer rating [99]. The HC is also dependent on the PV energy generation and the self-consumption of the residential user [100]. Therefore, if users take the liberty to install as much PV as they can, this can be a problematic situation for the network operators. The operation of the grid within the limits of standardized power quality indexes becomes a problem. As one example, distribution lines' ampacity limits are exceeded [101]. Utility operators have to replace these lines or use some smart grid (SG) driven solution to overcome the problems of overloading and overvoltage, voltage unbalances and transformer overloading.

One of the most important parameters that limit the HC is the increase in line voltage. Increased penetration of PV in LV networks can cause an overvoltage problem and it can become extremely difficult for the grid to operate within the defined limits [102]. This study concluded that the main reasons for this are the flow of the power in the opposite direction and the disturbance in the reactive power balance. Most of the studies have researched this problem in the medium voltage (MV) networks [103]–[105]. However, rooftop photovoltaics have become more popular and will be even more due to the concept of nZEBs and the increasing usage of electric vehicles (EV) [12]. Therefore, the residential PV installation is mostly done in the LV network. This voltage rise can occur when the PVs are producing at their peak generation hours, usually, in the middle of the day, and at that time the residential load is lowest. Countries, where air conditioners are used during the day, can have peak loads at the same time, so this is not a big problem there. However, in other regions, this peak power injection causes overvoltage in the network due to low load and power flow reversal.

Grid-connected photovoltaics were required to inject only active power with a unity power factor, thus disturbing the balance of active and reactive power on some occasions [106]. Many studies have proposed voltage control mechanisms in the inverter and the substations to keep the operating voltage within limits. The voltage control mechanisms based on the increase in reactive power demand from the substation and the high-frequency switching inverter can reduce voltage fluctuations but increase harmonics [107]. On-load tap changer (OLTC) and feeder control voltage capacitor banks have also been proposed for the overvoltage problem [108], [109]. A demand response method (DR) [110] and a battery energy storage system (BESS) [111], [112] have been proposed to increase HC. Another important factor limiting the HC is the ampacity of the distribution lines [113]. This is a much bigger problem in the urban networks as compared to the voltage violation that is a major concern in rural and suburban networks [114]. Distribution lines have a fixed current rating, and PV injection above limits can overload the lines [115]. In this case, the network operator may have to replace the distribution line with a higher power transformer, a very costly solution.

2.4 Machine Learning

The RES energy availability is stochastic and difficult to model. The precision of energy availability and load forecasting has a direct impact on economic analysis. Accurate forecasting of RES can help better manage the energy demand and economic usage of the grid [116], [117]. PV energy generation usually depends on the season and the area. However, wind energy is highly stochastic [118], [119] and variations in energy output make it more challenging to predict. Wind energy generation is dependent on weather, season and location therefore accurate forecasting is difficult [120]. The economic analysis is based on the forecasted future profit and the initial investment, thus making the forecasting of energy an important task.

Mostly this kind of forecasting is carried out with the help of statistical tools [120], e.g., probability distribution, moving average and autoregressive algorithms; however, these algorithms have lower accuracy. Therefore, machine learning algorithms have seen a growing increase in this energy forecasting application due to superior accuracy [121], [122], [123]. Machine learning algorithm forecasting usually requires large data sets for training. Training enables these algorithms to learn about the patterns and non-linearities in the data. Therefore, usually larger data sets are required and sometimes these algorithms need retaining as well to learn about new patterns or for increased accuracy [121]. Therefore, the algorithm results are then tested and validated to confirm the accuracy and whether retention is required or not. Forecasting models can be for short, medium- and long-term forecasting [124]. Short-term means a few hours ahead to one day, medium-term is for a few days to a few weeks and long term is between a few months to a few years.

2.4.1 Solar Energy Forecasting

Several machine learning algorithms have been described for PV energy forecasting [125]–[128]. The algorithms show a capability for accurate forecasting of around 90% [129], [130]. Figure 2.1 shows a biometric visualization of the keywords used in research papers published in the last five years on PV energy forecasting using machine learning techniques and keywords from 179 studies were used. The diagram shows that machine learning-based forecasting has become more popular in the last five years. A survey of machine learning (ML) and deep learning (DL) techniques for forecasting PV energy generation is given in Table 2.3.

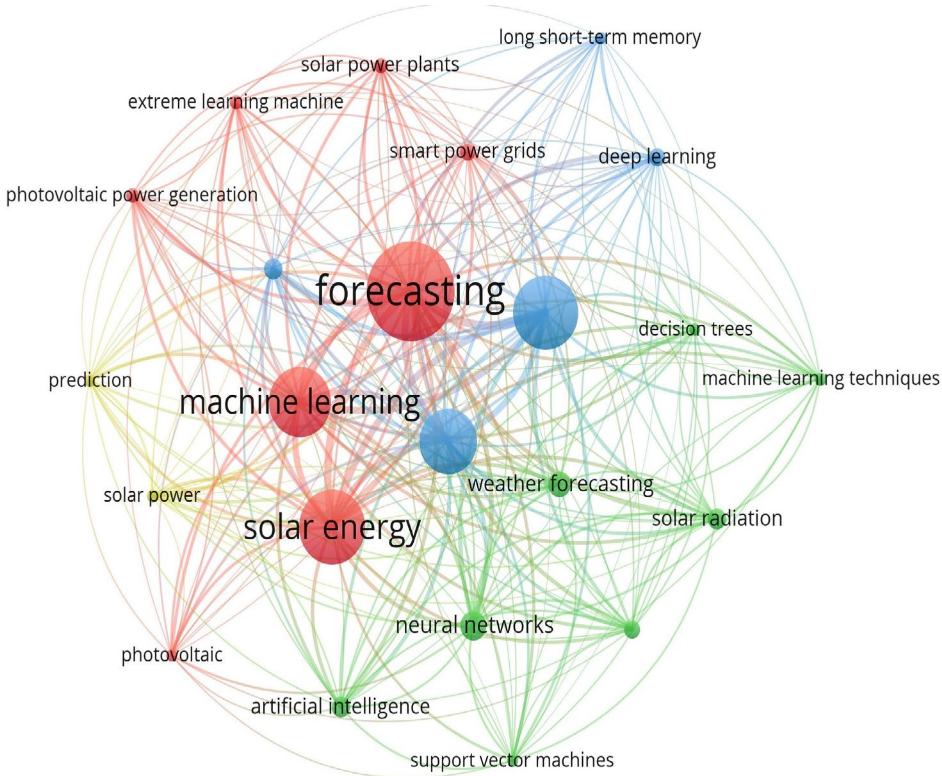

Figure 2.1. Bibliometric visualization for the keywords supplied by the author for PV energy forecasting (Larger circle means more use of the keyword)

2.4.2 Wind Energy Forecasting

Similar to PV energy forecasting, machine learning techniques are also widely used in wind energy forecasting. These models are usually used to predict wind speed and wind energy generation. Many studies have been conducted on comparative analysis of different machine learning algorithms such as support vector machine (SVM), random forest (RF) k-nearest neighbor (KNN), and linear regression (LR) [131]–[133].

Table 2.3. A survey of ML and DL techniques for PV energy forecasting

Survey	Year	Location	Algorithms	Forecasting
[127]	2020	South Korea	RNN-LSTM	14 hours
[134]	2019	Pakistan	ANN	1 day
[135]	2018	Taiwan	BPNN	1 day
[136]	2017	South Korea	Short Term multivariate	1 day
[137]	2018	Germany	Regression Trees/Probabi -listic	1 day
[138]	2021	Morocco	CNN-LSTM	3 days
[139]	2021	China	CNN-LSTM	1 day
[140]	2021	China	LSTM	1 hour
[141]	2021	Italy	LSTM	1 hour
[142]	2019	USA	LSTM	1 day

Abbreviations: Back Propagation Neural Networks (BPNN)

Most of the studies found that SVM gives better forecasting also experimental results [143] showed that SVM gave better predictions. Furthermore, artificial neural network (ANN) based deep learning algorithms are gaining more attention as they are more accurate as compared to machine learning algorithms [144], [145]. A detailed comparison of the previous studies on wind energy forecasting is given in Table 2.4.

Table 2.4. A Survey of wind energy forecasting using machine learning techniques

Survey	Country	Year	Proposed algorithm	Data size	Forecasting duration	Description of the proposed study
[146]	USA	2019	Deep belief neural networks	3 years	1 – 24 hours	A fuzzy-based hybrid deep-belief neural network predicts robust features and real-time variations.
[147]	UK	2019	SVM, ANN	3 years	1 day	ANN is more accurate than SVM.
[148]	Spain	2019	RNN-LSTM	1 year	1 – 24 hours	LSTM gives accurate 24 h foresting with 10.43% RMSE.
[149]	Germany	2015	RNN-LSTM	4 years	1 day	LSTM gives better forecasting.
[150]	France	2020	Linear regression	2 years	6 hours	ML algorithms give more accurate.

Table 2.4. Continued

Survey	Country	Year	Proposed algorithms	Data size	Forecasting duration	Description of the proposed study
						forecasting than statistical methods.
[151]	Canada	2020	SVM, ANN	2 years	1 day	A hybrid SVM-ANN model outperforms individual models.
[152]	Estonia	2019	RNN-LSTM	1 year	3 days	LSTM gives 25% more accurate than statistical methods.
[153]	Spain, Canada	2020	TDCNN	4 years	1 – 24 hours	TDCNN gives a lower RMSE for up to 24 h before forecasting.
[154]	Greece	2019	SVM/ANN	2.5 year	6-24 hours	SVM gives better 24 h ahead forecasting results than ANN.
[155]	China	2019	RNN, KNN	3 years	1 day	LSTM is 18.3% more accurate than KNN and SVM.
[156]	Italy	2019	MLP	3 years	70 hours	ANN based MLP gives accurate forecasting for 70 hours.

Abbreviations: Multilayer perceptron (MLP), Long Short-term memory networks (LSTM), Two-stream deep convolutional neural networks (TDCNN), Mean absolute percentage error (MAPE).

2.4.3 Residential Load Forecasting

Residential load forecasting is a challenging task as it depends on many variable factors such as season, time, number of household appliances and their energy rating, together with a greater dependency on occupants and their behaviours [121]. A single ML forecasting method cannot provide a viable solution in all implementation situations; therefore, these algorithms are selected and trained according to the datasets and the variable factors included in the data. A detailed comparative analysis of different machine learning and deep learning algorithms is given in [157]. The survey of related machine learning and statistical algorithms used for load fore acting is given in Table 2.5.

Table 2.5. A literature survey of load forecasting techniques

Survey	Year	Location	Algorithms	Forecasting
[158]	2012	USA	SVM	1 hour
[159]	2013	Switzerland	SVM	1 day
[160]	2009	USA	KNN	10 hours
[161]	2013	France	Statistical models	1 hour
[162]	2018	USA	LSTM	1 day
[163]	2017	China	LSTM	1 day
[164]	2019	France	CNN, SVM	1 day
[165]	2020	China	IRBDNN	1 day
[166]	2021	Pakistan	LSTM	1 day
[167]	2019	China	LSTM	1 day
Abbreviations: Iterative Resblocks Based Deep Neural Network (IRBDNN)				

2.5 Chapter Summary

This chapter provides an in-depth literature review about EMS and its components, operational optimization, congestion control strategies and an overview of machine learning techniques. The main conclusions are as follows:

- The EMS for residential homes will consist of a PV-BESS system and possibly EVs. However, an efficient control strategy is required to make this system economically viable. The initial deployment cost of these systems is high and payback time is rather long, but optimization techniques can help in reducing the energy cost and the payback can be lowered. Previously several optimization algorithms have been proposed for cost reduction. However, mostly these techniques lack optimized controlled algorithms to address the challenges and the complexities of control, and stochasticity in PV energy generation along with BESS and dynamic market electricity prices.
- PV HC in distribution networks has gained importance as PV penetration is increasing. However, large-scale PV installation creates problems in the network in terms of overloading of lines along with the transformer and overvoltage in the network. Many congestion control techniques, such as peak power curtailment and DSM have been proposed. However, DSM alone cannot solve these problems and usually grid reinforcements are needed. On the other hand, power curtailment has economic implications. The localized solution for these problems is missing without the requirement of grid reinforcements.
- Machine learning-based forecasting techniques are useful tools in power system applications. In particular, neural network-based deep learning algorithms can predict energy generation and electrical load more accurately. However, some of these techniques require large historical data sets.

3 Residential Operation Improvement

The EMS for nZEBs discussed here will be incorporated into the domestic energy router (ER) for the management and utilization of energy. The ER is primarily a power electronics device that is similar to an inverter but with additional functionalities. In future smart residential homes, AC and DC buses will be used separately for AC and DC loads to save energy [168]. The ER will be responsible for both AC and DC conversion from the RES or grid. The ER will be connected to RES, BESS, EV, and the local grid. Therefore, this proposed EMS will be implemented in the ER for managing the energy resources. The EMS will decide when to charge or discharge the BESS and sell or buy energy from or to the grid considering the local market electricity prices. The concept of a smart home with ER and EMS is depicted in Figure 3.1. Further details of the ER can be found in [169].

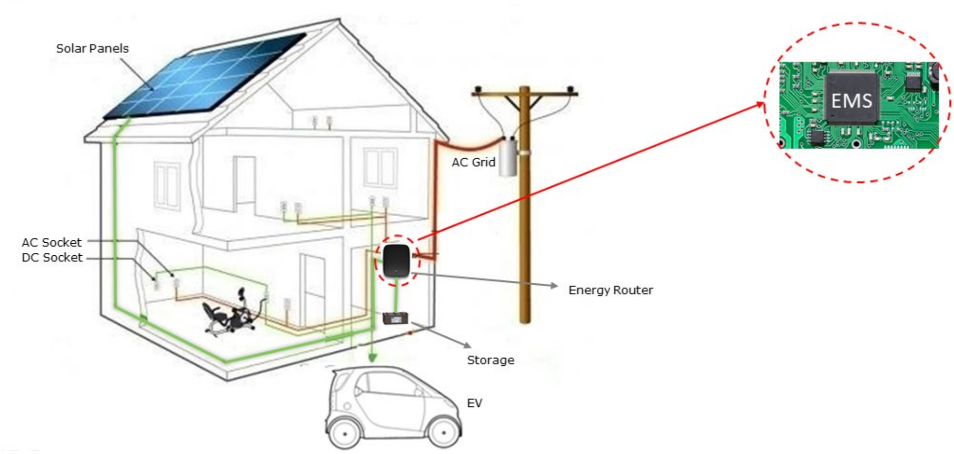

Figure 3.1. The concept of a future home with EMS

Battery storage technologies have seen tremendous growth in recent years in applications such as portable communication devices, EVs, industry and PV-based BESS [35]. Lithium-Ion (Li-ion) and Nickel Manganese Cobalt Oxide (NMC) are the most widely used, however, Lithium Polymer (Li-Po) batteries are also gaining attraction [12]. At the same time, the cost of BESS has decreased substantially due to the latest developments in manufacturing technologies and bulk generation [170]. The cost of 1 kWh of BESS is estimated at around 100 € [171]. However, there are still many limitations that require improvements such as low usage cycle and limited life span. In the coming years is to increase the BESS life cycle of the BESS to around 20 years [172].

In residential BESS, Li-ion batteries are preferred, as they do not require periodic maintenance, are compact, and have relatively higher efficiency compared to other batteries [173]. On the negative side, its useful life span is up to 5 years [174]. Therefore, it becomes a challenging task to make their repayment time economically viable [175]. Usually, the government provides subsidies or lower tariffs to overcome this problem [94], [176]. Therefore, choosing the appropriate battery size becomes very critical, as it will directly affect the economic indicators.

Considering that the installed PV rating is greater than the residential household load, the remaining energy can be stored in the BESS and later utilized for in-house usage.

Similarly, if the PV is not generating energy, then BESS can be charged from the grid. In addition, some of this stored energy can be sold later to the grid the same way as excessive PV-generated energy is sold to the grid. This will result in more income by in feeding energy to the grid. The margins when to buy energy or sell energy to the grid are selected by the LP optimization method.

3.1 Battery Parameters

In this study, real-time load and PV data were measured on an hourly basis from a suburban Estonian distribution network for one year. Figure 3.2 shows the layout of the grid with all its connections. There are eight residential loads and three auxiliary loads in this network. Th load 1 (small house), load 2 (medium-size house) and load 3 (apartment building) are taken into account for the design of the BESS.

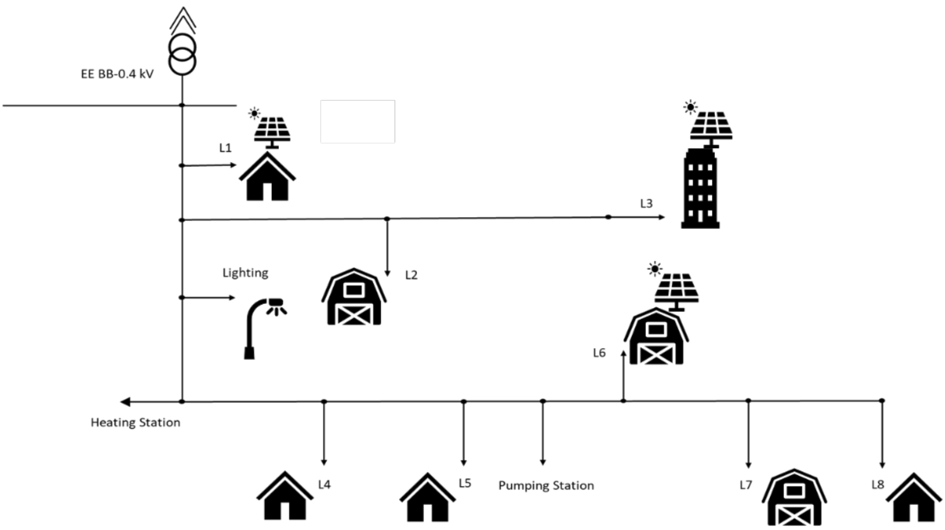

Figure 3.2. The suburban distribution networks under consideration

The battery size is usually calculated based on the daily energy consumption, efficiency and number of days for which BESS backup is required. The BESS size is calculated using Eqn. (3.1) [35]:

$$E_{BC} = \frac{E_{Day}}{\eta * DoD * 1000} * N \tag{3.1}$$

Here, E_{BC} is BESS capacity in kWh, η is the efficiency, N is the number of BESS backup, depth of discharge is DoD and E_{Day} is the daily average energy used. The peak load value is not used here, as it occurs only a few times a year. The other important parameter state of charge (SoC) of the BESS that specifies the stored energy in BESS is calculated using Eqn. (3.2) [35]:

$$SoC_{n+1} = SoC_n + \frac{\eta * P_z * K_p * \Delta t}{E_{BC}} \tag{3.2}$$

where n represents the number of states, Δt is the sampling interval, K_p indicates the online and offline status (typically 0 or 1), and P_z is the charging power in kW and it is calculated using Eqn. (3.3) [35]. The BESS parameters and load profiles for all three cases are described in Table 3.1.

$$P_z = \frac{BC*V*0.15}{\eta} \tag{3.3}$$

Table 3.1. Load profiles & BESS parameters

Parameters	Small house	Medium house	Apartment building
Average load (kW)	0.1	0.8	11.9
Peak load (kW)	1.9	6	36.7
Annual energy consumption (kWh)	741	6640	103860
Rated PV power (kW)	5	10	20
E_{BC} (kWh)	4	33	518
P_z (kW)	0.6	5.4	86

3.2 The Proposed Heuristic Algorithm

The proposed method is realized as an algorithm considering data of load, PV energy generation, and electricity prices on an hourly basis to charge or discharge the BESS. The algorithm is designed in a simplified manner to reduce the overall energy cost for residential users. The method aims to minimize the dependence and use of the grid throughout the year. The algorithms used linear and convex optimization to find out the most optimal charging and discharging electricity prices for the grid. The basic principle is that if PV is generating more than the load then the BESS will be charged and if the load is higher, the BESS will be discharged. Moreover, BESS will sell/buy energy from to/from the grid if the prices are higher/lower than the specified threshold values. A detailed description of this algorithm is given in Table 3.2.

3.3 Optimization Technique

The selection of electricity prices to buy and sell energy to the grid is a complicated optimization problem. The market electricity price changes every hour in Estonia as it is a member of the Nord Pool electricity market. In addition, there can be a huge fluctuation in hourly prices [177]. In this study, the electricity prices of 2020 for the Estonian energy market have been taken under consideration. The main objective is to minimize the overall energy cost during the year and make it closer to a nZEBs. The objective function, along with the constraints, is defined as follows:

$$Minimize\ f = \sum_{t=1}^{N}\left\{C_{grid}^{pur,u}(t) * \hat{E}_{grid}^{pur}(t) + C_{grid}^{sell,u}(t) * \hat{E}_{grid}^{sell}(t) + C_{bat}^{ch,u}(t) * \hat{E}_{bat}^{ch}(t) + C_{bat}^{dis,u}(t) * \hat{E}_{bat}^{dis}(t) + C_{PV}^{u}(t) * \hat{E}_{PV}(t)\right\} \tag{3.4}$$

Subject to

Table 3.2. The proposed heuristic algorithm

Algorithm: Battery Charging & Discharging

Input: Load data, photovoltaic data, electricity price

1. Calculate battery E_{BC}, P_z
2. SoC_{max} = 0.9 and SoC_{min} = 0.2
3. **While (n <= 8760)** %n is the number of hours
4. **If** PV > Load and 0.2 > SoC (n) > SoC_{max} then charge battery (But not above SoC_{max})
5. Calculate SoC (n+1) and P_{Bat} (n)
6. a = a +1 %no. of charging hours with PV
7. **else if** Load > PV and SoC_{min} > SoC (n) > SoC_{max} then discharge battery (But not below SoC_{min})
8. Calculate SoC (n+1) and P_{Bat} (n)
9. b = b + 1 %no. of discharging hours for internal use
10. **else if** Electricity Price < threshold value and SoC(n) < 0.5 then Charge battery from the grid (But not above SoC_{max})
11. Calculate new SoC (n+1) and P_{Bat} (n)
12. c = c +1 %no. of charging hours with Grid
13. **else if** Electricity Price > threshold value and SoC(n) > 0.4 then discharge battery to the grid (But not below SoC_{min})
14. Calculate SoC (n+1) and P_{Bat} (n)
15. d = d +1 %no. of discharging hours to the grid
16. **else**
17. SoC (n+1) = SoC (n)
18. P_{Bat} (n) = 0
19. **end if**
20. n = n +1
21. **end while**

$$E_{grid}^{pur}(t) - E_{grid}^{sell}(t) - E_{bat}^{ch}(t) + E_{bat}^{dis}(t) + E_{PV}(t) = E_L(t) \tag{3.5}$$

$$-E_{bat}^{ch}(t) + E_{bat}^{dis}(t) \leq E_L(t) \tag{3.6}$$

$$E_{grid}^{pur}(t) - E_{grid}^{sell}(t) \leq E_L(t) \tag{3.7}$$

$$-E_{bat}^{ch}(t) + E_{bat}^{dis}(t) \leq E_{bat}^{max}(t) \tag{3.8}$$

$$E_{bat}^{ch}(t) - E_{bat}^{dis}(t) \leq E_{bat}^{max}(t) \tag{3.9}$$

$$-E_{grid}^{pur}(t) \leq 0 \tag{3.10}$$

$$-E_{grid}^{sell}(t) \leq 0 \tag{3.11}$$

$$-E_{bat}^{ch}(t) \leq 0 \tag{3.12}$$

$$-E_{bat}^{dis}(t) \leq 0 \tag{3.13}$$

$$-E_{PV}(t) \leq 0 \tag{3.14}$$

$$E_{PV}(t) \leq E_{PV}^{max}(t) \tag{3.15}$$

where f is the objective function, t is the number of hours, $E_{grid}^{pur}(t)$ and E_{grid}^{sell} are electrical energy purchased from and sold to the grid, respectively; E_{bat}^{ch} and E_{bat}^{dis} are the charged and discharged energy. E_{PV} is the energy generated from PV, E_{PV}^{max} is the maximum energy generated by PV, E_L is the electrical energy consumption by the nZEBs; E_{bat}^{max} is the maximum energy stored in the battery, N is 8760 (number of hours in one year). All energy values are in kWh. The cost of energy purchased from the gird is $C_{grid}^{pur,u}$; $C_{grid}^{sell,u}$ is the cost of energy sold to the grid, $C_{bat}^{ch,u}$ is the cost of battery charging, $C_{bat}^{dis,u}$ is the cost of discharging energy from the battery to the grid, $C_{PV}^{u}(t)$ is the cost of PV energy sold to the grid. All unit costs are in cents per kWh. The hat symbol in the equation represents the normalized values. The normalization values are calculated using Eqn. (3.16). Further details on the operation of the algorithm can be found in [178].

$$X_{new} = \frac{X - X_{mean}}{X_{max} - X_{min}} \tag{3.16}$$

where the $X_{min} = 0$ kWh.

3.4 The Impact of EMS

The EMS in nZEBs should be viable in financial terms to encourage others to incorporate a similar solution in other conventional buildings. This makes the economic analysis of PV-BESS-based nZEBs very important from a business perspective as well. Therefore, an economic analysis was performed for all three cases in this study. Economic analysis requires consideration of several parameters. One of the most important parameters is the initial investment in solar PV and batteries. The investment cost C_{PV} is calculated as [23]:

$$C_{PV} = C_{PV}^{u}(t) * P_{rated} * \frac{i(1+i)^n}{(1+i)^n - 1} \tag{3.17}$$

where $C_{PV}^{u}(t)$ is the per-unit cost of PV, P_{rated} is PV rated power, n is the number of years representing PV lifetime, and $\frac{i(1+i)^n}{(1+i)^n-1}$ is the net present cost as compared to investment. Similarly, the initial cost of the BESS system is computed as [23]:

$$C_{Bat} = (C_{bat}^{ch,u}(t) * E_{BC} + C_{Inv./Unit} * P_{rated}) \frac{i(1+i)^n}{(1+i)^n - 1} \tag{3.18}$$

where $C_{bat}^{ch,u}(t)$ is the unit cost for BESS charging, $C_{Inv./Unit}$ is the inverter unit cost, E_{BC} is the maximum energy storing capacity of the BESS, n is battery lifetime, and $\frac{i(1+i)^n}{(1+i)^n-1}$ is the ratio of present cost and the annual investment. The electrical load values from the Eqn. (3.4) are also used here to balance the energy requirements of the nZEBs. The amount of energy sold to and purchased from the grid is also used.

The price of a battery on the Estonian market is around 100 €/kWh and the price for PV panels is around 400 €/kW [12], [57]. The cost of a 5-kW inverter is around 1000 €. Table 3.3 shows the impact of PV-BESS based EMS for the whole year. The number of hours of grid usage is significantly reduced for all three cases. Moreover, the BESS is used for internal usage for around 40%-50% of the time for all three cases. A detailed economic analysis for all three cases is given in Table 3.4.

For case 1 and case 2, the net energy cost is negative, indicating the surplus energy sold to the grid, but case 3 still has a positive net energy cost. The main reason is higher load values as compared to the installed PV-rated power. The peak load for case 3 was 36 kW and the installed PV is 20 kW. Thus, the energy available to charge the BESS is limited. This scenario requires a high-rated power PV system.

Table 3.3. The Impact of PV-BESS based EMS

	Small house	**Medium house**	**Apartment building**
a (hours)	3131	1880	1035
b (hours)	433	313	157
c (hours)	179	337	621
d (hours)	3984	4422	4864
j (hour)	1391	2482	3325
Peak power drawn from the grid (kW)	2.8	5.95	36.71
	1.9	2.4	22.9
	1.2	1.7	16.9
	1.3	2.5	27.3
Peak power injected into the grid (kW)	1.4	5.8	34.7
	4.9	9.8	12.7
	4.9	9.7	12.6
	4.8	9.2	11.7

Abbreviations: a = no. of charging hours from PV, b = no. of discharging hours to grid, c = no. of charging hours from the grid, d = no. of discharging hours for internal usage, j = no. of total hours of grid usage

The same calculations with a 60-kW rated PV are shown in Table 3.4. With this rated PV, the net energy cost is very close to zero and the users will have significant savings on their energy bills. The payback periods for all cases are also presented in Table 3.4. The payback periods for these PV-BESS systems are varying between 10 to 16 years. The payback periods along with yearly savings are shown in Figure 3.3.

Table 3.4. The payback period for different cases

	Small house	**Medium house**	**Apartment building**	
Rated PV power(kW)	5	10	20	60
Cost of PV & inverter (€)	3000	6000	12000	36000
Cost of the battery (€)	400	3300	51800	51800
Total saving per year (€)	341	713	2363	5482
Payback period (years)	10	13	27	16

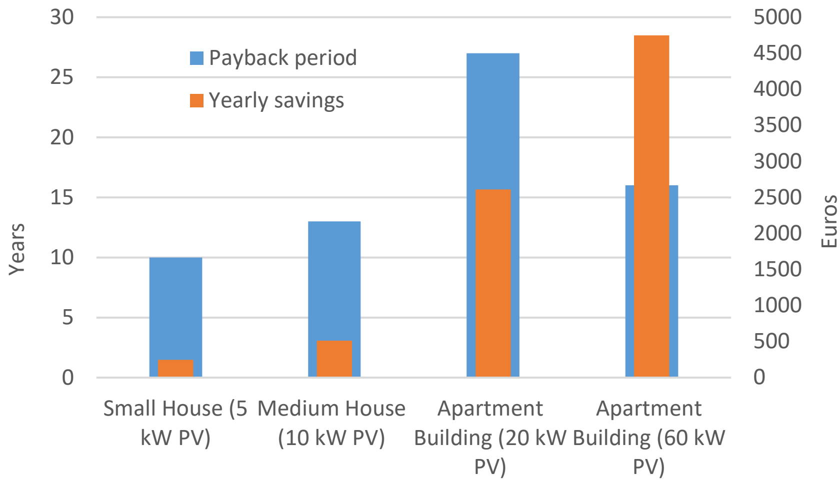

Figure 3.3. Payback periods and yearly savings

3.5 Case Study with Electric Vehicles (EV)

The same case study is now extended with the addition of the EV load. One EV load was added for small house, 2 to 4 for medium houses and 10 EVs for apartment building. EV load profiles are generated using an activity-based model presented in [76]. Now, the peak loads are 4.6 kW, 14.4 kW, and 60 kW for cases 1,2, and 3, respectively. The rest of the parameters were assumed identical including the PV and BESS sizes. The payback periods for these PV-BESS-EV systems are shown in Table 3.5. The payback period for these systems varies between 14 and 19 years. Here again for case 3, PV with higher rated power is required. The values shown in the table are calculated with a 20 kW PV system for Case 3. Further details of this work can be found in [179].

Table 3.5. Payback periods for PV-BESS-EV systems

	System	**PV rated power (kW)**	**Cost of PV and inverter (€)**	**Cost of BESS (€)**	**Total savings per year (€)**	**Payback period (years)**
Small house	PV-BESS-EV	5	3000	400	377	9
	PV-BESS	5	3000	400	341	10
	PV-EV	5	3000	-	212	16
Medium house	PV-BESS-EV	10	6000	3300	776	12
	PV-BESS	10	6000	3300	713	13
	PV-EV	10	6000	-	315	19
Apartment building	PV-BESS-EV	20	12000	51800	2198	29
	PV-BESS	20	12000	51800	1995	32
	PV-EV	20	12000	-	307	39

3.6 Chapter Summary

In this chapter, an EMS has been presented. An LP-based heuristic algorithm was incorporated into the EMS to minimize the cost of energy utilization. The proposed technique is analysed using the real-life residential load, PV energy generation and market electricity prices data from an Estonian suburban grid. The data was recorded for the whole year on an hourly basis. The simulation results of the algorithm show that the energy utilization costs are significantly reduced. The payback period using the proposed PV-BESS based EMS is found to be between 10 to 16 years. Furthermore, the possibility of EVs integration with the EMS is also explored. The payback periods for PV-BESS-EV are estimated to be further lower and vary between 9 to 12 years. The comparison of different systems along with their payback periods is shown in Figure 3.4.

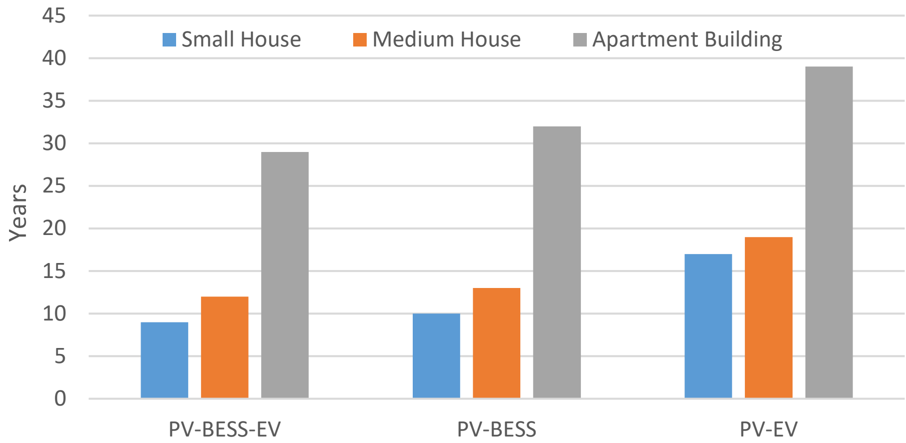

Figure 3.4. Comparison of payback periods for different systems

4 Congestion Control & Hosting Capacity

The installation of PV systems is increasing and on one hand, these RES are good for the environment, but they can create technical problems in the network. This penetration of PV in higher numbers can cause overloading, congestion, and overvoltage problems [179]. Usually, the PV panels are installed on the rooftop of the residential users and then connected to the low voltage (LV) distribution network [6]. Therefore, the network operator needs to be aware of the maximum HC of the network in particular locations or distribution lines [180]. If HC levels are exceeded, the network cannot provide service quality and ensure safety, therefore operation of supply services could even be halted. The EMS proposed in this thesis including the BESS and a control algorithm can provide a possible solution for these problems.

In this work, a practical network is considered which is a typical regional rural network. This particular network is selected because in this rural network segment there are fifteen residential users, and the length of the lines is average. Moreover, rural residential users usually have the possibility to install large PV panels as extra space is available on their premises as compared to residential homes in urban areas. These large PV installations could cause overloading in the distribution lines and overvoltage in the electrical network. The target here is to decrease the disruptions in network availability and improve the quality of service for uses without additional grid reinforcements like the replacement of distribution lines or transformers. Therefore, the focus is on the employment of new methods. Here, it is presented that how a BESS and more adjusted method for BESS control can benefit the grid services. It is shown based on the results that these methods can increase the HC.

4.1 Case Study of Rural Grid

For investigation and verification of the proposed strategy, a feeder of 0.4 kV is observed from an Estonian rural network. This 10 kV feeder was modelled in DIgSILENT Power Factory 2022. The model discussed here includes the existing 10 kV line connection to the substation, where a detailed 0.4 kV grid is laid out. The load profiles were provided by AS Elektrilevi in the framework of the project LEEEE20025. This real-life data allows us to model the system for simulations and perform power flow analysis and observe the loading of the lines and voltage fluctuations. The single-line diagram of the network is presented in Figure 4.1.

The detailed parameters of the line are presented in Table 4.1. The transformer rating is 100 kVA, and the nominal value of the switch breaker is 100 A. The capacity of the cable AXMKA 3x50, from the largest part of the line constructed, is 140 A. The sum of the main fuses in the line is 345 A. Despite the relatively small consumption, at the customers’ connection points, the main fuses vary from 10 A to 25 A in three phases. Given these ratings, the possibility that customers install photovoltaic systems according to the nominal fuse current is considered a first case. In such a case called **Case 1 “Max profit”**, the total capacity of PV systems might be up to 238 kW (345 A) and the whole grid will be overloaded. That is why it is considered that the PV system's nominal power will be based on the nominal fuse, but a margin down. For example, if the connection point has a contract for 25 A fuses, PV installed capacity will be 13.8 kW (20 A). This way, the total installed capacity of all 15 PV systems is 189.1 kW. The list of installed loads and PV systems rating are also presented in Table 4.1.

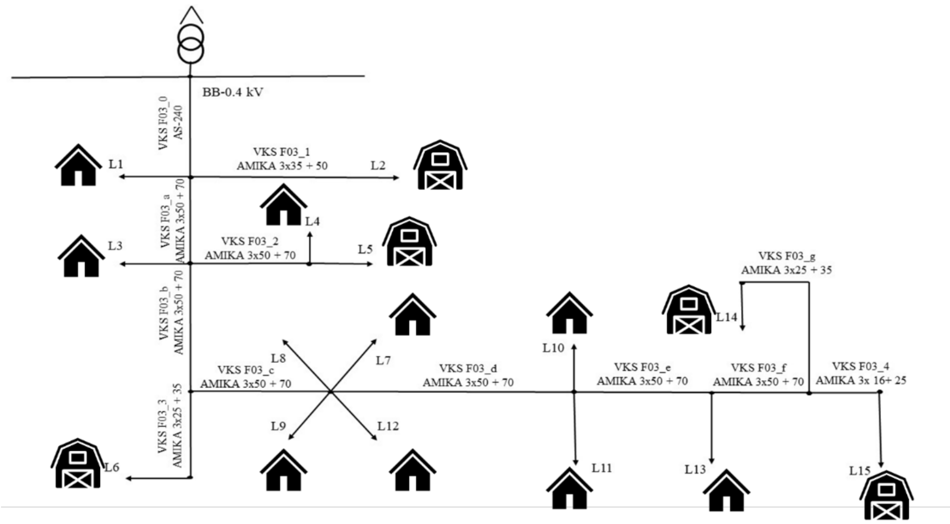

Figure 4.1. The schematic diagram of the LV distribution network

For the simulation of PV system generation, the profiles used are based on one-year measured data for an existing 600 kW PV system connected to the nearby substation. The values were obtained for 1 kW and multiplied by the nominal installed capacity of planning individual PV systems. The grid modeled in DigSILENT is shown in Figure 4.2. Simulations shows, that in such a scenario, the grid faces several problems such as overloading of lines and transformers, and overvoltage problem in most of the nodes. Analyzing simulation results and the equipment data we can see that sections VKS_F03_a, and VKS_F03_b have the highest load, and the cable rated current there is 140 A, the maximum hosting capacity for the line 96 kW which is near transformer nominal value of 100 kVA.

Several solutions can be implemented in this case. For the overloading issue, grid reinforcement; for voltage problems, the voltage control via smart inverters are the most common approaches. The PV output curtailments and installation of BESS is also common practice to reduce abnormal regimes. If the grid is remodelled with reinforcement to carry on installed 189 kW, it is necessary to change the transformer to at least 200 kVA and lines from AMKA 3x50+70 to AMKA 3x120+95. The implementation of voltage regulation via inverters containing reactive power control (RPC) gives an improvement in voltage profiles, but the loading of lines and transformers is significantly increased. This can be explained by the increasing reactive power flow, which is used for voltage regulation. If there is no grid reinforcement planned and the limitation of PV systems applies uniformly, then we can see that each customer has to reduce the PV system output power by about two times.

Table 4.1. Grid parameters, rated PV powers, and the BESS sizes

	Peak load (kW)	PV installed capacity (kW)				Grid parameters			
		Case 1	Case 2-1	Case 2-2	Case 3	Lines	Cable type	Nom. current (A)	Length (m)
L1	3.0	13.8	5.0	5.0	4.4	VKS F03_0	AS-240	605	60
L2	4.8	11	6.8	6.8	6.0	VKS F03_1	AMKA.3 x35+50	115	342
L3	3.7	11	5.7	5.7	4.1	VKS F03_2	AMKA.3 x50+70	140	44
L4	0.7	4.2	2.7	2.7	0.7	VKS F03_3	AMKA.3 x25+35	90	23
L5	6.6	11	8.6	8.6	3.9	VKS F03_4	AMKA.3 x16+25	70	11
L6	5.8	13.8	7.8	7.8	4.4	VKS F03_a	AMKA.3 x50+70	140	45
L7	3.1	13.8	5.1	5.1	2.7	VKS F03_b	AMKA.3 x50+70	140	79
L8	3.4	13.8	5.4	5.4	4.1	VKS F03_c	AMKA.3 x50+70	140	38
L9	2.2	13.8	4.2	4.2	2.1	VKS F03_d	AMKA.3 x50+70	140	38
L10	2.3	13.8	4.3	4.3	2.1	VKS F03_e	AMKA.3 x50+70	140	44
L11	4.1	13.8	6.1	6.1	2.8	VKS F03_f	AMKA.3 x50+70	140	39
L12	1.3	13.8	3.3	3.3	1.6	VKS F03_g	AMKA.3 x25+35	90	102
L13	3.4	13.8	5.4	5.4	3.9	-	-	-	-
L14	4.0	13.8	6.0	6.0	1.3	-	-	-	-
L15	4.2	13.8	6.2	6.2	5.2	-	-	-	-

However, the less stressful cases for the grid are considered. In **Case 2 named "Close to maximum power"**, the installed capacity of PV systems is based on the maximum loads in nodes plus 2 kW. In **Case 3 named "Net Zero"** PV selection is based on annual electric energy consumption and annual possible energy generation. The installed capacities are presented in Table 4.1. Moreover, for case 2 and subcase 2.1 with one additional large PV is connected to the substation directly to evaluate. In case 3 large PV system is also connected to the substation for the same reason. PV installed maximum output for Case 2.2 and Case 3 is 51.5 kW and 82.2 kW correspondingly.

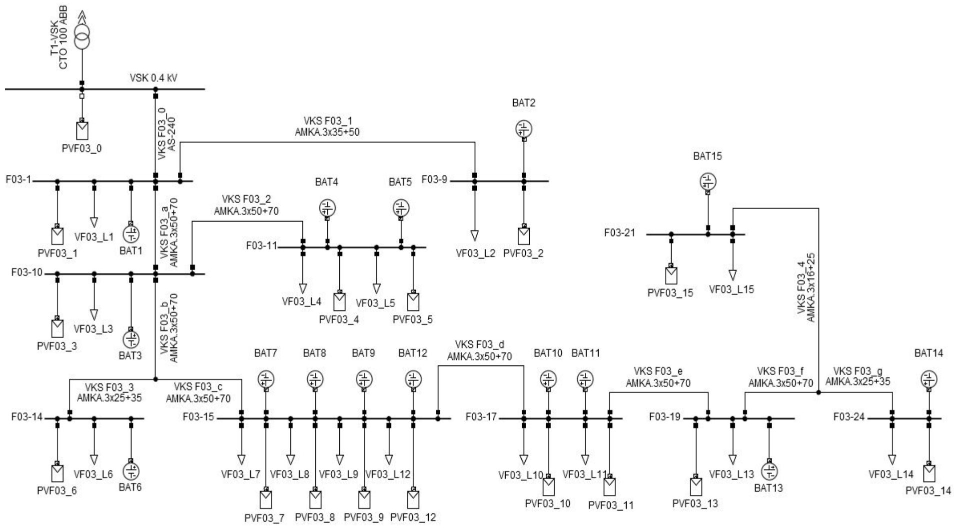

Figure 4.2. The grid under consideration modelled in DigSILENT

4.2 Strategies for Congestion Control

In this study, three different congestion control scenarios are taken into consideration. The aim here is to find the best-case scenario with increased PV hosting capacity and minimal congestion in the distribution network. The emphasis is also given on the local control in the distribution network using BESS control, PV power curtailment, and not using extra devices such as reactive power control and OLTCs. In the following, two levels of battery control are considered:

- Trivial battery control – only user motivated BESS usage. Very simple and has no connection to utility.
- HC motivated control – user manages but is aware of possible HC limitation issues.

4.2.1 Trivial Battery Control (TBC)

In this first scenario, the BESS is installed with all residential users. The BESS capacity is established using the Eqn. 3.1 [178]. BESS capacities for all four cases are listed in Table 4.2. The same BESS charging/discharging algorithm as described in the previous chapter has been implemented. While these BESS capacities could be expected to shave off the peak energy generation from the PV and reduce the congestion in the network, trivial BESS control is actually not able to do this.

4.2.2 HC Motivated Control (HMC)

In the second scenario, the BESS is controlled mildly. The idea here is to use the surplus of PV-generated energy at the peak generation hours and utilize it to charge the BESS. The BESS in this scenario is set accordingly to be able to shave off the high peaks of energy injection into the network. The previously applied BESS control algorithm is modified in a way that the BESS is set to charge during the peak energy generation hours, usually in the middle of the day. Then, the energy in BESS is sold in a higher amount to the grid in the evening hours when the electricity prices are comparatively higher.

Table 4.2. BESS capacities considered in the analysis

	BESS Capacity (kWh)			
Loads	**Case 1**	**Case 2.1**	**Case 2.2**	**Case 3**
L1	42	16	16	14
L2	34	22	22	18
L3	34	18	18	14
L4	14	10	10	4
L5	34	26	26	12
L6	42	24	24	14
L7	42	16	16	10
L8	42	18	18	14
L9	42	14	14	8
L10	42	14	14	8
L11	42	20	20	10
L12	42	10	10	6
L13	42	18	18	12
L14	42	16	16	4
L15	42	20	20	16

The PV generation data and grid power flow analysis initially showed that the peak overloading in the lines occurs in the middle of the day from 10 AM to 3 PM. This corresponds to summer periods when the PV energy generation is at its peak and the load is lowest. This process makes sure that the BESS capacity is available for energy storage to meet the in-house the next day demand. Otherwise, the rest of the capacity is used to support the PV peak shaving capabilities. Therefore, the algorithm only charges BESS during these times during summer and discharges the BESS to sell energy to the grid later in the evening, with greater intensity.

4.3 Results and Discussion

4.3.1 Technical Impact

Several solutions are implemented for Case 1. For the overloading issue, usually grid reinforcement is required and for overvoltage problems, voltage control via smart inverters is the most common approach. The PV output curtailment and installation of BESS is also common practice to reduce abnormal regimes. The grid reinforcement for the installed 189 kW would require a necessary replacement of the transformer for at least 200 kVA rating and lines up-gradation from AMKA 3x50+70 to AMKA 3x120+95. The implementation of voltage regulation via smart inverters gives an improvement in overvoltage profiles, but the loading of lines and transformers is significantly increased as demonstrated in [Paper I]. This can be explained by the increase in reactive power flow which is used for voltage regulation. If there is no grid reinforcement planned and the limitation of PV systems applies uniformly, usually each customer must reduce the PV system about two times and must take an economical hit. Therefore, the scope of this work was limited to reducing congestion with BESS installation and its efficient control. The comparative analysis of different methods for case 1 is shown in Figure 4.3.

In the first case (Maximum profit), the installation of BESS can reduce the overvoltage problem in the lines to 70%, however, the overloading in the lines is slightly increased. The duration of abnormalities is still the same in both cases. The implementation of HMC in the BESS significantly decreases the overloading in the lines to 15% and 25% for the transformer. In addition, there is a 25% improvement in the overvoltage problem as well. However, such kind of control is still not enough to make grid operation stable. Additional investigations with PV output curtailment and voltage regulation via smart inverters and the results are presented in [Paper I]. The details of schemes used for Case 1 are given in Table 4.3.

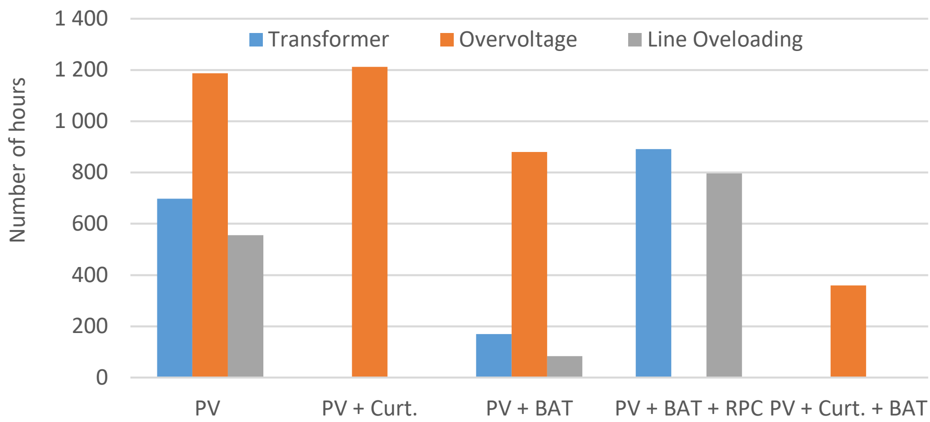

Figure 4.3. Comparison of different methods for Case 1

Table 4.3.Energy generation using different Techniques for Case 1

Utilization scheme	E gen. (kWh)	Utilization
PV	224 106	100%
PV curtailment	156 874	70%
PV with BESS TBC	224 106	100%
PV with BESS HMC	224 106	100%
PV + RPC with BESS HMC	224 106	100%
PV curtailment with RPC and BESS HMC	214 099	96%

Grid simulations were performed for all the cases and with three control scenarios of BESS. The comparison of BESS control strategies for all the cases is given in Tables 4.4 to 4.7.

Table 4.4. Comparison of BESS control scenario for case 1

	Without BESS		BESS TBC		BESS HMC	
	Count (hours)	**Max values**	**Count (hours)**	**Max values**	**Count (hours)**	**Max values**
Transf. overloaded	698	159	689	200	170	134
Lines, overloaded	556	159	558	176	84	119
Nodes, U>1.1 p.u.	1 187	1.20	1 154	1.24	880	1.18

For Case 1 “Maximum profit” high penetration scenario, the installation of none controlled batteries could create more problems for the grid. While the duration of the abnormal operation is still almost the same, the fluctuation of voltage becomes higher together with the overloading value for the transformer. The implementation of the HMC technique shows better results for both overloading and overvoltage appearance and their maximum values. However, such control is still not enough to improve grid operation reliability. The author made additional investigations with PV output curtailment and voltage regulation via smart inverters.

Table 4.5. Comparison of BESS control scenario for case 2.1

	Without BESS		**BESS TBC**		**BESS HMC**	
	Count (hours)	**Max values**	**Count (hours)**	**Max values**	**Count (hours)**	**Max values**
Transf. overloaded	0	69	0	93	0	58
Lines, overloaded	0	62	0	82	0	52
Nodes, U>1.1 p.u.	304	1.12	21	1.12	0	1.09

For Case 2.1, the PV is installed close to the peak load power. The results show that installation of BESS can significantly reduce voltage fluctuations and with the use of an HMC technique, it can reduce the hosting capacity problem both in terms of overloading and overvoltage.

Table 4.6. Comparison of BESS control scenario for case 2.2

	Without BESS		**BESS TBC**		**BESS HMC**	
	Count (hours)	**Max values**	**Count (hours)**	**Max values**	**Count (hours)**	**Max values**
Transf. overloaded	211	117	254	141	0	99
Lines, overloaded	0	62	0	81	0	52
Nodes, U>1.1 p.u.	434	1.13	117	1.12	0	1.09

In Case 2.2, like Case 1, installation of BESS does not leverage the problems and increases loading in the components. However, the overvoltage hours were reduced four times as compared to the scenario without batteries. Here, the HMC strategy again reduces all the major problems. For the net-zero energy (Case 3), the installation of BESS even TBC can fix the voltage issue, but to reduce the load on the transformer the implementation of an HMC strategy is necessary. A comparative analysis of the different congestion control strategies is given in Figure 4.4.

Table 4.7. Comparison of BESS control scenario for case 3

	Without BESS		BESS TBC		BESS HMC	
	Count (hours)	**Max values**	**Count (hours)**	**Max values**	**Count (hours)**	**Max values**
Transf. overloaded	373	126	244	134	0	102
Lines, overloaded	0	42	0	46	0	28
Nodes, U>1.1 p.u.	704	1.15	0	1.09	0	1.07

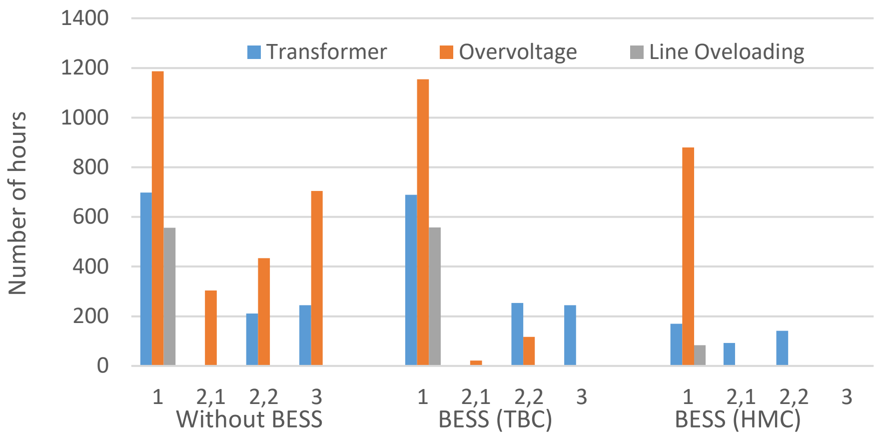

Figure 4.4. Comparison of different congestion control techniques

4.3.2 Economic Impact

The economic analysis using both BESS control strategies and with no BESS has also been carried out for all the cases. The results of the economic analysis for all the 15 customers are presented in Table 4.8. The results indicate that PV installations significantly reduce the cost the energy for all the customers and the users can even earn money by selling energy to the utility company. The negative cost values in the table show that more finance was earned from energy sold to the grid rather than spent on buying from the grid in the whole year.

In all four PV installation cases, all 15 users would be able to get financial gains. In Case 1, as the installed PV-rated power is the highest, here users will earn more money. The installation of BESS can further increase the revenue from selling this energy. In the first control technique, the financial gains are the highest; however, in the BESS HMC technique for congestion management, the gains are 8 to 15% higher. Also, there is a significant economic loss when curtailment in PV injected power to the grid is employed. Because using this method, there is any or every small curtailment in power needed, and the electrical grid will be operational throughout the year with good quality of service.

In Case 2.1 and Case 2.2, the economic numbers for all the customers again show a negative cost. The decrease in financial gain varies from 9% to 19% for all the customers employing a TBC strategy. However, BESS with HMC indicates the best results. For case 3, the economic numbers verify that it was a nZEBs case as the value to financial gains for the users is not that high but only up to tens of euros. The BESS with HMC techniques provides better economic numbers for all the 15 users in this case as well.

Table 4.8. Economic analysis for all simulation cases

User		Case 1			Case 2.1			Case 2.2			Case 3		
	OC	CPV	CB1	CB2	CPV	CB1	CB2	CPV	CB1	CB2	CPV	CB1	CB2
1	**175**	-450	-483	**-517**	-64	-72	**-86**	-64	-72	**-86**	-35	-46	**-52**
2	**85**	-532	-574	**-606**	-98	-120	**-131**	-98	-120	**-131**	-15	-22	**-44**
3	**124**	-499	-534	**-571**	-138	-167	**-185**	-138	-167	**-185**	-9	-21	**-49**
4	**64**	-552	-595	**-628**	-81	-94	**-102**	-81	-94	**-102**	-13	-17	**-38**
5	**168**	-457	-491	**-524**	-92	-96	**-102**	-92	-96	**-102**	-18	-27	**-64**
6	**55**	-557	-604	**-638**	-168	-184	**-198**	-168	-184	**-198**	-7	-11	**-39**
7	**207**	-420	-452	**-487**	-93	-98	**-107**	-93	-98	**-107**	-41	-56	**-66**
8	**246**	-257	-279	**-307**	-91	-93	**-95**	-91	-93	**-95**	-41	-54	**-63**
9	**178**	-322	-347	**-374**	-87	-94	**-109**	-87	-94	**-109**	-18	-29	**-59**
10	**29**	-159	-171	**-182**	-87	-100	**-108**	-87	-100	**-108**	-4	-8	**-38**
11	**162**	-334	-363	**-393**	-223	-248	**-272**	-223	-248	**-272**	-24	-35	**-54**
12	**181**	-445	-478	**-510**	149	-192	**-209**	149	-192	**-209**	-30	-38	**-61**
13	**115**	-505	-544	**-578**	-105	-129	**-144**	-105	-129	**-144**	-14	-24	**-49**
14	**172**	-453	-487	**-521**	-88	-92	**-101**	-88	-92	**-101**	-24	-37	**-60**
15	**87**	-530	-571	**-605**	-98	-113	**-125**	-98	-113	**-125**	-13	-20	**-44**

*All the costs are in euros (€).
Abbreviations:
Accumulated cost of energy usage (OC),
CPV = Cost with only PV,
CB1= Cost with PV and BESS (Trivial battery control),
CB2= Cost with PV and BESS (HC motivated control)

4.4 Chapter Summary

The chapter presented the methods to increase the renewable penetration in the local grid without disrupting its operation. The study incorporated a real-life case study of a rural Estonian network for verification of the results. Several PV installation scenarios are discussed here that include PV installations according to fuse rating (max. profit), peak load and net-zero energy. The initial analysis of the PV installation presented severe overloading of the lines and overvoltage in the network having values way above the defined standards. Techniques like PV power curtailment, RPC, inclusion of BESS and BESS with HMC are explored as possible solutions. The results indicate that in max. profit PV installation scenario the BESS with an advanced control is a must, but it will still require some power curtailment and RPC. In the peak load and net energy PV installation scenarios, BESS with HMC will solve both above-stated problems. The BESS with HMC is done using the same EMS strategy defined in the previous chapter but with slight modifications.

5 Machine Learning for Energy Management System

5.1 Machine Learning Perspectives in EMS

The RES infeed energy generation forecast can help in efficient charging and discharging schedule for the BESS that as a result will decrease the congestion in the local network. Similarly, residential load forecasting would help in better management of the load and reduction in electricity costs from the grid. Therefore, the incorporation of machine learning applications can add another dimension to the efficient operation of the EMS. Big data analytics applications are witnessing a rapid increase in machine learning and deep learning techniques for application in many sectors including power systems. These are also quite popular in forecasting applications like residential load forecasting [181], transportation loads [182] and energy consumption. These machine learning techniques can provide additional functionalities and capabilities for the EMS.

As shown in chapter 4, the HC improvements are significant if HC-oriented controlled scheduling of BESS is implemented. However, that was achieved by the static control method. Thus, it is obvious that this kind of control strategy would not necessarily be optimal all over the year. The stochasticity in the daily energy RES infeed would require more dynamic solutions regarding the BESS usage strategy. There is a need for tools to make a forecast about the availability of RES energy generation. This energy forecast will help in higher local energy usage and make the system more economical.

There are conventional machine learning techniques like linear regression, tree-based regression, SVM, and deep learning neural network-based techniques like AR, NAR, CNN, and RNN [183]. Recently, deep learning algorithms have gained more attention due to their superior accuracy compared to traditional machine learning algorithms [183]. These algorithms are a subset of machine learning techniques that requires an even larger data set and are having highly complex architecture, usually unreal network-based. The other difference is that these algorithms continuously monitor and consider past data before making future predictions and therefore better track nonlinearities in the data [184]. These algorithms are usually classified as Artificial Neural Networks (ANN) their layered based architecture is derived from the human brain. Several deep learning and deep learning algorithms were considered and compared in the study [183]; however, RNN-LSTM was found to provide the most accurate forecast. Therefore, RNN-LSTM is used here for the PV and wind energy and residential load forecasting case studies based on the Estonian data sets.

5.1.1 Long Short-Term Memory Networks (LSTM)

LSTM belongs to the category of RNN. These algorithms keep the previous data stored in the memory cell and use it in every iteration before making future predictions. For time series analysis, dataset-based LSTM forecasting is very suitable. This algorithm uses a cell architecture and stores the information to be used in the decision-making process. The information in the cells is updated after every iteration. The architecture of the LSTM algorithm is shown in Figure 5.1 [129]. LSTM consists of three layers, the first is the input features and the number of steps. The second is the hidden state, and in between these two layers, there is the third layer containing the memory cells, which is called the LSTM layer. The stored data is used to perform sequence-by-sequence regression in a one-time interval; then the data in the cells are updated and then it shifts to the next state.

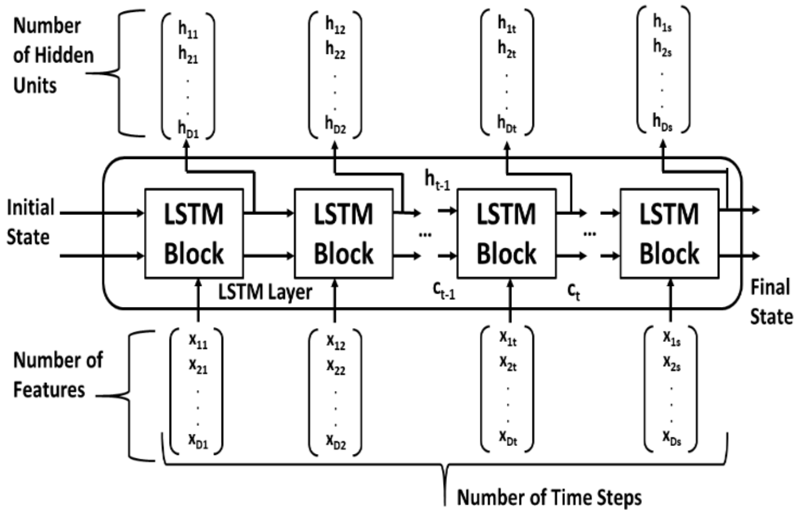

Figure 5.1. The architecture of LSTM

5.2 Case Study of Solar Energy

In Estonia, energy generation and consumption have a big gap here of around 200 MWh to 600 MWh [177]. The energy demand is higher in winters having a peak value of around 1500 MWh and energy generation of around 1000 MWh [177]. Being a member of the Nord Pool energy market [185], Estonia buys more energy from its neighboring countries to overcome this deficit [177]. The energy generated in Estonia is mostly from fossil fuels, however, the RES also has a significant and growing portion of the energy mix. The distribution of RES and non-RES in Estonia is shown in Figure 5.2 [177]. The share of renewable energy is around 30%, which is higher than the EU's renewable energy penetration goal [186]. The share of wind energy is around 11% and PV is around 1%. However, in the coming year, the share of photovoltaic energy is expected to increase rapidly further supported by increased deployment of nZEBs.

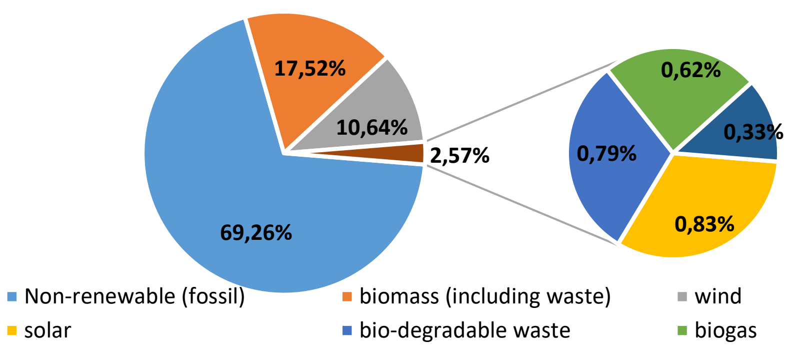

Figure 5.2. Share of renewable and non-renewable energy in Estonia

The total installed capacity in Estonia is around 2337 MW according to the Estonian TSO [187]. The PV installation in Estonia accumulates around 128 MW [187], 70 MW in Latvia, and 120 MW in Lithuania [11]. Solar irradiance values on average in Estonia range from 900 to 1100 kWh/m^2 [186], [188]. However, the day times have a huge variation in summer and winter between 18 to 20 hours and 5 to 7 hours, respectively [189]. The energy generation potential is not huge but still enough for residential homes and buildings. Even the excess energy can be sold to the grid and customers can have some monetary benefits. In the prospect of nZEBs, the extra energy generated in summer can be sold to the grid and bought back in winter times.

5.2.1 Exploratory Data Analysis

In this study, a 10 kW PV system's energy generation data measured in 2016 for the whole year is used [190]. Data was measured in Tallinn, Pärnu, Narva, and Saaremaa on four different houses with a one-hour frequency. Data for all these four locations and their moving average and moving standard deviation values are shown in Figure 5.3. The figure shows that the energy generation in all regions is lower from November to March while it is higher from April to October. Peak values are in June and July. Also, the figure shows that Pärnu and Saaremaa regions have a slightly higher energy generation pattern than the other two regions.

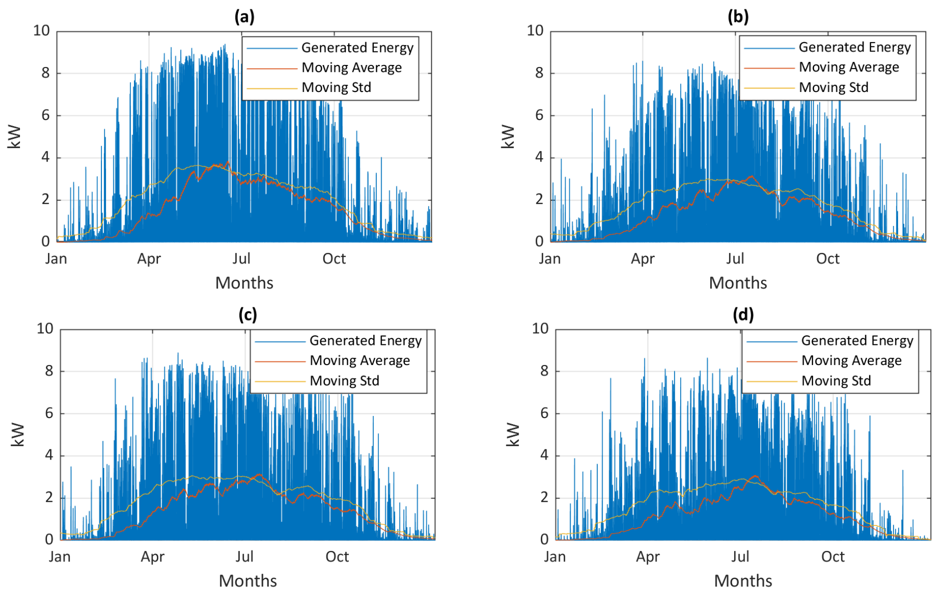

Figure 5.3. Statistical analysis of solar PV generation data for (a) Tallinn (b) Saaremaa, (c) Pärnu (d) Narva

For further data analysis, histogram analysis was conducted and then its values were normalized to calculate the probability. The results are depicted in figure 5.4. The results indicate that in the Saaremaa region, the probability of generating energy is even slightly higher than in the Pärnu region. For the 5.4 kW generation, the probabilities are 14%, 27%, 20%, and 20% in Tallinn, Saaremaa, Pärnu, and Narva, respectively.

The autocorrelation analysis is a very important method to reflect the pattern in the time series analysis that is useful for the selection of parameters for further regression analysis. The correlation analysis gives the number of lags that describe the dependency of the signal's current value on its previous values. Further details of this phenomenon are given in [191]. These autocorrelation values do not depend on weather or season. These numbers of lags are a useful input parameter for regression analysis with machine learning techniques. The autocorrelation analysis is shown in Figure 5.5 with 72 lags, indicating the dependence of the current data on the last 72 hours.

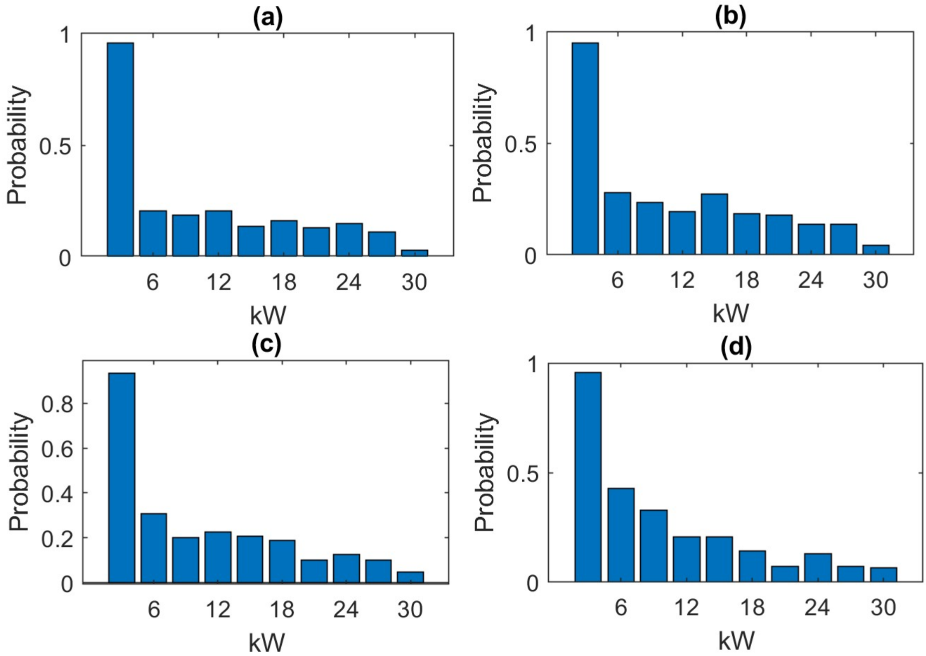

Figure 5.4. Histogram of power generation for (a) Tallinn, (b) Saaremaa, (c) Pärnu and (d) Narva

The autocorrelation value greater than 0.5 indicates higher dependence. All regions show a periodic pattern, showing the dependence of specific-hour data on the previous day's data on these specific hours, indicating long-term dependence. The periodic and rapid changes in autocorrelation values also indicate the day and night patterns in the solar data.

5.2.2 PV Energy Forecasting

RNN-LSTM algorithm is used here for energy forecasting. Due to its, deep neural network architecture, it gives superior accuracy as compared to other algorithms [5], [129] [139]. The RNN-LSTM algorithm is trained to make a short-term to medium-term forecast [58]. Data was distributed in training and test data with a 90% and 10% distribution, respectively. After running the simulation 50 times, 200 hidden layers are chosen with the number of epochs to be 250. The algorithm is then used to make three days ahead forecast separately for the last three days of June. A comparative analysis of actual energy generation and forecast energy generation for 3 days is shown in Figure 5.6. The forecasting results give an RMSE value of around 184 W and up to 92% accuracy.

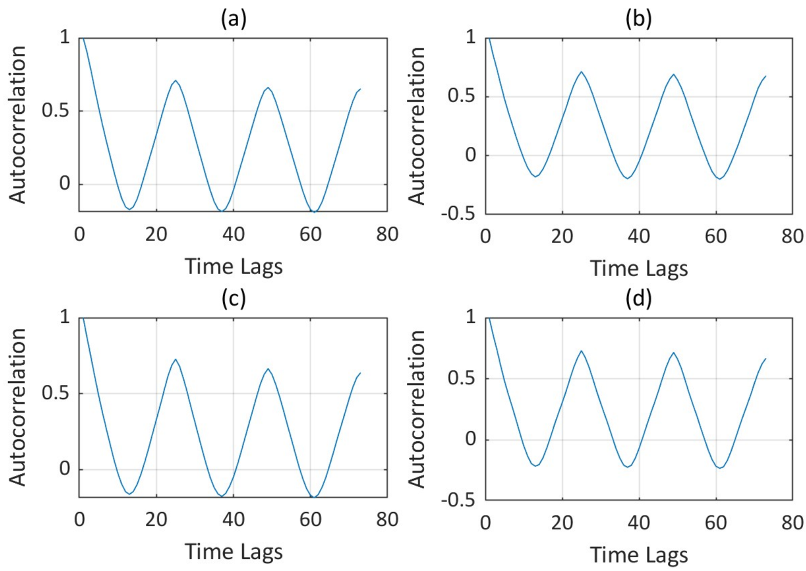

Figure 5.5. Autocorrelation analysis

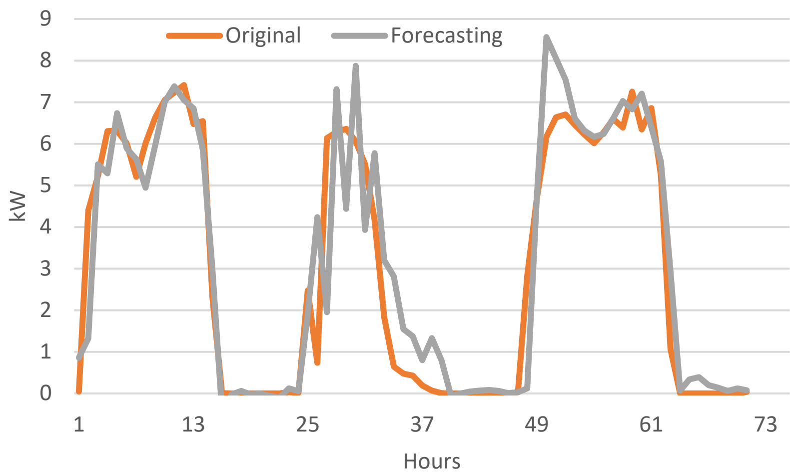

Figure 5.6. Comparison of actual and forecasted energy in summer

5.3 Case Study of Wind Energy

The share of wind energy is around 10% of the total energy mix in Estonia. However, this share is increasing with every passing year due to environmental factors, energy security and EU regulations. The installed capacity of wind energy sources in Estonia is around 300 MW and most of these wind turbines are installed on the coast of the Baltic sea [193]. Meanwhile, 11 off-shore and 2 on-shore projects are also in the development phase as part of the government plan to have 1800 MW by 2030 [193].

5.3.1 Exploratory Data Analysis

The Estonian wind energy generation data set is used here with a one-hour frequency and spanning from January 2011 to May 2019. Hourly wind power generation is highly stochastic, a similar pattern is visible in this data set. The maximum, average and median values in this data set are 273 MW, 76 MW, and 57 MW (hourly average power), respectively. However, the standard deviation is around 62 MW which is a high value. In the first step, the moving average and moving standard deviation are also calculated to demonstrate the variation in the time series dataset. Wind energy generation data from January 2018 to May 2019 are shown in Figure 5.7 along with moving average and moving standard deviation values. This figure shows the stochastic nature of wind energy, as there are no seasonal highs or low values. The moving average is comparatively high from November to March, but still, in between, it shows lower values and then again goes up.

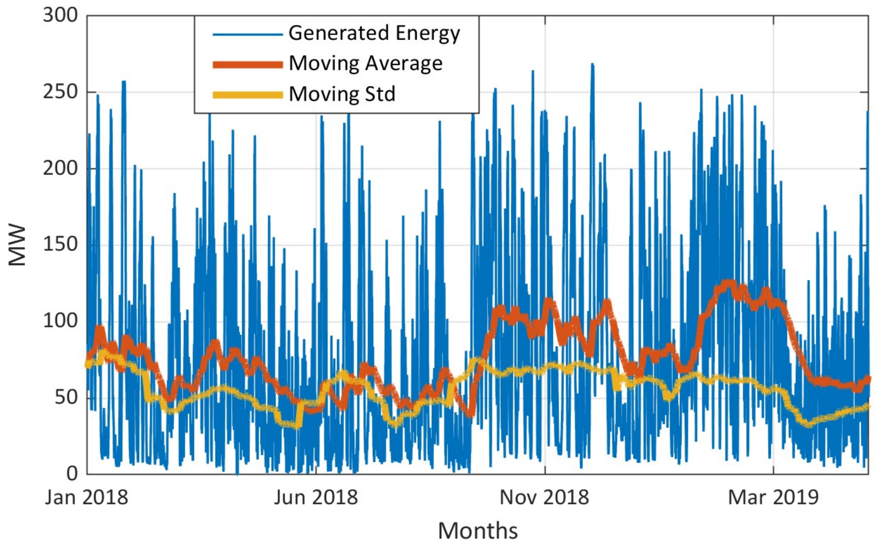

Figure 5.7. Generated power, moving average and moving std. deviation

The histogram analysis and probability density function (PDF) analysis are shown in Figures 5.8(a) and 5.8(b), respectively. Figure 5.8(a) shows that the wind power ratings are mostly below 50 MW and rarely does it go above 200 MW. Figure 5.8(b) shows the probabilities which are calculated after the normalization of the number of occurrences. These values are also showing the same pattern. The probability of getting less than 50 MW is greater than 40% and for 200 MW is less than 10%. This makes the accurate forecasting of wind energy a very challenging task. Furthermore, the autocorrelation analysis result is shown in Figure 5.8(c). Figure 5.8(c) shows a graph of 20-hour values and indicates that the last 16-hour values have autocorrelation values higher than 0.5, which means a higher dependency. The correlation values decrease after that.

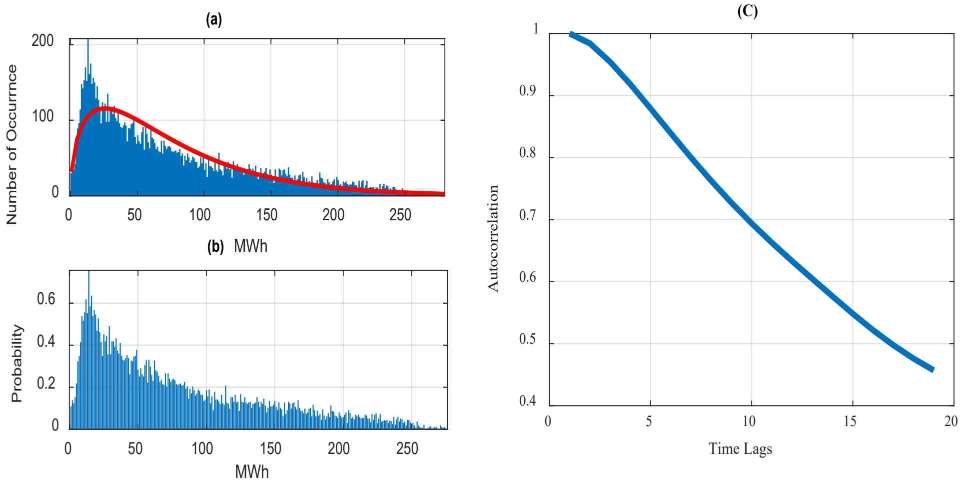

Figure 5.8. (a) Histogram (b) PDF of the data, (c) Autocorrelation analysis

5.3.2 Wind Energy Forecasting

The Estonian TSO also forecasts wind energy generation on daily basis for 24 hours ahead. The actual energy generation and the forecasting by TSO's algorithm for May 2019 are shown in Figure 5.9. [194]. There are clear gaps in energy generation and forecast energy. Sometimes, the variation is even greater than 50 MW. Therefore, it highlights the need for more accurate forecasting.

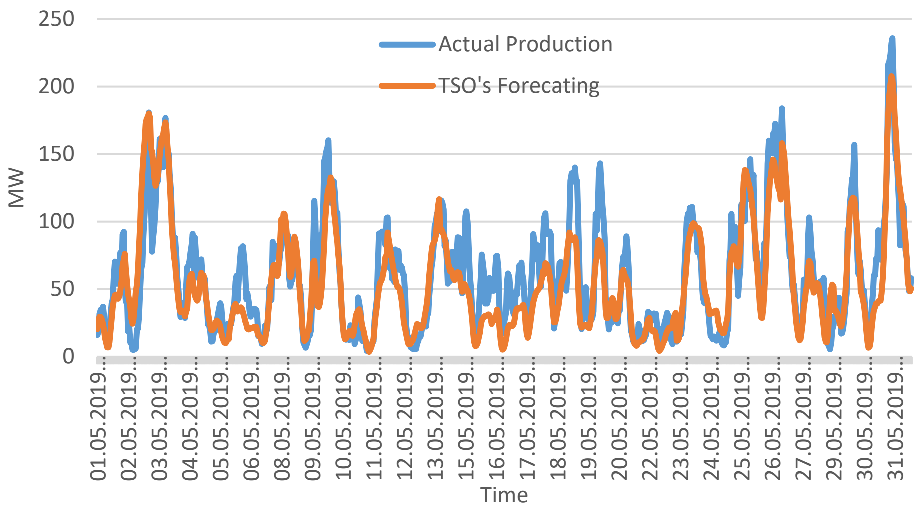

Figure 5.9. Actual and Forecasted wind power for May 2019

The Estonian wind energy generation data set was divided into three categories, 80% data for algorithm training, 10% for testing, and 10% for the validation of results. The simulation results for the multistep forecasting were generated. The forecasting error results of the proposed RNN-LSTM algorithm along with actual energy generation and TSO forecasting are depicted and compared in Figure 5.10.

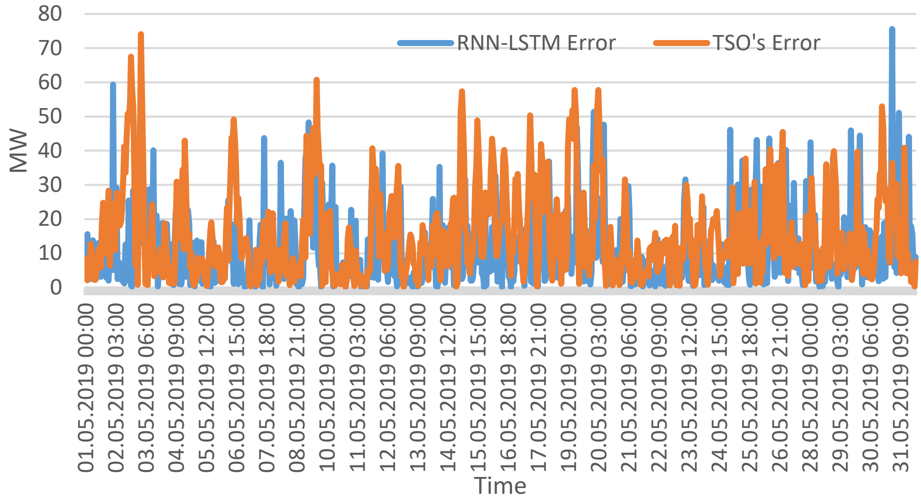

Figure 5.10. Forecast error of the TSO's algorithm and LSTM forecasting

From the above figure, it is clear that the RNN-LSTM algorithm gives better forecasting results. In terms of the RMSE value, the TSO algorithm provides a value of 25; however, the RNN-LSTM algorithm results are around 15. The variations in TSO's forecasting are much higher, this forecasting algorithm predicts slow variations in the output but fails in case of faster variations. The RNN-LSTM algorithm, on the other hand, predicts this more dynamic variation in a better way; however, it sometimes fails in the case of very slow variations. Therefore, a hybrid algorithm can be more beneficial here.

In this study, the size of the data set was varied from 12 months to 96 months. However, the algorithm showed the same accuracy in terms of RMSE values after 24 months of data. The number of epochs, learning rate, and hidden states were also varied to find the optimal solution. Further details of the simulation parameters and results can be found in [183].

5.4 Case Study of Residential Load

In the study, the residential load dataset used was recorded in an Estonian household [195]. The data was measured for one month with a one-minute frequency. The residential home was a 67.8 m^2 flat housing four occupants and it included domestic appliances like a dishwasher, electric stove, entertainment system, TV, microwave oven, vacuum cleaner, etc [121]. The residential load along with its moving average and the standard deviation is depicted in figure 5.11. Most of the time, the overall load value is lower than 1000 W. The load value rarely goes above 4000 W or higher. This usually occurs on the weekend when all occupants are at home, or they are using heavy loads like washing machine and dishwasher.

5.4.1 Residential Load Forecasting

In the analysis, comparative research has been conducted between different machine learning and deep learning algorithms. The details of these algorithms can be found in [157]. A comparison is to find out which algorithm is more capable of identifying the linear and nonlinear patterns in the load data. The algorithms compared here are LR, TR, LSTM, autoregressive neural network (AR), non-autoregressive neural network (NAR) output error (OE), and auto-neuro fuzzy integrated systems (ANFIS), SVM and its different versions. The comparative analysis shows that the NAR, AR and cubic SVM are given good forecasting results. However, the best results are given by the LSTM algorithm as it has the lowest RMSE value. The forecasting results of RNN-LSTM are shown in Figure 5.12. The comparative analysis of RMSE of values is given in Table 5.3.

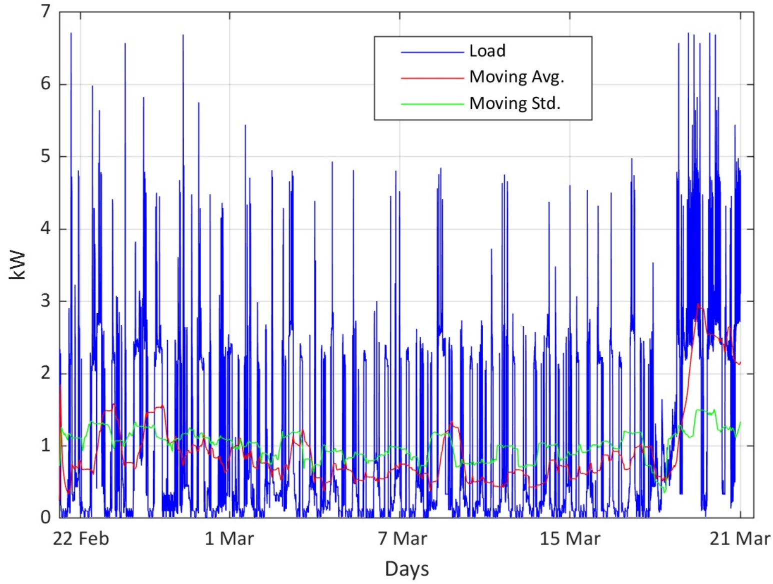

Figure 5.11. Load data with moving average and moving standard deviation

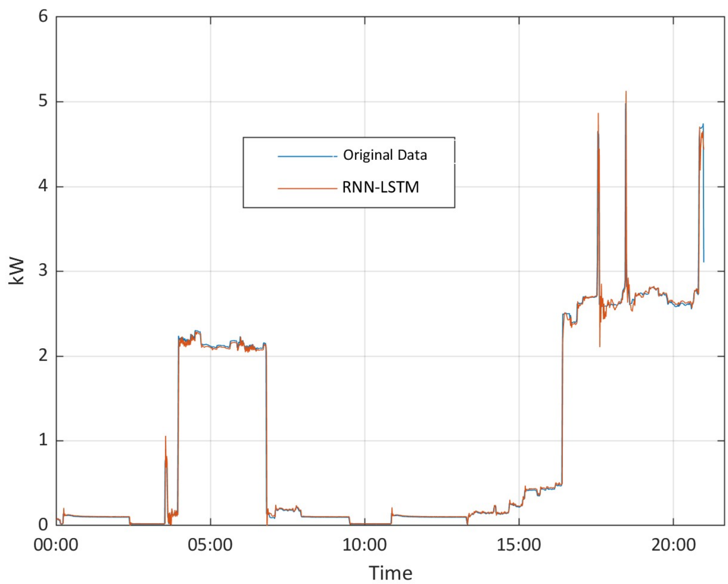

Figure 5.12. RNN-LSTM forecasting for residential load

Table 5.1. Comparison of RMSE values

Algorithm Name	RMSE Value	Algorithm Name	RMSE Value
Linear Regression	381	Non-Linear Regression	325
Tree-Based Regression	241	Gaussian SVM	234
Linear SVM	619	OE	167
Quadratic SVM	187	ANFIS	168
Cubic SVM	172	AR	169
RNN-LSTM	159	NAR	163

5.5 Chapter Summary

In this chapter, the possibility of ML techniques adding extra functionalities and capabilities to the EMS has been explored. The forecasting applications of machine learning techniques can help in the efficient operation of the EMS. Accurate PV energy forecasting can help in better scheduling of BESS to avoid congestion and overvoltage problems. Several ML and DL algorithms are designed and evaluated in this work. The results indicate that the RNN-LSTM algorithm provides better forecasting capability and lower RMSE values as compared to other techniques. Therefore, the RNN-LSTM algorithm is used to develop a forecasting algorithm for 24 hours ahead of energy generation. Similarly, algorithms for 24 hours ahead wind energy generation and residential load forecasting have also been developed.

6 Conclusions

The future energy supply grids will include a large portion of RES like wind and PV along with an added load of EVs and capabilities of localized BESS. One of the most potent solutions to provide an advantage in this mix is an enhanced active residential energy management system (EMS). This EMS will efficiently manage all such resources relying on the electrical load, market electricity prices, etc. The EMS proposed in this thesis will be a subsystem of an energy router which is a flexibility providing power electronic unit. This EMS will be connected to domestic RES, BESS, EV and the local grid.

Costs at this time for the BESS and PV installations are noticeably high. Therefore, one of the main goals of EMS here is to decrease the energy usage costs from the grid and maximize profits by selling extra energy to the grid. This way, it will help in decreasing the payback period of the components needed, such as PV and BESS systems. BESS installation along with PV, if not only used for local energy storage, can also help in uninterrupted grid operations. However, this BESS operation needs optimization and an efficient control algorithm for the aforementioned tasks. As the first step in this thesis, a heuristic LP-based control strategy is developed to decrease the cost of energy in a BESS-equipped system considering the nZEBs scenario. The BESS sizes were also varied to find the appropriate case when the energy utilization hours from the grid are minimum, PV energy is maximally used and the overall energy utilization in the whole year is at a minimum. The economic analysis of these PV-BESS EMS indicated that for small apartment and residential home the payback period is between 10 to 13 years. The payback period for the large apartment building is around 27 years. This can be further reduced to 16 years if a larger rated PV is installed with this building of 60 kW rather than 20 kW. The inclusion of EVs with the EMS and their impact has also been evaluated here. The payback periods for small and medium houses for PV-BESS-EV systems were found to be between 10 to 12 years, even further increasing system feasibility.

The second level approach in this thesis, a study is focused on different aspects to increase the reliability of the grid upon high RES penetration in the electrical network. The increased renewable penetration is easily promoted, but it can also create challenges for the network operators. Bottlenecks can emerge in the LV grid creating overloading and voltage fluctuation in the networks. Furthermore, if PV-BESS-EV integration can increase hosting capacity (HC) it decreases the cost of energy service from the grid for the residential users incorporating EMS. This is due to avoiding costly network upgrades. For the described tasks, installation of BESS and control strategies are discussed to reduce the effect of bidirectional power flows and resulting congestion problems while increasing the HC of PV in LV networks.

The simulation results show that BESS with the proposed hosting capacity motivated control (HMC) strategy can significantly improve the situation and reduce hours of abnormal regimes. Most of the time, it reduces the problems except for the case in which the PV penetration level is nearly at its peak. The proposed control was compared with other methods available. The installation of BESS without congestion control might be suitable in cases with lower PV penetration levels. In the case of the peak penetration scenario of renewable sources at the customer side integrated with the LV, the line leads to huge voltage fluctuations and overloading. The curtailment of the PV output reduces these problems but leads to a 70% reduction in HC. The voltage regulation with smart inverters employing RPC improves voltage profile but leads to overloading of the equipment due to increased reactive power flow. The installation of BESS with trivial control in the considered case is not helping with the normalization of grid operations. The implementation of proposed HMC for BESS however significantly reduces the loading of lines and slightly reduces voltage fluctuation. And, together with RPC and slight curtailment of the PV systems, the proposed HMC technique shows much better results from the grid operation perspective together keeping the energy utilization ratio to 96%.

The knowledge of available RES energy infeed to the grid is of prime importance, as it can help in better management of the resources and smooth operation of the grid. Therefore, possibility of additional capabilities for the EMS with the incorporation of ML and DL techniques has also been evaluated here. The accurate forecasting of energy generation from RES and residential load is beneficial in demand and supply management and impacts the power flows in the grid. In this thesis, case studies for PV and wind energy forecasting along with residential load forecasting were conducted. The case study for PV energy forecasting containing the four most populous regions of Estonia was conducted. The results also showed that the RNN-LSTM algorithm made good forecasting up to 92% for 24 hours ahead of PV energy generation. In addition, a similar forecasting algorithm was also developed for wind energy forecasting. The simulation results indicated that SVM, NAR, and RNN-LSTM could provide respectively 10%, 25%, and 32% better match compared to TSO's forecasting algorithm. Moreover, a residential load forecasting algorithm has been developed for a day ahead load forecast. The cast study of residential load showed that the RNN-LSTM algorithm made good forecasting with 24 hours ahead load with a match rate of around 94%.

7 Future work

For future work, the proposed energy management strategy can be implemented in the energy router for a small residential home to verify its real-time performance testing and measure the accuracy of the results. The energy router is being developed and built at this time within another research project. The author of this thesis is looking forward to testing the features described in this thesis to verify the achieved merits. Moreover, it can be extended to any size of residential premises and its feasibility and payback periods can be determined for real-life cases. The possibility of a small wind generator as RES can be explored. This would add another dimension to the EMS and further increase its capabilities.

With the real implementation of EMS, the potential of ML techniques for the operation of EMS can be evaluated. ML-based RES energy generation forecasting benefits would be observed for a longer period. Rather than the scheduled HMC control for the BESS that showed good results, this ML RES forecasting-based charge/discharge could provide even better results. The ML tools have already been designed and implemented and the potential is clearly there. The EMS can make all these decisions based on the residential load and energy generation forecasting. This can further increase the efficiency of the EMS operation and the grid services in terms of reliability, flexibility, and lower interruptions.

Moreover, a web-based application/mobile app is to be developed for the proposed EMS. That application can include live monitoring of these energy parameters and their future predictions in the software application. The parameters that could be included in the application can be RES energy generation, residential load, market electricity prices, BESS status, and the forecasting of RES energy and load using ML techniques. In addition, the application would be able to give the users some options and guidelines to schedule their energy utilization optimally. This can provide a convenient solution and enable the residential users to further deploy and utilize the EMS efficiently.

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Acknowledgements

First, I would like to thank all my friends, colleagues, and the staff in the Department of Electrical Power Engineering & Mechatronics, Tallinn University of Technology, for giving me all the support and encouragement during my doctoral study. Moreover, I would like to say special gratitude to my supervisor Lauri Kütt for his unvarying guidance, creative ideas, and motivation. I would also like to express my gratitude to Dr. Oleksandr Husev, Dr. Roya Ahmadiahangar and Dr. Victor Astapov for their experience and insightful help in my research work. Also, a sincere thanks to Dr. Payam Shams Ghafaroki, Maris Velström and Eve Kit, whenever I had a problem, they were the ones to guide me and find a solution.

Moreover, I would like to say special thanks to my family for their patience and untiring support during this time and a special commemoration to my late Mom and Dad, they are not here but I know they will be very proud of me. A very special thanks to Mona for her never-ending support and encouragement.

Furthermore, I would like to mention the financial support from DoRA Plus program for financial assistance and the Estonian Research Council project PSG142 for the funding support, without their contributions, this work would have not been possible.

Abstract

Residential Energy Management System to Support Increased Renewable Penetration

The deployment of nearly zero-energy buildings (nZEBs) using renewable energy resources (RES) is expected to increase in the coming years. For residential users, the combination of photovoltaic (PV) sources such as RES and battery energy storage systems (BESS) is a potent and one of the most convenient solutions to reach nZEBs targets. These systems are easy to install, environment friendly and can reduce the customers' energy utilization from the grid significantly. The main aim of this work is to further reduce costs related to electric energy supply system use and installation for residential users and make them self-reliable and less dependent on the electrical grid by using PV-BESS based localized energy management system (EMS). The high initial investment costs of PV & BESS, longer payback periods and the present electrical grid infrastructure are still challenges in achieving these goals. The deployment of PV integrated systems in large numbers can lead to energy delivery congestion and overvoltage issues in the low voltage (LV) networks. Such problems are, for example, possible to arise when the PV energy generation is near its peak and the domestic loads are around their lowest value. This calls to increase the hosting capacity (HC) limits, i.e., levels of PV infeed operating when utility supply quality and reliability conditions are still met.

The PV-BESS based EMS investigated in this thesis can serve as a solution to increase the benefits to install and maintain the domestic energy management system. The demand-side management (DSM) techniques previously proposed cannot alone solve the challenges introduced above. As a novel multidimensional solution, EMS proposed incorporates a PV-BESS system with an efficient usage strategy. For BESS size optimization and an efficient BESS control algorithm/usage strategy, a heuristic algorithm based on linear programming incorporating residential load, PV energy generation, and market electricity prices is proposed ins this thesis. To evaluate the outcome, real-time measured data of load, PV energy generation, electric energy market prices and electric vehicle (EV) charging load data have been used. The proposed solution to the optimization problem is using simplex and interior-point methods. The algorithm motivates to charge and discharge the BESS on the optimized schedule and thereafter decides to sell or buy energy from or to the grid based on the dynamic electricity market prices. Techno-economic analysis of the different rated PV-BESS and PV-BESS-EV systems has also been carried out to determine the feasibility of the system by calculating the payback periods. The results indicate that different proposed configurations for EMS under consideration are self-reliant to an increased extent and have a feasible nominal payback period.

Furthermore, the proposed EMS has the potential to eradicate congestion and voltage fluctuation in the electrical network. To evaluate the proposed local grid supporting functionality, a wider view of the real-life rural LV network has been considered along with the real-time load and PV energy generation measured data for the whole year. Four different PV installations case studies have been made and investigated through the power flow analysis. For evaluation of localized congestion control strategies for maximizing the HC in the distribution network using the EMS, two different BESS utilization techniques along with peak power curtailment, and reactive power control

(RPC) are proposed. The results clearly indicate that power curtailment once the HC limits are reached, is not a suitable solution both technically not economically. The BESS incorporation significantly reduces the congestion; however, it cannot solve the overvoltage problem fully in the case of large PV installations. A solution of BESS, RPC is required to solve both these overvoltage problems. However, for PV installed according to electric-energy net-zero yearly energy balance or in another case the peak loads of respective users, grid could operate without major problems with the inclusion of BESS with hosting capacity motivated control (HMC). The economic analysis for all the cases has been carried out to verify the assumptions presented.

The information about the future RES energy generation is needed for the further optimal EMS operation and can add extra capabilities for the customer. Therefore, in this research work, several machine learning (ML) and deep learning (DL) algorithms are set up and evaluated for residential load, PV and wind energy generation forecasting. For the PV energy infeed forecasting, cases from regions of Estonia are considered with a day-ahead target. This presents a successful case of the recurrent neural networks based long-term short-memory network (RNN-LSTM) algorithm. Similarly, for the wind energy availability forecasting, Estonian wind energy data set of up to eight years was used and the forecasting results of eight different ML and DL algorithms are compared for day-ahead values. The results indicate that RNN-LSTM provides the most accurate forecasting in terms of the lowest root mean square (RMSE) values. Moreover, the residential load forecasting algorithm based on LSTM is developed for a 24-hour ahead load forecast. This load and RES energy forecast will be very beneficial for the EMS in residential applications.

Lühikokkuvõte

Taastuvenergiaallikate kasutustihedust toetav energiahaldussüsteem

Taastuvenergiaallikatel põhinevat energiatootmist rakendavate liginullenergiahoonete (*i.k near-zero energy building, nZEB*) levik laieneb lähiaastatel. Üks potentsiaalsemaid ja mugavaimaid lahendusi nZEB tingimuste täitmiseks kodukasutajate jaoks on päikesepaneelide, s.t fotogalvaaniliste (*i.k photovoltaic, PV*) taastuvenergiaallikate ja akudel energiasalvestussüsteemide (*i.k battery energy storage system, BESS*) kombinatsioon. Taolisi keskkonnasäästlikke süsteeme on lihtne paigaldada, ja need võimaldavad olulisel määral vähendada võrgust tarbitava energia kulu tarbija jaoks. Käesoleva töö põhiliseks eesmärgiks on pakkuda kodutarbijatele elektrienergiavarustussüsteemi kasutuse ja paigaldusega seotud kulude vähendamise täiendavaid võimalusi, rakendades päikesepaneelide ja akuseadmete kombinatsiooni ning kohalikku energiahaldussüsteemi (*i.k energy management system, EMS*), suurendades seeläbi kodutarbijate iseseisvust ja väikesemat sõltuvust välisvõrgust. Siiski, nimetatud eesmärkide saavutamiseks vajalike päikesepaneelide ja akusüsteemi soetamiskulu on märkimisväärne ja tasuvusaeg pikk, teisalt võib piiranguid tekitada ka olemasolevate elektrivõrkude infrastruktuuri valmidus. Päikesepaneelidega integreeritud süsteemide intensiivse rakendamise korral võivad tulemuseks olla madalpinge jaotusvõrkude energiaülekande piirangud või ka ülepinge esinemine. Sellised probleemid võivad ilmneda näiteks juhul, kui päikeseenergiast toodetud elektrienergia tootmisintensiivsus on tipulähedane, aga kodutarbijate koormus minimaalne. See tingib vajaduse suurendada jaotusvõrkude päikeseenergial töötavate allikate kasutustihedusvõimekust (*i.k hosting capacity, HC*), s.t päikeseenergiaallikate poolt sisestatava võimsuse taset, mille korral jaotusvõrgus on võimalik tagada varustuskindluse ja kvaliteedi nõuded.

Antud doktoritöös uuritud päikesepaneelidel ja akusüsteemil põhinev energiahaldussüsteem omab võimekust, millega pakub kodukasutuseks paigaldatuna täiendavaid hüvesid. Eelnevalt teadaolevad tarbimise juhtimise meetodid üksi toimides ei ole võimelised ülalloetletud väljakutseid lahendama. Väljapakutud uudne ja mitmetasemeline energiahaldussüsteem töötab päikesepaneelide ja akusüsteemi kombinatsioonil ning rakendab tõhusat talitlusstrateegiat. Akusüsteemi salvestusmahu optimeerimiseks, samuti tõhusaks aku juhtimisalgoritmi ja kasutusstrateegia sisseseadmiseks kasutatakse heuristilist lineaarprogrammeerimise (*i.k linear programming*) algoritmi, mis võtab arvesse koduse energiatarbe, päikesepaneelide poolt toodetava elektrienergia koguse, elektrituru hinna ja ka elektriauto laadimiskoormuse andmed. Optimeerimiseks välja pakutud lahendus kasutab simpleks ja sisepunkti meetodeid. Algoritm pakub akuseadme laadimiseks ja tühjendamiseks optimeeritud ajalist plaani ning seejärel otsustab energia ostu või müügi võrku, kasutades dünaamilist elektribörsi energiahinda. Süsteemi tasuvuse ja tasuvusaja hindamiseks, on läbi viidud tehnilis-majanduslik analüüs erinevatel võimsustasemetel päikeseenergiaallikad-akuseade ja päikeseenergiaallikad-akuseade-elektriauto kombinatsioonidele. Tulemused näitavad, et erinevad pakutud energiahaldussüsteemi konfiguratsioonid on suurema iseseisvusmääraga ja omavad motiveerivat tasuvusaega.

Lisaks eeltoodule on vaadeldud väljapakutud energiahaldussüsteemi võimekust vähendada energiaülekande piirangute ja pinge kõikumiste võimalikku ulatust

jaotusvõrgus. Taolise kohalikku elektrivõrku toetava funktsionaalsuse hindamiseks on käsitletud tegeliku maapiirkonna elektrivõrgu laiemat vaadet koos tegelike aastaste koormusandmete ja päikeseenergial toimivate elektrienergiaallikate energiatoodangu andmetega. Uuriti nelja erinevat päikesepaneelide paigaldise näidet, kasutades võimsusvoo analüüsi. Kohalike elektrienergiavoogude läbilaskevõime haldamise strateegiate analüüsiks ja kasutustihedusvõimekuse maksimaalseks kasvatamiseks jaotusvõrgus rakendati kahte erinevat akuseadme talitlusmeetodit, mida kooskasutati ja võrreldi muude tuntud meetoditega, s.h reaktiivvõimsuse reguleerimine ja võimsustipu piiramine. Tulemused näitavad selgelt, et võimsuse piiramine kasutustihedusvõimekuse piirideni jõudmisel ei ole sobilik tehniliselt ega majanduslikult. Lihtjuhtimisega akuseadme rakendamine vähendab talitluspiiranguid oluliselt, kuid ei lahenda suurte võimsustega päikeseenergia allikatega kaasnevaid ülepinge probleeme. Täiendavalt on sellisel juhul vaja nii akuseadme kui ka reaktiivvõimsuse reguleerimisvõimekust. Samas, kui päikeseenergiaallika võimsus on valitud lähtudes aastasest elektrienergia võrgust tarbitava energia null tasakaalust või teisel juhul vastavalt kasutatava koormuse tippväärtusele, võib elektrivõrk talitleda praktiliselt täiendavate probleemideta, kui akuseadet kasutatakse kasutustihedusvõimekust toetava juhtimisega. Kõikide kirjeldatud juhtumite puhul kasutatud eelduste kinnitamiseks on esitatud majanduslik analüüs.

Eesmärgiga tulevikus kasutajale täiendavaid energiahaldussüsteemi optimeerimisega seotud lisavõimalusi pakkuda, on vaja enam teavet eeldatava taastuvenergiaallikate poolt toodetava energiahulga kohta. Seetõttu on käesolevas uurimistöös loodud ja vaadeldud mitmeid masinõppe (*i.k machine learning*) ja süvaõppe (*i.k deep learning*) algoritme koduse elektrienergia tarbimise, päikeseenergiaga ja tuuleenergiaga toodetud energiahulkade ennustamise analüüsiks. Päikeseenrgiaallikate poolt genereeritud energiahulga ennustamist vaadeldakse Eesti erinevate piirkondade kohta eesmärgiga saada päev-ette andmeid. Nimetatud stsenaarium kirjeldab tulemusliku rekurrentse närvivõrgu (*i.k recurrent neural network, RNN*) pikaajalise lühimäluga võrgu (*i.k RNN-LSTM*) kasutusjuhtumit. Sellele sarnaselt rakendatakse tuuleenergia saadavuse ennustamiseks kaheksa aasta pikkust andmemassiivi, ning rakendati kaheksa erineva masinõppe ja süvaõppe algoritmi, et võrrelda nende tööd päev-ette väärtuste leidmisel. Tulemused näitavad ruutkeskmise vea väärtusele tuginevalt täpseimat ennustust, kasutades RNN-LSTM. Lisaks sellele, on arendatud LSTM-meetod kodutarbimise ennustamiseks 24-ks tunniks. Kirjeldatud taastuvenergiaallikate saadavuse ja tarbimise ennustamisega saab koduse energiahaldussüsteemi rakendustes võimekust kasvatada.

Appendix

Publication I

Shabbir, N.; Kütt, L.; Astapov, V.; Husev, O.; Ahmadiahanagr, R.; Kull, K.; Wen, F. (2022). Congestion Control Strategies for Increased Renewable Penetration of Photovoltaic in LV Distribution Networks, Energy Reports [Accepted for Publication]

Available online at www.sciencedirect.com

ScienceDirect

Energy Reports 00 (2022) 000–000

7th International Conference on Advances on Clean Energy Research, ICACER 2022
April 20-22, 2022, Barcelona, Spain

Congestion Control Strategies for Increased Renewable Penetration of Photovoltaic in LV Distribution Networks

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Abstract

Domestic photovoltaic (PV) installations are increasing their spread due to decreased cost, environmental friendliness, and relatively easy installation. However, the massive domestic PV deployment can bring the LV network (LV) distribution network to its sustained operating limits, as overvoltage and congestion can arise. The overvoltage problems can emerge due to reverse power flows and congestion can be caused if the installed PV capacity is higher than the distribution line loading capacity. The limitations of the LV networks arise especially during the seasons when domestic power demand is minimal, and PVs are generating at their peak. The research presented here incorporates a real suburban LV network with fifteen residential users. The measured load and PV generation data for one year are used to carry out power flow simulations. Several congestion leveraging strategies such as battery energy storage system (BESS) incorporation, reactive power control (RPC), and curtailment of peaks are discussed.

Peer-review under responsibility of the scientific committee of the 7th International Conference on Advances on Clean Energy Research (ICACER 2022).

Keywords: Photovoltaic; Renewable energy; Congestion control; Hosting capacity; Battery energy storage systems.

1. Introduction

The price of photovoltaic (PV) systems has decreased significantly in recent years [1]. The promotion of PV systems deployment has also increased due to their lower carbon footprint, clean energy production, and the deployment of nearly zero energy buildings (nZEBs) [2]. These rooftop PV installations are usually connected to the low voltage

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Peer-review under responsibility of the scientific committee of the 7th International Conference on Advances on Clean Energy Research (ICACER 2022).

(LV) distribution network [3]. However, large-scale deployment of PV installations in LV networks can exceed the hosting capacity (HC) of the distributed energy generation [4], advising caution not to impose limitations on network service. For example, high reverse power flows and reactive power disturbances can cause an increase in the voltage of the lines [5]. Rather often demand response (DR) and demand-side management (DSM) techniques are proposed as a solution, but they have also limitations to solve these LV grid problems [6].

The HC of the power lines is dependent on many factors such as installed PV rated power, load, load-to-feeder ratio, transformer rating [7], etc. The situation becomes problematic for the network operator when residential users install PV according to their own installed power targets, being often close to the point of common coupling (PCC) breaker installed rating. Due to the simultaneous PV input from multiple customers, grid operators are then required to upgrade transformers and distribution lines for uninterrupted grid operation according to the service quality standards. Without expensive upgrades, there could be few options to avoid overvoltage, congestion, and overloading problems in the network [8]. Overvoltage is a major concern for the grid operator and many solutions like reactive power control (RPC), on-load tap changer (OLTCs) and capacitor banks have been proposed [9], [10]. Nowadays, power electronics switching converters, such as PV inverters, capabilities are increasing. For example, many PV inverters contain the RPC options. On the other hand, these can increase the harmonics in the network [11].

Overvoltage can be a greater issue in the suburban and rural grids, whereas in urban grids ampacity of lines is a major problem [12]. Distribution lines have a specific load rating designed to sustain operation under expected end customer loads and their coincidence expectations. However, excessive power from the multiple PV producers can lead to the overloading of the line components. Instead of upgrading the most potentially overloaded lines, a costly and time-consuming solution, several studies have proposed a BESS-based solution to overcome this problem [13].

This paper discusses different strategies for congestion control due to high PV infeed on the LV distribution network. The objective of the research is to increase the HC in the distribution lines while minimizing the grid congestion and overvoltage problem. A control strategy incorporating a BESS with a charging/discharging algorithm including market energy prices has been proposed. In addition, the capabilities risen by the deployment of the RPC technique have also been elaborated. The peak PV power curtailment has been discussed to refer to the impact of the discussed methods.

2. Case Study of Suburban Grid

In this study, a line section of an Estonian suburban LV network containing a 0.4 kV distribution substation has been considered. This network has fifteen residential users and a total of thirteen distribution line sections. The schematic layout of the network is shown in Fig. 1. The load data of the residential users and the generation of photovoltaic energy assigned are based on measurements for the entire year, with a 1-hour time-step.

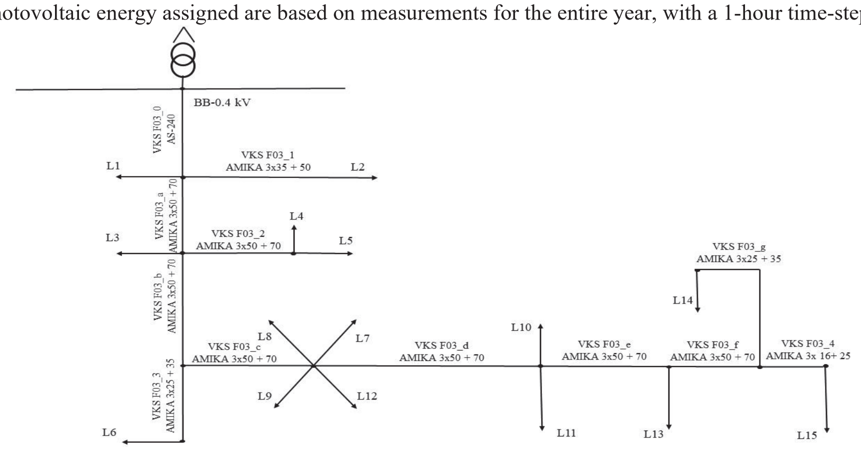

Fig. 1. Layout of the suburban grid under observation.

The transformer rating is 100 kVA and the rated value of the switch breaker is 100 A. The capacity of the cable AXMKA 3x50, from the largest part of the line constructed, is 140 A. The sum of the main fuses ratings in the feeder is 345 A. The assumption is that each customer installs PV according to the nominal values of the fuses, but slightly less than these marginal loads. When the switch breaker is 25A then PV is rated at 20 A. For example, customer 1 has a 3x25A connection, which means, that PV1 installed capacity would be 16 A or 11 kW. This way, the total installed capacity of 15 PV systems is 189 kW. The PV generation profile is taken from the data measured for the existing PV system connected to the nearby substation. The values were obtained by using the scaling factor, according to the nominal installed capacity of planning individual PV systems. A detailed description of the grid parameters is given in Table 1. The BESS sizes for all the residential users are calculated based on the peak load of the specific user using the following equation [14]:

$$E_{BC} = \frac{E_{Day}}{\eta * DoD * 1000} * N_d \tag{1}$$

where the E_{BC} is the BESS capacity (kWh), η is the BESS efficiency, N_d represents the number of days for which the BESS backup is required and is considered as 1 in our experimentation, DoD is the depth of discharge for the BESS, and E_{Day} is the peak energy usage of the customer on a day throughout the year (kWh).

Table 1. Grid parameters, rated PV powers, and the BESS sizes

Load characteristics			PV	BESS Parameters		Grid parameters			
Name in scheme	Average load (kW)	Peak load (kW)	Rated power (kW)	Capacity (kWh)	Charging power (kW)	Line section	Type of cable	Nominal current (A)	Length (m)
L1	0.6	3.0	13.8	31	3.8	VKS F03_0	AS-240	605	60
L2	0.6	3.7	11	25	3.1	VKS F03_1	AMKA.3x35+50	115	342
L3	0.1	0.7	11	25	3.1	VKS F03_2	AMKA.3x50+70	140	44
L4	0.5	6.6	4.2	10	1.3	VKS F03_3	AMKA.3x25+35	90	23
L5	0.6	5.8	11	25	3.1	VKS F03_4	AMKA.3x16+25	70	11
L6	0.4	3.1	13.8	31	3. 8	VKS F03_a	AMKA.3x50+70	140	45
L7	0.5	3.4	13.8	31	3.8	VKS F03_b	AMKA.3x50+70	140	79
L8	0.3	2.2	13.8	31	3.8	VKS F03_c	AMKA.3x50+70	140	38
L9	0.3	2.3	13.8	31	3.8	VKS F03_d	AMKA.3x50+70	140	38
L10	0.4	4.1	13.8	31	3.8	VKS F03_e	AMKA.3x50+70	140	44
L11	0.2	1.3	13.8	31	3.8	VKS F03_f	AMKA.3x50+70	140	39
L12	0.5	3.4	13.8	31	3.8	VKS F03_g	AMKA.3x25+35	90	102
L13	0.2	4.0	13.8	31	3.8	-	-	-	-
L14	0.7	4.2	13.8	31	3.8	-	-	-	-
L15	0.8	4.8	13.8	31	3.8	-	-	-	-

3. Congestion Control Strategies

3.1. Peak Power Curtailment

In this scheme, the maximum power generated by the PV panels is limited down to 70% and 50% [4], [13] to overcome network congestion rather than cutting off the user off altogether. The peak power is generated usually in the middle of the day and mostly in summer times when the residential loads are lowest. In this case, rather than injecting all the generated power, only a specific percentage is allowed into the grid. In this way, the PV energy peak is shaved off and as a result, the congestion in the network is leveraged as shown in Fig 2(a). On the negative side, curtailing PV power will have an economic implication for all customers as the amount of energy sold to the grid will be limited.

3.2. Reactive Power Control (RPC)

The RPC mechanism can help in avoiding overvoltage problems in the network. The grid integrated PV systems most commonly inject active power into the grid and do not provide reactive power. However, due to power flow in the opposite directions at different times, excessive active power infeed and weak cross-sections of the lines could result in voltage fluctuations. The solution here is to use inverters with smarter functionality to absorb or generate reactive power when necessary. However, incorporating RPC in solar inverters can provide decreased efficiency and sometimes lead to increased harmonic distortions in the network. The results of RPC are shown in Fig. 2(b).

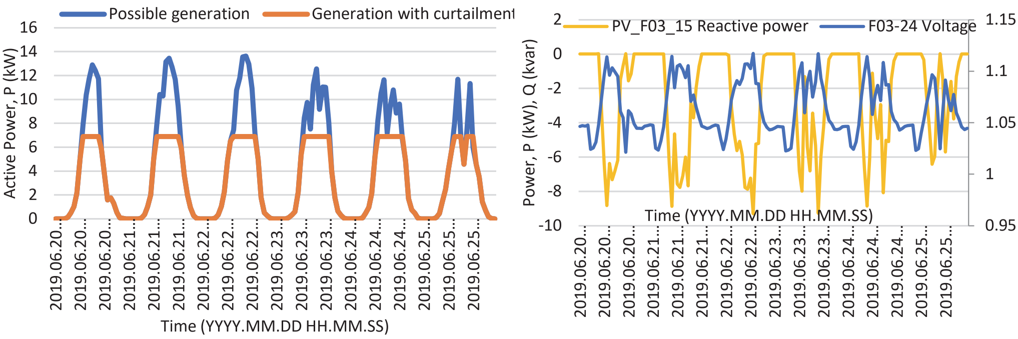

Fig. 2. (a) PV power curtailment (b) Reactive Power Control

3.3. Congestion Control with BESS

The inclusion of a residential BESS with the PV system may be a viable solution to overcome congestion. The main principle is to charge the BESS when PV is generating excessive energy and rather than injecting all the energy into the grid, a significant portion of that energy is stored in the BESS. Later, that energy can be used for domestic load or can be sold to the grid for monetary benefits. Therefore, this scheme can be feasible in terms of economic numbers compared to curtailment. The details of the heuristic BESS control algorithm are described in [5], [14], the flow chart of the algorithm is depicted in Fig. 2(a) and the results are given in Fig. 2 (b) for the load 15.

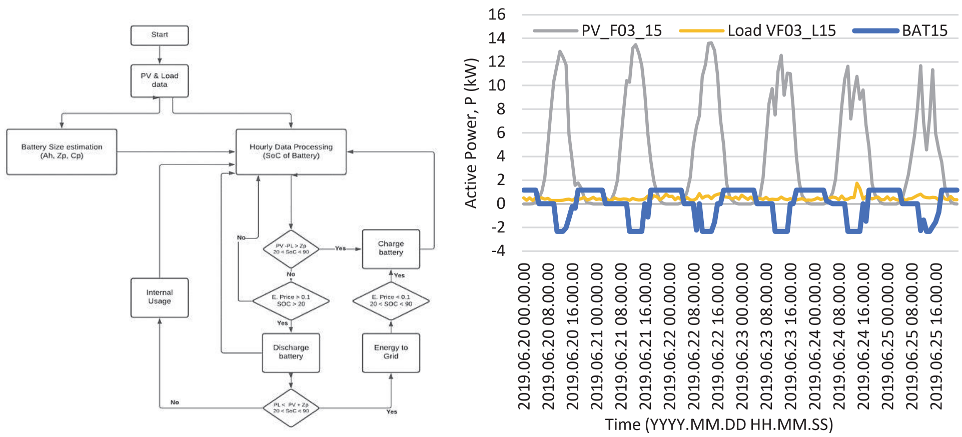

Fig. 3. (a) The flow chart of the BESS control algorithm (b) BESS control

4. Results & Discussions

The simulation results for the BESS profiles have been obtained using the heuristic algorithm implemented in Matlab. Meanwhile, the power flow analysis is carried out in DIgSilent Power Factory 2022. The results of the comparative analysis are shown in Table 2 presenting the total hour count for the whole year. The total number of hours in year are 8760. The results are presented with the main evaluation outcome for the overloading of the lines and the network supply transformer. The overvoltage implies the situation only when the endpoint voltage result is higher than 1.1 p.u. (nominal voltage) values as described by the CENELEC - EN 50160 standard [15]. The standard indicates that the voltage on any node in the distribution network must not be greater or less than 10% of the nominal values but not more than 10 mins. The comparative analysis also shows the number times in which any of the nodes had over voltage problem.

Table 2. Comparative analysis of all control strategies.

Condition	Number of times for all nodes	Number of hours	Max. value	Number of times for all nodes	Number of hours	Max. value
	Only PV (Initial Case)			PV + CURT. (6.9 kW)		
T VKS, overloaded	698	698	159	0	0	84
Lines, overloaded	1,618	556	159	0	0	84
Nodes, U>1.1 p.u.	15,919	1,187	1.2	14,334	1,212	1.14
	PV + BESS			PV + RPC + BESS		
T VKS, overloaded	170	170	134	891	891	191
Lines, overloaded	84	84	119	1,748	796	175
Nodes, U>1.1 p.u.	5,868	880	1.18	2	2	1.10
	PV CURT. (6.9 kW) + BESS			PV CURT. (10 kW) + RPC + BESS		
T VKS, overloaded	0	0	97	870	870	180
Lines, overloaded	0	0	92	1,065	575	170
Nodes, U>1.1 p.u.	1,539	360	1.14	0	0	1.10

The initial results indicate that the considered photovoltaic installations, operated without control, cause severe overloading and overvoltage on the distribution lines for 556 and 1187 hours in the year, respectively. The peak voltage value of 1.2 p.u violates the standard operating limits of the grid and it is entirely unacceptable to the operate the grid. This is a major concern as it can cause problems in the residential appliances of the customers.

The PV curtailment to 50% peak power eliminates the overloading but still, the overvoltage problem exists. The incorporation of BESS significantly lowers these numbers to 15% and 76% of the non-control values. In addition, the peak values are reduced as well. The combination of BESS and RPC reduces the overvoltage, only to remain for a span of 2 hours. However, the overloading of the lines and the transformer is increased, and the peak values are also higher. BESS plus curtailment of PV generation to 6.9 kW (50%) per user can reduce the overloading to zero, but the overvoltage is remaining for 360 hours.

5. Conclusions

Different options have been evaluated here to mitigate the congestion and overvoltage problems that can occur in the LV distribution network due to the excessive PV installations by residential customers. Reaching the installation power rating ceiling is more and more probable due to the encouragement by governments and environmental organizations. Reaching the hosting capacity limits is more likely when the customers have the liberty to install as much PV power as they desire and then connect it to the grid. At first glance, this is good for the environment and customers in terms of monetary benefits. However, this can create a serious problem in the electrical grid, and it can become difficult for the operator to keep the grid running within the limits defined in the standards. If the latter terms are violated, no one can access the grid for PV infeed in any case, dismissing the initial noble intentions.

Requiring customers to reduce or turn off their photovoltaic injection to the grid would need to meet the same service terms to all parties connected to the grid. Therefore, utilities would often prefer to upgrade and reinforce their distribution line in most scenarios. However, the full upgrade would also likely impose limitations and is costly. Therefore, in this study, some localized solutions for congestion control are proposed and their expected effects are discussed. For example, if some specific high-PV infeed customers would be needed to provide specific functionality in addition to the PV production capabilities, the utility could be leveraged from the most expensive upgrades. In such a case, the higher PV infeed capability would also mean greater responsibility for the customer.

The results indicate that the reduction in PV generation power alone is not a good solution to congestion control. The integration of BESS can drastically reduce this congestion drastically; however, it would not be sufficient to eliminate overvoltage problems to acceptable margins. However, in conjunction with voltage control and slight curtailment of the PV systems, the proposed algorithm shows much better results from the grid operation perspective together with the utilization ratio at 96%. The economic implication of these schemes can be explored further in future work.

Acknowledgments

This work was supported by Estonian Research Council grants PSG142, PRG675, PSG739, and European Commission through H2020 project Finest Twins grant No. 856602. The measurement data was taken from the project LEEEE20025.

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Publication II

Shabbir, N.; Kütt, L.; Astapov, V.; Jawad, M.; Allik, A; Husev, O. (2022). Battery Size Optimization with Customer PV Installations and Domestic Load Profile. IEEE Access, 10, 13012-13025.

IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

IEEE POWER & ENERGY SOCIETY SECTION

Received December 21, 2021, accepted January 16, 2022, date of publication January 31, 2022, date of current version February 4, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3147977

Battery Size Optimization With Customer PV Installations and Domestic Load Profile

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This work was supported by the Estonian Research Council under Grant PSG142, Grant PRG675, and Grant PSG739.

ABSTRACT Photovoltaic (PV) is a highly feasible solution for modern renewable energy-powered residential buildings in terms of deployment and cost reduction of utility bills. The installation of solar PV systems along with optimal battery energy storage systems (BESS) size is the most popular energy cost minimization solution and will continue to increase rapidly in the coming years considering the European Union (EU) framework for nearly zero energy buildings (nZEBs). The current methods lack BESS size optimization and a comprehensive solution to charge/discharge BESS from PV and the grid. The main goal is to be self-sufficient and sustainable while having minimal dependence on the electrical grid. Therefore, this paper presents an efficient energy management model and optimal size of the BESS as two key factors to effectively minimize the total energy consumption cost of the nZEBs while having a minimum dependence on the grid. The energy management system is developed using linear programming and solved using simplex and interior-point methods. In addition, a heuristic algorithm is presented to determine the optimized charging and discharging schedule for nZEBs. A detailed techno-economic analysis of the proposed system is conducted for the whole year (covering all four seasons summer, winter, spring, and autumn) considering three common residential building cases and three different electricity pricing methods. We determined that seasonal electricity pricing is the favorable and economical option to schedule charging and discharging of BESS from the grid in several terms such as, minimum total hours of grid usage, the maximum number of charging hours of BESS from the solar PV system, maximum BESS discharging hours to sell energy, the minimum number of BESS charging hours from the grid, maximum number of discharging hours for energy usage within nZEBs, maximum revenue earned, and peak electrical load reduction for the grid.

INDEX TERMS PV systems, battery management systems, energy storage, linear programming, economic analysis.

NOMENCLATURE

A. ABBREVIATIONS

BESS	Battery energy storage systems
CoE	Cost of energy
DoD	Depth of discharge
DR	Demand response
DSM	Demand side management
ER	Energy router
EU	European Union
Li-Ion	Lithium-Ion
LP	Linear programming
MILP	Mixed integer linear programming
MPC	Model predictive control
NMC	Nickel manganese cobalt oxide
NPC	Net present cost
nZEBs	Nearly zero energy buildings
PV	Photovoltaic
RES	Renewable energy sources
SoC	State of Charge

B. VARIABLES AND TERMS

η	Efficiency
n	Number of years

The associate editor coordinating the review of this manuscript and approving it for publication was Guangya Yang.

N	Number of days
$C_{bat}^{ch,u}$	Battery charging cost per unit
$C_{bat}^{dis,u}$	Battery discharging cost per unit
$C_{grid}^{pur,u}$	Per-unit energy purchase cost
$C_{grid}^{sell,u}$	Peer-unit energy selling cost
C_{PV}^{u}	Per-unit PV energy selling cost
C_{Bat}	Cost of battery
$C_{Inv./Unit}$	per-unit inverter cost
C_{PV}	Cost of PV
E_{BC}	Battery capacity [kWh]
E_{Day}	Average daily energy consumption [kWh]
E_{bat}^{ch}	Energy received to the battery [kWh]
E_{bat}^{dis}	Energy supplied from the battery [kWh]
E_{grid}^{sell}	Energy sold to the grid [kWh]
E_{grid}^{pur}	Energy purchased from the grid [kWh]
E_{L}	Electrical energy consumption [kWh]
E_{bat}^{max}	Max. energy from the battery [kWh]
E_{PV}	PV Generated Energy [kWh]
E_{PV}^{max}	Max. Energy from PV [kWh]
INV_{rated}	Rated inverter power [kW]
P_{rated}	Rated PV power [kW]
P_{z}	Maximum charging power [kW]

I. INTRODUCTION

Buildings account for nearly 40% of the global energy consumption, which accords them prominence in the energy market [1]. According to studies, about 36% of buildings in the European Union (EU) are older than 50 years and are energy inefficient [1], [2]. Therefore, the EU framework 2010/31/EU and its amended version 2018/844/EU defined the energy targets for 2050. As per this directive, all the newly constructed buildings in the EU after 2020 must be nearly zero-energy buildings (nZEBs) [3]. These buildings will be powered through renewable energy sources (RES) while having a minimal dependency on the grid [4]. Therefore, the accumulated sum of energy consumption in the buildings will need be near zero. However, RES at the grid-scale for nZEBs requires efficient and smart energy management systems, including photovoltaic (PV) systems, battery energy storage systems (BESS), and power electronics equipment [5]–[7].

The optimal energy management in nZEBs designs has been the subject of a substantial amount of research work. In [8], the authors proposed a technique for optimal energy management and better air quality within the building. In another study, efficient energy usage employing demand response (DR) and demand-side management (DSM) are elaborated and implemented in smart buildings [9]. Although the aforementioned methods are effective to a certain level, they were lacking to address the problem of load shifting concerning consumers' behavior. Therefore, in [10], the authors solved this problem using an efficient energy management system using RES for optimal self-consumption. As electricity is a major component in the energy consumption share of any building; therefore, a comprehensive energy management model is required to control and manage the energy to certain levels required for nZEBs [11], [12]. A comprehensive energy management system must include a detailed energy usage strategy, sufficient RES availability, and optimal battery storage size. Furthermore, a robust control algorithm to manage battery charging and charging while minimizing dependence on the grid and maintaining an accumulated annual energy level near zero [13]–[15].

In [16], linear programming (LP) algorithm was developed for a photovoltaic-based energy management system to minimize peak electrical load. The forecasted PV and load data were used in the development of this algorithm. In [17], the authors further improved the performance of the proposed model given in [18] by improving the accuracy of the forecasted data. Another probabilistic method for efficient energy scheduling is proposed to reduce the cost of energy consumption [19]. A new LP algorithm was proposed to predict the usage schedule of electrical appliances while integrating electricity price, BESS, and RES to develop an energy management model [20]. The authors used the model predictive control (MPC) technique for the grid, RES, diesel generator, and BESS of an electric vehicle. In [19], the authors used both heuristic techniques and optimization methods to minimize the peak load of the grid. LP and Markov chain models were used to charge and discharge the battery. In [21], the LP algorithm was also used to optimize energy and cost management of energy generated from mixed sources, such as solar, gas generator, and batteries.

The Monte Carlo method was used to determine uncertainties in solar irradiance data for the BESS [22]. In [23], a Swiss study used a genetic algorithm to optimize the operation of a BESS for a residential building. Residential BESS was made economically viable by using a self-sufficient photovoltaic system and a load shifting technique at the dynamic energy price of the grid. The techno-economic analysis of a grid-connected solar PV-based system including BESS was presented in [24]. A learning-based optimization algorithm was used to minimize the net present cost (NPC) and cost of energy (CoE), the proposed technique was claimed to be 15.6% and 16.8% more efficient compared to the particle swarm and the genetic algorithm, respectively. A study on off-grid BESS optimization was conducted in the U.S. for two different residential locations [25]. The mixed-integer programming method was used to preschedule the load and forecast the energy from solar PV using solar irradiance. In another study, the cost and size of the BESS are optimized using the heuristic method and stochastic gradient for a campus area in Turkey. Both PV and wind were used as RES with large battery banks, these results of energy generation were initially optimized in a previous study by the same authors [26]. The economic analysis of a grid-connected PV system for residential users is also given in [27]. The authors also calculated the initial investment and the payback period.

All the above-mentioned studies indicate that there is a wide variety of algorithms for energy dispatch and management in residential buildings to minimize the cost of energy consumption. The energy generation system can contain a grid-connected PV and a BESS. However, to achieve the goal of nZEBs, the methods are still lacking the optimized size and capacity of BESS and the charging/discharging of available energy storage for internal usage or selling to the grid and making it economically viable. To address this challenging problem, the possible complexities are system designing, control, and stochasticity in energy generation. Moreover, if forecast data for electrical load and energy are used, there is always the possibility of forecasting errors.

This study is part of an energy router (ER) based building energy management system. The details of energy ER are given in [28]. Taking into account aforementioned conditions, the focus of this study is to optimize the size of the BESS and design an efficient control algorithm to minimize grid dependency and develop a self-sustained energy management model for nZEBs. The main contributions of the paper are:

- A battery size estimation method is presented for grid-connected BESS. To estimate the optimized size of the BESS and the feasible rated PV system for different residential buildings, the three most common cases of residential buildings are considered, such as a small flat/apartment, a medium-size residential home, and a residential apartment building.
- A heuristic-based algorithm is developed for optimized battery charging and discharging technique. The algorithm incorporates real-time data traces of residential load, PV energy generation, and electricity prices from the Estonian energy market. The algorithm is designed to minimize the usage of energy from the grid and to make the whole system self-sustained and self-sufficient. Moreover, the heuristics algorithm is tested for three battery bank charging scenarios from the grid: (a) price not applicable, (b) fix price, and (c) seasonal price.
- A linear and convex model is developed for the energy consumption cost minimization problem for the nZEBs. The model is solved using a simplex algorithm and the interior point method.
- A detailed techno-economic analysis of the proposed methodology is conducted to determine the feasibility of the proposed system. The analysis is carried out under different variations, such as different load cases, different BESS charging threshold prices, and BESS sizes.

The rest of the paper is structured as follows: Section 2 describes the data profiles that include the details of residential load cases, PV generation scenarios, and the energy market prices in Estonia. Section 3 discusses the estimation of battery size, battery charging/discharging algorithm, and the optimization algorithm for the total energy consumption cost of the nZEBs. Section 4 presents a detailed economic analysis of the proposed method for the three electrical load cases. Section 5 discusses the results of the study along with a detailed comparison with previous similar studies. The paper is concluded in Section 6 along with future research directions.

II. DATA PROFILES

This section presents a detailed description of the real-time residential electrical load dataset and real-time solar power generation profiles for three different rated solar PV systems.

A. LOAD PROFILE

In this study, the real-time residential electrical load data from the Estonian low-distribution network is used. The data was measured and collected in a rural county in Estonia for a whole year with a frequency of one hour. The schematic of the grid is shown in Figure 1. This grid segment has 8 residential loads and 3 auxiliary loads like lighting, pumping station and heat station. In the study, three different residential electrical load cases are under consideration: (a) case 1 (load 1): a small flat/apartment with a limited number of appliances and having an overall low load, (b) case 2 (load 3): a residential house, and (c) case 3 (load 7): a residential apartment building. Table 1 enlists the statistical details for the aforementioned three cases. From the collected data profile, it is illustrated that the average electrical load for a small apartment is 0.08 kW, 0.76 kW for a residential household, and 11.9 kW for the whole apartment building. The accumulated yearly power consumption for all these cases is also presented in Table 1.

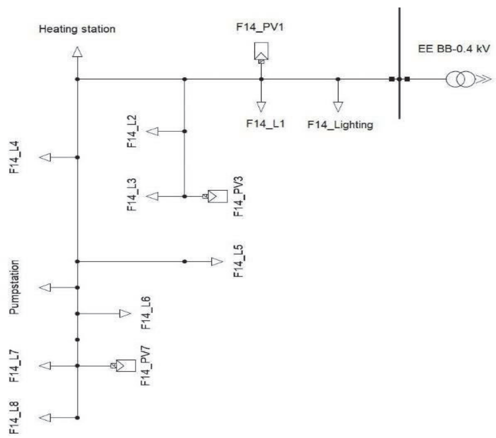

FIGURE 1. Schematic diagram of the distribution grid.

The hourly electrical load for all three cases is depicted in figure 2. It is observed from Figure 2 (a) that in an hour, the electrical load for case 1 rarely goes above 1 kW. There are only seven instants in a whole year when the power consumption surpasses 1 kW. Similarly, for Case 2, the peak load (hourly average) is around 6 kW and it only happened twice a year.

TABLE 1. Load profile for three different residential electrical load cases.

	Case 1	Case 2	Case 3
Average load (kW)	0.08	0.76	11.9
Peak load (kW)	1.95	6	36.7
Median load (kW)	0.05	0.48	11.1
Annual energy consumption (kWh)	740	6640	103860
Rated PV power (kW)	5	10	20

TABLE 2. Load profiles for three cases with PV installation.

	Case 1	Case 2	Case 3
Total Accumulated Energy (kWh)	-5265	-5133	80074
No. of Hours of energy utilization from the grid	4989	6037	7163
No. of Hours of energy injection the grid	3776	2723	1597
Peak power drawn from the Grid (kW)	1.95	6	36.7
Peak power injected into Grid (kW)	4.5	9.8	15.3

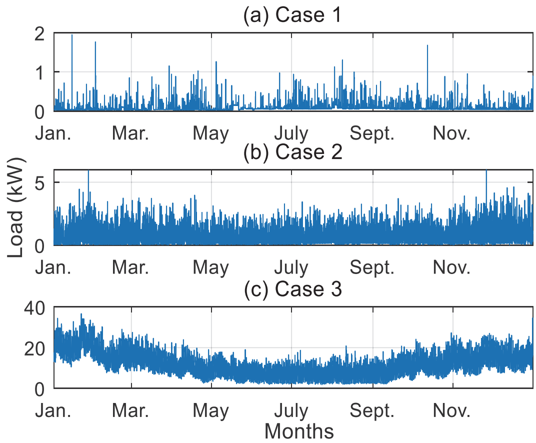

FIGURE 2. Yearly power usage for all three cases.

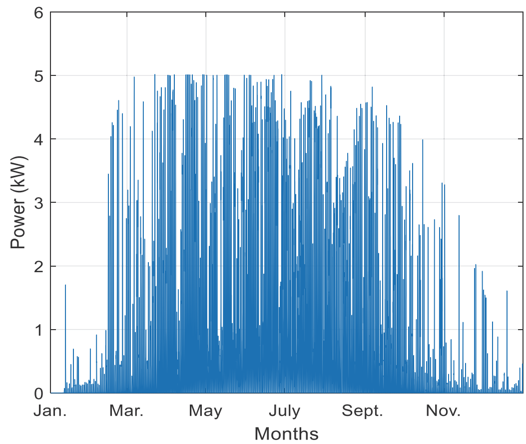

FIGURE 3. Solar power generation throughout the year.

However, the average electrical load is around 0.76 kW is considerably low compared to the peak load. As case 3 represents the energy consumption for a whole residential building; therefore, a seasonal trend of electrical load is clearly visible in Figure 1(c), which is low in summers (May-August) and high in winters (November - March) due to the heating load, and due to this fact, the peak load occurs in winter.

B. PV PROFILE

Estonia lies in the northeastern part of the EU and this region, the sunlight per day in summers is on average 16-18 hours while in winters it reduces to on average 4-6 hours in a day. Moreover, in Estonia, the solar irradiance intensity is nearly the same across the country. Therefore, solar power generation from PV installations in any part of Estonia does not have a significant variation in output. However, it is still highly dependent on the weather conditions. The solar PV systems proposed in this study are 5 kW, 10 kW, and 20 kW for case 1, case 2, and Case 3, respectively as mentioned in Table 2 [27]. The solar power output for a 5 kW PV system is shown in Figure 3.

From figure 2, it is evident that solar energy generation is high from March to September and low in the other months. The accumulated energy with solar PV installation and the respective residential electrical load is shown in figure 4. From March to September, solar energy generation is mainly greater while the electrical load is on the lower side; therefore, the overall energy is in surplus and can be sold to the grid. The maximum energy that can be sold to the grid is 4.5 kW, 9.6 kW and 15.2 kW, respectively, for the three load cases discussed in Table 1.

In case 1 and case 2, with the installation of the roof-top PV system, the dependency on the grid has fallen significantly in terms of the number of hours throughout the year. Throughout the year, the accumulated energy generated by the solar PV system is accessible compared to the electrical load required, as shown in Table 13. However, for case 3, the grid dependency still exists as the electrical load is higher compared to the installed PV system. Therefore, a larger rated PV system is required for case 3 and reduces the accumulated energy requirement from the grid by 22%, which is significant in terms of economics as the energy bill is substantially reduced.

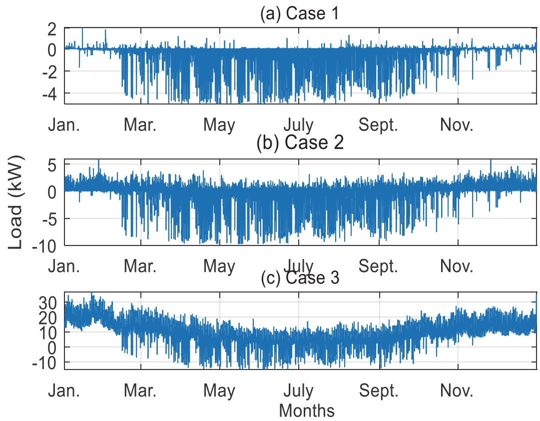

FIGURE 4. Energy usage with solar PV installations.

A more detailed economic analysis of the cases is given in section 4.

III. BATTERY ENERGY STORAGE SYSTEM (BESS)

In recent years, battery storage technologies have seen rapid growth for the applications, such as PV-based storage systems, portable devices, industry, and electrical vehicles [29]. The most commonly used batteries are Lithium-Ion (Li-ion) batteries and nickel manganese cobalt oxide (NMC) batteries [3]. Over the years, due to advanced technological developments and bulk generation, the cost of batteries has been significantly reduced [30]. An estimated cost of battery per kWh is around 100 € [31]. However, the life cycle and limited usage cycle still required significant improvements. It is expected that in the coming years, with the advancement in technology new batteries will be available having a life cycle of around 20 years [32].

Currently, most of the BESS installed with solar PV systems have Li-ion batteries for residential buildings. They are preferred due to their lack of maintenance requirements, compact size, and higher efficiency of more than 85% [33]. However, the practical life of these batteries is around 5 years due to the limited number of charge/recharge cycles [34]. Due to this fact, it is challenging in terms of economic viability as the payback period of a Li-Ion battery cannot be compensated for in 5 years [35]. Therefore, the installation of PV-based BESS is usually supported by the government in Estonia in terms of subsidy and reduced tariffs [36], [37]. However, optimal battery size calculation is still needed to further minimize operational costs.

A. BATTERY SIZE CALCULATION

The battery size calculation involves many important parameters, such as total energy used in a day, number of days for which the backup from the battery is required, the nominal voltage of the battery and the battery efficiency. The following Eqn. (1) is used to calculate the battery capacity [29]:

$$E_{BC} = \frac{E_{Day}}{\eta * DoD * 1000} * N \tag{1}$$

Here, E_{BC} represents the battery capacity is kWh, η is the battery efficiency, N is the number of autonomous days for which the battery operation is required, DoD is the depth of discharge for the battery, and E_{Day} is the average daily energy used. The battery size is usually calculated against the peak load in a single day. However, as the peak load happens only a few times during a year, the calculations for the battery capacity can be made using the average load in a day or median load value. Among the most important parameters in BESS is the state of charge (SoC) of the battery. The SoC indicates how much energy is stored in the battery. The SoC is computed using Eqn. (2) [29]:

$$SoC_{n+1} = SoC_n + \frac{\eta * P_z * K_p * st}{E_{BC}} \tag{2}$$

where n represents the number of states, st is the sampling interval, K_p indicates the online and offline status (typically 0 or 1), and E_z is the charging power in kW. The parameters P_z is calculated as [29]:

$$P_z = \frac{BC * V * 0.15}{\eta} \tag{3}$$

The proposed heuristic algorithm for battery charging and discharging is evaluated on hourly real-time data traces of electrical load and energy generation from the corresponding rated PV system. The estimated battery sizes and the parameters for all three cases described in table 1 are given in table 3.

TABLE 3. Parameters for the BESS.

	Case 1	Case 2	Case 3
E_{BC} (kWh)	4	33	518
P_z (kW)	0.57	5.4	86.3
Efficiency (η)		90%	
DoD		0.6	
Initial SoC		50%	

B. HEURISTIC ALGORITHM FOR BATTERY CHARGING AND DISCHARGING

If the energy generation from the solar PV system is greater than the electrical load, then the battery will be charged. Moreover, if the load is greater than the solar PV energy generation, then the battery will be discharged to compensate for the difference between solar PV energy and excessive electrical load. In the second scenario, if the battery is charged to a certain level and still the solar PV energy generation is greater than the electrical load, then the extra energy will be sold to the grid at a predefined cost. Similarly, the battery can be charged from the grid if the electricity price is below a certain threshold value. Furthermore, if the electricity price is greater than another defined threshold value, then the energy stored in the BESS can be sold to the grid. A detailed description of the heuristic algorithm is given in table 4.

TABLE 4. The proposed algorithm.

Algorithm: proposed battery charging & discharging

Input: Load data, PV data, electricity price

1. Calculate battery E_{BC}, E_z
2. $SoC_{max} = 0.9$ and $SoC_{min} = 0.2$
3. **While (n < 8761)**
   %n is the number of hour
4. **If** PV > Load and 0.2 > SoC (n) > SoC_{max} then charge battery (But not above SoC_{max})
5. Calculate SoC (n+1) and P_{Bat} (n)
6. a = a +1
   %no. of charging hours with PV
7. **else if** Load > PV and SoC_{min} > SoC (n) > SoC_{max} then discharge battery (But not below SoC_{min})
8. Calculate SoC (n+1) and P_{Bat} (n)
9. b = b + 1
   %no. of discharging hours for internal use
10. **else if** Electricity Price < threshold value and SoC(n) < 0.5 then Charge battery from the grid (But not above SoC_{max})
11. Calculate new SoC (n+1) and P_{Bat} (n)
12. c = c +1
    %no. of charging hours with Grid
13. **else if** Electricity Price > threshold value and SoC(n) > 0.4 then discharge battery to the grid (But not below SoC_{min})
14. Calculate SoC (n+1) and P_{Bat} (n)
15. d = d +1
    %no. of discharging hours to the grid
16. **else**
17. SoC (n+1) = SoC (n)
18. P_{Bat} (n) = 0
19. **end if**
20. n = n +1
21. **end while**

C. LINEAR PROGRAMMING (FOR ENERGY COST OPTIMIZATION)

The electricity pricing threshold selection for the charging of BESS from the grid and utilization of BESS for grid support is a tricky problem. In the Estonian energy market, the real-time electricity price dynamically changes every hour. Estonia is a member of the Nord pool which is a European power market consisting of 16 countries with 360 companies that trade in the power market [38]. Therefore, the electricity price depends on factors season, availability of RES, demand, and supply thus there are many variations in the electricity price. The real-time electricity price for Estonia in 2020 is shown in figure 5, which clearly illustrates the dynamic behavior of the energy market. In figure 5, the peak value for electricity is 0.25 €/kWh and the lowest value is 0.001 €/kWh. However, the average price range throughout the year is 0.05 €/kWh [38].

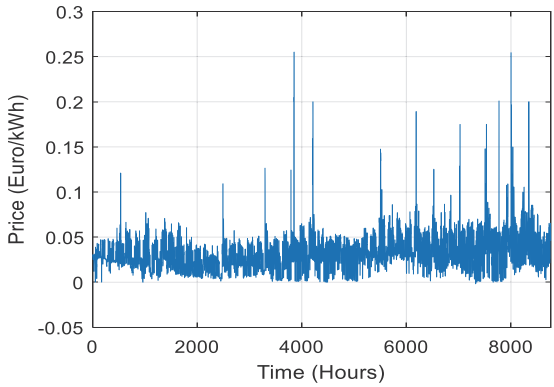

FIGURE 5. Electricity prices Nord Pool (Estonia) in 2020.

Therefore, by keeping in view, the dynamic electricity pricing, battery charging and discharging heuristics, solar power generation, energy purchase from and sell to the grid, and dynamic nature of energy consumption within the nZEBs, an LP model is developed to minimize the total energy consumption cost for the nZEBs. Moreover, the algorithm also decides the optimized value of electricity for charging the battery from the grid and discharging the battery to the grid. However, as a reliability constraint, battery cannot be charged more than 90% and discharged less than 20%. The battery management constraints are defined in such a way that minimizes the utilization of energy from the grid both for residential load and battery charging while utilizing a maximum of solar PV energy. Batteries are charged when the electricity price is low. The excess energy in BESS is only sold to the grid when the electricity price is high to make this system economically viable.

The following linear and convex optimization function is defined to minimize the net energy consumption cost for any nZEBs considering the installed PV system, BESS, and the electricity price constraints. The optimization problem is defined as:

$$\begin{aligned} Minimize\, f = \sum\nolimits_{t=1}^{N} \Big\{ & C_{grid}^{pur,u}(t) * \hat{E}_{grid}^{pur}(t) + C_{grid}^{sell,u}(t) \\ & * \hat{E}_{grid}^{sell}(t) + C_{bat}^{ch,u}(t) * \hat{E}_{bat}^{ch}(t) + C_{bat}^{dis,u}(t) \\ & * \hat{E}_{bat}^{dis}(t) + C_{PV}^{u}(t) * \hat{E}_{PV}(t) \Big\} \end{aligned} \tag{4}$$

$$\text{Subject to } E_{grid}^{pur}(t) - E_{grid}^{sell}(t) - E_{bat}^{ch}(t) + E_{bat}^{dis}(t) + E_{PV}(t) = E_L(t) \tag{5}$$

$$-E_{bat}^{ch}(t) + E_{bat}^{dis}(t) \le E_L(t) \tag{6}$$

$$E_{grid}^{pur}(t) - E_{grid}^{sell}(t) \le E_L(t) \tag{7}$$

$$-E_{bat}^{ch}(t) + E_{bat}^{dis}(t) \le E_{bat}^{max}(t) \tag{8}$$

$$E_{bat}^{ch}(t) - E_{bat}^{dis}(t) \le E_{bat}^{max}(t) \tag{9}$$

$$-E_{grid}^{pur}(t) \leq 0 \quad (10)$$
$$-E_{grid}^{sell}(t) \leq 0 \quad (11)$$
$$-E_{bat}^{ch}(t) \leq 0 \quad (12)$$
$$-E_{bat}^{dis}(t) \leq 0 \quad (13)$$
$$-E_{PV}(t) \leq 0 \quad (14)$$
$$E_{PV}(t) \leq E_{PV}^{max}(t) \quad (15)$$

where f is the objective function to be minimized that is defined in the standard minimization form having equality constraints, inequality constraints (all are in the form of less than equal to) and bounds of the problem. Moreover, in the aforementioned mathematical formulation t is the time interval [in an hour], $E_{grid}^{pur}(t)$ and $E_{grid}^{sell}(t)$ are electrical energy purchased from and sold to the grid [kWh], respectively; the E_{bat}^{ch} and E_{bat}^{dis} are the electrical energy supply to and received from the battery bank [kWh], respectively; the E_{PV} is the electrical energy supply by the installed PV system [kWh]; E_{PV}^{max} is the maximum electrical energy that can be taken from the PV system [kWh]; E_L is the electrical energy consumption of the nZEB [kWh]; E_{bat}^{max} is the maximum energy that can be taken from the battery bank [kWh]; N is the total number of hours in one year [8760]; $C_{grid}^{pur,u}(t)$ is the per-unit electrical energy purchasing cost from the grid [cents/ kWh]; $C_{grid}^{sell,u}$ is the per-unit electrical energy sell cost to the grid [cents/kWh]; $C_{bat}^{ch,u}$ is the per-unit BESS charging cost [cents/kWh]; $C_{bat}^{dis,u}$ is the per-unit BESS discharging cost [cents/ kWh]; $C_{PV}^{u}(t)$ is the per-unit cost incurred from the PV system [cents/kWh]. The "hat" symbol used with the electrical energies in the optimization cost function denotes the normalized values of the variables. The general formula used for the normalization process is:

$$X_{new} = \frac{X - X_{mean}}{X_{max} - X_{min}} \quad (16)$$

where the $X_{min} = 0\ kWh$ for every electrical energy.

The linear programming problem defined in Eqn. (4) is solved using the simplex algorithm and interior point method. Equation (5) is the equality constraint that represents the energy balance between the energy sources (such as grid, solar PV system, and battery bank) and the electrical load of nZEBs. Equation (5) clearly indicates that the energy imbalance between the electrical load of nZEBs and the power generation of the solar PV system is maintained using the energy purchased/sold from the grid and the charging/storage of the battery bank. However, this decision is made by the linear programming algorithm. Moreover, Eqn. (6) – Eqn. (9) are the inequality constraints and from Eqn. (10) to Eqn. (15), the bounds of the variables are defined.

The BESS charging is under consideration in three different electricity pricing scenarios from the grid: (a) price not applicable, (b) fixed price, and (c) seasonal price. In the price not applicable scenario, we eliminate the option of BESS charging from the grid at any offered cost by the grid. Equation (7) will ensure that the battery will never charge from the grid. In fixed price scenario, we have the option to charge BESS from the grid provided the electricity cost is less than a certain defined threshold field for the whole year. In the seasonal price scenario, the electricity cost threshold for BESS charging varies seasonally. Therefore, in the second and third cases the equality constraints of Eqn. (7) are ignored.

IV. RESULTS & DISCUSSIONS

This section presents the technical and economic impact of BESS charging and discharging heuristic algorithm under three different electricity pricing scenarios from the grid, such as (a) price not applicable, (b) fix price, and (c) seasonal price. Moreover, energy cost minimization model-based economic analysis results are also discussed in detail. The implementation and simulation of the proposed algorithms are carried out in MATLAB running on an Intel Core i7-9700 CPU with 64 GB RAM.

A. TECHNO-ECONOMIC ANALYSIS OF BESS CHARGING AND DISCHARGING

The first scenario includes no BESS charging from the grid at all; however, the BESS can be discharged to empower the grid, when the electricity cost is higher than 0.1 €/kWh (one of the highest costs, 90 percentile). The only viable option for BESS charging is from available PV energy. For the second scenario, the BESS can be charged both from the grid and PV system. However, the PV is the preferred source for BESS charging while the battery can be charged from the grid only if the electricity price is less than 0.01 €/kWh (one of the lowest values). This price threshold is low compared to the average electricity price, which is around 0.03 €/kWh during the year. Battery energy can also be sold to the grid if the price is greater than or equal to 0.06 €/kWh. The price threshold is computed using the LP algorithm. These values were initially obtained from the hit and trial method and later verified with the LP algorithm, as they showed the same results.

For the third scenario, the prices for battery charging/discharging from/to the grid are varied on a seasonal basis. These values of charging/discharging prices are again obtained from the LP method. The battery charging prices from the grid is less than 0.033 €/kWh, 0.024 €/kWh, 0.03 €/kWh and 0.038 €/kWh for winter, spring, summer, and autumn, respectively. Similarly, energy is sold to the BESS grid when prices are higher than 0.061 €/kWh, 0.058 €/kWh, 0.065 €/kWh, and 0.072 €/kWh for winter, spring, summer, and autumn, respectively. The electricity prices for purchasing and selling have a difference of around 3 cents, which provides a significant margin for the nZEBs to minimize total energy consumption cost. Moreover, we computed the SoC for BESS for all three pricing scenarios and plotted them in figure 6. In Figure 6, it is evident that SoC is on the lower side in winters and high in summers because in considered region (Estonia), total energy consumption increases in winters due to the heating and lighting load along with increased BESS utilization. Moreover, in Figure 6(c), the variations in SoC are observed to be more compared to

TABLE 5. A detailed analysis of BESS charging for three pricing scenarios from the grid for one year.

	Season	No Grid charging	Grid charging on fixed price	Grid charging on seasonal price
Battery Size (%)	-	100	100	100
j (hours)	-	4752	4701	4627
a (hours)	-	3163	3162	3131
b (hours)	-	293	351	433
c (hours)	-	0	83	179
d (hours)	-	3330	3618	3984
Revenue earned (€)	-	213.4	217	219.4
Peak power drawn from the grid (kW)	Winter	1.95	1.95	2.84
	Spring	0.80	1.34	1.86
	Summer	0.85	0.85	1.19
	Autumn	0.39	0.66	1.33
Peak power injected into the grid (kW)	Winter	0.95	0.95	1.40
	Spring	4.98	4.98	4.98
	Summer	4.96	4.96	4.96
	Autumn	4.76	4.76	4.76

Terms: a = no. of charging hours from PV, b = no. of discharging hours to grid, c = no. of charging hours from the grid, d = no. of discharging hours for internal usage, j = no. of total hours of grid usage

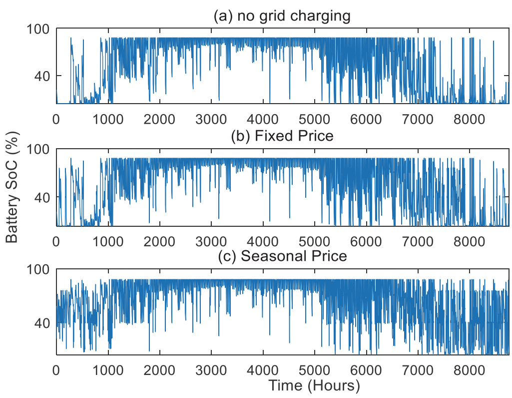

FIGURE 6. SoC of battery for entire year under three pricing scenarios.

the other two, as the battery is charged and discharged more times showing active status. Furthermore, there are not many intervals where there is a stagnant line showing no activity. Therefore, to compute the optimal economic impact of BESS, a detailed analysis is conducted and tabulated in Table 4 in terms of the number of hours of utilization, payback period, and peak power drawn and injected into the grid.

In table 5, for the calculated optimal BESS size, the total hours of grid usage are more for the price, not applicable scenarios compared to the other two pricing scenarios when we opt not to charge BESS from the grid because the energy is coming from a European market and the price can be high. Similarly, the total number of BESS charging hours from the solar PV system is greater for the first two scenarios compared to the seasonal pricing scenario. Moreover, the number of discharging hours of BESS for selling energy to the grid is more for the seasonal pricing scenario while the number of charging hours of BESS from the grid is also high for the seasonal pricing scenario due to low and feasible seasonal electricity cost offered for BESS charging and discharging.

Furthermore, the number of discharging hours of BESS for energy usage within the nZEBs is also on the higher side for the seasonal pricing scenario. Additionally, we computed the total revenue earned for the nZEBs under all three pricing scenarios and illustrate that the seasonal pricing scenario is the most viable option. We concluded that offering seasonal lower pricing for BESS charging from the grid and high pricing for BESS discharging to the grid is financially viable for BESS. However, the dependency of BESS on the grid also increases, which is indicated by the high peak load values from/ to the grid. Therefore, a tradeoff exists to optimize this challenge.

In a similar manner as illustrated in Table 5, to study the impact of increase and decrease in BESS size, we independently varied the BESS size from 10% of the proposed optimal value to 500% of the proposed value. Here, the size 100% indicates the theoretical battery size calculated using Eqn. (1). This variation in BESS size is tested for the three

TABLE 6. BESS size variation impact for case 1 (small flat/apartment).

Battery size (%)	j (hour)	a (hours)	b (hours)	c (hours)	d (hours)	Peak Power drawn from grid (kW)				Peak power injected into the grid (kW)			
						Wt.	Sp.	Sum.	Aut.	Wt.	Sp.	Sum.	Aut.
10	3429	3330	355	628	2274	1.95	0.99	1.26	0.94	0.95	4.98	4.96	4.76
25	2121	3482	401	374	3130	1.95	0.99	1.26	0.88	0.95	4.98	4.96	4.76
50	1605	3372	420	252	3615	1.95	1.32	1.26	0.79	0.95	4.98	4.96	4.76
75	1485	3257	429	211	3800	2.57	1.59	1.26	1.06	1.13	4.98	4.96	4.76
90	1447	3179	438	190	3886	2.73	1.75	1.08	1.22	1.29	4.98	4.96	4.76
100	1391	3131	433	179	3984	2.84	1.86	1.19	1.33	1.40	4.98	4.96	4.76
110	1271	3151	435	168	4071	2.84	1.86	1.19	1.33	1.40	4.98	4.96	4.76
120	1187	3163	441	162	4131	2.84	1.86	1.19	1.33	1.40	4.98	4.96	4.76
130	1185	3163	460	166	4118	2.84	1.86	1.19	1.33	1.40	4.98	4.96	4.76
150	1127	3173	460	148	4148	2.84	1.86	1.19	1.33	1.40	4.98	4.96	4.76
175	1089	3178	477	146	4162	2.84	1.89	1.14	1.33	1.40	4.98	4.96	4.76
200	1035	3188	500	152	4189	2.15	1.89	1.14	1.33	1.40	4.98	4.96	4.76
300	932	3204	526	143	4241	2.84	0.05	1.14	1.33	1.40	4.98	4.96	4.76
400	879	3205	548	147	4275	2.84	0.05	0.31	1.33	1.40	4.98	4.96	4.76
500	840	3206	580	157	4291	2.84	0.05	0.31	1.33	1.40	4.98	4.96	4.76

load cases, small apartment, residential house and residential building, as discussed in section 2.1. The results of the BESS variations for case 1, case 2, and case 3 are discussed in tables 6, 7 and 8, respectively.

From these tables, it is concluded that with increasing battery size, the value of 'j' decreases, indicating a lower dependency on the grid in the three cases. In addition, the value of 'd' increases which shows that the battery is now used more for internal usage. The number of charging hours 'a' shows a straight line around 110% for cases 1 and 2. Moreover, the battery discharging hours to grid 'b' also shows the lowest value before starting to increase again. This represents the optimal battery, and it also gives optimal values for other parameters as well. As the battery size is increased further, it may give good numbers, but affect the economic aspects badly.

B. ECONOMIC ANALYSIS

Considering Vision 2030, the concept of nZEBs is growing rapidly across the EU. Therefore, a detailed economic analysis of the installed energy management system of nZEBs is mandatory from a business perspective. If the energy management system is financially viable, it may encourage other building operators to convert conventional residential buildings and homes as nZEBs. Therefore, we separately evaluate and discuss the PV-based BESS designs for all three load cases. The economic analysis for a PV-based BESS requires considering several parameters that are sequentially discussed in this section. First, the initial investment cost, C_{PV} for the solar PV system is computed using Eqn. (17) [14]:

$$C_{PV} = C_{PV}^{u}(t) * P_{rated} * \frac{i(1+i)^n}{(1+i)^n - 1} \tag{17}$$

where $C_{PV}^{u}(t)$ is the per-unit cost incurred by the solar PV system, P_{rated} is the rated power, n is the lifetime of PV system in years, and $\frac{i(1+i)^n}{(1+i)^n-1}$ is the present cost compared to the annual investment. Similarly, the initial investment cost of the BESS system is calculated as [14]:

$$C_{Bat} = \left(C_{bat}^{ch,u}(t) * E_{BC} + C_{Inv/Unit} * P_{rated}\right) \frac{i(1+i)^n}{(1+i)^n - 1} \tag{18}$$

where $C_{bat}^{ch,u}(t)$ is the per-unit cost of BESS charging, $C_{Inv./Unit}$ is the inverter cost per unit, P_{rated} is the rated power of the inverter, n is the lifetime of the battery in years, and $\frac{i(1+i)^n}{(1+i)^n-1}$ is the present cost compared to the annual investment. Moreover, considering every available energy source to balance the electrical load of nZEBs, the energy balance equation for nZEBs is computed using Eqn. (5). Furthermore, the first two terms of Eqn. (4) are used to calculate the energy purchasing and energy selling prices to the grid, respectively.

In the Estonian electricity market price of electricity is dynamically changing every hour. Therefore, the sampling time considered in this study is taken as 1 hour. The current price of a battery in Estonian is around 100 €/kWh whereas

TABLE 7. Impact of BESS size variation for case 2 (residential house).

Battery size (%)	j (hour)	a (hours)	b (hours)	c (hours)	d (hours)	Peak power drawn from grid (kW)				Peak power injected into the grid (kW)			
						Wt.	Sp.	Sum.	Aut.	Wt.	Sp.	Sum.	Aut.
10	3863	2438	428	1541	1912	5.95	3.92	3.21	3.44	5.74	9.75	9.71	9.14
25	3016	2674	346	1087	2964	5.95	3.29	3.37	3.44	5.79	9.75	9.71	9.14
50	2947	1766	238	302	4111	5.95	2.59	3.62	2.67	5.79	9.75	9.71	9.14
75	2725	1842	281	298	4210	5.95	2.46	1.80	2.53	5.79	9.75	9.71	9.14
90	2588	1861	292	313	4332	5.95	2.38	1.73	2.53	5.79	9.75	9.71	9.14
100	2482	1880	313	337	4422	5.95	2.42	1.68	2.53	5.79	9.75	9.71	9.14
110	2425	1887	316	346	4478	5.95	2.42	1.68	2.53	5.79	9.75	9.71	9.14
120	2329	1904	313	341	4555	5.95	2.33	1.68	2.53	5.25	9.75	9.71	9.14
130	2303	1905	318	344	4578	5.95	2.33	1.68	2.24	5.79	9.75	9.71	9.14
150	2232	1915	345	370	4638	5.95	2.33	1.68	2.24	5.28	9.75	9.71	9.14
175	2136	1932	354	377	4715	5.95	2.33	1.68	2.02	5.28	9.75	9.71	9.14
200	2086	1942	373	393	4752	5.95	2.33	1.68	1.98	5.28	9.75	9.71	9.14
300	2012	1970	417	424	4785	5.95	2.33	1.68	1.98	5.28	9.75	9.71	9.14
400	1936	1990	443	443	4834	5.95	2.33	1.68	1.98	5.25	9.75	9.71	9.14
500	1912	1995	473	466	4846	5.95	2.33	1.68	1.98	5.25	9.75	9.71	9.14

the price of the PV system is around 0.4 €/W [3], [39]. Table 9 shows the economic analysis of all three load cases with PV installation and without the BESS. With the installation of the PV system, the dependence on the grid is significantly reduced in all three load cases. For case 1 and case 2, the energy purchase from the grid is zero for the whole year, instead, the energy is in excess for a certain number of hours and sold to the grid. However, in case 3, the electricity bill is not zero but has been reduced by very significant, nearly 65% margin. In case 3, the average and peak loads are 11.9 kW and 36.7 kW, respectively.

The BESS price for the under-discussion three load cases is taken as 400 €, 3300 € and 51800 €, respectively depending on their optimal BESS size calculation. Table 10 shows the net cost of energy with the different BESS sizes for the three load cases. The net price of energy usage is negative for both case 1 and case 2, indicating that the energy was surplus compared to the load requirements and was sold to the grid. In addition, there is a direct relationship between the BESS size and the net cost of energy. However, case 3 is presenting a different scenario. The net energy price is still positive, which means that the energy is still being used excessively from the grid. This is because the BESS is designed with respect to the high value of the load. The installed PV capacity for this system is low and it must compensate for the load and charge the BESS. Therefore, in most hours, after electrical load compensation, very little energy is available for the BESS to be charged to its full potential. The simulation results for PV systems with 30 kW, 40 kW, 60 kW, and 80 kW for case 3 are shown in table 11.

The simulation results with higher-rated PV systems for case 3 indicate that the net energy cost reduces significantly. The grid dependency decreases, and the net energy cost is surplus when the rating of the PV system is increased to 80 kW and 100 kW. The system will earn around 1800 euros revenue for one year. The maximum power drawn from the grid and injected into the grid is shown in table 12. The peak load from the grid is decreasing and energy transferred to the grid is increasing. The peak loads from the grid increase 2 to 4 times with the increase in BESS size.

The payback periods for all three load cases are shown in Table 13. The cost calculations in this table include some approximations in the prices of the inverters and batteries.

The installation cost and the cost of land in the case of ground installation have not been included, the payback period varies between 10 to 20 years for all three load cases.

The payback periods for case 1 and case 2 are around 10 and 13 years respectively, while for case 3 even with the increase in the PV capacity it is between 16 to 27 years. The cost of additional PV energy availability increases the total savings, but the increased cost of PV and inverter size keep the resultant payback period nearly the same.

V. COMPARISON WITH PREVIOUS STUDIES

Previously, many studies have been conducted on the optimal designing of batteries, control algorithms, and economic

TABLE 8. Impact of the BESS size variation for case 3 (whole residential apartment building).

Battery Size (%)	j (hours)	a (hours)	b (hours)	c (hours)	d (hours)	Peak Power drawn from grid (kW)				Peak power injected into the grid (kW)			
						Wt.	Sp.	Sum.	Aut.	Wt.	Sp.	Sum.	Aut.
10	3798	912	62	437	4425	36.71	22.04	16.97	27.32	34.63	14.89	15.13	12.87
25	3750	953	81	462	4438	36.71	22.16	16.97	27.32	34.63	14.59	14.49	13.63
50	3703	997	92	492	4460	36.71	22.42	16.97	27.32	34.63	13.95	13.85	12.99
75	3549	1035	133	552	4595	36.71	22.67	16.97	27.32	34.63	13.31	13.21	12.35
90	3433	1035	151	592	4733	36.71	22.83	16.97	27.32	34.63	12.92	12.82	11.96
100	3325	1035	157	621	4864	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70
110	3228	1035	158	643	4982	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70
120	3163	1035	155	655	5062	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70
130	3093	1035	158	670	5144	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70
150	3033	1035	181	714	5225	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70
175	2915	1035	178	737	5369	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70
200	2848	1035	202	782	5457	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70
300	2616	1035	224	851	5736	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70
400	2498	1035	253	898	5872	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70
500	2476	1035	285	936	5900	36.71	22.93	16.97	27.32	34.63	12.67	12.57	11.70

TABLE 9. The economic analysis with only PV installation.

	Case 1	Case 2	Case 3
Annual energy consumption (kWh)	740	6650	103859
Approx. initial cost of PV (€)	2000	4000	8000
Yearly energy price without PV (€)	27.6	251.7	4810.5
Cost of energy taken from the grid with PV (€)	-	-	2620
Cost of additional energy sold to the grid (€)	213.4	220.4	-
No. of hours of energy utilization from the grid	4989	6035	7163
No. of hours of energy injected into the grid	3776	2752	1597

TABLE 10. Battery sizes and net energy prices for the whole year.

Battery Size (%)	Case 1 (€)	Case 2 (€)	Case 3 (€)
10	-214.30	-220.42	2856.82
25	-215.23	-220.52	2858.80
50	-216.65	-248.62	2134.57
75	-218.32	-250.81	1935.24
90	-218.97	-255.55	1781.46
100	-219.39	-261.12	1698.39
110	-219.07	-263.09	1637.51
120	-219.03	-262.79	1591.09
130	-219.34	-264.31	1533.02
150	-218.74	-271.28	1363.27
175	-218.86	-274.82	1292.00
200	-219.42	-279.61	1102.60
300	-219.34	-291.24	852.68
400	-219.65	-299.38	654.84
500	-220.30	-306.76	498.58

*The negative price shows the surplus of energy sold to the grid. All energy prices are in euros.

feasibilities as discussed earlier in Section 1. The study in Greece found that BESS can reduce the cost of bills by 20% [40]. In [41], the economic analysis of PV paired with BESS showed that the system can reduce 41% to 74% of the cost of energy from the grid. The BESS alone can provide a 25% to 35% cost reduction in cost.

A Belgian residential data was used to develop a BESS sizing method based on voltage sensitivity. The BESS life was determined to be 15 years for 80% PV power threshold and 10 years for 70% threshold [42]. In [43], a study conducted in Japan indicated that PV-BESS can reduce the peak load of the grid to 1.1%. However, the value of the peak load varies by season. The payback period in the same study was found

TABLE 11. Battery parameters with an increase in photovoltaic rating for case 3.

Rated PV Power (kW)	Battery size (%)	j (hours)	a (hours)	b (hours)	c (hours)	d (hours)	Net energy cost (€)
30	100	2971	1384	172	536	4769	1384
40	100	2876	1470	198	490	4706	1006
60	100	2918	1502	260	451	4531	62
80	100	2962	1519	301	419	4397	-879
100	100	3014	1543	330	403	4276	-1794

TABLE 12. Peak loads with the increased PV rating for case 3.

Rated PV power (kW)	Battery size (%)	Peak Power drawn From grid (kW)				Peak power injected into the grid (kW)			
		Wt.	Sp.	Sum.	Aut.	Wt.	Sp.	Sum.	Aut.
30	100	36.7	22.1	16.9	27.3	34.6	22.6	24.7	20.8
40	100	36.7	22.1	15.6	27.3	34.6	34.1	34.6	32.4
60	100	36.7	22.1	15.6	24.8	34.6	54.9	54.3	50.5
80	100	36.7	19.9	15.6	24.8	34.6	74.7	74.1	68.6
100	100	36.7	19.9	15.6	26.8	34.6	94.6	93.7	86.8

TABLE 13. The payback period for the three cases.

	Case 1	Case 2	Case 3			
Rated PV power(kW)	5	10	20	40	60	80
Cost of PV (€)	2000	4000	8000	16000	24000	56000
Cost of battery (€)	400	3300	51800	51800	51800	51800
Cost of PV invertor (€)	1000	2000	4000	8000	12000	16000
Net energy cost (€)	-219.4	-261.1	1699	1005	62	-878
Total saving per year (€)	247	512.82	2612.11	3805.2	4748.9	5688.7
Payback period (Years)	10	13	27	20	16	16

to be 18 years. An optimal battery size tool was designed and the payback of the BESS was found to be around 40 years [3]. However, the author reported that if there is a 10% increase in the electricity sales cost to the grid, the payback time will reduce by up to 10 years.

In comparison to the studies mentioned above, the results presented in our study are more dynamic and cover a broader aspect of BESS. The proposed LP algorithm for energy cost minimization along with the optimized value of BESS presents a viable economic analysis for nZEBs. The results showed that the payback period of this PV and BESS system is around 10 to 13 years. The first two cases showed that there is no need to pay for energy at all and also that the domestic users will sell excess energy to the grid with 5 and 10 kW PV installations along with BESS. In the reduction in the third case, the electricity cost is around 65% with 20 kW PV-BESS.

VI. CONCLUSION

Optimal sizing of the BESS is an important prospect for nZEBs. The inappropriate BESS size can have both technical and economic implications. Similarly, the BESS requires an efficient control algorithm for the optimal performance of the battery. conversely, the BESS needs to be made economically feasible for the consumers to invest in it. Currently, the price of BESS is very high; therefore, in many countries, governments and grid operators offer several incentives to consumers. However, the price of BESS is also expected to drop in the coming years.

This study presents the findings to test different BESS sizes for the three most common residential buildings based on their electrical load and recommended rated PV systems. The purpose is to find the optimal size of the BESS that is technically viable and economically beneficial. For the three different residential buildings, the real-time residential load data was taken from the Estonian low voltage distribution network for a small apartment, a medium-sized household, and a whole apartment building. Moreover, real-case data for the corresponding three rated solar PV systems is also measured and used. Based on these three electrical loads and solar PV profiles, the theoretical size of the suitable BESS is determined for each residential building. An effective heuristic algorithm is proposed for the scheduling of BESS charging and discharging under the influence of two energy sources, such as solar PV system and grid.

Furthermore, we develop an LP model to compute the total cost of energy consumption of the nZEBs considering the viable electricity price of the grid, the available energy of the solar PV system and the grid, the BESS charging and discharging schedule, and the total electrical load of the residential building. The LP model is optimized to minimize the total energy consumption cost for nZEBs. The proposed LP model along with the heuristic algorithm for BESS battery charging and discharging schedule is rigorously tested by varying three different electricity pricing scenarios and variable BESS sizes. In addition, a detailed comparative analysis is conducted based on minimum utilization of the grid, maximum charging of BESS from the solar PV system, and maximum BESS discharging for internal usage. The economic analysis of the proposed BESS for all three cases with the implementation of the proposed algorithm indicates that the payback time of small and medium-size residential load scenarios varies from 10 to 13 years. The PV-BESS will have a payback period of around 20 years for large residential buildings if the PV size is small. However, it is around 16 years when a larger PV system is installed.

For future works, the proposed algorithm will be implemented in the energy router currently under development for the energy management system for nZEBs. In this way, the performance of the algorithm will be tested and verified experimentally in a real-time application. Moreover, different optimization algorithms can be investigated for this problem to have a comparative analysis with the proposed one.

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Publication III

Shabbir, N.; Kütt, L; Daniel, K; Astapov, V; Raja, H.A.; Iqbal, M.N; Husev, O. (2022). Feasibility Investigation of Residential Battery Sizing Considering EV Charging Demand. Sustainability, 14(3), 1079.

sustainability

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Feasibility Investigation for Residential Battery Sizing Considering EV Charging Demand

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Abstract: Photovoltaic (PV) systems along with battery energy storage systems (BESS) are an increasing trend for residential users due to the increasing cost of energy and environmental factors. Future sustainable grids will also have electric vehicles (EVs) integrated into these residential microgrids. However, this large-scale deployment of EVs and PV systems could mean several problems in terms of power quality, hosting capacity and as well economic implications. This paper aims to provide input to more optimal design and management of domestic PV and BESS for residential users with EVs. In this work, a measurement-based data set from a low-voltage distribution network in a rural area has been used. Investigation sees different household and PV-EV penetration levels to propose the BESS capacity and use cases. An economic analysis has been performed to check the feasibility of the proposed systems. The payback period is found to be between 13 to 15 years of the proposed systems.

Keywords: photovoltaic systems; electric vehicles charging; battery storage; battery size optimization; economic analysis

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Citation: Shabbir, N.; Kütt, L.; Daniel, K.; Astapov, V.; Raja, H.A.; Iqbal, M.N.; Husev, O. Feasibility Investigation for Residential Battery Sizing Considering EV Charging Demand. *Sustainability* **2022**, *14*, 1079. https://doi.org/10.3390/su14031079

Academic Editor: Aritra Ghosh

Received: 15 December 2021
Accepted: 12 January 2022
Published: 18 January 2022

1. Introduction

Electricity and transportation have been two of the most dominant sectors in the contribution of greenhouse gases [1]. The deployment of renewable energy resources (RES) such as photovoltaics (PV) in electrical grids is growing, and similarly, the usage of electric vehicles (EVs) is also increasing, as these vehicles fall into the category of potentially sustainable and green transposition systems [2–4]. Due to the expected preference for comfortability, it is expected that the users will most often charge their electric vehicles at home. Therefore, the integration of PV and EV in future sustainable distribution grids is of key importance.

PV in conjunction with battery energy storage systems (BESS) is expected to be the most popular RES solution in residential buildings and homes [5]. This system is usually connected to the local grid to reach better utilization for energy produced on-site and, if excessive energy is available from the photovoltaic, then it is sold to the grid. The main purpose is to reduce electric energy costs and obtain benefits by selling energy. However, large-scale photovoltaic and BESS installation can initially be costly, as the cost of photovoltaic is around 400–1000 €/kW while batteries are still around 100 € per kWh [6,7]. Therefore, the optimal design of these systems is very important.

The PV generation in residential grids [8–10] and the impact of EV charging on the residential grid have been discussed in [11–14]. While the benefits of PV and EV integration have multiple benefits [15–18], the large-scale PV and EV deployment can also impose extra challenges in the local grids. It is commonly discussed, that large-scale PV deployment with same-time production could mean overloading and overvoltage in the network [19–22]. At the same time, the high penetration of electric vehicle loads can cause higher peak loads and thus undervoltage in the network [23,24]. The time-wise distance of the PV production peaks, and peak EV domestic charging load could mean cumulation of these issues listed.

A way to mitigate these problems is to include BESS, sized according to the network design parameters and limits. The presence of BESS can ensure that PV energy generated but not utilized on-site is not injected into the grid and this stored energy is used for the charging of EVs. This way residential BESS can directly help to improve demand-side management, increase self-consumption, reduce peak load, and reduce photovoltaic consumption in the event of excessive energy generation [25]. One major problem that hinders large-scale installations of the BESS is the initial investment cost, however, it is expected to decrease over the coming years [26].

BESS provides financially and operation-wise optimal results when they are designed closely corresponding to load requirements [27,28]. There are several studies available on the optimal use of these BESSs to get maximum benefits. The most popular techniques are linear programming optimization [29–32], genetic algorithm [33], particle swan optimization [34,35], dynamic programming [11,36], convex programming [24,37] and mixed-integer linear programming [38]. Many of the studies listed above used real-time photovoltaic and load data to determine the optimal battery size for maximum reduction in electricity bills.

PV-BESS-EV integration has been investigated for residential users in numerous studies covering aspects of reduction in emissions of using EVs charged from the RES-based residential grid [39] until operational details and structure. In [15,40–43], the architecture, control algorithm, and their economical aspect are covered. The impact of EVs charging from the grid on the network power quality is discussed in [44]. The EV modeling techniques are presented in [16,45–47]. The utilization of EV batteries for domestic household load has also been investigated in [48].

The main focus of this study is to investigate the economic feasibility of the PV-BESS-EV system and EVs charging loads through it also considers the local market electric energy prices. A residential data set for one year from an Estonian rural grid was taken into consideration along with the PV generation data. The grid consists of eight different domestic users which have been classified as small, medium, and large residential loads. The resolution of the data is one hour. EV charging data is generated using a stochastic model [45]. Finally, the initial economic analysis has been presented. The following are the key points of this paper:

- A PV production-oriented BESS has been proposed for the electrical load and EVs in a residential household and eight different cases of small, medium and large scale have been discussed.
- A linear programming-based battery charging algorithm is used to target minimum annual energy costs by reducing the number of grid usage hours.
- The economic analysis of all the eight household cases with EVs along with variation in the BESS size has also been carried out.
- The payback period for all cases is estimated.

The paper is structured as follows: Section 2 presents residential load data profiles, PV generation data, and EV data used for the context analysis. Section 3 explains the methodology used in this research and gives the economic analysis of the proposed system. Section 4 specifies the results and the corresponding discussion. Finally, the conclusion of this research is presented in Section 5.

2. Data Profiles

This section is related to the detailed description of the data used in this study. The recorded residential load and PV energy generation data originate from an Estonian rural grid for a whole year (latitude: 58.2289). The time-resolution of the data was one hour. The EV load profiles are generated based on a stochastic model based on travel activity.

2.1. Load Profiles

The recorder electric load data from the low-voltage distribution network is analyzed in this study. An hourly time-step of measurement was used to collect data in a rural customer for an entire year. Figure 1 illustrates the grid layout and connection topology of the low voltage grid segment under consideration. Eight residential loads are present in this segment, as well as three auxiliary loads (pump station, street lighting, and local small-scale heating plant). These residential electrical load cases constitute a small apartment/flat, medium-size house, and residential apartment building. Table 1 presents the statistical details for all eight cases. Using the measured data profiles, the peak electrical load for a small apartment is between 1 to 4 kW (Cases 1, 4, 5, 8), for a household is 5 to 6 kW (Cases 2, 5, 6) and an apartment building around 37 kW (Case 3). All these cases are summarized in Table 1 as well as their accumulated annual energy consumption.

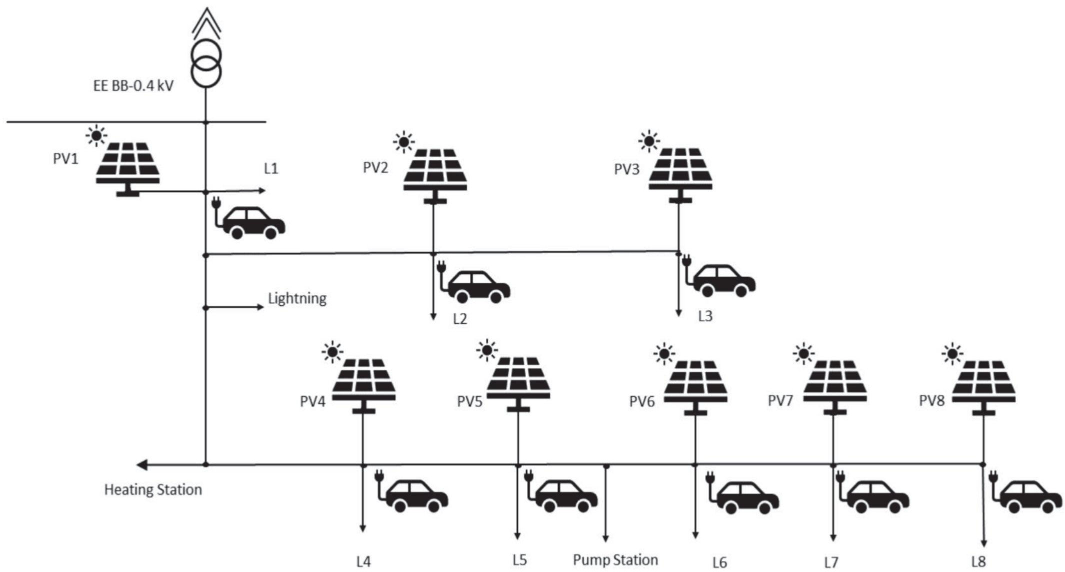

Figure 1. The layout of the low voltage distribution network.

Table 1. Load Profiles of eight different residential users (round up to 0.1).

Number of Load	Peak Load (kW)	Average Load (kW)	Median Load (kW)	Annual Energy Consumption (kWh)
Case 1	1.9	0.1	0.1	741
Case 2	5.4	1.1	0.7	9056
Case 3	36.7	11.9	11.1	103,842
Case 4	2.2	0.3	0.2	2176
Case 5	2.7	0.3	0.2	1975
Case 6	5.1	0.7	0.5	6482
Case 7	5.9	0.7	0.5	6639
Case 8	4.1	0.4	0.3	3765

In contrast, the average electrical load is relatively low, e.g., 0.8 to 0.3 kW in all the small apartments, which is rather low compared to the peak demand. However, for Case 3, it is around 12 kW considering a building total. The energy demand for the whole year varies between 700 to 3800 kWh for small apartments, for medium houses, it is varying between 6000 to 9000 kWh and for an apartment building, it is over 100,000 kWh.

2.2. PV Profile

A summer day in (latitude: 58.2289) lasts on average over 16 h, while a winter day is down to 4 to 5 h [22]. In this study, solar PV systems with capacities of 5 kW have been proposed for a small residence, 10 kW for medium households, and 20 kW for a small apartment building. Figure 2 represents the energy output of the 20 kW PV system for the whole year, scaled from power at the measurement site.

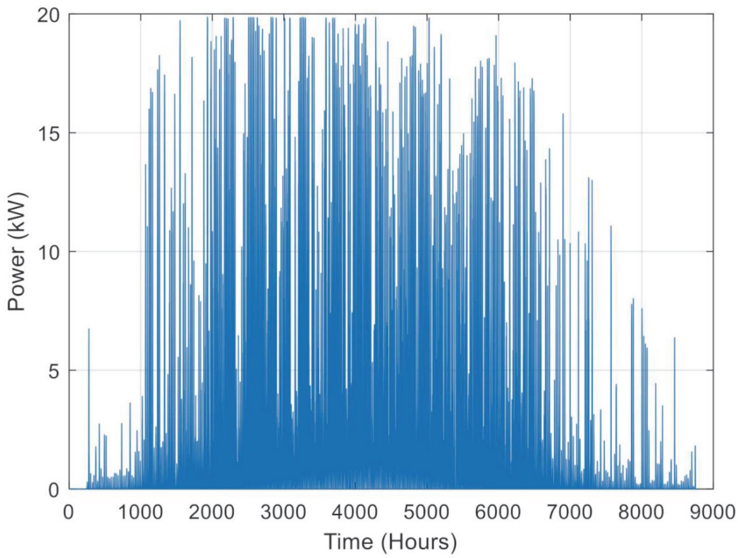

Figure 2. Energy generation from a 20 kW solar PV.

Based on Figure 2, it is clear that solar energy production is high between March and September and low in the remaining months. As a result, the overall energy generation during these months can be in surplus. The extra energy can be used to charge BESS and EVs as well while the remaining energy can be sold to the grid.

2.3. EV Profiles

The EV data used in this study was generated from an EV usage model described in [45]. It is an activity-based model (ABM) that incorporates several socioeconomic factors which influence the travel behavior of an individual. The model generates a travel schedule and based on that, the EV usage pattern is mapped and the load requirements for the grid are defined. The model incorporated a National Traffic Survey (NTS) to obtain information about user travel plans and categorize them. Then the probability distribution is used to define the departure and arrival times for individual trips. Thereafter, the decision is made to charge the battery of the EV or not based on the existing State of Charge (SOC) and the traveling distance. Trips are also classified as work, shopping, school, vacation, business, or any other activity.

In this study, there are eight different domestic household users as defined in Section 2.1. Different numbers of electric vehicles are added to these residential users. These details are shown in Table 2. The number of EVs ranges from 1 to 10. Small apartment and household cases only have one EV and medium load cases have 2 to 4 EVs. As Case 3 is a residential apartment building, therefore, 10 EVs are integrated with it. The one-year load profile of case 1, case 2, and case 3 is also shown in Figure 3. The peak loads of cases 1, 2 and 3 are 4.6, 15.4 and 60 kW, respectively. Further details of the other cases are given in Table 3.

Table 2. Number of EVs in different households.

Number of Load	Number of EVs	Number of Load	Number of EVs
Case 1	1	Case 5	1
Case 2	3	Case 6	2
Case 3	10	Case 7	4
Case 4	1	Case 8	1

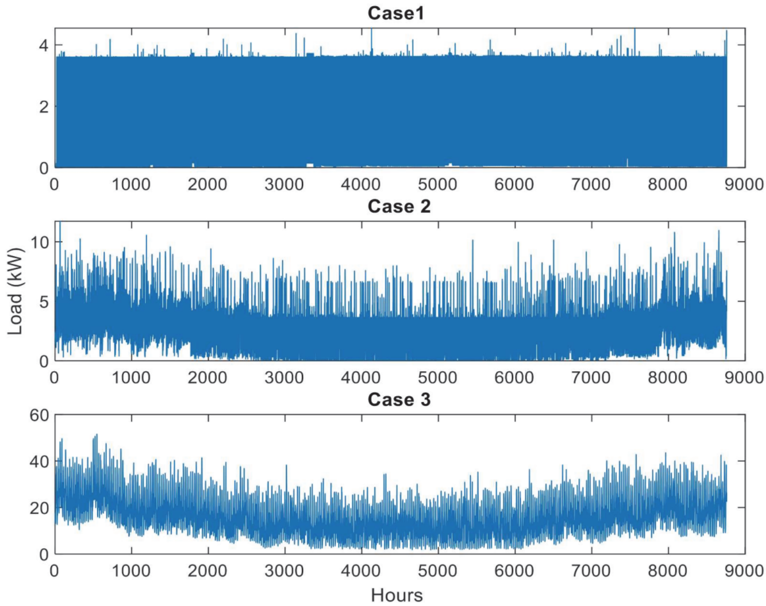

Figure 3. Comparison of small, medium and large scale cases.

Table 3. Load Profiles of eight different residential users with EVs integration.

Number of Load	Peak Load (kW)	Average Load (kW)	Median Load (kW)	Annual Energy Consumption (kWh)	Installed PV Power (kW)
Case 1	4.6	0.8	0.1	7250	5
Case 2	15.4	2.9	2.6	25,800	10
Case 3	60	16.4	15.4	143,725	20
Case 4	5.7	0.9	0.3	8686	5
Case 5	6.2	0.9	0.2	8485	5
Case 6	15.2	2.3	1.2	20,450	10
Case 7	16	2.3	1.7	20,610	10
Case 8	7.9	1.8	0.4	10,270	5

3. Methodology

3.1. Battery Energy Storage System (BESS)

In recent years, much effort and research have been put into battery storage technologies such as PV-based storage systems, electrical vehicles, and portable devices [24]. Over the years, research in battery technology and bulk generation has drastically reduced the prices and size of batteries [6]. This has resulted in the modern commonly used batteries of Nickel Manganese Cobalt Oxide (NMC) and Lithium-Ion(Li-ion) batteries [49]. Currently, the cost of a new battery is estimated to be around 100 € per kWh. It is also estimated that with advancements in technology and recent studies, the life cycle of batteries will be around 20 years [50].

Currently, Li-ion batteries are the widely used batteries in conjunction with BESS installed with solar PV systems. These are preferred mostly due to their compact size, lack of maintenance, and higher efficiency, roughly more than 85% [51]. However, due to their charge/recharge cycles, the practical life of these Li-ion batteries is estimated to be around 5 years [52]. This is not feasible and challenging as the payback period for these Li-ion batteries is not economically viable within 5 years. Therefore, these Li-ion battery installations in conjunction with PV-based BESS systems are often supported by government incentives in terms of reduced tariffs and subsidies [38]. However, to further minimize operational costs, it is still needed to calculate the optimal battery size. This includes several configurable parameters for the BESS system, which are shown in Table 4 for each case.

Table 4. Parameters of the BESS.

Number of Load	Battery Capacity (kWh)
Case 1	4
Case 2	41
Case 3	548
Case 4	10
Case 5	10
Case 6	35
Case 7	35
Case 8	20

The algorithm designed for charging and discharging PV-based BESS systems and calculating battery size is shown in Figure 4. The algorithm is designed with the optimal electric energy price value target and BESS charging is only done when it is needed and the electric energy price is low. Whereas when the cost of electricity is high, batteries can be discharged to inject power into the grid and be used for in-household purposes to keep the cost of energy to a minimum. Further details of the algorithm can be found in [53,54].

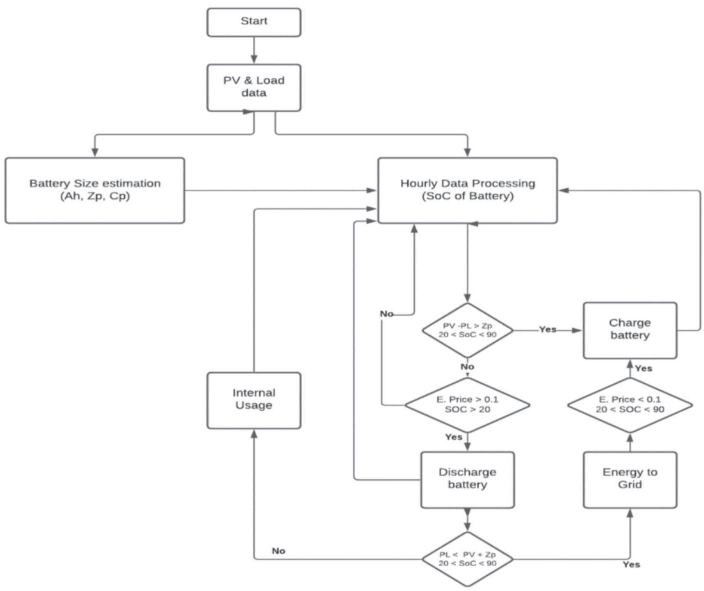

Figure 4. The flowchart of the proposed algorithm.

The impact on grid usage in terms of hours based on the designed algorithm for each case is shown in Table 5. The number of hours 'j' describes the total number of hours of grid utilization in one year. The impact of battery size variation is also shown; it can be seen that with the increase in battery size, the hours of power drawn from the grid have reduced. The number of hours reduced vary for each case according to the scenarios as; in case 7, the system with 50% battery size is already enough, so increasing the battery size will not improve it any further. Therefore, it is also essential to calculate the optimal and economical battery size for the implemented PV-based BESS systems.

Table 5. BESS size variation and impact on grid use.

Number of Load	Battery Size (%)	j (hour)	a (hours)	b (hours)	c (hours)	d (hours)
	50	2051	3040	292	286	3663
Case 1	100	1456	3139	400	248	4013
	200	1237	3171	473	241	4120
	50	3740	1616	248	395	3551
Case 2	100	3441	1701	310	441	3749
	200	3125	1742	359	524	4058
	50	3764	1690	227	416	3495
Case 3	50	3622	1002	96	489	4529
	100	3214	1035	156	614	4969
	200	2776	1035	205	769	5513
Case 4	100	2542	2400	335	383	3866
	200	2178	2449	367	411	4177
	50	2720	2372	254	330	3744
Case 5	100	2082	2495	344	320	4159
	200	1724	2538	401	342	4439
	50	3083	2002	261	347	3761
Case 6	100	2580	2173	341	347	4013
	200	2231	2243	382	401	4305
	50	2922	1770	242	305	4131
Case 7	100	2490	1879	322	347	4416
	200	2084	1942	372	394	4756
	50	2970	1818	273	349	4048
Case 8	100	2365	1999	338	352	4410
	200	2001	2059	381	400	4719

j = no. of hours of grid usage, a = PV usage hours, b = Battery discharging hours to the grid, c = Battery charging hours from grid, d = Batter discharging hours for on-site usage.

Similarly, the peak power drawn from the grid and injected into the grid by the PV-based BESS systems in each case is shown in Table 6. The table states the value for each season of the year, and a comparison can be made to see the difference between different seasons according to different battery sizes. It can be seen in Table 8 that the peak power drawn from the grid and injected into the grid are not much different in the case of case 1 and case 4. Even for different battery sizes, both cases have net negative energy, which states that the minimum battery size considered here is more than sufficient for those two cases. Whereas in the scenario of case 3, the battery sizes and PV power rating are still far from enough to reduce the difference significantly. Different scenarios for case 3 will be further discussed in the later section.

Table 6. Peak loads in the dependent season and variable BESS sizes.

Number of Load	Battery Size (%)	Peak Power Drawn from Grid (kW)					Peak Power Injected into the Grid (kW)			
		Wt.	Sp.	Sum.	Aut.	Wt.	Sp.	Sum.	Aut.	Wt.
	50	4.5	4.83	4.5	3.9	4.3	−4.9	−4.9	−4.7	4.5
Case 1	100	4.5	4.83	4.5	3.9	4.2	−4.9	−4.9	−4.7	4.5
	200	4.5	4.37	4.2	3.8	4.2	−4.9	−4.9	−4.7	4.5
	50	13.7	9.1	10	10	12.7	−9.7	−9.9	−9.6	13.4
Case 2	100	13.7	9.7	10	11.9	12.8	−9.7	−9.9	−9.4	13.4
	200	13.7	9.6	10	10	12.8	−9.7	−9.9	−9.4	13.4
	50	115.8	113.7	99.1	40.1	110	−75.2	−76.6	−73.6	115.5
Case 3	100	116.8	113.3	99.1	40.1	110	−75.2	−76.6	−75.5	116.7
	200	113.7	113.3	99.1	40.1	110	−75.2	−76.6	−75.5	113.6
	50	4.8	4.5	4.7	4.3	4.7	−4.9	−4.9	−4.4	4.8
Case 4	100	4.8	4.5	4.7	4.3	4.7	−4.9	−4.9	−4.6	4.8
	200	4.8	3.7	4.6	4.8	4.7	−4.9	−4.9	−4.6	4.8
	50	4.8	4.3	4.3	3.9	4.4	−4.8	−4.8	−4.6	4.8
Case 5	100	4.8	4.2	4.2	3.9	4.4	−4.8	−4.8	−4.6	4.8
	200	51	3.6	4.2	3.7	4.4	−4.8	−4.8	−4.6	5
	50	14.2	12	11.7	12.6	13.4	−9.6	−9.6	−8.6	14.2
Case 6	100	14.2	12	11.7	12.6	13.4	−9.6	−9.6	−8.6	14.2
	200	14.2	12	11.7	12.6	13.4	−9.6	−9.6	−8.6	14.2
	50	13.8	11.7	12.5	12.5	12.6	−9.7	−9.7	−8.8	13.8
Case 7	100	13.8	11.7	12.5	12.5	12.6	−9.7	−9.7	−8.8	13.8
	200	13.8	11.7	12.5	12.5	12.6	−9.7	−9.7	−8.8	13.8
	50	6.5	5.74	5.3	5.4	5.63	−4.8	−4.8	−4.6	6.5
Case 8	100	6.5	5.78	5.8	5.4	5.63	−4.8	−4.8	−4.6	6.5
	200	6.5	5.78	5.8	5.4	5.63	−4.8	−4.8	−4.6	6.5

3.2. Economic Analysis

The energy management system has to be financially sound to motivate the implementation of the nZEB system. Here we evaluate the PV-based BESS design for the eight different load cases. Economic analysis for PV-based systems depends on several parameters, which are discussed in detail. This section will discuss the economic analysis of all 8 cases, along with the impact of the PV-based BESS system on the grid.

The electricity price on the electric energy stock market is provided with hourly steps. For this reason, the observation time step considered in this study is also 1 h. Currently, the price for a battery suitable for the BESS is around 100 €/kWh whereas, for PV, it is around 400 €/kW [55]. Table 7 shows the economic analysis for all 8 cases at different battery sizes. As it can be seen that in all cases, the cost of electricity is significantly reduced after integrating PV-BESS based system.

Table 7. Battery estimates and net energy cost for the year.

Number of Load	Battery Size (%)	Accumulated Cost of Energy from the Grid (€)	Accumulated Cost with PV-BESS-EV (€)
	50	200	−35.0
Case 1	100	200	−45.0
	200	200	−56.6
	50	793	289
Case 2	100	793	270
	200	793	242
	50	5237	3556
Case 3	100	5237	3130
	200	5237	2565
	50	246	−4.4

Table 7. *Cont.*

Number of Load	Battery Size (%)	Accumulated Cost of Energy from the Grid (€)	Accumulated Cost with PV-BESS-EV (€)
Case 4	100	246	−16
	200	246	−30
	50	245	−5.3
Case 5	100	245	−17
	200	245	−31
	50	546	40.2
Case 6	100	546	33.2
	200	546	16.1
	50	875	374.2
Case 7	100	875	360.8
	200	875	344.3
	50	314	54
Case 8	100	314	50
	200	314	41

The net usage of the prices after the integration of the BESS system has gone negative in Case 1, regardless of the battery size. In comparison, it has reduced by approximately 50–90% in other cases. In most cases, this decrease is quite significant, whereas in Case 3, it is only up to around 50%, which could be due to insufficient PV power and battery size. This is discussed in more detail in the next section.

4. Discussion

As shown in Table 7, the net prices for electricity usage with a BESS system result in a drastic decrease other than case 3, where the price is still high even if it is decreased. Case 3 is further taken into account and different power PV systems are implemented in case 3 to get the relevant study. This also proves that the optimal solution for a specific case can be achieved by increasing PV or varying battery size and the net energy cost can be reduced significantly. In Table 8, results are shown for two scenarios where the PV power is increased to 40 kW and 60 kW. Net energy cost is also calculated for different battery sizes in each case.

Table 8. Parameters for Case 3 with increased PV ratings.

Rated PV Power (kW)	Battery Size (%)	j (hours)	a (hours)	b (hours)	c (hours)	d (hours)	Net Energy Cost (€)
	50	4131	1269	102	552	3810	2557.3
40	100	3505	1543	151	617	4178	2256.8
	200	3151	1580	189	786	4626	1636.1
	50	4088	1338	143	522	3713	1617.2
60	100	3314	1662	194	535	4125	1456
	200	2689	1832	227	664	4676	943

As shown from Table 10, the net energy cost for most cases also decreases per the increased power by increasing PV power. In the case where PV power is 100 kW, the net energy cost goes negative. This shows that a good PV power source and a good battery size should be selected for each case. Peak voltage variations for case 3 are also calculated for each season with the increased PV power and battery size and are shown in Table 9.

Table 9. Peak load variations for case 3 with increased PV ratings.

Rated PV Power (kW)	Battery Size (%)	Peak Power Drawn from Grid (kW)				Peak Power Injected into the Grid (kW)			
		Wt.	Sp.	Sum.	Aut.	Wt.	Sp.	Sum.	Aut.
40	50	113.9	113.3	99.1	40.1	110	−106.6	−112.1	−103
	100	115.8	113.3	99.1	40.1	110	−73.5	−104.1	−77.4
	200	113.7	106.6	99.1	40.1	110	−73.5	−76.7	−77.4
60	50	113.7	102.6	99.1	40.1	110	−111.9	−131.7	−113.4
	100	115.5	109.8	95.6	40.1	110	−126.3	−131.6	−110.9
	200	116.7	106.5	95.6	40.1	110	−126.3	−128.1	−76.7

From Table 9, it can be stated that the power injected into the grid increases with an increase in PV power, while the increase in battery size does not make much of a positive difference. For different seasons, the power drawn from the grid varies according to consumption, but the power injected into the grid is overpowering the drawn power with an increase in PV power. This also has a positive impact on the grid, as surplus power can be utilized elsewhere. The payback period for PV is calculated and shown in Table 10.

Table 10. Payback periods for different BESS sizes.

Number of Load	Battery Size (%)	PV Rated Power (kW)	Cost of PV and Inverter (€)	Cost of BESS (€)	Total Savings per Years (€)	Payback Period (years)
Case 1	50	5	3000	200	235	14
	100	5	3000	400	245	14
	200	5	3000	800	256	15
	No EV (BESS 100%)	5	3000	400	245	14
	No BESS	5	3000	-	241	12
Case 2	50	10	6000	2100	506	16
	100	10	6000	4100	524	19
	200	10	6000	8100	552	26
	No EV (BESS 100%)	10	6000	4100	472	16
	No BESS	10	6000	-	472	13
Case 3	50	20	12,000	27,500	1680	24
	100	20	12,000	54,900	2107	32
	200	20	12,000	109,800	2672	46
	No EV (BESS 100%)	20	12,000	54,900	954	20
	No BESS	20	12,000	-	954	13
Case 4	50	5	3000	500	250	14
	100	5	3000	1000	262	15
	200	5	3000	2000	275	18
	No EV (BESS 100%)	5	3000	1000	241	13
	No BESS	5	3000	-	241	12
Case 5	50	5	3000	500	250	14
	100	5	3000	1000	261	15
	200	5	3000	2000	275	18
	No EV (BESS 100%)	5	3000	1000	241	13
	No BESS	5	3000	-	241	12
Case 6	50	10	6000	1800	506	15
	100	10	6000	3500	513	19
	200	10	6000	7000	530	25
	No EV (BESS 100%)	10	6000	3500	513	14
	No BESS	10	6000	-	472	15

Table 10. *Cont.*

Number of Load	Battery Size (%)	PV Rated Power (kW)	Cost of PV and Inverter (€)	Cost of BESS (€)	Total Savings per Years (€)	Payback Period (years)
Case 7	50	10	6000	1800	506	15
	100	10	6000	3500	500	19
	200	10	6000	7000	514	25
	No EV (BESS 100%)	10	6000	3500	514	14
	No BESS	10	6000	-	472	13
Case 8	50	5	3000	1000	260	15
	100	5	3000	2000	264	19
	200	5	3000	4000	272	26
	No EV (BESS 100%)	5	3000	2000	264	14
	No BESS	5	3000	-	241	12

The payback period of PV and BESS integrated systems varies according to the implemented PV power rating. Therefore, the payback period varies from 13 years to 40 years, depending on the case and the PV-BESS system implemented. On average, the payback period is around 13–15 years for each case depending on the BESS size variation, whereas the specific payback periods can be seen from the table. The repayment period is calculated based on the units saved plus the current electricity price in Estonia, which may vary with time in the future, so this can be referred to as a rough estimate.

5. Conclusions

Worldwide use of electric vehicles will continue to increase in the coming years. On the other hand, the load of EVs is high and they require more energy from the grid as compared to other residential loads. Therefore, a PV-BESS and EV integrated system can be a feasible, green, and more economical solution. However, the initial cost of the PV-BESS system and the PQ issues generated by the higher number of PV-BESS-EV integration needs some solution as well.

This paper concerns the economical and feasibility study of these integrated PV-BESS-EV systems for residential users. The real-time residential load and PV data were used from an Estonian distribution network, and EV load profiles generated via travel activity-based stochastic modeling were added. The main aim here was to minimize the dependency on the local electrical grid. Then the BESS size for these residential users was calculated and a control algorithm was implemented to charge or discharge the BESS depending on the load and availability of the PV energy. Moreover, the BESS size was also varied to find the optimal economic numbers and the payback period. The payback period is around 13–15 years.

The results indicate that the proposed method gives a significant reduction in energy bills and in one case the user will even earn money by selling extra energy to the grid. Two cases have a nearly zero balance thus fulfilling the criteria of nZEBs. The other cases also showed a significant drop in electricity bills varying from 45 to 80%.

For future work, the proposed energy management scheme can be implemented in a real-time small residential network to measure the accuracy of the results. Moreover, it can be extended to a bigger network and its feasibility and payback periods can be determined.

Author Contributions: Conceptualization, N.S. and L.K.; methodology, N.S. & L.K.; software, N.S. & H.A.R.; validation, H.A.R. and K.D.; formal analysis, M.N.I.; investigation, V.A. & O.H.; data curation, M.N.I. & V.A.; writing—original draft preparation, N.S.; writing—review and editing, L.K. & O.H.; visualization, H.A.R. & K.D.; supervision, L.K. & O.H.; project administration, L.K., O.H.; funding acquisition, L.K. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Estonian Research Council grants PSG142, PRG675 and PSG 739.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare that they have no conflict of interest.

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Publication IV

Shabbir, N.; Kütt, L.; Raja, H.A.; Jawad, M.; Allik, A.; Husev, O. (2022). Techno-Economic Analysis and Energy Forecasting Study of Domestic and Commercial Photovoltaic System Installations in Estonia. Elsevier Energy, 253, 124156.

Energy 253 (2022) 124156

Contents lists available at ScienceDirect

Energy

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

Techno-economic analysis and energy forecasting study of domestic and commercial photovoltaic system installations in Estonia

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ARTICLE INFO

Article history:
Received 20 September 2021
Received in revised form
5 April 2022
Accepted 28 April 2022
Available online 1 May 2022

Keywords:
PV Systems
Economic analysis
Energy forecasting
Machine learning
Payback time

ABSTRACT

The Baltic countries have good potential for solar photovoltaic (PV) energy generation, as on average 15 hours of sunlight is available in summer. Another potential option is to encourage the construction of nearly zero-energy buildings (NZEBs) according to the EU framework. This study focuses on solar irradiance and energy generation potential in different regions of Estonia as a case study. Techno-economic analysis of possible solutions to use differently rated domestic and commercial PV systems' feasibility and payback periods are presented. The results illustrate that all PV systems studied in the research are self-sufficient while selling excess energy to the grid with a nominal payback period. Furthermore, for short-term energy management, we developed an efficient deep learning-based forecasting algorithm. Apart from the inherent non-linear nature of solar energy data, what makes forecasting particularly challenging is to efficiently cope with the issue of data regression and random noise. The RNN-LSTM algorithm is chosen for the prediction of solar energy. This is the first comprehensive report that can encourage potential Estonian users to invest in solar PV systems and gain economic benefits. The results presented in this study cover a broader perspective and are more useful keeping in mind the real market situation of the Baltic countries.

1. Introduction

The electricity demand and associated prices have a substantial impact on the economic activity of any country. Over the past decade, policymakers are rapidly shifting towards environment-friendly and cheap renewable energy resources (RES). Similarly, in the last few years, the economy of Estonia has also been affected by the gradual increase in the demand and supply gap. Therefore, the Estonian government is taking initiatives to integrate more RES into the national grid, which is still surpassing the European Union (EU) framework of 32% energy production from RES until 2030. Photovoltaic (PV) systems are one of the fastest-growing fields of renewable energy (RE) in the world due to the advancement of solar cell technology [1–4]. The global solar power generation was between 120 and 140 GW in 2019, while China and Germany were the biggest manufacturers of solar PV systems [5]. Solar PV is the lowest cost distributed RES for electricity generation with prices expected to fall furthermore [6,7]. The concept of PV windows [8] and nearly zero energy buildings (nZEBs) [9,10] is in the implementation phase and the interest in them is increasing with every passing year. The nZEBs are defined as buildings that are capable of producing almost the same amount of energy as their energy consumption throughout the year [11–13]. According to the EU framework, all newly constructed buildings in the EU must be nZEBs [14,15]. These nZEBs will further increase domestic and commercial PV installations.

China, USA, India, Japan, and Turkey are the five biggest producers of solar energy in the world [16]. In the Baltic countries, the total installed capacity of solar PV systems is 128 MW in Estonia [17], 70 MW in Latvia and 120 MW in Lithuania [5]. The energy production and consumption gap in Estonia is increasing every

Abbreviations: PV, RES; RE, nZEBs; TSO, NCEP; ROI, RNN; LSTM, SM; NM, ARIMA; ANN, KNN; ANFIS, CNN; BPNN, CAP, MAPE.

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https://doi.org/10.1016/j.energy.2022.124156
0360-5442/

year. According to Elering, which is the Estonian transmission system operator (TSO), the total installed capacity of various sources in Estonia is 3041 MW in 2020 [17]. In 2020, the share of conventional and renewable energy was 46% and 54% [18], which is already well ahead of the European Union's goal of renewable energy for 2020 [19]. The accumulated share of RE resources was 54% biomass, 36% wind, 5% solar, 3% biodegradable waste, 1% hydro and 1% biogas [18]. The overall energy production in Estonia for 2020 was 23184 MWh, while the energy consumption was 45690 MWh. Therefore, a clear demand and supply mismatch exists in Estonia.

In the year 2020, the average energy consumption in Estonia was computed to be 905 MWh, while the energy production was around 500 MWh, as shown in Fig. 1 [18]. As the geographical location of Estonia is in the Baltic region; therefore, in winters, the energy demand is higher and can reach up to 14o0 MWh due to the electrical load of heating equipment, while the energy generation is around 800 MWh on average. Conversely, in a few months of summer, the energy production is higher than energy consumption. However, on average there exists a gap of around 500 MWh during a year. Estonia, along with other Baltic states, such as Sweden, Finland, Norway and Denmark, is part of the Nordic electricity exchange, which is regulated by Nord Pool [20]. Nord Pool offers an electricity trade between different countries with a day ahead and intraday market prices. The energy trade based on predicted demand keeps the balance between demand and supply among the partnering countries. The energy gap in Estonia is overcome by importing energy from Finland and Latvia most of the time. Therefore, an efficient energy forecasting method is vital for the short-term energy management of Estonia, and the accuracy of prediction is a major area of concern for the operators.

According to the report of the Estonian National Energy and Climate Plan (NCEP 2030) [19], Estonia plans to reduce greenhouse gas emissions by 80% by the end of 2050. Moreover, there is a goal of 100% energy production from RE by 2030 for sustainable energy needs. The report also highlighted the decrease and efficient use of biomass and shale oil while focusing on locating optimal sites and recommended more investment in offshore and onshore wind and solar energy production.

As per the EU framework of renewable energy, the Estonian government started to invest heavily in the RE sector. The installed capacity of wind energy in Estonia is around 329 MW [21] and solar PV is 128 MW. As Estonia is in the northern part of Europe, the solar irradiance is between 900 and 1100 kWh/m^2 [19,22]. Although this PV potential is kept in view that winter in Estonia is much longer compared to summer. Normal daytime in winter is around 6–7 h and in summer it is around 18–20 h [23]. This solar potential is not large, but it is still sufficient to supply small households and residential buildings. Customers can generate excess solar energy in summer and sell it to the grid while buying more energy from the grid in winter, which is closely related to the nZEBs framework. In addition, the incorporation of battery energy storage technology (BESS) can be used to store the extra generated energy that can be utilized later of sold to the grid [24]. Moreover, according to the EU requirement, all new buildings in 2021 should be nZEBs; therefore, solar PV presents a good practical solution in Estonia.

The relationship between energy generation prediction accuracy and economic analysis is very important. As the economic analysis is primarily based on the future income/profit of the proposed PV system while keeping in view the initial investment cost. Therefore, the accurate forecasting of energy generation will give accurate numbers in terms of future income. Usually, statistical algorithms are used for energy forecasting, however, these tools lack precision [25,26]. In comparison, the ML and DL tools are more accurate, and they give better results. Therefore, accurate energy forecasting directly impacts the calculation of economic numbers. In the last decade, various studies have been conducted on grid and off grid PV solutions in many countries with a detailed analysis of feasibility, risk factors, economic indicators and net metering solutions [27–30]. Moreover, multiple machine learning-based forecasting methods have been used for PV energy generation forecasting [31–34]. The reason for the wide use of machine learning algorithms for forecasting is the capability and accuracy of the models compared to statistical forecasting [35,36]. A bibliometric visualization of the authors supplied keywords from 179 impact factor journal articles published in the last five years related to PV generation forecasting is given in Fig. 2. The image is created

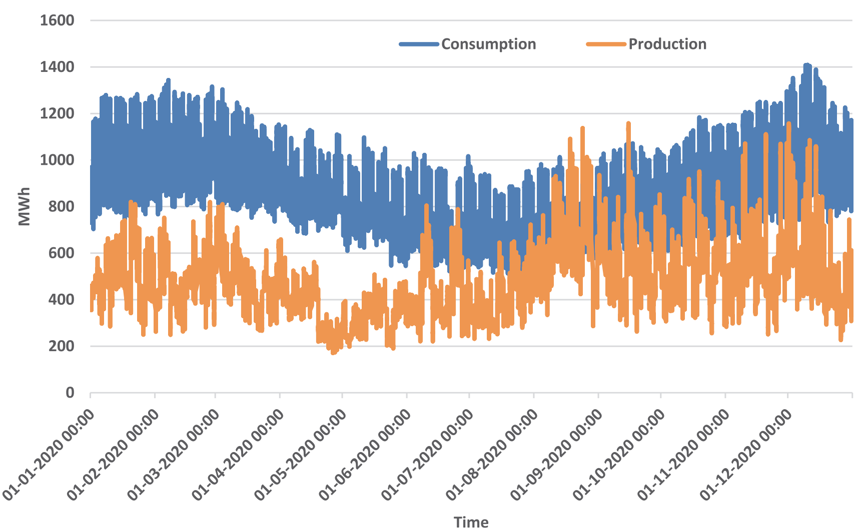

Fig. 1. Energy generation and consumption of Estonia for 2020.

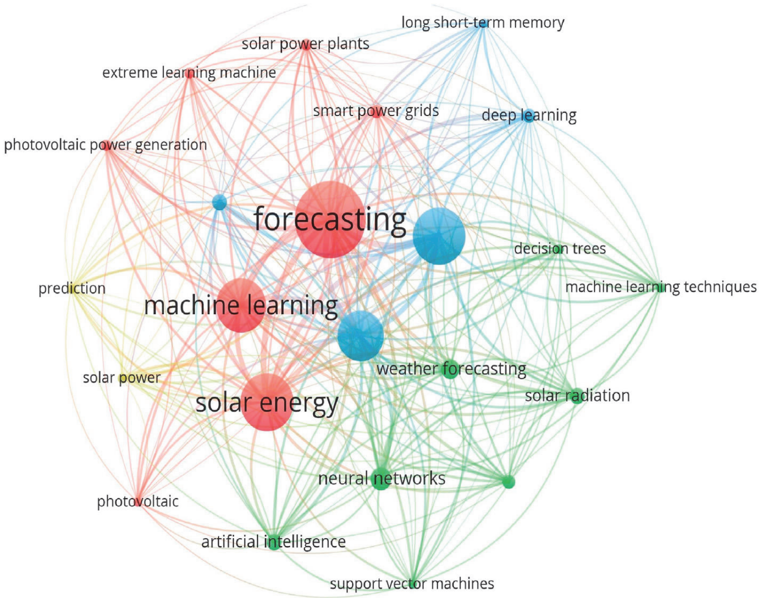

Fig. 2. Bibliometric visualization for the author-supplied keywords, created with VOSviewer Software.

using VOSviewer software, where the large circles represent the higher frequency of research articles on a specific topic or area. Fig. 2 illustrates that the forecasting of solar energy generation is a major area of concern while the majority of articles are using different machine learning algorithms for improved accuracy and reliability.

A detailed overview and comparative analysis of recent studies are presented in Table 1. In Table 1, we emphasize tabulating all major studies conducted recently around the world, which focus on complete system design to tackle the problem of demand-supply management for on-grid and off-grid photovoltaic systems. The key points discussed in all mentioned studies are the system design, optimal PV angle calculations for maximum power point tracking, optimal payback period, electricity bill reduction using different metering techniques, and forecasting algorithms for demand-response programs. However, the viability of these

Table 1
Comparison of our study with previous studies.

Survey	Country	System Design	Optimal angle for max. power output	Payback Time	Bill Reduction	Bill Reduction with Net metering	Energy Forecasting
[37]	Cyprus	✓	×	×	×	✓	×
[38]	Netherlands	✓	×	✓	×	✓	×
[39]	USA	✓	×	×	×	✓	×
[40]	Brazil	✓	×	×	×	✓	×
[41]	Ghana	✓	×	✓	×	×	×
[42]	Chile	✓	×	×	×	✓	×
[43]	Pakistan	×	×	×	×	✓	×
[44]	India	×	×	✓	✓	✓	×
[45]	Palestine	✓	✓	✓	×	×	×
[46]	Italy	✓	×	×	×	✓	×
[47]	China	×	×	✓	✓	✓	×
[48]	Egypt	✓	×	×	×	×	×
[49]	Australia	✓	×	✓	×	✓	×
[50]	Iran	✓	✓	×	×	×	×
[51]	Brazil	✓	×	×	×	×	×
[52]	Finland	✓	×	✓	✓	✓	×
[53]	Thailand	✓	✓	×	×	×	×
[54]	Brazil	✓	×	×	×	×	×
[53]	Thailand	✓	×	✓	×	✓	×
[55]	Palestine	✓	×	✓	×	×	×
[56]	Turkey	✓	×	×	×	×	×
[57]	Brazil	✓	×	×	×	✓	×
[58]	Jordan	✓	×	✓	×	×	×
[59]	Jordan	✓	×	×	×	×	×
[60]	Pakistan	✓	×	✓	×	✓	×
This article	Estonia	✓	✓	✓	✓	✓	✓

systems varies due to different geographical locations and different regulations. These studies have offered a detailed analysis of different PV systems, but none of them has included economic analysis for domestic and commercial users based on machine learning-based energy forecasting with net metering.

To the best of the authors' knowledge, this study is the first of its kind to propose different rated PV systems for residential and commercial sectors, while presenting a thorough financial analysis of PV installation in Estonia. Moreover, an efficient deep learning algorithm is used for solar energy forecasting problems, which is an essential part of short-term demand response problem design incorporating domestic and commercial PV systems. Furthermore, the viability of grid-connected PV systems in four different parts of Estonia is discussed and evaluated to cover all counties and climates. The regions selected are Tallinn, which is the capital and most populous city in the north, Saaremaa Island in the western part, Parnu in the south and the third biggest city, and Narva located in the east and the fourth biggest city in Estonia. These four regions combined inhabit nearly 70% of the population of Estonia. The calculations are made for three different rated PV systems for the domestic, workplace, and commercial usage. The energy forecast for the whole year is made using the proposed algorithm and based on the forecasted data the economic analysis is made. The solar radiation pattern in Estonia is similar in all regions; therefore, the results of this study are extended to every city and region in Estonia.

The outline of the article is given in Fig. 3, while the main key points of the article are listed as:

- The feasibility and effectiveness of three different rated PV systems for domestic, workplace and commercial usage are discussed, and their installation impact is computed considering the climate conditions and optimal PV panel angles of four major cities/regions of Estonia.
- The Long-Short Term Memory (LSTM) network of Recurrent Neural Network (RNN) is tuned for a challenging solar energy forecasting problem in order to efficiently deal with the issues of fast varying data, severe nonlinearities, random uncertainties, and time-dependent measurements. This is achieved by conducting a detailed exploratory data analysis to carefully select the input parameters for the RNN-LSTM model. Whereas a two-layered RNN-LSTM model is optimized via the Adam algorithm for accurate prediction of short-term solar energy forecasting. The prediction horizon considered in the study is 3-day ahead or 72 h ahead.
- The Return over Investment (ROI) is calculated keeping in view the initial investments, governmental subsidy, and projected returns. The payback period of the proposed solar PV installations varies from 8 to 18 years.
- In an effort to closely replicate the practical financial dynamics and to have more realistic findings with respect to the actual setups of all three rated PV systems, we computed and analyzed initial investment cost, subsidy and billing methods, payback period, and impact of PV energy production on the national grid.

2. PV systems design

The PV system installation requires certain criteria and standards to be fulfilled while utilizing the full potential of the technology. The PV systems design and requirements in Estonia are different from many other parts of the world. It needs continuous monitoring for the efficient use of the system. The PV system is required to generate power for 16–18 h a day in summer while around 5–6 h a day in winter. The system also requires protective devices to be installed on the AC/DC interfaces such as energy routers and invertors.

One of the important criteria to conduct feasibility analysis and site selection for solar PV system installation is the solar radiation pattern of the area. The parameters that need to be observed during the study of solar radiation patterns are solar irradiance, and solar panel angles for elevation, declination, and incidence [61,62]. The solar irradiance pattern for the four regions of Estonia is shown in Fig. 4 [63]. It is evident from Fig. 4 that the irradiance is high in the summertime lasts from April to August and is low in winter from November to March. Moreover, the solar radiation pattern is nearly similar in all four different regions of Estonia. Furthermore, the intensity of solar radiation in all four areas is enough to achieve high solar cell efficiency. The angle of incidence for the PV system is calculated using the methods described in Refs. [64–67]. The solar panel tilt angle β for Estonia is computed to be 38° to 40° for fixed PV installations [68].

In this study, three different rated solar PV systems are considered and evaluated: (a) The first system is for a small household or an apartment with 12 kW of electrical load with an approximate annual energy usage of 10000 kWh, (b) The second system considered in this study is a small office or a small apartment building with a 50 kW load with an approximate annual energy usage of 55000 kWh and (c) Third is a commercial PV power plant of 300 kW generation capability. Table 2 provides more detailed information on the design parameters and capabilities of

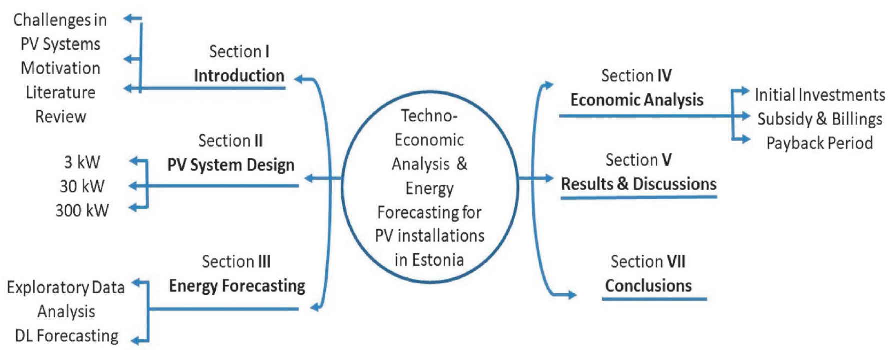

Fig. 3. Outline of the paper.

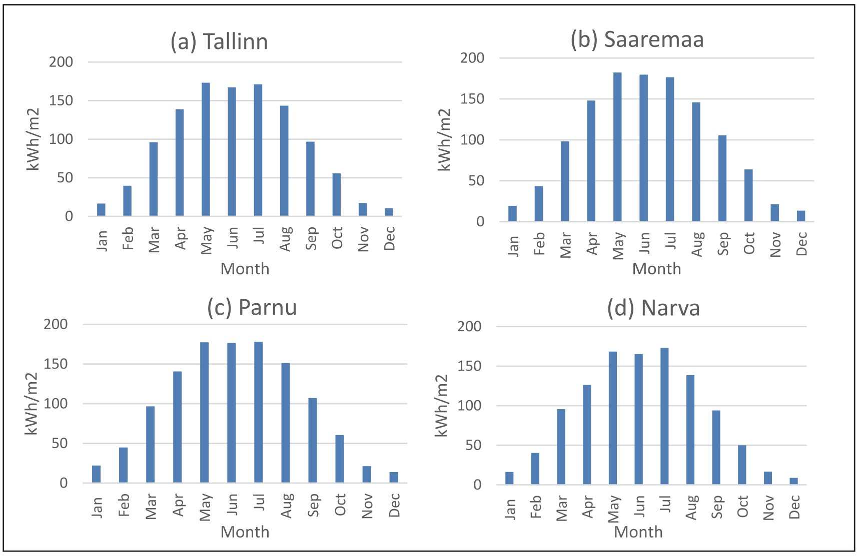

Fig. 4. Solar Irradiance chart for different cities of Estonia.

Table 2
PV System design parameters.

Installation Method	Gable Roof	Flat Roof	Ground	Flat Roof	Ground	Ground
Available Area for Installation (m^2)	85	85	85	300	340	1800
Annual Energy Consumption (kWh)	10000	10000	10000	55000	55000	–
No. of Panel	34	19	39	80	160	938
System Capacity (kW)	12.4	7	14.3	25.6	51.2	300
Annual Production (kWh)	12294	6396	14167	22843	49476	290051

all three rated PV systems. Similar to the European architecture of residential houses and buildings, in Estonia, there exist two different types of rooftops for a house or a small building, such as flat or gable. Therefore, three different locations for PV panel installation are considered in this study, such as flat roof installation, gable roof installation, and ground installation. All three PV panel installation scenarios are further elaborated in Table 2.

In Table 2, it is evident that the maximum power generation is achieved from the ground installation of PV panels, while the PV panel installation on the gable roof in the small household is not that far behind either. However, for the second-rated PV system (medium scale, 30 kW), the difference is quite significant in terms of the number of PV panel installations, system capacity, and annual production, as illustrated in Table 2. The number of PV panels in this description varies due to the variation in respective rated power. In Estonia, the average area of gable roof for a common residential home is 85 m^2 and a single 350 W PV panel takes on average around 2.5 m^2 area [69]. Therefore, the average number of PV panels on a gable roof is computed to be 34 with an installed PV system capacity of 12.4 kW. Moreover, in Estonia, the average tilt angle of a gable roof is usually 45°, which is sufficient for maximum power point tracking in summers [70]. Similarly, for the same PV panel power generation capacity, the number of panels that can be installed on a flat roof household is reduced to be 19 with a rated power of 7 kW on average [69]. The installation of solar panels on a flat roof needs the adjustment of the tilt angle of the solar panels that are necessary for maximum power point tracking. Therefore, to provide a tilt angle, a hard frame must be attached to the solar panels and due to this reason, the area required for the installation of a single solar panel will increase and we will have fewer solar panels installed on the flat roof. In comparison, the gable roof has a default tilt angle and the installation of solar panel do not require a tilted stand to be installed and we can apply solar panels straight off the gable roof and therefore, the number of panels installed on the gable roof is more than the flat roof with same free space available for solar panel installation. The ground installation in the same area will have a greater number of PVs installed and a higher rated power of 14.3 kW. All these installation scenarios ate numbers have been calculated using the online tool available at [69].

Fig. 5 describes the graphical representation of energy consumption for every month along with the expected amount of energy generation for a 12 kW system in a small household considering all three locations of the PV system installation (gable, flat and ground). Fig. 5 illustrates that the power consumption is lower while the generation is higher in summer and vice versa in winter. The energy generation and energy consumption gap is very high in summer. Moreover, the energy generation for three different types of PV installations is different. Gable and ground installations are almost the same and a bit on the higher side, while the PV system installed on the flat roof has lower energy generation throughout the year.

A similar analysis is presented in Fig. 6, for energy generation and consumption comparison for a 55000 kWh annual energy usage-based small office building. From Fig. 6, we observed that the energy generation from a flat roof is higher in November and December. Moreover, in the months of May, June, and July the flat

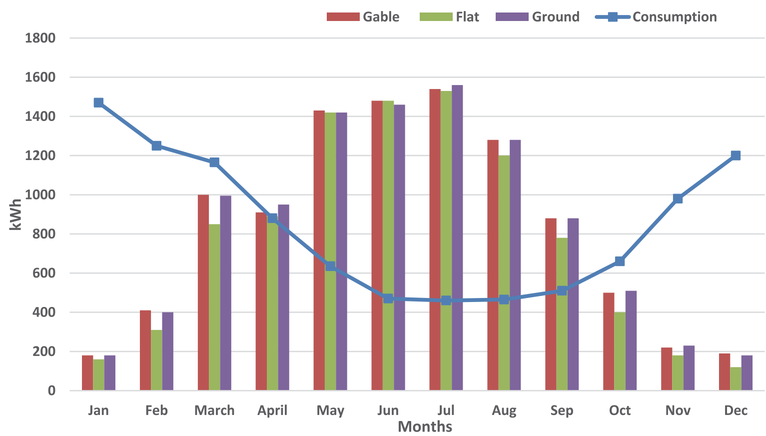

Fig. 5. Energy consumption and generation based on different types of PV installation scenarios for a househol0d.

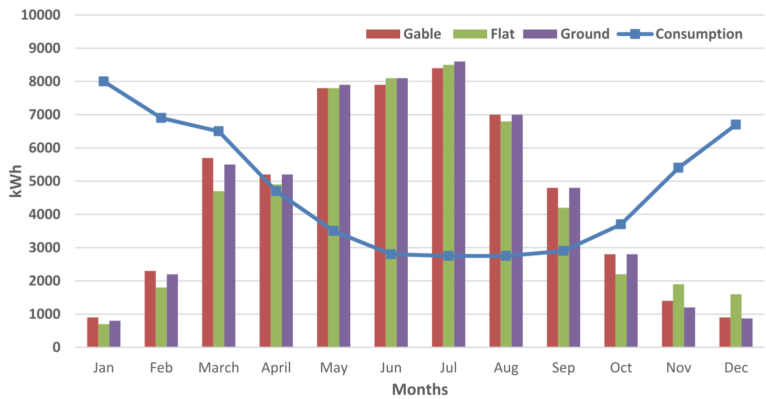

Fig. 6. Energy consumption and generation for different types of PV installation scenarios for a commercial building.

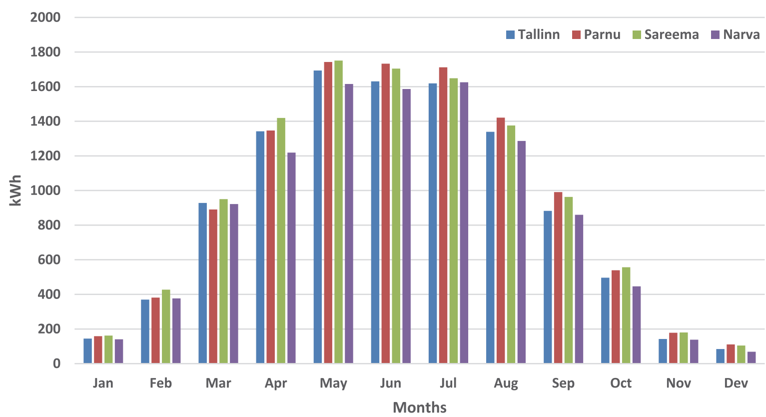

Fig. 7. Energy generation for 12 kW system during the year in four different regions.

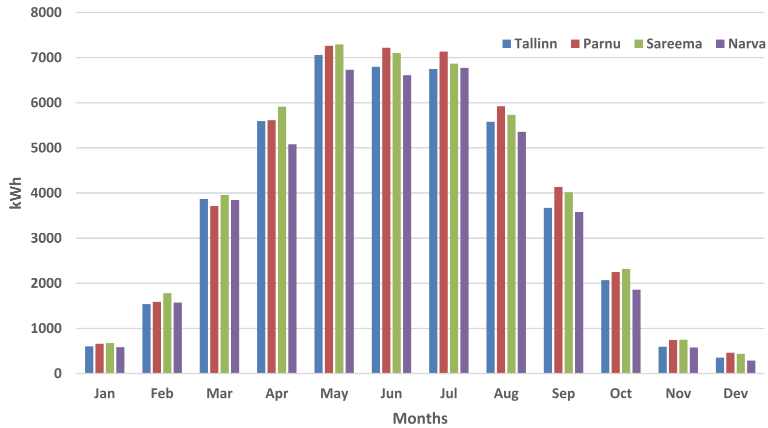

Fig. 8. Energy generation for 50 kW system during the year in four different regions.

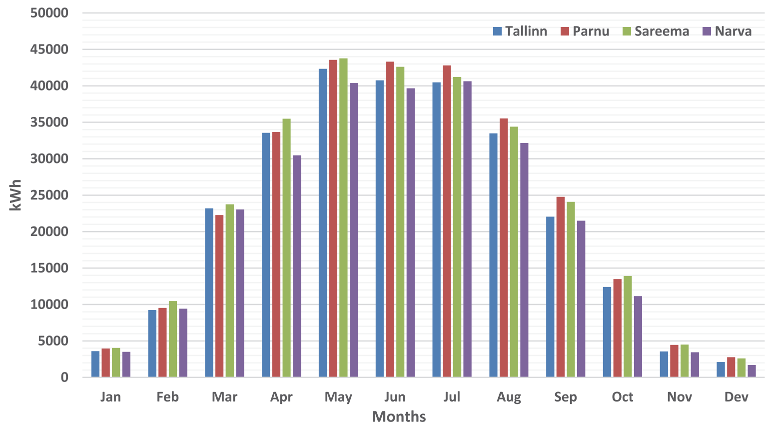

Fig. 9. Energy generation for 300 kW systems during the year in four different regions.

roof energy generation is greater than gable roof installations.

Furthermore, we evaluate and compare the energy generation capability of a 12 kW solar PV system in all four regions of Estonia and the results are presented in Fig. 7. Similarly, Fig. 8 and Fig. 9 show the energy generation results for 30 kW and 300 kW solar PV systems, respectively. From all these figures, the energy generation pattern is higher from April to September and lower from November to February in winter. The results presented in all three figures show higher energy generation in Parnu and Saaremaa regions compared to Tallinn and Narva. Moreover, the energy generation in Parnu is also a bit on the higher side compared to Saaremaa.

It is also evident from the above figures that energy generation in Tallinn and Narva is the lowest overall. However, in some months it matches Tallinn's energy generation. The overall difference between these two regions is not much. Comparing the output of the 300 kW rated PV systems, it is observed that Parnu and Sareema regions are better candidates for large-scale commercial installations. Small and medium scale PVs can be installed in all four regions and there would not be a big difference in the output of these systems.

3. PV energy forecasting using deep learning algorithm

Generally, energy forecasting is considered a regression-based time series problem. Over the past two decades, the problem of renewable energy forecasting has been addressed either using statistical methods [14] or using different machine learning techniques, such as auto-regressive integrated with moving average (ARIMA), support vector machine (SVM), artificial neural network (ANN), k-nearest neighbor (KNN), adaptive neuro-fuzzy inference system (ANFIS) [41]. These algorithms work based on large historical datasets and can incorporate different parameters as inputs of the model. Due to high performance and accuracy, modern deep learning algorithms, such as recurrent neural networks (RNN) and convolution neural networks (CNN) are other widely used deep learning algorithms in prediction problems. However, for any machine learning and deep learning algorithm, exploratory data analysis of the problem is mandatory to carefully analyze and select the input parameters of the model.

3.1. Exploratory data analysis

The PV generation data of a 12 kW PV system in four different

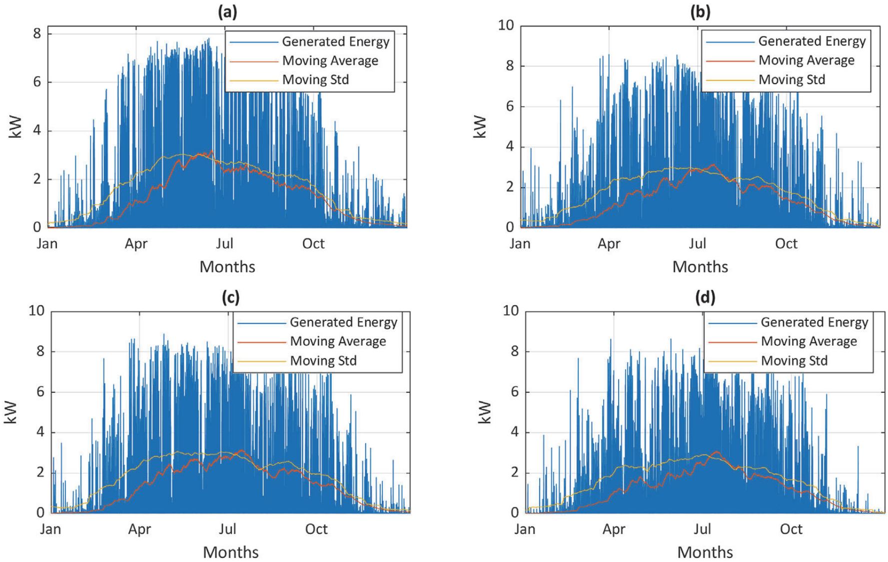

Fig. 10. Statistical Analysis of solar PV generation data for (a) Tallinn (b) Saaremaa, (c) Parnu (d) Narva.

areas of Estonia was collected for this study. This section presents the statistical analysis of the yearlong dataset gathered in 2016 from four local houses situated in Tallinn, Saaremaa, Parnu, and Narva. Figure 1o shows two important statistical parameters, such as moving average and moving standard deviation of the hourly data gathered in all four regions throughout the year. From Fig. 10, It is evident that in all four regions, the density of solar energy generation is higher from April to September. The maximum generated power can go up to 8.5 kW in June. From October, the energy generation value starts to drop significantly, and it remains the same through winter until March, where the generation rarely goes up to 1 kW. Moreover, in winter, there are many days when there is no power available for the whole 24 h. Therefore, a clear bell-shaped curve is visible with a mean occurring around June or July.

The normalized histogram for the daily energy generated in Fig. 11, indicates that the probability of power generation close to 3 kW is high in all regions. Moreover, the results indicate that the probability of getting 15 kW in a day is higher in the Saaremaa region than 12 kW. While in other regions, it is the opposite. Narva region has a mostly high probability of power generation in the lower values. In the Saaremaa region, the values are slightly high compared to the Parnu region for high power output. For example, the probabilities of generating 5.4 kW daily in Tallinn, Saaremaa, Parnu, and Narva are around 14%,27%, 20%, and 20%, respectively.

For the time series prediction, first, we conducted an autocorrelation analysis that indicates the regressive nature of the time

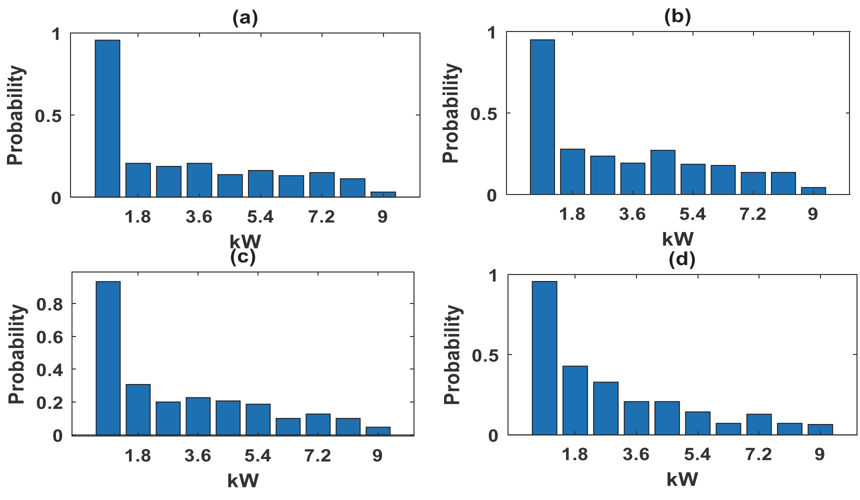

Fig. 11. Histogram with respect to Power generation for (a) Tallinn, (b) Saaremaa, (c) Parnu (d) Narva.

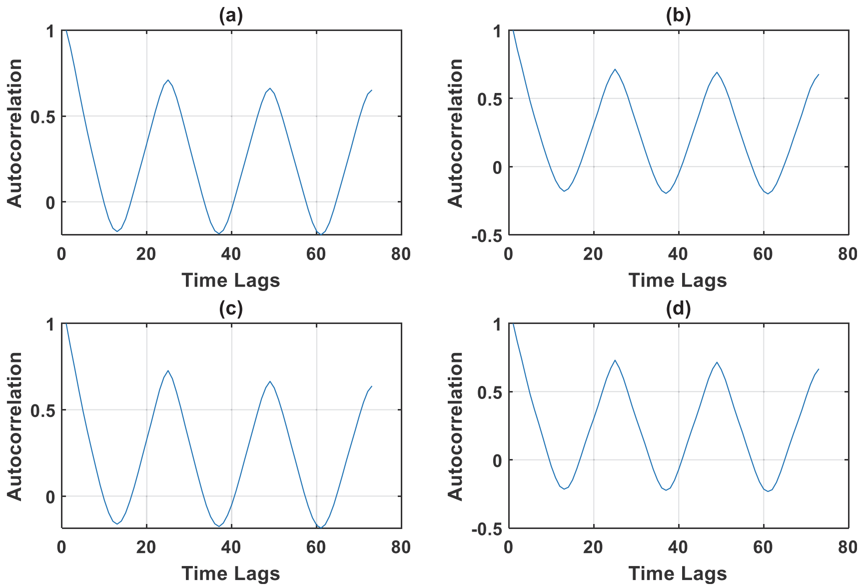

Fig. 12. Autocorrelation analysis.

series data. The analysis for the number of lags indicates the dependency of a present data value on the previous values. The autocorrelation analysis with 72 lags is shown in Fig. 12, which indicates the autocorrelation of the current data sample value with the previous 72 h. We defined a threshold of 0.5, which means 50% dependency of the current data sample with the corresponding sample [42]. In all four regions of Estonia. The high autocorrelation value above 0.5 shows the high dependency with the past 5-h data. In Fig. 12, a clear sinusoidal/periodic behavior is visible from the autocorrelation graph as we can observe that the correlation value is again higher than 0.5 with hours ranging from 22 to 28 and 46 to 52. These two intervals show the dependency of data samples on similar hours of the previous day and the day before yesterday, which indicates long-term data dependency. The autocorrelation value of the solar PV energy generation changes rapidly and periodically, which shows the dependency on day and night times. This data analysis is useful in the design, estimation, and selection of parameters for the deep learning forecasting algorithm.

3.2. Deep learning forecasting algorithm

The multiple layers in a deep structured neural network proficiently extract the higher-level features from the raw input data provided for training, and each layer level memorizes to transform the provided input data into a more composite and abstracted way. Deep learning structures consist of substantial credit assignment path (CAP) depth, which is the transformations and from the input of the model toward the output. The casual connections between the inputs and outputs are described using CAPs. The CAP depth is unlimited in the case of RNNs, in which the signal may distribute more than once through a network layer. Better features extraction than shallow structured neural models can be obtained using deep models having CAP greater than two. Therefore, the extra layers are quite proficient in learning and feature extraction more proficiently.

The RNN is a class of ANNs where a directed graph along a

Table 3
A survey of ML and DL based forecasting techniques.

Survey	Year	Location	Algorithms	Forecasting
[74]	2019	Pakistan	ANN	1 day
[75]	2018	Taiwan	BPNN	1 day
[76]	2017	South Korea	Short Term multivariate	1 day
[33]	2020	South Korea	RNN-LSTM	14 h
[77]	2018	Germany	Regression Trees/Probabilistic	1 day
[78]	2021	Morocco	CNN-LSTM	3 days
[79]	2021	China	CNN-LSTM	1 day
[80]	2021	China	LSTM	1 h
[81]	2021	Italy	LSTM	1 h
[82]	2020	China	LSTM	1 day
[83]	2019	USA	LSTM	1 day
This paper	2021	Estonia	RNN-LSTM	1 day

Abbreviations: Back Propagation Neural Networks (BPNN).

temporal sequence is formed by the interconnection between nodes. The temporal dynamic behavior is exhibited using interconnection schemes. RNNs are basically derived from a feedforward neural network (FF-NN). RNNs utilize their internal state to proceed with the variable-length sequences of inputs. Tasks such as connected handwriting recognition, segmentation, and speech recognition can be proficiently performed using RNNs. RNN-LSTM algorithm is used for the forecasting of energy. This algorithm is selected as it gives better forecasting results for this type of time series data set [35,71]. A survey of the ML and DL methods used in various studies is given in Table 3.

In this study, the RNN-LSTM architecture is trained for short-term PV energy generation forecasting [72,73]. The defects in the original cyclic RNN can be successfully eliminated using the LSTM training algorithm. LSTM is the most proficient and popular among all other RNN training algorithms; therefore, we found it most suitable for our solar PV energy forecasting data as the LSTM avoids the vanishing gradient problem inherently associated with such nonlinear time series data. The architecture of the LSTM algorithm is shown in Fig. 13. The targeted prediction horizon is 3-days ahead to

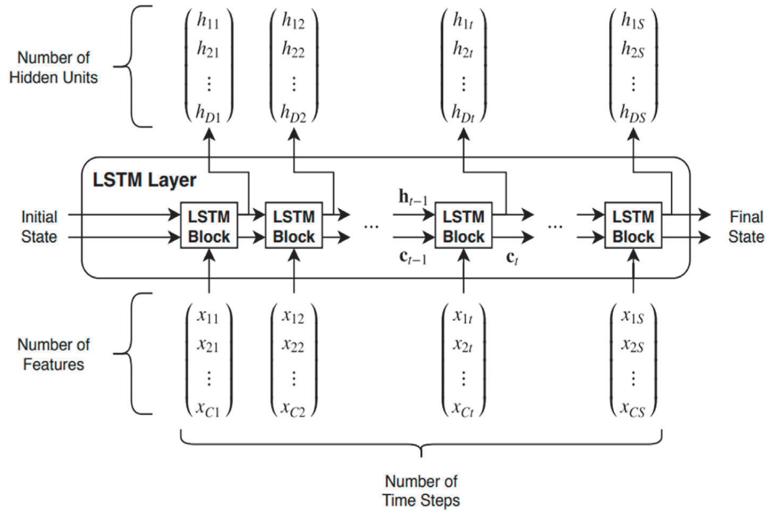

Fig. 13. The architecture of RNN-LSTM.

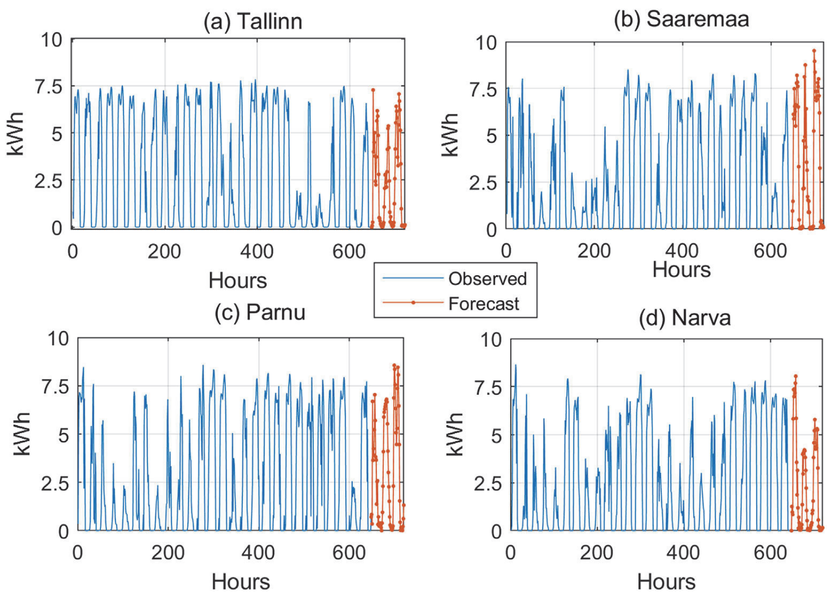

Fig. 14. 3-day ahead energy forecasting in summer.

gather a better and broader picture of the energy demand. The RNN-LSTM architecture consists of a three-layered structure known as the input layer, LSTM layer, and output layer. The initial state or LSTM layer consists of a cell and after each iteration, the values in these cells are either updated or deleted. In each iteration, a sequence-to-sequence regression is performed to predict the future value.

In this study, all the simulations are performed in MATLAB 2020b using a Core i7-9700 CPU with 64 GB of RAM. A 5-year dataset with 1-h frequency, from 2012 to 2016 of a 12 kW crystalline-based PV system with 14% loss is used in the training of the RNN-LSTM forecasting model [63]. We use 90% of the data for training the RNN-LSTM model, while the model is validated and tested on the remaining 10% of data. Based on 50 run trails, the optimized number of hidden layers is selected as 200 and the number of features is one. The ADAM solver is used to train the model with 250 epochs. The 3-day ahead forecasting results are obtained for both summer and winter seasons, separately. Fig. 14 shows the 3-days ahead forecasting results in summer for the last three days of June in all four

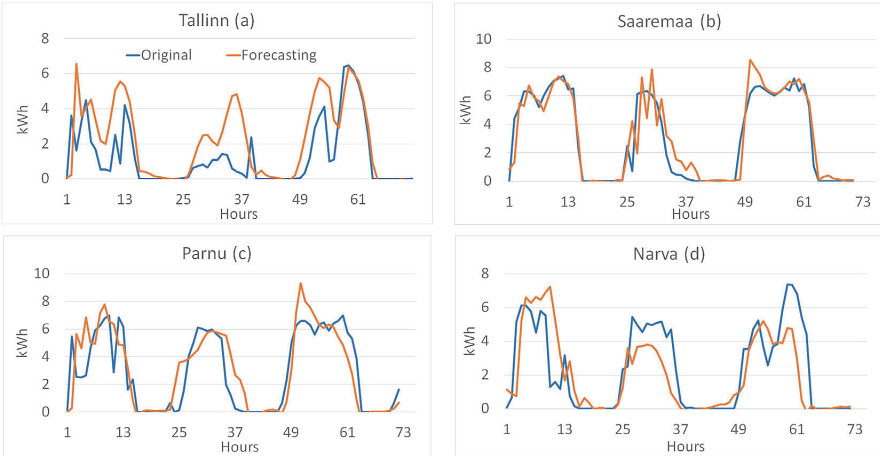

Fig. 15. Comparison of actual energy generation and forecasted energy in summer.

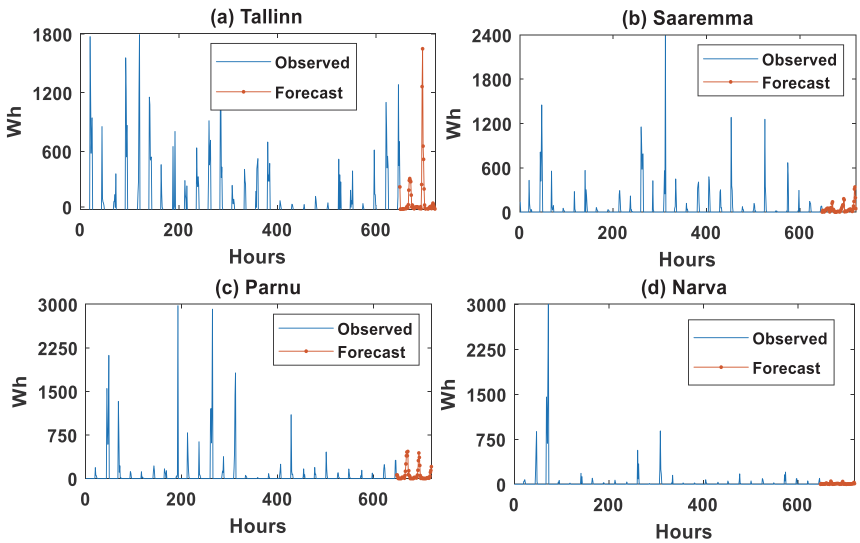

Fig. 16. 3-day ahead energy forecasting in winter.

regions. For the comparison purpose, the predicted results for the last 3 days of June are plotted against the actual energy generation in the last 3 days of June and the graphs for all four regions are shown in Fig. 15. The overall RMSE value between the actual and forecasted output in all four regions is 184.12 (8.03%), which indicates good accuracy of the RNN-LSTM algorithm.

Similarly, Fig. 16 shows the energy forecasting for the last 3-days of December. In December, for a 12 kW solar PV system, the average energy generation in Tallinn, Saaremaa, Parnu, and Narva is around 45Wh, 26Wh, 31Wh, and 14Wh, respectively. The results can be reciprocated and for more accurate results, the model can be trained with the new dataset and then it can be used for more precise forecasting results. Moreover, the comparison of actual and forecasted energy production for the last 3-days of December is given in Fig. 17.

4. Economic analysis

The economic analysis for all three rated solar PV systems for residential and commercial purposes needs a detailed analysis of the following: (a) initial investment analysis (b) subsidy and billing (c) payback period, and (d) impact of electricity unit production on grid.

4.1. Initial investment analysis

The initial cost of solar panels is computed for different available installation methods, such as gable roofs, flat roofs, and ground installation. The initial investment cost of the projected annual production according to the local market of Estonia is given in Table 4 [69].

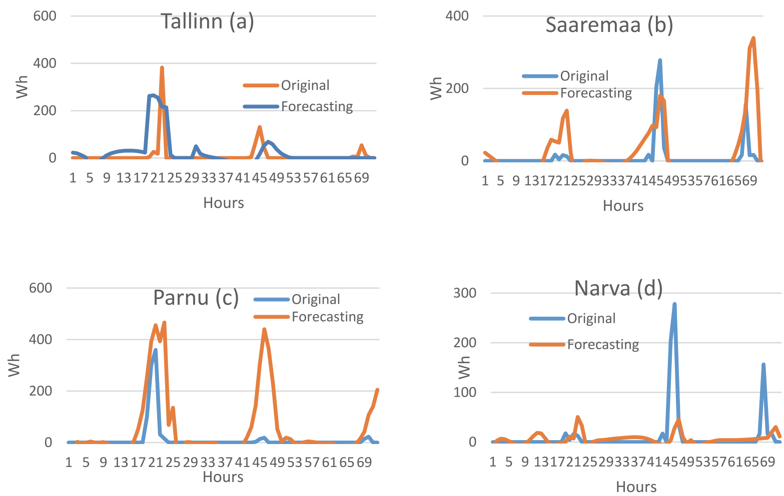

Fig. 17. Comparison of actual energy generation and forecasted energy in Winter.

Table 4
Initial investment for the three different rated PV systems.

PV System rating	12 kW			50 kW		300 kW
Installation method	**Gable Roof**	**Flat Roof**	**Ground**	**Flat Roof**	**Ground**	**Ground**
No. of panels	40	22	45	80	160	938
System capacity (kW)	12.8	7.04	14.4	25.6	51.2	300
Initial cost (k€)	13.4	8.5	14.7	23.1	39.3	154.4

4.2. Subsidy and billing

The billing analysis was conducted based on the unit price of electricity, i.e., kWh in Estonia. In Estonia, the unit price of electricity is a variable power market price; therefore, a general-purpose tariff is defined for this scenario. In Estonia, a subsidy of 5.37 cents per kWh is given to prosumers who installed their PV stations before the end of 2020 by purchasing renewable energy from the TSO [18]. Although the purchase price of TSO for renewable energy is 11% less compared to the sale price of renewable energy with the provided

Table 5
Sales prices of PV energy.

Time	Sale Price per kWh (Euro)	Purchase Price (11% less than the purchase price)	Subsid per kWh (Euro)	Final Purchase Price (Euro)
00:00	0.05	0.044	0.06	0.104
01:00	0.017	0.015	0.06	0.075
02:00	0.016	0.0145	0.06	0.0745
03:00	0.016	0.014	0.06	0.074
04:00	0.017	0.015	0.06	0.075
05:00	0.047	0.042	0.06	0.102
06:00	0.052	0.047	0.06	0.107
07:00	0.065	0.059	0.06	0.119
08:00	0.073	0.065	0.06	0.125
09:00	0.075	0.067	0.06	0.127
10:00	0.069	0.062	0.06	0.122
11:00	0.056	0.05	0.06	0.11
12:00	0.053	0.047	0.06	0.107
13:00	0.058	0.052	0.06	0.112
14:00	0.049	0.044	0.06	0.104
15:00	0.05	0.045	0.06	0.105
16:00	0.049	0.044	0.06	0.104
17:00	0.058	0.052	0.06	0.112
18:00	0.05	0.045	0.06	0.105
19:00	0.07	0.058	0.06	0.118
20:00	0.075	0.067	0.06	0.127
21:00	0.077	0.068	0.06	0.128
22:00	0.066	0.059	0.06	0.119
23:00	0.062	0.056	0.06	0.116

subsidy, an investor was able to take advantage to gain some revenue. As the electricity prices are variable in Estonia, Table 5 shows an overview of the renewable energy sale price offered by TSO in a day along with the purchase price for TSO for the same day.

4.3. Payback period

The payback period of a solar panel installation is another critical economic indicator. A typical payback period for the solar panel installation may vary from 10 to 18 years. The payback period of the different rated PV installations is shown in Fig. 18. However, for end-users, gaining a handsome profit, in the long run, is guaranteed. All the small-scale PV installations have a payback period of around 18 years. The large-scale PV installation has the lowest payback period of around 10 years. However, there can be variations in the payback as it is calculated with the same tariff throughout all the years, if the tariff changes the payback time can increase.

In this study, a period of 25 years [61,69,84] is considered to show the general gain after the installation, considering a specific division of production between the own usage of the facility and the sales portrayed, as shown in Table 6 [18]. The financial gain here is shown after the breakeven point. The hourly electricity prices for March 28, 2021 were taken into consideration and the final prices are projected including the subsidy. This subsidy can vary with every hour and compensate for the difference between the agreed lowest offer and the market price. The estimated average price is around 11 cents per kWh.

Another important factor in economic analysis is the profitability index (PI) or the cost-benefit ratio. It gives information about the feasibility of any project by calculating the ratio between initial investment and the present value of future income. The value of PI equal to 1 indicated the breakeven point, less than 1 means the project won't be able to even cover up the cost of initial investment and greater than 1 shows that it will show some profit. It is calculated by using Eqn. (1) [84]. The calculated PI values are also described in Table 6.

$$PI = \frac{Net\ Present\ worth}{Initival\ Inverstment} + 1 \tag{1}$$

Moreover, Fig. 19 shows the ROI over 25 years for all three rated PV systems. The ROI is calculated using this equation:

$$ROI = \frac{Net\ Income + (Current\ Value - Original\ Value)}{Original\ value} * 100 \tag{2}$$

The annual deprecation is the solar PV is computed as:

$$CV = PV\left(1 + \frac{\gamma}{100}\right)^{n} \tag{3}$$

where the CV is the current value, PV is the previous value, γ% is the annual depreciation rate, and n is the number of years.

4.4. Impact of PV energy production on the national grid

In this section, the impact of solar PV installations on the national grid of Estonia is projected. Here, different cases are considered which include various installation scenarios based on different rated PV systems. The number of small-scale installations is varied between 100 and 10000, the medium-scale between 10 and 1000, and the large scale between 1 and 10. Later, the accumulated energy generation throughout the year is calculated. These projected calculations are given in Table 7. It can be seen from this table that these PV installations can have a significant effect on the national grid of Estonia. If there are 10000 small-scale, 1000 and 10 large-scale installations in one year, then they will be providing an accumulative energy generation of 192 TWh. A similar number of these installations every year will substantially reduce the overall load on the national Estonian grid and will help in the reduction of the demand and supply gap.

5. Results analysis and discussions

This study has been made for the four different regions of Estonia, including the capital and two other populous regions. These four regions are geographically the eastern, northern, southern, and western parts of the country and are comprised of more than 60% of the Estonian population. Therefore, this study covers the aspects of solar energy generation and diversifying the Estonian energy market, reducing its energy import bills, improving energy forecasting, and directly reducing the carbon footprint as well. The results of this study can be extended to the other Nordic and Baltic countries of the region as they also have quite a similar solar irradiance profile.

Three different scale PV systems are proposed and tested foreseeing the individual energy requirements of residential homes, residential apartment buildings/Office buildings, and micro-PV

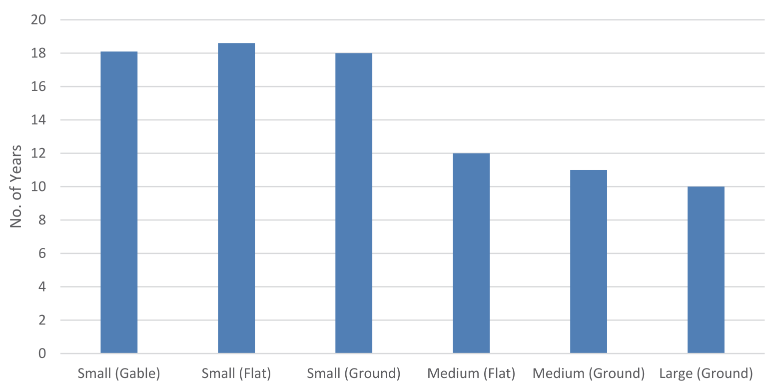

Fig. 18. The payback period for different PV installations.

Table 6
Comparison of initial investments and financial gain.

PV System	12 kW			50 kW		300 kW
Installation Method	Gable Roof	Flat Roof	Ground	Flat Roof	Ground	Ground
System Capacity (kW)	12.8	7.04	14.4	25.6	51.2	300
Initial Cost (k€)	13.4	8.5	14.7	23.1	39.3	154.4.
Division of Production (Own usage % – Sales %)	27–73	43–57	24–76	54–46	34–66	–
Financial Gain in 25 years (k€)	5.6	2.7	6.6	26.8	52.4	229.7
PI	1.42	1.32	1.45	2.16	2.33	2.49

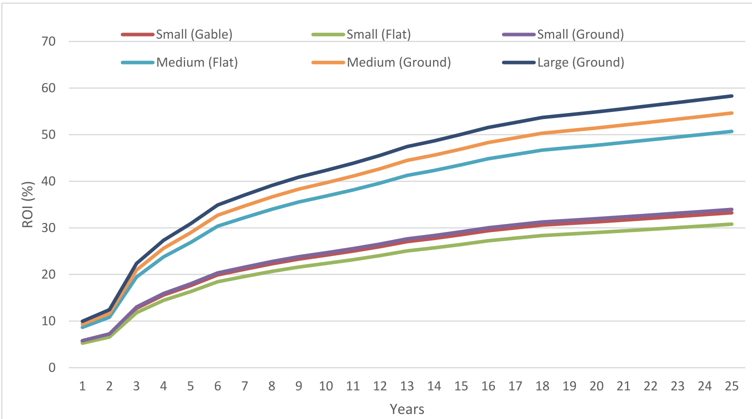

Fig. 19. Return over Investment for different rated PV systems.

Table 7
PV systems' impact on the grid.

Small (12 kW)	Medium (50 kW)	Large (300 kW)	Annual Production (MWh)
100	10	1	2176
500	50	3	10301
1000	100	5	20312
5000	500	7	96343
10000	1000	10	191526

plants based on local investments. We proposed a 12 kW PV system for residential homes, a 50 kW PV system for the apartment building, and a 300 kW PV system for the installation of the commercial PV plant. All three PV systems are tested and compared for a gable roof, flat roof, and ground installation methods based on annual energy generation. The comparative analysis of energy generation illustrates that the generation is nearly the same in all four regions; however, Narva remains slightly on the lower side throughout the year followed by Tallinn. While Parnu and Saaremaa have similar energy generation and are slightly higher compared to the other two regions due to better altitude positions for solar PV generation.

Another important feature for the future prospect of PV system installation in Estonia is to estimate solar power generation accurately. As solar PV systems are expected to become a bigger part of the electric power generation mix, the power system operators require better visibility of how much solar power will produce. Therefore, an optimal schedule can be devised to dispatch solar and grid energy for demand-supply management of residential homes, apartment buildings, and distributed microgrids. Improving solar energy forecasts will allow more flexibility to adopt condition changes while helping to minimize disruptions and the overall cost of operation. Foreseeing the need, we implement a short-term forecasting model for solar energy using RNN-LSTM deep-learning algorithm. Only the use of an analytical method on time series data cannot predict the exact future behavior. A detailed exploratory data analysis is mandatory to understand the relationships that exist in the time series data. Therefore, we employed quantitative methods, such as moving average, moving standard deviation, regression, and correlation analysis to find similar patterns in the historical time series data of solar PV energy generation. Based on detailed exploratory data analysis, we select the input parameters to be considered in the RNN-LSTM short-term forecasting model. The prediction horizon considered in our study is 3-day ahead for short-term hourly demand scheduling of generating units, economic analysis, and secure operation of installed PV systems.

One of the major contributions of this study is to analyze the long-term economic prospects of PV system installation. The study includes initial investment, subsidy and billing, financial gains, payback period, and long-term impact on the national grid. For a 12 kW PV system, the initial investment cost per kW is computed to be €1052, €1205, and €1025 for a gable roof, flat roof, and ground installation, respectively. Moreover, for a 50 kW PV system, the initial investment cost per kW is calculated as €900 and €768 for flat roof and ground installation, respectively. Furthermore, for a 300 kW commercial PV plant, the per kW initial investment for ground installation is €514. Currently, the TSO is offering 5.37 cents/kWh subsidy to renewable energy generator customers. However, the TSO is purchasing renewable energy at an 11% subsidized rate. Despite this fact, the overall per hour final purchasing price per unit is reasonable, which is computed to be €0.10.

The payback period considered in the study is 25 years to analyze ROI and long-term financial gain. For 12 kW PV systems, flat roof installation is more feasible and easier than gable and ground installation, but it will produce less electricity and most of the small households in Estonia may not be having a flat roof. Therefore, a ground or gable roof solution is a better option, they will also generate more energy. The payback period is around 18 years. In the case of an apartment/office building, a flat roof with 300 m^2 PV installations with 25 kW capacity will have a payback period of 12 years. However, the ground installations with 340 m^2 and 50 kW capacity will be having a payback period of 11 years, but their profit margin in the next years will be significantly higher. For the large-scale commercial PV system, the payback period is around 9 years for a 300 kW rated system, but it will reach 2.5 times the financial gain than its initial investment. These financial indicators are given in Table 6.

5.1. Comparison of study with existing research work

Many studies have been conducted on the PV installation methods, its impact on the national grid, calculation of payback periods, effects of net metering and energy generation forecasting in different parts of the world as mentioned earlier in Table 1. The payback period of 5 kW PV systems in Turkey was found to be varying between 7 and 14 years [84]. The study was conducted in nine different provinces of Turkey. A similar study made in Saudi Arabia found the payback period of 12 kW solar PV system to be around 12 years in case of off grid installation and 8 years while connected to the grid [85]. A study conducted in Australia found the payback period of 16 years for a 3-kW residential PV system. Moreover, a Moroccan study estimated that a 4-kW PV system has a payback period of 12 years. The payback period was estimated to be between 17 and 23 years in a study made in Jordan [58]. The payback periods using net metering and different PV installation scenarios gave a payback period between 8 and 16 years for a study conducted in Pakistan [61]. Moreover, a study conducted in Estonia considered eight different residential household scenarios along with PV and Electric Vehicles (EV) installation [86]. The authors investigated the potential of PV-BESS-EV integrated with grid and computed the payback period to be between 16 and 20 years [86]. In comparison, the results of this study show the payback period between 10 and 18 years. The payback period of small residential PV is higher because the solar potential in Estonia is not that high compared to the other regions in the Baltic Sea Area. In addition, the winter in Estonia is very long with mostly dark days and very little PV energy generation.

Moreover, many machine learning based forecasting studies have been conducted in different parts of the world. The accuracy of the forecasting results is usually measured in RMSE or mean absolute percentage error (MAPE). The deep learning based hour-ahead PV energy forecasting algorithm gave RMSE value of 61 kW (7%) [4]. The PV energy forecasting was made using Artificial Neural Networks (ANN) and the MAPE was estimated to be around 15% [74]. A study conducted in South Korea for a PV power plant using LSTM algorithm concluded that the RMSE value is around 8% and the MAPE is around 11%. A similar study for 24 h ahead PV energy forecasting in China using LSTM technique showed that RMSE value is around 9% [82]. The hybrid forecasting algorithm based on LSTM and Genetic Algorithm (GA) gave an RMSE value of 1.118 kW (around 4%) for a 30 min ahead PV energy [80]. In comparsion, the results of our LSTM forecasting algorithm give an RMSE values of 184 W (around 8%). This forecasting is relatively accurate as the algorithm is generating forecasting values for 3-days ahead.

6. Conclusions and future works

This paper presents the feasibility, comprehensive analysis, and broader picture of solar energy generation potential and prospects in all different regions of Estonia, such as Tallinn, Saaremaa, Parnu, and Narva. These regions cover around 70% population of Estonia. The analysis of solar radiation patterns in all four regions of Estonia for the summer and winter seasons reveals the feasibility of solar power generation as the radiation pattern is nearly similar. In this study, three different PV-rated systems for domestic and commercial installations are discussed. These cases included a small residential household, an office building and a small commercial PV power plant. The PV installation methods like the flat roof, gable roof and on-ground are also discussed here.

Moreover, the benefits of using accurate and effective PV energy forecasting algorithms are mandatory to manage demand-supply and short-term energy policymaking for the residential sector, commercial buildings, and private micro-PV plants. The relationship between energy generation prediction accuracy and economic analysis is very important. As the economic analysis is primarily based on the future income/profit of the proposed PV system while keeping in view the investment cost. Therefore, we developed and analyzed the RNN-LSTM algorithm for short-term PV energy forecasting over the prediction horizon of 3-days ahead. There is a huge variation in solar energy generation during summer and winter days. However, the proposed algorithm showed good forecasting results both in the summer and winter seasons. The forecasting results are evaluated based on the RMSE values.

Furthermore, a detailed economic analysis is conducted to compute financial gains for potential investors in PV energy generation. The economic analysis is based on the initial investment of the installation of PV systems, financial gain in 25 years, the payback period, ROI and PI. The payback period in all small households is around 18 years. However, the gable roof installation gives better results as compared to flat roof PV installation. The payback period for an office building/a small apartment building is between 11 and 12 years and for a small commercial PV plant is 10 years. Moreover, all the cases show a positive and profitable PI varying between 1.4 and 2.5.

Based on this conducted study, in the future, we will develop an efficient energy management model and will compute the optimal size of the battery energy storage system as a key factor to effectively minimize the total energy consumption cost of the nearly Zero Energy Buildings (nZEBs) while having a minimum dependence on the grid. Moreover, a detailed techno-economic analysis will be conducted for the whole year including all four weather seasons, different residential buildings, and different electricity pricing techniques.

Author contributions

Conceptualization, N.S. and L.K.; methodology, N.S., L.K & O.H.; software, N.S.& H.A.R; validation, H.A.R., M. J. and A.A.; formal analysis, M.J. & A.A.; investigation, A.A. & O.H; data curation, H.A.R &; O.H.; writing—;original draft preparation, N.S. & H.A.R.; writing—;review and editing, L.K & O.H; visualization, M.J. & A.A.; supervision, L.K & O.H; project administration, L.K, O.H.; funding acquisition, L.K, O.H. All authors have read and agreed to the published version of the manuscript.

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.

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Publication V

Shabbir, N.; Kütt, L.; Jawad, M.; Husev, O.; Rehman, A.U. et al. (2022). Short-Term Wind Energy Forecasting Using Deep Learning-Based Predictive Analytics. CMC-Computers, Materials & Continua, 72(1), 1017–1033.

Computers, Materials & Continua
DOI: 10.32604/cmc.2022.024576
Article

Short-Term Wind Energy Forecasting Using Deep Learning-Based Predictive Analytics

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Received: 22 October 2021; Accepted: 10 December 2021

Abstract: Wind energy is featured by instability due to a number of factors, such as weather, season, time of the day, climatic area and so on. Furthermore, instability in the generation of wind energy brings new challenges to electric power grids, such as reliability, flexibility, and power quality. This transition requires a plethora of advanced techniques for accurate forecasting of wind energy. In this context, wind energy forecasting is closely tied to machine learning (ML) and deep learning (DL) as emerging technologies to create an intelligent energy management paradigm. This article attempts to address the short-term wind energy forecasting problem in Estonia using a historical wind energy generation data set. Moreover, we taxonomically delve into the state-of-the-art ML and DL algorithms for wind energy forecasting and implement different trending ML and DL algorithms for the day-ahead forecast. For the selection of model parameters, a detailed exploratory data analysis is conducted. All models are trained on a real-time Estonian wind energy generation dataset for the first time with a frequency of 1 h. The main objective of the study is to foster an efficient forecasting technique for Estonia. The comparative analysis of the results indicates that Support Vector Machine (SVM), Non-linear Autoregressive Neural Networks (NAR), and Recurrent Neural Network-Long-Term Short-Term Memory (RNN-LSTM) are respectively 10%, 25%, and 32% more efficient compared to TSO's forecasting algorithm. Therefore, RNN-LSTM is the best-suited and computationally effective DL method for wind energy forecasting in Estonia and will serve as a futuristic solution.

Keywords: Wind energy production; energy forecast; machine learning

1 Introduction

The worldwide energy demand is increasing with every passing year so is the environmental pollution due to the brown energy generation from fossil fuels. Therefore, the uses of Renewable Energy Resources (RES) like solar and wind have gained popularity due to lower carbon emissions. However, wind energy generation is variable and unstable due to variations in wind speed [1,2]. The variable nature of wind depends on geographical area, weather, time of day, and season. Therefore, predicting wind power generation with 100% accuracy is a very difficult task [3]. However, this prediction is highly important for the management of demand and supply in power grids and also has an economic impact [4,5]. This prediction was usually made using statistical methods [6], such as moving average and autoregressive, but the accuracy of the models was relatively low. Machine learning (ML) based forecasting algorithms are a widely used tool due to their property to capture nonlinearities in the data with high accuracy, but machine learning algorithms usually require a large dataset of formation to develop an efficient forecasting model. These models are trained, validated, and tested; sometimes they still require retraining to obtain more precise results [7]. The forecasting models are usually divided into three categories, such as short-term forecasting (few minutes to 24 h), medium-term forecasting (days-ahead to week-ahead), and long-term forecasting (month-ahead to year-ahead) [8]. In this study, the real-time dataset of Estonian wind energy generation is used [9,10] for the development of these forecasting models.

In the past, several research works have been developed using deep methods for wind speed forecasting and wind power generation forecasting. A bibliometric visualization of the keywords used in previous studies conducted in the past 5 years related to wind energy furcating has been made in VOS viewer software and depicted in Fig. 1. The figure shows the keywords used in 238 articles in the last five years related to wind energy forecasting. The forecasting of the wind speed in a university campus in Switzerland is being made using the ridge regression technique [11]. In a similar study [12], different ML algorithms like Support Vector Machine (SVM), K-Nearest Neighbor (KNN) regression, and random forest are compared for the forecasting of wind speed and corresponding energy generation for the day-ahead prediction horizon. A hybrid genetic algorithm and SVM-based algorithm are developed and tested for under-learning and overlearning scenarios of forecasting to determine the optimal solution [13]. A review of a supervised ML algorithm is made in [14]. In another work, ANN-based algorithms are developed and simulated to predict wind energy generation for grid stability [15]. A novel Cartesian genetic Artificial Neural Network (ANN) based algorithm is also proposed for wind energy forecasting in [16], which includes Hybrid regression based on SVM, Convolutional neural network (CNN), and singular spectrum analysis (SSA). The experimental results showed that SVM gave better predictions [17]. In [18], Extreme Machine Learning (ELM) algorithms have been used to forecast the wind speed for energy generation. A comparison of ELM, Recurrent Neural Networks (RNN), CNN, and fuzzy models is also given in [19–22] and future research directions are also explored. Tab. 1 provides a summary and comparison of the few known research articles related to wind energy forecasting using ML algorithms including Self-adaptive Evolutionary Extreme Learning Machine (SAEELM), Multilayer Perceptron (MLP), Random Forest (RF), Linear Regression (LR), Extremely Randomized Trees (ET), Radial Basis Function Neural Network (RBFNN), Gradient Boosting Algorithm (GBM), Tree Regression (TR), Long Short-Term Memory Networks (LSTM), Two-stream Deep Convolutional Neural Networks (TDCNN), Mean absolute percentage error (MAPE).

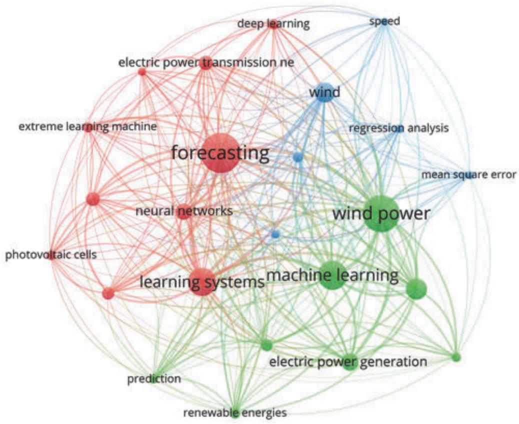

Figure 1: Bibliometric visualization of the keywords used in previous studies, created using VOSviewer

Table 1: Comparison of proposed work with other studies on wind energy ML-based forecasting

Paper	Algorithms	Data size	Duration	Description
[18]	ELM	4 months	1 h	ELM has better accuracy for multistep ahead forecasting.
[20]	SVM	4 years	1 day	Feature extraction based SVM outperforms KNN.
[21]	Randomizable filter classifier	4 years	1 day	Randomizable filter classifier gives better forecasting and a lower error compared to KNN.
[23]	SVM, ANN	3 years	1 day	ANN is found to be more accurate than SVM.
[24]	RNN-LSTM	1 year	1 h	LSTM forecasting with 10.43% RMSE.
[25]	SVM, KNN	4 years	1 day-1 month	KNN algorithm outperforms SVM, RT, and ET.
[26]	SVM, RBFNN	2 years	2 h	A hybrid model based on SVM and RBFNN gives only 6.84% MAPE.
[27]	RNN-LSTM	4 years	1 day	LSTM gives better forecasting.
[28]	DNN	10 years	1 day	DNN gives better forecasting compared to SVM.

(Continued)

Table 1: Continued

Paper	Algorithms	Data size	Duration	Description
[29]	ANFIS	2 years	1 h	ANFIS gives 2.25%, 3.35% and 3.86% MAPE.
[30]	Linear regression	2 years	6 h	ML algorithms give more accurate forecasting compared to statistical methods.
[31]	SVM, ANN	2 years	1 day	A hybrid SVM-ANN model outperforms individual models.
[32]	RNN-LSTM	1 year	3 days	LSTM gives 25% more accurate than statistical methods.
[33]	ARIMA, ELM	1 month	1 day	Hybrid ARIMA-ELM gives MAPE of 2.21%, 2.94%, and 3.2% for three different sites.
[34]	TDCNN	4 years	1–24 h	TDCNN gives lower RMSE for up to 24 h before forecasting.
[35]	GBM	3.75 years	21–45 h	The improvement in GBM reaches on average 1% on MAE and 0.9% on RMSE.
[36]	SVM/ANN	2.5 year	6–24 h	SVM gives better 24 h ahead forecasting results than ANN.
[37]	RNN, KNN	3 years	1 day	LSTM is 18.3% more accurate than KNN and SVM.
[38]	MLP	3 years	70 h	ANN based MLP gives accurate forecasting for 70 h.
Our work	LR, TR, SVM, ANFIS, AR, ARIMA, NAR, LSTM	2–8 years	24 h	RNN-LSTM gives better forecasting compared to LR, TR, SVM, ANFIS, ARIMA, AR and NAR.

From all the above studies, it is clear that ML and DL algorithms are very useful in wind energy forecasting. However, it is still a very difficult thing to make an accurate prediction and a universal model is not possible. Therefore, every scenario requires a local dataset of wind speed, weather information, and location. Each model needs to be customized, built, and then trained. This accurate forecasting will help in the better management of demand and supply, smooth operation, flexibility and reliability and as well as economic implication.

In this research, a comparison has been made between different machine learning and DL forecasting algorithms for a day-ahead wind energy generation in Estonia. The historical data set on one-year Estonian wind energy generation was taken from the Estonian Transmission System operator (TSO) called ELERING [9]. This historical data contains all of the above-stated factors that affect wind energy generation. On the basis of this data, different forecasting algorithms are modeled, trained, and compared.

The key contributions of this paper are summarized as follows:

- To address the problem of wind energy forecasting in Estonia, state-of-the-art ML and DL algorithms are implemented and rigorously compared based on performance indices, such as root mean square error, computational complexity, and training time.
- A detailed exploratory data analysis is conducted for the selection of optimal models' parameters, which proves to be an essential part of all implemented ML and DL algorithms.
- A total of six ML NAR and two DL algorithms are implemented, such as linear regression, tree regression, SVM, ARIMA, AR, NAR, ANFIS, and RNN-LSTM. All implemented algorithms are thoroughly compared with currently implemented TSO forecasted wind energy and our proposed RNN-LSTM forecasting algorithm proves to be a more accurate and effective solution based on performance indices.

The structure of the paper is shown in Fig. 2.

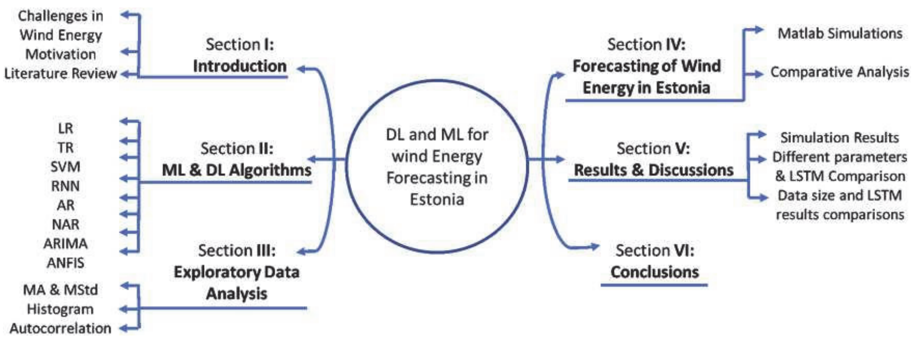

Figure 2: Paper outline

2 Machine Learning Algorithms for Forecasting

The most common ML tool for forecasting is regression-based algorithms [19]. Regression-based learning is categorized into supervised learning algorithms that use past data sets of the parameters in the training of the model and then predict the future values of the parameters based on the regressed time lag values of the parameters, where the number of lag selections is based on observation. Moreover, the most used DL algorithms in time series prediction are RNN and CNN. In CNN, the output only depends on the current input while in RNN, the output depends both on the current and previous values that provide an edge to RNN in time series prediction. In this section, machine learning and deep learning algorithms used in this study are elaborated.

2.1 Linear Regression

This simplest and most commonly used algorithm computes a linear relationship between the output and input variables. The input variables can be more than one. The general equation for linear regression is along with its details can be found in [7].

2.2 Tree Regression

This algorithm deploys a separate regression model for the different dependent variables, as these variables could belong to the same class. Then further trees are made at different time intervals for the independent variables. Finally, the sum of errors is compared and evaluated in each iteration, and this process continues until the lowest RMSE value is achieved. The general equation and the details of the algorithm are described in [7].

2.3 Support Vector Machine Regression (SVM)

SVM is another commonly used ML algorithm due to its accuracy. In SVM, an error margin called 'epsilon' is defined and the objective is to reduce epsilon in each iteration. An error tolerance threshold is used in each iteration as SVM is an approximate method. Moreover, in SVM, two sets of variables are defined along with their constraints by converting the primal objective function into a Lagrange function. Further details of this algorithm are given in [7,39,40]:

2.4 Recurrent Neural Networks

The RNN is usually categorized as a deep-learning algorithm. The RNN algorithm used in this paper is the Long Short-Term Memory (LSTM) [41]. In LSTM, the paths for long-distance gradient flow are built by the internal self-loops (recurrences). In this algorithm, to improve the abstract for long time series based different memory units are created. In conventional RNN, the gradient vanishing problem is a restriction on the RNN architecture to learn the dependencies of the current value on long-term data points. Therefore, in LSTM, the cell data are kept updated or deleted after every iteration to resolve the vanishing gradient issue. The LSTM network in this study consists of 200 hidden units that were selected based on the hit-and-trial method. After 200 hidden units, no improvement in the error is observed.

2.5 Autoregressive Neural Network (AR-NN)

This algorithm uses feedforward neural network architecture to forecast future values. This algorithm consists of three layers, and the forecasting is done iteratively. For a step ahead forecast, only the previous data is used. However, for the multistep ahead, previous data and forecasted results are also used, and this process is repeated until the forecast for the required prediction horizon is achieved. The mathematical relationship between input and output is as follows [42]:

$$y_t = w_0 + \sum_{j=1}^{h} w_j.g\left(w_{0,j} + \sum_{i=1}^{n} w_{i,j}.y_{t-1}\right) + \varepsilon_t \tag{1}$$

where $w_{i,j}$, w_j $(i,j = 0, 1, 2, \ldots, n, j = 1, 2, \ldots, h)$ are parameters for the model; n represents the input nodes, h is the number of hidden nodes. In addition, a sigmoid function is used for the hidden layer transfer function as defined in Eq. (2) [42].

$$sig\ (x) = \frac{1}{1 + \exp(-x)} \tag{2}$$

2.6 Non-Linear Autoregressive Neural Network

The Nonlinear Autoregressive Neural Network (NAR-NN) predicts the future values of the time series by exploring the nonlinear regression between the given time series data. The predicted output values are the feedback/regressed back as an input for the prediction of new future values. The NA-NN network is designed and trained as an open-loop system. After training, it is converted into a closed-looped system to capture the nonlinear features of the generated output [43]. Network training is done by the backpropagation algorithm mainly by the step decent or Levenberg-Marquardt backpropagation procedure (LMBP) [44].

2.7 *Autoregressive Integrated Moving Average (ARIMA)*

This model is usually applied to such datasets that exhibit nonstationary patterns like wind energy datasets. There are mainly three parts of the ARIMA algorithm. The first part is AR where the output depends only on the input and its previous values. Eq. (3) defines an AR model for the p-order [45]:

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \ldots \emptyset_p y_{t-p} + \in_t \tag{3}$$

where t is the number of lags, Ø is the coefficient of the lag, c is the intercept term and $\in_t$ is white noise. MA is the second part that describes the regression error as a linear combination of errors at different past time intervals. Eq. (4) [45] describes the MA as follows,

$$y_t = \in_t + \emptyset_1 \in_{t-1} + \emptyset_2 \in_{t-2} + \ldots \emptyset_p \in_{t-p} \tag{4}$$

The third part 'I' describes that the data have been updated by the amount of error calculated at each step to improve the efficiency of the algorithm. The final equation of ARIMA is as follows [45]:

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \ldots \emptyset_p y_{t-p} + \emptyset_1 \in_{t-1} + \emptyset_2 \in_{t-2} +, \ldots, \emptyset_p \in_{t-p} \tag{5}$$

2.8 *Adaptive Neuro-Fuzzy Inference System (ANFIS)*

This algorithm is a hybrid of ANN and Fuzzy logic. In the first step, Takagi and Sugeno Kang's fuzzy inference modeling method is used to develop the fuzzy system interference [46]. The overall model in this algorithm consists of three layers. The first and last layers are adaptable and can be modified accordingly to the design requirements while this middle layer is responsible for the ANN and its training. In the fuzzy logic interference system, the fuzzy logic structures and rules are defined. Moreover, it also includes fuzzification and defuzzification as well.

This algorithm works on Error Backpropagation (EPB) model. The model employs Least Square Estimator (LSE) in the last layer which optimizes the parameters of the fuzzy membership function. The EBP reduces the error in each iteration and then defines new ratios for the parameters to obtain optimized results. However, the learning algorithm is implemented in the first layer. The parameters defined in this method are usually linear [46,47].

3 Exploratory Data Analysis

Estonia is a Baltic country located in the northeastern part of Europe. Most of its energy is generated from fossil fuels, whereas the RESs are also contributing significantly. The distribution of RES and non-RES energy gen is shown in Fig. 1. The average share of fossil fuels is around 70% for the year 2019, while renewables are around 30% [9]. Although 30% is still higher as per the EU plan for renewable integration in the grid by 2020 [9]. As per the 35% share in RE, wind energy is the second most used resource in Estonia after biomass in 2019 [9], which makes it very important. The energy demand in Estonia is usually high in winter and the peak value is around 1500 MWh, while the average energy consumption is around 1000 MWh. Meanwhile, the average energy generation is around 600 MWh and the peak value is around 2000 MWh [9]. The demand and supply gap can vary between

200 to 600 MWh and is almost the same throughout the year. This gap is overcome by importing electricity from Finland, Latvia, and Russia if needed [9].

In Estonia, a total of 139 wind turbines are currently installed, mainly along the coast of the Baltic Sea [10]. Fig. 3 shows the geographical location of the installed sites. The installed capacity of these wind turbines is around 301 MW. In addition, there are 11 offshore and two offshore projects under the development phase. The plan is to have 1800 MW of wind power generation by the year 2030 [10]. The current share of wind energy is only around 10% of the total energy generated in Estonia. However, according to EU regulations, environmental factors, and self-dependency, this share will increase rapidly in the future. Therefore, due to the stochastic nature of wind speed, accurate prediction of wind power generation will be essential to manage demand and supply. A good and advanced prediction technique is required for an accurate wind power generation prediction in Estonia. This study provides a detailed and wide exploratory and comparative analysis for wind power generation forecasting by employing multiple linear and nonlinear ML and Deep Learning (DL) techniques.

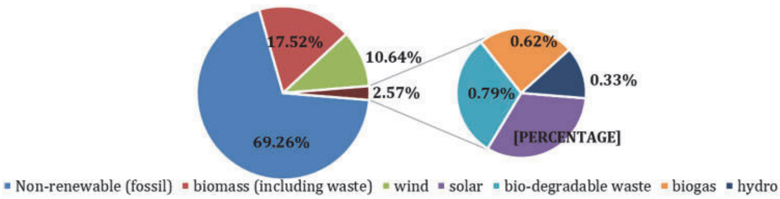

Figure 3: Share of renewable and non-renewable energy in Estonia

The data set used in this article is the Estonian general data on wind energy generation from 1 January 2011 to 31 May 2019. The frequency of the data set is one hour. This data set for wind energy generation is highly variable due to the weather conditions in Estonia. The maximum value of wind energy production in the aforementioned period is nearly 273 MWh, the mean value is 76.008 MWh, the median is 57.233 MWh, and the standard deviation is 61.861 MWh. To demonstrate the variable nature of the time series dataset for Estonian wind power generation, the moving average and the moving standard deviation are the best tools to elaborate on this dynamic nature of the dataset. Fig. 4 shows the wind energy production data along with the moving average and the moving standard deviation from Jan. 2018 to May 2019. It is clear from Fig. 4 that there are no clear peaks in wind energy or low seasonal values. Wind energy production is variable throughout the whole year. As indicated by the moving average, wind energy generation is high in winter (November to March), but even in that time, its value drops for a few weeks and then again increases.

The histogram and the probability density function (PDF) of the data are shown in Fig. 5a, which indicates that the wind energy production is below 50 MWh most of the time and its value rarely goes above 250 MWh. The histogram data is now normalized to compute the actual probability of different energy production values. The resultant probabilities are depicted in Fig. 5b. These probability values also indicate the same analogy. For example, the probability of getting 100 MWh energy is around 20% and 250 MWh is only around 3%. Therefore, the accuracy for the prediction of peak power generation or above-average power generation is a challenging task. Further analysis of this data set is performed using autocorrelation analysis. Fig. 5c shows the autocorrelation analysis of the data set.

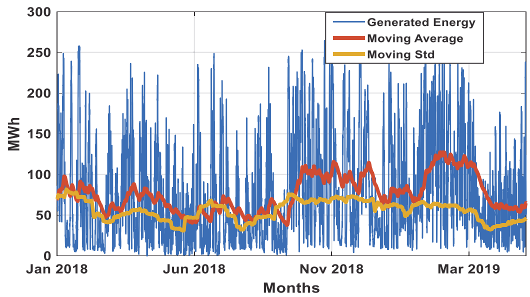

Figure 4: Energy production, moving average and moving std. deviation

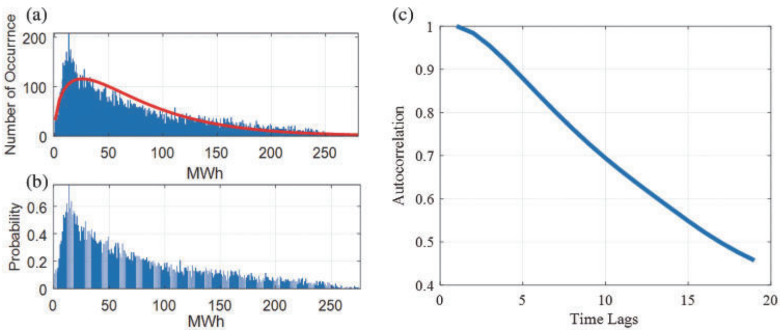

Figure 5: (a) Histogram (b) PDF of the data, (c) Autocorrelation analysis

In time-series analysis, the autocorrelation measure is a very useful tool to observe the regression nature of the time-series data and provides a birds-eye view for the election of the number of lags if any regression-based forecasting model is employed. It is the correlation of the signal with its delay version to check the dependency on the previous values. In this graph, the lag of 20 h is shown, in which the lags up to the previous 16 h have a regression value above 0.5 percent and after which it drops significantly below 0.5. The confidence interval is identified by the calculated 2σ values. The correlation decreases slowly over time, which shows long-term dependency. The description of this observation is described in [48]. However, the autocorrelation of wind energy generation does not decrease rapidly with weather changes related to different seasons. This exploratory data analysis helps us to estimate design, and parameter selection for all ML and deep-learning algorithms defined earlier.

4 Forecasting of Wind Energy

The Estonian wind energy dataset has been used in this research. The dataset is then divided into training, testing and validation and the divisions of data are 80%, 10% and 10%, respectively. All these simulations are carried out in Matlab2021a in a Windows 10 platform running on an Intel Core i7-9700 CPU with 64 GB RAM. Initially, the training data was converted into standard zero mean and unit variance form to avoid convergence in the data. The same procedure was carried out for the test data as well. The prediction features and response output parameter has also been defined for a multistep ahead furcating. The Estonian TSO is responsible for the forecasting of wind energy generation on an hourly basis. Their prediction algorithm forecasts wind energy generation 24 h in advance. It also generates the total energy production and the anticipated energy consumption. Fig. 6 shows the values of wind energy production and the values forecasted by the TSO algorithm for May 2019 [49].

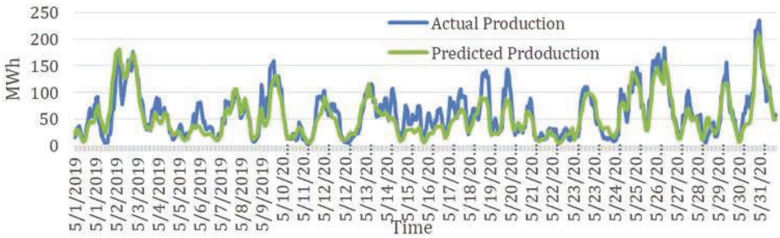

Figure 6: Actual and projected generation of wind energy in May 2019

Most of the time, the actual energy generation is much higher than the forecast values. The gap can go up to 70 MWh, which is too much. The forecasting algorithms need to be more accurate than that. This variation can falsely tell the energy supplier to use alternative energy sources rather than wind. This may be fossil fuel or any other resource, which will cost more to the supplier and eventually the customer. This low accuracy allowed us to study, develop, and propose a comparatively suitable forecasting algorithm for the prediction of wind power generation in Estonia.

In this study, the emphasis is on the accurate prediction of wind energy generation in Estonia. Eight different algorithms based on machine learning and DL are simulated and tested using the 1-year wind energy generation data set for a day-ahead prediction horizon. The results of all employed algorithms are compared based on RMSE values. Fig. 7 shows the comparison of actual wind energy generation and the forecast wind energy generation of TSO for 31 May 2019. It is clear from the figure that there is a substantial gap between the original and predicted values. The RMSE value for TSO forecasting is 20.432. The forecasting of all algorithms is tested on the same day as shown in Fig. 8.

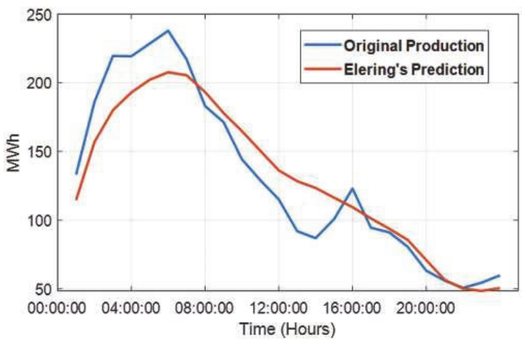

Figure 7: Wind energy actual *vs.* forecasted generation on May 31

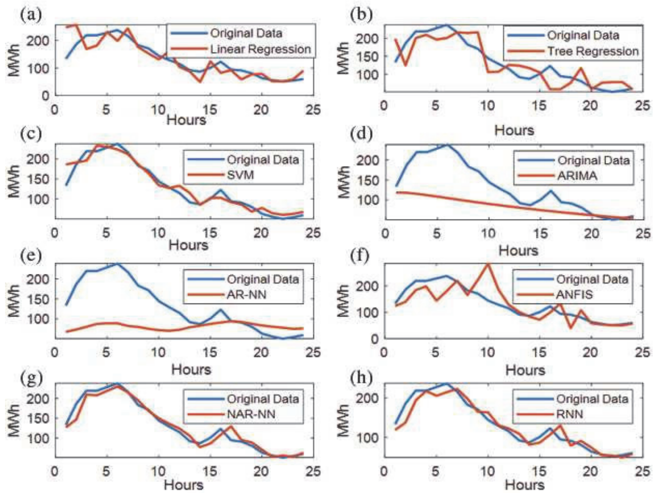

Figure 8: Forecasting of different algorithms: (a) Linear regression; (b) Tree Regression; (c) SVM; (d) ARIMA; (e) AR-NN; (f) ANFIS; (g) NAR-NN; (h) RNN-LSTM

5 Results and Discussions

The wind power generation data understudy has a highly nonlinear nature; therefore, a vast variety of linear and nonlinear forecasting algorithms need to be tested to find an appropriate option. A thorough comparative analysis is conducted to compare the accuracies of all forecasting algorithms employed in this paper. Machine learning algorithms, such as linear regression, AR, ARIMA, and tree-based regression, are not performed adequately, while SVM is given good forecast accuracy.

On the contrary, deep-learning algorithms, such as NAR and RNN, have a high degree of accuracy compared to all other algorithms employed as the architectures for both algorithms have the capability to capture nonlinear features of the data. However, the ANFIS also gives relatively low accuracy. The ML algorithms are not showing accuracy as the data is highly non-linear and therefore the ML algorithms do not perform better curve fitting and result in lower accuracy as compared to DL methods.

DL models, in contrast, due to the ANN fitted the curve better and therefore gave more accurate forecasting results. Thus, these results indicate that for this time series-based forecasting the efficiency of DL methods is higher as compared to ML methods. The comparative analysis of ML algorithms and DL algorithms based on the RMSE value is depicted in Tab. 2. In addition, to the best of the author's knowledge, this study is the first comprehensive comparative analysis between the know ML and DL algorithms for wind power generation data in Estonia.

Furthermore, it is pertinent to mention that this energy forecasting topic has been under investigation for decades. The main issue is still the accuracy of forecasting. The main focus is to forecast wind energy on the basis of past data and not wind speed. Some researchers have tried to develop some hybrid models as well. However, it is extremely difficult to compare the results of these studies with our study as there are many parameters involved like the size of the dataset, location, time span, and then the algorithm used.

Table 2: Comparison between ML and DL algorithms

Algorithm name	RMSE value	Algorithm name	RMSE value
Linear regression	37	AR	64
Tree-based regression	34	ARIMA	78
SVM	18	ANFIS	44
RNN-LSTM	13	NAR	16

In this study, the best results are shown by the RNN-LSTM algorithm. The algorithm consists of 100 hidden units in the LSTM layer. This number of hidden units is obtained by the hit and trial method, the numbers are varied from 20 to 250. The models showed the best results for 100 units and after that, the results remained almost the same. It is using historical data only. Therefore, the number of features is one and the response is also one. The training of the algorithm is carried out by an 'ADAM' solver and the number of Epochs was also varied from 50–250 epochs. When the whole data set passes through the back or forward propagation through the neural network then it is called an Epoch. Learning rate is used to train the algorithm and when a certain number of Epochs are passed then it is dropped to a certain value. The initial learning rate was defined as 0.005. The gradient threshold is also one. The simulation parameters are described in Tab. 3.

Table 3: Comparison of the different parameters of the LSTM network

Data size (Years)	No. of hidden states	Epoch	Learn rate drop period	Training time	RMSE
2	50	250	125	3:34	9.47
2	100	250	125	8:03	9.44
2	200	250	125	14:23	9.44
2	100	200	100	7:15	9.44
2	100	100	50	2:31	9.99
2	100	50	25	1:16	11.9
2	200	50	25	3:18	12.67
2	200	100	50	7:54	9.53

In order to make multistep predictions, the prediction function makes a forecast of a single time step; and then updates the status of the network after each prediction. Now, the output of the first step will act as the input for the next step. The size of the data is also varied and tested between 1 month and 96 months to observe its impact on the forecasting algorithm. The simulation results show that after the data size is more than 24 months, the performance of this algorithm does not affect. Almost, the same RMSE value is obtained for 36, 60, and 96 months. The comparison is shown in Tab. 4. The RMSE values and the corresponding training time are also shown in Tab. 4.

Table 4: Comparison of training data size and RMSE of LSTM

Data size (Months)	No. of hidden states	Epoch	Learn rate drop period	Training time	RMSE
1	100	200	100	0:23	46.45
6	100	200	100	1:42	18.43
12	100	200	100	3:27	13.67
24	100	200	100	7:15	9.44
36	100	200	100	10:40	9.44
60	100	200	100	17:49	9.44
96	100	200	100	28:22	9.44

Fig. 9 shows the compression of actual wind energy production of TSO, the forecasted production and our algorithm for May 2019. It is clear from the graph that RNN-LSTM is providing better forecasts throughout the month. The RMSE value of the TSO furcating is 25.18 while the RNN forecasting is 15.20 for the whole month. Fig. 10a shows the error of both the TSO forecasting algorithm and the proposed RNN-LSTM algorithm. It is also clear from the graph that TSO's forecasting error is higher. The TSO's algorithm predicts a small variation in output energy well but fails when there are large fluctuations. On the other hand, RNN-LSTM is forecasting the large functional well but sometimes does not work that well with continuous low values of energy prediction. Therefore, a hybrid of both algorithms can be proposed here that will overcome both the low and high fluctuation. The results are shown in Fig. 10b. The error in forecasting is also depicted here. The error in forecasting is quite low now as is observed from the graph. The RMSE value for this hybrid forecasting is 8.69.

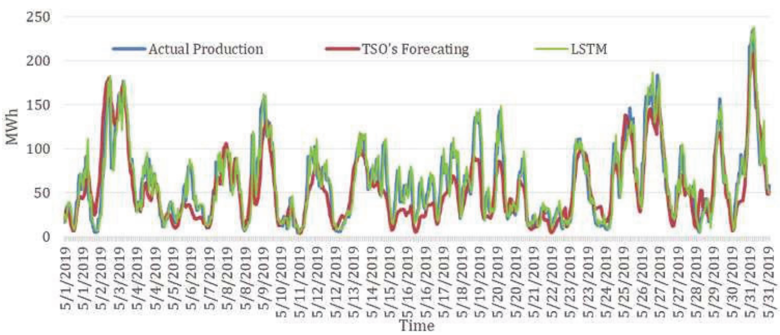

Figure 9: Comparison of wind energy actual generation, TSO's and RNN based forecast for May 2019

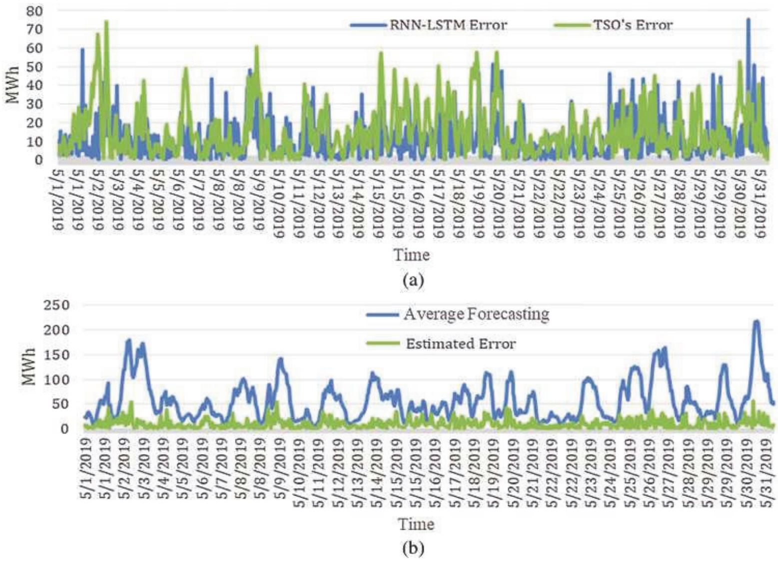

Figure 10: (a) Forecasting error of TSO's algorithm and LSTM forecasting; (b) Average value of both forecasting algorithms and error in average forecasting

6 Conclusions

In the past decade, ML and DL have become promising tools for forecasting problems. The highly nonlinear behavior of weather parameters especially wind speed makes it a valid challenging problem to use ML and DL algorithms for wind energy forecasting for smart grids. Moreover, an accurate time-series forecasting algorithm can help provide flexibility in modern grids and have economical and technical implications in terms of demand and supply management and for the study of power flow analysis in power transmission networks. In this paper, six ML and two DL forecasting algorithms are implemented and compared for Estonian wind energy generation data.

Wind energy accounts for approximately 35% of total renewable energy generation in Estonia. This is the first attempt to provide an effective forecasting solution for the Estonian energy sector to maintain power quality on the existing electricity grid. We target the day-ahead prediction horizon, which is the normal practice for the TSO forecasting wind energy model. Real-time year-long wind energy generation data are used for the comparative analysis of the ML and DL algorithms employed. Moreover, the results of all employed models are also compared with the forecasting results of TSO's algorithm. The comparison of all ML and DL algorithms is based on performance indices, such as RMSE, computational complexity, and training time. For example, the results for May 31, 2019, illustrated that TSO's forecasting algorithm has an RMSE value of 20.48. However, SVM, NAR, and RNN-LSTM have lower RMSE values. The results conclude that SVM, NAR, and RNN-LSTM are respectively 10%, 25%, and 32% more efficient compared to TSO's forecasting algorithm. Therefore, it is concluded that the RNN-LSTM based DL forecasting algorithm is the best-suited forecasting solution among all compared techniques for this case.

Acknowledgement: We acknowledge the support received from the Estonian Research Council Grants PSG142, PUT1680, Estonian Centre of Excellence in Zero Energy and Resource Efficient Smart Buildings and Districts ZEBE, Grant 2014-2020.4.01.15-0016 funded by European Regional Development Fund.

Funding Statement: This work was supported by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2021-2016-0-00313) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation).

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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Publication VI

Shabbir, N.; Kütt, L.; Raja, H.A.; Ahmadiahangar, R.; Rosin, A.; Husev, O. (2021). Machine Learning and Deep Learning Techniques for Residential Load Forecasting: A Comparative Analysis. 2021 IEEE 62nd International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON): Riga, Latvia. IEEE. DOI: 10.1109/RTUCON53541.2021.9711741.

2021 IEEE 62nd International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON)

Machine Learning and Deep Learning Techniques for Residential Load Forecasting: A Comparative Analysis

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***Abstract*—Load forecasting has become a very important parameter in modem power systems. These smart power systems require flexibility, smooth operation, scalability, and better demand-side management. Thus, making load forecasting is an essential thing. However, accurate load forecasting is a very challenging task as it involves variables such as the number of devices in the residential household and their many types, time, season, area, and occupants' behavior. In this study, a comparative analysis has been performed between different machine learning and deep learning-based residential load forecasting models. These models are trained based on the dataset of an Estonian household and they are tested, and forecasting has been made for a day-ahead load. Based on the simulation results, it was observed that Recurrent Neural Network (RNN) based algorithms give more accurate forecasting as it showed the lowest lower Root Mean Square Error (RMSE) value compared to other algorithms.**

***Index Terms*—Residential Load, Load Forecasting, Machine Learning, Deep Learning, Neural Networks**

INTRODUCTION

The modern energy market has gone through a paradigm shift. The number of distributed Renewables Energy Resources (RES) is increasing with every passing year. The world is slowly moving towards the goal of 100% energy generation from renewable energy sources and smart grids [1], [2]. Future grids aim to provide green, flexible, reliable, and economical energy. However, on the downside, these distributed RES create many serious Power Quality (PQ) issues [3]. The energy generation from these RES is highly dispersed and stochastic. Therefore, future smart grids require a solution to Demand Side Management (DSM). This DSM problem can be catered by the accurate forecasting of the future load [4].

Residential load depends on many factors like the number of loads inside the household, energy rating of the appliances, number of residents, weather and season, time, and occupant's behavior (cultural aspects can have a significant effect) [5]. Therefore, a single forecasting algorithm cannot be a solution in every scenario. Moreover, the data acquisition and transmission of the household is quite a challenging task. The larger number of devices and the high sampling frequency need a large database. Then processing these data and making some sense of them requires a lot of processing.

Forecasting can be short-term, medium-term, and long-term. Many statistical and machine learning-based algorithms have been described in the literature for load, energy consumption, and energy forecasting applications. Statistical forecasting techniques are easy and time convenient, but they lack accuracy [3]. The comparison between statistical methods and machine learning-based forecasting has been made in [6]. A performance evaluation of seven different machine learning algorithms has been performed in [7] and the foresting results of the Support Vector Machine (SVM) were found to be more accurate. SVM-based machine learning algorithms give 75% accuracy compared to statistical methods [4]. A similar study has been carried out in New York to analyze and forecast the residential load [8]. The forecast was made for up to 10 hours. Short-term prediction was made in Texas using machine learning [9]. The Nearest Neighboring algorithm is used in [10] for residential load forecasting. The data was measured using a sensor network and the simulation results showed a forecasting accuracy of 90%.

A long-term residential load forecasting model for one year was developed in [11]. The residential load consisted of many household appliances like a heater, washing machine, oven, etc. Long Short Term Memory (LSTM) that belongs to the category of deep learning-based Recurrent Neural Networks (RNN) was found to be more accurate for residential load forecasting in [12]. Similarly, LSTM was also found to be more accurate in [13]. Algorithms based on SVM, Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) are proposed in [14]. In [15], a short-term deep learning-based algorithm was also found to be more accurate as it gave lower Root Mean Square Error (RMSE), mean absolute error, and mean absolute percentage error. A similar study for short-term residential load forecasting also observed from simulation results that LSTM-based RNN outperforms other machine learning-based algorithms [16].

From all the above-mentioned researchers, it is clear that machine learning-based residential load forecasting is more

This work was supported by Estonian Research Council grants PSG142, PUT1680, Estonian Center of Excellence on Zero Energy and Resource Efficient Smart Buildings and Districts ZEBE, 2014-2020.4.01.15-0016 funded by European Regional Development Fund.

accurate compared to statistical methods. However, the design of such models requires much larger and more accurate past measurement data sets. Larger data is required to train the forecasting model, as residential loads have many types and are highly variable. For the same reason, a single forecasting algorithm is not a viable solution to be used in every scenario. Each model will have its own merits, demerits, and forecast period.

The remaining article is divided into the following sections: Section II gives some theoretical information about the machine learning algorithms used in this study. Section III presents an exploratory analysis of the data used in this research. Section IV contains the simulation results, and finally, the conclusions are presented in Section V.

Machine learning algorithms

Forecasting is similar to a regression problem. This belongs to supervised machine learning that requires past data sets and learns from them [3]. However, deep learning algorithms, a subset of machine learning, are more complex and require more computational time and larger datasets [5]. The neural network-based deep learning algorithm is known as ANN. As their architecture is quite similar to a human brain. The main two categories of ANN are CNN and RNN.

Linear Regression is the simplest and commonly used machine learning algorithm. It just calculates the relationship between the independent variable and the dependent variables and then performs regression for forecasting [3]. Tree-based regression is another algorithm that is based on linear regression, but regression is performed on each branch. As a different variable belongs to a different class. SVM-based regression is quite popular and useful. In this method, an error margin is defined at first and then with every iteration, it is recalculated and updated to reduce the error until the threshold value is achieved [3].

Autoregressive (AR) neural networks use a feed-forward three-layered structure. For a single-step ahead forecast, only the previous values are used. For multistep ahead forecasting, both previous and forecasted values are used. The process continues until the error is minimized. Non-Linear Autoregressive Neural Network (NAR) uses a backward propagation algorithm with nonlinear regression based on past data. Initially, it is an open-loop system that is converted into a closed-loop system after training. Auto-Regressive Integrated Moving Average (ARIMA) is suitable for stationary non-datasets. The first stage of this algorithm applies AR and the second stage Moving Average (MA) is used. In the third step, the error is reduced to improve the efficiency of the algorithm. The Adaptive Neuro-Fuzzy Inference System (ANFIS) consists of both ANN and fuzzy logic. The fuzzy logic is applied using Takagi and Sugeno algorithm [17], which is also based on three stages. Then, back error propagation is used in the first layer that optimizes the parameters of the fuzzy logic and Least Squares Estimator (LSE) in the third layer.

RNN belongs to the deep learning category. The RNN LSTM algorithm is used here in this study. LSTM used recurrence to build paths for long-distance gradient flows. The network consists of cells or hidden units that store information. In traditional RNN, only the current values are stored, while the previous values are deleted [18]. In LSTM, after every iteration, the cell data is updated while keeping the previous values. The LSTM network used in this study has 200 units. This number was selected by the hit-and-trial method, while varying the value between 50-300. After 200 units, the results were almost the same.

Exploratory Data Analysis

The data set used in this study was measured in an Estonian household located in Tallinn, Estonia. It was a 3-room house built-in 2005. The area of this house is 67.8 m^2. Four people are residing in this house, two adults and two kids.

Measurements were made in 2015 with a measurement error of less than 5%. The data were measured for the months of February and March, which is usually winter in Estonia. The frequency of the measurement was one minute. There were many different housed appliances, e.g., dishwasher, vacuum cleaner, TV & stereo, heating units, refrigerator, and washing machine. Individual load usage was measured and then accumulated to calculate the overall load of the household.

The electricity tariff in Estonia is usually higher in winter between 7 and 11 AM and 8 AM and 12 PM in summer. The use of electricity in Estonia is higher in winter compared to summer due to the use of internal heating systems. In this household, the normal electricity usage pattern is between 7 and 9 AM and then between 5 and 9 PM on weekdays. On the weekends, the patron is different, the high usage is between 5 PM to 12 PM. The maximum load recorded during this period was 6913 W. The load patterns for the whole duration along with the moving average and the moving standard deviation are shown in Figure 1. The moving average is around 1000 W on weekdays and some weekends, it goes higher to 2500 W. Figure 2 shows the histograms and the probability of occurrence of each load value throughout the period.

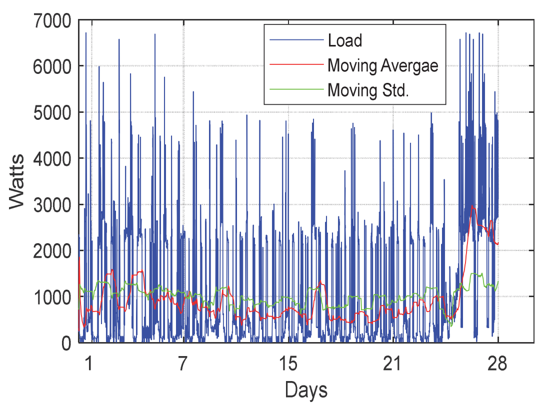

Figure 1. Data loaded with moving average and moving standard deviation

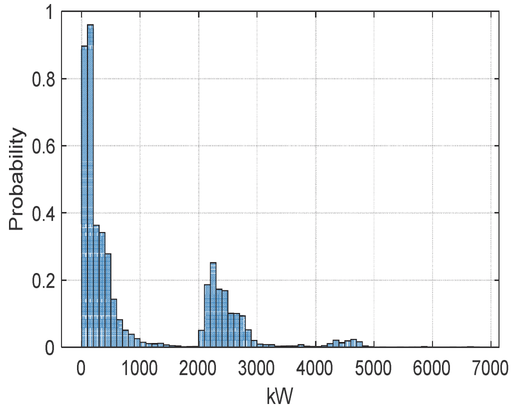

Figure 2. Histogram and probability of occurrence of load values

From Fig. 2, it is clear that the high probabilities are in the low load regions. This is an indication that it is late or that residents are not present at home at that time. Rarely the load value goes above 4000 W and mostly it is between 2000 to 3000 W indicating the normal device usage pattern. Sometimes, the value goes above 4000 W and, in extremely rare cases, above 6000W. This may be an indication of the weekend and washing machines plus dishwasher are being used as well for the regular loads. The further analysis of the load is made by autocorrelation, which is shown in Fig. 3.

Autocorrelation gives useful observations in the regression analysis for the selection of the number of lags in the time-series analysis. In Fig. 3, the lag for 100 hours (roughly 4 days) is shown. The 72 hours value has a dependency of 0.5 or higher on the previous values. Even after that, it doesn't fall significantly but steadily. The confidence interval is defined by 2σ values. The slow decay of the correlation shows the dependency on the previous data indicates the long-term dependency. This observation is explained in more detail in [19]. This data analysis helps to select the machine learning and deep learning parameters of the algorithms explained earlier.

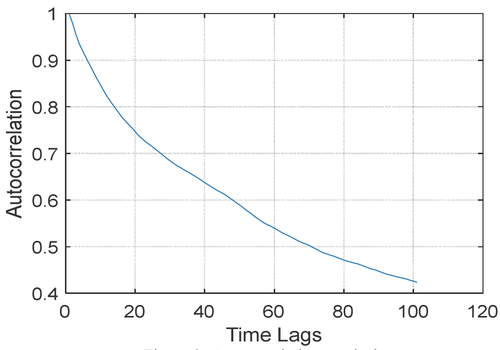

Figure 3. Autocorrelation Analysis

IV. Simulation Results

Residential load forecasting depends on many variable factors. Therefore, a comprehensive analysis of linear and non-linear algorithms is required to identify a suitable load forecasting model. In previous studies, linear algorithms [3] and RNN based algorithms [5], [20] were tested. Here, they are further compared with quadratic SVM, non-linear SVM, AR, NAR, ARIMA, and ANFIS algorithms. These simulations are performed on Matlab 2020b on the Windows 10 operating system using a Core i7-9700, 3 GHz processor with 64 GB of ram. Every model was trained first, and then forecasting was made for one day ahead. The simulation results and a comparative analysis are shown in figure 4. Table I describes all the RMSE values of the forecast results. It can be seen from the figure that machine learning algorithms like linear regression, tree-based progression, AR, and ARIMA performed very poorly. Simple SVM did not give good results as well. However, the cubic SVM gives better accuracy and fits the curved well. The deep learning algorithms NAR and RNN-LSTM fit the curve expectantly well and therefore their forecasting results are more accurate. The comparison of training time is made in Table II.

Table I. Comparison of RMSE values

Algorithm Name	Time (sec)	Algorithm Name	Time (sec)
Linear Regression	2.49	Non-Linear Regression	1.59
Tree-Based Regression	2.63	Gaussian SVM	2.51
Linear SVM	1.68	OE	0.88
Quadratic SVM	1.75	ANFIS	14.32
Cubic SVM	1.06	AR	0.92
RNN	33:27	NAR	4.06

Table II. Comparison of training time

Algorithm Name	RMSE Value	Algorithm Name	RMSE Value
Linear Regression	381.15	Non-Linear Regression	325.36
Tree-Based Regression	241.11	Gaussian SVM	234.02
Linear SVM	619.85	OE	167.34
Quadratic SVM	187.73	ANFIS	168.32
Cubic SVM	172.11	AR	169.54
RNN-LSTM	159.52	NAR	163.54

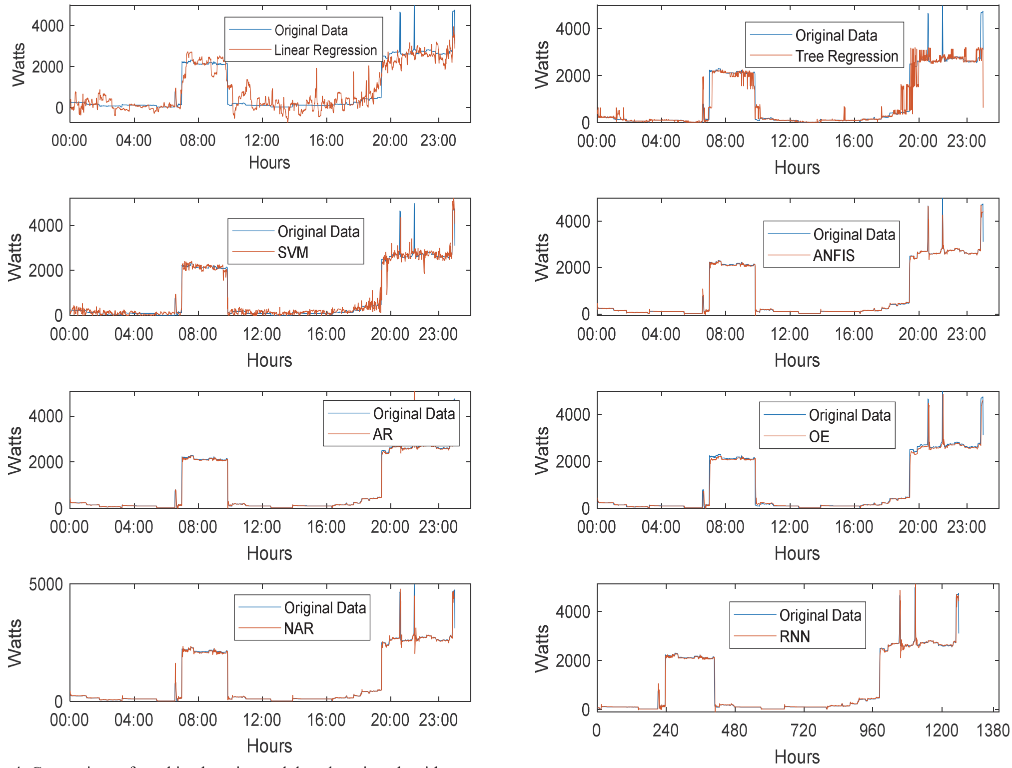

Figure 4. Comparison of machine learning and deep learning algorithms

V. Conclusions

Residential load forecasting is very vital for a better DSM in smart grids. The integration of more and more RES and nearly zero energy buildings requires this forecasting for smooth operation, flexibility, and reliability. The residential load is dependent on many factors; therefore, its accurate forecasting is a difficult task. Machine learning and deep learning algorithms are used for such forecasting, as traditional statistical algorithms lack consistency and accuracy. However, these models require a very large historical dataset and computational power.

In this article, residential load data from an Estonian household are taken into account and ten different machine learning and deep learning algorithms have been developed for the 24 hours ahead forecast of the residential load. The forecasting results of all these algorithms are compared in terms of the RMSE value. The simulation results showed that the RNN-LSTM algorithm has the lowest RMSE value among all others. The NAR, AR and cubic SVM algorithms also have a comparatively good forecast as well. Although, in terms of the training time of the algorithm, RNN-LSTM has the worst performance as the complex neural network calculations require lots of processing. It is almost eight times higher than the next closest NAR algorithm. However, in this load forecasting case, NAR and cubic SVM can also be very good options, as their training time is much lower, and their efficiency is quite high.

For future work, the data size can be increased, and the load forecast of a week ahead can be made. In addition, the current forecasting model is only based on historical data. The algorithms can be enhanced by incorporating temperature, humidity and other environmental factors which can make it more accurate and detail.

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ISSN 2585-6901 (PDF)
ISBN 978-9949-83-858-5 (PDF)