Energy Economics 66 (2017) 1–8

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Regime-switching based vehicle-to-building operation against electricity price spikes

Lei Zhang [a], Yaoyu Li [b,*]

[a] Paypal, Inc., 2211 North 1st St., San Jose, CA 95131, USA
[b] Department of Mechanical Engineering, University of Texas at Dallas, 800 W. Campbell Rd., Richardson, TX 75080, USA

ARTICLE INFO

Article history:
Received 18 July 2015
Received in revised form 22 April 2017
Accepted 31 May 2017
Available online 8 June 2017

JEL Classification:
Q41
Q47
C61
C44
D81
C53

Keywords:
Vehicle-to-building
Electricity price modeling
Spikes
Regime switching models
Risk management
Smart grid
Demand response
Electric vehicles

ABSTRACT

Electricity price may present very large spikes due to imbalance between generation and demand, especially during heavily loaded periods. Such peak price may incur significant cost to building operation. With the vehicle-to-building (V2B) technology, electric vehicle battery can be used as temporal energy source for the building load for a short period, which leads to a possible solution for reducing the energy cost during peak-price periods. In this paper, the problem of reducing the energy cost due to the peak price is approached from the prospective of risk management. A regime-switching based risk management scheme is proposed for the V2B operation based on the availability of electric vehicles (EV) plugged in the parking lots attached to the building. In the low risk regime, the objective is to minimize the EV charging cost. While in the high risk regime, the objective is to reduce the potentially high energy cost due the peak price via the power stored in EV batteries. Based on Markov regime-switching model, the operation minimizes the conditional value at risk involved. Simulation results show that the proposed framework can greatly reduce the energy cost against the electricity peak prices.

1. Introduction

Electricity market has been the most volatile market in the US and Europe (Weron, 2008). Without economic solution of long-term storage, electricity must be consumed very shortly after generation. The balance between generation and demand is crucial to the normal operation of power grid. However, under particular circumstances, e.g. unexpected high demand and/or equipment failure, such balance may be lost, resulting in temporary electricity scarcity. With random bidding activities, the electricity price can rise up to several to even over 100 times the normal price, which is known as *price spike*. As electricity is primarily consumed by buildings (e.g. 70% electricity consumed by buildings in the U.S.), price spike is extremely costly for utility retailers or smart building operators (SBO). For example, the price spikes in Texas electricity market can reach as high as $3000/MWh (Electric Reliability Council of Texas (ERCOT), n.d.), which implies very high building power cost. To be worse, price spikes may occur repeatedly within several hours before the grid is recovered to balanced status. Without fixed price contract in place, the SBO may suffer tremendous energy cost.

The Electric Vehicles (EV) have emerged as promising solution to sustainable transportation, especially for the commuters. One remarkable potential for EV is the possibility of bi-directional power flow. The on-board battery power can supply grid for short-term dispatch or power quality control, i.e. the so-called vehicle-to-grid (V2G) operation. In particular, the vehicle-to-building (V2B) operation can be considered as a subset of V2G (Briones et al., 2012), in which vehicle batteries can be used as temporal energy storage for smart buildings. The EV owners plug the vehicles into the power outlets in the building-attached parking lots, and assign a departure time. The SBO manages the power flow for both building operation and vehicle charging/discharging, with the typical objective of minimizing the overall energy cost. For instance, many high-tech companies in California have provided free charging services for their employees' EVs. For such building owners, the electricity cost is the combination of buildings and EVs. Furthermore, with the booming trend of smart community development,

* Corresponding author.
E-mail addresses: sesime@gmail.com (L. Zhang), yaoyu.li@utdallas.edu (Y. Li).

http://dx.doi.org/10.1016/j.eneco.2017.05.019

a smart community operator (SCO) can participate in the electricity market as a 'large consumer' subject to the dynamic price, and also can manage an even larger fleet of EVs. During spike price periods, EV battery can supply building load with justifiable economy.

Previous research on demand-side management mainly focuses on V2G as ancillary services aggregator. Sortomme and El-Sharkawi (Sortomme and El-Sharkawi, 2012) propose an optimal charging algorithm for scheduling energy sales and ancillary services. Liang et al. (2013) apply a stochastic inventory theory to handle the randomness of the vehicle mobility by dividing the electricity price range into the regimes of on peak, mid-peak and off-peak, each bearing fixed price. Ma et al. (2012) developed a probabilistic model and several rule-based V2G operation. In addition, grid power quality (e.g. frequency) control has also been studied (Lopes et al., 2011; Han et al., 2010; Shimizu et al., 2010; Ota et al., 2010).

Although less research has been reported on V2B (Pang et al., 2012; Gamallo et al., 2013; Nguyen and Song, 2012; Cardoso et al., 2013; OZOE et al., 2014), V2B is deemed closer to practical implementation in near future especially for the micro-grid demand-side management, compared to general V2G operation with large-scale power grid due to the complexity and cost involved. Pang et al. (2012) study the benefit of V2B operation under peak load and during outage condition with a rule based strategy, also with the regimes of off-peak, mid-peak, on-peak as in (Liang et al., 2013). Gamallo et al. (2013) study the optimal storage capacity and its equivalent number of EVs for V2B operation in the hotel energy management. The optimal charging-discharging strategy is obtained by minimizing the energy cost, including total energy bought to the grid, battery acquisition cost and the reward paid to the car owners. Nguyen and Song (2012) propose a distributed algorithm for scheduling EV charging and discharging action in order to smooth the building load. Cardoso et al. (2013) study the investment and scheduling problem with EV as the distributed energy resource. Stochastic programming is performed for optimal sizing of the micro-grid by considering random behavior in vehicle arrival and departure. Ozoe et al. (2014) optimize the scheduling of a smart house with photovoltaics and fuel cell cogeneration by stochastic programming under uncertain electricity demand, heat demand, and PV power generation.

To the author's best knowledge, none of the current research targets one the most extreme situations in the power grid, which is when spike price occurs. As battery discharging operation sacrifices battery life, V2B operation would be economically viable only when the price of grid power is high enough. The scenario of electricity price spike makes a reasonable case for the V2B power flow.

Based on the risk management theory in finance (Reida and McNamara, 2013; Dowd, 2002), we propose a regime-switching based optimal operation strategy. Such a problem formulation is rooted from the fact that occurrence of price spike typically indicates some *unbalanced* status for the grid. Often, such status would last for certain duration of time, i.e. following the first spike, multiple price spikes would appear. It would be ideal if one can predict the exact occurrence of all spikes, but this has turned out extremely difficult in practice with price information only; while applying some risk management strategy to reduce the loss due to the following spikes (after the first one) could yield realistic benefit in cost saving. In this study, the authors propose a regime-switching V2B operation with a hidden Markov model method for price regime identification and stochastic programming based risk management strategy, anchored on the concept of Conditional Value at Risk (CvaR) (Rockafellar and Uryasev, 2000).

For the V2B operation that involves spike electricity price, the possible regime-switching scenarios are construed as follows. In response to the first price spike, the operation can switch from the normal strategy to some conservative strategy against the aftershock of the first spike. For the *normal grid* scenario, the objective is to minimize the EV charging cost; while for the *unbalanced grid* (i.e. price spike) scenario, the objective is to reduce the impact of spiky prices. Based on a Markov regime-switching model, these two strategies can be switched to

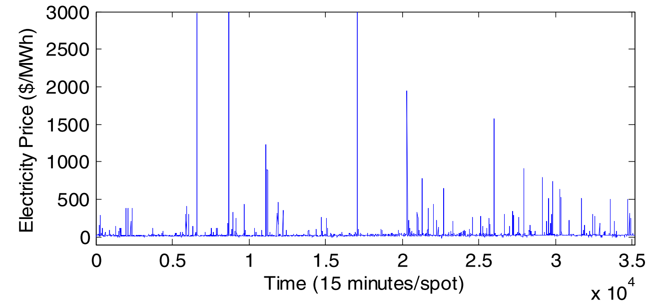

Fig. 1. The whole-year spot price of the North Texas market in 2012 (Electric Reliability Council of Texas (ERCOT), n.d.).

minimize the operation cost that includes both the building load and the EV charging load. The building load is mandatorily satisfied at any time. EVs can be left not fully recharged, with the uncharged amount reimbursed with some penalty price higher than the normal electricity price. Impact of discharging on battery life is addressed as a cost term.

The remainder of this paper is organized as follows. The spike price characteristics are first illustrated with example of market data, and then the Markov regime switching model is presented. The risk management theory associated with the problem of interest is briefly reviewed in Section 3. The regime-specific operation framework is described in Section 4, as well as the related operation strategies. Numerical simulation is given in Section 5, while Section 6 concludes the paper with discussion on possible future work.

2. Electricity price analysis and regime switching model

2.1. General statistical model

As illustration, Fig. 1 shows the annual electricity price profile for the North Texas real-time electricity market in 2012 (Electric Reliability Council of Texas (ERCOT), n.d.), with a 15-minute interval. The annual average price is $25.41/MWh. If on-peak hours are from 11 a.m. to 7 p.m., the average price of the on-peak hours is $35.06/MWh, and that of the off-peak hours is $21.24/MWh. The average from November to April is $23.35/MWh and $25.75/MWh for April to October. Although the spot price remains at a relatively low level around $15–$60/MWh for most of the time, the spot price can go far above this level, from $100/MWh to even $3000/MWh. The volatility (i.e. the standard deviation of the return series) is as high as 1000%, as compared to 1–1.5% for the stock market and 1–4% for the oil/gas commodity market, and 50% for the electricity price in the European market (Weron, 2008).

The histogram of the spot prices in Fig. 1 is obtained as shown in Fig. 2. The 99th percentile of the distribution is at $82.09/MWh. If the spot price less than the 99th percentile price (i.e. $82.09/MWh) is deemed the normal price range, then the tail portion ranges from $82.09/MWh to $3000/MWh, which is extremely long. The distribution shown has longer tail than typical financial and commodity markets.

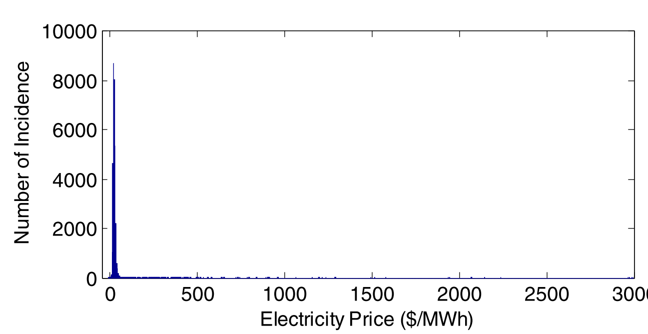

Fig. 2. Histogram of spot price of 2012 North Texas electricity market.

2.2. Regime and regime switching

Historical data (Electric Reliability Council of Texas (ERCOT), n.d.) and earlier studies (Christensen et al., 2011; Weron, 2008; Huisman and Mahieu, 2003) have shown that, if a spike price is present, there is a high probability that another peak price will happen in the future short period. Therefore, a spike price, when present, should not be regarded as an isolated event, but rather the start of a time duration of high volatility in spot price. In finance terminology, such duration is called a *regime*. In this study, a regime with high volatility of spot price is defined as the High Risk Regime (HRR); while the low volatility regime, which covers a majority of the time, is defined as Low-Risk Regime (LRR).

Fig. 3 shows a diurnal profile of spot price that contains both LRR and HRR. From midnight to 1 p.m., the price demonstrates mild fluctuation at low price level. After 1 p.m., the price deviates from the average price and becomes volatile, which indicates an unbalanced situation of grid status. Such an HRR lasts till 7 p.m. when the price returns to the level of average price and the volatility of spot price diminishes. Throughout the day, the spot price changes from low volatility to high volatility, and later, returns to the low volatility. Each transition presents a regime-switching scenario related to the grid status: from the balanced to the unbalanced, and then back to the balanced status.

2.3. Markov regime switching model

Regime-switching is a natural way to describe fundamental, persistent changes of a system in terms of structure and function (Biggs et al., 2009). In this study, the Markov Regime-Switching Model (MRSM), an embodiment of the well-known Hidden Markov Model (HMM), is adopted. MRSM has become a popular tool in finance, economics and management areas (Goldfeld and Quandt, 1973; Kritzman et al., 2012). MRSM divides complex process/scenario into simpler and interactive ones, which facilitates the capture of stylized behavior, e.g. fat tail, turbulence and other periodic occasions (Ang and Timmermann, 2011).

MRSM includes three key components: regimes (states), emissions (observations) and transition matrix. The regimes cannot be directly observed, but can be estimated from the emissions and transition matrix. The transition matrix shows the probability for the transition of one regime to another regime, which is typically estimated from historical data. In this study, two regimes are defined, *Balanced* and *Unbalanced* status of the power grid, corresponding to the LRR featuring spot price around the average price, and the HRR featuring spiky prices, respectively. As building owners cannot collect the power grid information, the regime of grid status can be estimated from its *emissions* - the spot price, along with transition matrix obtained from the historical price data.

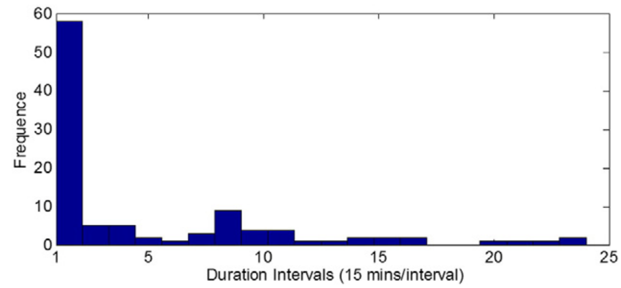

Fig. 4. Duration of high risk regime for 2012 North Texas electricity market.

To estimate the emission distribution and transition matrix, the 99th percentile price is used as the threshold for defining peak price. For the year 2012 spot price data (Fig. 1), the threshold is found to be \$82.09/MWh. The histogram of the HRR duration is shown in Fig. 4. The single-spot spike is the majority case, but its impact on energy cost is limited as simple V2B power flow can handle it easily. In contrast, cases of longer duration (i.e. multiple emissions) deserve more concern because they require significant capacity of battery storage to supply the building load therein.

The transition matrix is estimated from the spot price by MRSM using the Baum-Welch algorithm (Rabiner, 1989), which is given in Table 1. The probability for an LRR to switch to an HRR is shown to be quite low; but once it is in HRR, the probability of staying in HRR is high. The emission distribution for each regime can be summarized from spot prices that belong to each regime. Once the MRSM is built, given a time series of price, its corresponding regime can be found through the Viterbi Algorithm (Rabiner, 1989). The initial regime of the price series is always set to LRR with probability 1.

The above analysis reveals that electricity spike price rarely happens; but once it happens, it can cause significant (building) energy cost. For V2B operation, the building load can be supplied from EV batteries instead of power grid. To achieve V2B, the batteries should have enough storage to meet the load demand. However, as mentioned earlier, it is almost impossible to predict when the first spike price occurs. For such unpredictable event, a counter measure is to keep certain amount of energy storage in the batteries, and prepare for the spike price. In order to determine how much energy should be reserved in the batteries, a method is needed to quantify the risk which the spike price impacts the building energy cost. Such decision-making scenario falls into that of *Risk Management*. A brief overview of the relevant theories of risk management is introduced in next section.

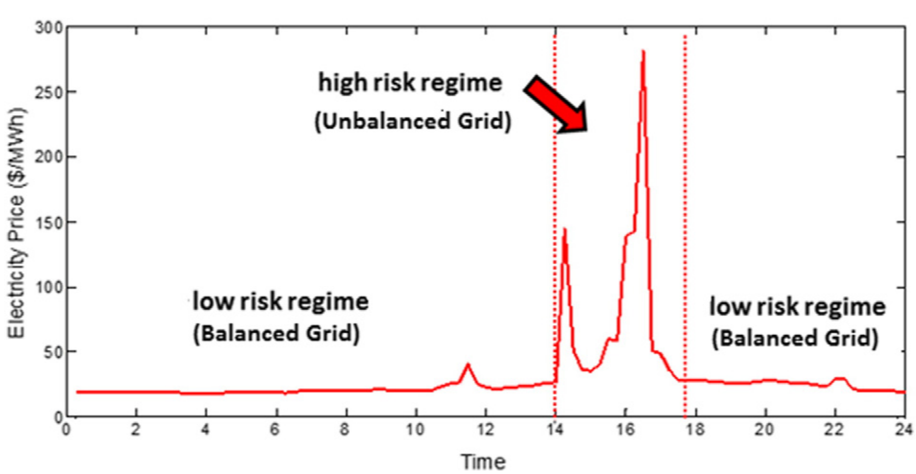

Fig. 3. Illustration of regime-switching with spot price profile on 08/08/2012.

Table 1
Samples transition matrix between LRR and HRR.

From/to	LRR	HRR
LRR	0.997	0.003
HRR	0.1962	0.8038

3. Overview of risk management

Risk management is a process of identifying potential risks, problems or disasters before their occurrences and determining policies to avoid or minimize the associated impacts (Dowd, 2002). It is widely applied in portfolio management, banking and insurance, among others (Rockafellar and Uryasev, 2000; Liu and Tan, 2004; Wang et al., 2005). If occurrence of certain risk is known, the critical issue is then how to quantify the risk. The metric to quantify the risk is called *Risk Measure*. JP Morgan proposes the first risk measure in 1994 to evaluate extreme loss, the so-called Value at Risk (VaR) (Dowd, 2002), which is intended to quantify the bank risk exposure. VaR can be defined as the minimal loss under extraordinary market price.

Let $f(\mathbf{x},\omega)$ be the loss function for decision vector $\mathbf{x}\in X$ and random vector ω (e.g. market price), where X is the feasible set for decisions. The probability of the loss function $f(\mathbf{x},\omega)$ not exceeding threshold ζ is given by

$$\Psi(\mathbf{x},\zeta) = \int_{f(\mathbf{x},\omega)\le\zeta} p(\omega)d\omega \tag{1}$$

where $p(\omega)$ is the probability density for ω to happen. The α-VaR of the loss associated with decision x is the minimum loss not exceeding threshold ζ with confidence level α. i.e.

$$\zeta_\alpha(\mathbf{x}) = \min\{\zeta\in R|\Psi(\mathbf{x},\zeta)\ge\alpha\} \tag{2}$$

Although VaR is an efficient and effective measure to evaluate risk, however, it does not consider the size of losses beyond VaR. Also, it is non-subadditive and non-convex. To overcome these drawbacks of VaR, the Conditional Value at Risk (CVaR) was introduced (Rockafellar and Uryasev, 2000). The α-CVaR is a measure of the expected loss under the condition that it exceeds VaR, which is defined by:

$$\phi_\alpha(x) = (1-\alpha)^{-1}\int_{f(x,\omega)\ge\zeta_\alpha(x)} f(x,\omega)p(\omega)d\omega \tag{3}$$

$\phi_\alpha(x)$ is effectively the conditional expectation of the loss associated with x relative to that loss being equal or greater. To formulate an equation without the component of $\zeta_\alpha(x)$ and obtain convexity for CVaR, Rockafellar and Uryasev (2000) proposed a characteristic function F_α defined on $X\times\mathbb{R}$ as

$$F_a(x,\zeta) = \zeta + (1-\alpha)^{-1}\int_{\omega\in\mathbb{R}}[f(x,\omega)-\zeta]^+p(\omega)d\omega \tag{4}$$

where $[\bullet]^+=\max\{0,\bullet\}$. $F_a(x,\zeta)$ is the expected loss with confidence level α for given decision variable x and loss boundary ζ. They have shown that $F_a(x,\zeta)$ is convex on ζ and continuously differentiable. Therefore, the α-CVaR of the loss associated with x can be determined from

$$\phi_\alpha(x) = \min_{\zeta\in\mathbb{R}} F_\alpha(x,\zeta) \tag{5}$$

Eq. (5) provides an alternative way to calculate CVaR. It is easier to approximate the integral with numerical method.

4. Regime-switching operation framework

In this section, the risk management framework for building integrated EV charging/discharging against spike price loss is formulated. There has been noteworthy work reported on regime-switching based electricity price modeling (Ethier and Mount, 1998; Huisman and Kilic, 2011). However, it is rather difficult to build a feasible model for highly volatile electricity spot price of interest in this study, like that of the North Texas electricity market, as the tail portion of the distribution is extremely long and thin. Building energy management based on such price model may not be sufficient to generate good results. Instead of constructing a pricing model and simulating the model, we propose a regime-switching vehicle-to-building (RSV2B) operation framework which is described below.

4.1. Problem formulation

The objective of the building integrated EV charging is to minimize the total electricity cost including both the building electricity load and that for EV charging. The building load must be satisfied mandatorily at any time, either by purchasing power from the electricity market (grid), or by discharging the EV batteries. From the EV charging standpoint, the V2B action might leave some EVs not fully charged by the departure time. So the uncharged amount by departure will be reimbursed at a penalty rate set much higher than the average electricity price. Also, battery degradation due to V2B induced discharging is reimbursed with a compensation rate for vehicle owners.

As shown in Fig. 5, there are two key steps in the proposed framework: regime detection and regime-wise operation. At the start of a new time interval, the MRSM is used to detect the nature of the current operation regime. The primary information for detection includes the current price, the past price and the past regime states. The Viterbi algorithm is used to find the maximum likelihood of the current operation regime. Then, the regime-specific operation strategy is applied.

In the LRR, because the electricity price is lower than the compensation price, any V2B action would undesirably increase the cost. Thus, the building load and EV charging load are satisfied separately: SBO will purchase power directly from the grid to supply building load, and also charge the EVs during the periods when the electricity price is low. The associated risk management strategy is applied to reserve a proper amount of energy in EV batteries to forestall the possible regime-switching and peak price in the future.

If the operation is in HRR, the SBO will supply the building load demand with battery energy when a spike price occurs; meanwhile, the associated risk management strategy will allocate more energy into EV batteries as forestallment when price becomes favorable. Notice that even in the HRR, the spot price can be low due to the stochastic behavior of the electricity, but the volatility in the HRR is definitely high. A low spot price in the HRR presents great opportunity for purchasing energy into battery storage in order to forestall the possible huge cost due to future possible peak prices.

As for the associated optimization problem, the objective of the SBO is to minimize the operational cost over the entire horizon $t\in[1, n]$ under stochastic electricity price, i.e.

$$\min E\left\{\sum_{t=1}^{n}[c(t)X(t)+c_bG(t)]\right\}+c_pX_p \tag{6}$$

where $c(t)$ is the electricity price for time interval t, $X(t)$ is the total amount of energy purchased from power grid for time interval t, c_b is the compensation rate for battery degradation, $G(t)$ is the discharging amount for time interval t, X_p is the total uncharged amount by $t = n$, and c_p is the penalty price.

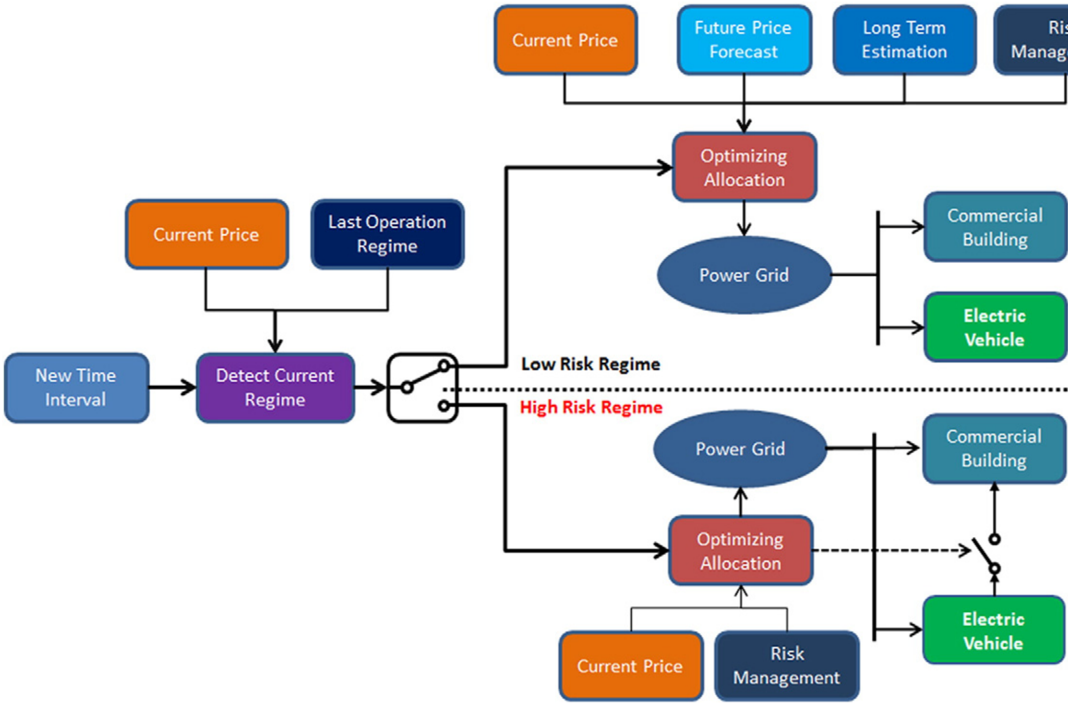

Fig. 5. Regime switching V2B operation framework.

The total amount of purchased energy $X(t)$ can be decomposed into two parts, i.e.

$$X(t) = X_d(t) + X_v(t) \tag{7}$$

where $X_d(t)$ is the energy used for supplying building load at t, and $X_v(t)$ is the energy used for charging EVs at t. The building load must be satisfied at any time, i.e.

$$\eta X_d(t) + \eta G(t) = d(t) \tag{8}$$

where $d(t)$ is the building load at time t, and η is the charging/discharging efficiency (assumed to be the same). Battery operations should meet the following constraints:

$$X_v(t)G(t) = 0 \tag{9}$$

$$\eta X_v(t) \le B - R(t) \tag{10}$$

$$G(t) \le R(t) \tag{11}$$

$$X(t) \le F \tag{12a}$$

$$X_d(t) \ge 0, X_v(t) \ge 0, G(t) \ge 0 \tag{12b}$$

where B is the total battery capacity corresponding to the healthy upper limit of state of charge (SOC) in amount, $R(t)$ is the battery SOC in amount at t, and F is the building transformer capacity. Eq. (9) is to avoid simultaneous charging and discharging. Eq. (10) ensures that the charging amount not exceed the battery capacity. The power purchased from grid cannot exceed the capacity of the distribution transformer for the building. For high charging demand situation, i.e. only a portion of vehicles can be charged simultaneously.

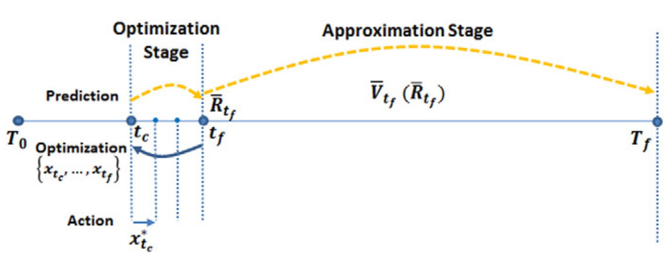

Fig. 6. Illustration for two-stage approximate dynamic programming.

4.2. Low risk regime operation

In the LRR, as the building load is directly supplied from the grid, the optimization problem is to minimize the EV charging cost under the stochastic electricity price. Such problem is solved by two-stage approximate dynamic programming (TSADP) (Zhang and Li, 2013) recently proposed by the authors. The TSADP determines the optimal policy for the current time from two stages, as shown in Fig. 6: the optimization stage and the approximation stage.

The TSADP determines the optimal policy for the current time from two stages, as shown in Fig. 6: the optimization stage and the approximation stage. At current time t_c, the electricity price between current time t_c and short-term future t_f is predicted. The possible range of battery SOC $\bar{R}(t_f)$ at time t_f is estimated, by considering the feasible charging decision $X_v = \{X_v(t_c), X_v(t_c+1), \ldots, X_v(t_f)\}$ between $[t_c, t_f]$, and current battery SOC $R(t_c)$. At the optimization stage, for each possible battery SOC, $\bar{R}_i(t_f)$, the minimal operation cost between $[t_c, t_f]$ can be found by solving:

$$\min \sum_{t=t_c}^{t_f} c(t) X_v(t) \tag{13a}$$

$$R(t_c) + \sum_{t=t_c}^{t_f} \eta X_v(t) = \bar{R}_i(t_f) \tag{13b}$$

where, $X_v(t) \in \mathcal{F}$, and $\mathcal{F}$ is the feasible set of the charging decision $X_v(t)$. $c(t)$ can be real price or prediction of future price. The feasible state (SOC) trajectory starts from $R(t_c)$ and ends at $\bar{R}_i(t_f)$, and the optimal state trajectory is that of the minimal cost. For each state $\bar{R}_i(t_f)$, for which the corresponding minimal cost is denoted as $C_{OS}[\bar{R}_i(t_f)]$.

The approximation stage is to approximate the future cost $\overline{V}_{t_f}(\overline{R}_i(t_f))$ of state $\overline{R}_i(t_f)$, which is the core of approximate dynamic programming (ADP) (Powell, 2011). The approximation can be done by simulation or machine learning. In this study, the sample path simulation method (Powell, 2011) is applied, which is based on 30 days of electricity price profiles by removing the spikes.

The global optimal policy is one with the minimal costs of both the optimization stage and approximation stage, i.e.

$$X_v^* = \arg\min\left[C_{OS}\left(\overline{R}^*(t_f)\right) + \gamma^{t_f - t_c}\overline{V}_{t_f}\left(\overline{R}^*(t_f)\right)\right] \tag{14}$$

In the last step, the optimal policy for the current time, and $X_v^*(t_c)$ is executed.

The reason of risk management for LRR is its potential possibility of switching to HRR. Such switching is always caused by a sudden jump price. In this study, the loss function caused by random electricity price ω can be written as:

$$f(X_d, \omega) = \omega X_d \tag{15}$$

At a spike price, the SBO will purchase energy from the grid only if the battery is empty. Combining Eqs. (15), (8) and (11) yields the loss function related to the battery SOC at time t:

$$f(R(t), \omega) = \omega\left[\hat{d}(t) - \eta R(t)\right]^+ \tag{16}$$

Here, $\hat{d}(t)$ is the expected building load, which can be forecasted from historical data. By adapting the characteristic function in the discrete-time domain, we add the risk management in the form of constraint (Krokhmal et al., 2002), in order to limit the potential loss within a certain threshold T, i.e.:

$$\zeta + \frac{1}{M(1-\alpha)}\sum_{k=1}^{M}\left[\omega_k\left[\hat{d}(t) - \eta R(t)\right]^+ - \zeta\right]^+ \le T \tag{17}$$

where ζ can be calculated from Eq. (2), and M is the number of electricity price in the sample set. From Fig. 4, since the single spike regime is the majority case, it does not require a huge amount of energy reservation when operating at low risk regime. A serious risk management in the low risk management would results in high energy reservation amount in the EV battery, and consequently the SBO loses the flexibility to minimize the EV charging cost by charging at low-electricity-price time spot.

4.3. High risk regime operation

In the high risk regime, due to the high volatility of the electricity price and the uncertainty of the duration of the high risk regime, traditional operation strategies based on low volatility and fixed horizon cannot be directly applied. In this study, because the focus is on the operation strategy at the current time t_c, by approximating the future duration of high risk regime, we are able to apply two-stage stochastic programming with CVaR (Schultz and Tiedemann, 2006; Noyan, 2012). A brief introduction on two-stage stochastic programming is given in the appendix. The associated optimization problem can be formulated as:

$$\min\left\{c(t_c)X_d(t_c) + \hat{L}_h E[\omega X_d(t_h)] + \hat{L}_h \lambda CVaR_\alpha[\omega X_d(t_h)]\right\} \tag{18}$$

s.t.

$$\eta X_d(t_c) + \eta G(t_c) = d(t_c) \tag{19a}$$

$$R(t_h) = R(t_c) - G(t_c) \tag{19b}$$

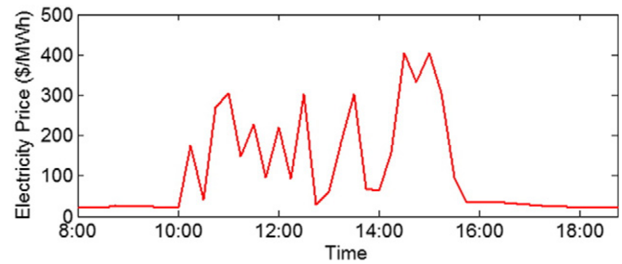

Fig. 7. The real-time spot price of March 2, 2012 (Electric Reliability Council of Texas (ERCOT), n.d.).

$$\eta X_d(t_h) + \eta G(t_h) = \hat{d}(t_h) \tag{19c}$$

$$R(t_h) - G(t_h) \ge 0 \tag{19d}$$

where t_h, $X_d(t_c)$, $X_d(t_h) \in \mathcal{F}\ t_h$ is the time after t_c in the high risk regime, $\hat{L}_h$ is the expected time duration of the high risk regime after t_c, $X_d(t_h)$ is the purchasing amount in the rest of the high risk regime, λ is the risk-averse factor, and $\hat{d}(t_h)$ is the expected demand after t_c in the high risk regime. Such linear programming problem can be solved with general solvers.

To calculate $\hat{L}_h$, the MRSM is used to perform a sequence of forward forecast, based on the probability of current regime and the transition matrix in Table 1, until the probability of the high regime at a certain forecast regime below 0.5.

5. Simulation study

The proposed framework is simulated with the actual building load data of the ECS building at the University of Texas at Dallas. The building is assumed to be attached with 1000 EVs. The EVs are charged at Level 2, which is rated at 6.4 kW. The transformer capacity is set at 4.0 MVA, which can support the building load itself and around 400 vehicles being charged simultaneously. The battery size of each EV is set at 16 kWh, with SOC∈[0.2, 0.9]. The initial SOC of all EV batteries is assumed to be at the low limit of SOC (i.e. 0.2). The compensation rate for the battery degradation is set at \$105/kWh, based on 7000 charging-discharging cycles according to (Buderi, n.d.), and the cost is around \$500 per kWh at present (Hensley et al., 2012). More benefit of V2B operation can be revealed if the battery cost drops in the future. The round-trip efficiency of battery charging and discharging is set as 86.5% (Forward et al., 2013). By departure, the uncharged amount will be reimbursed with a penalty rate of \$110/kWh.

The operation horizon is assumed from 8 a.m. to 7 p.m. The real-time North Texas electricity price is obtained from ERCOT (Electric Reliability Council of Texas (ERCOT), n.d.), with 15-minute interval. In order to demonstrate the idea in this study, 25 days are selected in 2012, when the electricity spike prices occurred frequently. The days where only single spike price occurred are not selected because such situation is less harmful as discussed earlier.

The proposed method is compared with two other methods. One is a non-V2B method in which the building and EV are supplied separately,

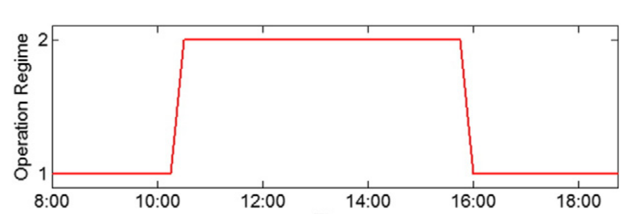

Fig. 8. The operation regime corresponding to spot price.

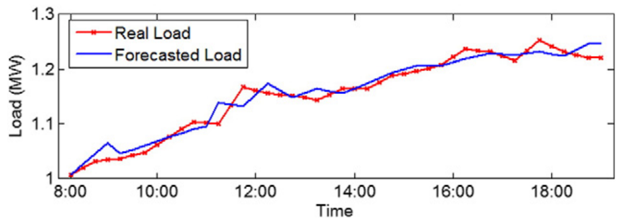

Fig. 9. The real and forecasted building load.

i.e. no V2B activity between them and EVs are charged from the beginning until the battery is full. The other is a rule-based V2B (RV2B) method is implemented as follows: if the electricity price exceeds $120/kWh (i.e. the battery compensation cost divided by the discharging efficiency), RV2B will use battery to supply building load; otherwise, TSADP is applied. Therefore, the key distinction of the proposed regime-switching framework over the RV2B operation is the adoption of the concept of regimes, along with the associated risk management strategies.

The electricity data on March 2, 2012 is used for the case study, as shown in Fig. 7. It indicates that the grid was in unbalanced status for a long time. Obviously, the grid appeared unbalanced from 10:15 to 16:00, resulting in tremendous volatility in the spot price. The corresponding operation regime detected by RSM is shown in Fig. 8, where “1” and “2” represent LRR and HRR, respectively. The building load and load forecast are shown in Fig. 9.

The charging and discharging actions of RSV2B and RV2B are compared shown in Fig. 10. Between 8:00 a.m. to 10:15 a.m., both methods have the same charging actions, as they are both operated by TSADP. However, at 10:15 a.m., a spike price of $175/MWh occurred. The RSV2B switches to the high-risk strategy, purchasing energy to supply building load and stop charging batteries. In contrast, RV2B decides to use batteries to support building load. Such different operations suggest different attitude toward the peak price at $175/MWh. RSV2B considers it as a medium price for which charging is not worthwhile, but the price is not high enough either to use battery. The RV2B considers there is benefit to use batteries.

After the peak price is a normal price $41.22/MWh. If this is a normal day, without previous peak price, the $41.22/MWh at 10:30 a.m. is a relative high price, as the average off-peak price is $21.24/MWh, which is mentioned in Section 2. Therefore, RV2B decides not to charge its batteries, and waiting for better price in the next time. Because of the time persistence property of the regime-switching model, RSV2B is still in the high risk regime. It decides to charge its battery at maximum rate, because the price is very low in the high risk regime. Different price attitudes lead to different operations.

In the next time interval, the price jumps to $268.82/MWh. Both RSV2B and RV2B decide to discharge battery to supply building load, as the spike price is high enough to both methods. As time goes, the decision trajectories of the two methods act significantly. As expected, RSV2B always makes aggressive charging action in the high risk regime as opposed to RV2B, because risk management bears cautious attitude toward future price. Such cautious action reveals its benefit

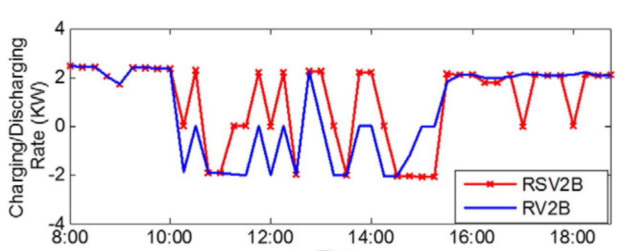

Fig. 10. The charging/discharging actions of RSV2B and RV2B.

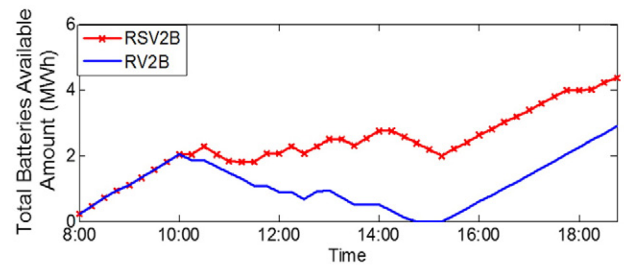

Fig. 11. The total battery capacity available.

later. From 15:00 on, the spot price becomes more severe, reaching $400/MWh. RSV2B decides to use batteries to supply building load. The RV2B, however, having no energy left to supply building load, has to purchase energy from power grid, and suffering huge energy cost. The total available battery capacity is shown in Fig. 11. After 15:40 p.m., the spot price becomes normal, and at 16:00, the regime switches to low risk regime. Both methods charge the batteries at the maximal rate. Because of the empty batteries, RV2B is impossible to fully recharge its batteries by the end. RSV2B is able to fully recharge because the charging demand is low enough for the remaining time. The total cost is $3161.6, $2520.7, and $1786.3 for the Non-V2B, RV2B and RSV2B, respectively. RSV2B has obviously the lowest cost, as it properly avoid high electricity price while fully recharged the batteries. Even without fully recharging the batteries, RV2B still saves more than $600 compared to the non-V2B method, indicating significant benefit in energy cost saving with V2B.

The operation costs of the selected days are summarized in Table 2. Overall RSV2B outperforms RV2B. However, in several days, RSV2B and RV2B are almost same, and in some days RV2B is better than RSV2B. That is because regime-switching framework and related risk management strategy provides a methodology to make cautious and sophisticated decision for forestallment the unfavorable event, i.e. the spike price in this study, but there is no guarantee that such event would come.

Table 2
Operation cost of the selected days (unit: $).

Date	RSV2B	RV2B	Non-V2B
1/21	982.00	1150.00	2120.00
3/2	1786.30	2520.70	3161.60
3/31	1400.00	1590.00	5050.00
4/5	1220.00	1270.00	1180.00
4/10	1430.00	1490.00	1800.00
4/25	1090.00	1220.00	1610.00
4/26	2130.00	2210.00	3780.00
5/3	1640.00	1810.00	1840.00
5/7	1360.00	1430.00	1470.00
5/24	1120.00	1170.00	1090.00
5/29	1220.00	1350.00	1170.00
6/26	4210.00	3300.00	10,000.00
7/30	1740.00	1880.00	2510.00
7/31	1700.00	1430.00	1570.00
8/1	1630.00	1630.00	1610.00
8/6	1720.00	2850.00	2220.00
8/9	2060.00	2370.00	2650.00
8/13	1580.00	1610.00	1660.00
8/17	1190.00	1310.00	1310.00
8/24	1080.00	1160.00	1250.00
9/27	1330.00	1150.00	2480.00
10/17	1490.00	1740.00	2400.00
11/3	1040.00	1250.00	1380.00
11/11	855.00	912.00	1580.00
11/12	1030.00	1460.00	1790.00
Total	38,063.30	41,262.70	58,681.60

6. Conclusion and discussion

This study aims to handle the peak price in the electricity market through V2B method. Different from rule-based V2B method, we propose a regime-switching operation framework with corresponding risk management strategy. In the low risk regime, the TSADP is applied to minimize the charging cost. In the high risk regime, the two-stage stochastic programming with CVaR is applied to decide the energy management operation. The proposed method is tested in the real-time electricity market. Case study is provided and total operation cost of the selected days is listed. The results show that the proposed method is able to save operation cost.

In this study, the regime-switching risk management framework has been applied to deal with the spike price issue at the V2B level; while on a broader sense, it is also applicable to smart community or V2G operation as future work. The proposed framework will be enhanced with stochastic availability of vehicle battery storage and aggregation of spatially distributed resources.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2017.05.019.

References

Ang, Timmermann, A., Jun. 2011. Regime Changes and Financial Markets. NETSPAR Discussion Papers Network for Studies on Pensions, Aging and Retirement (Paper #DP06/2011-068).

Biggs, R., Carpenter, S.R., Brock, W.A., Jan. 2009. Turning back from the brink: detecting an impending regime shift in time to avert it. Proc. Natl. Acad. Sci. U. S. A. 106 (3), 826–831.

Briones, Francfort, J., Heitmann, P., Schey, M., Schey, S., Smart, J., September 2012. Vehicle-to-grid (V2G) Power Flow Regulations and Building Codes Review by the AVTA, INL/EXT-12-26853.

Buderi, R., d. A123 inks deal to develop battery cells for GM electric car. online source:. http://www.xconomy.com/boston/2007/08/10/a123-inks-deal-to-develop-battery-cells-for-gm-electric-car/.

Cardoso, G., Stadler, M., Chehreghani Bozchalui, M., Sharma, R., Marnay, C., Oct. 2013. Stochastic programming of vehicle to building interactions with uncertainty in PEVs driving for a medium office building. 39th Annual Conference of the IEEE Industrial Electronics Society, Austria (Vienna).

Christensen, T.M., Hurn, A.S., Lindsay, K.A., Jan. 2011. "Forecasting Spikes in Electricity Prices", NCER Working Paper Series #70.

Dowd, K., 2002. An Introduction to Market Risk Measurement. John Wiley, Hoboken, NJ.

Electric Reliability Council of Texas (ERCOT), d. http://www.ercot.com/.

Ethier, R., Mount, T., Dec. 1998. Estimating the Volatility of Spot Prices in Restructured Electricity Markets and the Implications for Option Values. Cornell Univ. (Working Paper).

Forward, Glitman, K., Roberts, D., Mar. 2013. An Assessment of Level 1 and Level 2 Electric Vehicle Charging Efficiency. Vermont Energy Investment Corporation (online source: http://www.veic.org/documents/default-source/resources/reports/an-assessment-of-level-1-and-level-2-electric-vehicle-charging-efficiency.pdf).

Gamallo, R. Alvaro, Fraile-Ardanuy, J., Fuentes, M., Dec. 2013. Evaluation of the utilization of electric vehicles for building energy management in hotels. Proc. Int. Conf. New Concepts in Smart Cities: Fostering Public and Private Alliances, Gijon, Spain, pp. 1–6.

Goldfeld, S., Quandt, R., 1973. A Markov model for switching regressions. Econometrics 1, 3–16.

Han, S., Han, S., Sezaki, K., Jun. 2010. Development of an optimal vehicle-to grid aggregator for frequency regulation. IEEE Trans. Smart Grid 1 (1), 65–72.

Hensley, R., Newman, J., Rogers, M., July 2012. Battery technology charges ahead. McKinsey Q. (online source: http://www.alta-energy.com/reports/Battery%20technology%20charges%20ahead%20-%20McKinsey.pdf).

Huisman, R., Kilic, M., 2011. Extreme Changes in Prices of Electricity Futures. Insurance Markets and Companies: Analyses and Actuarial Computations vol. 2 pp. 21–25.

Huisman, R., Mahieu, R., 2003. Regime jumps in electricity prices. Energy Econ. 25, 425–434.

Kritzman, M., Page, S., Turkington, D., 2012. Regime shifts: implications for dynamic strategies. Financ. Anal. J. 68 (3), 22–39.

Krokhmal, P., Uryasev, S., Palmquist, J., Mar. 2002. Portfolio optimization with conditional value-at-risk objective and constraints. J. Risk 7, 43–68.

Liang, H., Choi, B.J., Zhuang, W., Shen, X., Dec. 2013. Optimizing the energy delivery via V2G systems based on stochastic inventory theory. IEEE Trans. Smart Grid 4 (4), 2230–2243.

Liu, R., Tan, H., 2004. How banks' value-at-risk disclosures predict their total and priced risk: effects of bank technical sophistication and learning over time. Rev. Acc. Stud. 9, 265–294.

Lopes, J.A.P., Soares, F.J., Almeida, P.M.R., Jan. 2011. Integration of electric vehicles in the electric power system. Proc. IEEE 99 (1), 168–183.

Ma, Y., Houghton, T., Cruden, A., Infield, D., May 2012. Modeling the benefits of vehicle-to-grid technology to a power system. IEEE Trans. Power Syst. 27 (2), 1012–1020.

Nguyen, H.K., Song, J.B., Dec. 2012. Optimal charging and discharging for multiple PHEVs with demand side management in vehicle-to-building. J. Commun. Netw. 14 (6), 662–671.

Noyan, N., Mar. 2012. Risk-averse two-stage stochastic programming with an application to disaster management. J. Comput. Oper. Res. 39 (3), 541–559.

Ota, Y., et al., Jul. 2010. Effect of autonomous distributed vehicle-to-grid (V2G) on power system frequency control. Proc. Int. Conf. Ind. Inf. Syst. (ICIIS), pp. 481–485 (Karnataka, India).

Ozoe, S., Tanaka, Y., Fukushima, M., 2014. A two-stage stochastic mixed-integer programming approach to the smart house scheduling problem. Electr. Eng. Jpn. 186 (4), 885–895.

Pang, P. Dutta, Kezunovic, M., Mar. 2012. BEVs/PHEVs as dispersed energy storage for V2B uses in the smart grid. IEEE Trans. Smart Grid 3 (1), 473–482.

Powell, W.B., September 2011. Approximate Dynamic Programming: Solving the Curses of Dimensionality. 2nd edition. Wiley.

Rabiner, L.R., 1989. A tutorial on hidden Markov models and selected applications in speech recognition. Proc. IEEE 77 (2), 257–287.

Reida, G.E., McNamara, M., 2013. Principles of Risk Management and Insurance. 12th ed. Prentice Hall.

Rockafellar, T., Uryasev, S., 2000. Optimization of conditional value at risk. J. Bank. Financ. 26, 1443–1471.

Schultz, R., Tiedemann, S., Feb. 2006. Conditional value-at-risk in stochastic programs with mixed-integer recourse. Math. Program. 105 (2–3), 365–386.

Shimizu, K., Masuta, T., Ota, Y., Yokoyama, A., Oct. 2010. Load frequency control in power system using vehicle-to-grid system considering the customer convenience of electric vehicles. Proc. 2010 Int. Conf. Power Syst. Technol, pp. 1–8 (Hangzhou, China).

Sortomme, E., El-Sharkawi, M.A., Mar. 2012. Optimal scheduling of vehicle-to-grid energy and ancillary services. IEEE Trans. Smart Grid 3 (1), 351–359.

Wang, Shyu, D., Huang, H., 2005. Optimal insurance design under a value-at-risk framework. Geneva Risk Insur. Rev. 30, 161–179.

Weron, R., 2008. Heavy-tails and regime-switching in electricity prices. Math. Meth. Oper. Res. 69 (3), 457–473.

Zhang, L., Li, Y., 2013. Optimal charging strategy for EV charging stations by two-stage approximate dynamic programming. Proc. 6th IFAC Symposium on Mechatronic Systems, pp. 423–430.