Robust Energy Scheduling in Vehicle-to-Grid Networks

Zhenyu Zhou, Changhao Sun, Ruifeng Shi, Zheng Chang, Sheng Zhou, and Yang Li

Abstract

The uncertainties brought by intermittent renewable generation and uncoordinated charging behaviors of EVs pose great challenges to the reliable operation of power systems, which motivates us to explore the integration of robust optimization with energy scheduling in V2G networks. In this article, we first introduce V2G robust energy scheduling problems and review the state-of-the art contributions from the perspectives of renewable energy integration, ancillary service provision, and proactive demand-side participation in the electricity market. Second, for each category of V2G applications, the corresponding problem formulations, robust solution concepts, and design approaches are described in detail based on the characteristics of problem structures and uncertainty sets. Then, an adjustable robust energy scheduling solution is proposed to address the over-conservatism problem by exploring chance-constrained methods. Results demonstrate that the proposed algorithm not only can efficiently shift the peak load and reduce the total operation cost, but also provide great flexibility in adjusting the trade-off between economic performance and reliable operation. Finally, we present key research challenges and opportunities.

Introduction

The smart grid provides an open platform for integrating every piece of equipment involved in energy generation, transmission, distribution, storage, and consumption into a network with up-to-date information and communication technologies. As a key component of the smart grid, the emerging vehicle-to-gird (V2G) technology can explore the batteries of electric vehicles (EVs) to reduce energy demand and supply imbalance by absorbing excess energy during off-peak hours and delivering it back to the grid when needed. As a result, V2G networks can benefit the grid by facilitating the integration of intermittent renewable energy sources, enhancing system reliability and safety through ancillary services, and promoting the demand-side liberalization of the electricity market through demand response and virtual power plant (VPP) programs [1].

However, due to the dynamic nature of EV charging time, locations, user behavior, and load profiles, the large-scale penetration of uncontrolled and uncoordinated EVs into power systems, especially distribution networks, may cause a high level of volatility and increase potential sources for system disturbances. Furthermore, intermittent and fluctuating renewable generation provides little controllability and predictability, and poses new challenges in balancing generation and load. Hence, intelligent energy scheduling schemes are required to harness the full potential of the aforementioned benefits brought by V2G networks.

Two main methodologies, i.e., stochastic optimization and robust optimization, have been widely applied in handling data uncertainties in optimization [2]. Stochastic optimization provides an effective solution if the uncertain numerical data follow a well known probability distribution. However, considering the complex operation details and various practical constraints, it is difficult to identify accurate probability distributions for uncertain factors. Hence, stochastic optimization based energy scheduling approaches may not sufficiently address the impacts of uncertainties on the reliability performance.

In comparison, robust optimization can overcome the aforementioned limitations of stochastic optimization, and provide the following advantages for V2G energy scheduling [3]:

- It allows a distribution-free model of uncertainties and only requires moderate information, which can be implemented more easily in practical V2G networks.
- The worst-case operation scenarios of V2G networks have been taken into consideration during the modeling process, and the generated solution is proved to be immune against all possible realizations of the uncertainties.

Realizing robust energy scheduling in V2G networks is not trivial. First of all, the computational complexity increases exponentially with the number of optimization stages and EVs. It would be infeasible to take every detail into consideration as the problem size increases [4]. Second, the robust version of a tractable energy scheduling problem is not guaranteed to be tractable, which mainly depends on the problem structure and the design of uncertainty sets. Finally, it will take an unrealistically high price to ensure robustness when the worst case scenarios are considered simultaneously for numerous uncertain factors of EVs and renewable energy sources.

There are existing works that investigated the robust optimization oriented approaches. A group coordination-based robust charging strategy and robust linear optimizations based energy management scheme were proposed to solve the energy scheduling problem in [5] and [6], respectively. In [7], a robust optimization framework was proposed to solve the frequency regulation capacity scheduling problem with the consideration of the performance-based compensation scheme and the random charging and discharging behaviors. The robust energy scheduling problem in the sce-

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nario of V2G-based ancillary service provision was solved by the mix-integer quadratic programming approach in [3]. However, most previous works are restricted to limited aspects of V2G applications, and have not provided a comprehensive framework for how to integrate robust optimization with energy scheduling in V2G networks.

In this article, we will provide a unified treatment of robust energy scheduling design in V2G networks. First, a novel classification of robust energy scheduling problems was proposed based on the V2G application scenarios. For each category of applications, the corresponding problem formulation and robust solution design methodology are presented based on the characteristics of problem structures and uncertainty sets. Then, we propose an adjustable robust energy scheduling algorithm to tackle the over-conservatism problem by exploring chance-constrained methods. Simulation studies are conducted for a V2G network to validate the economic efficiency and robustness of the proposed algorithm. Finally, we conclude the article, and present major open research issues.

Energy Scheduling

Traditional energy scheduling is aimed at scheduling thermal power generators to meet the load demand with minimum operating cost [8], which is no longer suitable to deal with the uncertainties caused by the large-scale integration of intermittent renewable energy sources and uncontrolled EVs. This section provides a detailed illustration of the new energy scheduling challenges in smart grid, with a particular emphasis on V2G networks.

Energy Scheduling in Smart Grid

Smart grid represents a new paradigm shift for energy scheduling design. On one hand, the utilization of the advanced communication and control technologies enables the smart grid to efficiently control millions of devices in the field from a remote operation center. On the other hand, with bi-directional energy exchanging and sharing becoming possible, any consumer is both a contributor and a beneficiary of the energy exchanged on the network. Therefore, novel energy scheduling methodologies are required to realize the unprecedented level of cooperation between energy providers and consumers for reducing the energy supply-demand imbalance by making efficient use of widespread renewable energy resources and EVs. The following section describes the energy scheduling scenarios in V2G networks in details.

Energy Scheduling in Vehicle-to-Grid Networks

Figure 1 presents the conceptualized structure of a V2G network with large-scale EV and renewable energy penetrations. EVs can be charged via private chargers at home or via public chargers in work places, parking lots, and charging stations. EV aggregators in these places perform real-time status monitoring, seamless data collection, and coordinated charging/discharging management. The conventional generators and renewable generators submit their pre-schedule generation plans (or predicted renewable output intervals) to the control center of the utility. In the centralized energy scheduling scenario, the control center

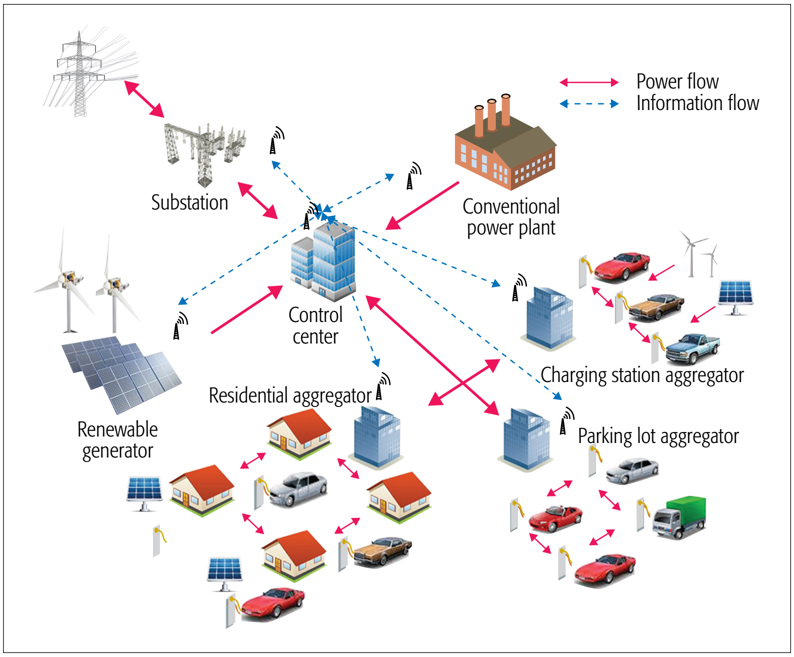

FIGURE 1. A conceptualized structure of a V2G network with large-scale EV and renewable energy penetrations.

calculates the scheduling problem based on the collected information and then issues dispatch signals to EV aggregators. Depending on the dispatch signals, EV aggregators can either act as a well defined responsive load or as an energy source to provide additional generation capacity. In comparison, distributed energy scheduling does not require the knowledge of global information and thus avoids the large communication and computational cost. Each EV owner can actively adjust the charging and discharging behavior in accordance with properly designed electricity pricing or incentive mechanisms.

However, in real-world V2G energy scheduling problems, a small uncertainty in the coefficient data can sometimes make the solution heavily infeasible or even completely meaningless to the original problem from a practical viewpoint. These data uncertainties, i.e., the values are not known exactly when the problem is being solved, can arise from implementation, measurement, and estimation errors. For example, the uncertainties brought by renewable energy sources and EVs may result in a significant mismatch between generation and load, which leads to numerous critical issues such as power imbalance, interarea oscillations, voltage instability, and frequency fluctuations[9]. This motivates us to explore the integration of robust optimization with energy scheduling, which provides an effective way to reduce the adverse effects caused by uncertainties.

Robust Energy Scheduling in Vehicle-to-Grid Networks

The goal of robust energy scheduling is to alleviate the negative effect of data uncertainty on the solution quality [10]. To explain the robust energy scheduling paradigm, we consider a problem with a linear-form objective function, which is defined as

Considering the linear-form objective functions and constraints, the V2G energy scheduling problem for integrating renewable energy can be described as a linear optimization problem and solved by robust linear energy scheduling (RLES) algorithms.

$$\left\{\min_{x}\left\{c^T x : Ax \le b\right\}, (c, A, b) \in \mathcal{U}\right\}. \tag{1}$$

where $x \in R^k$ is the vector of decision variables, and $c \in R^k$ is the vector of coefficients. The $m \times k$ matrix A and $b \in R^m$ specify the coefficients for the constraints. The proposed robust energy scheduling paradigm in this article is *worst-case-oriented*, that is, the robust feasible solution is guaranteed to be feasible and meaningful to all the possible realizations of (c, A, b) from the uncertainty set $\mathcal{U}$. In other words, the best possible robust feasible solution is the one that optimizes the worst case value $\sup\{c^T x: Ax \le b, \forall (c, A, b) \in \mathcal{U}\}$. The corresponding optimization problem is given by

$$\min_{x}\left\{\sup_{(c,A,b)\in\mathcal{U}} c^T x : Ax \le b, \forall (c, A, b) \in \mathcal{U}\right\}, \tag{2}$$

which is equivalent to the optimization problem

$$\min_{x,\varepsilon}\left\{\varepsilon : c^T x \le \varepsilon, Ax \le b, \forall (c, A, b) \in \mathcal{U}\right\}. \tag{3}$$

The latter optimization problem is also called the robust counterpart of the original linear programming program. Here, the minimum value of the variable ε represents the worst case value $\sup\{c^T x: Ax \le b, \forall (c, A, b) \in \mathcal{U}\}$. In general, the robust counterpart is computationally tractable when the uncertain set $\mathcal{U}$ is a nonnegative orthant or polytope with a convex hull, and can be efficiently solved by traditional programming approaches such as the interior point algorithm and Lagrangian relaxation methods, and so on.

In this section, the V2G energy scheduling problems are classified into three categories according to the application scenarios: renewable energy integration, ancillary service provision, and proactive demand-side participation in the electricity market. For each class of applications, how to design robust energy scheduling based on the structures of the problem and properties of the uncertainty set is described in detail. A comprehensive summary of the classifications of V2G robust energy scheduling problems and the state-of-the art contributions is provided in Table 1. The objective of the utility is usually to minimize the total cost or to improve the reliability of the overall power system. The utility may pay a subsidy to EV owners for their contributions in supporting V2G applications, which can be generally considered as a linear function of discharging power and subtracted from the objective function of the utility. In comparison, the objective of each EV owner is to maximize individual benefits rather than the total benefits of the overall power system.

Large-Scale Renewable Energy Integration

With robust energy scheduling, V2G networks can act as a source of backup for renewables by storing excess energy during off-peak hours and discharging the batteries into the grid to meet the peak demands. In robust energy scheduling problems for integrating renewable energy, most object functions can be efficiently modeled in linear forms, which include [13]:

- The active power generation cost of fossil fuel-based distributed generators such as gas and diesel turbines.
- The absolute value of maximum deviation between renewable generation and load.
- The utilization of the clean and sustainable renewable energy.

The following constraints can also be represented in linear forms [7]:

- Active power balance constraint: the total power generated any time is equal to the sum of the total load demand and transmission losses.
- Spinning reserve constraint: in each power control area, a certain amount of the total active generator power is kept available for unforeseen cases such as voltage and frequency fluctuations.
- Ramp rate constraint: the power generated by each generator in certain intervals cannot exceed that of the previous interval by more than a specified amount.
- Active power generation limits: the active power output of each generator is within the upper and lower generation limits.
- Charging and discharging power limits: the charging/discharging power of each EV is within the upper and lower charging/discharging limits.
- Energy balancing constraint for each EV: the total charged energy is equal to the sum of the EV owner's charging demand and discharged energy.

Even if a studied object has nonlinear features, the objective function can still be transformed into a linear from by employing linear approximation methods.

Furthermore, direct current (DC) distribution networks have emerged as a promising solution to integrate renewable energy sources since many small-scale renewables and energy storage systems operate as DC resources. In DC load flow analysis, the nonlinear model of alternating current (AC) systems can be simplified to linear forms because DC load flow only focuses on active power flows and neglects reactive power flows.

Therefore, considering the linear-form objective functions and constraints, the V2G energy scheduling problem for integrating renewable energy can be described as a linear optimization problem and solved by robust linear energy scheduling (RLES) algorithms. The collection of uncertain data in a RLES problem should be closed and convex, for example, the box or ellipsoid uncertainty models. The robust counterpart of the RLES problem is to minimize the largest value of the objective over all robust feasible solutions. In particular, the RLES methodology can be extended to solve the more general mixed-integer linear optimization problems, where only some of the decision variables are constrained to be integer values.

Categories	Application scenarios	Optimization goals	Practical constraints	Solution methods
Renewable energy integration [6, 7]	Backup for intermittent and fluctuating renewable energy	Minimizing the active power generation Minimizing the maximum deviation Maximizing the utilization of renewable energy	**DC linear constraints:** • Active power balance constraint • Spinning reserve constraint • Active power generation limits • Ramp rate limit constraint • Charging and discharging power limits • Energy balancing constraint for each EV **AC non-linear constraints:** • Active and reactive power flow balance constraint • Branch megavolt ampere limits	RLES, RMES
Ancillary service provision [3, 5]	Voltage regulation, frequency regulation, spinning serve and peak-load shaving	Minimize the generation cost of large thermal generation unit Minimize the active power loss in transmission networks		RLES, RCES, RMES
Demand-side participation in electricity market [11, 12]	Day-ahead electricity market bidding, price-based and incentive-based demand-side management	Maximizing the profit of EV owners or VPPs Minimizing the total operation cost of power system		RLES, RCES, RMES

TABLE 1. A comprehensive summary of the classifications of V2G robust energy scheduling problems and the state-of-the art contributions.

Ancillary Service Provision

V2G networks represent a new paradigm for providing ancillary services, such as voltage regulation, frequency control, and spinning reserve, to power grid in a cost-efficient way. V2G robust energy scheduling enables fast response to dispatch signals and low cost for short-duration grid support, compared to the costly process of ramping large generators up and down under real-time control.

In this application scenario, the overall goal is to improve the reliability and flexibility of the power system. Not only the active power, but also the reactive power needs to be adjusted and controlled properly to provide better voltage control, minimize real power loss, and improve power coefficients. As a result, the RLES methodology is not suitable to deal with nonlinear optimization problems in complex AC systems. The nonlinear objective functions and constraints include [5]:

- Generation cost of large thermal generation units, which can be described as a quadratic function of power output.
- Active power loss in transmission networks, which can be described as a quadratic function of bus voltage.
- Power flow balance constraint, including the real and reactive power balance equations for each load bus, which can be represented as a quadratic polynomial function of bus voltage based on the complex phasor representation of the voltage-current relationship.
- Branch megavolt ampere power, which is the quadratic function of active power and reactive power, should be within the upper and lower limits to avoid damage to transmission lines.

Robust conic energy scheduling (RCES) of polynomial complexity can limit the solution search space to a finite convex cone, and avoid mass calculation of power flow, which makes it a fast and effective method to handle an extremely wide variety of energy scheduling problems in convex form [14]. The uncertain set is a closed pointed convex cone with a nonempty interior, such as the direct products of nonnegative rays, Lorentz cones, or semidefinite cones. The objective function and constraints should be in linear forms and nonlinear conic forms, respectively. Most of the AC-flow based energy scheduling problems can be formulated as mixed integer quadratic programming, quadratically constrained quadratic programming, and second-order cone programming problems, which can be transformed into conic-form problems by methodologies such as lift and project relaxation, and then solved by RCES algorithms. Therefore, RCES problems can be treated as a "conic version" of RLES problems, and the goal of the corresponding robust counterpart is also to minimize the guaranteed value of the objective over all robust feasible solutions.

Proactive Demand-Side Participation in the Electricity Market

V2G networks enable EV owners to proactively participate in electricity market programs such as demand response and VPP by integrating robust energy scheduling with electricity market information in a holistic framework. Taking demand response as an example, both price signals and monetary incentives can be employed to modify EVs' electricity usage patterns [11]. On one hand, price-based demand response programs such as real-time pricing, critical peak pricing, and time of use pricing rates, enable EVs to manage their charging/discharging behaviors according to the time-varying rates that reflect the value of electricity in different times. On the other hand, incentive-based demand response programs pay EV owners for adjusting their electricity usage behaviors according to the demand reduction instructions. Furthermore, a sufficiently large number of aggregated EVs can be centrally coordinated and managed to form a VPP, which provides a competitive edge for individual EV owners to take part in day-ahead capacity biddings and long-term electricity auctions.

For electricity market related applications, the overall goal is to maximize the expected profit of EV owners or VPPs, which can be represented as the difference between the total benefit of market participation and the total cost of operation. Commonly used cost-benefit models are summarized as follows [12]:

- The benefits (or cost) of selling (or purchasing) electricity in real-time or day-ahead markets.
- The generation cost of small-scale dispatch-

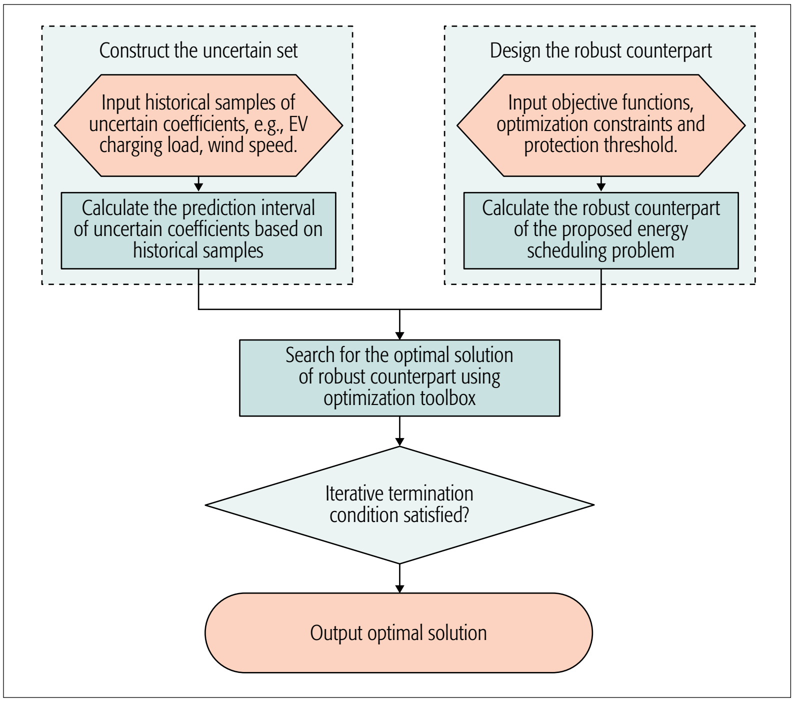

FIGURE 2. The diagram of the simulation program.

able generators, including fossil fuel and renewable-based distributed generators.

- The battery degradation cost, which is related to the number of cycles, operation temperature, rate of charge and discharge, and the depth of discharge.
- Start-up and shut-down costs of generators, which represent the costs of cooling down and preheating boilers and turbines of generators.

Since the probability distribution of electricity price in the next time period depends only on the current period and not on the sequence of periods that preceded it, the time series of electricity price can be modeled as a Markov chain [15]. However, despite the well known "curse of dimensionality," there exists another critical challenge for Markov decision process (MDP) based solutions, i.e., the "curse of uncertainty," which refers to the fact that coefficient uncertainty may have significant influence on the state transition probability and finally cause a change of decision strategy. The reason is that optimality performance is very sensitive with respect to the precision of the state transition probabilities, while the accurate estimation of these probabilities can be a tremendous challenge in practical applications of the electricity market. Hence, in the design of robust MDP energy scheduling (RMES) algorithms, the curse of uncertainty is addressed by assuming that the transition probabilities can be changed at will by a second player within prescribed bounds. Examples of the uncertainty set include the scenario model, the interval model, the likelihood model, the entropy model, and the ellipsoidal model. The robust counterpart of the RMES problem is to minimize the expected value of the cost function under the worst-case estimated transition probabilities. Furthermore, RMES can be combined with on-line learning methods such as reinforcement learning and Q-learning algorithms to solve problems even without explicit specification of the transition probabilities.

The Adjustable Robust Energy Scheduling Approach and a Case Study

V2G robust energy scheduling faces the over-conservatism problem, which is inherited from robust optimization. Although considering the worst-case scenario for each uncertain factor provides the highest protection against uncertainties, the economic performance is also severely degraded in order to ensure robustness. For some non-urgent applications, probabilistic guarantees for the robust solution are more preferred which allow the ability to choose the level of protection based on practical requirements. Therefore, how to provide the flexibility of adjusting the robustness of the solution and offer full control of the degree of conservatism for every uncertain constraint are exciting research directions.

Our Proposed Scheme

We propose an adjustable robust energy scheduling scheme to address the over-conservatism problem, which is able to adjust the level of robustness in terms of probabilistic guarantee for constraint violation. Since it is unlikely that all uncertain coefficients change simultaneously in a constraint, our aim is to protect the constraint feasibility against uncertainties with high probability while improving the economic performance. First of all, we need to construct the uncertainty set in order to implement the proposed adjustable robust energy scheduling scheme. One advantage of robust energy scheduling is that the partial information on the stochastic nature of data uncertainty can also be explored to build the uncertainty sets and improve the economic performance. To demonstrate this advantage, we can assume that the total charging load of each EV aggregator can be well approximated as the normal distribution by employing the central limit theorem. Denote L as the total number of aggregators. Based on the normal distribution assumption, the uncertainty set of the l-th aggregator's charging load can be designed by using the prediction interval method as $[\overline{P}_l - \hat{P}_l, \overline{P}_l + \hat{P}_l]$. $\overline{P}_l$ and $\hat{P}_l$ are the sample mean and standard deviation, respectively, which can be calculated by using the previous N observed samples. $P_{l,N+1}$ is the $(N + 1)$-th observation. δ is the probability that $P_{l,N+1}$ falls in the prediction interval $[\overline{P}_l - \hat{P}_l, \overline{P}_l + \hat{P}_l]$. A future observation $P_{l,N+1}$ which will fall within the interval, has a certain probability δ, that is, $\overline{P}_l - \hat{P}_l \leq P_{l,N+1} \leq \overline{P}_l + \hat{P}_l) = \delta$. It is noted that the robust energy scheduling algorithm is still valid even though the distribution of the aggregator charging load is completely unknown. The reason is that we can always construct a loose uncertainty set for robust energy scheduling based on historical data, which may not be as tight as the one based on partial stochastic information.

Then, we introduce a protection threshold α for the L uncertain charging loads, that is, $P_1, \cdots, P_L$, which controls the trade-off between the probability of constraint violation and the impact on the optimal objective values. α can take values (not necessarily integers) from the interval $[0, L]$. The solution is robust feasible deterministically if

$\lfloor\alpha\rfloor$ (the largest integer that does not exceed α) uncertain charging loads are allowed to change with the prediction intervals, and up to one load, for example, P_l, is allowed to change within the interval $[\bar{P}_l - (\alpha - \lfloor\alpha\rfloor)\hat{P}_l, \bar{P}_l + (\alpha - \lfloor\alpha\rfloor)\hat{P}_l]$. Furthermore, the solution will be feasible with high probability even if more than $\lfloor\alpha\rfloor$ uncertain coefficients change, which is validated later by numerical results. The mathematical proof is omitted here due to space limitations and will be included in the future journal version.

To validate the proposed algorithm, simulation studies are conducted for a V2G network scenario as shown in Fig. 1, which is composed of one gas generator, four wind turbines, one hundred EVs, and six aggregators. With robust energy scheduling, the utility schedules EVs to absorb excess wind power during valley periods and deliver power back to the grid during peak load periods to improve the economic performance. The optimization goal is to minimize the generation cost of the gas generator and the maintenance cost of wind turbines under the uncertainties of EVs' arrival time, initial state of charge of the battery, and wind turbine outputs. Practical constraints such as active power balance, active power generation limits, EVs' charging and discharging power limits, EVs' energy balance, and spinning reserve, have been taken into consideration. The simulation program diagram is shown in Fig. 2. RLES has been applied since both the objective function and constraints can be represented in linear forms based on the DC load flow analysis.

Illustrative Results

Figure 3 compares the energy supply and demand profiles with and without V2G robust energy scheduling capabilities. When the peak load starts at 19:30 p.m. during periods of low wind generation, the gas generator without V2G robust energy scheduling (abbreviated as RES in Fig. 3) has to increase output dramatically to satisfy the power balance constraint. On the other hand, during the off-peak times from 23:00 p.m. to 3:00 a.m., high wind generation at times of low residential and EV charging loads results in the waste of excess wind energy. Hence, it is clear that the uncoordinated charging behaviors of EVs and the intermittent output of wind turbines will significantly increase the total operation cost, which is 1,860 dollars. With the adoption of V2G robust energy scheduling, both the peak load and the total operation cost can be reduced by 49 percent and 54 percent, respectively. V2G robust energy scheduling can efficiently shift the peak load and reduce the cost of gas generators by enabling the batteries to discharge during peak hours and absorb excess energy during off-peak hours.

Figure 4 shows the relationship between the probability of constraint violation and the total operation cost. When the protection threshold α increases, the probabilistic guarantee of constraint violation is improved at the expens of increased operation cost. It is interesting to note that the minimum operation cost is only marginally affected when the robustness is increased. For instance, when α is increased from zero to six, the chance of constraint violation is reduced by 95 percent, while the minimum operation cost is only increased by 14 percent (from 740 US dollars to 852 US dollars). Therefore, the proposed robust energy scheduling algorithm does not heavily penalize the objective value to reduce the constraint violation probability, which provides an adjustable tradeoff between reliable operation and economic dispatch.

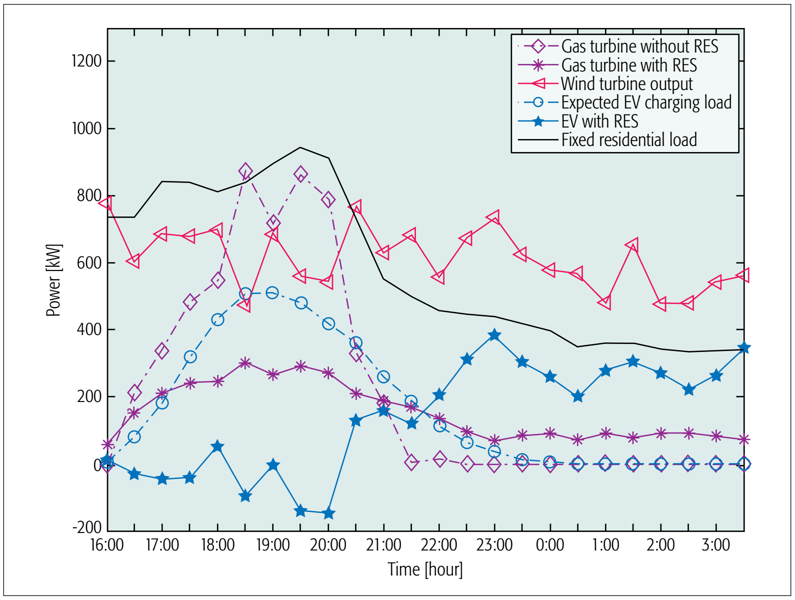

FIGURE 3. A comparison of the energy supply and demand profiles with and without V2G RES.

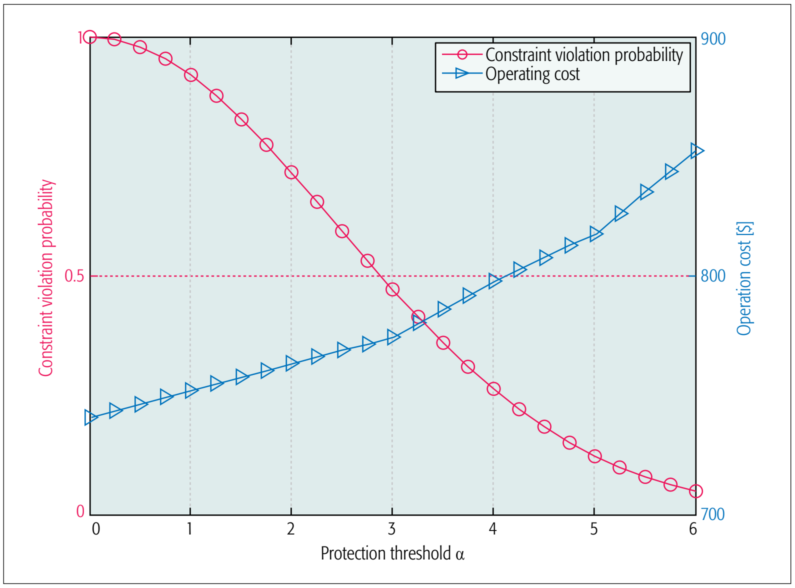

FIGURE 4. The relationship between robustness and economic performance.

Figure 5 shows the impact of the protection threshold α on the EV charging/discharging strategies. α = 0, 4, and 6 represent the weak-level, middle-level, and strong-level protections, respectively. As α increases from 0 to 6, EVs charge their batteries more aggressively and take more conservative approaches during the discharging phase in order to reduce the probability of constraint violation. This again demonstrates that large values of α are able to reduce the chance of constraint violation at the expenses of economic performance.

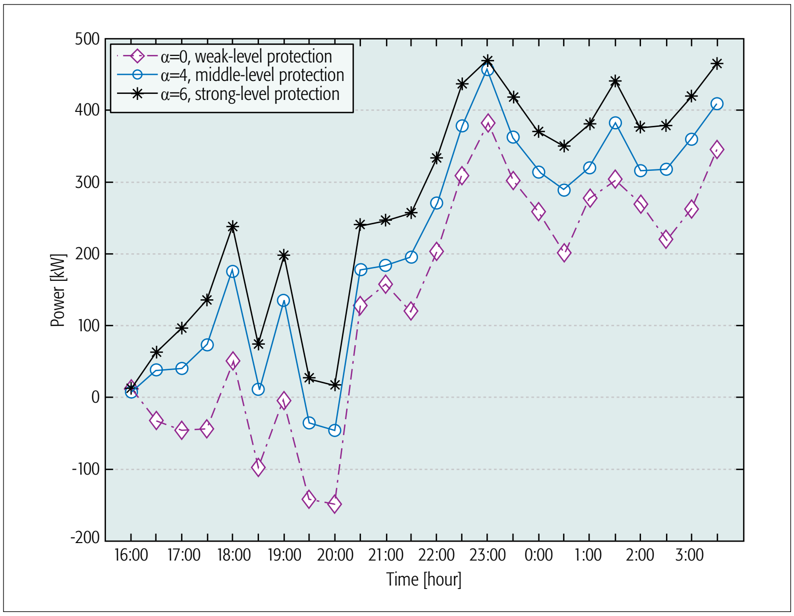

FIGURE 5. The impacts of protection threshold a on EV charging/discharging strategies.

Conclusion and Open Issues

In this article, we provided a holistic tutorial on the use of robust optimization for addressing uncertain energy scheduling problems in emerging V2G networks. First, we introduced the basic application scenarios and new challenges of energy scheduling in V2G networks. Then, we classified robust energy scheduling problems into three categories based on application scenarios and provided a detailed treatment of how to formulate problems and design robust solutions for each category. Finally, we proposed adjustable robust energy scheduling to address the over-conservatism problem by exploring chance-constrained methods. Some important challenging issues that need to be addressed in the context of robust energy scheduling in V2G networks are pointed out as follows.

Adding robustness to conventional V2G energy scheduling problems comes at the expense of computational complexity, which increases dramatically with the number of optimization stages and EVs. Most of the previous algorithms for solving robust energy scheduling problems are centralized. Unfortunately, it would be infeasible to have the complete information and knowledge of every EV in a large-scale V2G network due to the prohibited communication and computational costs. Therefore, alternative distributed solutions that explore game-theoretical approaches or aggregator-based group coordination should be investigated to tackle this challenge. In our proposed centralized algorithm, the tradeoff between robustness and optimality has been characterized both analytically and numerically. However, in a distributed robust energy scheduling design, the more complex three-dimensional tradeoff among robustness performance, optimality gap, and communication overheads has not been investigated sufficiently for V2G applications.

With the development of advanced information and communication technologies, large volumes of data are routinely collected in every aspect of V2G networks including EV locations, travel patterns, charging/discharging behaviors, battery states, historical demand profiles, and so on. Learning from these massive amounts of data is expected to bring significant improvements in robustness and economic performance. Data-driven optimization approaches that utilize the historical realizations of the random variables for designing uncertainty sets can be explored to adapt traditional robust energy scheduling to this new data-centered paradigm. Without prior knowledge of data probability distribution, the data-driven robust energy scheduling approach can develop a probabilistic guarantee on the optimality of the solution, which is less conservative than traditional counterparts while retaining several robustness properties. However, since the robust counterpart of an original tractable problem is not guaranteed to be tractable, how to incorporate data-driven approaches into the uncertainty set design to preserve tractability is a valuable yet challenging issue.

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