



## ORIGINAL RESEARCH

# Smart coordination of predictive load balancing for residential electric vehicles based on EMD-Bayesian optimised LSTM

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**Abstract**

The charging load forecasting of residential Electric Vehicles help grid operators make informed decisions in terms of scheduling and managing demand response. The residence can include integrated residential appliances with multi-state and high-frequency features. For this reason, it is difficult to estimate the total load of residence accurately. To overcome this problem, this paper proposes a hybrid forecasting model using the empirical mode decomposition and Bayesian optimised Long Short-Term Memory for load balancing based on residential electricity meter data. The residential electricity meter data includes three datasets as Electric Vehicle, heat pump and photovoltaic system. To decompose of the data characteristics, the empirical mode decomposition method performs to the original data. Then, the Bayesian optimised Long Short-Term Memory is applied to forecast for each sub-component of the data sequentially. The main features of the proposed model include a significant improvement in prediction accuracy and capture the local maximums. The advantage of the proposed method over existing methods are also verified over with experiments of data-driven on the IEEE 33 busbar test system. The result of simulation forecasting model indicates that predict closely the busbar outflow power, voltage drop, transformer loading states and power losses to compare with actual load model.

## 1 | INTRODUCTION

Globally, the International Energy Agency (IEA) forecasts that the number of electric vehicle (EV) stocks from around 8 million in 2019 will approach 50 million in 2025 and 140 million in 2030 [1]. The Norwegian energy market regulator suggests that an average 1kW increase in household load will result in 4% overload in distribution transformers [2]. In Denmark, distribution companies anticipate network overload and voltage drop for 20% EV penetration [3]. UK utilities see into a 20% EV penetration rate resulting in a 36% increase in daily peak load [4]. Taking into account all of these, the EV adoption requires an ecosystem that ensures reliable operation of its charging and mobility. Currently, lots of EVs are fed from residences installed power in low voltage networks [5]. The EV in a typical home requires more power than any other appliance, such as a heater and dryer. Also, the EV is requested one or more times charging per day. Therefore, EVs are devices that require accurate modelling in household electricity consumption [6], and residential charging of

EVs might create challenges on the grid. This challenges are summarised in [7] from three aspects: proper planning of residential onboard charger, interoperability of charging infrastructure powered by Photovoltaic (PV) generation systems, and peak power demand of EVs. The rising penetration of EVs may require increasing the residence installed power. Increasing the installed power in the residences may cause a change in the infrastructure and equipment [8]. To overcome this problem, the modern forecasting models might be applied to help using current infrastructure in smart grid systems [9]. Inputs structure of forecasting models can be created using historical datasets collected from measurements, or designed based on the relationship between other environmental factors. The forecasting models can be classified as ultra-short-term, short-term, medium-term and long-term according to the time period to be estimated. Among them, short-term forecasting (STF) for estimating hourly load demands is considered the most important task for the power grid [10]. Since the dataset consists of 1 h of data, this paper mainly focus on short-term forecasting period.

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Residential load creates from the EV charging load and the non-EV loads such as heat pump, heater and washing machine. For this reason, the forecasting of EV load, and non-EV loads like heat pump as a critical load of demand side management [11] are also required to provide for residential demand prediction models. In this way, these models facilitate increasing the reliability of the installed power in the residential power system, interoperability with renewable energy sources and making the demand fulfilment processes more convenient. Today, residential demand forecasting models based on smart meter data has become quite common with its increasing popularity. To improve the training model performance of artificial intelligence (AI), these models need high resolution time series datasets [12]. However, the relatively limited historical data of newly built houses and new residential meters is an important constraint for these models. Therefore, the researchers prefer dwellings with approximately 1 year of data for prediction model accuracy [13, 14]. Residential demand forecasting models are classified as traditional machine learning [15], deep learning [16] and modern hybrid models [17]. The traditional forecasting models based on statistical calculations for residential load series are assumed linear and stationary [18]. However, these models cannot meet with the requirements during the power system getting more complex. Under some non-linear conditions such as EV customer behaviour, these models cannot be effective due to possible high errors [19]. The modern hybrid forecasting models aims to achieve higher performance with low error [20]. Thus, these models are developed for best performance, and are being widely used in the short-term forecasting for residential [21]. In addition, these models are important to use the advantage of load balancing with PV generation system in a residential electricity network with EV and non-EV loads [22].

The forecasting of EV charging load has been attractive in recent years with increasing real-world data in research and industry. Some studies have focused on EV charge load forecasting using the historical power series of real data analysis [23, 24]. High temporal resolution consumption data from meters at the charging point can be used to forecast EV charging load to the day-ahead planning. The charging load forecasting is vital in terms of successfully EV integration on grid [25]. It is accepted as a foresight to the uncertainty problem of the EV charging power during peak hours of the grid. In particular, the specified foresight is required to supply the EV charging load along with other basic loads in the existing electrical infrastructure in a house [26]. In a paper following this foresight [27], they improved EV charging demand error performance in the parking lots by estimating conventional load and EV load separately. The paper result strengthens the argument that the EV load is structurally different from conventional loads and requires special load forecasting models. According to this argument, accurate forecasting of EV charging load is of great importance to reliability and stability of the power systems. Following with the increasing penetration of EVs in power systems, the EV charging load makes traditional forecasting methods less accurate. A new data-driven method that is a double-layered prediction model combined with the Pearson correlation coefficient and the max information coefficient

is used for high-precision forecasting of EV charging load [14]. Despite of low rate of training data, it has high accuracy and stability with compared to traditional forecasting methods. In this context, AI-based forecasting methods improve to accuracy in load forecasting of EVs compared to statistical time series analyses [28, 29]. The one of AI methods is a conventional model, the multi-layer perceptron (MLP). An MLP with a tilted loss function was proposed for probabilistic estimation of EV load in [30]. The error performance of MLP was compared using a core density estimator and quantitative regression analysis for the same EV charge load data. Accordingly, it is claimed that MLPs have higher performance in estimating EV charge load compared to other machine learning and statistical estimation methods. However, the disadvantage of EV charging forecasting with MLP is not interpretable due to its complex computational capability [31]. In the literature, detailed AI architectures such as convolutional neural network (CNN) [32] and recurrent neural network (RNN) [33] are compared for forecasting of EV charging load. In a recent paper for EV load forecasting [34], the long short-term memory (LSTM) architecture performed best on the datasets examined. However, it is not investigated to reduce the training time and improve the performance using optimiser such as Bayesian (BO) optimisation algorithm. According to the evaluation of the aforementioned papers, it is a big challenge to decide which AI architecture is the best for EV charging load forecasting. However, based on the net results of error metrics, the LSTM operating in the RNN structure showed as a higher performance feature as it takes into account the past EV load data. In the context of the EV load estimation process, information from time steps is used. Therefore, RNNs with larger time steps than CNNs are more likely to be used in EV load estimation as the most useful AI model until real-time communication channels are available in [35].

In modern hybrid forecasting approach category, AI-based methods can be applied to different problems such as generation and consumption for short-term electric forecasting. Recently, AI-based hybrid forecasting models have been developed to overcome the disadvantages of physical and statistical methods [36, 37]. These models outperform physical models in prediction, as they do not require very precise EV charging and user information that can occur in residential buildings. So far, the results obtained with these models are promising for use in residential load forecasting applications. The main idea of using such models for the balance between generation and demand in time series data is that LSTM and MLP networks can capture sequence model information, while decomposition models [38] are useful in extracting signal patterns. Although LSTM networks designed to work with temporal correlations, only use features provided in the training set. MLPs can used to infer in momentum-based weight update [39] for short-term load forecasting. The time series data is generally not adapted for long temporal dependencies. Therefore, a hybrid model that takes advantage of both the benefits of deep learning technique and the valuable features of decomposition can improve production and demand forecasting accuracy. Based on the empirical mode decomposition (EMD) method, Xiping and Yaqi [10] developed a hybrid model by combining

support vector regression (SVR), and particle swarm optimisation (PSO) techniques for improving the accuracy of short-term load forecasting. The EMD–PSO–SVR model was found to have superior efficiency and stability for the residential short-term load forecasting. However, In [10], energy forecasting of residential PV solar system were not used and compared with modern hybrid models.

The original time series data is a fundamental challenge in short-term forecasting as it is non-linear and non-stationary. Therefore, the decomposition of time series improves forecast performance. Hybrid models use decomposition methods to figure out time series characteristics and apply a pre-processing step that improve forecasting model performance. In this pre-processing step, methods such as Wavelet-based decompositions [40, 41], empirical mode decomposition (EMD) [42], ensemble empirical mode decomposition (EEMD) [43], fast ensemble empirical mode decomposition (FEEMD) [44], complete ensemble empirical mode decomposition (CEEMD) [45] and complete ensemble empirical mode decomposition adaptive noise (CEEMDAN) [46] have been widely applied in the literature. Each decomposition method has advantages and disadvantages according to the process. The empirical wavelet transform fails to detect components when the signal contains multiple chirps in both the time and frequency domains. If several useless components are produced during a single spectral analysis, information may be lost due to difficulty in selecting individual parameters. Variable mode decomposition takes time as it requires trial and error to determine the number of modes [47]. Huang et al. [48] proposed EMD overcomes the problems to decompose non-linear and non-stationary time series. To our knowledge, no research has attempted to use EMD in estimating residential load, with the exception of [49]. Considering the performance of EMD in non-stationary signals, it is to improve the model results as in [49]. Although Sulaiman et al. [49] have combined EMD with ELM, LSTM-based EMD model has yet to be investigated for residential loads.

With the motivations stated above, this paper is to develop a hybrid forecasting tool for residential EV, HP and PV data. As such, it aims to contribute to reliability and stability in grid assets. For the first time in this article, the current critical loads such as HP and EV, and PV power output included in the residential load are estimated individually using the EMD–BO–LSTM model. To evaluate the proposed model, a real household dataset from the Open Power System Data (OPSD) platform is used, which contains all load and generation information. The advantages of the proposed model compared to the state-of-art; EMD–BO–LSTM appears to have a large capacity and can achieve good performance in modelling residential power load. The model predicts and captures the trend in the range of maximum and minimum values for training. In this way, the model helps to create an electricity distribution plan that provides a seamless supply of electric power by accurately predicting the charging demand of EVs. This hybrid strategy, incorporating components detrended by EMD, overcomes to capture the trend limitation of statistical models. The proposed approach takes advantage of Bayesian optimiser with LSTM and EMD to produce stationary and regular subseries from the original data.

Moreover, the hybrid model is investigated for load balancing using IEEE 33 busbar test system. It confirms the advantages of the proposed estimation model with busbar voltage, transformer power and loss values.

The remainder of the paper is organised as follows: Section 2 presents multiple decomposition techniques in the study. Section 3 includes the proposed approach time series data, forecasting result, performance evaluation, and analysis of predictive load balancing on distribution grid using the test system. Section 4 evaluates the results of the proposed predictive load balancing and prediction methods compared with real data on distribution grid.

## 2 | MATERIAL AND METHODS

The proposed methodology presents to improve the forecasting accuracy of residential generation and demand signals in this section. First, the original signal is decomposed into multiple IMFs and a single residue using EMD method in the hybrid model. Then each of IMFs and residue are used as inputs in BO–LSTM network and MLP network. For comparison other models, namely BO–Bi–LSTM and Bi–LSTM are also built in this research.

### 2.1 | Decomposition based on empirical mode decomposition

The EMD method is an crucial part of the Hilbert Huang Transform (HHT) algorithm to extract IMFs and a residual signal  $R_n$  from the original signal [48]. HHT is used to analyse non-linear and non-stationary signals. Since PV generation and load signals in residential have these characteristics, the implemented EMD algorithm performs to obtain more reliable and stationary signal from the original data.

The EMD algorithm decomposes an original signal into several IMFs by a sifting process. Each IMF is a function that has properties that contain only one endpoint between zero-crossings and have a mean value of zero. Where there is a particular original PV generation or load demand time series  $x(t)$ , the process steps of the EMD are described as follows [49]:

- Step 1: Find all local extremes in signal  $x(t)$ . Then, the upper envelope  $u(t)$  is obtained by combining all local maximums using a cubic spline line, and the lower envelope  $l(t)$  formed by applying the same process for local minimums.
- Step 2: Average the envelopes and calculate the difference between the real time series data and the mean  $m(t)$  as (1) and (2), respectively:

$$m(t) = \frac{x_u(t) + x_l(t)}{2}, \quad (1)$$

$$d(t) = x(t) - m(t). \quad (2)$$

Step 3: According to the condition in (3), the process continues until  $d(t)$  becomes an IMF:

$$\sum_{i=1}^l \frac{[d_{j-1}(t) + d_j(t)]^2}{[d_{j-1}(t)]^2} \leq \delta (j = 1, 2, \dots; t = 1, 2, \dots, l), \quad (3)$$

where,  $l$  is the signal length and  $j$  is the iteration number of sifting process.  $d$  is selected as a constant value usually between 0.2 and 0.3.

Step 4: First three steps apply until all IMFs and detailed signal are obtained. Finally, the original time series  $x(t)$  can be expressed as a sum of IMFs  $c_i(t)$  and single residue  $R_n(t)$  as given (4) follows:

$$x(t) = \sum_{i=1}^N c_i(t) + R_n(t). \quad (4)$$

## 2.2 | Bayesian optimised long short-term memory

RNN uses information from current state sample and previous state hidden layer as an input at each time. According to the given hidden state, the output is calculated. The hidden state is like memory unit in terms of RNN. Each input has effect on the output due to constantly continues the relation of sequential states. This problem is known as the RRN vanishing gradient problem. To overcome this problem, LSTM network solves with its memory cell configuration by re-parameterising the RNN [50]. This configuration provides LSTM to use historical data efficiently. The LSTM network is special one of the RNNs which has special capabilities such as using feedback functions and weighted coupling with memory. LSTM network is mainly feasible to processing modelling time-sensitive sequences. Thus LSTM is the one of most suitable candidate for the aforementioned forecasting task. To eliminate the problem of vanishing gradient [51], LSTM architecture that combines several LSTM cells create a stable memory sequence. LSTM cells consist of status boxes, which use the inputs sequentially over time. An input vector for each timestamp is taken into the LSTM cell, then the output is calculated accordingly as (5) follows:

$$h_t = f_w(b_{t-1}, x_t), \quad (5)$$

where the input vector represents  $x_t$ ,  $h_t$  and  $h_{t-1}$  represent state vector at time  $t$  and  $t-1$ , respectively, and also the  $f_w$  represents the non-linear activation function that is  $w$  as the weight parameters.

The LSTM cell expressed stated in Equations (6)–(13). The LSTM cell architecture is controlled by the input gate, the forget gate, and the output gate [34].

$$F(t) = \sigma(W_f \cdot [H_{t-1}, X_t] + b_f), \quad (6)$$

$$I(t) = \sigma(W_i \cdot [H_{t-1}, X_t] + b_i), \quad (7)$$

$$\tilde{C}(t) = \tanh(W_c \cdot [H_{t-1}, X_t] + b_c), \quad (8)$$

$$C(t) = f_i * (C_{t-1} + I_t * \tilde{C}_t), \quad (9)$$

$$O(t) = \sigma(W_o \cdot [H_{t-1}, X_t] + b_o), \quad (10)$$

$$H(t) = O_t * \tanh(C_t), \quad (11)$$

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}}, \quad (12)$$

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}, \quad (13)$$

where the sequential input is expressed by  $X_t$ . The bias weights denote as  $b_f$ ,  $b_i$ ,  $b_c$  and  $b_o$ . The input weights depicts with  $W_f$ ,  $W_i$ ,  $W_c$  and  $W_o$ . Also  $t$  is the latest time step and  $t-1$  is the previous time step;  $H$  and  $C$  describe the output and the cell state, respectively.

The LSTM network is applied in residential short-term forecasting for PV generation, EV load and heat pump load in this study. Given historical data, the LSTM model intends to forecast the short-term horizon in the future with precision accuracy. The LSTM model uses the previous information of the data to forecast the next hour of the electricity generation and consumption.

The LSTM techniques are interest for the prediction of discrete or non-linear systems. However, the automatic tuning of LSTM hyperparameters such as learning rate, batch size, and number of layers have a major impact on a network performance. In this paper, Bayesian optimisation (BO) algorithm is used to find optimal LSTM hyperparameters. the LSTM cell and BO-LSTM algorithm showed in Figure 1.

The basic idea of this algorithm is to extract an optimised cost function and continuously update the posterior distribution of this function by adding sample points[52]. Thus, this algorithm is proposed for problems with multi-modal, non-convex, high-dimensional and high evaluation cost features, also they are known as complex black box problems [53]. The algorithm takes into account the previous parameter information, which was determined on the basis of the Gaussian process, and constantly updates the previous value. In our proposed model, to find of the test or validation loss minimum, Bayesian optimisation searches the optimum hyperparameters. Here the search space of the hyperparameter is denoted by  $P$ , wherein the number of hidden layers, dropout rate and batch size and so on in hyperparameters are, respectively, denoted as  $N_a$ ,  $N_b$ ,  $N_c$ , etc. Thus, the cost function  $F$  can be defined as in (14) [54]:

$$F : P(N_a, N_b, N_c, \dots, N_n) \subset R^n \rightarrow R. \quad (14)$$

To find the configuration of optimal model hyperparameter, the hyperparameter search space can be determined as  $p^* \in P$  in (15):

$$p^* = \arg \min_{p \in R} F. \quad (15)$$

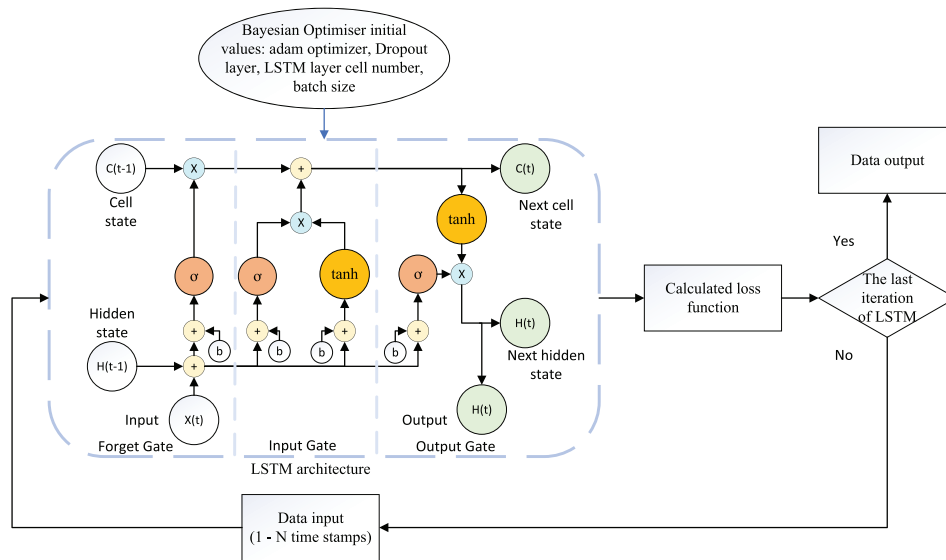


FIGURE 1 LSTM cell architecture and BO-LSTM algorithm flowchart

TABLE 1 LSTM and BO-LSTM hyperparameters for the model training

Parameters	Epochs	Batch size	ILR	Dropout value	Optimiser	NLN/neurons	TLW (hours)
LSTM	1000	16	0.005	0.5	Adam	4/100	24
BO-LSTM	1000	8	0.01	0.5	Adam	4/200	14

Abbreviations: BO-LSTM, Bayesian optimisation-based long short-term memory; ILR, initial learning rate; LSTM, long short-term memory; NLN, network layer number; TLW, time lag window.

Residential production and consumption forecasting model based on LSTM and BO-LSTM proposed in this paper mainly includes the hyperparameters such as epoch, batch size, initial learning rate, dropout value, optimiser, number of layers, number of neurons in each layer, and time lag windows (Table 1).

In this study, the Bi-LSTM network is used to compare with the proposed BO-LSTM network. Therefore, the same parameters as for LSTM in Table 1 are also used for Bi-LSTM. Bi-LSTM network is derived as the cyclic bidirectional architecture of the traditional LSTM network [55]. This architecture splits traditional LSTM in two directions, but there is a link to the same output layer for both LSTMs. The purpose of Bi-LSTM is to increase the learning function from future data to overcome the problem that the one-way LSTM network can only process historical information [56]. Detailed information about the Bi-LSTM process in this step can be found in [57].

### 2.3 | Short-term prediction based on multi-layer perceptron network

Multilayer perceptron (MLP) is a layered feedforward well-known AI model that maps input to output using historical data to produce the desired output. The MLP uses computational nodes, known as hidden neurons, to intervene usefully between

external input and network output, while manifested by one or more hidden layer entities. Artificial nerve cells form the main components of MLP. In MLP networks, these cells within layers are fully interconnected by each inputs, numerical weights and biases corresponding to the inputs [39]. These cell functions are calculated by Equation (16):

$$y_m = \varphi \left( \sum_{i=1}^n w_{mi} \cdot x_i + b_m \right), \quad (16)$$

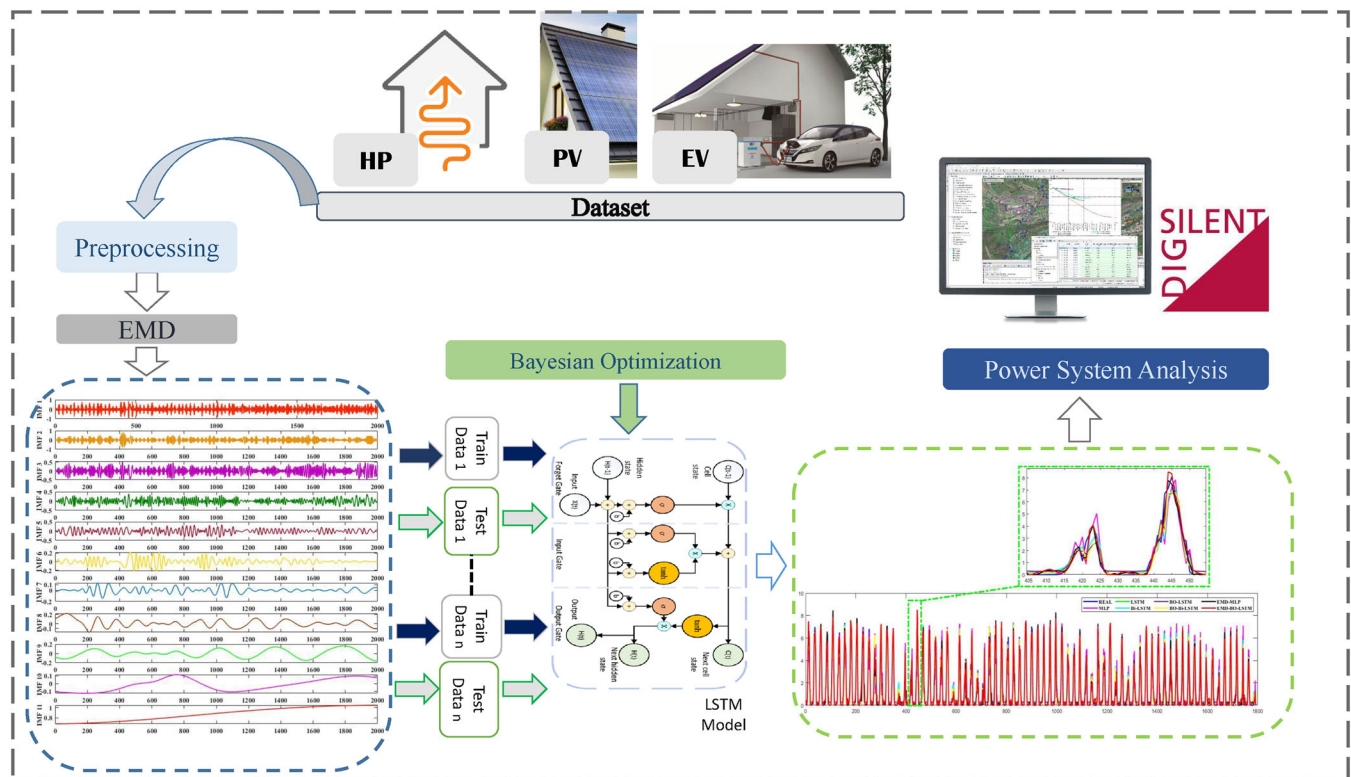
where the inputs of each cell, the weights between two cells, the bias value, the activation function and the output value of cell expressed as  $x_i$ ,  $w_{mi}$ ,  $b_m$ ,  $\varphi$  and  $y_m$ , respectively.

In MLP, higher order statistics can be extracted by adding more hidden layers. Despite MLP local connectivity, the MLP network gains a global perspective with flexible capability, that is, provided an extra dimension to set of synaptic connections, and neural network interconnections. Detailed information about MLPs can be found in [7].

In this study, an MLP network with one input layer, three hidden layers and one output layer is used for short-term prediction. The MLP network has only one input, which is the original time consumption or production data. In the literature, tansig is called hyperbolic-tangent function. The researchers in

**TABLE 2** MLP parameters for the model training

Parameters	Epochs	Iterations	Learning rate	Hidden layer	Output layer	Gradient value
MLP	1000	10	0.01	3	1	1.06

**FIGURE 2** The structure of the proposed method with EMD and BO-LSTM

[58] revealed that the network structure using the combination of Tansig in the first layer and Purelin in the second layer performs the best in terms of the average number of iterations and the number of training networks in the network configurations. Also it was trained using Levenberg–Marquardt technique as it is more powerful than traditional gradient descent techniques [59]. In this paper, for residential production and consumption forecasting model based on the MLP, its parameters include their values as epochs, learning rate, hidden layers, output layers, and training percentage shown in Table 2.

## 2.4 | Hybrid approach with EMD–BO-LSTM

In this section, the BO-based forecasting model and pre-processing step using EMD is introduced in detail. Figure 2 presents the flowchart of the study, and the three stages, decomposition phase, forecasting phase and combination phase, are described. At the first step, the residential original time series data as EV, HP and PV are decomposed using EMD after normalisation. The implementation detailed process of the EMD

method is presented in Section 2.1. To obtain the more reliable and stationary data, the decomposition phase performed in the pre-processing step. The EMD is realised to decompose the EV, HP and PV dataset into a set of IMFs with different frequencies. The decomposed signal is divided as training set and test set ratio of 70:30. In forecasting phase, all IMFs are fed into BO-based forecasting models. In other words, each decomposed signal is independently used as input to forecasting model such as LSTM. The hybrid model uses sliding window technique for learning procedure. Here, it performs univariate analysis without other external inputs such as atmospheric condition. At the last stage, the test and train results of the decomposed signals are aggregated. Hybrid models results are compared using performance metrics such as the root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE).

To validate the models performance, this paper also presents a power system analysis based on IEEE 33 bus test system using hybrid model results. An efficient optimisation tool for power system operators, the Digsilent software, is selected for analysis in this paper. The best and worst forecasting results are transferred to the Digsilent software. Hence, the aim of the power

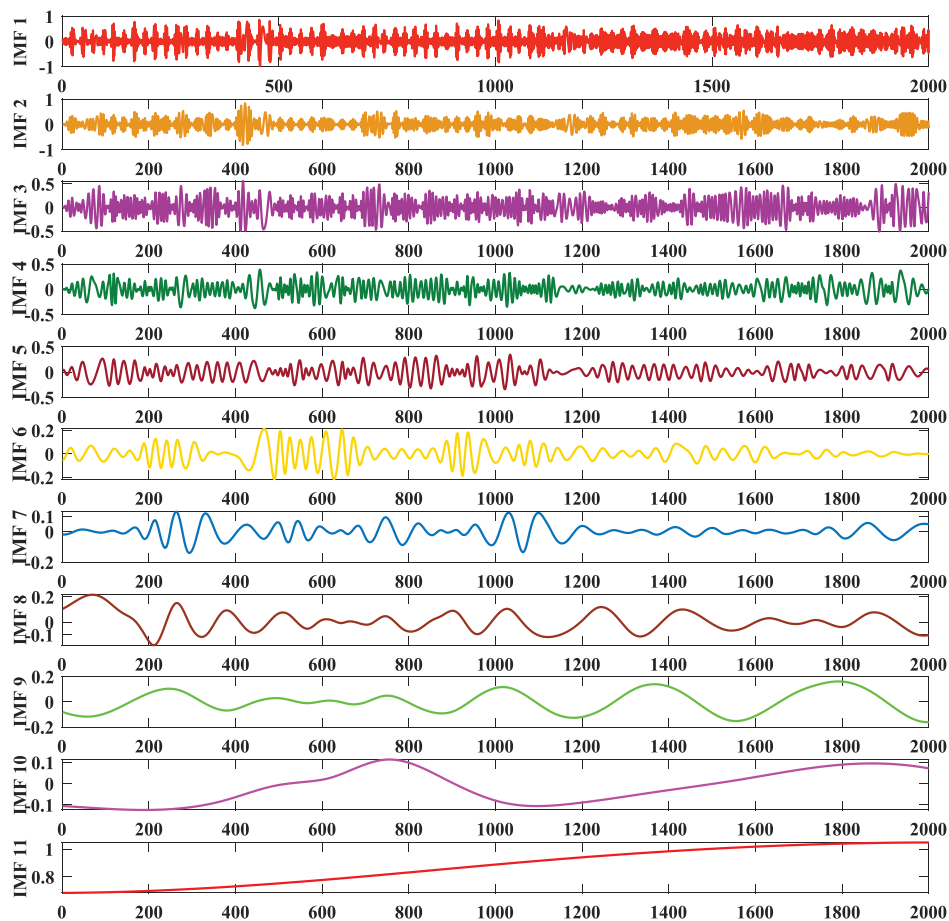


FIGURE 3 EMD processing outputs: IMFs and residual of heat pump data

system analysis is to study the effect of the forecasting performance on grid. Busbar voltage, transformer power and loss values are obtained and compared in terms of load balancing. The analysis results of the systems are discussed in detail in the following sections.

### 3 | EXPERIMENTS AND ANALYSIS

#### 3.1 | Time series data

Evaluating the residential grid impact of EVs today requires a real-world dataset of charge load, baseload, and PV generation measurement results. On the Open Power System Data (OPSD) platform, a publicly available dataset for solar power generation and detailed baseloads, with minute-to-hour resolution, containing EVs for 11 households of approximately 4 years under the European CoSSMic project are selected for this study [60]. To the best of our knowledge, there is no publicly available dataset for meter measurements with high-resolution historical data along with EV charging load, other base loads and PV generation system in residential buildings. For example, Lee et al. [61] shared an open dataset containing measurements of

charging sessions at U.S. charging stations. However, this dataset does not provide information on base loads and PV generation meter data outside residential EVs. Thus, this is not an effective solution for residential EV charging effects. Another example is data based on smart meter measurements in a total of 25 U.S. households [62]. However, since these data are 6 months data of households in three different states, they cannot provide an accurate prediction at the point of estimation.

All data with energy values in kWh on the OPSD platform was taken from MID certified meters. The residential-4 that includes EV charge load, heatpump (HP) as a base load, and PV generation datasets was pre-processed by evaluating the historical time series information measured from the low voltage level power system on this platform in this study. The proposed hybrid model was experimentally performed on the MATLAB 2021a platform. The model was operate on a personal computer with an intel Pentium (R) dual-core microprocessor of 2.40 GHz, 2 GB NVIDIA GeForce 940MX and RAM of 8 GB.

In terms of smart grid, Heat Pumps (HP) are a vital load in demand response. Smart grid operational flexibility can be achieved through the use of thermal storage and HPs in households. Because HPs can act as a shiftable load, they facilitate the use of renewable energy with a low consumption price [63].

Moreover, HP technology for heating and cooling in residential buildings is becoming more attractive with its high efficiency and low CO<sub>2</sub> emission features nowadays. The most popular single and hybrid models are performed to estimate the HP load as a base load. The forecasting model of HP load in the literature suggests that the best time period is 1 h [64]. In this way, the specified time resolution is used in the HP load dataset. Although the HP load dataset includes a horizon of approximately 12,240 h, the estimation focuses on the 2000 h time series between 10,000 and 12,000 time periods, because daily HP load data often has strong weekly periodicity. Average hourly electricity consumption and standard deviation value of HP are calculated as 0.85 kWh and 0.428 kWh. Also, the maximum and minimum measurements are equal to 2.661 kWh and 0 kWh, respectively. The network training used 70% of the HP load energy usage time series and 30% of the remaining data samples are used for validation purposes. These time series are first separated by EMD, since the real-time series data is not linear and stationary. Figure 3 shows the decomposed signals, IMFs, by using EMD. The last IMF signal is known as residue. In the second stage, each decomposed signal is independently used as input to forecasting model. All training and test forecasting results from each IMFs are aggregated in the final step. According to this time series, standalone models such as MLP, LSTM, Bi-LSTM and BO-LSTM methods, and hybrid models that contained EMD–MLP, EMD–LSTM, EMD–Bi-LSTM and EMD–BO-LSTM, are applied to improve the forecasting, respectively.

The idle values are removed and significant data are found into a specific range, since EV datasets contain some null and outlier values. Although the EV charge load dataset consists of approximately 850 days of consumption, data of only the first 2000 h time series was selected, which is the most significant from the charge consumption measurement results in the charging sessions. Average hourly electricity consumption and standard deviation value of EV charging are calculated as 1.145 kWh and 0.686 kWh excluding the idle times. Also, the maximum and minimum measurements are equal to 2.76 kWh and 0 kWh, respectively. While 70% of the EV charging energy usage time series are used for training the network, 30% of the remaining data samples are used for validation purposes. These time series are used as inputs single MLP, LSTM, Bi-LSTM and BO-LSTM methods for the short-term forecasting of EV charging load in residential. Since real-time series data are non-linear and non-stationary, these time series are decomposed by EMD. Figure 4 depicts EV charging loads with eight EMD signals. The last IMF signal is equal residue signal of EV charging load. In the final stage, EMD–MLP, EMD–LSTM, EMD–Bi-LSTM and EMD–BO-LSTM hybrid models are used to make precise forecasting and test and train results of the decomposed signals are aggregated. According to results, error performance metrics use for find the best and worst forecasting method.

An approach to how to select EV modes based on the estimated PV power generation has been proposed [65]. However, predictive load balancing for household appliances such as EV charging and HP based on PV power generation is not considered. Furthermore, the predictive load balancing described in

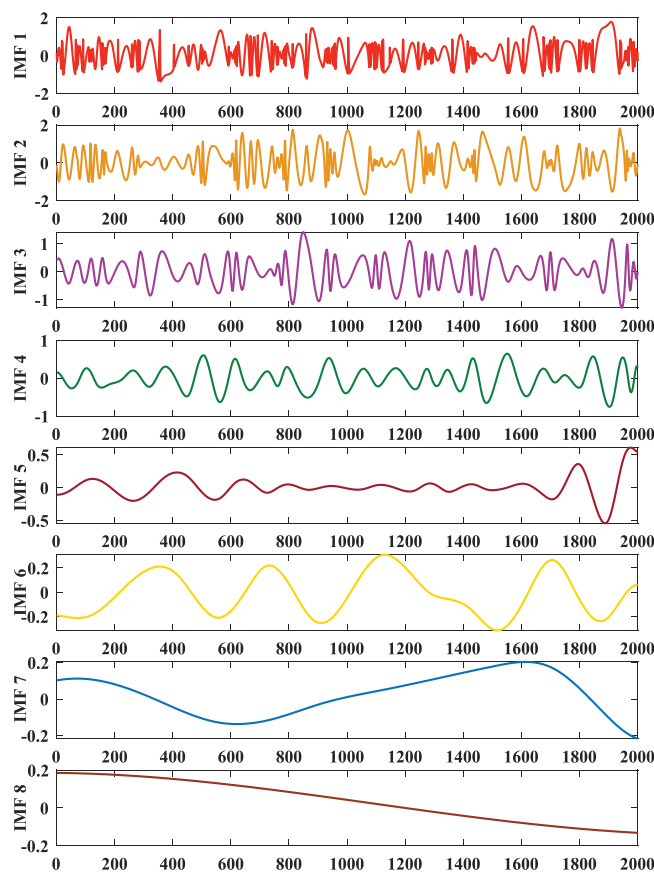


FIGURE 4 EMD processing outputs: IMFs and residual of EV charging data

this paper for charging EVs forms an essential part of smart charging coordination at the charging station. The PV power output profile is discrete compared to the residential load profile due to some cloud shading condition. However, the profile exhibits a certain periodicity. Residential PV power generation is essential for grid load balancing of EVs and loads such as heat pumps. The PV time series contains 833 days of data from October 2015 to February 2018 in this study. Average hourly electricity generation and standard deviation value of PV system for residential-4 are calculated as 2.954 kWh and 2.515 kWh excluding times of no production. Also, the maximum and minimum measurements are equal to 8.785 kWh and 0 kWh, respectively. Accordingly, the 6000-h zone between 12,000 and 18,000 is preferred for the training and testing process of the PV generation system. Training percentage for forecasting of the PV time series is 70% and 30% of the remaining data samples are used for testing. Since original data are non-linear and non-stationary, these time series are decomposed by EMD for improved forecasting. Figure 5 indicated PV system generation with 10 IMFs and residue signals obtained by EMD. These time series are used as inputs of single methods such as MLP, LSTM, Bi-LSTM and BO-LSTM and the hybrid models with EMD for the PV generation forecasting in residential. As a result, test and train results of the decomposed signals are aggregated to compare the forecasting and original time series by the error

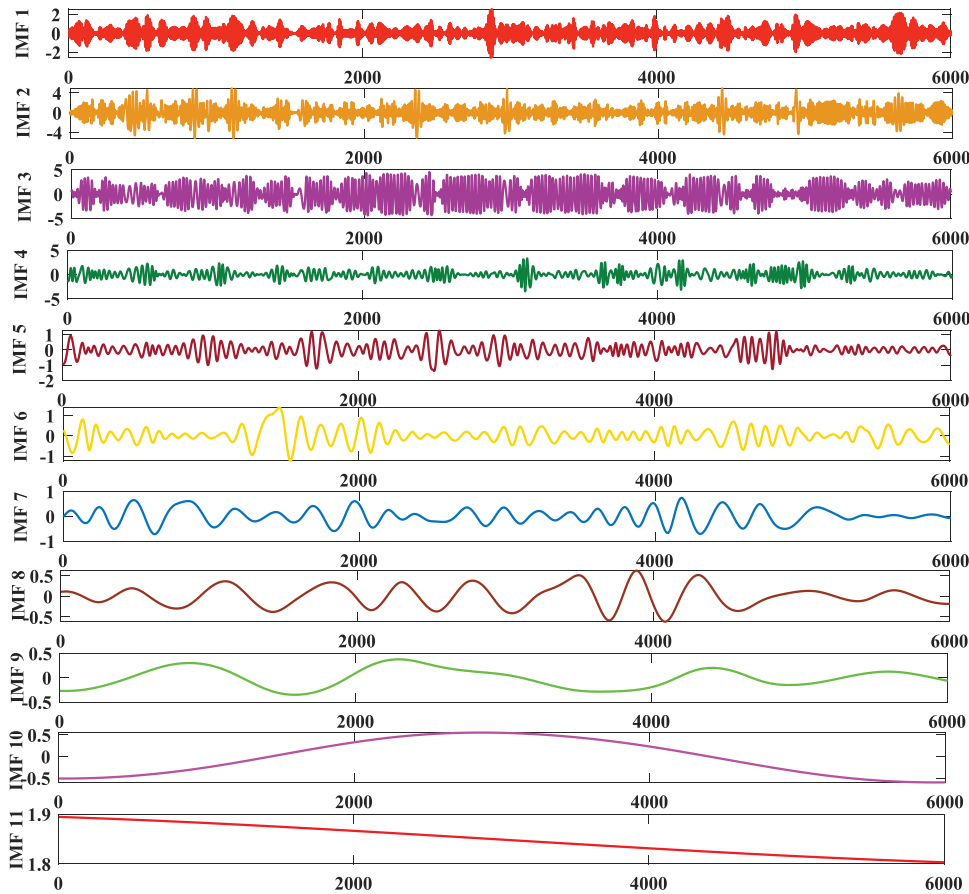


FIGURE 5 EMD processing outputs: IMFs and residual of PV data

performance metrics in Section 3.2. In this study, the residential grid  $P_{grid}$  is assumed to be the sum of the EV and HP energy consumption amount  $ECA(t)$ , and the PV system energy production amount  $EPA(t)$  expressed in Equation (17). When  $P_{grid}$  is negative, that means PV powered to grid. The relationship of historical data such as  $P_{grid}(t-2)$ ,  $P_{grid}(t-1)$ ,  $P_{grid}(t)$  can be used for the proposed hourly predictive load balancing  $P_{grid}(t+1)$  given in Equation (18).

$$P_{grid}(t) = ECA(t) - EPA(t), \quad (17)$$

$$P_{grid}(t+1) = \left( \sum_{i=1}^{24} (W_{PV}^i - W_{EV}^i - W_{HP}^i) \right), \quad (18)$$

where the load balancing is depicted to  $P_{grid}(t+1)$ . The PV system time series, the EV charging loads and the HP load are expressed as  $W_{PV}^i$ ,  $W_{EV}^i$  and  $W_{HP}^i$ , respectively. According to this, PV system generation data is used to balance EV and HP consumption in residential. Hence, the PV generation power supply to EV and HP. In this context, the predictive load balancing does not occur at values below zero. Especially when solar energy cannot be produced, it is of great importance to store the excess power that can be transferred to the grid. However, due to the extra cost of storage systems, it is necessary to use load balancing from the PV

system as much as possible to estimate EV and HP consumption here. Storage units to be installed without foresight of load balancing may cause EV charging and other consumption equipment to not be used efficiently, especially for households.

### 3.2 | Forecasting results and performance evaluation

In this section, the forecasting results of all models for EV charging load, heat pump load and PV generation time series are evaluated to use the common metrics. All time series, MLP, LSTM and BO-LSTM models are used for the forecasting of each decomposed component generated using EMD. Meanwhile, the hybrid models are compared to the single models in details in terms of forecasting accuracy.

The original data of PV generation system and the HP load is a combination of 10 IMF and residual, while EV consists of seven IMF and residual signal. All the different components of each original dataset are predicted separately in the hybrid models and then these components are combined to form the main prediction signal in the final step. Accordingly, the corresponding forecasting data to the real data can control for error performances.

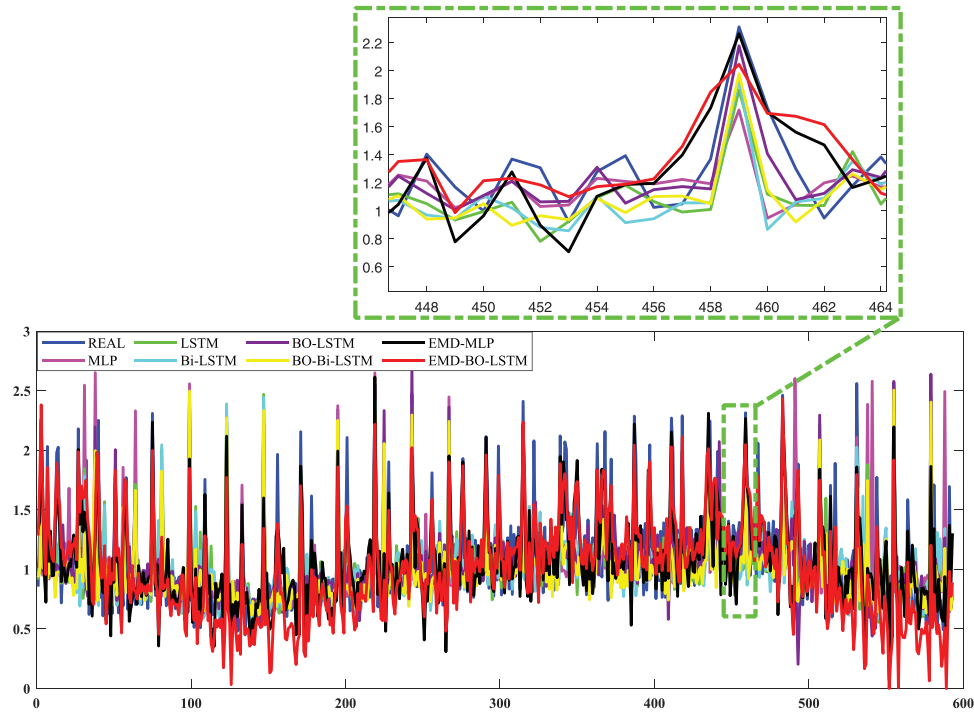


FIGURE 6 Forecasting test results of Heat pump

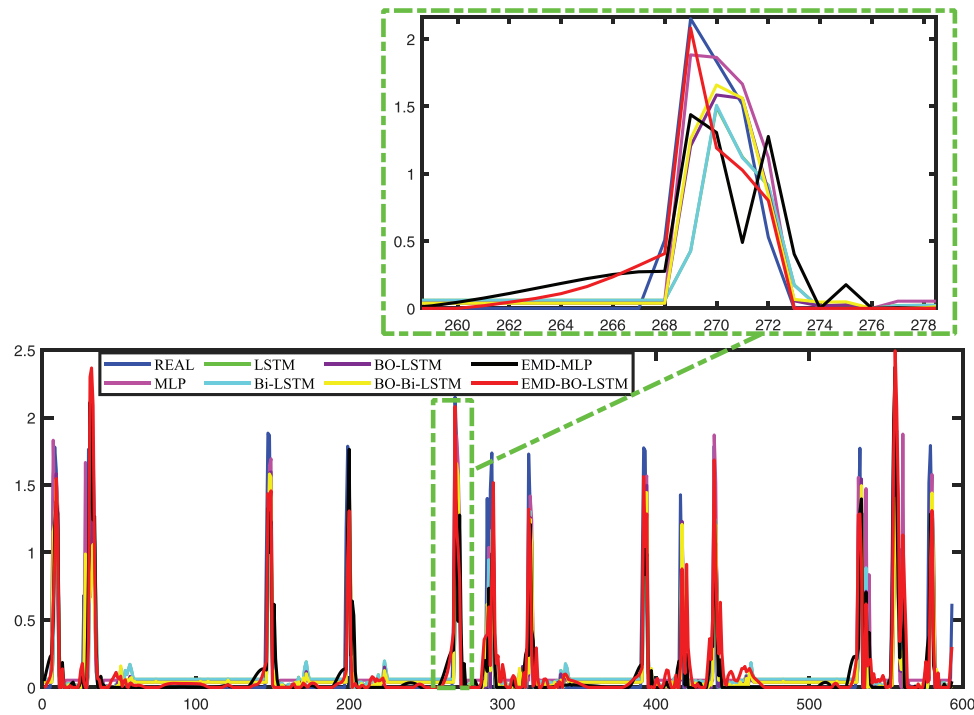


FIGURE 7 Forecasting test results of EV charging

Figures 6–8 are illustrated from the best prediction results to worst prediction results of the above models applied for HP load, EV load and PV system generation, respectively.

The performance of all models are expressed by errors between the predicted value and the target value in the test step. In this context, Three metrics are calculated, Mean Square Error (MSE), Root Mean Square Error (RMSE) and

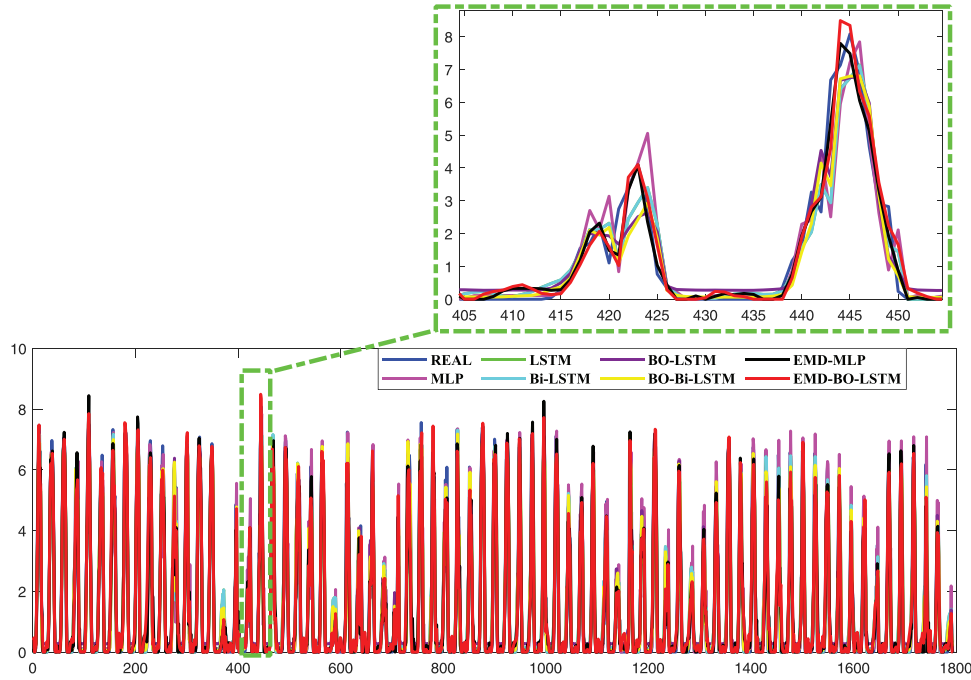


FIGURE 8 Forecasting test results of PV

Mean Absolute Error (MAE), between actual value and forecasting value in testing stage. These metrics are mathematically indicated in 19, 20 and 21, respectively. The actual value  $y_i$  in testing, the corresponding forecasting value  $\tilde{y}_i$  and the total number of time steps are depicted  $N$ .

$$MSE = \frac{\sum_{i=1}^N (y_i - \tilde{y}_i)^2}{N}, \quad (19)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - \tilde{y}_i)^2}{N}}, \quad (20)$$

$$MAE = \frac{\sum_{i=1}^N |y_i - \tilde{y}_i|}{N}. \quad (21)$$

The BO algorithm is used to find the best hyperparameters of the short-term forecasting models, and the optimal results are shown in Table 3. In this way, BO algorithm has been applied to reduce the training time and increase the training accuracy of the model. In addition, with the help of BO algorithm, the optimal values of LSTM hyper-parameters were found for PV, EV and HP.

The EMBOLSTM hybrid model has good performance for EV load forecasting. However, The EMBOLSTM hybrid model given in Table 4 shows that the error performance of the EMD-MLP hybrid model is better in PV generation and HP load forecasting. Meanwhile, among the prediction models, LSTM has the worst error performance for EV as a single model. However, MLP was the single model with the worst failure performance in PV system and HP load. Table 4 provides a complete comparative analysis of all forecasting models used.

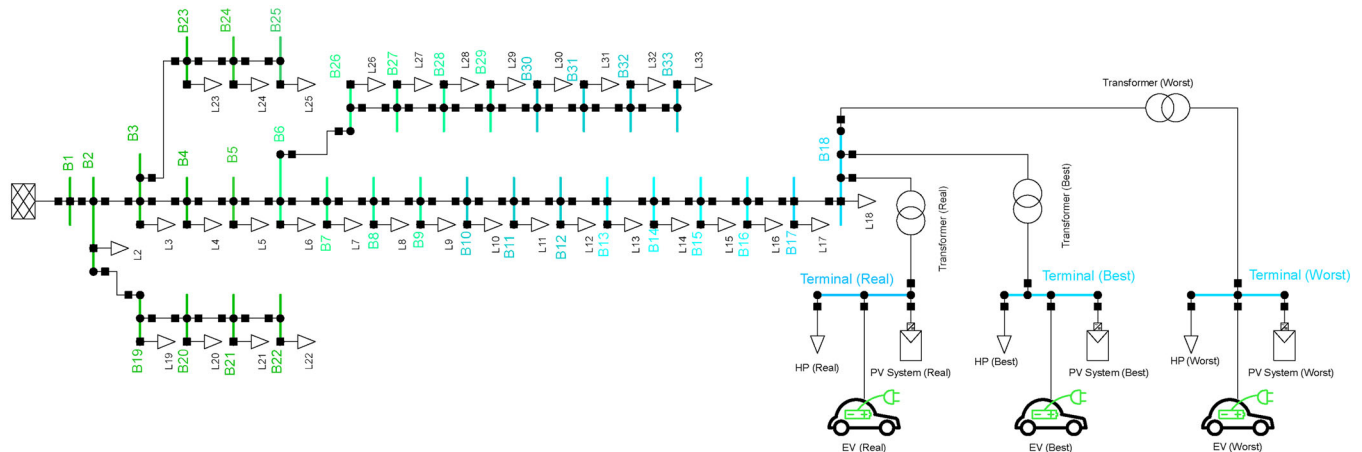
TABLE 3 BO Algorithm optimal results for PV, EV and HP

Hyperparameters	Data type	PV	EV	Heat Pump
Learning rate	float	0.021	0.022	0.018
Batch size	int	16	8	8
Neurons per LSTM layer	int	58	51	57
Number of LSTM layer	int	2	4	2

Here, unlike the literature, it is presented to compare the performance of both production and consumption energy short-term forecast models at peaks with real-world datasets in a household. It can be observed that the proposed model outperforms the predictive models applied for all metrics in EV charging. Especially for MSE and RMSE metrics, it reaches the lowest values with 0.0520 and 0.2281, respectively. This means that the prediction approach of the proposed model is close to the real data. The proposed model reduced the estimation error by approximately 17% and 9% for the MSE and RMSE, respectively, compared to the non-EMD version. A similar amount of estimation error reduction was observed for the other performance metric. Thus, the data correlation strength of the proposed model between the actual and predicted values of HP load and PV system generation for EV charge load is higher. In this respect, it has been concluded that the proposed EMD-BO-LSTM estimation model is effective and reliable for the EV charge load. In conclusion, the findings are modelled in the IEEE 33 busbar test system in Section 3.3 to verify that the proposed hybrid model is successful in the distribution network.

**TABLE 4** Comparison table

Dataset	Metric	MLP	LSTM	BiLSTM	BOLSTM	BOBiLSTM	EMDMLP	EMDBOLSTM
HP	MSE	0.1646	0.1301	0.1339	0.1222	0.1244	0.0642	0.0893
	RMSE	0.4057	0.3608	0.366	0.3495	0.3528	0.2533	0.2988
	MAE	0.2568	0.2571	0.2589	0.2461	0.2462	0.1931	0.2378
EV	MSE	0.0735	0.0757	0.0754	0.0629	0.0616	0.0522	0.0520
	RMSE	0.2712	0.2752	0.2747	0.2508	0.2482	0.2284	0.2281
	MAE	0.1172	0.1202	0.1194	0.0977	0.0987	0.0852	0.0837
PV	MSE	0.5815	0.5257	0.5251	0.5229	0.4816	0.2375	0.2629
	RMSE	0.7626	0.7251	0.7246	0.7231	0.6940	0.4874	0.5127
	MAE	0.4159	0.4189	0.4185	0.3970	0.3777	0.2870	0.3127

**FIGURE 9** IEEE 33 bus system modelling

### 3.3 | Analysis of predictive load balancing on low voltage grid

The one of the main objectives examined in this study predict non-stationary and non-linear electricity demand and generation accurately and quickly using real-world data. Thus, the validation of the best and worst forecasting models provides on the distribution network by the Digsilent software as well as performance metrics. In this context, the differences between the original data and the forecast data are evaluated from software environment in terms of parameters such as busbar voltage drop, transformer loss, distribution transformer loading and load balancing with PV in the distribution network. Meanwhile, the HP, EV and PV system in a household is modelled in the IEEE 33 busbar distribution system by choosing the best and worst among all the proposed forecasting models. The households are integrated into the distribution system via a 25 kVA transformer via Bus B-18, one of the farthest busbars. Figure 9 shows the integration model of PV generation systems, HP and EV on the IEEE 33 busbar test system. In addition, the real power, best and worst predictive powers of a sample daily HP, EV and PV system for the total household

profile are shown with Figure 10. According to the simulation results, the HP actual power and the best forecasting model have nearly same consumption power at 17.00 hour. However, the HP power in the worst prediction model is about 16% less than the actual consumption power. The EV actual charging power and the power of the best estimate model are 2151 kW and 2.08 kW at 12 noon, respectively. On the other hand, the worst forecast model has a charging power of 0.42 kW in the same hour. While the PV system produces 8.08 kW at the highest power at 12 noon, the best predictive power is 7.48 kW and the worst predicting power is 7.21 kW at the same hour.

The voltage levels in the busbars named terminal for the voltage drops of the prediction models and the original data are given in Figure 11. According to the simulation results, PV generation power reduces the busbar voltage drop at 11.00 in the daytime in the total household profile. Accordingly, while a voltage drop of 0.9507 occurs in real terms, the voltage drop is found to be 0.9518 and 0.9497 in the best prediction model and the worst prediction model, respectively. The indicated voltage drops of bus between actual data and best forecasting value nearly equal, because of the best forecasting track to actual data at the time series of one day. The transformer loading

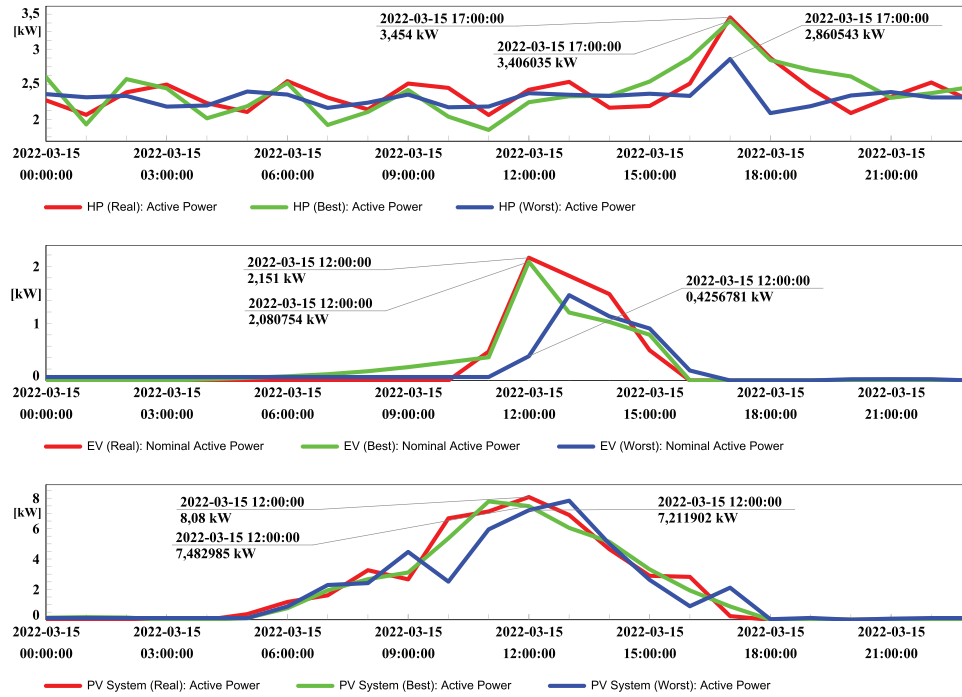


FIGURE 10 The instant powers of heatpump, electric vehicle and PV system in a sample day

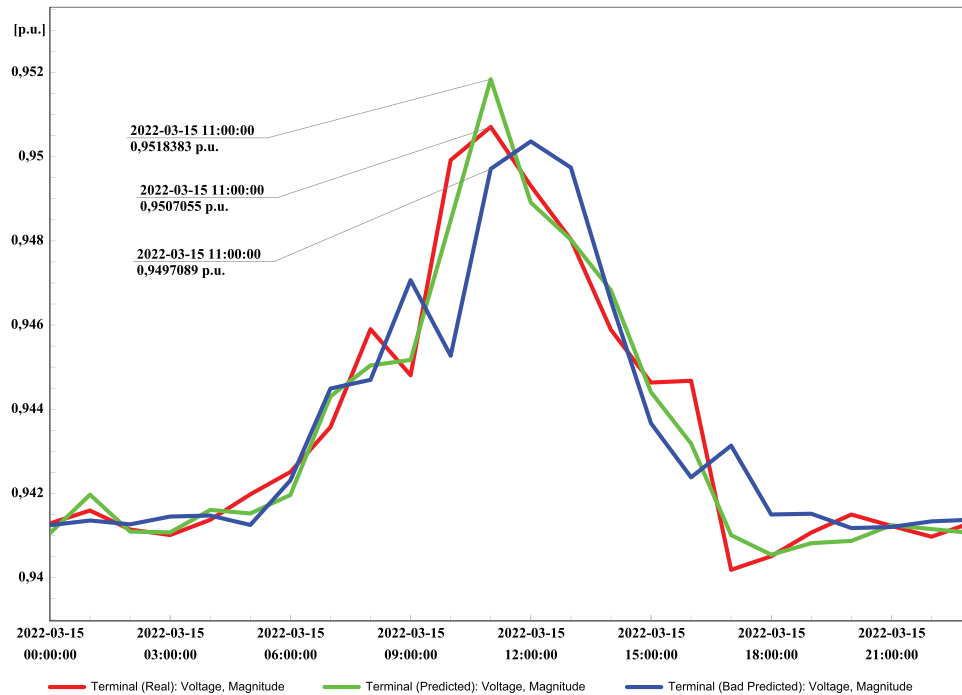
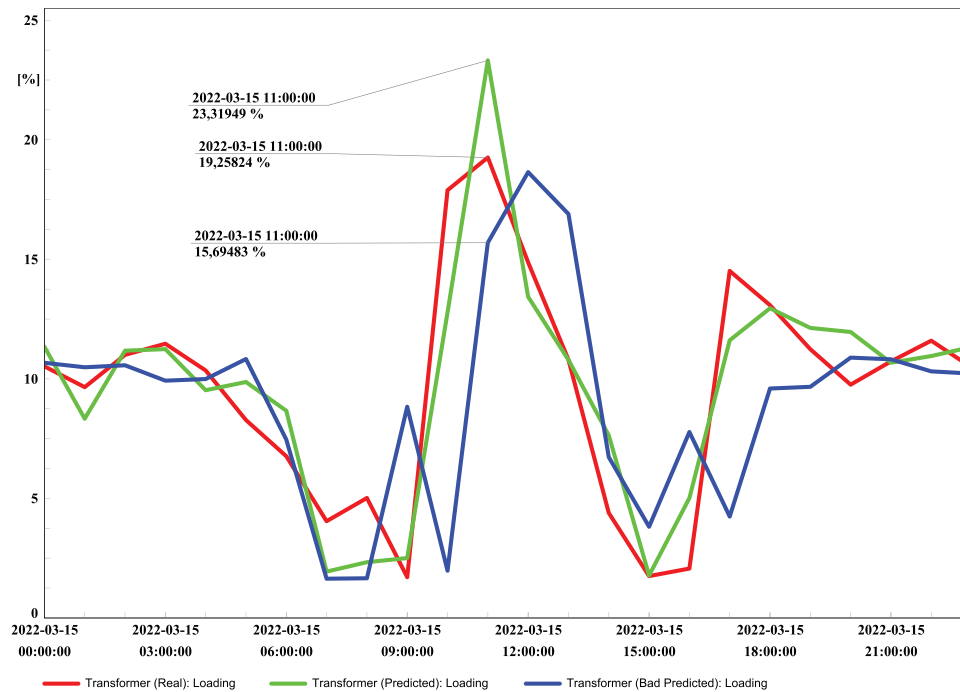


FIGURE 11 Comparative results of the voltage drop

has affected by consumption power in the variable time. The power failure occurs at the residential due to highly the transformer loading. Therefore, forecasting models created by using real data from the past are of great importance in the planning

of transformer power capacity. In this way, demand response is maintained in the distribution network. Thus, changes in equipment or connection conductors are prevented in case of power increase later. According to simulation results, the transformers



**FIGURE 12** Transformers loading condition results

loading of the prediction models and the original data are given in Figure 12.

In the total household profile, PV generation power at 11 am is the most important reason for the load on the transformer. Accordingly, while transformer loading occurs at 19.25% in real terms, transformer loading is 23.31% and 15.69% in the best estimation model and the worst estimation model, respectively. Although the best prediction model predicts 1% more than the worst prediction model at peak transformer loading times, in daily average, the best prediction model provides estimation at values suitable for real-time data. Despite the time changing, the transformer loading for actual system and best forecasting system is similar for local maximums and minimums on average.

The transformer power losses additionally increases to electricity price of residential. Meanwhile, these losses can affect some devices that simultaneously run the same time stamps. The transformer losses for the total household profile are shown in Figure 13, similar to the loading on the transformer. The forecasting results provide to a prediction about the transformer losses of residential consumption and generation.

Although the best prediction model predicts less accurately than the worst prediction model at peak transformer losses times, the daily average best prediction model gives more accurate results on average to real-time data.

In the light of the increasing demands in a residential electricity grid with EV and non-EV loads, it is preferable to take advantage of load balancing with a PV generation system. With this motivation, it is used to estimate the EV, heat pump actual consumption load and PV generation energy datasets at 1-h time intervals of the same house to achieve a more successful consumption. The powers of

load balancing for the total household profile is depicted in Figure 14.

According to the simulation result, the real data and the best prediction model provided 8.08 kW and 7.49 kW power to the system at the highest load balancing times, respectively. However, the worst estimation model estimated at 7.21 kW, about 10% lower than the actual data. As a result, the predictive load balancing with PV, EV and HP performs by hybrid forecasting models in this paper. It is understood from the simulation results that the load balancing between the best prediction model and the real-world dataset is supportive in terms of predictive power management that can be created in the future. As a result, the predictive load balancing with PV, EV and HP performs by hybrid forecasting models in this paper. It is understood from the simulation results that the load balancing between the best prediction model and the real-world dataset is supportive in terms of predictive power management that can be created in the future.

## 4 | CONCLUSION

The integration of EV charging in residential buildings has increased in recent years. Moreover, deployment of HP and PV in the residential sector become widespread. This paper presents a hybrid model results for HP, PV and EV charging forecasting of residential building.

The results generally show that hybrid models have given more accurate results for estimating both production and consumption data than single estimation models. Here, EMD-MLP hybrid method has better results estimating of PV

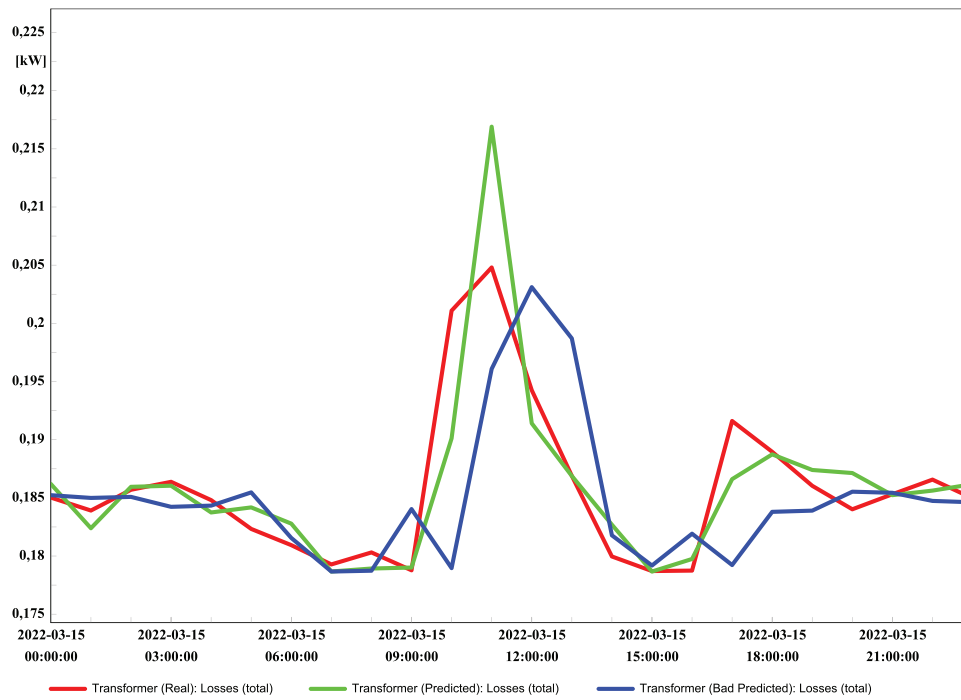


FIGURE 13 Transformer losses results

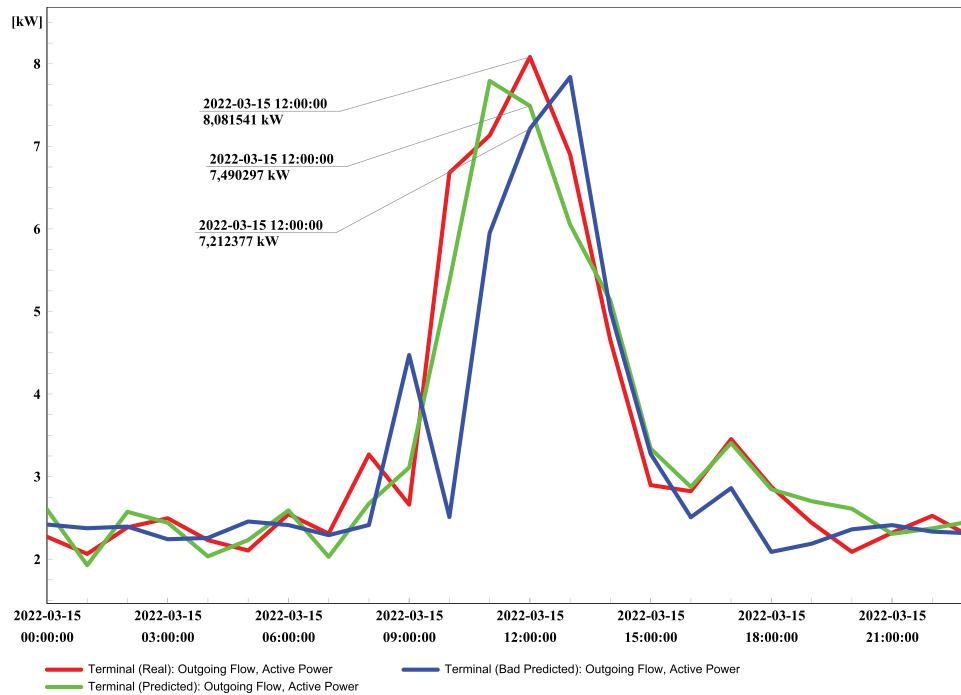


FIGURE 14 Load balancing results

production and HP consumption profiles, while EMD–BO–LSTM has more accurate results for EV charging forecasting. Moreover, Bayesian optimiser has improved the model performance of the LSTM. It has been seen that

the BO–LSTM hybrid model with EMD, which is pre-processed to use the linearity and stationarity of the production and consumption signals, provides more accurate predictions.

Future studies can be made on the consumption profiles of households, the charging time of EVs and the estimation of charging start times by utilising the real charging session data of large power EVs. Moreover, the smart coordination could also be considered by combining the predictive load balancing approach specified with EV charging scheduling in future studies.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author.

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