Assessing the Effect of Bidding Strategy of an Electric Vehicle Parking Operator (EVPO) in the Day-Ahead and Real-Time Markets on the Power System Reliability

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***Abstract*— Besides environmental benefits of using electric vehicles (EVs), the presence of EVs in the parking lots, acting as the power consumer or generator, have created widespread changes in the operation of power systems. The Electric Vehicle Parking Operator (EVPO) can strategically purchase and sell power in both the day-ahead and the real-time markets. Here, the effect of bidding strategy of an EVPO based on risk appetite is considered. A complete probabilistic model of the EVs in the range of parking is used to determine the allowed times of battery charge and discharge processes. The proposed model is applied on a realistic case study, forced to function in island mode, and the cost of energy not supplied is investigated. Results show that a risky strategy in addition to trading more power in the real-time market, not only supplies and guarantees the car owners' SOC requirement for daily trips, but also improves the reliability of the system.**

Keywords—bidding strategy; day-ahead market; electric vehicles; real-time market; smart grid.

I. Introduction

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. In fact, the right response to the load highly depends on the way in which the demand side is managed [1]. 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 EVs 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 first is the load when the batteries of vehicles are being charged and the other is the energy generating resources while they are being discharged [2].

In most of the researches carried out in the domain of charging and discharging vehicles in parking lots, no attention is paid either to the probabilistic behavior of the EVs or to the reaction of customers to the forecasted price in the price-responsive 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 [3]. Also, in [4] and [5], 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 [6] the energy scheduling of the EV batteries has been optimized by probabilistic modeling of EVs in urban parking lots to decrease the peak load and the charge price. In [7], the optimum charging of EVs has been investigated only for filling the off-peak periods of the load curve.

However, none of the aforementioned studies has paid attention to the price forecast as one of the main factors affecting the optimal charge and discharge scheduling of the batteries.

In this environment, EVPO can strategically buy and sell its required energy in both the day-ahead (DA) and the real-time (RT) markets based on forecasted price.

The optimal bidding strategy of an EVPO has been analyzed in few papers [8,9]. In [8], an intelligent method is presented to control EV charging loads in response to time-of-use (TOU) price in a regulated market. Using a stochastic programming, the authors in [9] studied the problem of an aggregator bidding into the DA electricity market with the objective of minimizing charging costs, while satisfying the EVs' flexible demand. The aggregator places only demand bids (no vehicle-to-grid is considered).

Within this context, we consider an EVPO in charge of a cluster of EVs in the residential and administrative parking lots. The proposed model is applied on the NordPool spot market data (region SE3), assuming that it is forced to function in island mode, and then the system reliability indices are studied.

The remainder of this paper is organized as follows: in section 2, the problem is described. The proposed model is

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presented in section 3. Numerical results are presented in section 4. Finally, section 5 concludes the paper.

II. Problem Statement

Using electric vehicles' fleet, an energy resource which does not need initial investment, will be considered as a key factor for smart grids in the future [8].

Besides the environmental issues, using EVs is very important, because 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 [9]. This kind of load results from the difference between the network load and the amount of load supplied by distributed generation sources, such as parking lots.

In this paper, we investigate the problem of bidding strategy in the deregulated market from the perspective of an EVPO utilizing administrative and residential parking lots in the network. We consider that the EVPO can buy and sell energy in two different trading floors: the DA and the RT markets. The EVPO participates strategically in the DA market by deriving its bidding strategy. This is done one day in advance and on an hourly basis. On the other hand, the EVPO can also strategically bid in the RT market once the DA market is cleared.

It should be mentioned that the first priority is to use personal vehicles and the proposed model supplies and guarantees state of charge (SOC) requirement for EV owners' daily trips. At the time of deciding the bidding strategy in both the DA and the RT markets, the EVPO faces a number of uncertainties, namely, DA market prices, RT market prices, and EVP power generations.

In this paper, a multi-stage model is proposed to solve this problem.

III. Prepare the Proposed Model

Fig. 1, shows the proposed model containing three steps.

A. Price Forecasting

The first step in deciding about bidding decision is forecasting DA and RT prices. In this paper, one of the most successful clustering models, called fuzzy c-means (FCM), is used [10]. 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 artificial neural network.

The DA electricity price is forecasted in this stage. The simultaneous use of load and price in this block causes the mutual effect of load and price to be tracked in this model [11]. Therefore, in order to extract the dynamics of the price forecast problem in the price-responsive environment of smart grids, the effect of elasticity and sensitivity of the load and price is studied.

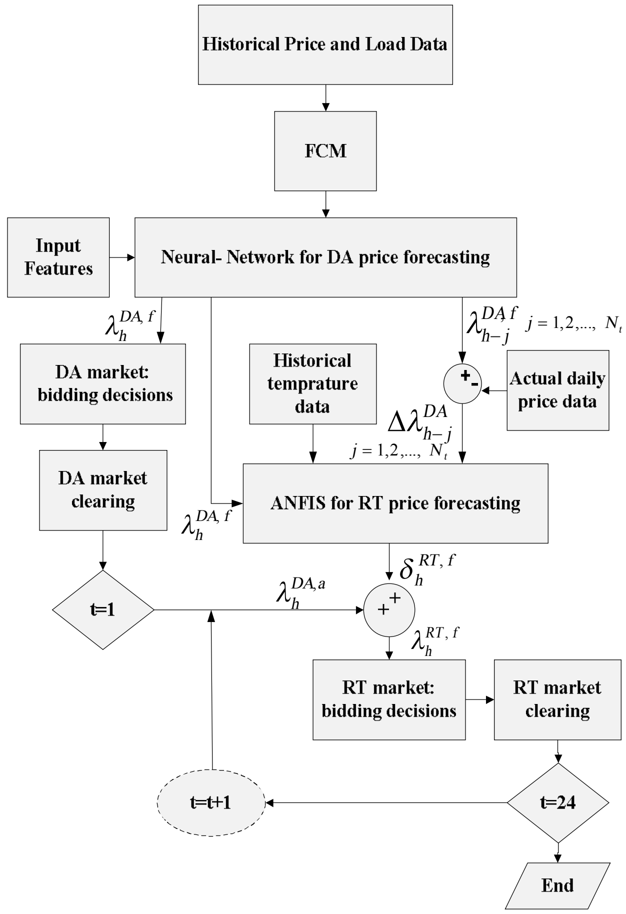

Fig. 1. The proposed model

In this block, the multi-layer perceptron neural network is used to forecast the DA price. The clustered price and load data are simultaneously applied to its input. The output of this block includes two data sets. The first set is the forecasted price for the objective day ($\lambda_h^{DA,f}$).

To this end, the forecasting cycle must be repeated until the DA price of the next 24 hours are forecasted by 24 iterative predictions according to feature inputs. The second set is the forecasted price for the past N_t hours.

In addition, the difference between the actual and forecasted loads for the past N_t hours is calculated as follows:

$$\Delta\lambda_h^{DA} = \lambda_h^a - \lambda_h^f \tag{1}$$

where, λ_h^a and λ_h^f are actual and forecasted price for the past N_t hours, respectively.

The following inputs are used for training the ANFIS network based on corresponding $\Delta\lambda_h^{DA}$ as well as extracting the if-then rules:

- The temperature data for past N_t hours,
- λ_h^f for past N_t hours.

Under such conditions, the ANFIS network extracts the rules including the extensive changes in the price-responsive behavior of customers. Eventually, the difference of the DA and RT prices is forecasted ($\delta_h^{RT,f}$). So, the RT price is calculated by the following equation:

$$\lambda_h^{RT,f} = \lambda_h^{DA,a} + \delta_h^{RT,f} \tag{2}$$

In this equation, $\lambda_h^{DA,a}$ is the accepted price in the DA market. Moreover, $\delta_h^{RT,f}$ can be either negative or positive.

B. DA Bidding Strategy

To sell and buy energy, EVPO takes part in both the DA and the RT markets through a two-stage procedure. First, the EVPO determines its bidding strategy in the DA market. Insomuch the EVPO has chance to participate in the RT market (the second stage), the decision in the DA market can affect the strategy in the next stage. Therefore, it is necessary to remark the RT market variables for determining the bidding strategy in the DA market [12].

The problem in this stage can be formulated using the following linear programming (LP):

$$\min \sum_h [\lambda_h^{DA,f}(P_h^{DA,T} + P_h^{RT,T})\Delta + \delta_h^{RT,f} P_h^{RT,T}\Delta - u_h(E_h^{agg})]$$
$$+ \beta^{DA}\upsilon^{DA} + \sum_h (\eta_h^{DA} + \eta_h^{RT}) \tag{3}$$

In the first term, $P_h^{DA,T}$ and $P_h^{RT,T}$ are total power traded by EVPO in the DA/RT market in hour h and Δ is power-energy conversion. Also, u_h is the utility function of the energy generated or consumed by the set of the vehicles' batteries. The aim of the second term is to minimize the worst case of minus total utility that can take place due to the uncertainty of forecasted data. It comprises the following two parts: i) The nominal value of the minus total utility corresponding to the mean value of the market prices; ii) The worst case of the cost deviation that can result due to the possible deviation of β^{DA} prices from their mean values. The parameter β^{DA} controls the degree of risk appetite with respect to the uncertainty in the forecasted prices. β^{DA} takes values within [0,48] (i.e. 24 DA market prices and 24 RT market prices). Here, $\beta^{DA} = 0$ results in a risky strategy and $\beta^{DA} = 48$ protects the objective function against all uncertainties in forecasted prices.

C. RT Bidding Strategy

As soon as the DA market is cleared, the EVPO knows its determined energy (bought or sold) and the market prices in this DA market. Therefore, EVPO can update and improve the modeling of the uncertain prices in the next hours of the day. Then, in a second stage, the EVPO decides its bidding strategy in the RT market hourly using the following LP problem:

$$\min \sum_h [(\lambda_h^{DA,a} + \delta_h^{RT,f})P_h^{RT,T}\Delta - u_h(E_h^{agg})]$$
$$+ \beta^{RT}\upsilon^{RT} + \sum_{h \ge t} \eta_h^{RT} \tag{4}$$

In this equation, parameter β^{RT} controls the degree of risk appetite with respect to the uncertainty in the forecasted prices in the RT market. β^{RT} can take values within $[0, 24 - t + 1]$. If this parameter is equal to zero, we relinquish possible RT deviations (a risky strategy).

IV. Numerical Results

In this paper, we proposed a model considering the effect of bidding strategy of an EVPO based on risk appetite in the DA and RT markets. To this end, the proposed model is applied on a realistic case study.

A. Data

To better utilize the EVs, these vehicles must be utilized by the aggregators as a set of vehicles [13]. Considering the probabilistic nature of vehicles' operation, the probabilistic models must be used for determining the model of these vehicles [14]. The probabilities which must be considered include the 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 [15], 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 [15]. Once the distance traveled by each vehicle is determined, its SOC is obtained based on (5):

$$SOC_{\text{int}}^i = \left(1 - \frac{D^i}{D_{\max}}\right) \times 100\% \tag{5}$$

The value of parameter D_{max} is considered to be equal to 128 km. The SOC of the vehicle during charge/discharge in parking lots is calculated by:

$$SOC_t^i = [SOC_{t-1}^i \pm \Delta_t \cdot (Ch_{rate} \text{ or } Dch_{rate})] \times 100\% \tag{6}$$

where, Ch_{rate} and Dch_{rate} are charge/discharge rate, respectively. The energy generated or consumed by the set of the vehicles' batteries is calculated at each instance by the aggregator:

$$E_{agg}^t = \sum_{i=1}^{B} K^i \Psi_t^i SOC_t^i \tag{7}$$

Parameter K^i is the capacity of i^{th} vehicle. If Ψ_t^i is equal to one, this means that the i^{th} vehicle is connected to the network, and if the value of this parameter is equal to zero, it means that the vehicle is not connected to the network. Now, 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 objective function in range of parking lots.

As mentioned, the first priority is to use personal vehicles. Also,vthe SOC requirement for EV owners for their daily journey has been considered in the model.

The proposed model is applied to the load and the price data of NordPool spot market region SE3 [16]. Therefore, the model is carried out to forecast the 24 hours of 6th of February 2017 (the target day). The set of 34 lagged data (the price and load data of 1, 2, 3, 24, 25, 48, 49, 72, 73, 96, 97, 120, 121, 144, 145, 168 and 169 hours ago) are proposed as the set of input features for the DA market price prediction in this paper.

To forecast the RT deviation and extract the if-then rules, after carrying out a large enough number of experiments, the forecast is done 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, $N_t = 28$.

The ANFIS network uses the Gaussian membership function to carry out the forecast. In addition, for the aforementioned 2 inputs, the number of membership functions are selected as 3 and 5, respectively. In this case, the ANFIS network classifies the input data based on the determined membership functions.

B. Results

Fig. 2, shows the forecasted price in the DA market on the target day (06/02/2017).

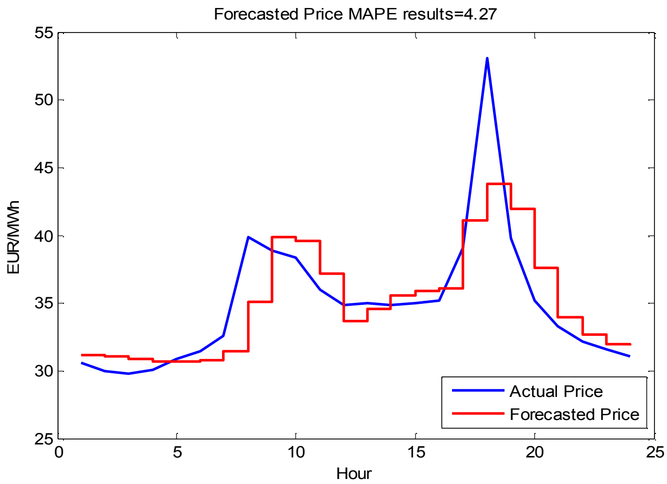

Fig. 2. Forecasted price on the target day

As it can be seen, the model forecasted the DA price by mean absolute percentage error (MAPE) results equal to 4.27. According to this forecasted price, EVPO decides about bidding curve in both the DA and RT markets.

To analyze the impact of considering risk on the power traded in these markets, two controlling parameters β^{DA} and β^{RT} are used and compared:

1) **Conservative Strategy**: It is modeled when these two parameters take maximum values of 48 and $24-t+1$, respectively.

2) **Risky Strategy:** It is modeled by taking these two parameters equal to 30% of the 48 and $24-t+1$, respectively.

The power traded in the DA market during the 24 hours of the target day is shown in Fig. 3. As it can be seen, for risky strategy, the power is bought from the DA market during hours with low-prices, while the power is sold to this market in hours with high-prices.

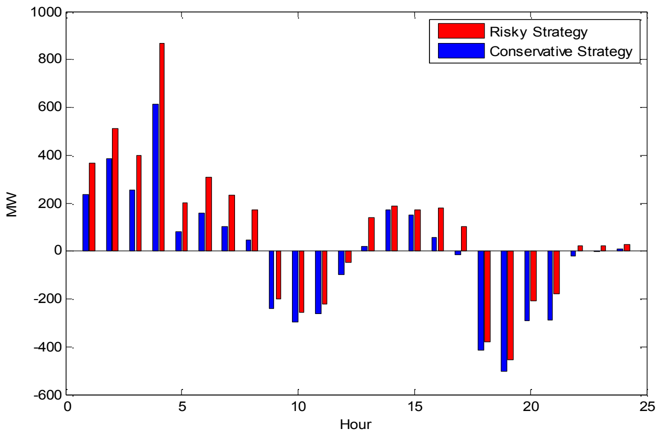

Fig. 3. Power traded in the DA market.

Also, the power bought from the DA market during low-price hours is comparatively higher than the power purchased in high-price hours by adopting a conservative strategy.

It is noteworthy that by adopting a risky strategy, the willingness to buy energy in the DA market increases and the willingness to sell energy decreases. It is because of the fact that the predicted mean value of the RT deviation prices are considered throughout the day. These predicted mean values are generally close to zero, but are positive during most hours of the considered day ($\delta_h^{RT,f} > 0$). This means that the nominal value of the DA market price is lower than the nominal value of the RT market price during most hours. Thus, adopting a risky strategy, which is equivalent to ignoring the possible deviation of all market prices from their predicted mean values ($\beta^{DA} = 0$) persuades the EVPO to buy energy in the DA market.

By increasing the β^{DA} parameter (a conservative strategy), the willingness to buy energy in the DA market decreases and the willingness to sell energy increases.

Now, we analyze the bidding strategy in the RT market. Fig. 4, shows the power traded in the target day.

As it can be seen, the total power traded in the RT market is lower than the total power traded in the DA market.

It is observed that the total power bought from the RT market decreases and the total power sold to the RT market increases by adopting a risky conservative strategy.

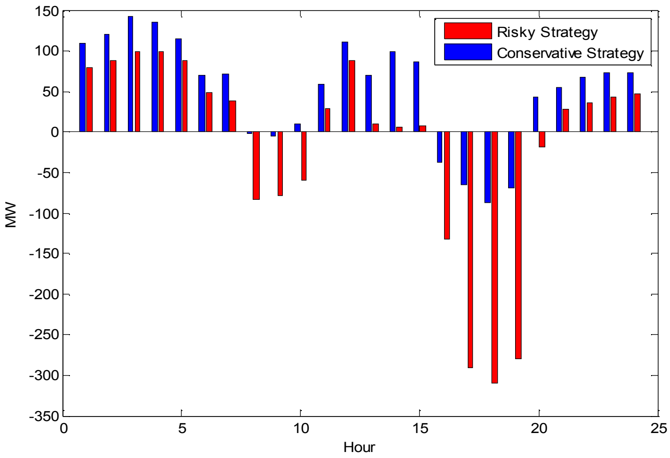

Fig. 4. Power traded in the RT market.

Additionally, a risky strategy yields the increase of total power traded in the RT market. Comparative analysis of the power traded in both markets concludes that the impacts of the risk strategy on the power traded in these two markets are in opposite direction.

C. Assessment of Effect of Bidding Strategy on the System Reliability

In this paper, the presence and bidding strategy of an EVPO in the NordPool DA and RT market is investigated. The Nord Pool markets are divided into several bidding areas. The available transmission capacity may vary and congest the flow of power between the bidding areas, and thereby different area prices are established.

Fig. 5, shows Stockholm city, the capital of Sweden (region SE3). The capacities of transmission lines between regions during the target day are indicated.

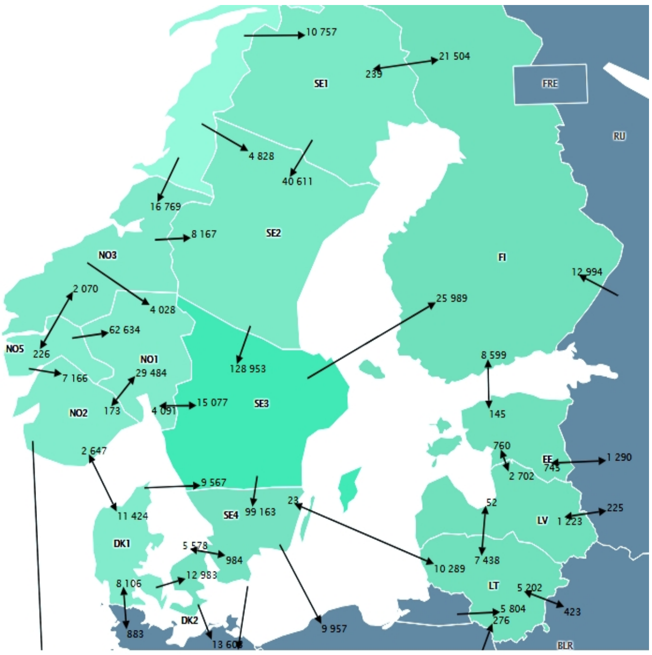

Fig. 5. Capacities of transmission lines in the region SE3 (06/02/2017).

In this section, it is assumed that due to generation constraints, planned maintenance or congestion in transmission, region SE3 is forced to function in island mode. Therefore, the effect of presence of EVP in this situation is studied.

Fig. 6, shows production and consumption power in the region SE3 in the target day. As it can be seen, production is lower than consumption during most hours. In this situation, it is necessary to apply load-shedding in order to respond to important loads. Also, in this situation the RT price increases rapidly.

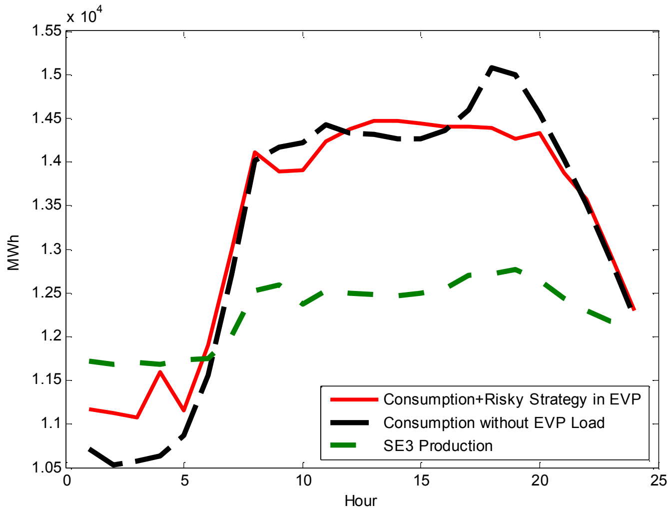

Fig. 6. Production and consumption power in the region SE3.

The existence of EVP load in the system acts as a negative load and can decrease demand requirement by selling energy to the grid.

Therefore, energy not supplied (ENS) and cost of energy not supplied (CENS) are decreased. This results have improved the system's reliability indices.

Table I, represents the values and compares the amounts of ENS and CENS indices in the case of no EVP existing in the network with two mentioned bidding strategies during the target day. Since risky strategy has the opportunity to sell more energy in high-price periods, the total utility of EVPO would be increased.

TABLE I. RELIABILITY INDICES IN THE TARGET DAY

	ENS (MWh)	CENS (Eur)
Without EVPs	28388	1066400
Conservative Strategy in the EVPs	27287	1012200
Risky Strategy in the EVPs	**27138**	**1001600**

So, adopting a risky strategy not only increases the total utility of EVPO, but also improves the system's reliability indices and daily network load characteristic when the value of parameter $\delta_h^{RT,f}$ is positive (i.e., the RT market price is higher than the DA market price).

V. CONCLUSION

In this paper, an approach to derive the optimal bidding strategy of an EVPO in both DA and RT markets based on risk appetite is proposed. The two risk strategies adopted influence the bidding, utility and power traded in the mentioned markets. The results indicate that the performance of these strategies depend on the difference between DA and RT market prices. For example, when there is a disturbance and system is forced to work in the island mode (i.e., RT prices are higher than DA prices), a risky strategy can sell more power with higher prices to the network and decreases the ENS. In this case, it will be beneficial for EVPO to buy in the DA market at low prices and then to sell energy in the RT market at high prices.

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