Utilization of Electric Vehicles for Improvement of Daily Load Factor in the Price-Responsive Environment of Smart Grids

M. R. Aghaebrahimi and H. Taherian

Abstract — Using electric vehicles, in addition to decreasing the environmental concerns, can play an important role in decreasing the peak and filling the off-peaks of the daily load characteristics. In other words, in smart grids' infrastructure, the load characteristics can be improved by scheduling the charge and discharge process of electric vehicles. In smart grids, the customers are instantaneously informed about the load and its price and are able to react to the prices. This reaction pattern results in a wide range of changes in the load curve of the network. In this paper, a multi-stage model based on neural networks and the neuro-fuzzy network is presented for forecasting the daily electric load in the price-responsive environment of smart grids. Then, in order to determine the load and generation models of the set of electric vehicles based on the forecasted load for the next day, a complete probabilistic model of these vehicles in the range of parking lots is presented by considering three utilization strategies. These utilization strategies are: Uncontrolled Charging Mode (UCM), Controlled Charging Mode (CCM) and Smart Charge/Discharge Mode (SCDM). Finally, the proposed model is applied on the data of a target day in 2015 in NSW region of Australia's National Electricity Market and the charge and discharge schedule of electric vehicles are determined based on the forecasted load for the next day. The results indicate the most improvement in the daily load factor when the SCDM utilization strategy is employed.

Index Terms - electric vehicles, load forecast, load factor index, price-responsive loads, sequential Monte-Carlo, smart grids.

I. INTRODUCTION

WITH the emergence of smart grids, it has become possible to generate, transmit, and consume electric energy with higher efficiency and reliability, compared to conventional electric networks. The bidirectional flow of power and data in these networks is more efficient, more flexible, and more reliable. Therefore, there is a better coordination between the customers and the producers.

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The main problem in smart grids is the way in which the demand side must be managed so that the peak of electricity load is decreased [1,2]. In fact, the right response to the load highly depends on the way in which the demand side is managed. In addition, it depends on accurate forecast of price, load, available renewable energies and storage resources such as electric vehicles. With the advance of battery technology, using electric vehicles is growing rapidly in some countries. In the future, the aggregators of power systems can consider electric vehicles parking (EVP) as distributed sources of energy. These resources play two different roles for power systems: the role of load when the batteries of vehicles are being charged and as the energy generating resources while they are being discharged [3,4].

In smart grids' infrastructure and in the domain of online control of these networks, the charge and discharge of EVs can be controlled in such a way that the efficiency of the power system is increased. To investigate the effects of presence of electric vehicles, it is necessary to completely and accurately model the behavior of these vehicles based on the way their owners use them.

In most of the researches carried out in the domain of charging and discharging vehicles in parking, no attention is paid either to the probabilistic behavior of the EVs or to the reaction of customers to the forecasted load in the price-sensitive environment of smart grids. For example, a controlled charging strategy aimed at decreasing the loss and increasing the loadability of the distribution network has been proposed in [6]. Also, in [7] and [8], a smart load management model has been presented for charging the batteries of EVs in order to decrease the peak load, to decrease the loss, and to improve the voltage, but the probabilistic behavior of EV has not been considered. In addition, in [9] the energy scheduling of the EV batteries has been optimized by probabilistic modeling of EVs in urban parking lots, in order to decrease the peak load and the charge price. In [10], the optimum charging of EVs has been investigated only for filling the off-peak periods of the load curve. In [11] and [12], the authors have focused on the optimum charge and discharge scheduling of batteries for peak shaving, decreasing the load fluctuations, and decreasing the price required for electrification of transportation fleet.

However, none of the aforementioned studies has paid attention to the load forecast as one of the main factors affecting the accurate charge and discharge scheduling of the batteries. With the emergence of smart grids and by means of advanced metering infrastructure (AMI), the customers instantaneously become aware of the electric load and prices. Therefore, in future smart grids it is expected that, based on the forecasted prices, the demand side customers change their consumption pattern by cutting off the load, transmitting the load, or even by locally generating the load. Thus, forecasting the electric load in the price-sensitive environment of smart grids seems necessary for scheduling the charge and discharge of EV batteries in parking lots in order to modify the power system's load.

Patterns of customer's side do not have considerable variations due to the forecasted price, and as a result, the forecasted load remains intact against the reactions of customers [13-16]. Therefore, in this paper, a model is presented for forecasting the load, taking into account the awareness of customers of the forecasted load and price. The presented multi-stage model includes the perceptron neural network and a neuro-fuzzy network. This forecast is obtained by extracting the reaction of the customers to the prices announced for the next day. Now, knowing the changed electric load for the next day, the charge and discharge of EV batteries in parking lots is determined in order to modify the system's load characteristics.

In this paper, the complete and probabilistic model of EV sets as the load, storage devices, and energy generating devices is determined. The presented model is extracted based on UCM, CCM and SCDM utilization strategies. The sequential Monte Carlo simulation is used for simulating and modeling EVs. Finally, using the presented models, the effects of these strategies on the load curves and load factor index of a target day (2015/01/10) in NSW region of Australia's National Electricity Market are investigated.

The remainder of this paper is organized as follows: in section III, the problem is described in details. The proposed model is presented in section IV. Numerical results and simulations are presented in section V. And finally, section VI concludes the paper.

II. PROBLEM STATEMENT

A. Elasticity of the load and the price of electricity in smart grids

The reaction of customers to the forecasted price has been considered only in a small number of papers published so far. The reaction of customers to the forecasted price brings about significant changes in the demand pattern of the target day, which consequently, causes the price of electricity to change. The main reason that a unidirectional relationship has been used in conventional load and price forecasting techniques is the low elasticity of load to electricity price [17,18]. With the development of smart grids, the electric load tends to change its conventional inelastic behavior to a price-sensitive environment. In such an environment, using a bidirectional relationship for load and price forecasting will be possible and it seems necessary to consider the mutual impact of these two factors.

Generally, the load is considered as the key of electricity price and has been reported as the input of many price forecasting models [19,20]. The effect of this input on improving the accuracy of price and load is more obvious in the interactive environment. Fig. 1 shows the mutual dependency of load and electricity price in the Australian power market (NSW region) in February 2012.

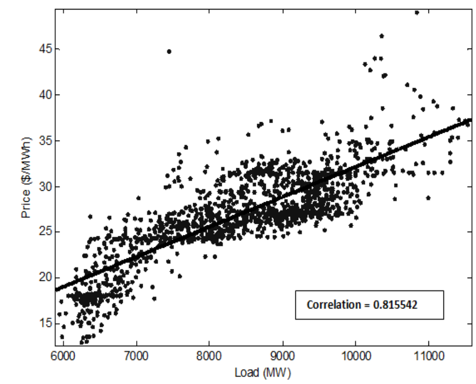

Fig. 1. Correlation between price and load in the Australian power market (NSW region) in February 2012.

In order to further investigate the dynamics of load and price in power markets, the load and price data of Australian power market (Victoria region) on December 13th 2012 has been used. Although the forecasted price for a considerable number of customers is higher than their tolerance threshold, it is very likely that these customers reduce their consumption in reaction to these prices. Consequently, only a 30MW reduction in load, decreases the price from 2184.8 $/MWh to 405.9 $/MWh. This is shown in Fig. 2.

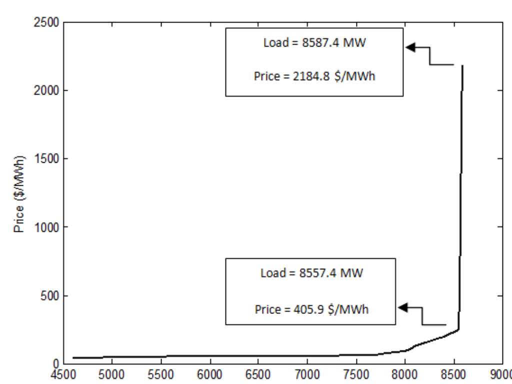

Fig. 2. The load and price data of Australian power market (Victoria region) on December 13th 2012.

B. Elecrtic vehicles utilization

Using electric vehicles' fleet, as an energy resource which does not need initial investment, will be considered as a key factor for smart grids in the future [21].

Discharging vehicles for peak shaving means that little need will be felt for spending extra budgets to build new power plants in order to supply the peak load. On the other hand, charging the set of EVs causes the off-peak periods of the load to be filled, and as a result, it increases the efficiency of the power system.

Using EVs is so important that, in addition to environmental issues, the power generated by parking lots can be considered as negative load, and the utilization schedules can be carried out based on the net or residual load. This kind of load is actually resulted from the difference between the network load and the amount of load supplied by distributed generations such as parking lots.

In this paper, it is assumed that there are administrative and residential parking lots in the network. In this network, the customers become aware of the forecasted load and price instantaneously and are able to react to the prices. The electric load forecast is carried out on a daily basis.

It should be mentioned that the first priority is to use personal vehicles and this is done in order to help the network shift and modify the load characteristics of the next day.

III. THE PROPOSED MODEL

A. FCM

Clustering is one of the unsupervised techniques and is an automatic process through which a certain data set is divided into a set of classes or clusters. The aim of data classification by using this kind of process is to separate the data in such a way that two data objects in a cluster are as similar as possible and two data objects in two different clusters are as distinct as possible.

In this paper, one of the most successful clustering models, called Fuzzy C-Means (FCM), is used [22]. In this model, each data is assigned to a cluster to a certain degree that is determined by a membership function. By creating membership functions, the FCM output helps in constructing fuzzy inference system for stating the fuzzy quality of each cluster. Fig. 3 shows the proposed model containing four blocks.

Through clustering, the input data is classified according to the load type (peak or off-peak), day type (weekday or weekend) and so on. In this paper, the historical price and load data are classified by FCM and proper data is obtained for training the neural network.

B. The neural network for initial forecast of the load and the price of electricity

The initial load and the electricity price are forecasted in this block. The simultaneous use of load and price in this block causes the mutual effect of load and price to be tracked in this model. Therefore, in order to extract the dynamics of the load forecast problem in the price-sensitive environment of smart grids, the effect of elasticity and sensitivity of the load and price is studied. In this block, the multi-layer perceptron neural network is used to forecast the initial load and price. The clustered price and load data are simultaneously applied to the input of this block. The output of this block includes two data sets. The first set is the initial forecasted load for the d[th] objective day. The second set is the forecasted load and price for the past N_d days.

Also, the difference between the actual and forecasted loads for past N_d days is calculated as follows:

$$DL_d = L_d^a - L_d^f \tag{1}$$

To extract the if-then rules, many inputs can track the reaction of customers to the price. The previous temperature data, which is one of the factors effective on the demand of the system, is used in this model. Furthermore, the economic-based load management schedules in the power market under the study are used as the inputs of the ANFIS network.

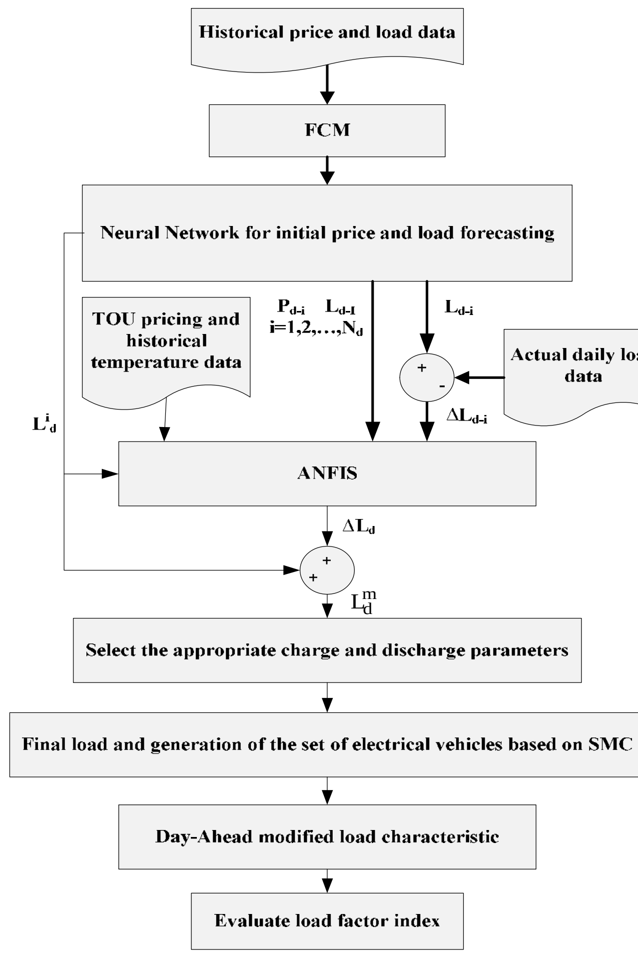

Fig. 3. The proposed model

These schedules which are implemented based on time-of-use (TOU) pricing, are common in most of the smart grids. This schedule is announced to the customers who are equipped with the measurement tools of smart grids. In this pricing system, the workdays have three different prices; shoulder peak, peak, and off-peak. In addition, weekends and holidays have two prices; shoulder peak and off-peak. Therefore, in smart grids the customers equipped with measurement tools are able to change their load range each hour so that by shifting the consumption from expensive hours to cheap hours they can better save money.

The following inputs are used for training the ANFIS network based on corresponding ΔL_d as well as extracting the if-then rules:

- The time index of the economic-based load management schedules,
- The temperature data for past N_d days,
- P_d^i and L_d^t for past N_d days.

Under such conditions, the ANFIS network extracts the rules, which include the extensive changes in the price-sensitive behavior of customers. These rules show how the system load will change according to the reaction of customers to the announced prices and the load.

For example, the loads forecasted for the past N_d days are divided into the following groups: very high (VH), high (H), medium (M), low (L), and very low (VL). Also, the temperature data for the past N_d days are divided into the following groups: hot (H), mild (M), and cold (C), and finally, the load variations for the past N_d days can be divided into the following groups: high drop (HD), low drop (LD), negligible deviation (ND), low rise (LR), and high rise (HR). It must be mentioned that for each hour in the day d, a time index is selected based on the economic-based load management schedules.

Eventually, the final forecasted load in the price-sensitive environment of smart grid is calculated by the following equation:

$$L_d^m = L_d^i + \Delta L_d \tag{2}$$

In this equation, ΔL_d can be either negative or positive.

C. Modeling the load and generation of parking lots based on the forecasted load for the next day

In this section, the goal is to select the proper charge and discharge parameters of EV batteries during the hours of the next day. Once the parameters of charge and discharge are determined, the Monte Carlo simulation is carried out for a long period of time in order to extract the load and generation of the set of EVs based on the forecasted load for the next day.

By doing so, the scheduling and probabilistic modeling of EVs is carried out in order to modify the load characteristics. To better utilize the EVs, these vehicles must be utilized by the aggregators as a set of vehicles [23]. Considering the probabilistic nature of vehicles, the probabilistic models must be used for determining the model of these vehicles [24]. The probabilities which must be considered include battery capacity of the vehicle, the distance traveled by the vehicle, the time of leaving home, travel duration, and the time period during which the vehicle is parked in the administrative or residential parking lots. In [24], the limited normal distribution function has been used in order to obtain these random variables for limiting the generation of random variables to the range of interest. It should be mentioned that the mean and standard deviation of random variables are obtained from [24]. Once the distance traveled by each vehicle is determined, its state of charge (SOC) is obtained based on (3) [25].

$$SOC_{int}^i = \left(1 - \frac{D^i}{D_{max}}\right) \times 100\% \tag{3}$$

The value of parameter D_{max} is considered to be equal to 128 km [25]. The state of charge of the vehicle during charge and discharge in parking lots is calculated using (4):

$$SOC_t^i = [SOC_{t-1}^i \pm \Delta_t \cdot (Ch_{rate} \text{ or } Dch_{rate})] \times 100\% \tag{4}$$

The energy generated or consumed by the set of the vehicles' batteries is calculated at each instance by the Aggregator using (5) [26]:

$$E_{agg}^t = \sum_{i=1}^{B} K^i \Psi_t^i SOC_t^i \tag{5}$$

If ψ_t^i is equal to one, this means that the vehicle is connected to the network, and if the value of this parameter is equal to 0, it means that the vehicle is not connected to the network. In order to optimize the load and generation models, by using its online communication capability, the aggregator must schedule the smart charge and discharge of vehicles' batteries within the range of parking lots according to the forecasted load of the next day.

D. load and generation model of parking lots

Utilization of electric vehicles includes uncontrolled charging mode (UCM), controlled charging mode (CCM), and smart charge/discharge mode (SCDM). In uncontrolled mode of charge, there is no control over the charging of EV batteries and the vehicles are charged as soon as they are connected to the network. In CCM and SCDM, however, it is necessary to determine the allowable times for scheduling the charge and discharge of EV batteries. Furthermore, the SOC required by the vehicle for its daily journey has to be determined. Moreover, factors such as charge and discharge rates of EV batteries are also effective on modification of the system load characteristics.

Therefore, the parameters like the rates and allowable hours of charge and discharge must be selected according to the forecasted load and penetration of EVs in the case study. The allowable hours of charge and discharge of batteries are determined based on X_p% and X_{op}% which are the peak-shaving percentage and off-peak filling percentage, respectively.

In this paper, the SCDM utilization strategy is used to modify the forecasted load characteristics of the next day. The sequential Monte Carlo simulation is carried out for a long period of time in order to extract the load and generation model of EV sets based on the load forecasted for the next day. Thus, the probabilistic modeling and scheduling of EVs are carried out to modify the load characteristics. In the Monte Carlo simulation, the charge, discharge, and the daily journey of the vehicles are simulated based on the probabilistic and selected parameters for a long period of time. Once the convergence criterion is met, the simulation is terminated and the load and generation models are extracted based on the load forecasted for the next day. In this paper, the coefficient of variations of mean and peak of load and generation of parking lots is considered as the convergence criterion.

IV. Numerical results and simulations

In this paper, a model based on the load forecasted for the next day in the price-sensitive environment of smart grids is presented for scheduling the charge and discharge of EV batteries in order to modify the system load characteristics.

In this model, in order to obtain the initial forecast of load and price, the data of the past 48 days are used for training the MIMO model used for forecasting the dth target day. To extract the if-then rules, after carrying out a large enough number of experiments, the forecast is carried out for four weeks before the target day. The length of this interval is selected considering the short-term and long-term tendencies of the load and price. Therefore, N_d=28.

The ANFIS network uses the Gaussian membership function to carry out the forecast. In addition, for the aforementioned 4 inputs, the number of membership functions are selected as 5, 3, 5, and 5, respectively. In this case, the ANFIS network classifies the input data based on the determined membership functions.

In this paper, the load and price data of NSW region in Australia's National Electricity Market are used. This electricity market, which is the largest connected network in the world, experiences severe variations as well as many exits and unexpected disturbances [27]. Therefore, the forecast is carried out for January 10, 2015. In this market, customers become instantaneously aware of the forecasted load and price and are able to react to this factor.

There are many indices for evaluating the efficiency of the forecast models, the most common of which is the mean absolute percentage error (MAPE) index. This index is defined by the following equation:

$$\%MAPE = \frac{1}{N}\sum_{h=1}^{N}\frac{\left|Act.\_L(t) - For.\_L(t)\right|}{Ave.\_Load}\times 100 \tag{6}$$

To schedule the charge and discharge of vehicles in parking lots, it is assumed that there are 300000 electric vehicles in the network under study. In the morning, the owners of EVs commute from the residential parking to their workplace and park their vehicles in the administrative parking. Also, once their job is done, they commute back to their home and park their vehicles in the residential parking. The optimization of charge and discharge scheduling of EVs is aimed at shifting the load. Therefore, the demand for energy is shifted from the load peak to the load off-peak.

Table I shows the appropriate parameters of CCM and SCDM according the forecasted load for the target day, i.e. January 10, 2015. In this table, SOC_{min} is related to the post-midnight SOC of administrative and residential parking lots. For the pre-midnight period, assuming a depth of discharge of 0.8 for EV batteries, the SOC_{min} of residential parking lot is 0.2.

TABLE I
THE APPROPRIATE PARAMETERS OF SCDM AND CCM BASED ON THE FORECASTED LOAD FOR TARGET DAY (JAN. 10, 2015).

Parameters	Utilization strategy	
	CCM	**SCDM**
X_p%	100%	92%
X_{op}%	70%	70%
SOC_{min}	-	45%
Residential charge rate of EVP	10 percent per hour	10 percent per hour
Administrative charge rate of EVP	10 percent per hour	10 percent per hour
Residential discharge rate of EVP	-	20 percent per hour
Administrative discharge rate of EVP	-	20 percent per hour

Fig. 4 shows the expected load and generation models of residential and administrative parking lots on the target day for three utilization strategies. As it can be seen in the SCDM, the discharge capability of EVs is used so that when the load of system is greater than X_p% (8418MW), using the smart grid concept, the batteries of vehicles are discharged with the selected rate. In addition, when the system's load is smaller than X_{op}% (6405MW), the batteries of vehicles are charged with the proper rate. Then, by adding up the forecasted load and the expected load and generation in parking lots obtained by sequential Monte Carlo, the modified load characteristics of the system for the next day is obtained.

Fig. 5 shows the modified load model for the target day based on three utilization strategies. As it can be seen, in SCDM utilization strategy, vehicles in administrative and residential parking charge in the morning in other to decrease the peak load in the evening. In CCM, the vehicles are being charged in the off-peak, and finally, in UCM, due to probabilistic nature of model, the vehicles are being charged in various hours of the day. The best load curve is achieved using the SCDM utilization strategy.

In this case, the forecast error for this day is MAPE=2.0933%. It is observed that the online control of charge and discharge of EVs results in peak shaving and filling the off-peak. As it can be seen in the SCDM, the peak load is decreased and shifted from 9150 MW at 3 p.m. to 8653 MW at 6 p.m., and the off-peak load is increased and shifted from 5895 MW at 5 a.m. to 6862 MW at 3 a.m.

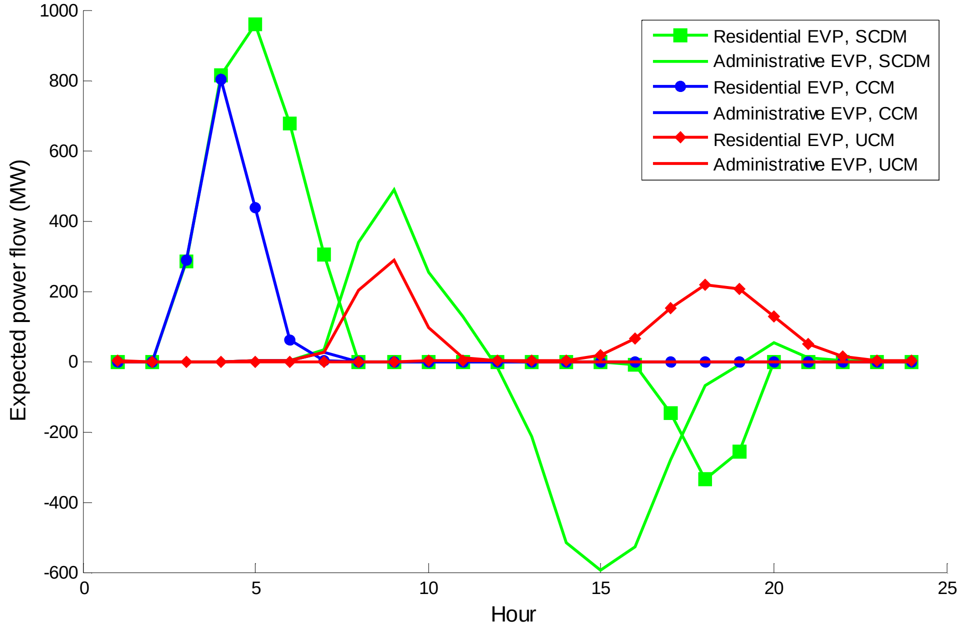

Fig. 4. Generation and load of the EVPs according three utilization strategies for the target day

This shows the considerable advantages of smart scheduling of EVs. In other words, the smart charge and discharge strategy not only has overcome the challenge of increased peak caused by the energy demanded by vehicles, but also it has improved the load characteristics of the system by shifting a significant portion of the peak load to the off-peak.

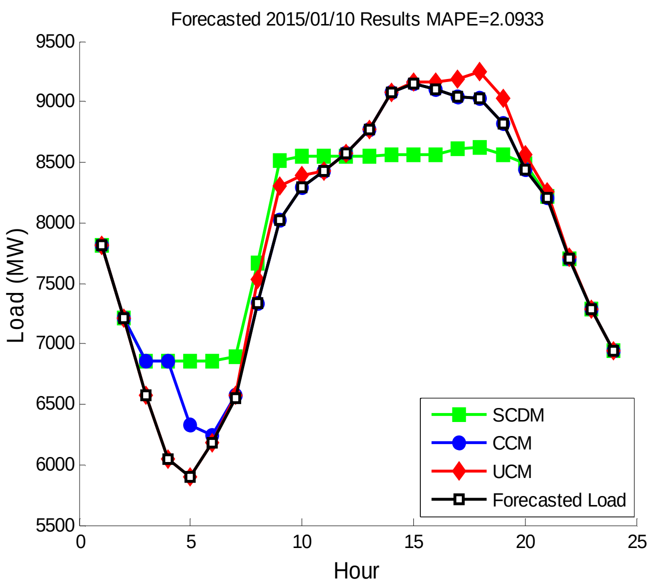

Fig. 5. the modified load model for the target day based on three utilization strategies

Load factor (expressed in terms of percentage) is a measure of the uniformity and efficiency with which electrical energy is being used.

A good load factor implies a more constant rate of electrical use, because MW demand is held to a minimum relative to total overall use. In essence, the better the load factor (near 100%), the lower the established demand in relation to Megawatt hour (MWh) use and the lower the relative cost for electric service.

The load factor is defined as the average load divided by the peak load in a specified time period. So, Table II compares the amount of load factor index in the case of no EV existing in the network with three mentioned strategies during the target day.

TABLE II
EVALUTE THE LOAD FACTOR INDEX DURING THE TARGET DAY

Utilization strategy	Load factor index
without EVs	0.8583
UCM	0.8560
CCM	0.8656
SCDM	0.9173

The results show that in UCM, because of lack of control over the charging process, the lowest load factor is occurred. This fact shows that, in the UCM, the charging process can be imposed on the network as a large load that reduces the network load factor, compared with when there are no cars on the grid. In CCM, the index is improved, but in SDCM, through smart charging and discharging method, the best amount of load factor is achieved.

As it can be seen, the proposed model not only helps the owners to supply and guarantee SOC requirement for their daily trips, but also improves the daily network load characteristic and load factor index. Also, EVP operator can determine the variable tariffs based on the proposed model to encourage vehicle's owners to attend in the parking lots in different hours of a day and by utilizing proper quote strategy, participate in the electricity power market.

V. CONCLUSIONS

Besides deceasing the environmental concerns, using electric vehicles causes the efficiency of the system to increase. In this paper, in order to modify the load characteristics, a model is proposed for scheduling the charge and discharge of the batteries of EVs in parking lots based on the forecasted load in the price-sensitive environment of the smart grids. This model uses a neural network and a neuro-fuzzy network to extract the pattern of customers' reaction to the prices and consequently to obtain the modified forecasted load for the next day.

To modify the forecasted load characteristics of the next day, a new method is presented for peak shaving, filling the off-peak times, smoothing the load curve, and preventing the severe fluctuations of the load curve. Once the parameters of charge and discharge are determined based on forecasted daily load, the Monte Carlo simulation is carried out for a long period of time in order to extract the load and generation of the set of EVs based on the forecasted load for the next day. The proposed model is applied on the actual sets of data from the NSW region in Australia's National Electricity Market for a target day (2015/01/10), and the results show the effectiveness of this model. Daily load characteristic and load factor improvement, reduction of net cost of purchase and sale of batteries' energy and a pattern for EVP operator to determine a proper bid strategy in the electricity power markets, are examples of the benefits of the proposed model which can be further investigated.

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VII. Nomenclature

d	each day in a year
L_d^a	actual load in day d
L_d^f	forecasted load in day d
L_d^i	initial load forecast in day d
P_d^i	initial price forecast in day d
L_d^m	modified load forecaste in day d
i	each electric vehicle in the case study
D^i	distance travelled by the i^{th} vehicle
D_{max}	max distance which can be travelled by the vehicle

D_t	time step in the interval under study
Ch_{rate}	charge rate
Dch_{rate}	discharge rate
K^i	battery capacity of the ith vehicle
Ψ_t^i	state of connected vehicle to the network
N	number of forecasted hours
Act._L(t)	actual load of the network at hour t
For._L(t)	forecasted load at hour t
Ave._L(t)	average actual load of the network