Optimal Coordination of Charging and Frequency Regulation for an Electric Vehicle Aggregator Using Least Square Monte-Carlo (LSMC) with Modeling of Electricity Price Uncertainty

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Abstract – Recently, many studies have suggested that an electric vehicle (EV) is one of the means for increasing the reliability of power systems in new energy environments. EVs can make a contribution to improving reliability by providing frequency regulation in power systems in which the Vehicle-to-Grid (V2G) technology has been implemented and, if economically viable, can be helpful in increasing power system reliability. This paper presents a stochastic method for optimal coordination of charging and frequency regulation decisions for an EV aggregator using the Least Square Monte-Carlo (LSMC) with modeling of electricity price uncertainty. The LSMC can be used to assess the value of options based on electricity price uncertainty in order to simultaneously optimize the scheduling of EV charging and regulation service for the EV aggregator. The results of a numerical example show that the proposed method can significantly improve the expected profits of an EV aggregator.

Keywords: Electric Vehicle, Frequency Regulation, Least Squares Monte-Carlo

1. Introduction

Increases in fuel prices and concern over environmental issues have led to alterations in the configuration of power systems. In a new energy environment, electric vehicles (EVs) are one of the means for increasing the reliability of power systems. Some studies [1-5] have demonstrated the usefulness of EVs in terms of increasing the reliability of power systems in new environments, due to the fact that like a battery, EVs can influence both supply and demand. For example, electric vehicles can improve the reliability of a power system by providing frequency regulation through implementing the Vehicle-to-Grid (V2G) technology in the power system. The electric vehicle's ability is demonstrated to provide frequency regulation services by performing real-time regulation in a practical demonstration of V2G [4].

Battery capacities of individual electric vehicles are not sufficient to satisfy participation conditions for frequency regulations set by independent system operator (ISO). Therefore, an aggregator is needed for EVs to combine individual EVs and participate in frequency regulation markets as client representatives.

In a smart grid environment, the objective of an EV aggregator is to maximize its profit by controlling EV charging for frequency regulation while simultaneously meeting customer needs for services such as maintaining battery charge levels. To achieve this dual role, coordinated strategies of EV charging and regulation service are vital. Maximization of profits for the EV aggregator requires optimal coordination of EV charging and regulation decisions using the updated real-time data such as the market clearing price.

This paper presents a stochastic method for optimal coordination of charging and frequency regulation decisions for an EV aggregator using Least Square Monte-Carlo (LSMC) [6]. The expected contribution of this method originates from the fact that it provides an algorithm for EV charging and frequency regulation decisions based on an options theory utilizing real-time market data, which allows for charging and regulation decisions that are not simply scheduled in advance for implementation during parking periods, but rather evolve dynamically based on hourly decisions. Because an EV aggregator can receive hourly price data and other electricity market-related information from ISO, the proposed method is designed to provide the basis for better, more economical EV charging solutions compared to simple prior scheduling methods. The information will help the EV aggregator to optimally coordinate scheduling decisions for EV charging and regulation service. In this paper, an LSMC simulation that can evaluate the value of options arising from electric price uncertainty is used for optimal coordination of charging and frequency regulation decisions for the EV aggregator.

The remainder of this paper is organized as follows. In Section II, technical issues relating to electric vehicle charging and frequency regulation are discussed. In Section III, a stochastic method for optimal coordination of charging

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and frequency regulation using LSMC is proposed, and in Section IV, numerical results are presented and analyzed in order to show the effectiveness of the proposed method.

2. Problem Description

The increasing growth of intermittent renewable resources in generation mix poses reliability issues for power systems. EVs, which can be used to mimic the load charging and discharging qualities of batteries, represent one possible solution to this problem. However, as the battery capacity of a single EV is too small for participation in a regulation market, an aggregator of individual EV owners is required.

The objective of this paper is to maximize the profits of an aggregator in electricity markets such as regulation market by scheduling EV charging and frequency regulation based on an evolving charging strategy.

Profits of the EV aggregator depend on three factors: price, capacity, and EV states. There are two types of price considered in this study; the real-time regulation market clearing price (RMCP) and the real-time energy market clearing price (EMCP). As these prices represent future values characterized by uncertainties in electricity demand and power system conditions, both can be modeled by means of stochastic processes. To model the uncertainties in the electricity market, various price paths can be developed using the Geometric Brownian motion (GBM) method [7], and in this study, price scenarios are generated using the GBM model.

Similarly, capacity can refer either to the regulation market participation capacity or the energy market participation capacity. In this study, it is assumed that capacity is fixed based on the performance of the charger.

In a smart grid environment, The electrical power stored in the batteries of an EV can be sold to a power system in the energy market energy market. However, as frequent large changes in the state of charge (SOC) of an EV due to electric power sales to the energy market can shorten its battery life, participation in such sales to the energy market is not considered in this paper. Based on this restriction, it is assumed that an EV can be in one of the three states during its expected plug-in time: standing-by (the state of the m-th EV at time t, i.e., $U_{m,t} = 0$); participating in the energy market for EV charging ($U_{m,t} = -1$); or participating in the regulation market for regulation service ($U_{m,t} = +1$). These three states are illustrated in Fig. 1.

Profits of the EV aggregator can be expressed as a function of price, capacity, and the EV state as follows:

$$\underset{U^i_{m,t}}{Maximize} \sum_{m=1}^{M_{t_0}} \sum_{t=t_0}^{t_m^d} \left[\left\{ P_t^{R_i} \cdot C_m^R \cdot \left(U^i_{m,t} + 1 \right) + P_t^{E_i} \cdot C_m^E \cdot \left(U^i_{m,t} - 1 \right) \right\} \cdot \frac{U^i_{m,t}}{2} \right]$$
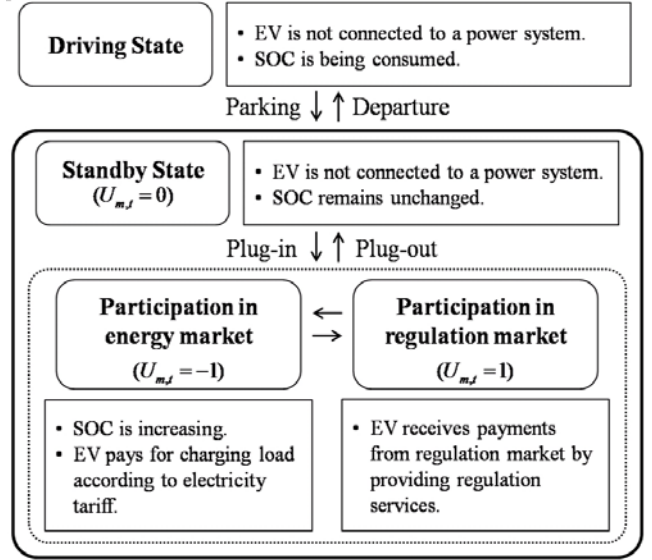
(1)

Fig. 1. States for EV

where $U^i_{m,t}$ is the state of the m-th EV at time t in the i-th scenario; t_0 is the time at which a charging or regulation strategy is implemented; M_{t_0} is the number of cars at time t_0; t_m^d is the departure time of the m-th EV; $P_t^{R_i}$ and $P_t^{E_i}$ are the RMCP and EMCP, respectively, at time t in the i-th scenario; and C_m^R and C_m^E are the regulation capacity and the battery capacity, respectively, of the m-th EV.

Eq. (1) attempts to maximize the profits of the EV aggregator that is defined as the revenue from regulation service minus the charging (or energy purchasing) cost. Eq. (1) can be more closely tailored to the purposes of this study by modifying it so that the state of the EVs at t_0 is constrained as follows:

$$\underset{U^i_{m,t_0}}{Maximize} \sum_{m=1}^{M_{t_0}} \left[\left\{ P_t^{R_i} \cdot C_m^R \cdot \left(U^i_{m,t} + 1 \right) + P_t^{E_i} \cdot C_m^E \cdot \left(U^i_{m,t} - 1 \right) \right\} \cdot \frac{U^i_{m,t}}{2} \right] + J_t^i$$

(2)

where U^i_{m,t_0} denotes the state of the m-th EV at time t_0 in the i-th scenario and J_t^i is a maximized level of profits after time t_0, which can in turn be evaluated as follows:

$$J_t^i = \underset{U^i_{m,t}}{Maximize} \sum_{m=1}^{M_{t_0+1}} \sum_{t=t_0+1}^{t_m^d} \left[\left\{ P_t^{R_i} \cdot C_m^R \cdot \left(U^i_{m,t} + 1 \right) + P_t^{E_i} \cdot C_m^E \cdot \left(U^i_{m,t} - 1 \right) \right\} \cdot \frac{U^i_{m,t}}{2} \right]$$

$$, \forall t = t_0 + 1, \cdots, t_m^d$$

(3)

Some constraints must be considered in order to determine $U^i_{m,t}$: the aggregator should charge the batteries to a target SOC, and the batteries cannot be charged above 100% SOC. These constraints can be expressed as follows:

$$SOC_m^T - SOC_{m,t_0}^i \le \sum_{t=t_0}^{t_m^d}\left(-C_m^E \cdot U_{m,t}^i\right) \le 100 - SOC_{m,t_0}^i \quad (4)$$

where SOC_m^T is the target SOC of the m-th EV, and SOC_{m,t_0}^i is the SOC of the m-th EV at time t_0 in the i-th scenario.

If the battery SOC is too high (i.e., above the criteria SOC), the EV cannot provide the V2G service and thus cannot participate in the regulation market. This condition is given as follows:

$$\left\{ U_{m,t}^i \in \{-1,+1\} \middle| SOC^C - SOC_{m,t}^i \ge 0 \right\}$$
$$\left\{ U_{m,t}^i \in \{-1,0\} \middle| SOC^C - SOC_{m,t}^i < 0 \right\} \quad (5)$$

where SOC^C is the criteria SOC.

On the other hand, if the amount of regulation is less than the minimum system regulation requirements at time t_0, the aggregator cannot participate in the regulation market and the EVs will be switched into the standby mode as follows:

$$\left\{ U_{m,t} = \{-1,0\} \middle| \sum_{m=1}^{M_t}\left(C_m^R \cdot \frac{U_{m,t}+1}{2}\right) - R^C < 0 \right\} \quad (6)$$

where R^C is the minimum regulation amount required by ISO for participation in the regulation market.

In this paper, LSMC is adopted to determine the EV charging and regulation strategy in which American Options can be exercised at any time between their purchase date and expiration date are evaluated [8], [9]. This approach can be applied to the problem of how to allocate electric vehicle charging and regulation during each interval of an exercise. For the purposes stated here, the purchase and expiration dates can be replaced by the expected plug-in times.

3. Optimal Coordination of Electric Vehicle Charging and Regulation Using LSMC

In this section, a proposed LSMC-based method for optimal coordination of charging and frequency regulation decisions is described. The proposed method consists of a stochastic price modeling component and a coordinated scheduling of charging and regulation decisions component. The first of these components involves EMCP and RMCP price-change modeling. In this approach, a GBM model, which is able to create various future price path scenarios, is adopted to derive a stochastic electricity price.

The coordinated scheduling of charging and regulation component uses LSMC to evaluate many possible charging and regulation paths based on the option theory and the probability theory.

3.1 Electricity price modeling using GBM

To determine a coordinated electric vehicle charging and regulation schedules, the aggregator needs to have the future price information. In the proposed method, the GBM model is applied to generate future EMCP and RMCP based on model parameters estimated from historical data. In the GBM model, which is the simplest and most commonly used method for price modeling in finance and economics, price volatility dP is defined as follows:

$$dP = \mu_t P dt + \sigma_t P dZ \quad (7)$$

where P represents the price, Z represents a generalized Wiener process, and μ_t and σ_t represent the mean of the past price change rates and the variance of the past price change rate at time t, respectively.

μ_t and σ_t can be defined as follows:

$$\mu_t = \frac{1}{N}\sum_{n=1}^N\left(\frac{P_{n,t+dt} - P_{n,t}}{P_{n,t}} \cdot \frac{1}{dt}\right) \quad (8)$$

$$\sigma_t = \sqrt{\frac{1}{N-1}\sum_{n=1}^N\left(\frac{P_{n,t+dt} - P_{n,t}}{P_{n,t}} - \mu_t\right)^2} \quad (9)$$

where $P_{n,t}$ and $P_{n,t+dt}$ represent the prices at times t and $t+dt$, respectively, and N represents the number of past price change rate data points.

As price cannot have a negative value and is commonly assumed to follow a log-normal distribution, Eq. (9) should be converted into a stochastic process for $d(\ln P)$. Using Ito's lemma on Eq. (9) produces:

$$\Delta P = P_{t+\Delta t} - P_t = \mu P_t \Delta t + \sigma P_t \varepsilon \sqrt{\Delta T}$$
$$\Rightarrow P_{t+\Delta t} = P_t + \mu P_t \Delta t + \sigma P_t \varepsilon \sqrt{\Delta T}, \quad \varepsilon \sim N(0,1) \quad (10)$$

where P_t represents the price at time t, and ε is the standardized normal random variable.

To obtain a $\Delta \ln P$ stochastic process, the natural logarithm can be substituted into Eq. (10) as follows:

$$\Delta \ln P = \left(\mu_t - \frac{1}{2}\sigma_t^2\right)\Delta t + \sigma_t \varepsilon \sqrt{\Delta T}, \quad \varepsilon \sim N(0,1) \quad (11)$$

where $\Delta \ln P$ represents $\Delta \ln \frac{P_{t+\Delta t}}{P_t}$.

From Eq. (11), $P_{t+\Delta t}$ can be defined as follows:

$$P_{t+\Delta t} = P_t \cdot \exp\left\{\left(\mu_t - \frac{1}{2}\sigma_t^2\right)\Delta t + \sigma_t \varepsilon \sqrt{\Delta T}\right\}, \quad \varepsilon \sim N(0,1) \quad (12)$$

Using Eq. (12) for $\Delta t = 1$, stochastic processes for EMCP and RMCP changes can be obtained as follows:

$$P_{t+1}^E = P_t^E \cdot \exp\left\{\left(\mu_t^E - \frac{1}{2}\sigma_t^{E2}\right) + \sigma_t^E \varepsilon\right\}, \quad \varepsilon \sim N(0,1) \quad (13)$$

$$P_{t+1}^R = P_t^R \cdot \exp\left\{\left(\mu_t^R - \frac{1}{2}\sigma_t^{R2}\right) + \sigma_t^R \varepsilon\right\}, \quad \varepsilon \sim N(0,1) \quad (14)$$

where P_{t+1}^E and P_{t+1}^R are the EMCP and RMCP, respectively, at time $t+1$, μ_t^E and μ_t^R are the mean of past EMCP and RMCP rates of change, respectively, at time t, and σ_t^E and σ_t^R are the variance of past EMCP and RMCP rates of change, respectively, at time t.

Based on the price points obtained in Eqs. (13) and (14), the price paths for both EMCP and RMCP can be obtained.

3.2 Evaluation of electric vehicle charging and regulation scheduling path using LSMC

A coordinated charging and regulation decisions can be made by comparing the value of joining the energy market (VJEM) with the value of joining the regulation market (VJRM) in the following time period. In this study, LSMC is applied to draw a comparison between VJEM and VJRM.

VJEM is the expected cost realizable by charging an electric vehicle during the next time period, whereas VJRM is the expected revenue from participating in the regulation market instead.

The pricing model from Section 3.1 can be used in order to calculate these two values. Based on the electricity price information, the aggregator can decide whether to participate in the energy market or to participate in the regulation market during parking time by calculating the VJEM and VJRM:

$$V_{m,t}^{E_i} = P_t^{E_i} \cdot C_m^E + J_t^i \quad (15)$$

$$V_{m,t}^{R_i} = P_t^{R_i} \cdot C_m^R + J_t^i \quad (16)$$

where V_m^E and V_m^R are the VJEM and VJRM, respectively, for the m-th electric vehicle in the i-th scenario.

In this study, the value of EV charging is estimated using the least-square method, which produces a forecast value based on the price at time t. In order to do this, model parameters should be obtained by minimizing the following residual sum of squares:

$$\sum_{i=1}^{S}\left(V_{m,t}^{R_i} - \hat{\alpha}_0 - \hat{\alpha}_1 V_{m,t}^{E_i} - \hat{\alpha}_2 V_{m,t}^{E_i 2}\right)^2 \quad (17)$$

where $\hat{\alpha}_0$, $\hat{\alpha}_1$, and $\hat{\alpha}_2$ are the estimated terms of the regression model, respectively, and i refers to the i-th generated scenario out of S total scenarios.

The charging value during the next time period is determined by comparing each estimated value, and the value of EV charging for each scenario is recalculated using the parameters obtained from Eq. (16). In i-th scenario, if VJRM is smaller than this recalculated VJEM, then the m-th electric vehicle is charged at time t_0; conversely, for recalculated VJEM smaller than VJRM, the m-th vehicle participates in the real-time regulation market at time t_0. After determining EVs state each scenario, to determine EV charging and regulation decisions, $E(V_{m,t}^R)$ and $E(V_{m,t}^E)$, which are the expected values for VJEM and VJRM at time t, are compared. $E(V_{m,t}^R)$ and $E(V_{m,t}^E)$ can be calculated as follows:

$$E\left(V_{m,t}^R\right) = \frac{1}{n_R}\sum_{i=1}^{S} s\_V_{m,t}^{R_i} \quad (18)$$

$$E\left(V_{m,t}^E\right) = \frac{1}{n_E}\sum_{i=1}^{S} s\_V_{m,t}^{E_i} \quad (19)$$

where n_R and n_E are the number of scenarios which determined participating in regulation market or energy market; $s\_V_{m,t}^{R_i}$ and $s\_V_{m,t}^{E_i}$ are the values of VJRM and VJEM determined participating in regulation market or energy market in the i-th scenario.

Based on Eqs. (18) and (19), the charging and regulation decisions for the m-th electric vehicle can be determined by comparing VJEM with VJRM at time t:

$$\left\{U_{m,t} = \left\{0, +1\right\} \,\middle|\, E\left(V_{m,t}^E\right) - E\left(V_{m,t}^R\right) \geq 0\right\}$$
$$\left\{U_{m,t} = \left\{-1, 0\right\} \,\middle|\, E\left(V_{m,t}^E\right) - E\left(V_{m,t}^R\right) < 0\right\} \quad (20)$$

3.3 Procedure of proposed method

The proposed algorithm procedure is composed of two steps: generation of price scenarios using the GBM model and determination of a charging and regulation strategy based on the expected profit from the LSMC method.

The proposed method involves the following steps:

Step 1) Prior to t_0, update information on parked EVs, RMCP, and EMCP.

Step 2) Using historical price data, calculate hourly μ_t and σ_t for the largest t_m^d from Eqs. (8) and (9).

Step 3) Generate RMCP and EMCP price scenarios from t_0 to the largest t_m^d from Eqs. (13) and (14).

Step 4) Determine a value of $U_{m,t}^i$ reflecting the constraints for each scenario.

Step 5) Using Eqs. (15) and (16), calculate VJRM and VJEM for each scenario.

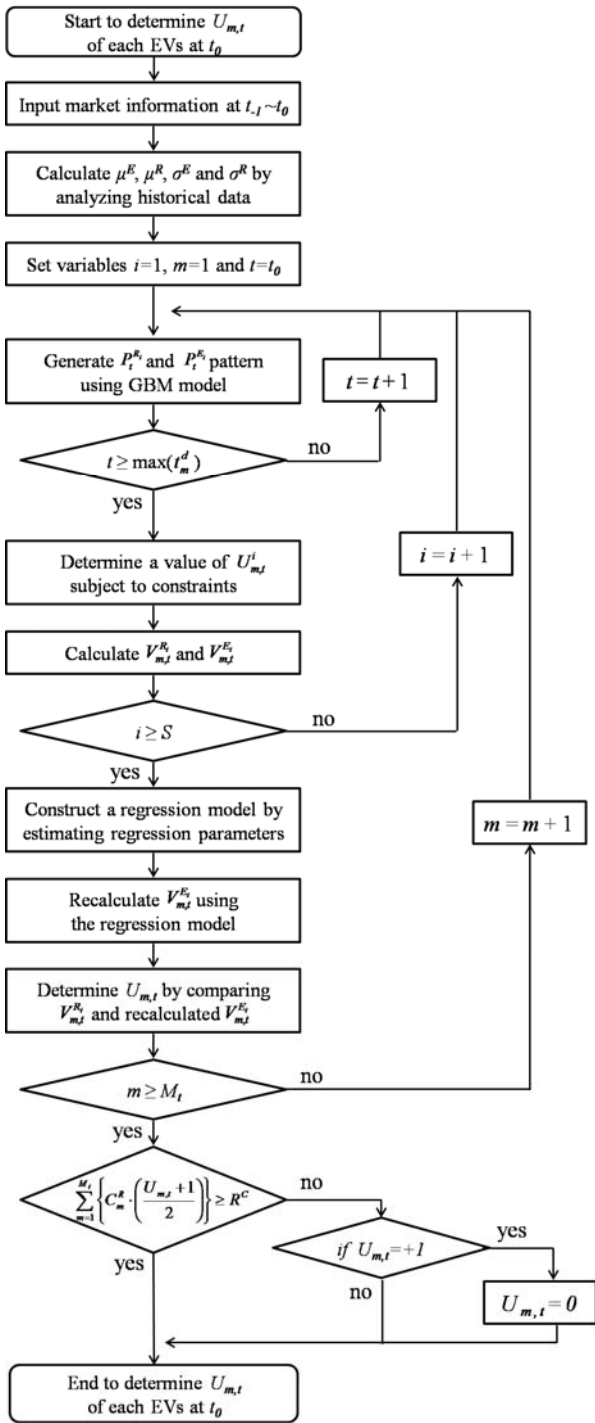Step 6) Estimate the regression constants and generate a regression model for VJRM and VJEM using Eq.

Fig. 2. Overall procedure of the proposed method

(17).

Step 7) Recalculate VJEM using the regression model.
Step 8) Using Eqs. (18-19), determine a value for U_{m,t_0} by comparing VJRM and the recalculated VJEM.
Step 9) Using Eq. (20), verify whether this solution satisfies the minimum requirements for participating in the regulation market.
Step 10) Decide upon a charging and regulation strategies for each EV at t_0.

The overall procedure of proposed algorithm is illustrated in Fig. 2.

4. Numerical Results

In this section, the numerical results are presented to demonstrate the performance of the proposed method. There are some assumptions made for these case studies, including (i) the aggregator runs a parking lot with 1,500 single spaces for electric vehicles; (ii) the EV battery type is Li-Pb with two capacities, i.e., 16 and 24 kWh; and (iii) the EV fleet is assumed to be broken down equally in terms of battery capacity. The regulation capacity is assumed to be 6.6 kWh; a battery can charge up to 3.3 kWh per hour; and the target SOC of all EVs is assumed to be 80%. The vehicle parking schedule is summarized in Table 1.

Based on these parameters, 10,000 MC simulations were then conducted. Historical price data for EMCP and RMCP during February to March 2012 were obtained from PJM [10] in order to generate values of μ_t and σ_t for a simulation day (March 31, 2012).

In the numerical example, the proposed method is compared with baseline method and deterministic charging method to demonstrate the effectiveness of the proposed method. Baseline method attempts to start charging EVs as soon as they are parked in the lot following charging of the target. On the other hand, deterministic charging method is designed to determine charging schedules of EVs based on estimated values of EMCP and RMCP for the simulation day generated by averaging historical price data for EMCP and RMCP over a past week.

The profit of the aggregator at time t, (Ω_t), can be expressed as follows:

$$\Omega_t = \sum_{m=1}^{M_t}\left[\left\{P_t^R \cdot C_m^R \cdot \left(U_{m,t}+1\right) + P_t^E \cdot C_m^E \cdot \left(U_{m,t}-1\right)\right\} \cdot \frac{U_{m,t}}{2}\right]$$

(21)

Table 1. Number of EVs in the parking time

Initial SOC	1h~19h		8h~19h		8h~24h	
	16 kWh	24 kWh	16 kWh	24 kWh	16 kWh	24 kWh
20%	50	50	150	150	50	50
30%	50	50	150	150	50	50

Table 2. The profit based on the each charging method during hours 8-19

Capacity (kWh)	Initial SOC (%)	The number of EVs	Baseline method ($)	Deterministic charging method($)	Proposed method ($)
16	20	150	98.3	98.8	98.7
	30	150	98.3	98.8	98.7
24	20	150	58.3	58.8	64.6
	30	150	78.3	78.9	84.7
Total		600	333.3	335.2	346.8

From the results obtained from the case studies, the profits of the aggregator are \$727.39/day and \$737.21/day, respectively, using the baseline method and the deterministic charging method. On the other hand, the profit of the aggregator is \$763.31/day using the proposed method. The profit results based on the EV characteristics from Table 1 during hours 8-19 are shown in Table 2.

It can be seen from Table 2 that the average difference in profit between the proposed method and the baseline method are 4.04%. It can be also observed from Table 2 that the average difference in profit between the proposed method and the deterministic charging method are 3.46%. The difference in profit is particularly pronounced at 24 kWh. Table 3 and Figs. 3, 4 and 5 show a comparison of the charging and regulation strategies for 501st EV (24-kWh-EV) obtained by the proposed method and the other methods. It is assumed that the initial EV SOC is 20%, and the parking time is from 8:00 to 19:00.

For the baseline method, charging was done five times at the beginning of parking, and after 13:00, the EV participated in the regulation market. For the deterministic charging method, charging decision was made according to charging schedules determined based on estimated values of EMCP and RMCP for the simulation day generated by averaging historical price data for EMCP and RMCP over the past week before the simulation day. Using the proposed method, the EV was charged from 12:00-14:00 and again from 18:00-19:00 and participated in the regulation market for the rest of the time.

Fig. 3 shows results of charging for 501st EV (24-kWh-EV) by baseline method. It can be seen from Fig. 3 that

Table 3. Results of charging and regulation strategies U_t for 501st EV (24-kWh-EV) from 8:00 to 19:00.

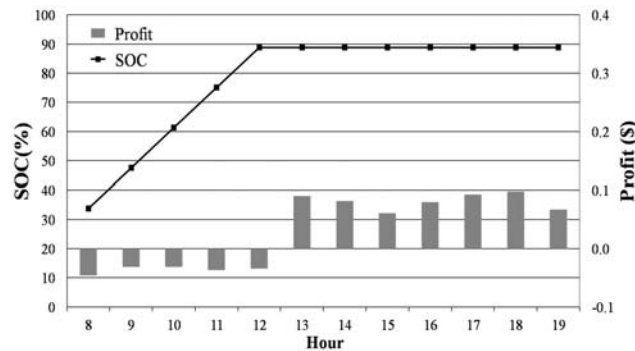| Time	8	9	10	11	12	13	14	15	16	17	18	19
Baseline method	-1	-1	-1	-1	-1	+1	+1	+1	+1	+1	+1	+1
Deterministic method	+1	+1	+1	-1	-1	+1	-1	+1	+1	-1	-1	+1
Proposed method	+1	+1	+1	+1	-1	-1	-1	+1	+1	+1	-1	-1

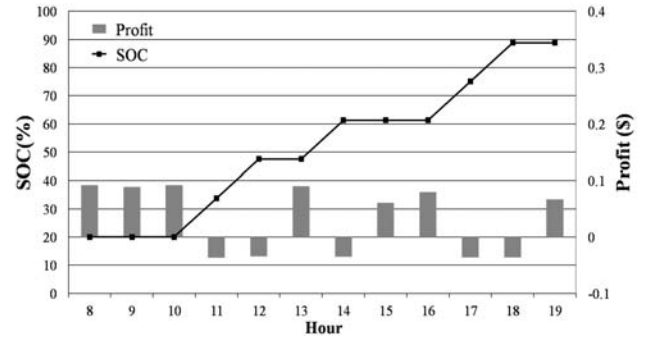**Fig. 3.** Result of charging for 501st EV (24-kWh-EV) by baseline method

Fig. 4. Result of charging for 501st EV (24-kWh-EV) by deterministic charging method
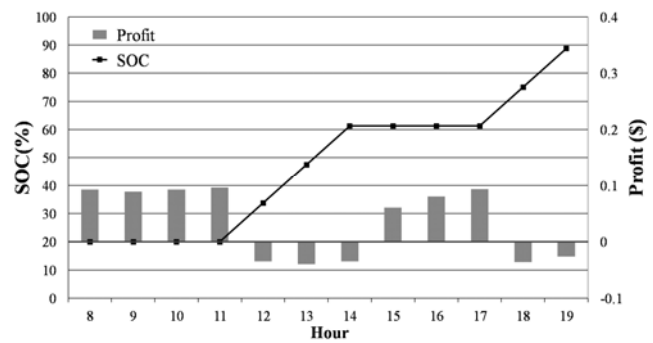
Fig. 5. Result of charging for 501st EV (24-kWh-EV) by proposed method

owing to participation in the energy market, net expense occurs and the SOC increases from 8:00 to 12:00. After reaching its target SOC, the EV earns income by participating in the regulation market. Fig. 4 shows results of charging for 501st EV (24-kWh-EV) by the deterministic charging method. On the other hand, Fig. 5 shows results of charging for 501st EV (24-kWh-EV) by the proposed method. It can be observed from Fig. 5 that charging and regulation strategies are followed in order to maximize the profit of the aggregator during every time interval. A charging decision is taken at 17:00, after which the EV starts charging its battery to satisfy the target SOC for the remaining time.

5. Conclusion

The electric vehicles can contribute to improved reliability of power systems by providing frequency regulation services. In this paper, a stochastic method for optimal coordination of charging and frequency regulation decisions for an EV aggregator that adopts an interdisciplinary approach to addressing power system problems caused by the complex interactions between engineering and economics was developed and described.

The LSMC approach was adopted to solve these problems by determining the coordinated schedules of

electric vehicle charging and regulation through evaluation of options based on the electricity price uncertainty.

Acknowledgements

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