Forecasting Plug-In Electric Vehicles Load Profile Using Artificial Neural Networks

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***Abstract*- Plug-in electric vehicles (PEVs) are becoming very popular these days and consequently, their load management will be a challenging issue for the network operators in the future. This paper proposes an artificial intelligence approach based on neural networks to forecast daily load profile of individual and fleets of randomly plugged-in PEVs, as well as the upstream distribution transformer loading. An artificial neural network (ANN) model will be developed to forecast daily arrival time (T_a) and daily travel distance (D_{tr}) of individual PEV using historical data collected for each vehicle in the past two years. The predicted parameters are then will be used to forecast transformer loading with PEV charging activities. The results of this paper will be very beneficial to coordination and charge/discharge management of PEVs as well as demand load management, network planning and operation proposes. Detailed simulations are presented to investigate the feasibility and accuracy of the proposed forecasting strategy.**

***Index Terms*—Plug-in electric vehicle, forecasting, load profile, neural network and distribution transformer loading.**

I. INTRODUCTION

Global warming and new environmental issues are motivating many countries to replace the conventional fuel based transportation systems with more sustainable technologies such as plug-in electric vehicles (PEVs). These pollution-free automobiles are powerful alternatives to the internal combustion vehicles. In the recent years, many developments in design and performance of electric vehicles (EVs) has been made. EV technology has been significantly improved in terms of battery capacity, performance and power management as well as efficiency and reliability of motor and acceleration system. For example, Tesla Motors has introduced the new S series with a battery bank of 85 Kwh which is capable of making a 500 Km course range [1]. Obviously, charging this enormous battery banks in short time periods requires very fast charging technology that will impose a huge load demand to the residential networks. This could cause different demand side management issues such as increased power losses, phase imbalances and power quality problems, as well as overloading and degradation of transformers [2]. A possible approach to meet the requirements of these bigger PEV consumers is to increase the capacity of power grids which is not economical and possible as they will be scattered throughout the residential and rural areas. Therefore, recent research directions are to establish new methods for recognizing the driving pattern of PEVs and predicting their behaviour and load patterns on daily basis. This will help grid operators to deal with rushes imposed by PEV chargers by introducing various demand side management and load shifting approaches. Unfortunately, only a limited number of researches have been carried on this issue which are mostly focused on studying PEV fleets in small areas to obtain stochastic models by surveying small groups of PEVs.

Ref. [3] develops a parking lot prediction unit based on the M/G/∞ queuing model that uses the current information of the PEVs in the parking lot along with their arrival and departure rates (based on historical data) to predict number of vehicles that will be simultaneously present in the parking lot during the next time interval. Ref. [4] develops a time series based method for predicting the first daily departure times of commuter vehicles which is used to schedule charging/ discharging in the parking period ending with the corresponding daily departure time to assure that all vehicles have reached the minimum required state of charge (SOC) levels. The proposed procedure is: i) classification of historical data of vehicles to different categories such as weekdays, weekends and holidays, ii) examining the historical data of each category and calculating their "mean" or "median" values and iii) using the information to forecast the next daily departure time of the vehicles. Ref. [5] proposes a stochastic approach based on Monte Carlo simulation to make the load demand of a fleet of commuter PEVs by deriving the probability distribution function of historical data of fleet of vehicles. Mont-Carlo analysis is then used to build the load profile of aggregated vehicles. Ref. [6] has developed a stochastic method using the historical data to forecast the arrival time, departure time and travel distance of PEVs by conditional and non-independent probability distribution function of above mentioned three parameters. This approach is compared with the other methods that only use a single distribution function of those parameters.

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None of the above mentioned models [3-6] have presented a complete online approach that can be continuously updated on daily basis and estimate the future states of individual PEVs.

This paper will first develop an artificial neural network (ANN) model based on historical data to predict the load profiles of PEVs connected to a feeder and then estimates the daily load curve of the upstream distribution transformer. The estimated PEV parameters are the arrival time and the daily travel distance. These predicted parameters are then used to forecast transformer loading with PEV charging activities. Detailed simulations are presented to investigate the feasibility and accuracy of the proposed forecasting strategy.

II. Proposed Methodology and Problem Formulation

This section presents the proposed strategy for ANN-based forecasting of PEV and distribution transformer daily load profiles. A communication and data management infrastructure within the smart grid and residential homes with PEVs is considered in which the smart chargers will communicate with power management system on daily basis. Fig. 1 shows the block diagram of the proposed strategy. Two separate ANN models have been developed for prediction of the future arrival time (T_a) and the daily travel distance (D_{tr}). These parameters will be sent to the power management system to update the prediction inputs for the next day.

The first stage in the model of Fig. 1 is the neural network predictor for D_{tr} and T_a values of the next day based on the historical data of the corresponding PEV and the updated data of the current day. The mathematical model used to predict T_a for the next day is:

$$T_a(t+1d) = F\{T_a(t),...,T_a(t-nd)\} \quad (1)$$

where, $T_a(t+1d)$, $T_a(t\text{-}nd)$ and $T_a(t)$ are the desired arrival time of each vehicle for one day ahead, "*n*" days before today and present day value, respectively. In Eq. 1, "*n+1*" is the dimension of input vector presented to neural network which is also the number of past historical values including the current date used to predict T_a for the next day. Selection of "*n*" depends on the correlation between the old data and future data. In this research, considering the fact that periodic weekly driving pattern commonly iterate on weekly basis, the selected input vector dimension is n=6. In reality, for each PEV an independent correlation analysis shall be performed to determine the number of old samples which should be used for prediction.

The mathematical model for the prediction of D_{tr} is:

$$D_{tr}(t+1d) = F\{D_{tr}(t),..., D_{tr}(t-nd)\} \quad (2)$$

where, $D_{tr}(t+1d)$, $D_{tr}(t\text{-}nd)$ and $D_{tr}(t)$ are the desired D_{tr} of each vehicle for one day ahead, "*n*" days before today and at present day, respectively.

In the next stage, the initial state of charge for each PEV at the plug-in time T_a will be calculated:

$$SOC_{int} = 100 \times (1 - \frac{D_{tr}}{Eff_{PEV} \times Cap_{bat}}) \quad (3)$$

where, D_{tr} is the daily travel distance estimated by neural network 2, Eff_{PEV} is the driving efficiency of each PEV in Km/Kwh and Cap_{bat} is the battery capacity in Kwh.

The full charge time will be calculated based on the following Eq. 4 and consequently the charging profile and load demand of battery charger will be extracted as well:

$$T_{full-charge} = 100 \times (1 - SOC_{int}) \times \frac{Cap_{bat}}{P_{ch} \times Eff_{ch}} \quad (4)$$

where $T_{full\text{-}charge}$ is the time required to fully charge the battery bank, P_{ch} is the rated power of battery charger and Eff_{ch} is the efficiency of the battery charging unit.

Based on the above calculation (Eqs. 1-4), the charger load profile for each individual PEV will be derived. After this stage, an aggregator will combine all individual PEV load profiles and predicts the load profile of upstream distribution transformer supplying the PEVs.

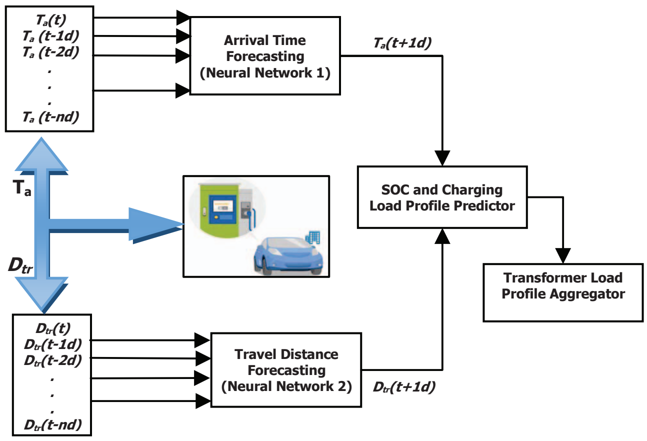


Fig. 1. Proposed strategy for ANN-based forecasting of PEV and transformer daily load profiles

III. Structure of Neural Network Prediction System

Neural network is a powerful tool for solving time series based problems and also prediction of the futures series based on the past values of the same time series. Neural network is established by layers of different neurons that are used to interconnect adjoin layers. A neuron is a nonlinear, parameterized, bounded function with input and output variables. A feed-forward neural network (FNN) is a nonlinear function of its inputs which is a composition function of its neurons. Each neuron will be modelled by below function:

$$a = f(\sum_{i=1}^{R} w_{ij} \times P_i + bi) \quad (5)$$

where P_i, *wij* and *bi* are the input of neuron *i*, weight matrix between neurons *i* and *j* and the bias vector for that neuron, respectively. Fig. 2 shows the base model for a layer of neurons. The ANN used in this research is a feed forward perceptron. Perceptron networks have attracted great interest due to their ability to generalize from their training vectors and learn from initially randomly distributed connections.

The perceptron structure used in this paper is shown in Fig. 3. It consists of three layers including:

- One input layer including 7 neurons with liner filtering function.
- One hidden layer with 10 neurons with a sigmoid filter function (*tansig(x)*).
- One output layer with 1 neuron and liner filter function.

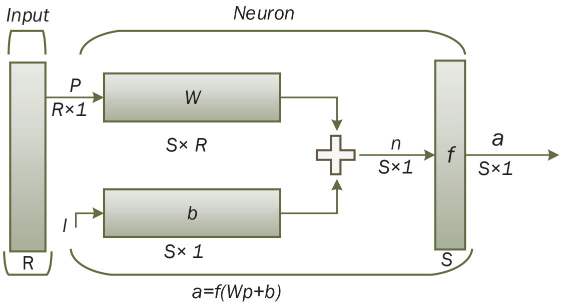


Fig. 2. Base model for a layer of neurons [7]

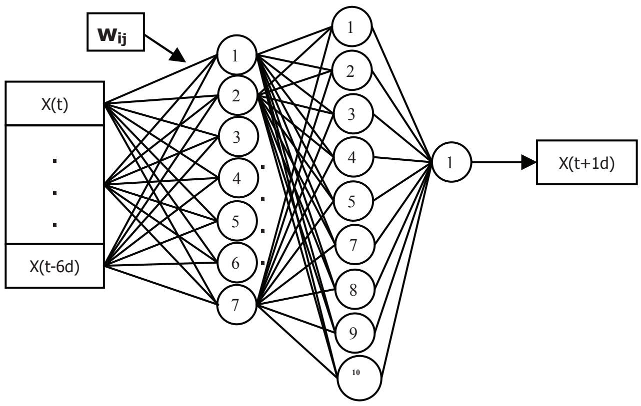


Fig. 3. Selected structure of perceptron ANN

IV. Smart Grid and PEV Data Sets

The selected smart grid for the analyses and simulations of this paper consists of the 19 nodes 415 V residential feeder of Fig. 4 which is extracted from the distribution network of reference [8]. The 19 bus feeder is fed through a distribution transformer and includes 12 buses with PEVs (e.g., PEV penetration of 63 percent). The maximum demand of each PEV charger is 3KW.

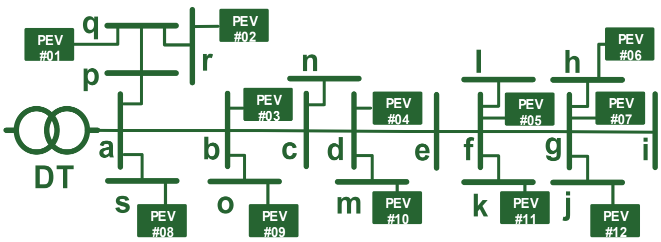


Fig. 4. Simulated network with 12 randomly plugged-in vehicles

The historical PEV data sets of reference [5] are used for the training and evaluation of the proposed ANNs. This reference presents the data sets of a study conducted for a PEV related research in Tehran. The employed datasets in the modelling algorithm have been gathered using questionnaires filled-out by the randomly selected owners of the commuter light duty ICE vehicles in Tehran. The owners were asked to give merely the commuting data. The datasets include home arrival time (T_a), daily travelled distance (D_{tr}) and home departure time (T_d) of the vehicles during weekdays. The survey has been done for duration of about 3 month. However for the analyses of this paper, the recoded data has been extended based on stochastic models to 18 months.

By using a distribution fitting model, the probability density functions of available data sets are derived and used to generate the data sets for 600 days. Referring to reference [5], for both T_a and D_{tr}, a generalized extreme value (GEV) distribution function has been fitted to the recorded datasets:

$$f_{T_a}(t)=\left(\frac{1}{\sigma_{T_a}}\right) exp\left[-\left(1+k_{T_a}\frac{(t-\mu_{T_a})}{\sigma_{T_a}}\right)\right]^{-\frac{1}{k_{T_a}}}\left(1+k_{T_a}\frac{(t-\mu_{T_a})}{\sigma_{T_a}}\right)^{-\left(1+\frac{1}{k_{T_a}}\right)} \quad (6)$$

$$f_{D_{tr}}(d)=\left(\frac{1}{\sigma_{D_{tr}}}\right) exp\left[-\left(1+k_{D_{tr}}\frac{(d-\mu_{D_{tr}})}{\sigma_{D_{tr}}}\right)\right]^{-\frac{1}{k_{D_{tr}}}}\left(1+k_{D_{tr}}\frac{(d-\mu_{D_{tr}})}{\sigma_{D_{tr}}}\right)^{-\left(1+\frac{1}{k_{D_{tr}}}\right)} \quad (7)$$

where the stochastic parameters of GEVs related to T_a and D_{tr} are presented in Table I.

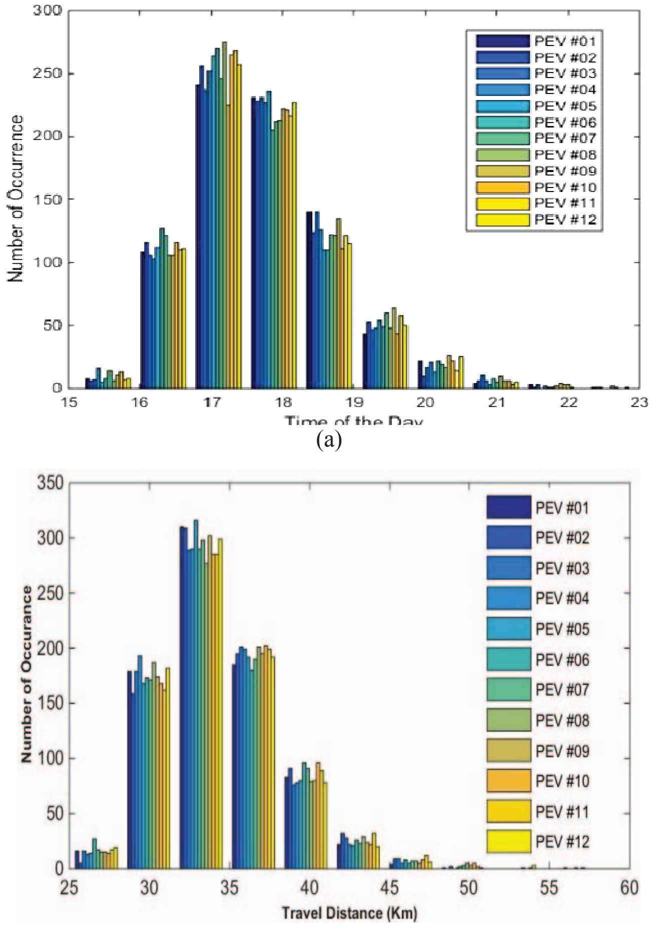
Using the Eqs. 6-7 and the related parameters of Table I, the time series of arrival time and travel distance of 12 individual vehicles for duration of 600 days have been randomly generated. Figures 5a and 5b show the histograms of the arrival time (T_a) and daily travel distance (D_{tr}) for 600 days.

Table I

Modelling parameters

Dataset	Distribution Parameters
Arrival Time (T_a) [5]	$k_{T_a}=-0.060798$ $\mu_{T_a}=17.27$ $\sigma_{T_a}=0.84832$
Travel Distance (D_{tr}) [5]	$k_{D_{tr}}=-0.052368$ $\mu_{D_{tr}}=32.6568$ $\sigma_{D_{tr}}=3.1222$
Cap_{bat}	30 Kwh
P_{ch}	3 Kw
Eff_{ch}	0.8
Eff_{PEV}	2 Km/Kwh

For the analyses and simulations of this paper, it is assumed that all PEVs will be plugged-in immediately after arriving at home (e.g., arrival time is equal to plugged-in time) and PEVs will be fully charged before departure in the next day (e.g., departure time is greater than the full charge time). Table I. shows the values of parameters used in simulation (Eqs. 1-4).



(a)

(b)

Fig. 5. Histogram of data for 12 vehicles during the 600 days of study; (a) arrival times, (b) travel distances (extracted from [5])

V. Simulation Results and Discussions

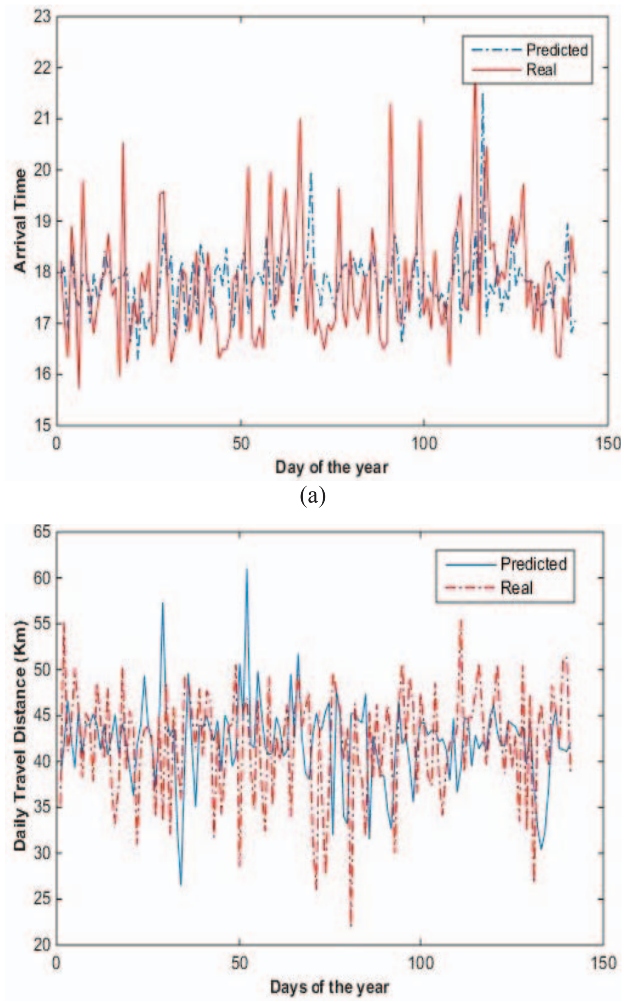
This section presents the simulation results of the predicted PEV parameters and transformer loading including the corresponding errors. The selected method used for training FNN is the Resilient Back Propagation (RBP). The data for 420 days of the year has been used for training the neural network and the data of the remaining 140 days has been used for verification and performance measurements of the system.

Figure 6a shows the predicted values of arrival time for vehicle #01 compared with the real (actual) measured arrival times for that vehicle in the same day for at least 140 days of the year. Figure 6b shows one day ahead daily travelled distance for vehicle #01 in comparison with the real data within a period of 140 days.

Four different error criteria were used to evaluate the simulation results for the predicted PEV parameters. These include mean absolute error (MAE), mean absolute deviation (MAD), mean squared error (MSE) and mean absolute relative error (Error). Table II presents detailed error comparisons for the predicted parameters of the 12 PEVs (Fig. 4). These results also include the maximum and minimum percentages of error in the prediction of T_a, D_{tr} and SOC_{int} values.

According to Table II, the prediction errors for arrival times are much less than the errors in predicting travel distance. This can be explained considering the nature of data, as most drivers have regular time frame for living their homes in the morning and coming back in the evening. However, the travel distance may significantly vary as it depends on many factors such as the traffic and road conditions. Therefore, the neural network was not able to find a strong and reliable pattern within the travel distance data sets.

Our detailed analyses and simulations for different case studies in different time intervals reveal that it might be necessary to introduce additional factors in the ANN to improve the predication accuracy, such as the weather and climate condition.



(a)

(b)

Fig. 6. Day ahead predicted information for PEV #01; (a) arrival time, (b) travel distance

Fig. 7 presents a typical predicted day ahead load profile for aggregated PEVs connected to the upstream transformer and compares it with the real load profile of the transformer. Fig. 8 shows the trend of changing in error of transformer load profile prediction during different days of the year. The corresponding maximum and minimum values are also presented in Fig. 8.

Fig. 9 shows a sample error profile of the predicted transformer loading for a typical day. There are two peaks in the error values, one in the evening when a large number of vehicles arrive at home and there is a rush of demand from PEV chargers and another peak point around midnight when most PEVs are fully charged and being disconnected from the network. This explains that the accuracy of the prediction falls down when the rate of changes in the transformer loading are relatively large

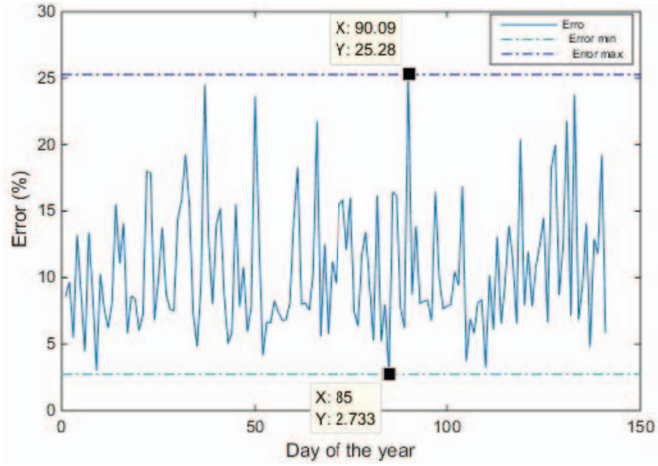


Fig. 8. Error trend on transformer load prediction

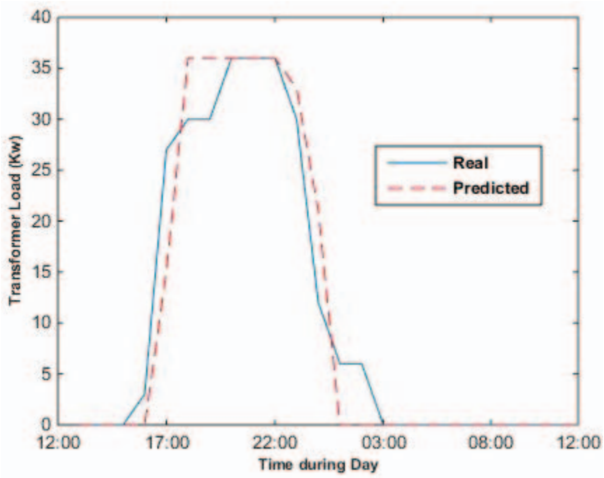


Fig. 7. A typical day ahead prediction of transformer load profile

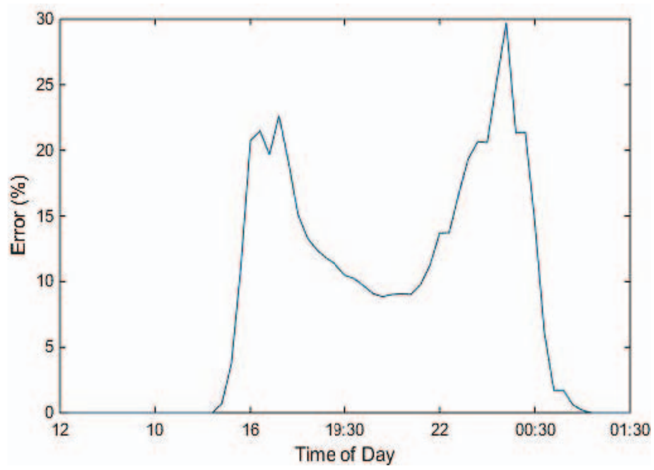


Fig. 9. Sample error profile of the predicted transformer loading

Table II
Detailed simulation results including error of the forecasting model

PEV Number	Error* in Predicted PEV Arrival (Plug-In) Time T_a					Error in Predicted PEV Daily Travel Distance D_{tr}					Error in Predicted battery SOC_{int}.				
	Error (Min.)	Error (Max.)	MAE	MSE	MAD (%)	Error (Min.)	Error (Max.)	MAE	MSE	MAD (%)	Error (Min.)	Error (Max.)	MAE	MSE	MAD (%)
#01	N.A.	N.A.	0.8	1.3	4.5	0.1	24.8	12.7	2.9	8.3	0.0	13.23	2.9	12.7	11.9
#02	N.A.	N.A.	0.8	1.0	4.5	0.2	30.5	15.4	3.2	9.3	0.2	21.5	3.2	15.4	12.9
#03	N.A.	N.A.	0.9	1.4	5.3	0.2	61.1	21.3	3.5	10.2	0.1	20.8	3.5	20.5	15.3
#04	N.A.	N.A.	0.9	1.6	5.3	0.2	47.0	20.6	3.5	10.2	0.2	21.9	3.5	20.6	15.3
#05	N.A.	N.A.	1.1	1.8	5.9	0.1	52.7	22.7	3.6	10.4	0.0	52.6	3.6	22.7	20.5
#06	N.A.	N.A.	0.8	1.1	4.7	0.1	43.3	14.1	2.9	8.5	0.0	19.6	2.9	14.1	12.1
#07	N.A.	N.A.	1.0	1.9	5.3	0.0	38.8	16.4	3.0	8.8	0.0	16.5	3.0	16.4	12.9
#08	N.A.	N.A.	0.9	1.4	5.0	0.1	35.4	19.6	3.6	10.3	0.0	20.6	3.6	19.6	14.8
#09	N.A.	N.A.	1.0	1.6	5.4	0.0	45.9	14.8	2.8	8.3	0.1	25.1	2.8	14.8	11.9
#10	N.A.	N.A.	0.8	1.1	4.6	0.1	70.5	18.0	3.3	9.7	0.0	14.4	3.3	18.0	13.3
#11	N.A.	N.A.	0.9	1.6	5.3	0.2	58.8	26.1	3.8	10.8	0.0	19.9	3.8	26.1	16.4
#12	N.A.	N.A.	0.9	1.3	5.0	0.0	39.1	18.2	3.2	9.3	0.0	21.2	3.2	18.2	13.9

*) Error: mean absolute relative error; MAE: mean absolute error; MSE: mean square error; MAD: mean absolute deviation error.

VI. Conclusion

An artificial intelligence approach based on neural networks is developed to forecast the parameters and daily load profiles of individual and fleets of randomly plugged-in electric vehicles. The proposed approach also predicts the daily load profile of the upstream distribution transformer feeding the PEVs. The ANN model is trained and tested for 12 PEVs. Main conclusions based on detailed simulation results are:

- The developed ANN model is capable of predicting arrival time of PEVs with high accuracy (less than 5% error as shown in Table II).
- The Prediction of travel distance is modelled with an acceptable accuracy (around 9%); however, this prediction error may be enhanced by implementing new parameters engaged with travel distance such as the traffic and road conditions and therefore, ANN model was not capable of finding a reasonable pattern within the travel history data set.
- Prediction of Transformer Load profile has been also investigated and modelled based on vehicles data with an average error of 13% which is within the acceptable prediction range for power system planning purposes.
- In overall, this developed model and its implemented simulations for different case studies show the necessity of introducing more factors in addition to the analysed input data in the ANN to improve the predication accuracy. The accuracy of model is affected by the rate of changes in number of connected/ discounted PEVs as well.
- To improve the solution, collection and classification of actual measured data on PEV parameters and enhancing the model design can be considered. This will lead to a significant improvement in the accuracy of the ANN by implementing new parameters.

Our future research will aim to collect, generate or measure more data (for plug-in times, plug-out times, SOCs, travel distances etc.) for longer periods of time and higher penetration PEVs, as well as improving the accuracy of the proposed ANN model.

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