

Article

Optimization of Sizing of Battery Energy Storage System for Residential Households by Load Forecasting with Artificial Intelligence (AI): Case of EV Charging Installation

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Abstract: This paper presents the optimization sizing of a battery energy storage system for residential use from load forecasting using AI. The solar rooftop panel installation and charging systems for electric vehicles are connected to the low-voltage electrical system of the Metropolitan Electricity Authority (MEA). The daily electricity demand for future load forecasting used the long short-term memory (LSTM) technique in order to analyze the appropriate size of the battery energy storage system (BESS) for residences. The solar rooftop installation capacity is 5.5 kWp, which produces an average of 28.78 kWh/day. The minimum actual daily load in a month is 67.04 kWh, comprising the base load and the load from charging electric vehicles, which can determine the size of the battery energy storage system as 21.03 kWh. For this research, load forecasting will be presented to find the appropriate size of BESS by considering the minimum daily load over the month, which is equal to 102.67 kWh, which can determine the size of the BESS to be 17.84 kWh. When comparing the size of BESS from actual load values with the load from the forecast, it can significantly reduce the size and cost of BESS.

Keywords: battery energy storage system; solar rooftop; electric vehicle



Academic Editors: Hideaki Ohgaki and Boonyang Plangklang

Received: 25 January 2025

Revised: 23 February 2025

Accepted: 25 February 2025

Published: 4 March 2025

Citation: Promasa, N.; Songkoh, E.; Phonkaphon, S.; Sirichunchuen, K.; Ketkaew, C.; Unahalekhaka, P. Optimization of Sizing of Battery Energy Storage System for Residential Households by Load Forecasting with Artificial Intelligence (AI): Case of EV Charging Installation. *Energies* **2025**, *18*, 1245. <https://doi.org/10.3390/en18051245>

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1. Introduction

To study the method of meeting the energy demand for residential use, mainly by using the energy generated from the solar rooftop system installation as shown in Figure 1, the selection of a battery energy storage system suitable for residential use in the case of solar rooftop installation is carried out using the developed software, which uses the residential load data to determine the most suitable solar rooftop system [1]. The battery energy storage system suitable for residential use, in the case of solar rooftop installation, can be applied to different scenarios to optimize the battery usage data with different renewable energy sources, and the solar rooftop model is developed to work with the grid system. The grid system can be tested under standard test conditions using MATLAB/SIMULINK [2,3].

It is possible to effectively reduce the fluctuation of new energy and reduce the impact on the power system by proposing a simple method that requires the measurement of increased conductivity to directly control the power from the solar rooftop system [4–6]. Nowadays, the use of electric vehicles has become widespread, so it is necessary to study

the relationship between electric vehicles and regular charging. It can use the dataset of charging at different locations, including each parameter, as well as the relevant charging time. The dataset includes information on the arrival and departure times of electric vehicles. The dataset collected from charging stations which meet the charging demand at different locations is used in the methodology and evaluation of electric vehicle (EV) charging models [7–9], affecting the availability of electric vehicles while maximizing the electricity generation from solar rooftop PV using EV batteries [10]. In this case study on the load impact for EV charging, a modeling framework is developed to utilize useful information from real EV charging event data and residential electricity consumption data [11,12].



Figure 1. Solar rooftop installation of 5.5 kWp.

EV charging is considered in conjunction with solar rooftop power generation. It provides both charging and discharging power for electric vehicles connected to the 50 Hz AC grid. Solar rooftop power is the primary power source for the EV charging system in conjunction with grid connection. It is generated using photovoltaic (PV) panels located at different locations, where the panels may be mounted on the roof or as a rooftop on a building. The energy consumption and capacity data of the EV are determined by the EV data, which can be used to describe and generate data on the charging time of the EV [13,14]. Considering the expected developments by 2030, the value of EVs can be improved by improving the design of the power system and charging strategies of both the power system and the EV usage level. These optimizations are balanced by using real-time electricity prices and efficient demand responses of the electrical load [15–17]. The proposed new approach uses a multi-stage optimization strategy that considers both the routing of the EVs and the overall energy management of the EVs in the power system. Each EV is used to determine their charging. Therefore, the optimal scheduling of EV charging is an extraordinary problem involving multiple sources of uncertainty. These uncertainties are often overlooked in demand management [18,19]. However, considering the demand management aimed at exploiting the flexibility of EVs, an optimal control theory has been proposed to determine the optimal battery energy storage system usage for the residential and solar rooftop installation cases. This study provides recommendations on the relevant framework conditions as well as the optimal sizing of the power grid for the best economic and technical results. The application of the optimal parameter set shows that the sizing of the power grid can handle these problems well, thus providing accurate results with

fast computational speed. The analysis of battery efficiency and lifetime as a concept for sizing EV charging stations has been extensively studied [20–22]. The calculations from the models must take into account the load profiles of residential energy usage, the solar rooftop system, and the battery so that the simulations can have high energy potential and further reduce energy consumption, unlike those observed in conventional models with solar rooftop and batteries [2,23–26]. For residential load forecasting using LSTM, the focus is on the impact of parameters on the forecasting performance, such as training data size and model accuracy. It has been shown that LSTM improves the load forecasting accuracy and energy management of the grid [27]. The load forecasting using LSTM is reliable for forecasting, with a comparative analysis based on the accuracy and efficiency metrics conducted [28]. The study utilized federated learning, transfer learning, and deep dynamic threshold compression to improve prediction accuracy in response to high data masking and dimensionality [29]. However, the predictive demand forecasting and real-time scheduling can optimize energy use [30,31].

Artificial intelligence (AI) techniques and optimization techniques have emerged as promising strategies in the pursuit of sustainability, with efficient AI in centralized LSTM. There are customizable modeling methods for data analysis and optimization. Effective applications of AI include machine learning, deep learning methods, and LSTM [32,33] to manage the limitations of current methods in forecasting, optimization, and control. Integrating these diverse approaches for better forecasting and management addresses the need for explainable AI in critical decision-making, which is being widely used with the rise of AI [34–38]. The principles and tools of the proposed explainable AI support the design and validation of models, while further customization of the system with regard to input data preparation, feature selection, and model implementation is possible [39]. However, to gain a deeper understanding of the forecast results and quickly respond to uncertain situations, and since practical engineering requires high standards of forecast reliability, interpretable deep learning methods have been proposed to solve multi-stage residential load forecasting problems, called explainable AI, to further improve their efficiency [40,41]. The use of AI has been investigated and evaluated using standardized datasets. Machine learning (ML) studies are continuously being improved through the use of training data and the exploitation of available, fully interconnected scenarios. In general, it has become a major research issue in the field of artificial intelligence. AI-driven technologies that exploit the ability of computer techniques to decode and understand have become the leading approach in forecasting. As a result, the development of machine learning methods that can provide accurate forecasting is a major issue [42–46]. Currently, environmental concerns are widespread all over the world, and solar power plays a major role in this discussion. Therefore, accurate forecasting systems are needed to improve the quality of the processes used in energy production. The data are situational, so the modeling and forecasting process using AI is important [47]. However, traditional and probabilistic methods are less adaptable to changes in demand and trends. With the development of AI, these new methods have become the most popular option due to their higher accuracy based on extracting features based on time, demand, and trends [48]. In recent years, it has been proposed that AI controllers, combined with deep learning techniques, be applied as advanced controllers that can achieve this goal. Due to the advancement of AI technology, intelligent diagnosis technology has been applied. This study developed an artificial neural network, LSTM, to diagnose the fault. Most traditional AI-based fault location methods rely on the selection of fault values. In addition, these methods are often very sensitive to the selected fault parameters and characteristics, so the efficiency of the conclusions is high [49–52]. AI, such as machine learning (ML) and supervised learning (SL), has been widely used by practitioners, and academic research projects have also been carried out

in various domains. However, the use of machine learning in operational forecasting is still limited for this reason [53]. AI techniques such as LSTM are used in this study for forecasting [54,55].

LSTM can model these time-dependent relationships, exploiting historical sequences of data to identify patterns and trends. This indicates that LSTM are particularly effective at identifying cases where outcomes are true positives, making them a reliable candidate. The use case is to operate on data with a simple LSTM network [35–39]. An LSTM model is used, with an input gate, a forget gate, and an output gate as the three gates of an LSTM unit. The input gate determines how much input data is needed to be retained in the existing state of the memory unit, the forget gate is the basic design for LSTM to learn long-term dependencies, and the output gate decides which state of the memory cell is to be sent to the hidden output state [45,50]. The recurrent neural network (RNN) is widely used in natural language processing (NLP) and time series forecasting, and improved methods have been proposed, particularly LSTM [51,52,54,56].

Root Mean Square Error (*RMSE*) is defined as the average deviation of the estimate from the observed value [57]. *RMSE* is used to assess the difference between the predicted and actual values to check the forecast accuracy of the model. The results show that the proposed approach provides more accurate forecasts and the lowest *RMSE* values. The research emphasizes its application in energy yield prediction, which can improve the supply and demand balance in the electricity network. The success of experimental results and artificial neural networks is determined by *RMSE* [58–60]. *RMSE* is used to measure the variability of the data; the smaller the value, the better the model accuracy [61]. In addition to *RMSE*, the error regression curve obtained from MATLAB was used to evaluate the network performance and the results of the validation of the adequate predictions of the trained ones [62].

In 2025, the number of electric vehicles worldwide is expected to exceed 85 million, which will significantly increase electricity demand and generate interest in using solar roofs and batteries as a power source for charging electric vehicles to reduce dependence on the main electricity grid. Therefore, studying the size of batteries used to store electricity for residential use is a challenge. Finding the right size will help to use energy efficiently and reduce energy costs in the long run, especially when it is necessary to charge electric vehicles in residential homes. This research focuses on calculating the appropriate battery size for residential use in cases where electric vehicles need to be charged, using artificial intelligence techniques to calculate the best value for installation in residential homes. This research will be important in helping to increase the sustainability of energy use and respond to the increasing demand from the use of electric vehicles in the future.

2. Methodology

2.1. Long Short-Term Memory (LSTM)

LSTM is able to model these temporal relationships is shown in Figure 2, leveraging historical sequences of data to identify patterns and trends [35]. LSTM, a variant of RNN, is designed to handle long-term data dependencies. A central unit called a state cell acts as a memory, retaining relevant information while discarding unnecessary information. This structure allows LSTM to process historical data more efficiently than standard RNN, making it ideal for electrical load forecasting. Recent developments in LSTM-based algorithms have provided robust models for electrical load forecasting. LSTM is designed to handle long-term dependencies and reduce potential problems in standards [48,49].

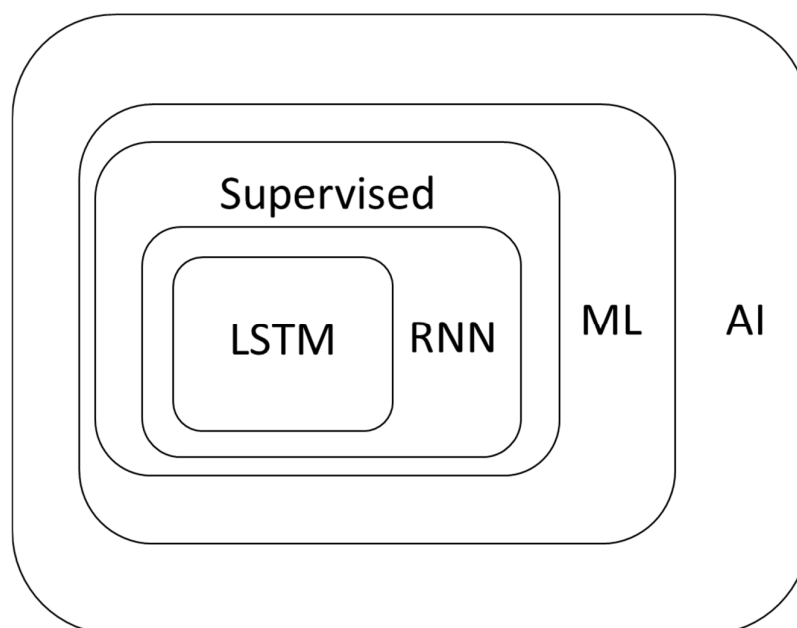


Figure 2. AI model for LSTM.

The structure of LSTM for long-term and short-term data relationships is shown in Figure 3. The forget gate layer will determine the information to be discarded from the previous output gate layer and the current input gate layer. To process the output gate layer, it will be multiplied by the cell state, while the input gate layer will determine the new information to be stored in the cell state.

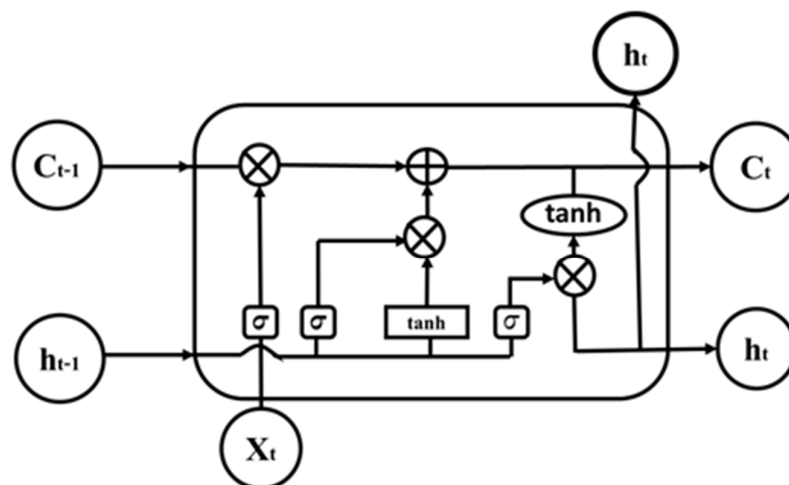


Figure 3. Structure of LSTM.

2.1.1. Forget Gate Layer

The forget gate layer is a gate responsible for determining whether the incoming data in the cell should be kept or discarded. The decision to keep the data is evaluated based on the input data that comes into that node, along with the results from the previous node's calculations. The equation is shown as:

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

where:

f_t is denotes the forget gate control signal;

W_f is about the hidden layer weights of state vector;
 h_{t-1} is indicates the hidden state of the previous moment;
 x_t is represents the input of the current moment;
 b_f is respective corresponding doors on the bias vector.

2.1.2. Input Gate Layer

The input gate layer is a gate that receives new input data and then records or writes the data into each node, with the operation divided into two parts. The first part is that if you want to update the cell state, the input gate is used to decide whether to update the cell state. The second part is that if the input gate chooses to update the cell state, the tanh function is applied to the state. The equation is shown as:

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

$$\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

$$C_t = (f_t \cdot C_{t-1}) + (i_t \cdot \widetilde{C}_t) \quad (4)$$

where:

i_t is denotes the input gate control signal;
 W_i is about the hidden layer weights of state vector;
 b_i is respective corresponding doors on the bias vector;
 $\widetilde{C}_t$ is represents the information candidate state;
 W_C is about the hidden layer weights of state vector;
 b_C is respective corresponding doors on the bias vector;
 C_t is denotes the memory cell of the current moment;
 C_{t-1} is denotes the memory cell (cell state) of the previous moment.

2.1.3. Output Gate Layer

The output gate layer is a gate that prepares for data to be output based on the cell state that has undergone various calculations. The function will determine which part of the cell state will be output. Then, the cell state value is passed through the tanh function (to find out if the output will be 1 or -1). Finally, the value obtained from the tanh function is used. The equation is shown as:

$$O_t = \sigma(W_O \cdot [h_{t-1}, x_t] + b_O) \quad (5)$$

$$h_t = O_t \cdot \tanh(C_t) \quad (6)$$

where:

O_t is denotes the output gate control signal;
 W_O is about the hidden layer weights of state vector;
 b_O is respective corresponding doors on the bias vector;
 h_t is denotes the hidden state of the current moment.

2.2. Root Mean Squared Error (RMSE)

RMSE is a function that compares the difference between the actual values and the forecasted values, but with the addition of a square root in the equation to reflect the average of the deviations of each point that are large in magnitude. Therefore, *RMSE* will give more weight to deviations that are closer to the actual values, thus helping to improve

the comparison of results. This function will be used in the step of evaluating the accuracy of the forecasting model as shown in equation:

$$RMSE = \sqrt{\frac{\sum (A_t - F_t)^2}{n}} \quad (7)$$

where:

F_t is the forecasted value for the time period or observations at t ;

A_t is the actual observations value at time;

n is the number of observations.

2.3. Battery Energy Storage System Design

A battery energy storage system combined with solar rooftops for residential use, in the case of electric vehicles, is installed as a charging system for electric vehicles, as shown in Figure 4.

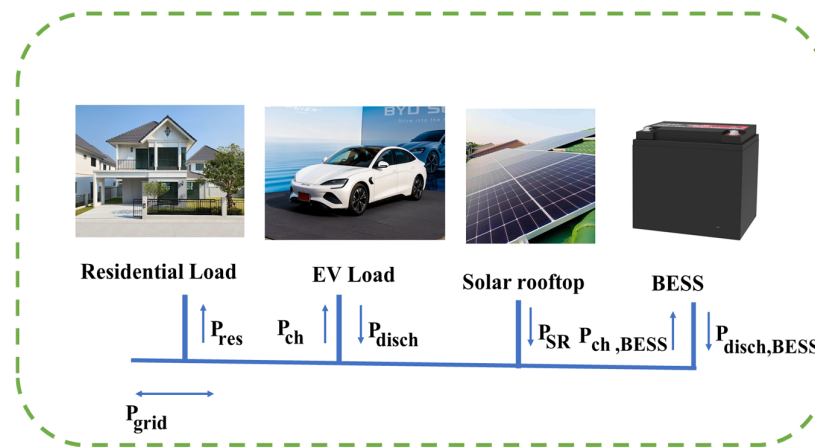


Figure 4. Battery energy storage system for residential use.

The battery energy storage system for residential use, in the case of installing a charging system for electric vehicles, will be analyzed based on the amount of remaining usable energy.

From the solar rooftop system installed on the roof, the size of the battery energy storage system can be determined as shown in the equation [63]:

$$E^{BESS} = \sum_{t_1}^{t_2} (P_{y,m,d,t}^{Load}) \times \Delta t \quad (8)$$

where:

$P_{y,m,d,t}^{Load}$ is the maximum power rating of the battery energy storage system;

E^{BESS} is Size of the battery energy storage system (kWh);

Δt is The Length of The Time Period: 0.25 h;

t_1 and t_2 is the start and end time when the battery energy storage system is charging (h).

3. Simulation and Results

3.1. The Load Profile Collection of Residential

The collection of electricity consumption data from the Metropolitan Electricity Authority for residential applications from January 2022 to December 2023 will be recorded every 15 min through the dashboard system as a basis for forecasting, as shown in Figure 5. Energy consumption data from the charging system for electric vehicles (EV) of the wall

charge type, with a capacity of 3.60 kW and a charging current of 16 A, is another type of electric consumption data with charging from 17.00 to 5.00, as shown in Figure 6. An analysis of the daily load from electricity consumption during EV charging, combined with residential electricity consumption, showed that the lowest electricity consumption of the month was 67.04 kWh, with electricity consumption at 33.67 kWh/day while electricity usage during the EV charging period was 33.37 kWh/day, as shown in Figure 7.

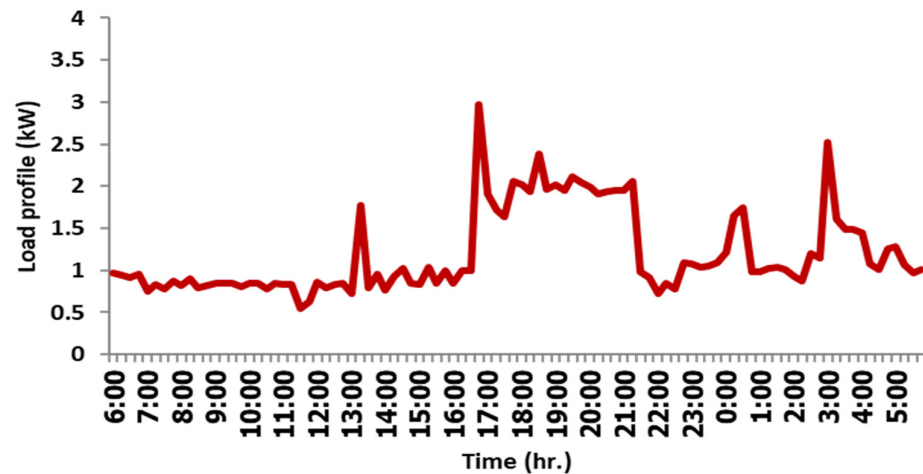


Figure 5. Load profile of residential was 33.67 kWh/day.

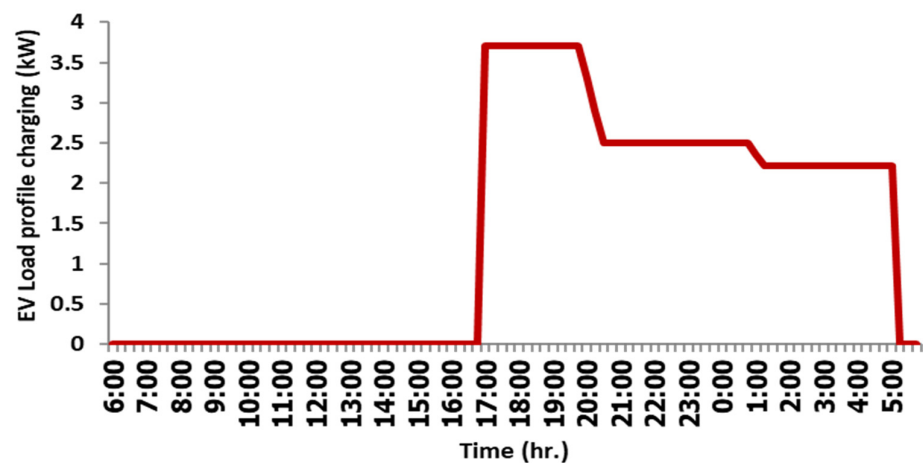


Figure 6. EV Load profile charging was 33.37 kWh/day.

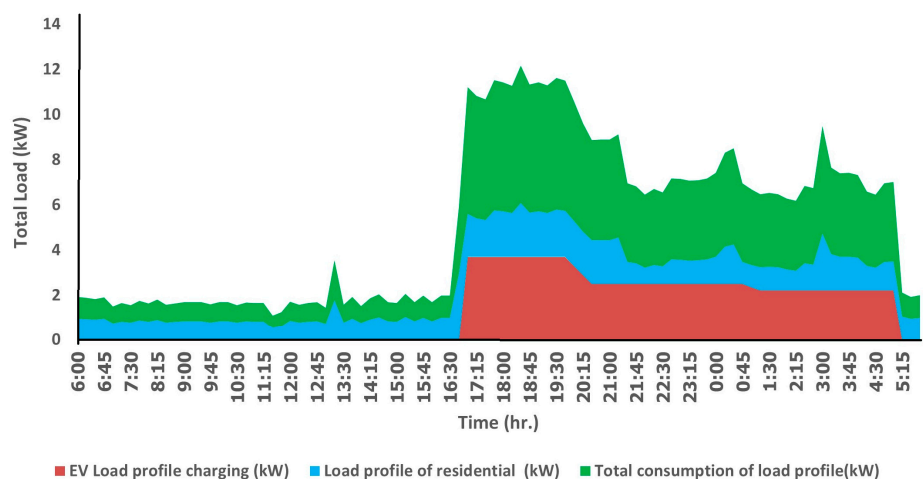


Figure 7. Total consumption of load profile was 67.04 kWh/day.

3.2. Load Forecasting

3.2.1. Specifications for Developing an LSTM Model

The parameters utilized in an LSTM model primarily have two components: trainable parameters and hyperparameters. The parameters acquired by the LSTM model during training encompass the weights and biases of the LSTM layers. Hyperparameters are parameters established before model training that remain constant during the training process. In this study, the optimal hyperparameters obtained from Random Search are LSTM units = 50, batch size = 32, epochs = 20, optimizer = Adam, and learning rate = 0.001, which resulted in the lowest *RMSE* according to the experimental results. Therefore, using Random Search enhances the accuracy of electricity consumption forecasting by reducing computational time and efficiently identifying the optimal hyperparameters within a limited number of iterations. These parameters dictate the model's performance. This investigation delineated the subsequent values. The types of parameters are shown in Table 1.

Table 1. Types of LSTM parameters.

Type of Parameter	Name of Parameter	Rate
Trainable Parameters	Total Parameters	10,451
	LSTM Units	50
	Dense Units	1
	Sequence Length	30
	Batch Size	32
Hyperparameters	Epochs	20
	Optimizer	Adam
	Loss Function	Root Mean Squared Error (<i>RMSE</i>)
	Validation Split	30

3.2.2. Data Training and Testing

The data used for the analysis consists of 730 sets, which were collected over a 24 month period from 1 January 2022 to 31 December 2023. The data was divided into two sets: the training set and the test set, with the last 30 sets of data used as the test set and the remaining data used as the training set. The data is arranged in chronological order to ensure that the model learns from the data in the correct temporal sequence, allowing for a comparison between the actual load and the forecasting load as shown in Figure 8.

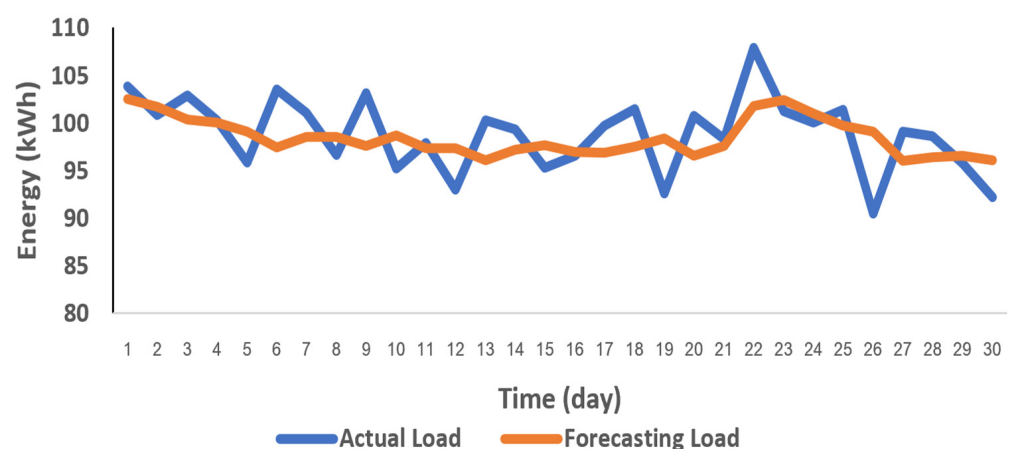


Figure 8. Comparison of actual load and forecasting load.

3.2.3. Forecasting and Evaluation

The process of forecasting electricity consumption was carried out using a test set of 30 monthly data points, resulting in an $RMSE$ value for the test set. (Test Set) which has the lowest error of long short-term memory. The Root Mean Squared Error ($RMSE$) is 3.554, allowing for a 30-day load forecast, as shown in Figure 9.

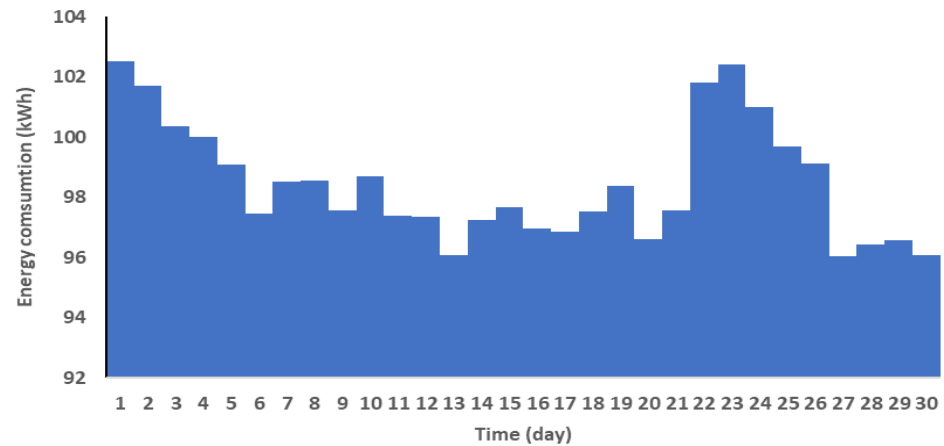


Figure 9. Results of 30-day load forecast.

3.3. Battery Energy Storage System

Determining the size of the battery energy storage system will be based on actual load values and forecasted load values to compare the size of the battery energy storage system and determine the most suitable size. The battery energy storage system size, as shown in Figure 10.

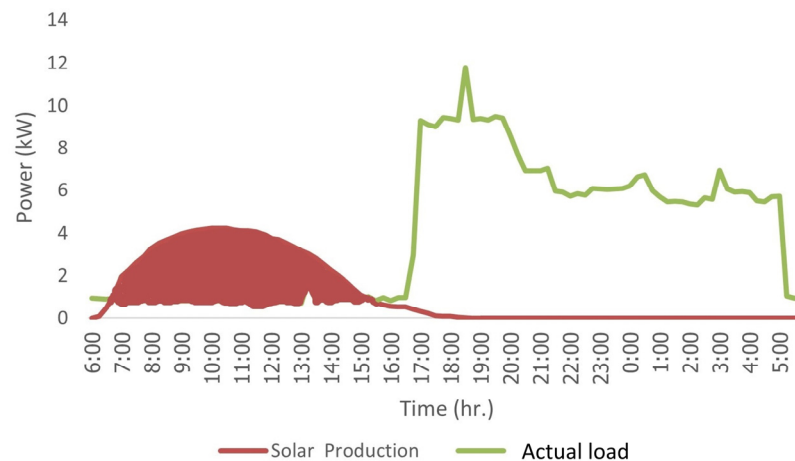


Figure 10. The graph shows the battery energy storage system size equal to 21.03 kWh.

3.3.1. Actual Load

From the data on the lowest daily actual load energy consumption over the month, which includes residential electricity usage combined with electricity usage from charging electric vehicles, the total is 67.04 kWh, which allows us to determine the size of the battery energy storage system from the surplus electricity generated by the solar rooftop, amounting to 21.03 kWh. The BESS can reduce the peak power consumption (peak shaving) base on BESS size, as shown in Figure 11.

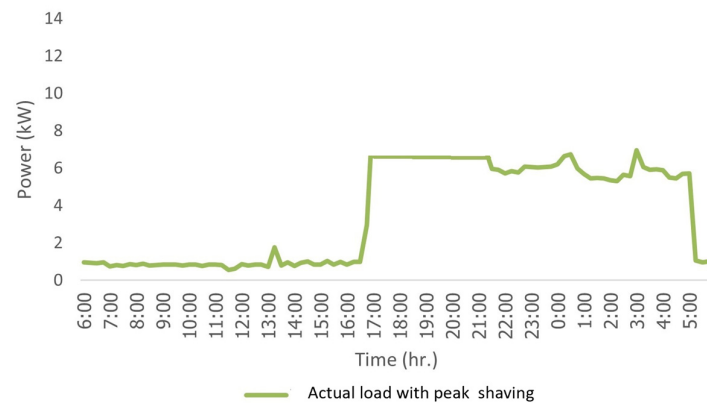


Figure 11. The graph shows the reduction in peak power consumption (actual load) from the installation of battery energy storage system.

3.3.2. Load from the Forecast

Based on the 30-day load forecast, the battery energy storage system size will be determined from the day with the lowest load usage, which is 102.67 kWh, allowing us to determine the battery energy storage system size to be 17.84 kWh. And it can reduce the peak power consumption from the installation of the battery energy storage system as shown in Figure 12. The BESS can reduce the peak power consumption (peak shaving) base on BESS size as shown in Figure 13.

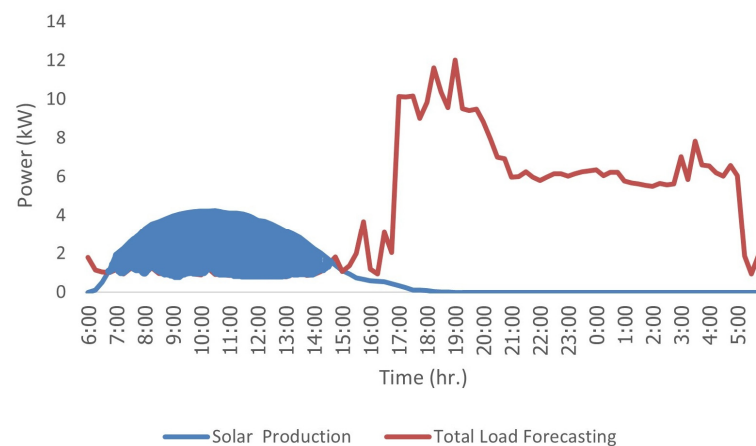


Figure 12. The graph shows the battery energy storage system size to 17.84 kWh and the reduction in peak power consumption from the installation of battery energy storage system.

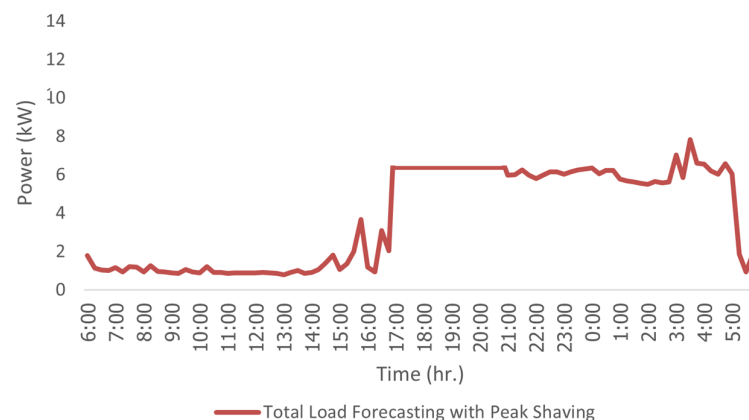


Figure 13. The graph shows the reduction in peak power consumption (load forecasting) from the installation of battery energy storage system.

4. Conclusions

Battery energy storage systems suitable for residential use, in the case of installing charging systems for electric vehicles, are combined with load of residential and already installing a solar rooftop. The calculations and analysis were conducted using MATLAB 2019a for normal electric vehicle battery charging combined with load of residential. It was found that the residence used a total of 67.04 kWh of electricity. The solar rooftop system installed on the roof was 5.5 kWp, which produces an average of 28.78 kWh per day. The solar rooftop system produced additional electricity, which can be stored in a 21.04 kWh battery energy storage system. The load forecasting will be presented to find the appropriate size of BESS by considering the minimum daily load over the month, which is equal to 102.67 kWh, allowing us to determine the size of the BESS to be 17.84 kWh. When comparing the size of BESS from actual load values with the load from the forecasting, it can significantly reduce the size to 3.19 kWh and BESS costs to 12,839.75 baht (366.85 U.S.). In particular, the solar rooftop system can also reduce CO₂ to 9.002 TonCO₂/y.

Author Contributions: Methodology, S.P. and K.S.; Software, E.S.; Validation, C.K.; Formal analysis, N.P.; Supervision, P.U. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study can be obtained from the corresponding author due to privacy concerns.

Conflicts of Interest: The authors declare no conflict of interest.

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