

Chapter 2

Related Work

Abstract The increased adoption of active end-nodes can negatively impact the reliable and economical generation, transmission, and distribution of power. This chapter gives an overview of these potential impacts and surveys related work on direct control of elastic loads to achieve both user-level and system-level objectives. Balancing these two types of objectives is nontrivial, giving rise to the design of various control architectures and many plausible control schemes as discussed in this chapter.

2.1 The Impact of Active End-Nodes on the Distribution Grid

Active end-nodes are becoming ubiquitous in distribution system [10, 11]. In view of this, many studies have explored the potential impacts of large-scale integration of these technologies on the electrical grid through the intensive use of steady-state and dynamic simulations [2, 24]. Performing these impact studies for a given power system is indeed quite complex owing to uncertainties about their point of connection and their size, and also the degree of correlation that might exist between loads and local renewable generation.¹

It must be remarked that elastic loads, except for EVs, have been connected in large numbers to distribution feeders for a long time and operators have never considered them a threat to system reliability. With the availability of low cost communications in recent years, elastic loads, such as air conditioners, and space and water heaters, have been even utilized in some jurisdictions to shave the peak demand and to provide regulation service to the grid (see for example the *peaksaver* program in Ontario [22]). But unlike these loads, demands of EV chargers can be significant, and are relatively unpredictable and highly correlated. For example, EVs can be charged at up to 80 A at 240 V with AC Level 2 charging [37, 52], an instantaneous demand of 19.2 kW,

¹For example, the workplace EV charging load is strongly correlated with solar generation, while the home-level EV charging load is usually correlated with wind generation.

which is equivalent to the average demand of about ten average homes in North America. We therefore next discuss the potential impacts of EV and PV adoption on the distribution system.

2.1.1 Impact of EV Adoption

Studies on the impact of EV charging on distribution, transmission, and generation systems go back to the 1980s. An early paper by Heydt in 1983 [19] anticipates that the load increase due to the future penetration of EVs would fall within generation planning limits; however, distribution circuits may be inadequate to accommodate the charging of EVs; therefore, transformer overloading and voltage deviations are expected. In this regard, load management strategies are necessary to alleviate peak loading stresses. A similar observation is made by Rahman et al. [32]. The authors anticipate that with future penetration of EVs, certain distribution branches may be subject to significant overloads, even if the entire system has sufficient capacity. This is attributed to the expected nonuniform growth of the EV charging load in a distribution network.

The potential impacts of EV integration into the distribution network, including increased energy losses, transformer and branch congestion, voltage deviations that affect power quality, and phase imbalance, have been explored extensively in the literature [8, 16, 21, 27, 30, 31]. In recent work, Fernández et al. [30] assess the impact of uncontrolled EV charging on large-scale distribution system planning in two different case studies. They show that the minimum reinforcement investment required to accommodate 62 % EV penetration can increase the total network costs by up to 19 % compared to a situation without EVs. Furthermore, energy losses increase by up to 20 and 40 % of actual values in off-peak hours for 35 and 62 % EV penetration respectively. The incremental investment can be reduced by 60–70 % if a smart charging strategy is adopted.

In an effort to underscore the need for coordinated charging, Qian et al. [31] analyze the impact of four different EV charging strategies on a typical UK distribution system. In the case of uncontrolled domestic charging, where EVs start charging nearly simultaneously, the daily peak load increases by 17.9 and 35.8 % for 10 and 20 % EV market penetration levels respectively. This drastic increase in the peak load overloads several branches and transformers, emphasizing the need for control.

In a similar line of work, Lopes et al. [27] evaluate the impact of EV integration into a typical medium voltage distribution network in terms of branch congestion levels and voltage profiles for different charging strategies. The authors show that the voltage lower limit is almost reached at several distant buses in the scenario with 10 % EV penetration and uncoordinated charging. However, the lower voltage limit is reached only when EV penetration reaches 52 % if a smart charging strategy is adopted. The branch congestion level, i.e., the ratio of the line loading to its rating, is only slightly higher for the case of 52 % EV penetration and smart charging than the

case of 10 % EV penetration and uncoordinated charging, indicating the effectiveness of a smart charging strategy in relieving congestion.

Clement Nyns et al. [8] also study the impact of low to moderate EV penetration on distribution system losses and voltage deviations. Their results imply that with 30 % EV penetration, uncoordinated charging leads to more than 10 % voltage deviations, whereas coordinated charging keeps voltage deviations below 10 % at all times. Moreover, for all charging periods and seasons, power losses noticeably decrease with coordinated charging.

The impact of EV adoption on aging of distribution transformers is explored by Gong et al. [16] and Hilshey et al. [21]. In [16], a transformer thermal model is used to study the impact of Level 2 EV charging on aging of the distribution transformers installed at residential neighbourhoods. Monte Carlo simulation results show that with poor coordination of charging times, the transformer insulation life is greatly affected at relatively high EV penetration rates. Simulation results presented in [21] indicate that coordinated charging of EVs can reduce the annual transformer aging rate by more than 12.8 and 48.9 % compared to uncoordinated charging when EV chargers are Level 1 and Level 2 (as established in [37]), respectively.

The above studies show that uncoordinated charging of a large population of EVs could have detrimental impacts on the existing distribution networks. Upgrading distribution circuits alone, would be quite costly for DSOs as discussed in [30]. Therefore, DSOs must incorporate a control strategy to reduce the required distribution reinforcement investment. Some of these control strategies are discussed in Sect. 2.2.

2.1.2 Impact of PV Adoption

The exponential growth of global PV cumulative installed capacity [11] has given impetus to the study of solar integration into power distribution networks and of the resultant architectural, technical, and operational problems, such as adverse impacts on power quality, protection coordination, voltage profiles, and feeder and transformer loading [24, 49]. The potential steady-state and transient impacts of PV systems on volt/var control, power quality, and power system operation depend on the penetration level and interconnection of PV units, and their interactions with loads and distribution equipment, making it extremely complex to evaluate these impacts.

Several attempts have been made to quantify the extent of local and system-wide problems associated with PV integration. In [45], it has been shown using simulations of a test network with rooftop PV systems connected to secondary distribution lines that a 30 % penetration of PV systems can be accommodated without any change to voltage control systems. Should the PV penetration increase to 50 %, over-voltage is observed in simulations; this suggests that the voltage control systems must be adjusted or re-engineered at this penetration. Another study examines the impacts of high penetration of residential PV systems on distribution system protection and voltage control [5]. The conclusion is that high PV penetration complicates

the coordination of protection equipment and creates unacceptable voltage swings (beyond pre-defined limits) on feeders. In [20], a control methodology is described for grid-scale battery storage systems to address the negative impacts of PV integration; this methodology enables storage systems to provide voltage stability and frequency regulation, and improves the economics of distributed solar generation.

2.2 Control of EV Chargers

The control of smart EV chargers is essential to address the potential distribution network problems discussed in Sect. 2.1, while satisfying user-level objectives. Additionally, smart EV chargers and other elastic loads can be controlled to support higher penetrations of distributed renewable generation, achieve a desired response to power system dynamics, or provide system services such as frequency regulation [1, 6, 15, 17, 25, 42]. This section only surveys control mechanisms that aim to mitigate the negative impacts of EVs on the distribution network and to optimize certain user-level objectives; thus, it does not touch upon control mechanisms for delivering electricity to the grid in vehicle-to-grid (V2G) applications.

The main focus of this section is on control schemes that do not put customers in the control loop, meaning that the customers may specify charging deadlines and preferences but cannot impede or delay the execution of control decisions that are computed by the utility based on their input. These schemes are referred to as *direct control* schemes. Unlike direct load control schemes, price-based schemes assume some specific response from the customers to changes in the electricity price. This assumption does not necessarily hold in practice and the demand response is neither predictable nor immediate, rendering these schemes of limited practical value [6]. For this reason, these control schemes are not discussed in this section.

Existing work can be categorized into two based on the objectives they seek to achieve. The first category encompasses approaches that take the perspective of the electric utility and satisfy one or several system-level objectives, whereas the second category encompasses approaches that take the perspective of users and satisfy one or several user-level objectives, where users are either EV owners or charge service providers (CSPs). These control objectives can be myopic or defined over a finite or infinite time horizon. Furthermore, there are several possible approaches to control EV chargers. In particular, EV chargers have been controlled using a schedule computed the prior day (known as *pre-dispatch scheduling*) or in near real-time. Control decisions can be made independently by EV chargers (a fully distributed approach), jointly by EV chargers and intermediate control nodes installed at transformers (a decentralized approach), or entirely by a computer cluster at the utility control center (a centralized approach). Finally, the control scheme may require the precise model of the distribution network along with load and generation forecasts, or only rely on recent measurements of certain network parameters. Thus, the extensive body of literature that has been developed around the control of elastic loads can be divided into several categories based on the following criteria:

Table 2.1 Taxonomy of related work

	Objective	Pre-dispatch	Real-time	
			Centralized	Decentralized
Utility	Avoid network congestion	[36]	[34, 35]	[18, 21, 50]
	Improve voltage profiles	[8, 48]	[4, 9]	
	Minimize losses	[8, 36, 38]	[9]	
	Flatten the load	[14, 38]		[14, 26]
	Shave the peak load	[29, 43]	[46]	[12]
	Minimize the cost of generation		[9]	
Users	Minimize charging cost	[28, 33, 36, 43]	[51]	[23]
	Minimize charging time		[53]	[39]
	Maximize EV owners' convenience		[50]	[50]
	Maximize CSP's revenue		[7]	
	Fair power allocation to EVs		[40]	[12]

- **Time of control:** The control algorithm can run in near real-time or several hours in advance of power delivery.
- **Information needs:** The control algorithm may require the precise model of the distribution network along with load and generation forecasts, or rely on recent measurements of certain network parameters only.
- **Decision-making approach:** Control decisions can be computed in a centralized or decentralized manner. The computation and communication overhead of control greatly depends on this.
- **Optimization horizon:** Control objectives can be myopic or defined over a finite or infinite time horizon.

Table 2.1 shows a taxonomy of existing work on coordinated charging according to their objectives and control approaches.

2.2.1 Pre-Dispatch Scheduling

Pre-dispatch scheduling approaches compute charging schedules for EVs by solving an optimization problem in advance of power delivery. In some cases, this optimization problem falls within the general class of optimal power flow problems [8, 29, 36, 48]. Solving the OPF problem requires a precise model of the distribution network and inelastic loads, as well as the knowledge of the point of connection of chargers and arrival and departure patterns of EVs. These parameters are difficult to determine or estimate in practice. Hence, pre-dispatch scheduling approaches either maintain a conservative operating margin to accommodate estimation uncertainties or perform power flow calculations for numerous instantiations of random variables,

e.g., EV arrival and departure times, their initial state of charge (SOC), and their point of connection. The former typically results in system under-utilization and the latter significantly increases the computation time.

For example, Mehboob et al. [29] solve a distribution optimal power flow (DOPF) problem to determine the hourly EV charging schedule and hourly tap and capacitor settings that minimize the system peak. This optimization problem incorporates voltage and feeder capacity constraints as well as EV charging constraints. They employ a genetic algorithm based approach to solve this DOPF problem. This approach generates many feasible EV load samples and performs power flow calculations for each set of samples to find a day-ahead most likely solution.

A DOPF problem is also formulated in [36] to control EV charging loads, taps, and capacitor switching decisions for the next day in an unbalanced three-phase distribution system. The authors consider various objectives and incorporate the distribution substation capacity constraint in the nonlinear programming problem. Specifically, they minimize the total energy drawn by the local distribution company and its cost, the total feeder losses, and the total cost of EV charging over the period of a day. The proposed day-ahead hourly scheduling approach is evaluated on the IEEE 13-node test feeder and a real distribution feeder. Compared to the uncontrolled charging case, their approach prevents undervoltage conditions and reduces the peak demand and losses.

Several other pre-dispatch scheduling approaches simply use the optimal control framework without relying on power flow calculations. In these cases, control might be computed more efficiently; however, it does not necessarily respect distribution network constraints such as voltage limits. Following is an overview of the most relevant work in this area.

In recent work, Gan et al. [14] and Ma et al. [28] use distributed control to obtain a day-ahead charging schedule for EVs. In [14], the EV charging control problem is formulated as a discrete optimization problem with the objective of flattening the aggregate demand served by a transformer. A stochastic decentralized control algorithm is proposed to find an approximate solution to this optimization problem. It is shown that this algorithm almost surely converges to one of the equilibrium charging profiles. To facilitate real-time implementation of this controlled charging scheme, the authors also propose an online version of their decentralized control algorithm in which EVs participate in negotiation on their charging profiles as they plug in for charging, over time. In [28], a decentralized algorithm is proposed to find the EV charging strategy that minimizes individual charging costs. It is shown that the optimal strategy obtained using this algorithm converges to the unique Nash equilibrium strategy when there is an infinite population of EVs. In the case of homogeneous EV populations, this Nash equilibrium strategy coincides with the valley-filling maximizing strategy, i.e., the globally optimal strategy.

In [43], a deterministic optimization problem is formulated to find a fleet charging schedule which minimizes the overall charging cost, subject to the available power, the battery capacity, and the charging power constraints. The optimization problem is deterministic because it is assumed that the connection and disconnection times of EVs, their energy demands, the price of electricity, and the total wind generation

are known a priori. The authors also compare linear and quadratic approximations of the EV battery behavior in terms of violations of the battery boundaries (minimum and maximum charge levels) for the obtained charging schedule.

A similar line of work by Rotering et al. [33] explores the possibility of using plug-in hybrid EVs for regulation and ancillary services while charging their batteries with minimum cost. Specifically, dynamic programming is employed to find a charging schedule that minimizes the EV charging cost based on forecasts of the electricity price, EV driving patterns, and energy demands in three different scenarios. If the control is incapable of supplying the energy demand, it is assumed that the lack of charge is fulfilled by the internal combustion engine consuming gas, which is presumably more expensive than electricity.

The relationship between the objectives that are based on load factor, load variance, and losses is investigated in [38]. The authors formulate three optimization problems to minimize the load variance, to maximize the load factor, and finally to minimize losses. These optimization problems are solved by a centralized approach using day-ahead load predictions, noting that the first two problems are convex and can be solved more efficiently compared to the third one. It is shown through simulations on practical distribution systems that solutions to these three problems are close, motivating the use of load factor or load variance as the objective function rather than losses. In any case, for practical systems the performance of the algorithm that minimizes the load variance is quite similar to the one that minimizes losses.

2.2.2 *Near Real-Time Control*

The near real-time computation of charging schedules improves utilization and reliability of the power system compared to the pre-dispatch computation of the schedules by continuously adapting the charging rate of EV chargers to the available capacity of the network. Hence, smart EV chargers use higher rates when the distribution network has sufficient capacity, reducing these rates once the network becomes congested. The real-time charging schedule could be computed using either a centralized or a decentralized/distributed approach. The following surveys related work in each category.

2.2.2.1 **Centralized Approaches**

Coordinated charging of EVs at parking facilities with a maximum total available amount of power is the focus of [7, 40, 51, 53]. In [53], the problem of finding a schedule in a charging station with stochastic EV arrivals, variable electricity prices, and intermittent renewable generation is modelled as a constrained stochastic optimization problem which can be studied using the Markov decision process framework. The objective is to minimize the mean waiting time of EVs. In [51], the scheduling

problem of EV charging with stochastic arrivals and renewable generation is formulated as an infinite-horizon Markov decision process. The objective is to maximize a social welfare function that takes into account the total utility of customers, the electricity cost associated with the charging schedule, and the penalty for failing to meet the deadlines. In [7], it is assumed that there is a CSP that uses collocated renewable sources and supplements the renewable with the energy purchased from the grid. The authors formulate an online scheduling problem with the objective of maximizing the operating profit of the CSP while meeting the charging deadlines. This optimization problem is a mixed integer program. A subset of EVs are selected for charging through an admission control process and admission decisions are made based on EV arrivals, output of renewable sources, and the electricity price. The scheduler can further optimize on the time and quantity of the energy purchased from the grid.

In an effort to provide a notion of fairness, an optimization problem is formulated in [40] that maximizes a weighted average of the state of charge of parked EVs in the next time step, subject to the amount of energy available from the utility, the maximum energy that can be absorbed by EVs, and the ramp rate of EV batteries. Each weight term incorporated in the objective function is a function of the energy price, and the remaining charging time and the present SOC of the corresponding EV. The authors use four computational intelligence-based algorithms, namely the estimation of distribution algorithm, the particle swarm algorithm, the genetic algorithm, and the interior point method, to solve this optimization problem and compare their performance.

A DR strategy is proposed in [34, 35] to avoid transformer and feeder overloads by controlling non-critical and controllable loads, including EVs. This strategy determines household demand limits using a simple algorithm which protects the distribution network from congestion, and issues the obtained limits to in-home controllers. Subsequently, every in-home controller determines which appliances should be on based on the priorities and preferences set by users in advance. The effect of the proposed DR on consumers comfort is quantified using comfort indices introduced in [35]. Nevertheless, the proposed DR strategy does not guarantee congestion prevention because appliances might be turned on to satisfy users' preferences even when the transformer is congested.

Deilami et al. [9] propose a real-time smart load management algorithm to coordinate EV chargers; this algorithm minimizes the total cost of generation and anticipated losses, while respecting user preferences. To solve this problem, their approach is to use the maximum sensitivities selection method, which selects EVs for charging from a queue sorted based on the sensitivity of the loss function to EV charging loads. A load flow analysis is performed in each time step to evaluate the objective function and ensure that system constraints, including voltage limits and the available generation capacity, are not violated. Nevertheless, this approach does not deal with the distribution network problems, such as line and transformer congestion, and does not provide fairness.

A two-stage controller based on a model predictive control (MPC) formulation is designed in [4] to regulate charging of a time-varying number of EVs and control a fixed number of distributed generation inverters under the assumption that the load is periodic with period length of 24 h. Using approximate power flow equations for radial distribution networks, the proposed controller charges EV batteries to a desired SOC while tracking an optimal reachable reference voltage at every bus. The proposed scheme handles plug-and-play charging requests (as EVs join or leave the system) by updating reference voltages to ensure stability and reliability under the new dynamics. This plug-and-play operation comes at the price of delaying charging of EVs that have arrived recently until bus voltages converge to the updated reference values. Note that this control scheme does not address branch and transformer congestion problems in the distribution network.

Turitsyn et al. [46] aim at maximizing the utilization of the excess distribution circuit capacity while keeping the probability of a circuit overload negligible by controlling EV chargers. Using one-way broadcast communication, the authors regulate EV charging start times by computing a single EV connection rate and sending it periodically to the chargers. This rate determines, on average, how many EV chargers can start charging per unit time.

In summary, most existing work on real-time centralized control of EV chargers suffers from a scalability problem since computing the charging schedule for a vast number of connected EVs is computationally expensive in a centralized fashion. Moreover, centralized control schemes may require communication of sensitive information, such as EV departure times, to a central controller. The central controller is also a single point of failure in the distribution network. These issues can be addressed by distributing control among the EV chargers and possibly other control nodes as suggested in [44]. Real-time decentralized control schemes are reviewed next.

2.2.2.2 Decentralized Approaches

This section describes decentralized and fully distributed control schemes that run in near real-time. These schemes are scalable, robust, and use real-time information instead of long-term predictions. However, they suffer from three major shortcomings. First, they do not use a realistic model of the distribution network, which includes all branches and transformers and their operational constraints. Second, they do not evaluate the proposed solution using power flow analysis when it is not originally found using power flow calculations. Instead, many of them focus on flattening the demand of the entire distribution network, ignoring bus voltages and loading of distribution lines and transformers. Third, they do not balance efficiency and fairness of the control algorithm. In fact, fairness is not a design goal of most of these approaches. These schemes are discussed in the following.

Wen et al. [50] propose a novel approach to the EV charging control problem, where a subset of EVs are selected for charging in every time slot such that user convenience is maximized and branch flow constraints are met. This selection problem is posed as a combinatorial optimization problem, whose convex relaxation can be solved in a control center using linear programming. An efficient decentralized algorithm is then proposed based on the alternating direction method of multipliers to determine the set of EVs that must be charged in a given time slot. Using numerical simulations for different EV penetration levels, the proposed centralized and decentralized approaches are compared in terms of performance, computational complexity, and communication overhead. The authors study the effects of the control timescale and the rounding method, which maps continuous selection variables into 0 and 1, on the performance of the decentralized algorithm. Nevertheless, this paper only addresses branch congestion and ignores other operational constraints of the distribution network, does not use power flow analysis to validate that computed charging schedules are feasible, and finally does not attempt to allocate power to connected EVs based on a well-established notion of fairness.

Fan [12] borrows the notion of congestion pricing from the Internet to reduce the peak load while providing weighted proportional fairness to end users. Exploiting two-way communications between the utility and users, congestion prices are sent to users, enabling them to adapt their demands to the capacity of the market in a fully distributed fashion. The user preference is modelled as a willingness-to-pay parameter, i.e., the weight factor in the utility function of users. The proposed algorithm is then applied to EV charging to obtain a charging rate allocation. Interestingly, the total EV charging load varies with the range from which the weight factors can be chosen. Thus, the utility has to limit this range to ensure that the total load is not greater than the market capacity. Convergence behavior of the algorithm is studied using both an analytical approach and a simulation-based approach. Note that this work does not model the distribution network and does not incorporate the capacity constraints of distribution lines and transformers and the charge rate constraints of EV chargers.

In [39], several additive-increase multiplicative-decrease (AIMD) based algorithms are used for distributed control of a set of EV chargers that share a single constrained resource. The EV chargers independently increase their demands by an additive factor until the shared resource becomes congested; following this event, they reduce their demands by a multiplicative factor to relieve congestion. The authors study the problem from the user perspective rather than the utility perspective; they consider various scenarios and user-level objectives, and propose an AIMD-like congestion control algorithm for each scenario. Moreover, this work does not investigate the potential distribution network problems and is not based on the theory of network utility maximization (NUM); it instead relies on an arbitrary choice of AIMD parameters.

In [18] a control mechanism is designed to deal with transformer overloading by modelling the transformer thermal limit as a constraint. Specifically, the authors formulate the EV charging problem as an open-loop centralized control problem with the objective of minimizing the SOC deviations from 100% and also minimizing

the control effort subject to the capacity constraint of batteries and EV chargers, the temperature constraint of the substation transformer, and the target SOC specified by EV owners. Using the dual decomposition method, an iterative price-coordinated implementation of this control mechanism is proposed which allows EV owners to compute their charging rate locally. A receding-horizon feedback mechanism is employed to account for unexpected disturbances, including fluctuations in inelastic demands, changes in the number of connected EVs, changes in the ambient temperature, and modelling errors. Note that this work deals with the substation transformer overloading problem and cannot prevent distribution line overloads. Furthermore, it does not use power flow analysis to validate the operation of the proposed algorithm in a test distribution network.

Li et al. [26] aim at flattening the load at the distribution network level by extending the “max-weight algorithm” to the EV charging control problem. Control rules solve an optimization problem that minimizes the L2 norm of the aggregate load. It is shown that, in the long term, the solution to this optimization problem can be made arbitrarily close to the solution of the optimization problem that minimizes the variance of the aggregate load. The former problem can be solved in real-time. Using numerical simulations of the IEEE 37-bus and 123-bus test feeders, the performance of the algorithm is compared with static charging algorithms that use perfect knowledge and imperfect forecast of the base load for different penetration levels. Note that the authors do not attempt to address the distribution network problems due to the simultaneous charging of EVs and their objective is merely to flatten the load.

Jin et al. [23] propose an EV charging scheduling algorithm to minimize the energy bill of users, and, at the same time, flatten the aggregated load imposed on the power grid. The authors employ a grouping algorithm and a sliding window iterative scheduling algorithm. The grouping algorithm reduces the computation and communication overhead of the scheduling algorithm. It runs at a centralized coordinator, which is called the information center, and classifies the EV population into several groups based on a similarity metric defined in terms of the start and end charging times, the energy requirement of an EV, and the maximum charge rate of its charger. Once EV groups are formed, the information center computes and broadcasts the charging characteristic of every group. The charging schedule is then computed using a sliding window iterative scheduling algorithm. Specifically, EVs belonging to each group solve an optimization problem to minimize the group bill and compute their charging schedule locally in a specific slot of every cycle, while charging schedules of other groups remain unchanged. When the charging rates of EVs within a group are determined, they send their updated charging profiles to the information center. The information center broadcasts real-time price/load information at the beginning of each slot of each cycle to coordinate EV chargers. When the algorithm converges, the obtained charging schedule also optimizes the total generation cost. This work does not take fairness into account, does not address distribution network problems due to the simultaneous charging of EVs, and does not validate the results through power flow analysis of a test distribution system.

Hilshey et al. [21] propose two automaton-based strategies for coordinating EV charging to limit the power supplied by transformers and decelerate their aging.

Their approach is to compare the transformer aging status against four thresholds to determine whether the number of EVs being charged should be increased, decreased, or held constant in the next time period. Once the number of active chargers is determined, one of the proposed decentralized automaton-based strategies is used for admission control. The first strategy is a first-come first-served strategy in which every EV sends a charge request to the transformer. If the request is denied due to congestion, it is queued and processed again in the next time slot. The second strategy is probabilistic; it allows chargers to specify urgency by agreeing to pay a higher rate. If charging is not urgent and the request is denied, the charge request is sent to the transformer in the next time slot with a probability p . If charging is urgent and the request is denied, a request is sent to the transformer in every future time slot until it is admitted. Note that both control strategies do not provide fairness, and are only applicable to a single transformer supplying fixed-rate EV chargers. Moreover, the aging thresholds are chosen in an ad hoc manner.

2.3 Control of Renewable Inverters

Control will not be limited to elastic loads in the smart grid. Smart inverters, which are capable of injecting and consuming reactive power and curtailment of real power, can also be controlled by the utility to address growing concerns over widespread adoption of PV systems, and also achieve several system-level objectives. The optimal control of PV inverters has received increased attention in recent years. For example, Farivar et al. [13] propose the fast timescale control of the reactive power injection of PV inverters to minimize line and inverter losses as well as the energy consumption through voltage optimization. This problem is formulated as an OPF for a radial distribution system and the optimal voltage regulation operation is evaluated on a distribution feeder on the Southern California Edison system. Similarly, the authors of [3] propose a real-time distributed control of the reactive power output of smart inverters to minimize feeder head real power consumption. They utilize a model-free control algorithm that relies on periodic measurements of the feeder head real power broadcast by the substation.

An OPF problem is formulated in [41] to determine an PV inverter control strategy that improves voltage magnitude and balance profiles, while minimizing network losses, inverter losses, and solar generation curtailment. This multi-objective optimization problem is solved using a sequential quadratic programming approach. The performance of this control strategy is evaluated through power flow analysis in a real unbalanced three-phase low-voltage distribution system in Australia. In a similar line of work, Turitsyn et al. [47] find the optimal dispatch of the inverter's reactive power to minimize line losses and maintain the voltage within an acceptable range in a radial distribution system. None of these control schemes takes advantage of elastic loads to minimize the curtailment of solar power.

2.4 Joint Control of Elastic Loads and Renewable Energy Systems

The impact studies presented in Sect. 2.1 suggest that PV systems and elastic loads might have opposite impacts on distribution circuits. Specifically, the uncontrolled charging of a large population of EVs can result in undervoltage and equipment overloading, whereas the uncontrolled operation of a large number of solar inverters can cause overvoltage and reverse power flow toward the distribution substation. Thus, it is reasonable to extend the optimal control framework to jointly control smart inverters and elastic loads. This control scheme enables the grid to safely accommodate higher penetrations of renewable generation and elastic loads, while enhancing the overall reliability and cost-effectiveness of the power system. Despite the significance of such a control scheme in future distribution systems, the synergy between inverter-based renewable energy systems and elastic loads has not been exploited in the literature to stabilize voltage, relieve congestion, prevent reverse flows, and minimize curtailment in a distribution system with a high concentration of renewable generation. Chapter 4 expands on this idea.

2.5 Chapter Summary

Large-scale integration of elastic loads and renewable energy systems can negatively impact reliable and economical generation, transmission, and distribution of power if these end-nodes are not controlled properly. This has given impetus to the design of mechanisms to control elastic loads and renewable inverters. However, most related work focuses on controlling elastic loads, very little work focuses on controlling smart inverters, and practically no work explores the joint control of these technologies. The extensive body of literature that has been developed around the control of elastic loads can be divided into several categories based on the following criteria:

- **Time of control:** The control algorithm can run in near real-time or several hours in advance of power delivery.
- **Information needs:** The control algorithm may require the precise model of the distribution network along with load and generation forecasts, or rely on recent measurements of certain network parameters only.
- **Decision-making approach:** Control decisions can be computed in a centralized or decentralized manner. The computation and communication overhead of control greatly depends on this.
- **Optimization horizon:** Control objectives can be myopic or defined over a finite or infinite time horizon.

A control scheme that fully meets the design goals specified in Chap. 1 must be decentralized and based on real-time measurements. This scheme should enhance power system reliability and efficiency, reduce its carbon emissions, satisfy user-level

objectives, and mitigate adverse impacts of large-scale adoption of solar PV systems and EVs, including large voltage fluctuations, network congestion, reverse flow, and violation of voltage limits. None of the control schemes surveyed in this chapter can satisfy all of these objectives while meeting the design goals specified in the previous chapter.

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