

Chapter 2

Literature Review

In this chapter, we provide a literature review of intelligent microgrid management and electric vehicle charging control with different decision objectives in different scenarios. We first give an overview of the energy management mechanisms in microgrids. We then review existing works concerning electric vehicle charging strategies. The limitations of previous literature and the advantages of our method over theirs are analyzed.

2.1 Energy Management in Microgrid

2.1.1 *Supply and Demand Management*

This problem can be viewed as containing two different parts. On the power supply side, we need to build a hierarchical demand control scheme so as to achieve the economic consumption scheduling and fulfill the requirements set by energy users; on the power demand side, there is a need to properly model the randomness of renewable energy generation, which may account for a significant portion of power supply in microgrids. Note that load balance constraints act as the connection between power consumption and generation.

Demand control techniques can be categorized into either price-based load control techniques, referred to as demand response methods, or direct load control, referred to as demand-side management. Under price-based load control scheme, users are encouraged to make energy consumption decisions individually according to the price information. Demand-side management strategies, however, are usually applied directly by a central controller and require consumer subscription to an economic incentive program. Some representative work has studied demand control techniques in residential microgrids. A recent paper [1] develops a real-time pricing

scheme which aims at reducing the peak-to-average load ratio (PAR) through demand response management in smart grid systems. A two-stage optimization problem is proposed and solved. Fathi et al. develop a stochastic model for scheduling in a local area network with the objective of cost minimization and PAR minimization [2]. The work in [3] presents a linear programming formulation for minimizing the energy cost through direct load control. In [4], a robust optimization approach is presented to adjust the hourly load level of a given consumer in response to hourly electricity prices. The uncertainties of renewable energies, however, are not considered in these studies. As such, the control schemes may not be readily optimal and applicable to the microgrid scenario where renewable energies constitute a significant portion of power resources.

There also exist some studies considering renewable energy uncertainties when scheduling the energy generation. Such work can be categorized into two groups: the stochastic-based approaches and the robust optimization-based approaches. For instance, Wang et al. define stochastic upper and lower supply curves to capture a broad range of fluctuations in the power system, where energy generated by each power source is modeled as stochastic arrivals in the queuing model [5]. In [6], scenario-based stochastic operation management methods are developed to tackle the fluctuant demands and renewable energies using the probability distribution function (PDF) of each uncertain variable. Hidden Markov models have also been adopted to characterize renewable energy generation [7–9]. Stimulated by observations that in practical scenarios, obtaining an accurate distribution function could be computationally costly and renewable energy may not follow Markov process or any simple distributions, robust optimization has recently received growing attention as a modeling framework for optimization under uncertainty. Instead of assuming explicit probability distribution, robust optimization confines the renewable generation in a pre-defined uncertainty set containing the worst-case scenario. For example, Zhang et al. consider a distributed economic dispatch problem for microgrid with high penetration of renewable energies [10]. The intrinsically stochastic properties of renewable energy sources are captured by a polyhedral uncertainty set with deterministic lower and upper bounds. Similar methods for modeling renewable energies can also be found in other recent work [11, 12]. The main topics concerning supply and demand management in microgrids are illustrated in Fig. 2.1.

Different from the existing work, our approach in Chap. 3 jointly considers power demand and supply management. Rather than assuming there is available knowledge of the specific distribution of renewable energy generation, the proposed approach describes the underlying uncertainty in a more detailed yet flexible manner. It allows more information of renewable energy generation to be effectively incorporated into the uncertainty model when such information is available.

2.1.2 Energy Generation Scheduling

Energy generation scheduling is the process of effectively scheduling different energy sources (local generators, central grid, renewable energy generations, etc.) to meet

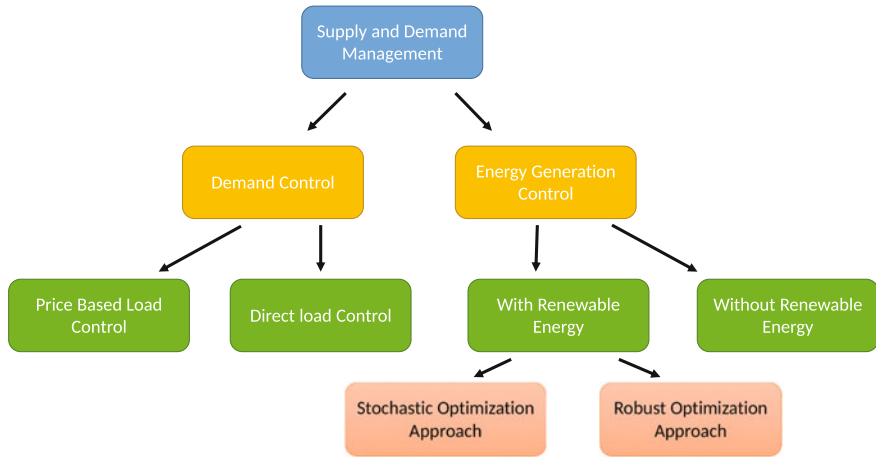


Fig. 2.1 Main topics concerning supply and demand management in microgrids

the energy requests at a minimum cost subject to various physical constraints of the power systems. It is a classic problem in electricity system which is composed of two aspects, namely unit commitment (UC) [13] and economic dispatch (ED) [14]. The UC problem involves determining the start-up and shut-down schedules of generator units to be used to meet forecast demand over a short time in future. It is a complex optimization problem with both integer and continuous variables and has been shown to be NP-Complete in general. The basic UC methods reported in the literature include priority listing [15], dynamic programming [16], Lagrangian relaxation [17], integer programming [18, 19]. After UC problem has determined the start-up and shut-down schedules, the ED problem seeks to find the optimal allocation of electric power outputs from various available generators without alternating their on/off status. Readers can refer to comprehensive surveys on UC [20] and ED [21] for more details.

Conventional energy generation scheduling is typically conducted 24 h in advance (day-ahead) and based on the fact that the system load can be forecast with reasonably good accuracy one day in advance. In microgrids, however, this is no longer the case due to the fact that accurate predictions of small-scale electricity and heat demands, renewable energy supplies, and electricity market prices are very difficult, as we stated earlier. Some recent literature has investigated energy generation scheduling of microgrids [22–26]. In [22], a multi-objective optimization of economic load dispatch for a microgrid is investigated using evolutionary computation. The paper aims at minimizing the emission of the thermal generators and minimizing the total operating cost. In [23], a generalized formulation for intelligent energy management of microgrid is proposed using artificial intelligence techniques jointly with linear-programming-based multi-objective optimization. Similarly in [24], an intelligent energy management system is proposed for optimal operation of a CHP-based microgrid over a 24-h time interval. Authors of [25, 26] also propose different energy management strategies based on different assumptions. The limitation of

these results, however, is that they all assume that the energy demands and supplies are known ahead of time, which is rarely the case in practice.

There also exist some studies considering demand and supply uncertainties when scheduling the energy generation. These works can be categorized into two groups: the stochastic optimization-based approaches [6, 27–31] and robust optimization-based approaches [10, 32–35]. In [27], the author develops a solution method for scheduling units of a power-generating system to produce electricity by taking into consideration the stochastic nature of the hourly load and its correlation structure. In [28], a stochastic model for the long-term solution of security-constrained unit commitment is proposed. A more complicated scenario can be found in [6], in which an efficient stochastic framework is developed to investigate the effect of uncertainty on the operation management of microgrids. The proposed stochastic framework would consider the uncertainties of load forecast error, wind turbine generation, photovoltaic generation, and market price concurrently. Paper [29] examines the impact of the stochastic nature of wind on planning and dispatch of a system. Similarly, authors of [30] compare stochastic and reserve methods and evaluate the benefits of a combined approach for the efficient management of uncertainty in the unit commitment problem. In [31], a two-stage stochastic objective function aiming at minimizing the expected operational cost is implemented. The stochastic optimization approaches¹ explicitly incorporate a probability distribution function of the uncertainty, and they often rely on enumerating discrete scenarios of the uncertainty realizations. Such approaches mainly have two practical limitations. First, it may be difficult and costly to obtain an accurate probability distribution of uncertainty. Second, the solution only provides probabilistic guarantees to the system reliability. To obtain enough high guarantee requires a huge number of samples, which poses substantial computational challenges.

In recent literature, robust optimization has received growing attention as a modeling framework for optimization under uncertainty. In [32], a two-stage adaptive robust unit commitment model is proposed for the security-constrained unit commitment problem in the presence of nodal net injection uncertainty. In [33], a robust optimization approach is proposed to accommodate wind output uncertainty, with the objective of providing a robust unit commitment schedule for the thermal generators in the day-ahead market. In [10], a power scheduling approach is proposed based on robust optimization to address the intrinsically stochastic availability of renewable energy sources. Papers [34, 35] also present robust optimization-based approach for optimal microgrid management considering wind power or energy consumption uncertainties. Instead of postulating explicit probability distribution,

¹As an example, consider two-stage linear programs. Here the decision maker takes some action in the first stage, after which a random event occurs affecting the outcome of the first-stage decision. A recourse decision can then be made in the second stage that compensates for any bad effects that might have been experienced as a result of the first-stage decision. The optimal policy from such a model is a single first-stage policy and a collection of recourse decisions (a decision rule) defining which second-stage action should be taken in response to each random outcome.

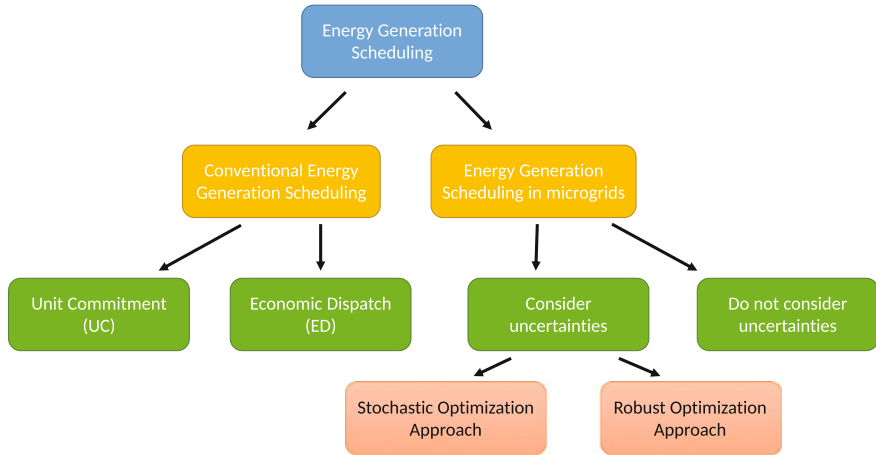


Fig. 2.2 Main topics concerning energy generation scheduling in electrical grids

robust optimization confines the random variable in a pre-defined uncertainty set containing the worst-case scenario. For instance, in [10–12, 32–35], uncertainties in price prediction or renewable energy generation are presented as interval values with deterministic lower and upper bounds, and the framework developed in [36, 37] is incorporated to solve the problem. Without requiring explicit probability distribution, uncertainty can be characterized more flexibly. In addition, the conservativeness of the solution can easily be controlled, and the problem is always computationally tractable both practically and theoretically even for large-scale problems. The main topics concerning energy generation scheduling in electrical grids are illustrated in Fig. 2.2.

In our study (Chap. 4), robust optimization concept is also applied to tackle the uncertainties in energy generation scheduling problem of microgrids. Different from the previous robust optimization works [10–12, 32–35] which confine the uncertainty within a lower and upper bounds, in our work, we propose a new uncertainty model to characterize the renewable energy and user demand uncertainties, which can provide more statistical details in describing the underlying uncertainty. Moreover, the proposed uncertainty model is also flexible enough that we can incorporate more information into the uncertainty model when such information is available. Whereas in Chap. 5, we further focus on investigating how the temporal-correlation information of the renewable energy impacts the scheduling performance bounds based on the framework in Chap. 4. To the best of our knowledge, we are the first to do such evaluations.

2.2 Electric Vehicle Charging Control

The existing EVs' charging scheduling mechanisms can be roughly classified into two categories: centralized charging strategies and decentralized charging strategies. The main idea of centralized control is utilizing centralized infrastructure to collect information from all EVs and centrally optimize EVs' charging considering the grid technical constraints. In such a strategy, the master controller makes decisions about the rate and time of charging EVs to get the optimal solution. References [38–41] develop various centralized charging strategies with different optimization objectives, including saving system cost, minimizing CO₂ emission, reducing power loss, adjusting power frequency, and satisfying EV owners. Either optimization methods or heuristic algorithms are adopted by researchers to solve such problems. In [42], a hierarchical control scheme is proposed for EVs' charging station loads in a distribution network while minimizing energy cost and abiding by substation supply constraints. The scheduling is based on the forecasted load information. Reference [43] proposes a dynamic programming (DP)-based optimization method of charging an EV fleet modeled as a single, so-called aggregate battery. In these papers, the dynamics of the EVs' arriving/departing times and charging patterns are not considered. Recent literatures [44–47] all adopt receding horizon-control-based techniques to tackle the uncertainties in the dynamic charging systems. References [48–50] develop online algorithms for coordinating the EVs' charging to save the system cost and lessen the EVs' harmful impacts on the distribution network. Jin et al. [51] study EV charging scheduling problems from a customer's perspective by jointly considering the aggregator's revenue and customers' demands and costs. Paper [52] studies risk-aware day-ahead scheduling and real-time dispatch for plug-in EVs, aiming to jointly optimize the EV charging cost and minimizing the risk of the load mismatch between the forecast and the actual EV loads. Different from previous papers, both static and dynamic charging scenarios are considered in [51, 52]. Though the centralized charging strategy is straightforward, the size of the centralized optimization increases with the number of EVs. Accurate information collection from a large number of EVs may also impose a challenge. Designing an effective centralized EV charging strategy therefore remains as a difficult problem.

In contrast, the vehicle owners can directly control their EVs' charging patterns employing the decentralized charging strategies [53–68]. Gan et al. [53] propose a decentralized algorithm to schedule EV charging to fill the electric load valley. This charging control strategy iteratively solves an optimal control problem in which the charging rate of each vehicle can vary continuously within its upper and lower bounds. In each iteration, each EV updates its own charging profile according to the control signal broadcast by the utility, and the utility company alters the control signal to guide their updates. In [54–60], various decentralized charging frameworks to coordinate charging demand of EVs are implemented based on game theory concepts. In [61], a decentralized online valley filling algorithm for EV charging is proposed. An optimal power flow (OPF) framework is adopted to model the network constraint that arises from charging EVs at different locations. Similarly, decentralized EV

charging schemes with valley filling objective can be found in [62, 63]. Considering the selfish nature of people, authors of [64] define some weighting factors in the objective function of EV charging management problem aiming at modeling users' convenience in the presented optimization procedure. Xi et al. [65] study a decentralized price-based EV charging control. They study a pricing scheme that conveys price and quantity information to the load aggregator and compare it to a simpler price-only scheme. In [66], a novel online coordination method for the charging of plug-in EVs in smart distribution networks is proposed. An innovative parking lot prediction unit is developed adopting M/G/ ∞ queuing model. In [67], the authors formulate the EV charging problem as a convex optimization problem and then propose a decentralized water-filling-based algorithm to solve it. A receding horizon approach (similar to [44–46]) is utilized to handle the random arrival of EVs and the inaccuracy of the forecast non-EV load. Although the decentralized charging strategy offers more ownership authority to EV owners, it may not ensure optimality in the charging of EVs and causes security concerns of the power grid [38, 54, 68].

In the above-mentioned literature, the charging energy is supplied purely from power grid, largely generated by conventional units. The main goal of introducing EVs, namely reducing the pollution and greenhouse gas of transportation sector, is consequently greatly abated, as the pollution is transferred from vehicle itself to conventional energy units. Renewable energy should play a role as significantly as possible to achieve the real environmental advantage. Renewable-energy-based EV charging hence becomes a practical and critical problem.

Though the topic has not been well investigated in the literature, a few related works can still be found dealing with the charging scheduling of EVs with renewable energy integration. Moeini et al. [69] propose a charging management framework considering multiple criteria including total loss of distribution networks, rescheduling cost, and wind energy utilization. In [69], it is assumed that the energy demand of EVs is known by the controller. In [70], a price-incentive model is utilized to generate the management strategy to coordinate the charging of EVs and battery swapping station (BSS). While in [71], the mathematical models are built for both smart charging and V2G operation with distribution grid constraints. Authors in [70, 71] both assume that the EVs are static and always available to be charged/discharged. In [72], a stochastic optimization algorithm is presented to coordinate charging of electric-drive vehicles (EDVs) in order to maximize the utilization of renewable energy in transportation. Due to the stochastic nature of transportation patterns, the Monte Carlo simulation is applied to model uncertainties presented by numerous scenarios. In [73], the charging problem is formulated as a stochastic semi-Markov decision process with the objective of maximizing the energy utilization. In recent work [74], the uncertainties of the EV arrival and renewable energy are described as independent Markov processes. In [75, 76], the authors tackle the EV charging scheduling problem adopting Lyapunov optimization techniques, such that statistics of the underlying processes does not need to be known in prior. The main topics concerning EV charging scheduling are illustrated in Fig. 2.3.

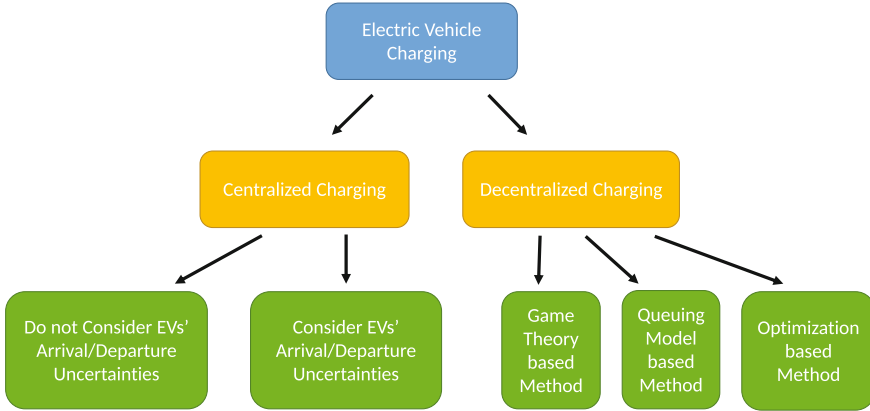


Fig. 2.3 Main topics concerning EV charging scheduling

Compared with what has been proposed in the past, our EV charging mechanism proposed in Chap. 6 mainly shows the following several advantages: (1) Renewable energies can be effectively utilized by the EVs; (2) compared with the online scheduling schemes, the proposed mechanism incorporates useful estimated information day-ahead to help reduce the uncertainties in the real-time scheduling stage; (3) compared with the offline scheduling schemes, our mechanism is fairly flexible such that it can effectively respond to real-time incidents; (4) a fast computing algorithm is designed which can easily tackle a large number of EVs; i.e., one weakness of the centralized charging strategies is overcome. Whereas in Chap. 7, compared with previous studies, the proposed hybrid centralized–decentralized (HCD) EV charging scheme offers flexible charging choices for customers, where EV owners can either assign the charging tasks to system controller or individually choose the charging profiles based on their own preferences. The stochastic characteristics of EVs such as the arrival/departure times and charging demands are all taken into account. Moreover, the communication burden between EVs and the system controller is low, and the proposed charging scheme is robust to poor communication channels.

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