Analysis of Electric Vehicle Charging Demand Forecasting Model based on Monte Carlo Simulation and EMD-BO-LSTM

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***Abstract*— The stochastic charging behaviors of Electric Vehicle (EV) users illustrate the negative effects of bulk charging during peak hours on the grid. To overcome this problem, the bulk EV charging demand forecasting approach is investigated using historical EV charge demand dataset and EV driver mobility statictics in this paper. In this model, a Monte Carlo Simulation (MCS) is perfomed that considers the charging behavior of EV users for the generation of EV charging times. Moreover, the EV charging times are combined with the bulk EV demand hybrid forecasting model using decomposition and deep learning time series method. In first stage, the EV demand time series dataset are divided to improve the model performance by empirical mode decomposition (EMD). Then, all decomposed signals are forecasted separately using the Bayesian optimized Long Short-Term Memory LSTM network (BO-LSTM). Finally, to evaluate the model perfomance, the power system analysis using IEEE 33 busbar test system is performed in terms of distribution network power losses, busbar voltage drops and transformer loading conditions.**

Keywords*— *Electric vehicles, stochastic charging behavior, short-term forecasting, decomposition methods, Monte-Carlo simulation, demand forecasting model.

I. Introduction

The rechargeable Electric Vehicles (EVs) powered by clean energy attract the interest of users in the field of transportation due to rising fuel prices. This growing interest creates uncertainty about the impact of EV bulk charging on the distribution network. This uncertainty is important for making decisions regarding the infrastructure retrofit and development planning of a successful network operator. The one of the studies suggests that strengthening the continuous infrastructure to avoid the grid effects of bulk EV charging loads would result in unsustainable costs [1].

Energy demand forecasting is necessary for the efficient operation of energy use in the smart grid. In addition, charging demand for electric vehicles is seen as a potential risk during grid peak times as it changes over time [2]. Therefore, a demand forecasting model needs to analyze the actual bulk EV charging loads. Most studies make assumptions for charging probabilities based on driving habit statistics of internal combustion engine vehicles due to the lack of real-world EV session data in the past [3]. There are studies in the literature that assume that demand of each EV is constantly charged with the maximum power allowed by the onboard charging station [4,5]. This assumption does not reflect actual charging profiles in evaluation results made with developing measurement equipment [6]. Several researchers have used synthetic data generator based on driver behaviors for EV charging demand forecasting due to scarcity of actual charging session data of EVs [7]. However, a demand model has not been established using the actual demand data of EVs on the grid and statistical data of charging sessions. Short-term forecasting methods are examined under two main groups as traditional statistical methods and new artificial intelligence methods [8]. Seasonal Autoregressive Integrated Moving Average (SARIMA), linear regression (LR) and Exponential Smoothing (ES) are used as the conventional methods [9]. However, these conventional methods disadvantage about due to weakness to deal with non-linear problems. There are many new AI-based approaches that have become a special research focus in recent years, especially for nonlinear problems such as EV charging. These new methods is showed higher estimation performance compared to traditional methods [10]. However, the charging times of bulk EVs and the use of new methods for estimating their charging demands require high transaction complexity and time costs. In this study, a hybrid demand forecasting model is proposed to overcome the aforementioned problems. In this model, EV charging times are estimated with Monte Carlo Simulation (MCS) based on the charging behaviors of EV users. Then the Long Short-Term Memory (LSTM) network uses to predicted charging times and a short-term forecasting approach based on the EV charging load in a real dataset for the bulk EV charging demands forecasting. Also, Bayesian optimization (BO) is used to find the optimal hyperparameters of the LSTM network.

The hybrid demand forecasting model can quickly provide the bulk demand forecasting by finding optimum values by the EMD-BO-LSTM hybrid method without the need for extensive parameter tuning. This method has not received attention in the bulk charge demand forecasting of EVs, so it has been chosen in the forecasting model of this paper.

Zonggen and Don developed a model that can make empirical charging decisions based on a machine learning algorithm using past charging session data at home [11]. In this model, a short-term EV demand forecasting model can be developed at home with measurements to be made by electrical meters. In study [12], a total charge estimation model is proposed for EV charging demand using Monte Carlo Simulation (MCS) based on driver mobility statistics. However, more realistic aggregated EV demand forecasts are created by using high resolution electrical meter charge consumption data together with mobility statistics. EV charging demand forecasting has been of interest in research in recent years. Some studies have focused on EV charge demand forecasting using historical charge session powers [13, 14]. With high temporal resolution charging power data from electrical meters, EV demand can be predicted in day ahead planning. This demand forecast is vital for grid integration of EVs [15]. In this way, demand forecasting provides a prediction for the bulk EV charging demand uncertainty problem during peak hours of the grid. In particular, the stated foresight is necessary to provide the EV charging demand simultaneously with other basic loads in a household [16]. The performance of artificial intelligence-based forecasting methods in EV charge demand forecasting is higher than statistical time series analysis [17, 18]. Therefore, a multilayer perceptron (MLP) model with oblique loss function is proposed for probabilistic estimation of EV demand power in [19]. It has been suggested that the MLP model has higher performance in predicting EV charging demand compared to other AI methods. However, in EV demand forecasting, MLP cannot be interpreted due to its complex computational capacity [20]. In [21], the long short-term memory (LSTM) network shows the best error performance for EV load estimation based on the original data. However, as a disadvantage of this, parameter values are not improved with an algorithm such as Bayesian (BO) optimization of hyperparameters. According to the evaluation of the above-mentioned papers, according to the net results of the error metrics, the LSTM operating in the RNN structure shows higher performance because it interprets the past EV load data and determines the future better. Actual charging data is a fundamental challenge in short-term EV demand forecasting as it is non-linear and non-stationary. Therefore, time series decomposition can be used to improve forecast performance. The hybrid demand forecasting model uses decomposition methods to understand time series features and preprocesses it to improve error performance. Wavelet-based decomposition [22, 23], empirical mode decomposition (EMD) [24], and ensemble empirical mode decomposition (EEMD) [25] have been widely preferred at this preprocessing step in the literature. According to the application areas, the advantages and disadvantages of each decomposition method change from the other.

The bulk charging demand forecast of EVs with grid addicted non-stationary charging powers over a historical time series is not investigated in the aforementioned papers. In this paper, a hybrid forecasting model for EV charging demand is developed by combining a residence's historical EV charge demand dataset and driver mobility statistics. In this way, it was aimed to give grid operators an insight into bulk EV charging demands. The proposed demand forecasting model has two main advantages: The charging times of EVs are estimated based on driver mobility statistics. the test results present the accuracy of model prediction for comparing with real EV charging and EMD-BOLSTM method.

The remainder of this paper is organized as follows: Section 2 describes the forecasting of charging demand from EV user mobility statistics. Section 3 presents short term demand forecasting modelling. The simulations of the proposed model mentioned in section 4 on distribution grid and the performance evulations and results are discussed. The conclusion is given in Section 5.

II. The Probability Forecasting of EV User Mobility Statistics

A. *The anaylzes of EV user charging behaviors*

Bulk charging demand uncertainties on the grid are depicted temporally and spatially by EV user movement statistics during the day. Charging start and end time varies according to EV user mobility statistics. The charge demand of an EV defined as the power drawn from the grid at the duration passed between the charging start and end time in the charging session. The bulk charging demands of the EVs can cause voltage drop, increase losses and overloads of equipments / lines at peak times of the grid. Therefore, in the light of historical mobility statistics of EVs, it is based on a probability distribution function (PDF) by simulating the daily travel distances, charging start and end times in different countries.

In this study, the simple charging method is assumed for EVs and the initial state of charge is depicted SOC_i^{init} within the specified limit values in Eq. 1. EVs drawn maximum power, maximum battery capacity and charging efficiency are indicated by P_i^{max} , $C_i^{max} = 50\ kWh$ and $\eta_c = 90\%$ respectively. Different values such as 3.7kW, 7.4kW and 19.2kW is chosen to assume that EVs are charged at stochastically different power levels from onboard chargers. Also, the arrival charging time and departure charging time for each i. EV are described with t_i^{arr} and t_i^{dep} in Eq. 2. The battery instentious SOC value of i. EV is depicted to SOC_i^c, and it is completed by following a day. The day is formulated with total $T = 96$ intervals with τ steps at $\Delta\tau = 1$ hours time resolution.

$$20\% \leq SOC_i^{init} \leq 100\%\ and\ 20\% \leq SOC_i^c \leq 100\% \quad (1)$$

$$SOC_i^c = \sum_{\tau=1}^{T} \frac{\eta_c P_i^{max} \times \tau.\Delta\tau}{C_i^{max}} forT \in \left[t_i^{arr}, t_i^{dep}\right] \quad (2)$$

In this study, each EV is same properties. SOC_i^{init} is chosen according to stocastically distribution function, see [19, 26] for detailed information.

B. *EV mobility data*

This study base on EV parking events from travel data from germany MiD2008 survey open dataset for EV user mobility behaviors. This dataset contains the daily mobility behaviors of 6,465 German car users [27]. Statistics is recorded on different days in order to examine the mobility patterns of the users according to the days. In this context, the data has been selected to exclude holidays. In this dataset, user mobility data includes EV location, parking duration, arrival time, departure time and travel distance data.

Figure 1 shows the probability distributions of the actual arrival time for the home charging event in the dataset during a day via curve fitting toolbox in MATLAB 2017b. The curve on the x-axis indicates that the home arrival event mostly occurs around noon or evening. According to curve fitting, the actual arrival times of EVs shows a gaussian distribution with number of terms equal three. The goodness of fit in this distribution values are 0.9846, 0.9764 and 0.0082 for R-square value, adjusted R-square and RMSE, respectively.

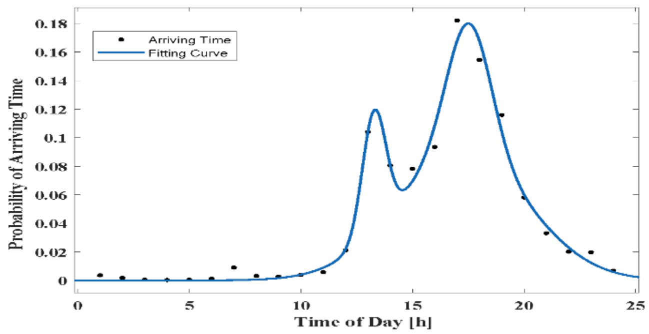

Fig. 1. Daily Arrival Time of EVs based on Gaussian Probability Distribution Function

In this study, arrival time of EVs are assumed as charging start times. According to dataset, most parking times are less than 14 hours. Figure 2 shows the parking duration of EVs and its probabilities. The curve on the x-axis indicates that only a few parking events reach the one day cooldown. Furthermore, the curve remains smooth, as the cars left for the next day usually leave the house at similar times. The parking duration of EVs shows a gaussian distribution with number of terms equal four. The goodness of fit in this distribution values are 0.9978, 0.9959 and 0.0028 for R-square value, adjusted R-square and RMSE, respectively.

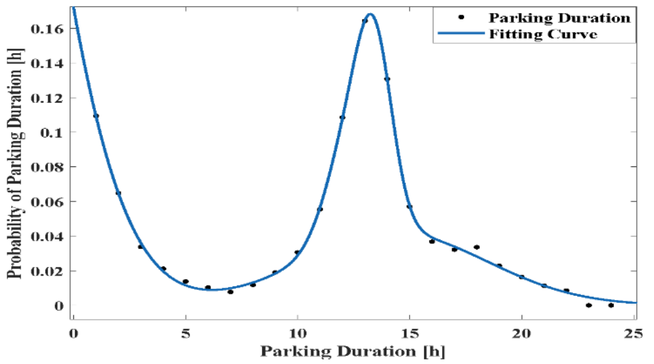

Fig. 2. The Parking Duration of EVs based on Gaussian Probability Distribution Function

Departure times are calculated by summing the arrival times and parking duration of the EVs. Figure 3 indicates the departure time of EVs and its probabilities during a day.

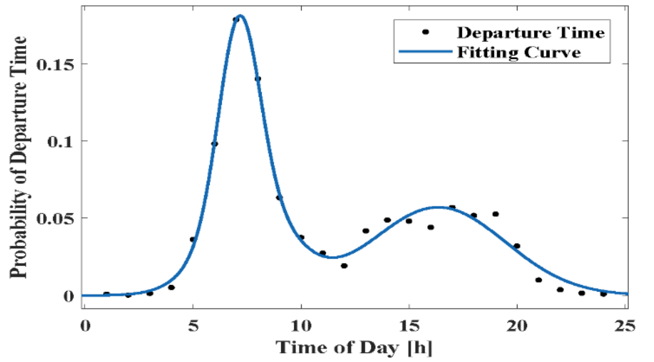

Fig. 3. The Departure Time of EVs based on Gaussian Probability Distribution Function

The curve on the x-axis indicates that the departure time event mostly occurs around morning or noon. The departure time of EVs shows a gaussian distribution with number of terms equal three. The goodness of fit in this distribution values are 0.9841, 0.9756 and 0.0069 for R-square value, adjusted R-square and RMSE, respectively.

By means of Equation 3, the initial state of charge SOC_i^{init} of the i. EV is calculated from the trip distance d and energy consumption efficiency is assumed $\varphi = 190Wh$ per km and maximum distance nearly 263 km.

$$SOC_i^{init} = 1 - \frac{\varphi . d_i}{C_i^{max}} \tag{3}$$

Figure 4 shows the trip distance and its probability for a home charging event in the dataset during one day. Travel distance cannot be defined with a distinctive feature for any time period of the day. However, the majority of trip departing from home are shorter than 50km.

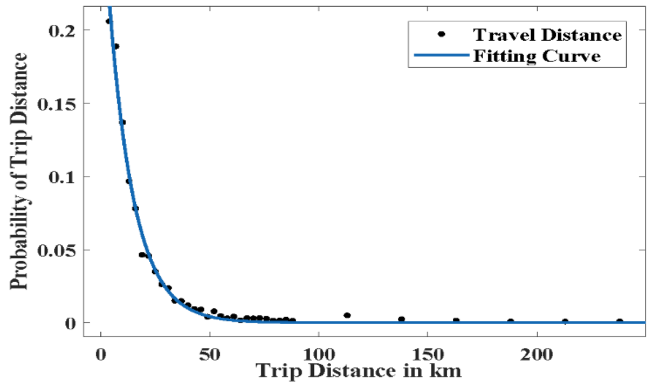

Fig. 4. The Trip Distance of EVs based on Log-normal Probability Distribution Function

The travel distance of EVs shows an exponential distribution, commonly known as a log-normal distribution, with the number of terms equal to one. The goodness of fit in this distribution values are 0.9898, 0.9894 and 0.0053 for R-square value, adjusted R-square and RMSE, respectively. Researchers [28] propose that the travel distance probability distribution in the same dataset is a Weibull distribution.

The stochastic charging behaviors of 100 EV users are produced by the monte carlo simulation taking into account the aforementioned arrival time, waiting time in the park, departure time and daily travel distance probability distributions. According to the MCS simulation, the bulk charging demand of EVs shows in fig. 5.

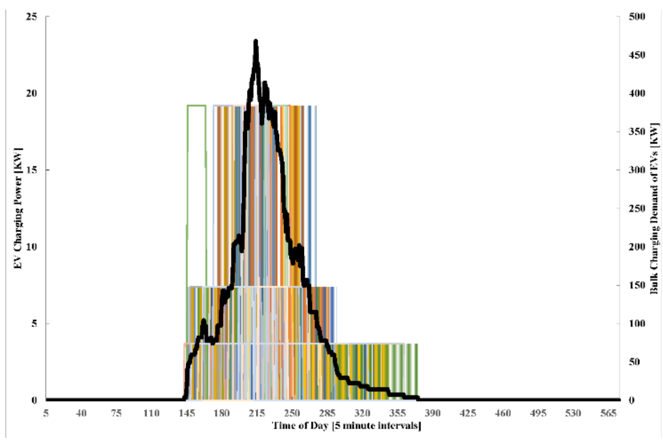

Fig. 5. The Bulk Charging Demand of EVs based on MCS simulation

The produced charging powers by the monte carlo simulation, fully is indicates to maximum charging powers such as 3.7kW, 7.4kW and 19.2 kW. These powers are not always used to during charging duration. Therefore, the MCS samples of EV user behaviour is applied as the inputs of demand forecasting model based on actual charging power data in section III.

III. Demand Forecasting Model and Evaluation

In general, few previous studies have looked into estimating the power outputs of renewable energy sources and the power load of appliances in household. Many new AI-based approaches are being used in recent years, which has become a particular research focus in EV charging demands along with other essential loads in households. However, general AI-based approaches often do not achieve the best prediction results due to poor learning ability and the ability to ignore time dependencies in the data. Therefore, there is a need for a hybrid forecasting model that performs better in features representation and takes into account time dependencies.

A. *Empirical Mode Decomposition (EMD)*

The EMD method is based on the Hilbert Huang Transform (HHT) algorithm. This method decomposes the original signal into multiple Internal Mode Functions (IMFs) and a single residue (Rn). non-linear and non-stationary signals can be analyzed with the help of HHT. In this study, EMD algorithm is applied to decompose the original data as a first step due to the electric vehicle load signals have these characteristics. each IMF is characterized by having only one endpoint between zero crossings and having a mean value of zero. Assuming a given original EV load demand time series x(t), the processing steps of the EMD are defined as follows [48]:

Step 1: Determine all local extremes in the $x(t)$ signal. Then, the upper envelope $x_u(t)$ is calculated by combining all local maximums through a cubic spline, and the lower envelope $x_l(t)$is formed by doing the same for local minima.

Step 2: Mean to the envelopes and calculate to the difference between the actual data series $x(t)$ and the mean $m(t)$ in Eq. (4) and Eq. (5), respectively:

$$m(t) = \frac{x_u(t)+x_l(t)}{2} \tag{4}$$

$$d(t) = x(t) - m(t) \tag{5}$$

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

$$\sum_{t=1}^{l} \left[\frac{d_{j-1}(t)+d_j(t)}{d_{j-1}(t)}\right]^2 \leq \delta(j = 1,2,.,; t = 1,2,.,l) \tag{6}$$

where, l and j are the signal length and the iteration number of sifting process, respectively. *d(t)* is selected as a constant value usually between 0.2 and 0.3.

Step 4: Repeating the first three steps is terminated when all IMFs and residue signal are found. Finally, the original time series x(t) can be expressed as an addition of IMFs $C_i(t)$ and single residue $R_n(t)$ as given follows:

$$x(t) = \sum_{i=1}^{N} C_i(t) + R_n(t) \tag{7}$$

B. *Bayesian Optimized Long Short-term Memory Network*

A recursive neural network (RNN) takes as input the current state sample and information from the previous state hidden layer in each loop. The output is calculated based on the given hidden state. The hidden state is similar to the memory unit in terms of RNN. Since the relationship of successive states is continuous, each input affects the output. To overcome this problem, it is proposed to reparameterize the RNN with the LSTM network. The LSTM network is a special RNN with special capabilities such as applying feedback functions and memory-weighted coupling [18]. The LSTM network is mainly suitable for modeling temporal horizon-based sequences. An input vector for the always horizon is included in the LSTM cell. The x_t input vector, state vector as h_t at time t and h_{t-1} at time $t-1$, the $f_w(h,x)$ non linear activation function, the w weight parameter is symbolized in eq. 8.

$$h_t = f_w(h_{t-1}, x_t) \tag{8}$$

LSTM operations are calculated by applying the operations between equation (9) and equation (16). In LSTM architecture, there are three gates for control as input gate, forget gate and output gate [28].

$$F(t) = \sigma\left(W_f \cdot [H_{t-1}, X_t] + b_f\right) \tag{9}$$

$$I(t) = \sigma(W_i \cdot [H_{t-1}, X_t] + b_i) \tag{10}$$

$$\tilde{C}(t) = tanh(W_c \cdot [H_{t-1}, X_t] + b_c) \tag{11}$$

$$C(t) = f_i * \left(C_{t-1} + I_t * \tilde{C}(t)\right) \tag{12}$$

$$O(t) = \sigma(W_o \cdot [H_{t-1}, X_t] + b_o) \tag{13}$$

$$H(t) = O_t * tanh(C_t) \tag{14}$$

$$sigmoid(x) = \frac{1}{1+e^{-x}} \tag{15}$$

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{16}$$

Where the sequential input is indicated by X_t. The weights of bias is given as b_f b_i b_c and b_o. The input weights represent with W_f , W_i , W_i and W_o, respectively. Also t is the step of latest time and $t-1$ is the step of previous time; $H(t)$ and $C(t)$ describes to the output and the cell state respectively. Also, Bayesian optimization algorithm [29] is used to find the optimal hyperparameters of the LSTM network as given in fig. 6.

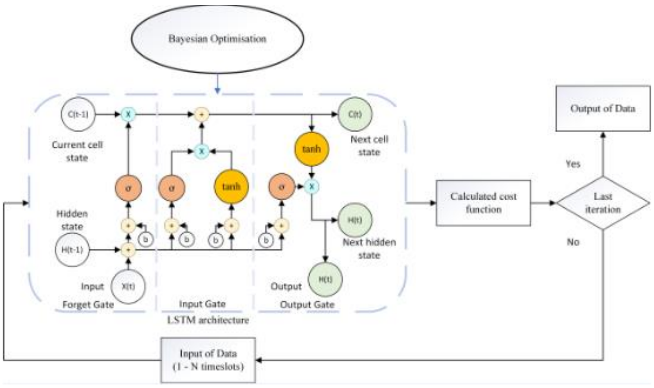

Fig. 6. The LSTM network architecture and Bayesian Optimizer

This algorithm is recommended for solving problems also known as complex black box problems [30, 31]. The algorithm deals with the previous parameter information determined based on the Gaussian process, and its previous value is constantly modified. The BO-LSTM based EV charge demand prediction model proposed in this paper is basically the hyper-parameters such as epoch, batch size, initial learning rate, dropout value, optimizer, number of layers, number of neurons in each layer, and time lag windows are shown in table 1.

TABLE I. LSTM AND BO-LSTM HYPERPARAMETERS IN TRAINING NETWORK

Parameters	Type of AI-based network	
	LSTM	*BO-LSTM*
Epochs	1000	1000
Batch size	16	8
Learning rate	0.005	0.01
Dropout value	0.5	0.5
Optimizer	Adam	Adam
Layers	4	4
Neurons	100	200
Time lag window	24	14

IV. SIMULATION RESULTS

The IEEE 33 bus test system is modeled through Digsilent PowerFactory software in order to investigate the effects of actual charging of electric vehicles on the distribution network with MCS-based charging behavior. The model for forecasting bulk charging of EVs with MCS simulation is connected into the distribution network via bus-1, MCS-based charging behavior and real charging powers bus-2, and EMD-BO-LSTM demand forecasting model based on real charging powers via bus-3 as given in Figure 7.

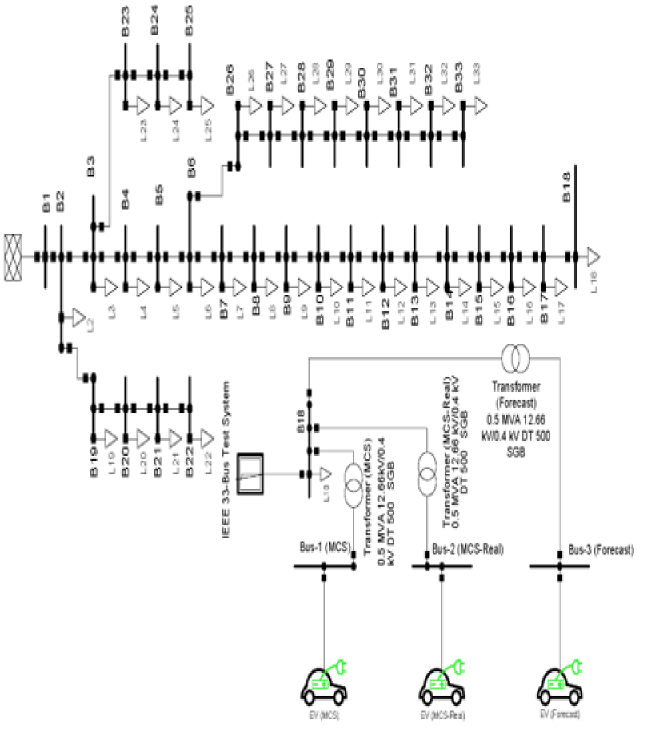

Fig. 7. The IEEE 33 bus test system

The step-down transformer with a 500kVA 12.66/0.4 kV connected to these busbars, hence the voltage value is reduced to the low voltage level. It is assumed that EV charging units are connected to 3-phase 50 Hertz (Hz) AC 0.4 kV busbars. In Figure 8, the grid effects of EVs charged on the basis of MCS during the day are given over transformer loading, transformer losses and voltage drops in the bus-1, which is the farthest busbar. According to the network effect indicators created according to MCS, it is observed that the transformer is overloaded and the busbar voltage is below the allowable values. In this case study, it is the scenario where EVs are charged at 3 different maximum charging power in user behavior according to MCS. However, in reality, EVs do not use the same maximum charging power during the charging period, due to their battery charge status and network status during the charging period. For its real grid application, the meter consumption profiles of the real charging are modeled on the charging behaviors and properties produced by MCS. Accordingly, transformer loading and busbar voltage drops are realized as in figure 9 within the allowed network and equipment limits. In addition, the level of transformer losses has decreased by about 5 kW compared to the previous situation. In order to compare the hybrid charge demand forecasting model with the actual consumption profiles here, it is desired to give the transformer load in the network, losses and voltage drop in the busbar in Figure 10. Accordingly, the hybrid demand forecasting model with EMD-BO-LSTM is more accurate to actual bulk charging demands than the maximum charging powers demand forecasting model with MCS. Especially at the grid peak time, the error of this accuracy is found to 0.79% in transformer peak load, 0.038 kW in transformer loss power and 0.0004 p.u. in busbar voltage drop.

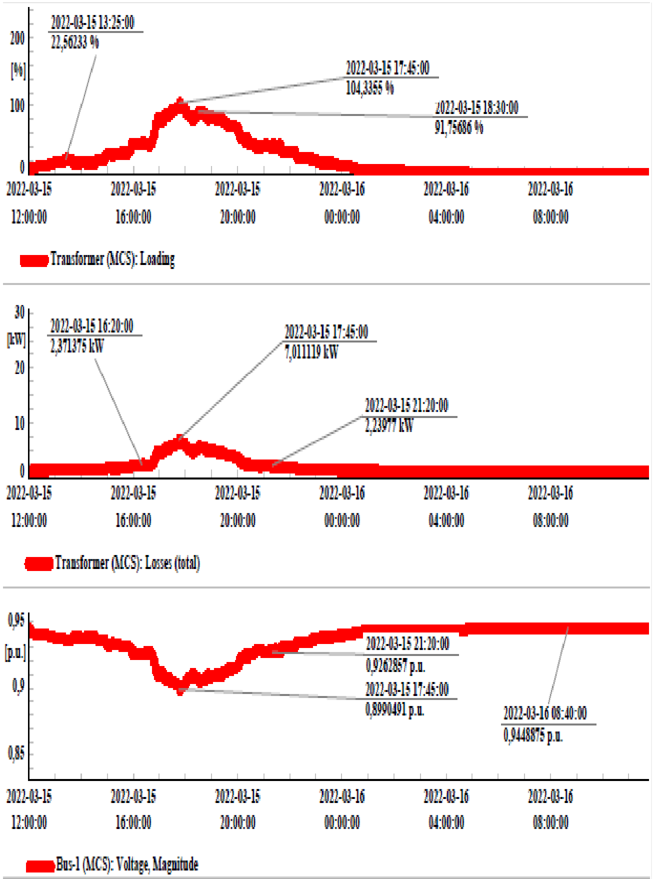

Fig. 8. The Bulk charging demand via MCS simulation

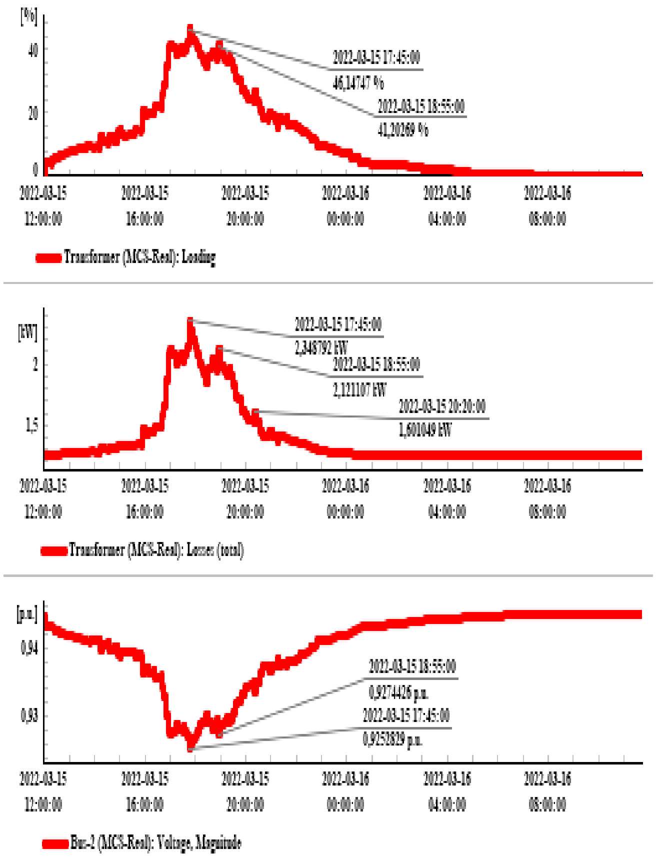

Fig. 9. The Bulk actual charging demand via MCS simulation and actual data

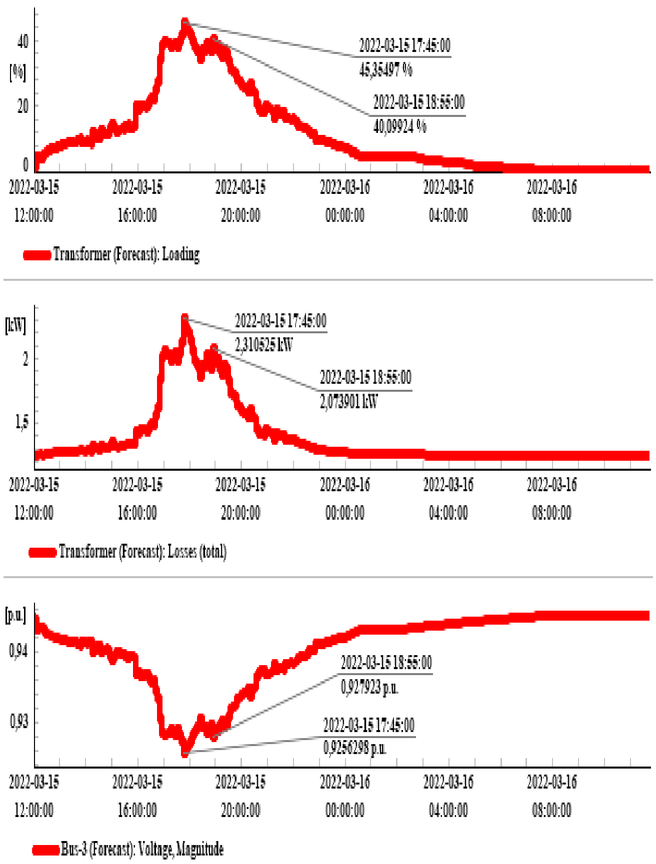

Fig. 10. The Bulk actual charging demand via MCS simulation and forecasting data

V. Conclusions

In this paper, the charging time model are derived from a real statistics based electric vehicles driver behaviour via MCS. By using the data produced by MCS, grid effects of EVs at maximum charging power were evaluated. A daily bulk charge demand profile was created with the combination of real EV charge consumption meter dataset, MCS simulation according to EV user statistics and charge times. The short-term bulk charge demand estimation model made with EMD-BO-LSTM is compared with the demand model with MCS using maximum charging powers for transformer loading, losses and busbar voltage drop at grid scale. The study here is that in areas with network problems, short-term demand forecasts here can be used to guide grid operators when real charging data is not available. This can facilitate grid operation of existing bulk EV charging demands. In future studies, temporal scheduling of load will be evaluated for short-term bulk EV charge demand forecasting based on actual charge demands.

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