Bounds for Optimal Control of a Regional Plug-In Electric Vehicle Charging Station System

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***Abstract*— In order to support the increasing penetration of plug-in electric vehicle (PEV) users, a novel regional PEV charging station system with DC level 3 fast charging is proposed in this paper. To promote sustainable energy, the proposed system is designed to be equipped with a distributed energy storage system charged by wind generation, solar PV generation, and electricity from the power grid, which can simultaneously charge multiple PEVs. The objective of the proposed system is to minimize operational cost. Wind/solar PV generation and electricity market price are input state variables in this problem and are predicted by support vector regression (SVR). The uncertainties of the SVR models are analyzed using a Martingale Model Forecast Evolution (MMFE). Finally, bounds of the optimal operational cost in this problem are evaluated with two stochastic measures, which can be solved using the expected value problem and the wait-and-see solution. Bounds from experiments simulating models of the Dallas-Fort Worth metroplex show that the largest uncertainty in the system occurs during weekdays in the summer.**

***Index Terms*—PEV Charging infrastructure, DC fast charging, Stochastic measures, Expected value problem, Wait-and-see solution.**

I. Introduction

Industrialization, modernization, and population growth have created an increased demand for energy and environmental concerns over greenhouse gas (GHG) emissions, global warming, and climate change. Considering increased demand and environmental concerns, considerable attention has been paid to investigating solutions for these two critical issues in many end-use sectors.

As an evolving remedy for both energy supply and environmental problems, a fundamental transformation in the transportation sector from conventional oil-based vehicles to electrical powered ones has been proposed and is being implemented. The Plug-in Electric Vehicle (PEV), one type of electric vehicle, is currently being promoted in the United States, and the number of PEVs is expected to be more than one million vehicles in the U.S. by 2017 based on the projection from the ISO/RTO Council (IRC) [1].

To encourage the acceptance and increase penetration of PEVs, PEV users must be able to drive their cars without suffering from range anxiety. A well-planned charging infrastructure plays a critical role in serving this purpose. Over the past few years, charging infrastructure development has been studied in various research areas.

In the existing literature, optimal PEV charging profiles have been widely proposed. For example, they have been presented in [2-5] considering charging behavior from demographical statistical data, cost minimization for PEV customers, and a stochastic algorithm from vehicle usage data. In addition to optimal PEV charging profiles, minimizing power losses and maximizing main grid load factor in residential distribution systems, where PEV charging stations are presented, have been studied in [6]. A study in [2] has indicated that a well-developed charging infrastructure helps reduce stress on the residential distribution system.

Furthermore, many researchers have developed models for coordinated PEV charging systems for different purposes, such as improving power utilization, avoiding overload in the utility grid, smoothing real-time power fluctuation in a regulation services, and using them with a decentralized system [7-10]. In order to improve sustainable energy in charging station systems, wind or solar PV generation has been used as one type of important energy resources in charging stations [11-13].

Although, these studies have proposed various effective approaches for developing PEV charging infrastructure, these proposed PEV charging stations are designed with level 1 or level 2 charging systems, which are not suitable for a public charging station. In addition, multiple renewable energy resources, which can simultaneously supply PEV demand, have not been considered in these PEV charging stations.

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Therefore, this paper presents a novel regional PEV charging station system to serve PEV demand with DC level 3 fast charging, which can fully charge a vehicle in minutes. Electricity resources of this charging station system can be simultaneously supplied by wind, solar power, and the utility grid. To control the proposed regional PEV charging station system efficiently, this paper studies the bounds of optimal charge control for maximizing profit of this charging system. To determine these control bounds, a stochastic simulation is developed using forecasting models [14] with a Martingale Model of Forecast Evolution [15].

The remainder of this paper is organized as follows. Background and contributions of this study are presented in section II. Then, details of a novel regional PEV charging station system, and the problem formulation for maximizing its profit are proposed in sections III and IV, respectively. Next, forecasting methods for wind/solar power and electricity price for the proposed charging station system are described in section V. Section VI describes the stochastic control process and calculating objectives bounds. Finally, sections VII and VIII describe a case study to illustrate the proposed approach and conclusions, respectively.

II. Background And Contributions

In this section, the bounds for the optimal control problem are briefly described. Next, the background of the optimal bounds in various applications is explained in the literature review. Finally, the paper contributions corresponding to the optimal bounds in regional PEV charging stations are discussed.

A. Bounds for Optimal Control

Lower and upper bounds for the stochastic control problem can be obtained by solving the expected value problem, and the wait-and-see solution as described in [16]. In this paper, the difference between these two bounds for the optimization problem is defined as the *stochastic gap*.

Below is a summary of the expected value problem and the wait-and-see solution. Given a stochastic optimization problem as shown in (1), the *expected value problem* (*EV*) or the mean value problem is given by replacing all random variables (ξ) with the expected value $\bar{\xi} = E(\xi)$ as shown in (2). Using an optimal solution $\bar{x}(\bar{\xi})$ to the expected value problem, the expected result of the expected value problem (EEV) is given in (3). EEV is an upper bound on the objective value of (1).

$$\min_x E_\xi(z(x,\xi)) \tag{1}$$

$$EV = \min_x z(x,\bar{\xi}) \tag{2}$$

$$EEV = E_\xi(z(\bar{x},(\bar{\xi}),\xi)) \tag{3}$$

In addition, the wait-and-see solution can be used to find a lower bound on the stochastic optimization problem in (1). In the wait-and-see solution, the decision maker can wait until the uncertainty is resolved. Specifically, the objective value $z(\bar{x}(\xi),\xi)$ is computed based on solutions with perfect information $\bar{x}(\xi)$, so the wait-and-see solution (*WS*) can be calculated by (4).

$$WS = E_\xi z(\bar{x}(\xi),\xi) \tag{4}$$

The stochastic gap (*SG*) is defined as the difference between the bounds *EEV* and *WS* for an optimal control problem, which can be calculated by (5).

$$SG = EEV - WS \tag{5}$$

B. Literature Review

Stochastic optimization has been adopted to solve many problems. Wait-and see solutions have been studied to obtain lower bounds in cost minimizing problems such as economic load dispatching with a system of wind and thermal turbines, generation and transmission expansion under risk, and two-stage adjustable optimization for unit commitment under uncertainty [17-19]. However, these studies have not yet focused on optimal bounds for their applications.

Optimal bounds have been evaluated by confidence level percentages for transmission planning models and integration of wind power into unit commitment with dependent loads and wind forecasts considering prediction uncertainties [20, 21]. Although optimal bounds can be verified by the confidence levels in these two studies, these bounds depend on adjustable confidence levels based on experiential consideration.

Both the expected value problem and the wait-and-see solution have been proposed to evaluate optimal bounds as a simple implementable paradigm [22]. To analyze the optimal bounds corresponding to uncertainties, cost minimization including investment, expected operation, and reactive load shedding costs for reactive power planning under contingencies has been studied [23]. The expected value problem and wait-and-see solutions have been used as optimal bounds for the minimum operational cost of power scheduling in a micro-grid [24]. However, this is the first paper to study optimal bounds for controlling a regional PEV charging station system. The bounds provide maximum and minimum operational costs in various scenarios, which PEV charging station operators can consider in their financial planning.

C. Contributions

The contributions of this paper are highlighted below.

1) Forecasts for electricity market price and solar radiation were presented in [14] and [32], respectively. However, this research develops SVR models for both wind and solar PV energy. In addition, a Martingale Model Forecast Evolution (MMFE), is adopted to model the uncertainty of these forecasting models.

2) A stochastic optimization formulation for optimal control of a PEV charging station system was presented in [25]. In this research, an optimal decision making process based upon this formulation and the aforementioned SVR and MMFE models is developed and simulated.

3) Bounds and the stochastic gap for the aforementioned proposed optimal control process are presented using the expected value problem and the wait-and-see solution.

4) Experiments analyzing the stochastic gap in the Dallas-Fort Worth metroplex (DFW) are presented. The results show that the largest gaps occur during summer weekdays when errors in market price forecasts are highest.

III. Control of The Regional PEV Charging Station System

The concept of the regional PEV charging station system and the stochastic programming formulation were already proposed in [25], which can be briefly described as follows.

A. Regional PEV Charging Station System

Current public charging stations rarely consider the installation of energy storage systems or the integration of renewable energy resources. This is because these charging stations are small and local due to the current low PEV demand. However, to support the increasing number of PEV users and to promote sustainable energy, the proposed PEV charging station is designed to be equipped with a distributed energy storage system charged by wind/solar PV generation and electricity from the power grid, which can simultaneously charge multiple PEVs.

The proposed distributed energy storage system is used as a buffer for the charging station to alleviate the load strain due to a high number of PEVs charging, which can reduce the need for distribution upgrade if the charging stations have an insufficient renewable energy supply. In addition, the proposed system can be used to mitigate the mismatch between renewable energy resources and the PEVs' demand by storing excessive wind/solar energy for future demand arriving at the station. Finally and very importantly, these proposed systems enable the charging station to participate in the deregulated market.

The participation of a PEV charging station in the deregulated market highlights the benefit of wind and solar energy as well as distributed energy storage systems with optimal operational strategies. However, the way the charging station operates should be determined from a regional point of view to achieve optimization of the above benefits. In addition, one charging station is insufficient to serve all of the PEV users throughout a metro area. Hence, the configuration of a regional PEV charging station system with *n* stations is proposed as shown in Fig. 1.

According to Fig. 1, all of the electricity from various sources is able to be directly used for charging PEVs, and the surplus can be either stored in the battery or sold back to the power grid. When a PEV arrives at the station, its demands can be served from both the direct charge and the battery storage. As proposed in this design, optimization can be achieved with optimal operation strategies, which highly depend on the available wind/PV energy and the power market price at each charging station location

The regional PEV charging station system should be established in the metro area. DFW, under the jurisdiction of the Electric Reliability Council of Texas (ERCOT), is selected for the case study in this paper. The charging stations are designed to be built near power nodes, which can serve as a Point of Interconnection (POI) of DC fast charging to the power grid. The power nodes in the DFW area are represented by red circles in Fig. 2. There are 26 power nodes in 11 clusters. The nodal market prices may be different at different clusters but are similar inside each cluster.

Since wind farms do not have to be at charging stations, this study uses the term *virtual wind farm* to describe the arrangement of purchasing power from a remote wind farm. Though it is located in a different market, a wind farm in Oklahoma with a 74.25 MW installation capacity is selected for the wind energy resource in this study. The algorithm proposed in this research is testable because the necessary wind power and wind speed data from this wind farm are available.

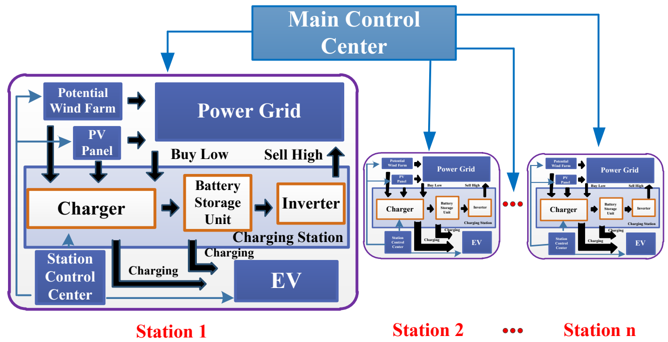

Fig. 1. Configuration of PEV charging stations

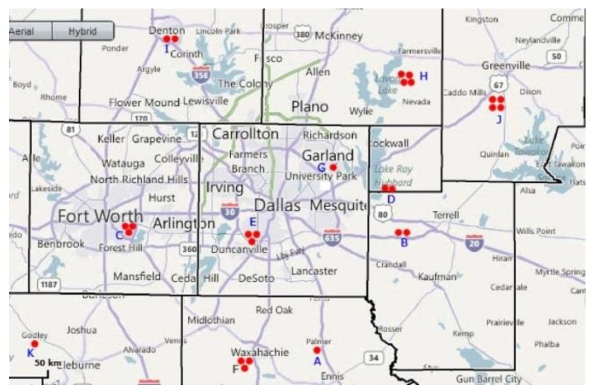

Fig. 2. Power nodes in DFW area

Moreover, it is assumed that roof-topped solar PV panels are installed on charging stations and supply part of the PEV energy demand in this study. As the highest efficiency option among all of the available PV technologies, the single crystalline PV module is selected for evaluating the PV generation. NREL has recorded the solar radiation data for several locations in the DFW area [26]. However, the PV generation calculated with this solar radiation data from these different locations is similar throughout the DFW metroplex. Therefore, solar radiation data at only the Dallas Redbird airport site are selected to calculate the PV generation with a single crystalline silicon panel. The panels have a 180 m^2 installation area (10 charging slots for one charging station) and 24.4% conversion efficiency [27], yielding the maximum power output profile of 33.82 kW.

B. Problem Formulation

Based on the variation of electricity price in the deregulated market, this regional PEV charging station stochastic programming problem can be formulated similar to the load control and demand response problems proposed in [28, 29]. The system is defined by a set of state variables that includes the battery (inventory) levels and the uncertain forecasts (random variables represented with tildes) for the market price of energy, solar production of each station, the total wind purchased from a remote wind farm to the system, and the total demand of each station. An operational cost is obtained when the system makes a decision, and then the system experiences a transition to the next stage. Electricity sold back to the grid from the battery and direct charge, electricity purchased from the grid, demand satisfied by the battery and direct charge, battery charging level, and wind allocation fraction among charging stations are the decision variables in this problem. The stochastic programming formulation can be briefly described as follows.

As shown in (6), the objective is to minimize operational cost, which is the cost of buying from the grid minus the revenue from selling back to the grid and charging the PEV both from the battery and the direct charge across all the stations.

$$\min \sum_{t\in T}\sum_{j\in J}\left(\widetilde{P}_t g_{tj}^{+} - \widetilde{P}_t (g_{tj}^{-} + R_{tj})\right) - r_t \widetilde{D}_{tj} \tag{6}$$

where $\widetilde{P}_t$ is the market buying/selling price of energy in time period t, g_{tj}^{+} is the electricity bought from the grid by station j in time period t, g_{tj}^{-} is the electricity sold back to the grid from the direct charge of station j in time period t, R_{tj} is the electricity sold back to the grid from the battery of station j in time period t, and $\widetilde{D}_{tj}$ is the total demand in time period t at charging station j. Although the total demand is modeled in this stochastic optimization formulation as a random variable, this study assumes it is deterministic, since it is usually considerably less uncertain than market price and wind/PV generation due to the volatile price scenarios in deregulated market and the intermittence characteristics of Wind/PV generation.

The set of energy balance constraints include the battery level transition as (7), the energy balance for the battery charge as (8), and the total demand in charging stations as (9).

$$I_{t,j} = I_{(t-1),j} + BC_{tj} - \frac{R_{tj}}{e_j} - \frac{D_{tj}^{2}}{e_j} \quad \forall j \in J, \forall t \in T \tag{7}$$

$$BC_{tj} = \widetilde{W}_t W_{tj} + \widetilde{S}_{tj} + g_{tj}^{+} - g_{tj}^{-} - D_{tj}^{1} \quad \forall j \in J, \forall t \in T \tag{8}$$

$$\widetilde{D}_{tj} = D_{tj}^{1} + D_{tj}^{2} \qquad \forall j \in J, \forall t \in T \tag{9}$$

where I_{tj} is the battery level of station j at the beginning of time period t, BC_{tj} is the battery charge of station j in time period t, D_{tj}^{2} is the demand satisfied by the battery of station j in time period t, and e_j is the storage efficiency of station j. In the computational experiments in section VI, the energy storage system efficiency e_j is assumed to be 79.8%. W_{tj} is the fraction of wind allocated to station j in time period t, $\widetilde{W}_t$ is the total wind purchased in time period t, $\widetilde{S}_{tj}$ is the solar production of station j in time period t, D_{tj}^{1} is the demand satisfied by the direct charge of station j in time period t.

The set of battery constraints consists of energy storage efficiency corresponding to discharge rate dc, the upper limit of battery charge (cr), and the battery level boundary between the minimum battery level (l_j) and the battery capacity (u_j) for each station, as (10), (11), and (12), respectively.

$$R_{tj} + D_{tj}^{2} \le dc * e_j \qquad \forall j \in J, \forall t \in T \tag{10}$$

$$BC_{tj} \le cr \qquad \forall j \in J, \forall t \in T \tag{11}$$

$$l_j \le I_{tj} \le u_j \quad \forall j \in J, \forall t \in T \tag{12}$$

The constraints in (13) are formulated to ensure the fraction of wind allocation among the stations sums to one. Finally, equation (14) provides the set of nonnegative constraints.

$$\sum_{j\in J} W_{tj} = 1 \; \forall t \in T \tag{13}$$

$$I_{tj}, W_{tj}, g_{tj}^{+}, g_{tj}^{-}, BC_{tj}, R_{tj}, D_{tj}^{1}, D_{tj}^{2} \ge 0 \quad \forall j \in J, \forall t \in T \tag{14}$$

IV. Forecasting Methods and Forecast Uncertainty Analysis

To represent the uncertainty of the system, it is simulated using forecasting models of wind/PV generation and power market prices, where the forecast errors are evolved using MMFE. These are among the critical input state variables discussed in the previous section. With more accurate predictions, the system control can efficiently optimize the operation of the proposed system of regional PEV charging stations. Due to the 15-minute settlement interval in the ERCOT deregulated market, all of the predictions are performed in the 15-minute ahead time period. The wind/PV generation and market price forecasting used in this paper are discussed as below. For a detailed description of the forecasting of these state variables, see the author's Ph.D. dissertation [30].

A. Wind Generation Forecasting

In order to accurately forecast wind generation, support vector regression (SVR) is used in this study. Wind generation, wind speed, and potential weather parameters including gusty wind, wind direction, and temperature are taken into consideration as the input parameters of the proposed SVR model. Wind power and wind speed data are from a wind farm website, and potential weather data are from the National Climate Data Center (NCDC) website [31].

After evaluating the prediction accuracy of many possible SVR models using the wind power data from the wind farm in Oklahoma, the most accurate SVR model includes only three predictor variables. These three predictor variables are the wind power 15 minutes before the prediction period, the wind power 30 minutes before the period, and the wind speed 15 minutes before the period.

B. PV Generation Forecasting

SVR is also adopted to predict PV generation in this study. Historical PV generation, humidity, temperature, cloud rating, wind speed, and the previous day of sunshine are taken into consideration for the predictors [32]. PV generation is calculated from solar radiation at Dallas Redbird airport. Other potential weather data can be extracted from NREL [26].

As with wind generation prediction, many SVR models for predicting PV generation were considered. Of these SVR models, the most accurate model uses the following three predictor variables: PV generation 15 minutes prior the prediction period, PV generation 30 minutes before the period, and the previous day of sunshine.

C. Market Price Forecasting

This study uses the forecasting model in [14] to predict prices in the deregulated market. There are two stages for this hybrid market price forecasting model including support vector classification for predicting spikes market prices and SVR for estimating the magnitude of market prices.

The model of historical market price and load profile at 15 and 30 minutes before the prediction time yields the best results for spike price occurrence prediction. As for the non-spike price magnitude prediction, the model with historical market price, temperature, and load profile at 15 and 30 minutes before the prediction time gives the most accurate results. The best spike price magnitude prediction performance model is the model of historical market price at 15, 30, and 45 minutes, as well as load profile at 15 and 30 minutes before the prediction time, respectively. The results from the proposed method show significant improvement over typical approaches and give similar accuracy results for all 11 power nodes in the DFW metroplex.

D. Forecast Uncertainty Analysis

The aforementioned SVR models for predicting wind/solar PV generation and electricity market price include uncertainty, which must be considered in the optimal control process. In this research, the uncertainties of the forecasts are modeled using MMFE. MMFE employs the multivariate normal distribution with an empirically derived variance-covariance (VCV) matrix. To calibrate MMFE for this system, actual forecast errors were calculated by applying the SVR forecasting models to real data. In theory, a single high-dimensional MMFE model could be constructed to incorporate forecast errors for wind, PV, and market price simultaneously. However, a correlation analysis identified little correlation between these three types of forecast errors; thus, allowing the MMFE models for wind, PV, and market price to be separately constructed.

Principal component analysis is used to obtain eigenvalues, $\lambda_1, \ldots, \lambda_n$, and eigenvectors, $v_1, \ldots, v_n$, of the VCV matrix of the forecast errors to construct diagonal matrix Λ and matrix V defined by (15)-(16):

$$\Lambda = (\lambda_1, \lambda_2, \ldots \lambda_n) \tag{15}$$

$$V = (v_1, v_2, \ldots v_n) \tag{16}$$

Then, the multivariate coefficient matrix $C = [C_1, C_2, \ldots, C_n]$ is calculated by (17), such that CC' is the VCV matrix:

$$C = V\Lambda^{1/2} = [v_1\sqrt{\lambda_1}, v_2\sqrt{\lambda_2}, \ldots, v_n\sqrt{\lambda_n}] \tag{17}$$

The distribution of the log normal function of these actual errors was analyzed using ARENA [33], and the normal distribution function was found to fit reasonably well. Hence, for each MMFE model, the forecast error vector ε at time period t can be characterized using (18).

$$\varepsilon_t = C_1 Z_1 + C_2 Z_2 + \ldots + C_n Z_n + \mu_{\varepsilon_t} \tag{18}$$

where $C = [C_1, C_2, \ldots, C_n]$ are from the coefficients from (17), $Z = [Z_1, Z_2, \ldots Z_n]$ is a vector of independent standard normal random variables, and μ_{ε_t} is the mean value of ε_t.

As an example, the MMFE model for the uncertainty of the PV SVR model is briefly described as follows. It is assumed that the number of time-ahead forecast predictions is the same as the number of 15-minute time lags of the best performing predictive model proposed in the previous section. The best performing predictive model for PV generation has two-time lags, so the corresponding MMFE model will employ two time-ahead forecast predictions. Therefore, the dimension of the actual forecast error matrix for PV generation prediction is 2×1. Hence, the V, Λ, and C matrices for PV generation prediction as well as an example generated ε_t matrix are given by

$$\Lambda = \begin{bmatrix} 0.004579 & 0 \\ 0 & 0.016638 \end{bmatrix} \quad V = \begin{bmatrix} -0.99863 & -0.05232 \\ -0.05232 & 0.99863 \end{bmatrix}$$

$$C = \begin{bmatrix} -0.06758 & -0.00675 \\ -0.00354 & 0.12881 \end{bmatrix} \quad \varepsilon_t = \begin{bmatrix} 0.99 & 1.04 \\ 0.98 & 1.05 \end{bmatrix}$$

V. Stochastic Control Process and Stochastic Measures

The stochastic programming formulation (6)-(14) is described and the expected value problem (EV) is solved and analyzed in [25]. However, [25] does not discuss practical implementation of EV or the stochastic control process. In this study, the stochastic control process of a regional PEV charging station system is developed and shown in Fig. 3.

According to Fig. 3, the initial storage capacity are set at 20% of maximum capacity at t=1. Next, three predictions of wind/PV generation and market price are calculated from t=1 until t=T using the proposed prediction methods in section V. Then, initial decision variables consisting of BC_{tj}^*, W_{tj}^*, D_{tj}^{1*}, D_{tj}^{2*}, I_{tj}^*, and R_{tj}^*, as well as initially planned values for g_{tj}^{+*} and g_{tj}^{-*} that satisfy constraints (7)-(14) in section IV, are obtained. In addition, the energy storage capacities at each charging station for the next time period are updated.

After sampling values for wind/PV generation using SVR and MMFE, the control process considers a two-case recourse function, which is used to practically adjust optimal decision variables, g_{tj}^+ and g_{tj}^- as shown in (19) and (20).

$$\text{if} \quad \tilde{w}_t W_{tj}^* + \tilde{s}_{tj} > E[\tilde{W}_t]W_{tj}^* + E[\tilde{S}_{tj}]$$
$$g_t^- = \tilde{w}_t W_{tj}^* + \tilde{s}_{tj} - E[\tilde{W}_t]W_{tj}^* - E[\tilde{S}_{tj}] + g_{tj}^{-*}, \tag{19}$$
$$\text{and} \quad g_t^+ = g_t^{+*}$$

$$\text{if} \quad \tilde{w}_t W_{tj}^* + \tilde{s}_{tj} \le E[\tilde{W}_t]W_{tj}^* + E[\tilde{S}_{tj}]$$
$$g_t^+ = E[\tilde{W}_t]W_{tj}^* + E[\tilde{S}_{tj}] - \tilde{w}_t W_{tj}^* - \tilde{s}_{tj} + g_{tj}^{+*}, \tag{20}$$
$$\text{and} \quad g_t^- = g_t^{-*}$$

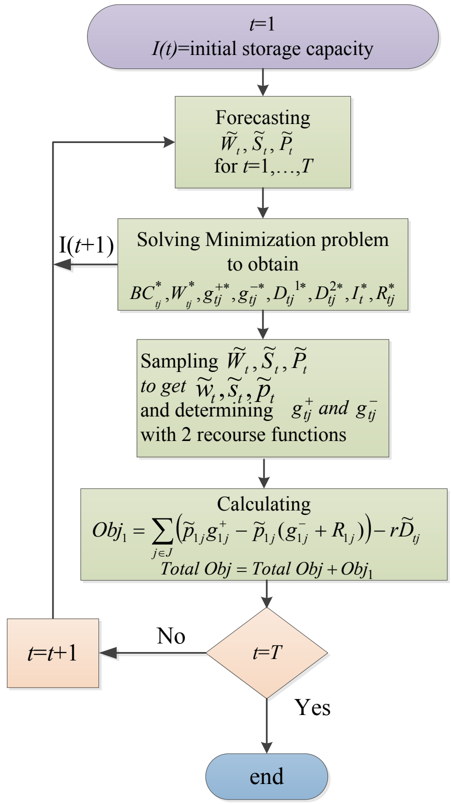

Fig. 3. Expected Value Problem process

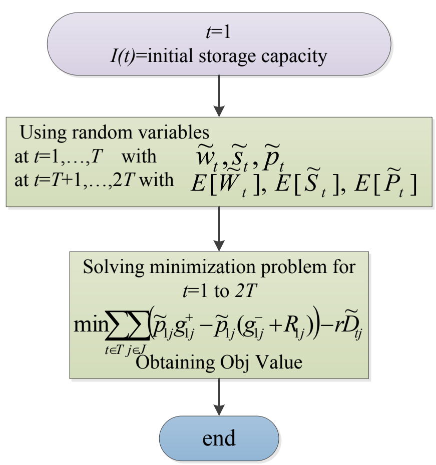

Fig. 4. Wait-and-See process

Next, the objective value at t can be calculated with adjusted decision values of g_t^+ and g_t^- from the above recourse functions and a sample of market price based on forecast uncertainty analysis using SVR and MMFE. In this study, this process is performed iteratively for t=1… T, where T= 96, which is 24 hours in simulation time.

By implementing this proposed stochastic optimal control process, the bound for optimal control by (5) can be calculated by two stochastic measures discussed as follows.

A. Expected Value Problem

As shown in (1), the expected result of the expected value problem (EEV) can be determined by simulating the abovementioned stochastic control process as depicted in Fig.3 in which initial decisions are made by replacing all random variables with the expected values from the forecasts at each time period t. Then, the cost minimization problem (6)-(14) can be solved. Simulating the control process using the expected value problem to make decisions over multiple scenarios and averaging the objective yields an upper bound on the objective of the stochastic optimal control process.

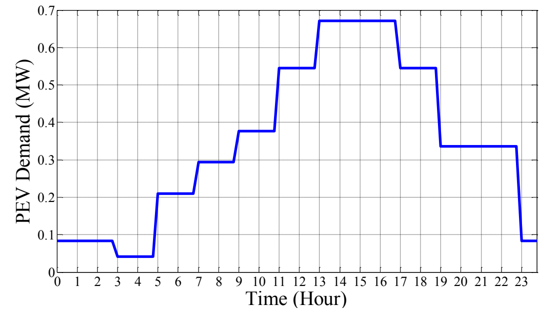

Fig. 5. PEV demand

However, there is an additional accounting issue when comparing EEV to the wait-and-see solution. As mentioned previously, the control process is performed iteratively over 96 15-minutes periods, and the total objective value is calculated over these 96 periods. However, decisions are made based upon the forecasts of periods 96 to 191. Similarly, the wait-and-see solution must also consider forecasts of these periods. In order to account for the second day of the horizon, an additional expected problem for periods t=97 to t=192 is added to EEV.

B. Wait-and-See Solution

Fig. 4 illustrates how the wait-and-see solution of the proposed regional PEV charging station system is estimated. First, scenarios of wind/solar PV and market price values are determined. Then, the cost minimization problem (6)-(14) is solved from t=1 to t=2T to obtain the objective value using perfect information of each scenario. These objective values are averaged to obtain a wait-see-solution, which is a lower bound on the objective of the stochastic optimal control process.

VI. Case Study and Results

To evaluate the proposed methods efficiently, the simulation of the *EEV* and *WS* are performed with 10 scenarios in four seasons for both weekday (WD) and weekend (WE) data of wind/PV generation and market prices. As proposed in [34], this paper uses the projected PEV demand in 2015 for 4 preliminary charging locations, which are designed to be built in the Fort Worth, Dallas, Garland, and Denton areas. The total PEV demand for 15-minute period is shown in Fig. 5. The comparison of averaged objective values for all cases, operational cost of regional PEV charging stations, for the *EEV* and *WS* are reported in Table I.

According to Table I, two significant points can be observed from the simulation results. As depicted in Fig. 6, the low values of operational costs (high negative values) of *EEV/WS* come from high foreseen market price fluctuations which can be calculated by (21).

$$P_{Fluctuation} = \frac{P_{\max} - P_{\min}}{P_{\min}} \times 100\ \% \quad (21)$$

where $P_{\max}$ is a maximum market price during operation times. $P_{\min}$ is a minimum market price during operation times. Meanwhile, high unforeseen fluctuations (high forecast error) create high values of stochastic gaps as shown in Fig. 7.

TABLE I
Comparison of Operational Cost for the Projected PEV Demand

Cases	Method	Operational Cost ($)	Cases	Method	Operational Cost ($)
Winter WD	EEV	-98,090	Summer WD	EEV	-126,338
	WS	-109,453		WS	-166,776
	Stochastic Gap	11,363		Stochastic Gap	40,438
Winter WE	EEV	-45,313	Summer WE	EEV	-147,772
	WS	-54,033		WS	-151,998
	Stochastic Gap	8720		Stochastic Gap	4226
Spring WD	EEV	-84,913	Fall WD	EEV	-106,170
	WS	-87,142		WS	-117,928
	Stochastic Gap	2229		Stochastic Gap	11,758
Spring WE	EEV	-111,084	Fall WE	EEV	-54,037
	WS	-119,862		WS	-62,234
	Stochastic Gap	8778		Stochastic Gap	8197

In term of operational cost, both *EEV* and *WS* give different optimal operational costs, which highly depend on foreseen market price fluctuation but less influenced by wind/solar PV generation. When high foreseen fluctuations occur, the operational cost is a very negative; otherwise, its value is high. This is due to the fact that predictable changes in market price allow operators to profit from purchasing power at low market prices and selling back to the power grid when the prices increase. It can be seen from Fig. 6 that operational costs of *WS* solutions are significantly lower both in weekdays and weekends in summer. This is because the high foreseen market price fluctuations always occur in this season. In addition, operational costs of winter and fall in weekdays are lower than those of weekends since higher foreseen market price fluctuations usually happen in weekdays. However, operational costs in spring weekends are lower than that of spring weekdays because generators often have yearly preventive maintenances in spring weekends leading to higher foreseen market price fluctuations compared to its variation in spring weekdays.

Stochastic gap is predominantly based upon the accuracy of market price predictions. With more accurate market price prediction, *EEV* performs well and obtains near optimal operational cost resulting in less difference from *WS*. On the other hand, high unforeseen fluctuations yield high values of the stochastic gap. It can be observed from Fig. 7 that the highest stochastic gap happens during summer weekdays because there are multiple spike prices during this time, which the proposed forecasting has more difficulty predicting accurately. However, the proposed forecasting method achieves more accuracy in summer weekends, giving less stochastic gap in this case. In addition, the same situations also happen in winter and fall, which the stochastic gaps in weekdays are higher than on weekends. However, due to less fluctuation of market prices in spring weekdays compared to spring weekends, more accurate market price predictions can be achieved in spring weekdays, leading to less stochastic gap in this case compared to weekends. Although this result may seem intuitive, this is the first study to show the strength of the relationship between market price forecasting error and stochastic gap in the optimal control process.

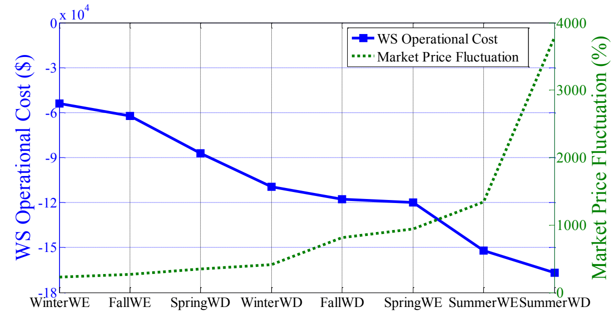

Fig. 6. Charging station operational cost and market price fluctuation

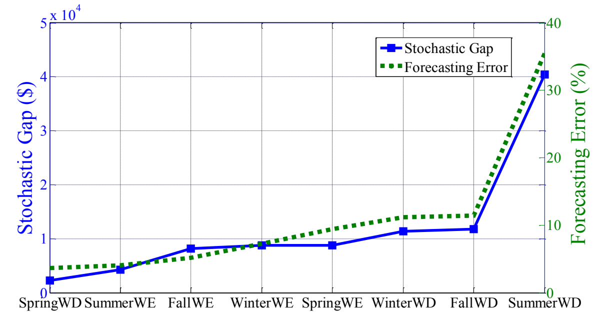

Fig. 7. Stochastic gap and market price forecasting error

VII. CONCLUSION

This paper discusses optimal control for a novel regional PEV charging station system, which serves its demand by wind/solar generation and electricity from the utility grid. The optimal control for this system is focused on minimizing its operational cost. Two important stochastic measures are introduced to determine bounds of operational cost including a stochastic gap found by the expected value problem and wait-and-see solution. The control algorithm of the proposed system is tested on weekdays and weekends of four different seasons. The results of the proposed algorithm show that the stochastic gap is greatest during weekdays in the summer, which is similarly when market price forecasting error is greatest.

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