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

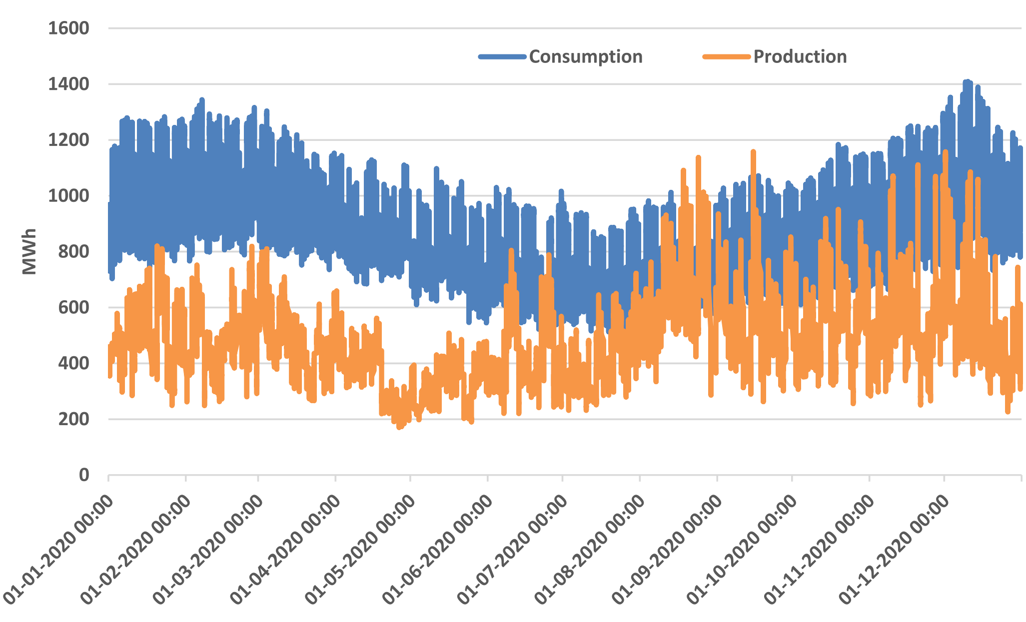


**Fig. 1.** Energy generation and consumption of Estonia for 2020.

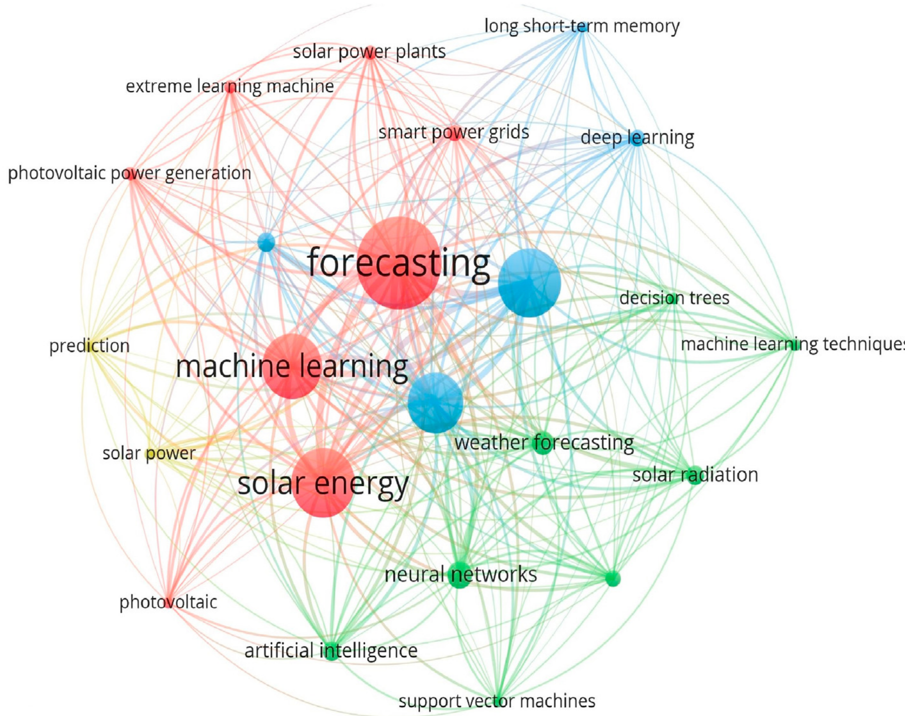


**Fig. 2.** Bibliometric visualization for the author-supplied keywords, created with VOSviewer Software.

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 $\beta$ 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

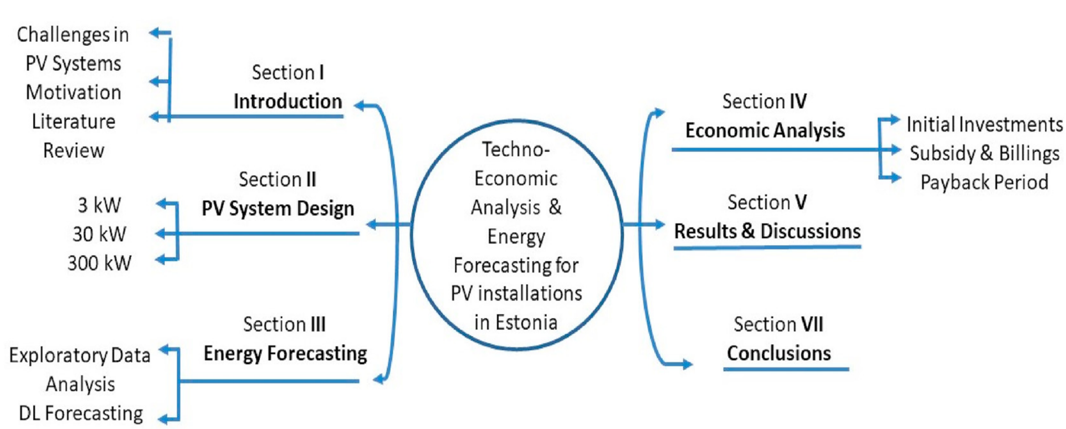


**Fig. 3.** Outline of the paper.

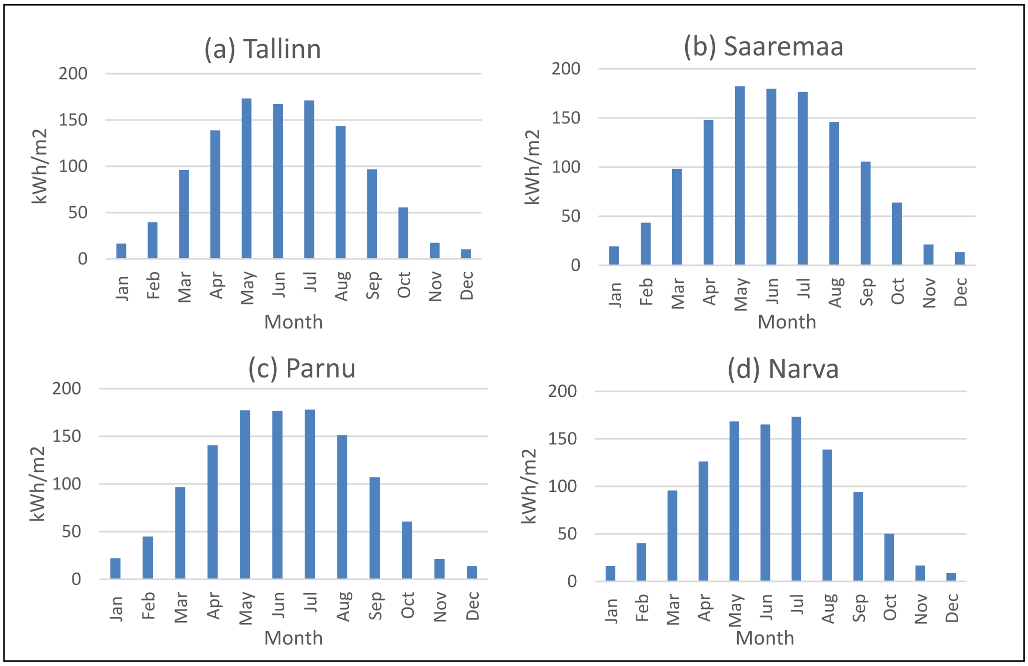


**Fig. 4.** Solar Irradiance chart for different cities of Estonia.

**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

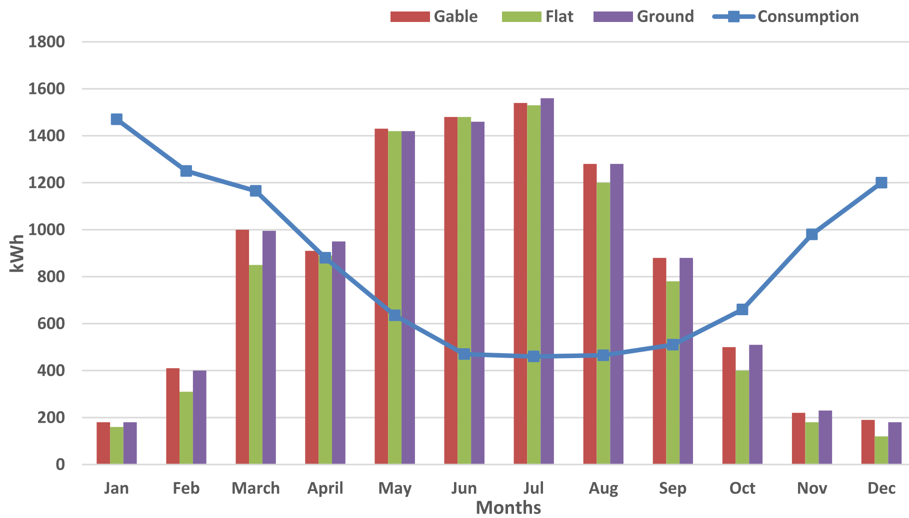


**Fig. 5.** Energy consumption and generation based on different types of PV installation scenarios for a househol0d.

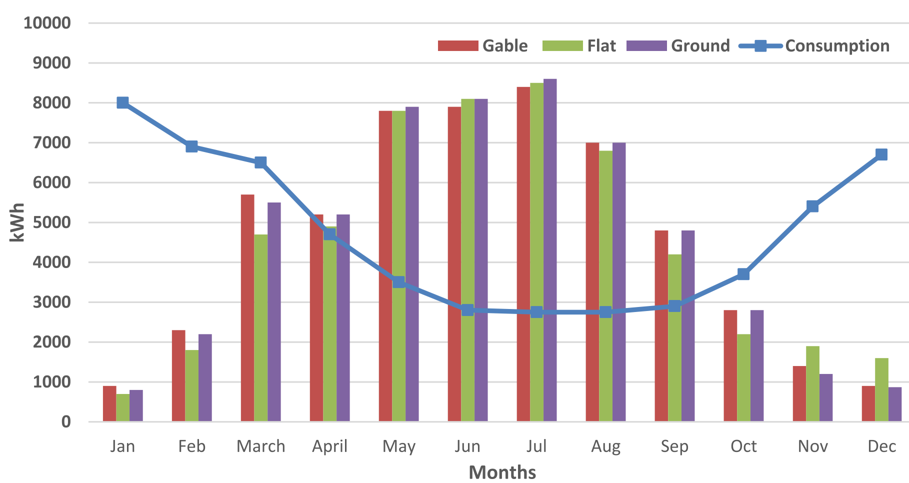


**Fig. 6.** Energy consumption and generation for different types of PV installation scenarios for a commercial building.

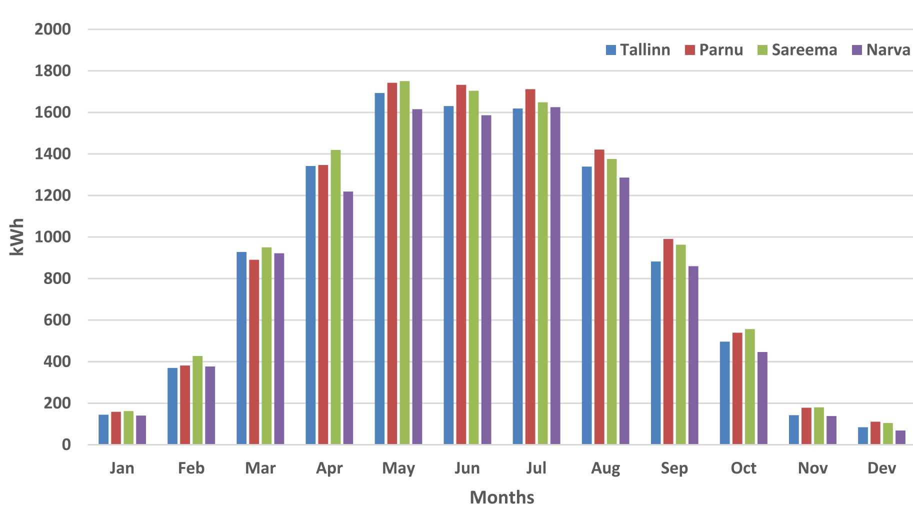


**Fig. 7.** Energy generation for 12 kW system during the year in four different regions.

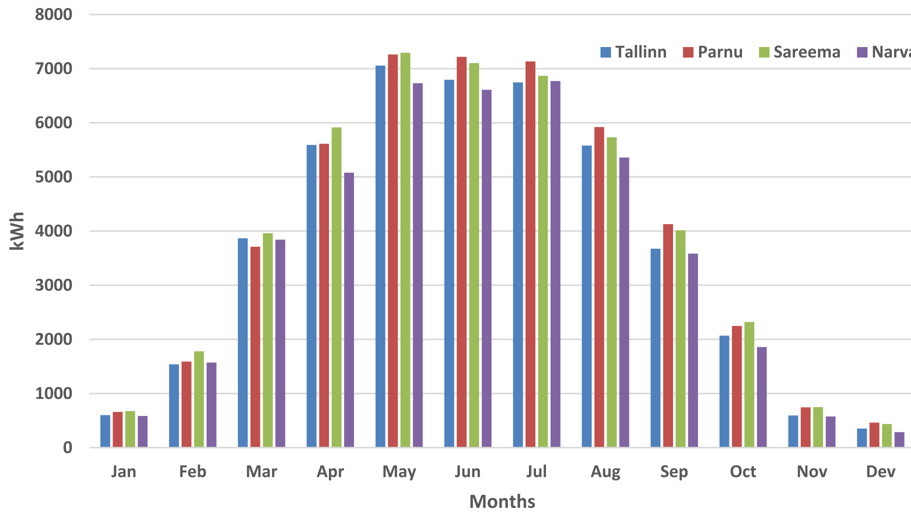


**Fig. 8.** Energy generation for 50 kW system during the year in four different regions.

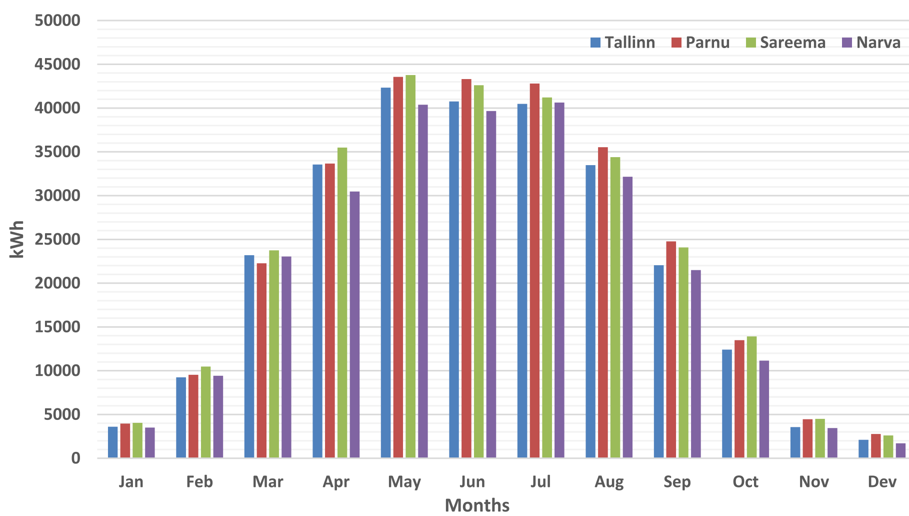


**Fig. 9.** Energy generation for 300 kW systems during the year in four different regions.

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

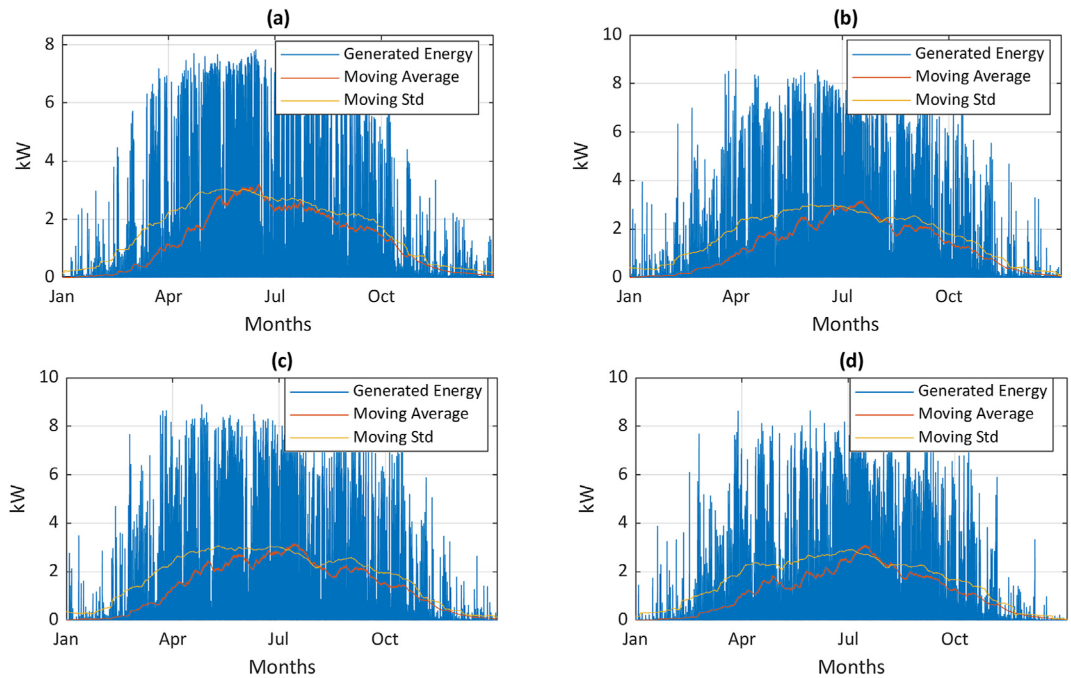


**Fig. 10.** Statistical Analysis of solar PV generation data for (a) Tallinn (b) Saaremaa, (c) Parnu (d) Narva.

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

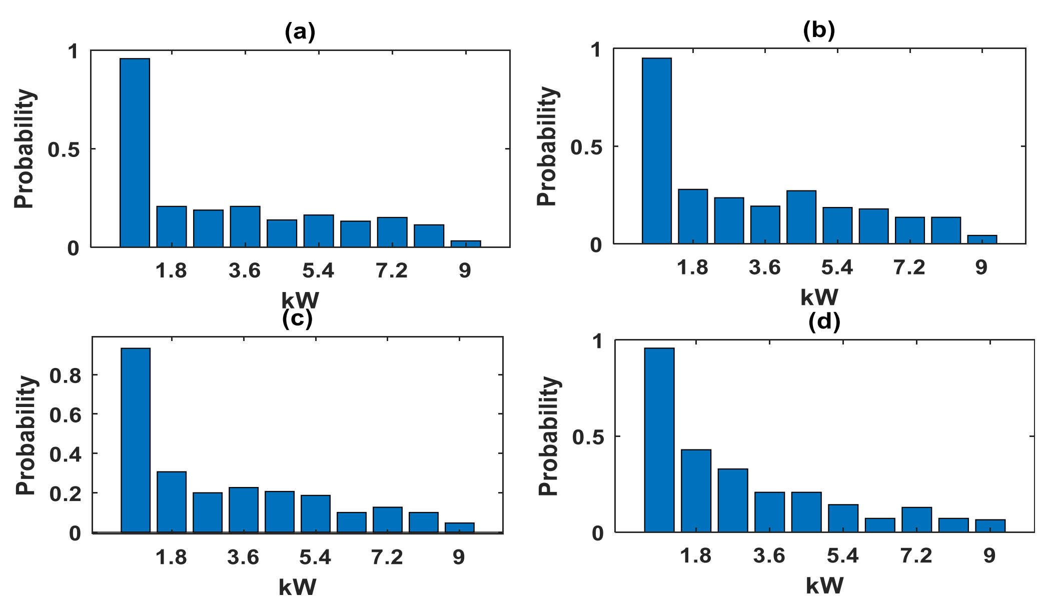


**Fig. 11.** Histogram with respect to Power generation for (a) Tallinn, (b) Saaremaa, (c) Parnu (d) Narva.

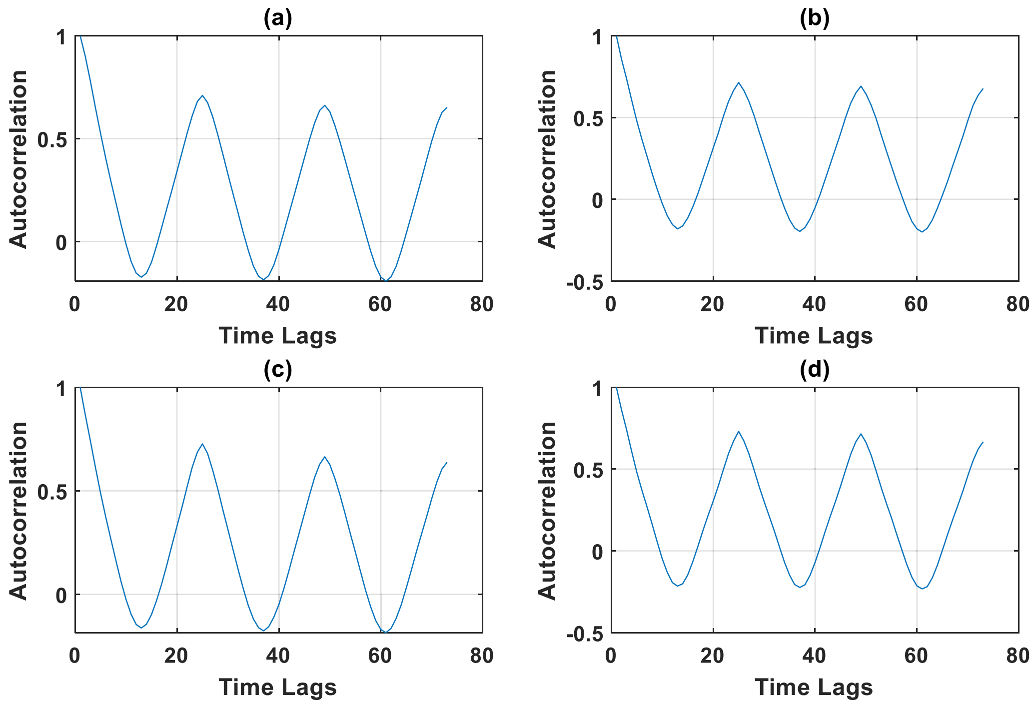


**Fig. 12.** Autocorrelation analysis.

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 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.

**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).

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

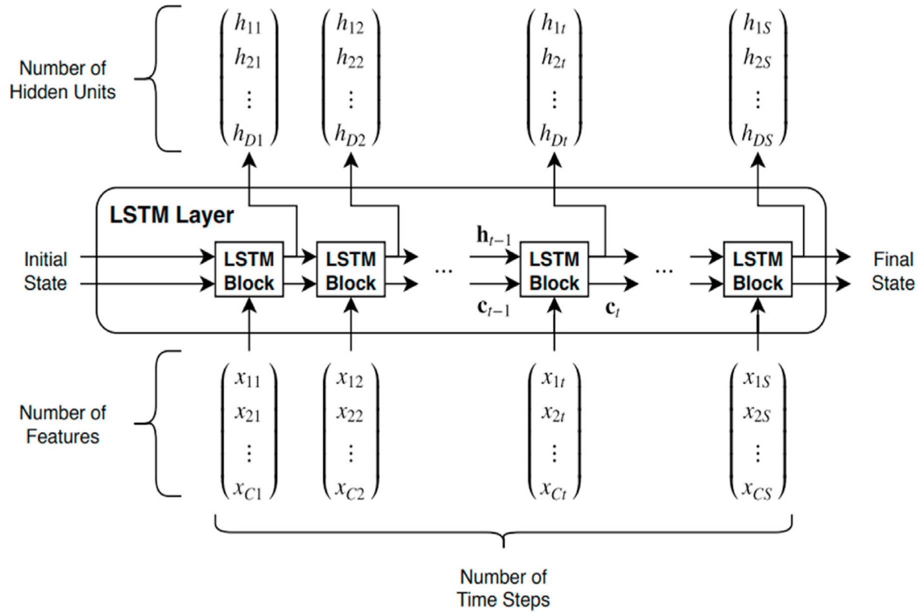


**Fig. 13.** The architecture of RNN-LSTM.

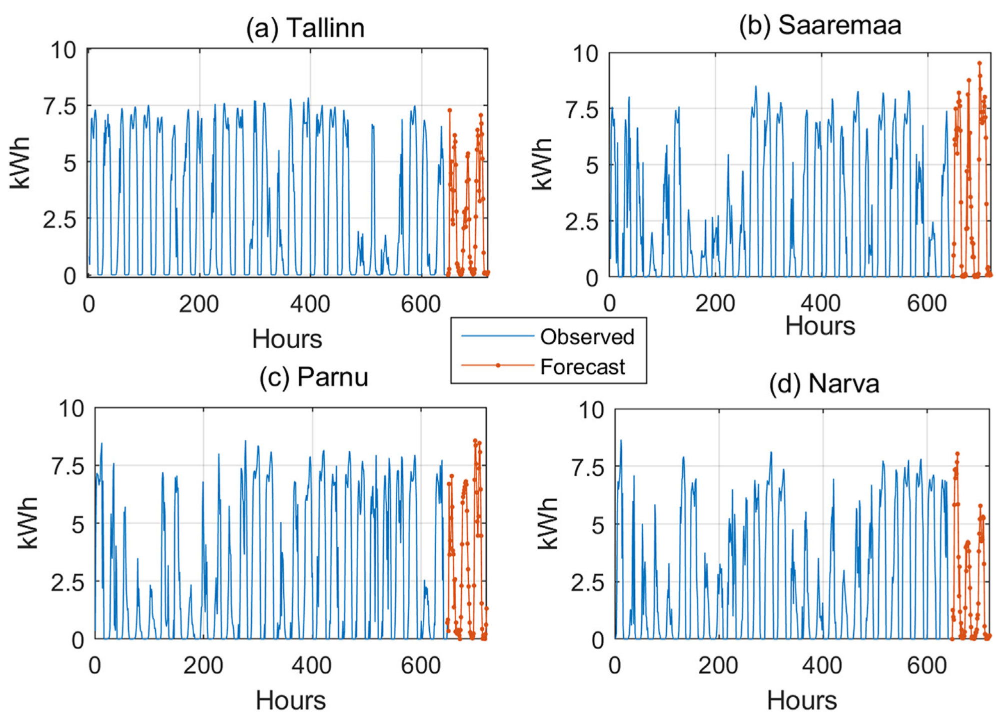


**Fig. 14.** 3-day ahead energy forecasting in summer.

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

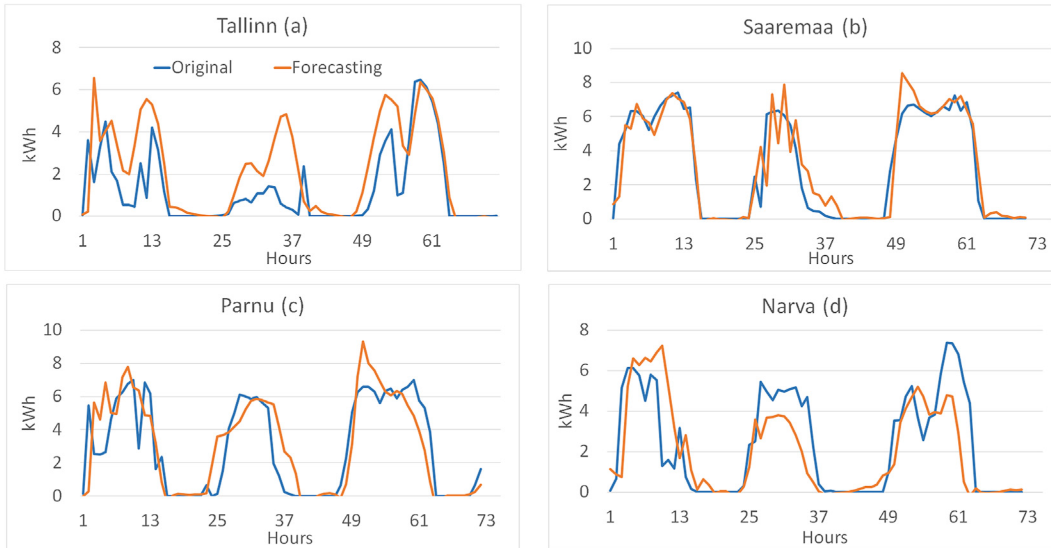


**Fig. 15.** Comparison of actual energy generation and forecasted energy in summer.

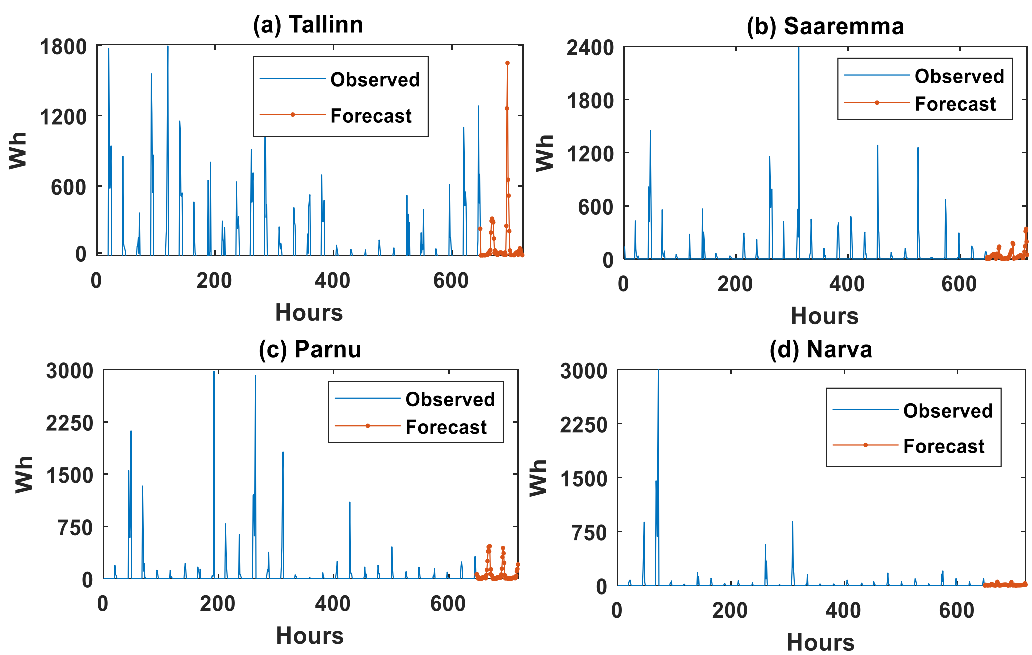


**Fig. 16.** 3-day ahead energy forecasting in winter.

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].

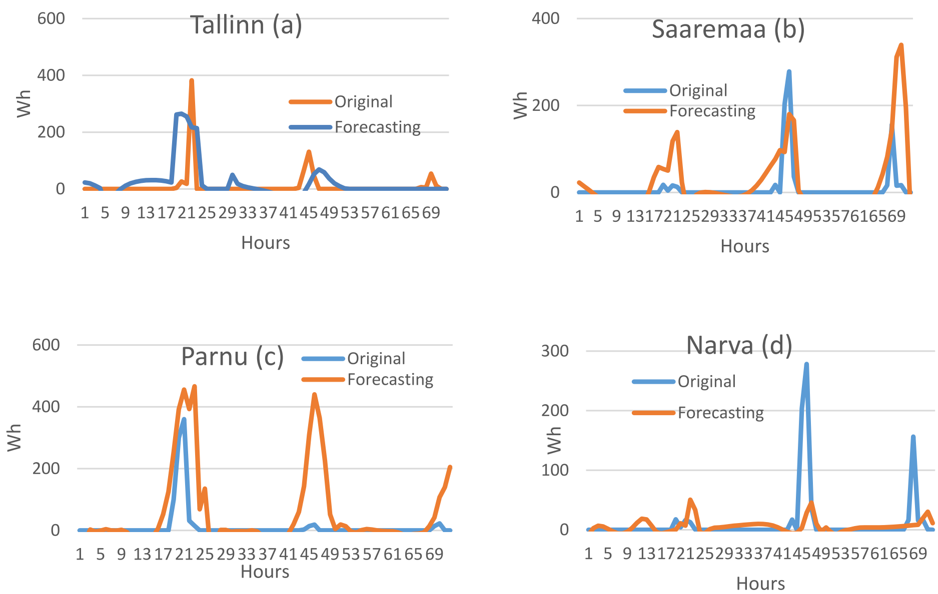


**Fig. 17.** Comparison of actual energy generation and forecasted energy in Winter.

**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, $\gamma$% 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

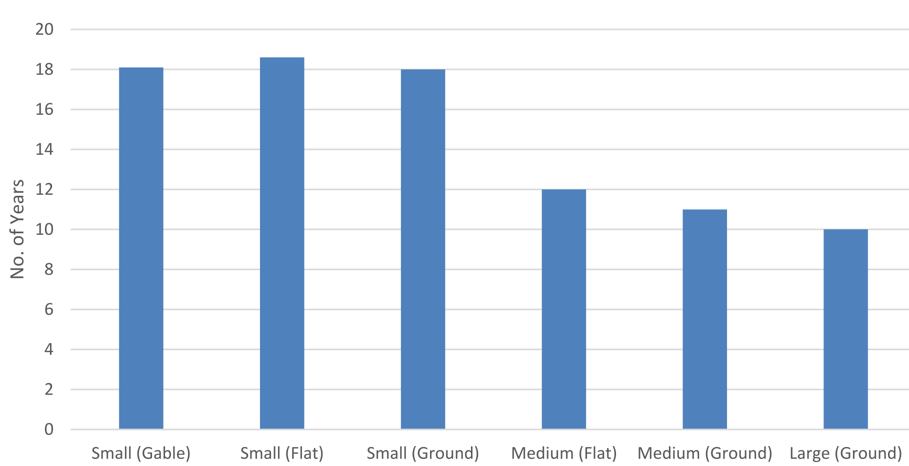


**Fig. 18.** The payback period for different PV installations.

**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 |

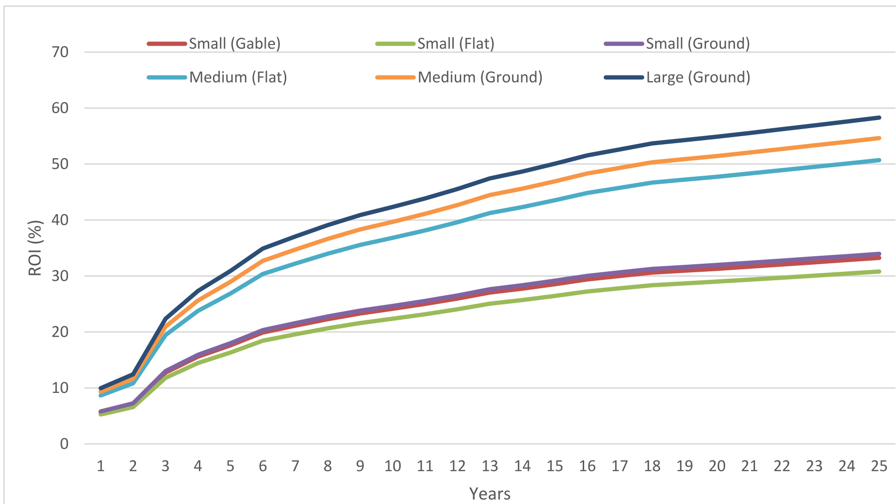


**Fig. 19.** Return over Investment for different rated PV systems.

**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.

## Acknowledgements

This work was supported by Estonian research council grants PSG142, PSG739, PRG675 and European Commission through H2020 project Finest Twins grant No. 856602.

## References

[1] Jamil E, Hameed S, Jamil B, Qurratulain. Power quality improvement of distribution system with photovoltaic and permanent magnet synchronous generator based renewable energy farm using static synchronous compensator. Sustain Energy Technol Assess 2019;35:98–116. https://doi.org/10.1016/j.seta.2019.06.006.
[2] Abdel-Basset M, Hawash H, Chakrabortty RK, Ryan M, Pv-Net. An innovative deep learning approach for efficient forecasting of short-term photovoltaic energy production. J Clean Prod 2021;303:127037. https://doi.org/10.1016/j.jclepro.2021.127037.
[3] Kaffash M, Bruninx K, Deconinck G. Data-driven forecasting of local PV generation for stochastic PV-battery system management. Int J Energy Res 2021:1–18. https://doi.org/10.1002/er.6826.
[4] Ozbek A, Yildirim A, Bilgili M. Deep learning approach for one-hour ahead forecasting of energy production in a solar-PV plant. Energy Sources, Part A Recover Util Environ Eff 2021:1–16. https://doi.org/10.1080/15567036.2021.1924316. 00.
[5] Jäger-Waldau A. PV status report 2019. 2019. https://doi.org/10.2760/326629.
[6] Puranen P, Kosonen A, Ahola J. Technical feasibility evaluation of a solar PV based off-grid domestic energy system with battery and hydrogen energy storage in northern climates. Sol Energy 2021;213:246–59. https://doi.org/10.1016/j.solener.2020.10.089.
[7] Das BK, Hasan M, Das P. Impact of storage technologies, temporal resolution, and PV tracking on stand-alone hybrid renewable energy for an Australian remote area application. Renew Energy 2021;173:362–80. https://doi.org/10.1016/j.renene.2021.03.131.
[8] Guo W, Kong L, Chow T, Li C, Zhu Q, Qiu Z, et al. Energy performance of photovoltaic (PV) windows under typical climates of China in terms of transmittance and orientation. Energy 2020;213:118794. https://doi.org/10.1016/j.energy.2020.118794.
[9] Kumar R, Waghmare A, Nayak S, Paswan M, Achintya. Design of self sustainable zero energy building. Mater Today Proc 2021. https://doi.org/10.1016/j.matpr.2021.04.263.
[10] Huo H, Xu W, Li A, Lv Y, Liu C. Analysis and optimization of external Venetian blind shading for nearly zero-energy buildings in different climate regions of China. Sol Energy 2021;223:54–71. https://doi.org/10.1016/j.solener.2021.05.046.
[11] Wei W, Skye HM. Residential net-zero energy buildings: review and perspective. Renew Sustain Energy Rev 2021;142:110859. https://doi.org/10.1016/j.rser.2021.110859.
[12] Madathil D VRP, Nair MG, Jamasb T, Thakur T. Consumer-focused solar-grid net zero energy buildings: a multi-objective weighted sum optimization and application for India. Sustain Prod Consum 2021;27:2101–11. https://doi.org/10.1016/j.spc.2021.05.012.
[13] Wang R, Feng W, Wang L, Lu S. A comprehensive evaluation of zero energy buildings in cold regions: actual performance and key technologies of cases from China, the US, and the European Union. Energy 2021;215:118992. https://doi.org/10.1016/j.energy.2020.118992.
[14] Camarasa C, Kalahasthi LK, Rosado L. Drivers and barriers to energy-efficient technologies (EETs) in EU residential buildings. Energy Built Environ 2021;2:290–301. https://doi.org/10.1016/j.enbenv.2020.08.002.
[15] Bienvenido-Huertas D, Sánchez-García D, Rubio-Bellido C, Pulido-Arcas JA. Analysing the inequitable energy framework for the implementation of nearly zero energy buildings (nZEB) in Spain. J Build Eng 2021;35. https://doi.org/10.1016/j.jobe.2020.102011.
[16] Secretariat REN21. Renewables 2020 global status report. 2020.
[17] Elering. Estonian electrical system security report. 2020. 2020. 2020.
[18] ELERING. Elering n.d. https://elering.ee/(accessed December 20, 2019).
[19] Republic of Estonia. Estonian national energy and climate plan 2030 (NECP 2030). Estonia 2019;9.
[20] Nord pool. Nord Pool n.d. https://www.nordpoolgroup.com/(accessed January 29, 2020).
[21] Estonian Wind Energy Association. WIND ENERGY IN ESTONIA n.d. http://www.tuuleenergia.ee/en/windpower-101/statistics-of-estonia/(accessed June 10, 2019).
[22] SOLARGIS. Solar resource maps of Estonia n.d. https://solargis.com/maps-and-gis-data/download/estonia (accessed February 1, 2021).
[23] Meesak A. Estonian PV Assosiation n.d. https://www.epea.ee/(accessed February 1, 2021).
[24] Shabbir N, Kütt L, Astapov V, Jawad M, Alik A, Husev O. Battery size optimization with customer PV installations and domestic load profile. IEEE Access 2022;10:13012–25.
[25] Shabbir N, Ahmadiahangar R, Kutt L, Iqbal MN, Rosin A. In: Forecasting short term wind energy generation using machine learning. 2019 IEEE 60th Annu Int Sci Conf power Electr Eng Riga Tech Univ RTUCON 2019 - Proc 2019; 2019. p. 22. https://doi.org/10.1109/RTUCON48111.2019.8982365.
[26] Shabbir N, Kutt L, Jawad M, Amadiahanger R, Iqbal MN, Rosin A. Wind energy forecasting using recurrent neural networks. 2019 big data. Knowl Control Syst Eng BdKCSE 2019:7–11. https://doi.org/10.1109/BdKCSE48644.2019.9010593. 2019.
[27] Mubaarak S, Zhang D, Liu J, Chen Y, Wang L, Zaki SA, et al. Potential techno-economic feasibility of hybrid energy systems for electrifying various consumers in Yemen. Sustain Times 2021;13:1–24. https://doi.org/10.3390/su13010228.
[28] Rinaldi F, Moghaddampoor F, Najafi B, Marchesi R. Economic feasibility analysis and optimization of hybrid renewable energy systems for rural electrification in Peru. Clean Technol Environ Pol 2021;23:731–48. https://doi.org/10.1007/s10098-020-01906-y.
[29] Parida A, Singh Y, Chatterjee D. Solar-PV augmented wind energy generation system with improved efficiency control of doubly fed induction generator through adjustable stator frequency. Int Trans Electr Energy Syst 2021;31:1–15. https://doi.org/10.1002/2050-7038.12690.
[30] Janzadeh A, Zandieh M. Design feasibility of a net-zero energy neighborhood in Qazvin. Energy Effic 2021;14. https://doi.org/10.1007/s12053-020-09909-w.
[31] Casteleiro-Roca JL, Gómez-González JF, Calvo-Rolle JL, Jove E, Quintián H, Diaz BG, et al. Short-term energy demand forecast in hotels using hybrid intelligent modeling. Sensors 2019;19:1–18. https://doi.org/10.3390/s19112485.
[32] Emilio P, Javier P, Segarra-tamarit J, Beltran H. A deep learning model for intra-day forecasting of solar irradiance using satellite-based estimations in the vicinity of a PV power plant. Sol Energy 2021;218:652–60. https://doi.org/10.1016/j.solener.2021.02.033.
[33] Jung Y, Jung J, Kim B, Han SU. Long short-term memory recurrent neural network for modeling temporal patterns in long-term power forecasting for solar PV facilities: case study of South Korea. J Clean Prod 2020;250:119476. https://doi.org/10.1016/j.jclepro.2019.119476.
[34] Massaoudi M, Chihi I, Sidhom L, Trabelsi M, Refaat SS, Abu-Rub H, et al. An effective hybrid NARX-LSTM model for point and interval PV power forecasting. IEEE Access 2021;9:36571–88. https://doi.org/10.1109/ACCESS.2021.3062776.
[35] Shabbir N, Kutt L, Jawad M, Iqbal MN, Ghahfarokhi PS. Forecasting of energy consumption and production using recurrent neural networks. Adv Electr Electron Eng 2020;18:190–7. https://doi.org/10.15598/aeee.v18i3.3597.
[36] Khairalla MA, Ning X, AL-Jallad NT, El-Faroug MO. Short-term forecasting for energy consumption through stacking heterogeneous ensemble learning model. Energies 2018;11. https://doi.org/10.3390/en11061605.
[37] Poullikkas A. A comparative assessment of net metering and feed in tariff schemes for residential PV systems. Sustain Energy Technol Assessments 2013;3:1–8. https://doi.org/10.1016/j.seta.2013.04.001.
[38] Londo M, Matton R, Usmani O, van Klaveren M, Tigchelaar C, Brunsting S. Alternatives for current net metering policy for solar PV in The Netherlands: a comparison of impacts on business case and purchasing behaviour of private homeowners, and on governmental costs. Renew Energy 2020;147:903–15. https://doi.org/10.1016/j.renene.2019.09.062.
[39] Barbose G, Wiser R, Heeter J, Mai T, Bird L, Bolinger M, et al. A retrospective analysis of benefits and impacts of U.S. renewable portfolio standards. Energy Pol 2016;96:645–60. https://doi.org/10.1016/j.enpol.2016.06.035.
[40] Jannuzzi G de M, de Melo CA. Grid-connected photovoltaic in Brazil: policies and potential impacts for 2030. Energy Sustain Dev 2013;17:40–6. https://doi.org/10.1016/j.esd.2012.10.010.
[41] Opoku R, Obeng GY, Adjei EA, Davis F, Akuffo FO. Integrated system efficiency in reducing redundancy and promoting residential renewable energy in countries without net-metering: a case study of a SHS in Ghana. Renew Energy 2020;155:65–78. https://doi.org/10.1016/j.renene.2020.03.099.
[42] Watts D, Valdés MF, Jara D, Watson A. Potential residential PV development in Chile: the effect of Net Metering and Net Billing schemes for grid-connected PV systems. Renew Sustain Energy Rev 2015;41:1037–51. https://doi.org/

10.1016/j.rser.2014.07.201.

[43] Qamar H, Qamar H, Khan MU. Solar irradiance & on grid solar power systems with net metering in Pakistan. Adv Sci Technol Eng Syst 2016;1:1−5. https://doi.org/10.25046/aj010201.

[44] Thakur J, Chakraborty B. Impact of compensation mechanisms for PV generation on residential consumers and shared net metering model for developing nations: a case study of India. J Clean Prod 2019;218:696−707. https://doi.org/10.1016/j.jclepro.2019.01.286.

[45] Omar MA, Mahmoud MM. Grid connected PV- home systems in Palestine: a review on technical performance, effects and economic feasibility. Renew Sustain Energy Rev 2018;82:2490−7. https://doi.org/10.1016/j.rser.2017.09.008.

[46] Congedo PM, Baglivo C, Zacà I, D'Agostino D, Quarta F, Cannoletta A, et al. Energy retrofit and environmental sustainability improvement of a historical farmhouse in Southern Italy. Energy Proc 2017;133:367−81. https://doi.org/10.1016/j.egypro.2017.09.364.

[47] Jia X, Du H, Zou H, He G. Assessing the effectiveness of China's net-metering subsidies for household distributed photovoltaic systems. J Clean Prod 2020;262:121161. https://doi.org/10.1016/j.jclepro.2020.121161.

[48] Nafeh AE-SA. Design and economic analysis of a stand-alone PV system to electrify a remote area household in Egypt. Open Renew Energy J 2009;2:33−7. https://doi.org/10.2174/1876387100902010033.

[49] Li HX, Zhang Y, Li Y, Huang J, Costin G, Zhang P. Exploring payback-year based feed-in tariff mechanisms in Australia. Energy Pol 2021;150:112133. https://doi.org/10.1016/j.enpol.2021.112133.

[50] Ghasemi G, Noorollahi Y, Alavi H, Marzband M, Shahbazi M. Theoretical and technical potential evaluation of solar power generation in Iran. Renew Energy 2019;138:1250−61. https://doi.org/10.1016/j.renene.2019.02.068.

[51] Nogueira CEC, Vidotto ML, Niedzialkoski RK, De Souza SNM, Chaves LI, Edwiges T, et al. Sizing and simulation of a photovoltaic-wind energy system using batteries, applied for a small rural property located in the south of Brazil. Renew Sustain Energy Rev 2014;29:151−7. https://doi.org/10.1016/j.rser.2013.08.071.

[52] Simola A, Kosonen A, Ahonen T, Ahola J, Korhonen M, Hannula T. Optimal dimensioning of a solar PV plant with measured electrical load curves in Finland. Sol Energy 2018;170:113−23. https://doi.org/10.1016/j.solener.2018.05.058.

[53] Rapapate N, Gol O. Use of photovoltaic systems for rural electrification in Thailand. Renew Energy Power Qual J 2007;1:638−44. https://doi.org/10.24084/repqj05.352.

[54] Silva SB, Severino MM, De Oliveira MAG. A stand-alone hybrid photovoltaic, fuel cell and battery system: a case study of Tocantins, Brazil. Renew Energy 2013;57:384−9. https://doi.org/10.1016/j.renene.2013.02.004.

[55] Mahmoud MM, Ibrik IH. Techno-economic feasibility of energy supply of remote villages in Palestine by PV-systems, diesel generators and electric grid. Renew Sustain Energy Rev 2006;10:128−38. https://doi.org/10.1016/j.rser.2004.09.001.

[56] Celik AN. Present status of photovoltaic energy in Turkey and life cycle techno-economic analysis of a grid-connected photovoltaic-house. Renew Sustain Energy Rev 2006;10:370−87. https://doi.org/10.1016/j.rser.2004.09.007.

[57] Holdermann C, Kissel J, Beigel J. Distributed photovoltaic generation in Brazil: an economic viability analysis of small-scale photovoltaic systems in the residential and commercial sectors. Energy Pol 2014;67:612−7. https://doi.org/10.1016/j.enpol.2013.11.064.

[58] Al-Salaymeh A, Al-Hamamre Z, Sharaf F, Abdelkader MR. Technical and economical assessment of the utilization of photovoltaic systems in residential buildings: the case of Jordan. Energy Convers Manag 2010;51:1719−26. https://doi.org/10.1016/j.enconman.2009.11.026.

[59] Dufo-López R, Zubi G, Fracastoro GV. Tecno-economic assessment of an off-grid PV-powered community kitchen for developing regions. Appl Energy 2012;91:255−62. https://doi.org/10.1016/j.apenergy.2011.09.027.

[60] Zahir A, Khan SA, Naseem A. Feasibility analysis of grid tied PV system based on net-metering incentive for a developing country: a case study of Pakistan. IEEE Int Conf Ind Eng Eng Manag 2018;2017. https://doi.org/10.1109/IEEM.2017.8290245. Decem:2014−8.

[61] Shabbir N, Usman M, Jawad M, Zafar MH, Iqbal MN, Kütt L. Economic analysis and impact on national grid by domestic photovoltaic system installations in Pakistan. Renew Energy 2020;153:509−21. https://doi.org/10.1016/j.renene.2020.01.114.

[62] Jawad M, Qureshi MB, Khan MUS, Ali SM, Mehmood A, Khan B, et al. A robust optimization technique for energy cost minimization of cloud data centers. IEEE Trans Cloud Comput 2021;9:447−60. https://doi.org/10.1109/TCC.2018.2879948.

[63] European Commission. Photovoltaic Geographical Information System n.d. https://re.jrc.ec.europa.eu/pvg_tools/en/(accessed February 2, 2021).

[64] Sen Z. Solar energy fundamentals and modeling techniques. first ed. Springer-Verlag London; 2008.

[65] Vliet GC. Principles of Solar Engineering122; 2000. https://doi.org/10.1115/1.1288930.

[66] Ghirlando R, Refalo P, Abela S. Optimising the inclination of solar panels taking energy demands into consideration. In: 30th ISES Bienn Sol World Congr 2011. 5; 2011. p. 3704−13. https://doi.org/10.18086/swc.2011.24.24. SWC 2011.

[67] John A, Duffie WAB. Wiley: solar engineering of thermal processes. fourth ed. John A. Duffie, William A. Beckman; 2013.

[68] Jacobson MZ, Jadhav V. World estimates of PV optimal tilt angles and ratios of sunlight incident upon tilted and tracked PV panels relative to horizontal panels. Sol Energy 2018;169:55−66. https://doi.org/10.1016/j.solener.2018.04.030.

[69] Eesti Energia. Renewable Energy - Eesti Energia n.d. https://www.energia.ee/en/era/taastuvenergia (accessed January 12, 2021).

[70] Vinnal T, Puusepp H, Shabbir N, Iqbal N. Case study of non-linear PV inverter devices attached to the LV distribution network. Agron Res 2020;18:2639−52.

[71] Shabbir N, Amadiahangar R, Raja HA, Kutt L, Rosin A. Residential load forecasting using recurrent neural networks. In: Proc - 2020 IEEE 14th Int Conf Compat Power Electron Power Eng CPE-POWERENG; 2020. https://doi.org/10.1109/CPE-POWERENG48600.2020.9161565. 2020:478−81.

[72] Jawad M, Qureshi MB, Ali SM, Shabbir N, Khan MU, Aloraini A, et al. A cost-effective electric vehicle intelligent charge scheduling method for commercial smart parking lots using a simplified convex relaxation technique. Sensors 2020;20:1−19. https://doi.org/10.3390/s20174842.

[73] Shivani Sandhu KS, Ramachandran Nair A. A comparative study of ARIMA and RNN for short term wind speed forecasting. In: 2019 10th Int Conf Comput Commun Netw Technol ICCCNT 2019; 2019. p. 8−14. https://doi.org/10.1109/ICCCNT45670.2019.8944466.

[74] Munir MA, Khattak A, Imran K, Ulasyar A, Khan A. Solar PV generation forecast model based on the most effective weather parameters. In: 1st Int Conf Electr Commun Comput Eng ICECCE 2019; 2019. p. 24. https://doi.org/10.1109/ICECCE47252.2019.8940664. 5.

[75] Lu HJ, Chang GW. Enhanced gret theory system model worth weight table for n0w-casting PV power generation forecast. In: 2018 IEEE Innov. Smart Grid Technol. - Asia (ISGT Asia); 2018. p. 952−6.

[76] Lee M, Lee W, Jung J. 24-Hour photovoltaic generation forecasting using combined very-short-term and short-term multivariate time series model. IEEE Power Energy Soc Gen Meet 2018. https://doi.org/10.1109/PESGM.2017.8274605. 2018-Janua:1−5.

[77] El-Baz W, Tzscheutschler P, Wagner U. Day-ahead probabilistic PV generation forecast for buildings energy management systems. Sol Energy 2018;171:478−90. https://doi.org/10.1016/j.solener.2018.06.100.

[78] Agga A, Abbou A, Labbadi M, El Houm Y. Short-term self consumption PV plant power production forecasts based on hybrid CNN-LSTM, ConvLSTM models. Renew Energy 2021;177:101−12. https://doi.org/10.1016/j.renene.2021.05.095.

[79] Qu J, Qian Z, Pei Y. Day-ahead hourly photovoltaic power forecasting using attention-based CNN-LSTM neural network embedded with multiple relevant and target variables prediction pattern. Energy 2021;232:120996. https://doi.org/10.1016/j.energy.2021.120996.

[80] Zhen H, Niu D, Wang K, Shi Y, Ji Z, Xu X. Photovoltaic power forecasting based on GA improved Bi-LSTM in microgrid without meteorological information. Energy 2021;231:120908. https://doi.org/10.1016/j.energy.2021.120908.

[81] Mellit A, Pavan AM, Lughi V. Deep learning neural networks for short-term photovoltaic power forecasting. Renew Energy 2021;172:276−88. https://doi.org/10.1016/j.renene.2021.02.166.

[82] Wang F, Xuan Z, Zhen Z, Li K, Wang T, Shi M. A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework. Energy Convers Manag 2020;212:112766. https://doi.org/10.1016/j.enconman.2020.112766.

[83] Sharadga H, Hajimirza S, Balog RS. Time series forecasting of solar power generation for large-scale photovoltaic plants. Renew Energy 2020;150:797−807. https://doi.org/10.1016/j.renene.2019.12.131.

[84] Duman AC, Güler Ö. Economic analysis of grid-connected residential rooftop PV systems in Turkey. Renew Energy 2019. https://doi.org/10.1016/j.renene.2019.10.157.

[85] Rashwan SS, Shaaban AM, Al-Suliman F. A comparative study of a small-scale solar PV power plant in Saudi Arabia. Renew Sustain Energy Rev 2017;80:313−8. https://doi.org/10.1016/j.rser.2017.05.233.

[86] Shabbir N, Kütt L, Daniel K, Astapov V, Raja HA, Iqbal MN, et al. Feasibility investigation for residential battery sizing considering EV charging demand. Sustain Times 2022;14. https://doi.org/10.3390/su14031079.