INVITED PAPER

A Cyber–Physical–Social Perspective on Future Smart Distribution Systems

This article discusses the coupling relationships among the cyber, physical, and social aspects in the digitalization evolution of smart grid.

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ABSTRACT | An increasing number of distributed energy resources (DERs), such as rooftop photovoltaic (PV), electric vehicles (EVs), and distributed energy storage, are being integrated into the distribution systems. The rise of DERs has come hand-in-hand with large amounts of data generated and explosive growth in data collection, communication, and control devices. In addition, a massive number of consumers are involved in the interaction with the power grid to provide flexibility. Electricity consumers, power networks, and communication networks are three main parts of the distribution systems, which are deeply coupled. In this sense, smart distribution systems can be essentially viewed as cyber–physical–social systems. So far, extensive works have been conducted on the intersection of cyber, physical, and social aspects in distribution systems. These works involve two or three of the cyber, physical, and social aspects. Having a better understanding of how the three aspects are coupled can help to better model, monitor, control, and operate future smart distribution systems. In this regard, this article provides a comprehensive review of the coupling relationships among the cyber, physical, and social aspects of distribution systems. Remarkably, several emerging topics that challenge future cyber–physical–social distribution systems, including applications of 5G communication, the impact of COVID-19, and data privacy issues, are discussed. This article also envisions several future research directions or challenges regarding cyber–physical–social distribution systems.

KEYWORDS | 5G communication; COVID-19; cyber–physical–social systems; data analytics; data privacy; demand response (DR); distribution systems; energy justice; smart grid; social–technological integration; wireless communication.

I. INTRODUCTION

Traditional distribution systems "passively" receive and consume electricity from main transmission systems and are operated without advanced monitoring and control but with simple open-loop control methods. In the new century, distribution systems are becoming more and more modernized. We can clearly see three transformations in future smart distribution systems, i.e., digitalization, decentralization, and decarbonization (3D) [1].

1) *Digitalization:* Large amounts of data collection, communication, and control devices are being installed in distribution systems for real-time monitoring and control, such as smart meters (SMs) and distributed energy storage control units. These devices are connected with each other or to the control center through wired or wireless communication techniques.

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Distribution systems become cyber–physical systems on the way to digitalization [2].

2) *Decentralization:* An increasing number of distributed energy resources (DERs), such as rooftop photovoltaic (PV), electric vehicles (EVs), and distributed energy storage, are being integrated into the distribution systems. Future distribution systems will be operated in a more decentralized way, where electricity consumers will be more involved in decision-making in distribution systems, such as home energy management and biding in peer-to-peer markets. Human behavior should be fully considered in this situation. Thus, the cyber–physical distribution systems should be extended to cyber–physical–social distribution systems [3].
3) *Decarbonization:* Countries around the world are sparing no effort to reduce carbon emissions and finally achieve carbon neutrality [4]. Decarbonization is the ultimate goal of constructing smart cyber–physical–social distribution systems, which can be realized by enhancing energy efficiency, promoting the accommodation of local energy, and providing flexibility to transmission systems.

Since the concept of "Smart Grid" was proposed in 2007 [5], the research of "cyber–physical" power systems has been receiving increasing attention, emphasizing bidirectional power and information flows. Extensive works have been done on the cybersecurity of power systems. Different types of cyberattacks and the modeling, simulation, and analysis approaches of these attacks in power systems were summarized [6]. The cybersecurity issues of microgrids were the main focus of Li *et al.* [7], where the impacts of potential risks attributed to cyberattacks on microgrids were examined, and the corresponding countermeasures were provided. The cyber–physical resilience in power systems was defined in [8]. The resilience of power systems was reviewed in [9] from the cyber–physical perspective, where how external environments, such as hazards, cyberattacks, and human behaviors, influence the system resilience was discussed. The vulnerability assessment and resilience quantification methods for cyber–physical power systems were summarized in [10].

Compared to the cybersecurity of power systems, there are fewer works on the cyber–physical–social power systems. How to model the behaviors of humans in power systems from the social perspective, especially for a massive number of electricity consumers, has not been well addressed. Nowadays, behavioral and social sciences research in different industries attracts increasing attention. For example, the Nature publisher set up an online community forum for researchers to discuss and share behavioral and sociological research and its applications in various industries [11]. The cyber–physical–social system is a new way of thinking about the control, operation, and planning of future distribution systems, covering broad research topics. Many works have been conducted at the intersection of cyber, physical, and social aspects in distribution systems. Take demand response (DR) as an example; it involves remote control in the cyber system, electrical appliances in the physical system, and behavior analysis in the social system. According to what the work emphasizes, this article roughly summarizes these works into three categories: cyber–physical, physical–social, and cyber–social couplings. It is impossible to provide an exhaustive review of all the works done for cyber–physical–social distribution systems, which is not the goal of this article. Instead, this article aims to select several interesting, important, and correlated topics from the three categories and summarize the works on these topics. In this way, any possible overlap with existing reviews of related topics can be avoided. We hope that this article can inspire novel and comprehensive research in distribution systems from the cyber–physical–social perspectives.

The contributions of this article are given as follows:

1) analyzing cyber–physical–social couplings in future distribution systems and conducting a comprehensive literature review of future smart distribution systems from a cyber–physical–social perspective;
2) providing a well-designed taxonomy for cyber–physical–social distribution systems from three categories: cyber–physical coupling, physical–social coupling, and cyber–social coupling;
3) discussing future potential research directions or challenges, including human behavior modeling, cyber systems operation and planning, and data supply chain in distribution systems.

The rest of this article is organized as follows. Section II introduces the coupling relationship among the physical system, the cyber system, and the social system of the distribution systems. Sections III–V summarize the recent research works on the cyber–physical coupling, physical–social coupling, and cyber–social coupling in distribution systems, respectively. Section VI provides several open research issues that need to be fully addressed for better operating future smart distribution systems. Section VII draws the conclusions.

II. CYBER–PHYSICAL–SOCIAL DISTRIBUTION SYSTEMS

The concept of cyber–physical–social systems comes from two possible ways. The first is the evolution and expansion from cyber–physical systems to cyber–physical–social systems by putting humans into the loop [12]. The second is the integration of cyber–physical systems and cyber–social systems, where the cyber system is the bridge between the physical system and social system [13]. Even though there is no universal definition of cyber–physical–social systems, deep fusion among humans, communication networks, computers, and things is the basic characteristic. Cyber–physical–social systems provide a new paradigm for the operation of real-world systems

Table 1 Illustrative Cyber–Physical–Social Coupled Businesses in Distribution Systems

Business	Cyber system	Physical system	Social system
SM installation	SM data collection	House distribution & network topology	Consumers' acceptance of SM
Demand response	Control signal transmission	Characteristics of DERs	Consumers' willingness for demand response
Electricity retailing	Load and price data analytics	Power balance constraints	Consumers' behavior & game among retailers
Network dispatch	Dispatch order transmission	Network constraints	Policy and system operator's preference

where cyber, physical, and social systems should be carefully and comprehensively considered for decision-making of real-world systems [14]. This concept has been used for the new-generation intelligent manufacturing [15], aeronautics and space [16], smart cities [17], and so on.

Distribution systems have undergone at least two upgrades. The first upgrade is from simple power distribution systems to cyber–physical distribution systems, accompanied by the construction of the smart grid. Various advanced communication and control infrastructures have been installed for the monitoring and closed-loop control of distribution systems. The second upgrade is from cyber–physical distribution systems to cyber–physical–social distribution systems, where human participation and interaction become more and more critical with the integration of DERs and the implementation of various business models. It is necessary to put humans in the decision loop of distribution systems [9]. In cyber–physical–social distribution systems, the cyber system (communication networks, control center, and so on), physical system (power networks, power transformer, and so on), and social system (consumers, retailers, system operator, and so on) are deeply coupled.

Table 1 provides several businesses in distribution systems that illustrate the coupling relationship among cyber, physical, and social systems. Take SM installation as an example; how to efficiently collect a large amount of distributed SM data is studied in the cyber system; the SM installation should follow the house distribution and power network topology in the physical system; and the attitude and acceptance levels of consumers for SMs should be carefully considered in the social system. Thus, installing and popularizing SMs in the distribution systems are an integrated cyber–physical–social problem. It is the same for DR, electricity trading, network dispatch, and so on in future smart distribution systems.

To facilitate the planning and operation of distribution systems, interdisciplinary research should be conducted. As shown in Fig. 1, the research involves power engineering, communication engineering, social psychology,

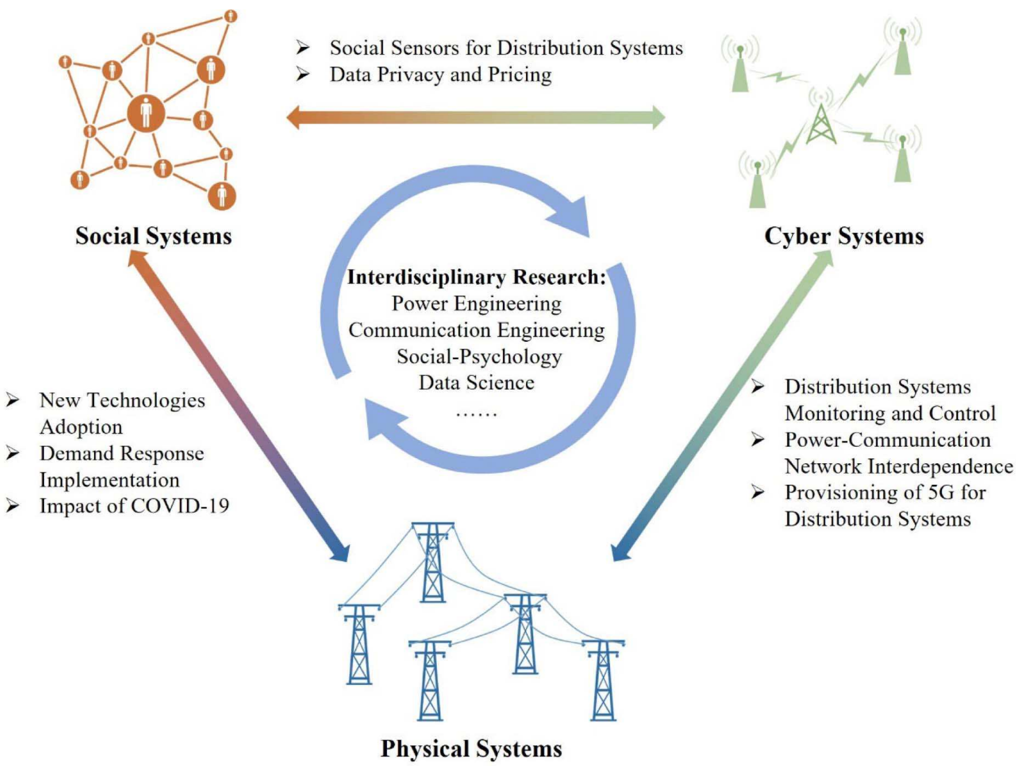

Fig. 1. ***Cyber–physical–social coupling in distribution systems.***

data science, and so on. Even though different businesses couple cyber, physical, and social systems, they may be more related to two of the three systems. Thus, this article roughly divides different businesses or technical issues into three categories according to which two systems are more coupled.

The first is cyber–physical coupling. Since several reviews of security and resilience of cyber–physical power systems already exist, to avoid overlap with these reviews, this article focuses more on methods or algorithms for wireless communication for monitoring and control of distribution systems and their interdependent relationships in distribution systems. In addition, since 5G is an emerging wireless communication technique, we will inevitably also discuss its role in distribution system communications.

The second is social-physical coupling. Adopting new technologies, including SMs, DERs, and EVs, is a typical social problem in distribution systems. Instead of establishing different optimization models for DR programs, how to efficiently implement DR will also be investigated from a social perspective. COVID-19 has a profound impact on the whole society of the world. How it influences distribution systems will be discussed.

The third is cyber–social coupling. In addition to communication networks, social networks, which are at the intersection of cyber and social systems, can also be used for situation awareness of distribution systems where the social sensors are widely distributed to consumers. Nowadays, people are paying more and more attention to privacy protection. The privacy issue in distribution systems will also be studied.

The following three sections will detail these businesses or technical issues in the three categories.

III. CYBER–PHYSICAL COUPLING IN DISTRIBUTION SYSTEMS

One basic characteristic of smart gird is the two-way electricity flow and communication flow. Future distribution systems will be equipped with sophisticated monitoring and control capabilities that require the support of advanced communication technologies and networks [18]. Different types of communication technologies and networks, such as power line communications, optical fiber communications, wireless sensor networks, and wide area communication networks, have been proposed to meet different communication requirements of distribution systems [19].

Power line communications use the existing power line cables for smart grid communications. By avoiding the need to install new communication links, power line communications can enable fast and economical deployment of smart grid communication networks [20]. Despite the benefits, power line communications do come with a few issues [21]. It is difficult to establish an accurate channel model for power line communications due to the noisy background of power cables. More importantly, power line communications have a low signal-to-noise ratio and, thus, are not suitable for high bit rate applications across a distance beyond a few hundred meters [22]. For high bit rate transmissions over a long distance, optical fiber communications can be used. With the inherent immunity to electromagnetic interference, optical fiber communications are suitable for applications within an interference-rich and noisy environment to which a power system belongs. Similar to power line communications, optical fiber communications suffer from problems that are common to wired communication technologies, such as the lack of flexibility in device locations. Compared to wired communications, wireless communications can be rapidly deployed to cover a large area with a desirable high bit rate. Wireless sensor networks, which are low-cost, energy-efficient, and capable of self-organize and self-healing, can be an essential part of the communication network of distribution systems [23]. Unfortunately, wireless sensor networks are usually private networks and do not provide universal coverage to all areas. It is likely that some devices in a smart grid are not reachable by a wireless sensor network. In this case, we need a wide-area wireless network, such as a cellular network or satellite communication network.

From the above, it is clear that communication technologies for smart grids are very diverse. For conciseness, this section focuses mainly on the use of wireless communication technologies. As shown in Fig. 2, this section consists of three subsections. The first subsection discusses various existing wireless communication schemes, which have been proposed to facilitate monitoring and control operation in a typical distribution system. The second subsection is dedicated to challenges that arise from the existence of interdependent relations between power and communication network. The roles of 5G cellular communication systems are discussed in the third subsection.

A. Distribution Systems Monitoring and Control

Fig. 3 shows the monitoring and control system of a power distribution network using wireless communications. The sensors and controllers, such as SMs and micro-phasor measurement units (PMUs), will be widely installed in distribution systems for better situation awareness. A reliable operation of distribution systems depends on reliable communication between sensors, controllers, and control center [24]. Various works have been done for demand-side monitoring, distribution network monitoring, and DER control.

1) Demand-Side Monitoring: In the context of supporting demand-side management, a scheme was developed in [25] to determine the optimal number and location of data aggregation points within a neighborhood area network. In the scheme, the data aggregation point placement is required to ensure that demand requests and price information can be transmitted with acceptable communication service quality. An integer programming problem was formulated in [26] to find the optimal

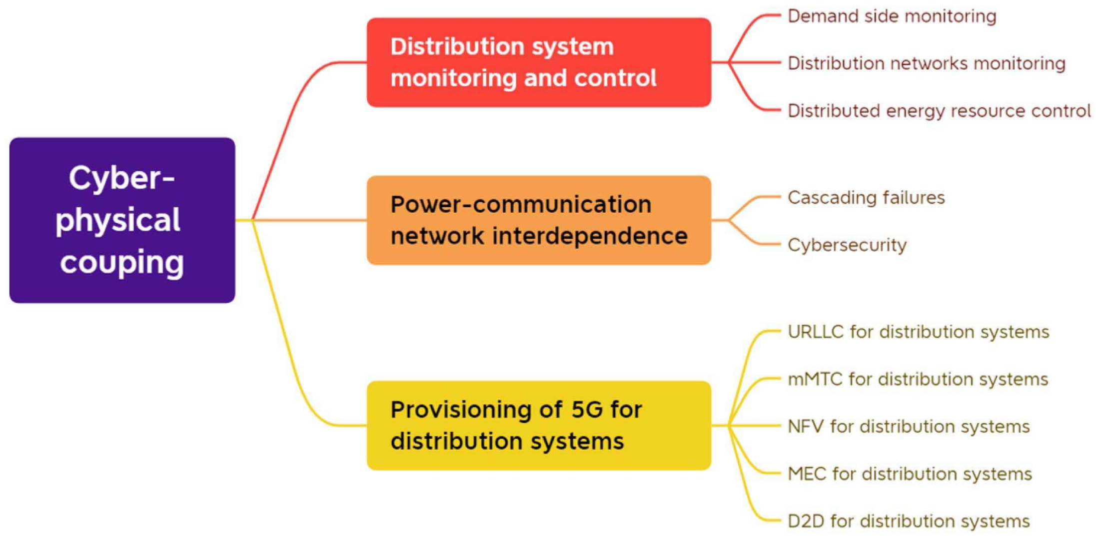

Fig. 2. *Cyber–physical coupling in distribution systems with a focus on wireless communication.*

data aggregation point placement to achieve the minimum installation and communication cost. A suboptimal solution was efficiently obtained by running the k-means clustering algorithm iteratively for the original integer optimization problem. With a system model and objective similar to [26], another method was proposed in [27] to solve the similarly complex integer program through performance-guaranteed approximation. More specifically, the approximation involved relaxing integer optimization variables to real-valued numbers so that the integer program could be solved as a linear program. An optimal data aggregation point placement problem in a multihop routing scenario was studied in [28], where SMs could play the role of relay nodes with limited capacities. The optimization model aimed to minimize the total installation, transmission, and delay cost, and it was solved by an iterative and heuristic approach.

2) Distribution Networks Monitoring: In transmission systems, some substations are installed with synchrophasors or PMU to measure time-synchronized phasor, frequency, and the rate of change of frequency in voltage and current. However, due to cost and small phasor angle differences, PMUs are rarely used in distribution systems. Compared to PMUs, micro-PMUs have a higher angle measurement accuracy in the range of millidegree and, therefore, are suitable for deployment in distribution systems. In future distribution systems, micro-PMU will also be installed at key nodes so that different power parameters, such as power phasors, can be obtained. The communication issues for PMU and micro-PMU are similar in nature. Therefore, we use the terms PMU to refer to both PMU and micro-PMU, hereafter.

The PMU data can be used for load modeling, fault analysis, and so on but will cause a high communication

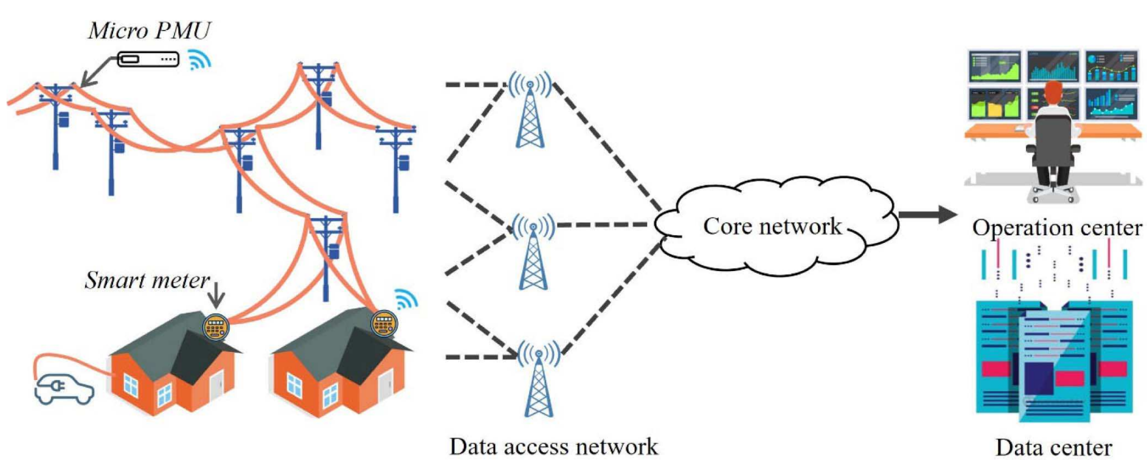

Fig. 3. *Monitoring and control of distribution systems based on wireless communication.*

burden [29]. The characteristics of communication delays incurred in centralized monitoring and control systems that utilized multiple PMUs distributed over a large geographic area were studied in [30]. Simulation results suggested that it is necessary to optimize the location of the control center based on the intended smart grid application. Apart from the control center, it is also critical to optimize the placement of PMUs [31]. Since PMUs are not usually installed at all substations, it is necessary to find out the subset of substations for PMU installation to achieve a desired performance metric, such as availability, reliability [32], and observability [33]. The optimal PMU placement problem has been solved using integer linear programming [34], genetic algorithm [35], differential evolution [36], particle swarm optimization [37], and so on.

In distribution network monitoring, PMUs and sensors may be installed on power line poles. These sensors require the support of an advanced communication network to deliver their data to the control center or substation. Wireless sensor networks offer a cost-efficient way to rapidly establish an end-to-end communication connection between such sensors and substations. In wireless sensor networks, some poles do not have a direct communication link with a substation. These poles must depend on their neighboring poles as relays in sending measurement and sensor data to the substation in a hop-by-hop transmission manner [38]. In such a way, packets from poles that are many hops away from substations may suffer from an unacceptably high delay and a low packet delivery ratio. As such, it is desirable to reduce the number of hops and shorten the communication route. The works [39] and [40] are separately proposed to shorten the communication route by installing cellular network modules on the poles. As further suggested in [41], it is not necessary to install a cellular network module on each pole but only on selected poles. The problem of selecting a subset of poles for cellular network module installation has been addressed in [42]. For the purpose of minimizing installation and operational cost, Fateh *et al.* [42] have formulated and solved a constrained optimization problem that finds the desired number and locations of cellular-enabled poles. In the optimization problem, the constraints are various communication requirements, such as delay, connectivity, and bandwidth.

Dynamic thermal rating for power equipment, such as power lines and transformers, can help to improve smart grid efficiency by increasing the power transmission capacity of existing systems without installing new transmission lines. For dynamic thermal rating, the communication network is required for timely and reliable transmissions of conductor temperature measurements from *in situ* sensors to the control center [43]. Take dynamic line rating as an example; sensors need to be installed on the power line to measure the line's instantaneous conductor temperature. This temperature may affect the line's ampacity, which is defined as the maximum electric current that is allowed to flow. Ampacity may change dynamically as a result of variations in ambient temperature and weather conditions over time. For example, a drop in ambient temperature alone may increase the ampacity of a power transmission line and, thus, allow the line to carry more current to support higher demand. Upon receiving the conductor temperature measurements, the control center can adjust the power injection into a power transmission line to operate it close to its technical limits.

3) Distributed Energy Resource Control: Future distribution systems will be integrated with a large number of DERs, such as distributed renewable energy, energy storage units, and EVs. Due to the intermittent nature of renewable energy outputs, it is critical to implement dynamic control mechanisms in the distribution systems to prevent an excessive supply–demand gap, leading to a catastrophic system-wide failure or blackout.

In dynamic pricing, consumers are offered varying electricity tariffs at different time intervals using a price-based program. Based on the latest price information, consumers will logically use less electricity during high electricity prices, and hence, demand is reduced during peak-load hours [44]. As an effective way of demand-side management, dynamic pricing requires a reliable communication network to transmit the latest price information to consumers. The impact of wireless communication channel impairments on the performance of dynamic pricing was analyzed in [45]. It showed that, in the presence of communication error and delay, a tolerable supply–demand gap would impose an upper bound on price update step size and update interval. In [46], a cooperative communication scheme was proposed to support dynamic pricing. The proposed scheme aimed to achieve reliable transmissions of demand requests and price information between a control center and a group of consumers. This method exploited the broadcast nature of the radio channel to enable a neighboring consumer to assist in retransmitting a failed request or price message after combining the failed request with its own demand request.

In distribution systems, energy storage systems (ESSs) are deployed to absorb excessive fluctuation in power flow. An ESS management scheme is needed to make charging and discharging decisions. An ESS management scheme was proposed in [47] to operate reliably over error-prone wireless communication channels. The proposed scheme uses the Markov decision process to make a local decision at each ESS and aims to minimize power loss while keeping the voltage violation probability below an acceptable level. In practice, not every house will have its own ESS. A realistic scenario may see multiple houses within a neighborhood share a single ESS and form a community smart grid. Such community smart grid may impose additional requirements on communication networks because houses that are close to each other in the distance may not be on the same electricity distribution bus [48].

There is a cost in achieving the desired level of communication reliability. This cost often appears in the form of reduced spectral efficiency, and it is charged to the communication service providers. While this is the cost of improving transmission reliability, there is also a cost that is imposed by deteriorating transmission reliability. Specifically, unreliable transmissions of power supply and demand information, as well as failures in sending a new electricity price to all consumers, may lead to an inaccurate demand-side management operation. As such, there is a tradeoff between incurring a cost to achieve perfect communication reliability and tolerating a cost associated with inaccuracy in demand-side management operation. This tradeoff has been dealt with in [49] through a radio resource allocation scheme.

B. Power-Communication Network Interdependence

In distribution systems, the power network depends on a reliable communication network to collect data and distribute control commands. On the other hand, the communication network also depends on the power network for electricity supply to its equipment [50], [51]. This section discusses possible cascading failures of interdependent power-communication networks and cybersecurity issues in distribution systems.

1) Cascading Failures: In smart grids, the interdependent relation between power and communication network is inevitable but may make the system more vulnerable [52], [53]. A failure in the communication network may result in a loss of sensor data and control command for the power network. The affected power network may trigger its protection mechanisms, which may cut the electricity supply to some communication equipment. With more communication nodes stopping functioning, the loss of sensor data and control command suffered by the power network may exacerbate with more electricity supply cuts. After a few iterations, this vicious cycle will eventually bring down the entire smart grid. The situation can get worse when the system recovery process is delayed by natural disasters, severe bad weather conditions, and so on [54]. While network interdependence is inevitable, we must work on minimizing its impact to materialize the full potential of a digitized power network.

The cascading failures across interdependent power-communication networks can be prevented by satisfying three requirements, namely, power independence, communication robustness, and power robustness. Given the requirements, Kong [55] developed a method to find the cost-minimum locations for the installation of data aggregation points, which are communication gateways. For each data aggregation point, it is necessary that its electricity supplier is not from the distribution bus that it monitors. This condition can ensure that the data aggregation point will continue to operate, while the distribution bus that it monitors has failed. Separately, Parandehgheibi *et al.* [56] and Chai *et al.* [57] have also studied the effects of internetwork interdependence in a smart grid but without considering the fact that sensors and actuators are connected to the control center through multihop communication routes. In a practical distribution system, communication routing is an important issue. The work [58] has proposed a scheme to optimally choose a communication route that can minimize the impact of internetwork cascading failures, which are triggered by an initial failure in either the communication or power network. In [59], the idea of a power-disjoint communication route has been proposed. Two communication routes are power disjoint if they do not have any router that draws electricity supply from the same power node, which is also an electricity supplier to the router of the other route. According to Kong [59], in the presence of power-communication network interdependence, system robustness can be maximized by maximizing the number of power-disjoint routes between communicating nodes.

2) Cybersecurity: With increasing information technologies integrated into distribution networks, the security of the cyber system has become a significant concern for operational efficiency [7]. Generally, there are three fundamental requirements for the security of the cyber system: availability, integrity, and confidentiality [2]. However, uncertain and unpredictable cyber contingencies, such as communication failures and malicious attacks, may cause violation of these requirements [60], [61], thus leading to energy market disorders and considerable economic losses in the distribution system.

There are two inevitable cyber factors that would threaten the operation of distribution networks [62].

1) *Packet loss:* Considering a large-scale distribution network, a number of SMs need to transmit data packets to the data aggregator unit for DR control. In this case, information congestion may occur due to the limited bandwidth of communication channels and, thus, causes random packet losses [63]. With data packet losses, the power supply or consumption received by the control unit may deviate from true values, which will break the power balance of the network.
2) *Transmission delay:* Since modern distribution networks contain various distributed resources and loads that are geographically dispersed, time delays would be introduced to the information transmission process [64] due to the physical distance between users and control centers. If a time delay happens, the energy management commands would not be able to be conducted in time, which will result in a slow reaction to external conditions, and the performance of energy scheduling will be degraded.

Apart from the inherent communication limitations, malicious cyberattacks would also adversely affect the distribution networks [65]. The most likely forms of cyberattacks could be divided into three categories as follows.

1) *Denial of service (DoS):* This kind of attack tries to block or break the information transmission between grid components [66]. For example, by using the worms to send a flood of fake requests, the devices (e.g., service providers and communication links) would be jammed with spurious packets, which will result in the loss of critical information exchange and, thus, deteriorate the system performance. Under constant DoS attacks, the functionalities of SMs will be disabled, and the measurements could not be delivered to the control center for several hours or even days.
2) *False data injection (FDI):* The FDI attack aims to inject malicious data packets to different network devices, including sensors, actuators, and communication links [67]. Then, the transmitted data will be tampered with, and erroneous values will be sent to the operator to disturb the whole system. For example, in the electricity market, an FDI attack can modify the electricity pricing information from the aggregator by injecting false data into the communication channels. As the prosumers decide their power consumption/generation according to the received electricity price, the electricity market will be greatly impacted by the FDI attack, and economic losses will be caused.
3) *Replay attack:* The basic principle of replay attack is to send the previously eavesdropped information packets from sensors to mislead the control center [68]. More specifically, the attacker first observes and records the readings of sensors at a certain condition and then sends the original data to spoof the system at the appropriate time. If the demand in a distribution network increases, the attacker may replay the measurements during normal operating conditions to make the control center issues an erroneous energy management command.

In recent years, with more diverse and widespread DERs integrated into distribution networks, the power system is becoming more distributed at the generation and control levels [69]. The management of massive DERs depends significantly on information technology, including the SM, the communication network, and the intelligent controller. As a result, the increased interconnection and interoperability of DERs bring more cyber vulnerabilities into distribution networks [70]. For example, the transmitted data are more likely to be intercepted, tampered with, misrepresented, or forged in the large-scale communication network [71]. Since the exchanged information is adopted for the dispatch of different energy resources, the corrupted data would result in decision error, which would further degrade the system operation or lead to cascading failure in distribution networks.

In order to sustain the safety and the efficiency of the distribution network operation, countermeasures against the above cyber threats should be designed and implemented [72]. Some solutions have been proposed in the literature to address the impact of cyber threats in different ways.

1) *Robust/resilient control:* Robust control methods could enhance cyber resilience by providing adaptive mechanisms in the control loop [73]. For example, in [74], a robust consensus-based distributed optimization method is proposed to schedule the flexible loads of distribution networks, where a corrective method is used to compensate for the impact of packet losses. Considering the time-varying delays and channel noises, a delay-tolerant distributed economic dispatch algorithm is presented in [75], where the delay tolerance is guaranteed by adaptively adjusting the gain coefficients during the optimization.
2) *Attack detection:* The system operator could utilize intrusion detection schemes to identify anomalous behaviors caused by cyber incidents and then isolate the compromised components from the network [76]. Several detection strategies, such as flow entropy and signal strength, have been proposed to identify DoS attacks [77]. A joint-transformation-based scheme is presented in [78] to detect the FDI attacks in real time, where the Kullback–Leibler distance between the real-time and historical measurement variations is used. In addition, Li *et al.* [79] develop a Bayesian inference mechanism to detect the onset of a replay attack in supervisory control and data acquisition (SCADA) systems.
3) *Secure state estimation:* Secure state estimation methods try to systematically analyze the dynamic behavior of the physical system and then reconstruct system states from possibly corrupted information [80]. For instance, in [81], a variance-based adaptive approach is established to estimate the renewable generation under unreliable communication links, where corresponding conditions are derived to minimize the estimation error covariance. Furthermore, by adopting Kalman filtering, preselectors and observers are developed in [82] to address the secure estimation issues in power networks with FDI attacks.

Nevertheless, there still exist some challenges in the reliability of cyber systems, and further improvements to current solutions need to be investigated [83]. In the future smart grid, cyberattacks may be intelligently designed with stealthy characteristics and bring more risks to the operation of active distribution networks [84]. To address these problems, blockchain technology could be implemented as a promising way to enhance data security, integrity, and trustworthiness [85]. On the other hand, the availability of immense data collected by various sensors makes data-driven approaches (e.g., machine learning algorithms and data mining algorithms) a possible solution to predict cybersecurity incidents [86] and foreshadows the cyber threats in advance.

C. Provisioning of 5G for Distribution Systems

There is a significant leap from 4G to 5G new radio (NR) cellular communication networks. Different from 4G, also coined as long-term evaluation (LTE) networks, the 5G network targets more diversified goals. To this end, the 5G network provides three types of services fitting different scenarios of applications, all of which could be of critical importance in future distribution systems: ultra-reliable low-latency communications (URLLCs), massive machine-type communications (mMTCs), and enhanced mobile broadband (eMBB). In the context of smart grids, it is not necessary to leverage the large data throughput of eMBB since the data generated by a local area power network are not that substantial. Meanwhile, URLLC and mMTC types of services could be of significant usage in smart grid, supporting highly real-time and reliable (such as protection), or low throughput but massive (such as SMs and micro-PMU), data flow [87]. In addition, network function virtualization (NFV), mobile edge computing (MEC), and device-to-device (D2D) communication are three new features of 5G NR, compared with 4G LTE, which makes the 5G network an information platform, which can accomplish the tasks of information collection, multiplexing, delivery, and computing, which is of substantial benefit for distribution systems. The applications of 5G for distribution systems are detailed as follows.

Two concerns on the employment of 5G technology in smart distribution systems deserve discussion.

1) *Compatibility:* 5G is being deployed together with existing 4G LTE systems, whose compatibility has been addressed in the standardization for the migration (e.g., the dual connection to both 4G and 5G). Therefore, the device hardware in smart grids can support the air interface of both 4G and 5G, while the function upgrading can be accomplished in the device software (e.g., in a remote manner).
2) *Network availability:* The 5G network is expected to be deployed in populated areas due to commercial motivations. Moreover, the coverage of 5G base stations could be much smaller than the counterparts in 4G systems. Therefore, the smart grid devices in rural areas (e.g., the sensors on transmission lines) may face the challenge of the availability of 5G network coverage.

1) URLLC for Distribution Systems: In this service, latency and reliability are the main focus, while data throughput is of secondary importance, thus being suitable for highly sensitive real-time control messages. In particular, the delay in the air interface is strictly limited to 1 ms, thus substantially improving the realtimeness of the corresponding applications. Meanwhile, the high reliability assures the operation with an error rate of up to 10^{-5}.

An illustration of possible URLLC traffic embedded in the eMBB traffic is given in Fig. 4. In 5G networks, orthogonal frequency-division multiplexing (OFDM) is used as the signaling technique. In OFDM signaling, communication data are modulated to multiple (e.g., 1024) subcarriers (a.k.a. tones). The signal carrying the same set of data is called an OFDM symbol, whose time duration is variant in different systems (e.g., 35.7 μs). Then, the new data are loaded into the next OFDM symbol, where the data and OFDM symbol are analogous to passengers and car boxes of an "information train." The frequency and time (in the units of subcarriers and OFDM symbols) form a grid, in which a predetermined subset of points in the grid is called a physical resource block (PRB). Different PRBs can be scheduled for different UEs, thus accomplishing the resource allocation and assuring the orthogonality of different data traffic. Note that, although the single-carrier frequency-division multiple access (SC-FDMA) may be used in the uplink, the conceptual image of the frequency–time grid is similar to OFDM.

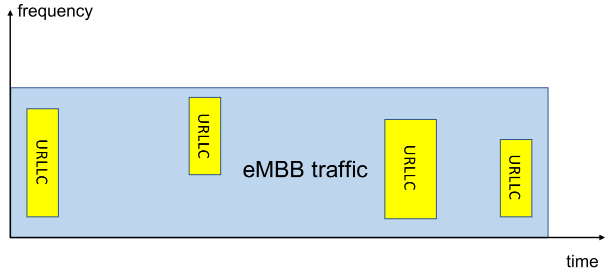

Fig. 4. ***Illustration of dynamic scheduling of URLLC sharing resource with eMBB traffic.***

In URLLC, due to the stringent requirement on the time delay, the data traffic can be scheduled within a very short period of time. In release 15 of the 3rd Generation Partnership Project (3GPP), the minimum time duration of a URLLC packet is two OFDM symbols, whose duration is tens of microseconds. As illustrated in Fig. 4, the URLLC packets can be dynamically scheduled, sharing the PRBs with ambient eMBB traffic (e.g., large-volume file transmission with low requirement on the latency).

The application of URLLC type of service has been discussed for smart grid in TR 22.804 of 3GPP in the following aspects.

1) *Power distribution grid fault and outage management:* The main focus is the distributed automation of switching for isolation and restoration. The reliability is required to be 99.9999%, and the latency is below 5 ms.
2) *Differential protection:* Due to the high requirement of the latency of the protection, the target peer-to-peer transfer interval is required to be 0.8 ms, while the data packet size is 250 bytes. Moreover, the end-to-end delay is expected to be no greater than 15 ms.

2) mMTC for Distribution Systems: mMTC can be considered as a high-end version of communication protocols for the Internet of Things (IoT), such as narrowband IoT (NB-IoT). The prominent feature of mMTC is not the narrow bandwidth for each user equipment (UE) but the capability of supporting massive UEs (e.g., sensors). The mMTC type of traffic is characterized by a large number of connections, each of which has low-throughput and time-sparse data traffic. According to [88], the related traffic can be categorized into the following three types.

1) *Command-response type:* It consists of small data packets of command from the center in the downlink (from the base station to UE) and response from the device in the uplink (from UE to base station). The payload could be around 20 B for the commands and 100 B for the response. The round-trip latency could be up to 10 s.
2) *Exception reports:* It could be meter alerts with data of 100 B with a latency of 3–5 s.
3) *Periodic reports:* The reports could be the power consumption measured by SMs. The data could be around 100 B, while a large latency is highly tolerable.

The main challenge of the mMTC type of service is the large and (possibly) random connections, despite the small packets and tolerable latency. It is suitable for supporting various types of sensor networks or IoT. Compared with the NB-IoT, mMTC has a much larger bandwidth (1.08 MHz in Release 13 compared to the 180 kHz in NB-IoT) while still being narrowband. The specific design for a narrowband operation has been added to the standards. For the applicability to sensors with limited power and computing capabilities in smart grids, the mMTC service can reuse the legacy data channels and synchronization pilot signals. Moreover, mMTC UEs are designed to skip the decoding of the wideband legacy control channels, thus saving the requirements on the radio frequency (RF) circuits and computational capability.

3) NFV for Distribution Systems: NFV is a technology for implementing various network functions in software running on decoupled hardware. A communication network that is built upon NFV is called a software-defined network. Software-defined networking (SDN) has been explored for smart grid [89]–[91]. Compared to a traditional communication network with specialized hardware, software-defined networks implement networking middleboxes in software on cost-efficient generic hardware [92]. With such hardware-software decoupling, SDN can quickly build a smart grid communication network in a cost-efficient manner. Also, by separating the control plane from the data plane, SDN helps the smart grid operators to manage the network and system flexibly. As presented in [93], with software programmability, protocol independence, and control granularity, the software-defined network can help smart grids to integrate different standards and protocols, cope with diverse communication systems, and perform traffic flow orchestration. More importantly, according to Dong *et al.* [94], the software-defined network can help smart grids in satisfying their diverse communication service requirements and improving their resilience and robustness through network slicing. Here, network slicing is the ability to allocate different sets of resources to different application virtual networks.

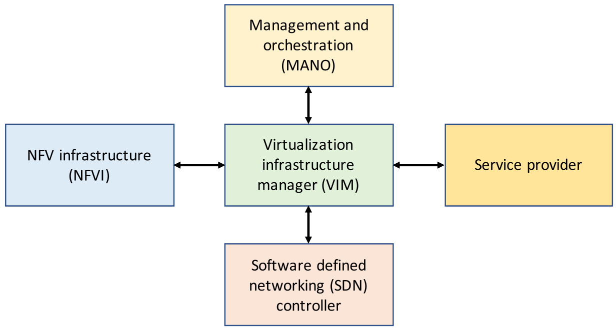

Fig. 5. *Architecture of 5G NR NFV.*

5G NR has provisions to facilitate the implementation of software-defined networks. In contrast to the 4G LTE system, which simply provides the infrastructure for data transmission (either in the air or in the core network), the 5G NR network endows the service providers (such as the smart grid operators) with the capability of operating their service systems in a virtual manner by a layer of abstraction, as if operating their own systems, without knowing the lower layer details. This is the NFV provided by the 5G NR network, which decouples the detailed operations of the communication, storage, and computing hardware from the software implementation of the service providers. Through such NFV, various network functions can be implemented in software running over the 5G network hardware, which is similar to generic computer hardware, such as CPU, hard drive, and input/output (IO).

The architecture of 5G NR NFV is illustrated in Fig. 5. The service provider uses the infrastructure through the virtualization infrastructure manager (VIM), similar to implementing software to define and control the network function. VIM is managed by the management and orchestration (MANO) module, which coordinates the resource for different services (e.g., between smart grid operator service and traffic monitoring service). The network is controlled by the SDN controller (e.g., setting the router configurations remotely using general-purpose network devices). Then, the VIM operates the NFV infrastructure (NFVI), such as base stations, core networks, and MEC, according to the instructions from the service provider. Although the authors have not been aware of real implementations of smart grid functions using NFV in 5G NR networks, there have been discussions on the potential applications [95].

4) MEC for Distribution Systems: Besides the service of data transmission, the 5G network also provides the substantial capability of computing at the network edge. Without traveling to the cloud through the 5G core network, the local computing using MEC can substantially reduce the computation latency and data traffic. Since many computing tasks of smart grids need to be accomplished locally (e.g., the differential protection), the MEC mechanism will be of critical importance for computing in smart grids.

Note that the above URLLC service can only reduce the latency between the UE and the RF front end of the base station. The latency incurred by the transmission within the core network (between the base station and the cloud) and the computing in the cloud is not guaranteed. As a remedy, MEC facilitates local computing without sending the data to the cloud, thus substantially reducing the latency [96]. It is of particular usage for real-time tasks of smart grids, such as differential protection.

5) D2D Communication for Distribution Systems: D2D communication is an important feature of the 5G communication system. In D2D communications, two devices are allowed to exchange messages directly without going through a cellular base station. For spectral efficiency, a D2D transmission may be performed concurrently with a cellular transmission in the same time slot. As such, the D2D transmission may impose additional interference on the cellular transmission. Hence, in D2D communications, it is crucial to control the transmission power to limit interference.

Advanced D2D communications have been adopted by Song *et al.* [97] to connect SMs to the control center, where the focus was on finding the optimal transmission power for each D2D transmission such that the aggregate cellular transmission rate could be maximized while achieving the desired service quality for D2D transmissions. In a 5G communication network, the cell radius can be small due to cell densification. As such, a D2D connection may span across multiple cells, but a typical D2D transmission should occur within one cell. This cross-cell D2D transmission scenario was considered in [98] in the context of hierarchical control of a microgrid system.

IV. PHYSICAL–SOCIAL COUPLING IN DISTRIBUTION SYSTEMS

Physical–social coupling in distribution systems can be divided into macrosocial coupling and microsocial coupling.

The macrosocial coupling is more related to energy policy and so on. The societal decarbonization plan is a good example. Decarbonization is the process when a society converts the economy from one that operates predominantly on energy derived from fossil fuels to one that runs almost on clean and carbon-free energy [99]. The goal of societal decarbonization plans generally has impacts on policies, utilities, and end-users from technology adoption, consumption patterns, and information infrastructure. Beyond the technical aspect, many state decarbonization policies have integrated the objectives of decarbonization with job promotion, economic development, urban planning, and energy inequality issue. For example, the electrification of consumer services in the transportation, buildings, and industrial sectors integrated with the decarbonization of electrification generation is one of the significant pathways to achieving a low-carbon society in the United States [100]. The impacts of electrification on the power grid and carbon emissions are also notifiable. Household energy behavior will change based on the societal level of decarbonization and electrification, which indirectly will affect utilities' decisions. For example, current DR programs promoted by utilities need to consider household EV charging time and patterns, and also the energy inequality issues that many LIHs do not own an EV. Regarding behavioral patterns, the adoption of energy efficiency or electrification can produce a rebound effect. For example, once the cost of EV charging stations or the electricity cost of charging EVs is reduced, users' charging behaviors might change, and more people will charge during the cheaper period, generating a rebound effect or people overall use more energy because of cheaper electricity cost [101]. Integrating social–technological and behavioral strategies is important to achieve deep reductions in greenhouse emissions. It is necessary to involve electrification and electricity decarbonization. Future research is needed to explore other potential implications of the wide adoption of electrification and the risks associated with electrification.

The microsocial coupling is more related to different participants/stakeholders, such as consumers, retailers, and system operators in distribution systems. This section focuses on how the microsocial system influences the new technologies adoption and DR implementation in the planning and operation of distribution systems, respectively. In addition, the impact of COVID-19 on consumers' electricity consumption behavior has also been studied.

A. New Technologies Adoption

SM, DERs, and EVs are the three main enabling technologies for the 3D transformation of future distribution systems. How the adoption of these three new technologies is influenced by the different social factors is discussed in the following.

1) Smart Meter Installation: SMs can collect fine-grained electricity usage data from consumers and communicate with utility companies in real time, which is an important part of distribution systems. Accurate load forecasting and optimal management of electricity generation and distribution can be undertaken using these fine-grained data, which could lead to increased overall energy savings, reduced greenhouse gas emissions, and lower consumer costs [102].

The opinion of residents is the most important component in determining whether an SM can be effectively installed in their homes, and large-scale SM installation can only be accomplished if the majority of people welcome this new technology. Despite the promising future of a large-scale installation of SMs, some opponents are

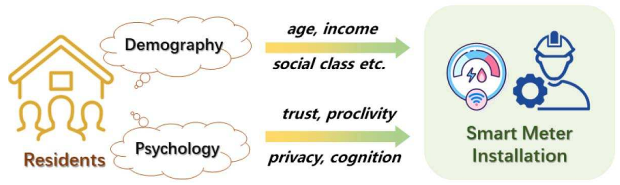

Fig. 6. *Factors that influence residents' attitudes toward SM installation.*

opposed to SMs being installed in their homes for a variety of reasons, including concerns about privacy leakage [103], radiation-related health concerns [104], unfamiliarity with the new technology [105], fears that SM installation will increase costs [106], and so on. Thus, it is important to investigate the factors that influence residents' attitudes about SMs to remove the hurdles to large-scale SM installation, which can be summarized into two aspects, namely, sociodemographic characteristics and social–psychological factors, as shown in Fig. 6.

Gender, age, social class, income, and other demographic characteristics are significant for understanding consumers' energy consumption behavior and adoption of new technologies [107]. Many studies have looked into residents' attitudes toward SM installation. Lineweber [108] conducted an online survey involving over 1100 residents in the United States and found that nonwhite and unmarried residents are more positive about SMs, while slightly older, white, and married customers were opposed. Another study looked at samples from 17 states in the United States with a high rate of SM installation and found that participants' income and political ideology were connected to their support for SMs. SM installation was more likely to be supported by people with higher incomes and who are identified as liberals [109]. Bugden and Stedman [110] further confirmed that SM involvement was influenced by age and income. Chawla and Kowalska-Pyzalska [111] investigated SM awareness and acceptance among Polish social media users and developed a model to predict residents' desire to install SMs. According to their research, consumers' propensity to accept SMs is dependent on their age, income, and family size that SMs are more likely to be accepted by older consumers with higher incomes and larger families. In addition to the works mentioned above, more demographic factors, such as level of education, occupation, and residential area, can be investigated in the future in order to better understand the relationship between willingness to install SMs and residents' sociodemographic characteristics.

Consumers' psychological elements, such as trust, privacy concerns, proclivity, and cognition, are the most influential in shaping their opinions toward SM installation. For starters, numerous studies have demonstrated that residents' trust in utilities is a critical factor in their acceptance of energy alternatives [112]. Consumers' faith in utilities may have a substantial impact on their attitudes toward SM installation when they are unfamiliar with SMs and lack the necessary knowledge to assess the risk and reward of installation [113]. Karlin [114] found trust as a key factor influencing consumers' reactions to SMs. Chen *et al.* [115] claimed that consumers' faith in utilities is a nonnegligible factor that influences their adoption of SMs in an indirect manner. Second, inhabitants' concerns about privacy leakage are a crucial element that influences their attitudes [116]. Chen *et al.* [115] found that acceptance of SMs is adversely correlated with perceived privacy risk, and they recommended that privacy concerns be addressed in order to increase adoption. According to Hmielowski *et al.* [109], consumers' opinions and experiences with privacy invasions are linked to levels of support for SM installation. Customers who do not trust utilities to protect their privacy are less likely to support SM installation [117]. Third, individuals' preferences influence whether or not an SM is installed in their homes. Customers are primarily interested in SMs because they can conserve energy (which means lower costs), rather than for environmental, technological, or regulatory grounds, according to a field experiment done in Germany by Berger *et al.* [118]. Idoko *et al.* [119] looked at SM installation from the perspective of a developing country and found that bill estimation anxiety and perceived behavioral control were the most important elements in determining SM purchasing intentions. According to Hmielowski *et al.* [109], individuals who believe that technology enhances people's lives are more inclined to install SMs in their houses. Furthermore, Nachreiner *et al.* [120] and Chawla and Kowalska-Pyzalska [111] discovered that providing homeowners with feedback information regarding energy use profiles and real-time electricity prices and, receiving recommendations from their neighbors, will increase their proclivity for SM installation. Cognition, or residents' judgment of usefulness or environmental problem, is the fourth aspect that influences their choice. Perceived utility was demonstrated to be a positive predictor of SM adoption intention in [115] and [121]. Chen and Sintov [122] conducted a survey in southern California and discovered that residents who are more connected to nature have a higher propensity of adopting SMs. Many additional studies have revealed that those who are concerned about the environment are more likely to approve the installation of SMs [123].

2) Distributed Energy Resources: DERs can help to promote the accommodation of local energy and enhance the energy efficiency of the distribution systems. However, developing DERs needs the acceptance and cooperation of the social public to a large extent. For example, rooftop PV needs to be installed on the rooftops of citizens' houses or flats, and thus, the installation needs negotiation with the house owners or the local authorities. Therefore, social acceptance of DERs plays an important role in this context and can even affect the development of DERs to some degree.

Social acceptance of DERs can be divided into three dimensions: sociopolitical acceptance, community acceptance, and market acceptance [124]. Sociopolitical acceptance concerns the public acceptance and the acceptance of key stakeholders (energy consumers and investors) of related energy policies. Despite the general support from the public in an opinion poll [125], there is a gap between the support in the polls and the actual success in constructing DERs [126]. The explanations of this social gap can be three aspects: democratic deficit (i.e., the decisions are made by the minority who opposed the DERs instead of the majority who are in favor) [127], qualified support (i.e., people questioned the problems of DERs' limits and controls) [128], and self-interest (i.e., people supporting the DERs may oppose due to the protection of their own self-interests) [129]. For example, those who are skeptical about community-scale battery storage are concerned with the problem of sharing [130]. Such concern reflects people's self-interests. Therefore, the government should develop some related policies to reduce the social gap, such as collaborative planning of sitting DERs and reliable financial incentives, and, thus, improve the acceptance of DERs.

Community acceptance focuses on the acceptance of local stakeholders (mainly refers to local residents) to DERs. One main hindrance to the acceptance of distributed energy by local residents is the attitude of NIMBY, as known as "Not In My Back Yard" [131]. Those who support NIMBY tend to express their initial support or acceptance of the distributed energy projects as long as they are not implemented in their back yards in the future. The community acceptance has a temporal nature, and in [132], a U-curve is proposed to describe the local acceptance before, during, and after project implementation. The U-curve starts from high acceptance to lower acceptance during the siting process, which may cause undesirable project implementation in their communities, and backs to a high level of acceptance after the project is finished and benefits the local community. Consequently, some approaches to improving community acceptance were concluded, such as the awareness of local benefits brought by DERs [133], the guaranteed management and maintenance of DERs in the future [134], and the financial compensation for installation [135]. These approaches can help the government develop related policies and take measures to raise social acceptance on the community level.

Last but not least, market acceptance describes the adoption level of actors (mainly refers to investors) in the distributed energy market. The investments in the DERs are mainly from two parts: traditional investors (such as large supply utilities, project developers, and financial institutions) and local citizens [136]. In the countries where DERs are being deployed and developed in rapid progress (such as Ireland, Spain, and the United Kingdom), traditional investors make up a major part of the investment [137], while, in the countries pioneering the development of this field (such as Denmark and Germany), more than 50% of the investment is sourced from local citizens [136]. The main concerns of local citizens of investing DERs include high-risk aversion, a lack of access to capital, and diffidence in making investment decisions [138]. Consequently, some top-down policies can be adopted to relieve the public of the financial pressure to invest and thus mobilize investment from local citizens, including feed-in tariffs, grants, and tax incentives [136]. Alternatively, traditional investors, such as renewable energy project developers, can take the lead in investing and alleviate citizens' concerns about investment risks [138]. In such a way investment from both traditional investors and local citizens can be mobilized. Therefore, studying these concerns and corresponding measures can effectively help increase market acceptance.

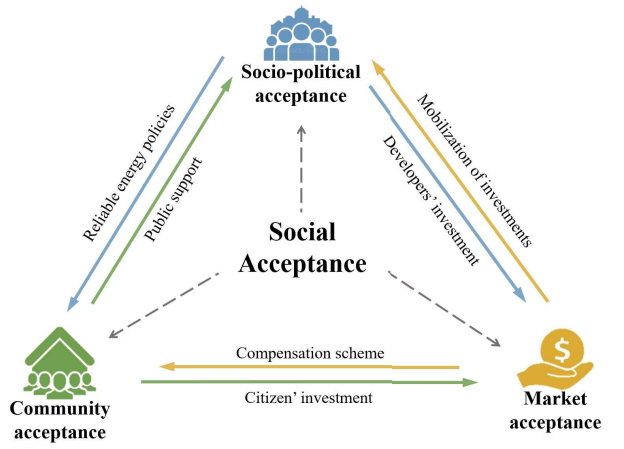

Fig. 7. *Structure of social acceptance of DER.*

Fig. 7 shows the structure of social acceptance mentioned. Although social acceptance of DERs can be divided into three dimensions, it can be seen that these three aspects are actually interrelated through the reviews above. Improving one aspect of social acceptance can also enhance other ones, forming a virtuous cycle. Therefore, future research can be concentrated on how to integrate sociopolitical acceptance, community acceptance, and market acceptance and form a general framework for social acceptance in the context of DERs. Meanwhile, some previous works trying to do so can also be referred to for further study. Peñaloza *et al.* [139] have researched the combined acceptance (sociopolitical and market) of PV panels and heat pumps. van Wijk *et al.* [135] proposed a compensation scheme to improve both market and community acceptance. Devine-Wright *et al.* [140] proposed a social acceptance framework for renewable energy storage based on the integration of sociopolitical acceptance, community acceptance, and market acceptance. These works are based on the three aspects of social acceptance and make fusion organic, which can be referred to in future studies.

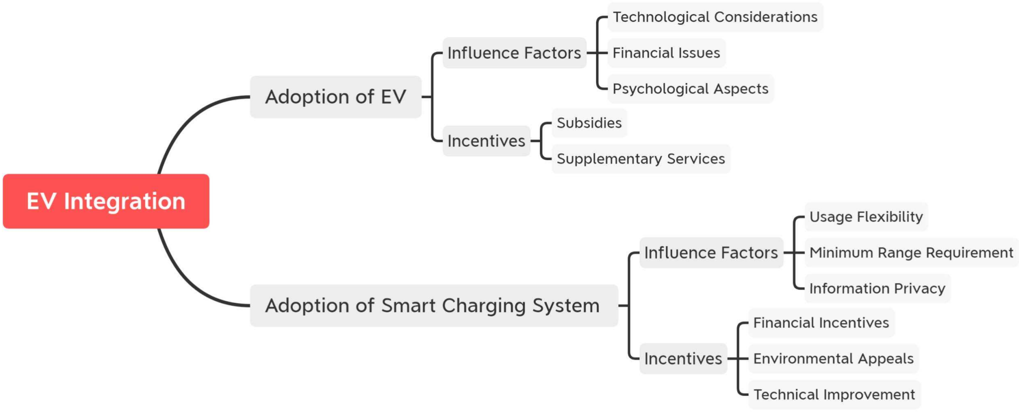

Fig. 8. ***Influence factors and incentives for EV integration.***

3) Electric Vehicle Integration: The traditional transportation sector is heavily reliant on fossil fuels and accounts for a significant portion of total greenhouse gas emissions. Electrification of the transportation sector is critical for reaching the decarbonization goal [141], where EVs are at the core of transportation electrification. With the use of vehicle-to-grid solutions, large-scale adoption of EVs would not only help cut greenhouse gas emissions but also provide the potential for saving surplus renewable output, peak load shifting, and power grid regulation [142]. However, the charging behavior of EV owners can have a substantial impact on vehicle-to-grid, which could pose problems when large-scale EVs are integrated into the power grid. According to Morrissey *et al.* [143], most EV customers charge in the early evening at peak load, making power balancing even more difficult. As a result, there is a requirement for smarter EV charging management and greater utilization of its benefits as flexible resources in the smart grid. Fig. 8 summarizes the elements that influence people's propensity to adopt EVs and smart charging, as well as incentives that could encourage more people to utilize these technologies.

Various factors influence public perceptions of EV adoption, which can be divided into three categories: technological considerations, financial issues, and psychological aspects. Technical considerations involve the characteristics of EVs and accompanying items, such as charging stations. The biggest impediments to the large-scale adoption of EVs are perceptions of their shortcomings, such as range restrictions, recharging time, and a lack of charging infrastructure [144]. Financial issues, such as purchase price, charging price, maintenance, and recycling cost, are critical when customers choose whether or not to purchase an EV [145]. Psychological factors also influence adoption. Customers are more likely to purchase EVs if they perceive that purchasing EVs may have favorable symbolic and environmental attributes according to Noppers *et al.* [146]. People are more inclined to adopt EVs when they believe that significant others will do so [147]. Many incentives methodologies, both financial and nonfinancial, have been used to reduce barriers and encourage more people to adopt EVs. Santos and Rembalski [148] indicate that current EVs are not cost-competitive with traditional cars, and appropriate subsidies can boost EV sales. Hardman *et al.* [149] investigate the impact of financial purchase incentives and suggest that instant incentives and tax exemptions are the most effective when customers buy an EV. Other studies advocate bundling EVs with auxiliary services or complementary items to encourage adoption, such as [150], which claims that bundling EVs and community solar power will improve customers' purchasing propensity. According to Hinz *et al.* [151] and Fojcik and Proff [152], providing supplementary services is necessary for EV adoption.

The adoption of EVs in the near future may pose additional challenges for power systems, increasing electricity demand, such as in the early evening [153]. Therefore, smart charging systems, where EVs are charged under control at variable power to meet the collective needs of grids (e.g., alleviating the load stress) and EV owners (e.g., charging when the electricity price is low), become a solution to secure grid stability and integrate renewable energy [154]. Smart charging systems inevitably require the participation of EV owners. The adoption of smart charging, however, is affected by various factors concerned by EV owners, which can be concluded in three aspects: usage flexibility, minimum range requirement, and information privacy. Usage flexibility describes EV owners' expectations of taking dominant control during smart charging. On account of the variable power input, the smart charging process can be longer than conventional charging (i.e., always at the maximum power). Consequently, PV owners expect to have the override option for emergency usage instead of charging under control during the whole process [155]. Meanwhile, PV owners tend to make minimum range requirements for the smart charging result. For example, in [156], EV owners stated that they hope to drive at least 100 km after the smart charging process to relieve their range anxiety. Besides, EV owners have privacy concerns. Since smart charging usually requires some information on vehicle usage, such as planned departure time, EV owners do not expect any leakage of their housing and private information leading to privacy problems [157]. It can be concluded that EV users prefer user-managed charging to supplier-managed charging due to personal control [158]. Apparently, for now, the complete implementation of smart charging systems is still faced with some requirements and worries from EV owners.

Consequently, measures should be taken by the authority to encourage EV owners to actively adopt smart charging systems, mainly from three aspects: financial incentives, environmental appeals, and technical improvement. The most common incentives are financial ones. An investigation in [159] showed that, with high enough financial benefits, EV users are willing to charge EVs under control. In addition to financial incentives, environmental appeals can act as another type of incentive. In [160], when informed that free-cost charging in a green way during midday hours is available (i.e., charge for free when power generation of renewable energy is at its peak), EV owners will change their charging behaviors and turn to smart charging, thus increasing renewable energy accommodation. Döbelt *et al.* [159] suggested that people are willing to smart charge their vehicles for the contribution that they can make to environmental friendliness and traffic decarbonization. Technical improvements on smart charging systems are as important as incentives, such as optimizing the location of smart charging stations [161], constructing more reliable charging systems [159], and translating battery state-of-charge (SoC) into user-friendly information based on their profiles (such as miles or working days that can be covered) [162].

In conclusion, the adoption of EV and EV smart charging systems is influenced by various factors, such as financial issues, psychological concerns, and security worries. To encourage the public to embrace such new technologies, different types of incentives should be applied. To facilitate decarbonization, both social and technical factors of the transition to EV have been gradually studied [163]. Thus, future works on EVs and their related technology should not only focus on the technical improvements but also consider the social adoption by the general EV owners.

Table 2 Multidimensional Challenges of Implementing DR and Smart Grid Technologies

Dimensions	Measures
Social-psychological factors	• Perceived personal constraints • Anxiety and uncertainty in technology adoption • Perceived fairness • Social support, social norms • Trust in utilities and internet providers • Energy and climate change concerns
Socio-demographics	• Income • Gender, race/ethnicity • Education • Location (rural vs. urban) • Employment status • Disadvantaged groups (elderly, disability)
Household characteristic & activities	• Household size • Type of housing (e.g., single house vs apartment) • Homeownership status • Type of household activities (e.g., cooking, laundry, entertainment, EV charging, etc)
Technology accessibility & energy inequality	• Building efficiency & weatherlization • Indoor environment quality • Availability of HAVC, energy management technology, and smart appliances • Energy service reliability and quality • Frequency of power outages
Behavioral & economic patterns	• Frequency of appliance use and travel behavior for EV • Energy saving behaviors • Changes in other activities (not flying, driving, more people at home during the pandemic) • Time of using energy • Energy efficient appliance purchase • Hourly energy/electricity wholesale and retail prices

B. Demand Response Implementation

DR has received great attention from energy policymakers. Implementing DR programs is one effective approach to decreasing or shifting energy demand by reducing customers' electricity usage during peak hours in response to changes in the electricity price [101], [164], [165]. One of the major benefits of DR is to help defer or avoid investment in new power generation or transmission capacity; other benefits of DR include securing power supply, improving system restoration capacity, avoiding power outages, reducing costly network reinforcements, improving the use of renewable sources, providing power frequency regulation services, reducing greenhouse gas emissions, and so on [166]. DR is commonly implemented through the decisions made by end-users in response to a price signal. Customers can curve down their peak load and potentially reduce overall energy consumption by changing thermostat setpoints [167], altering the frequency and time of using ACs and water heaters [168], white goods (washing machines, dryers, and dishwashers) usage [169], or EV charging [101]. Typically, utilities have designed several strategies to motivate customer participation, including demand reduction focusing on overall reduction in electricity use or DR focusing on decreasing or increasing electricity use at specific times [170].

To successfully implement or promote DR programs, utilities and policymakers need to understand how various factors and challenges influence user engagement. While a majority of DR barriers and policy focus on financial costs, electricity rates, program complexity and structure, and so on, we classify five main challenges based on consumers' perspectives: 1) social–psychological challenges; 2) sociodemographics; 3) household characteristics and activities; 4) technology accessibility and energy equity; and 5) behavioral and economic patterns, as shown in Table 2. Since the works on behavioral and economic patterns have been summarized in [171], only the first four challenges are discussed in the following.

1) Social–Psychological Challenges: Both price and incentive-based DR programs are based on the assumption of rationality and utility maximization borrowed from microeconomic theory, arguing that people are self-interested, instrumental, and behave as rational actors who consistently weigh the expected costs and benefits of their actions [165], [172]. However, individuals do not always make rational decisions [173]. Their decisions could depend on other social–psychological factors, such as cognitive load, motivation, emotions, trust, perceived risk, and behavioral control [174]. For example, some researchers have consistently identified trust and confidence in the utility companies as important influences on a customer's acceptance of direct load control (DLC) programs, an important type of DR [175]. Mistrust in utilities can arise before or after DR enrollment and is often linked either to technical issues or a lack of clarity on the types of DR and wondering whether utilities or customers benefit from DR [176], [177]. Other mistrust can come from concerns around data privacy and autonomy connected to DLC and consumers' ideas of why utilities pursue DR [178]. While bill reductions and financial benefits are the most common motivations identified, environmental and other social benefits are also important although they may not be obvious to users. For example, total electricity use will not necessarily reduce from DR [179]. Other motivations for considering DR, including override option provided [180], included free or reduced-cost technology [181], increased control over energy use and bills [179], and expected fun or interesting DR participation [182]. Other social motivations included pride discussing participation with neighbors [183], helping to increase electricity system reliability [178] or DR with a local focus [184]. Other social–psychological factors include efforts, time, convenience, and thermal comfort that can influence individuals' energy use [185], [186]. In addition, other factors, such as attitudes, social norms, and behavioral tendencies, affect people's energy use behaviors [187], [188]. Technology anxiety negatively affects residents' willingness to pay for home energy management systems with DR in Tokyo [177].

2) Sociodemographics and Household Characteristics & Activities: Compelling evidence has shown that complex sociodemographic and household characteristics are linked to energy use patterns and DR participation [189], [190]. For example, age, gender, education, employment status, income, household, and dwelling size, and homeowner status significantly impacted household energy use [191]. However, the relationships among sociodemographics, household characteristics, and residential energy consumption are not always consistent and somewhat mixed. For example, DR acceptance was higher by higher income households in the California SPP trial [192]. A review of ten empirical studies in Europe indicated that household size, dwelling size, income, employment status, and living conditions (i.e., rural versus urban) have almost always had a significant relationship with energy demand. In contrast, age and homeownership sometimes have a significant relationship, but the education level rarely matters [193]. Similarly, a study found that factors such as age, gender, income, education, employment status, social grade, and housing tenure were not consistently associated with the willingness to switch to a TOU pricing tariff in the United Kingdom [194]. Overall, the U.K. LCL trial found only weak correlations between household characteristics and DR [195]. Another study reported that willingness to switch to a TOU tariff was not related to gender or homeownership [196]. These social–demographical and household characteristics can influence residents' energy habits and household activities, which also influences residents' acceptance of the DR program. For example, a large-scale survey in the United States suggests that household appliance activities (e.g., electric water heaters and ACs) and load profiles are related to incentive-based DR participation for peak load curtailment through reward payment [164]. Another study conducted in Japan suggests that household heterogeneity and multifaceted factors of household activities, scheduling, and behavioral intention to accept DR are related to DR flexibility potential [190]. For example, younger residents, households with children, and household size with three or more people are more willing to participate in DR and accept a longer shiftable period than their counterparts. Full-time employees and those who typically use laundry appliances during the evenings are less likely to participate in DR and shift appliance use than their counterparts. Habitual and cultural factors also influence DR acceptance [177]. For example, the factors of difficulties in changing the time allocation of daily activities, preferring to dry clothes under the sun, concerns for hygiene, and machine noise at night are the main barriers to accepting DR and a longer shiftable period in Japan [190].

3) Technology Accessibility and Energy Inequality: The sociodemographic factors are much connected with the issues of technology accessibility and energy inequality [197], [198]. The fairness of DR programs becomes an energy equity issue based on the barriers that low- and moderate-income households have faced, including financial constraints, split incentives, aging, nonelectric appliances, internet or broadband connectivity, and work schedule [197], [199]. For example, households with more appliances or with a more flexible working schedule are more likely to accept DR [194]. In contrast, low-income households (LIHs) are facing the challenge of higher costs of peak electricity prices and smart appliances, building and appliance inefficiencies, inflexible schedules, and lack of awareness of energy-saving or difficulty using enabling technologies (e.g., inefficient thermoset usage) [197]. For example, LIHs have lower participation rates in many energy-efficient programs and own fewer appliances and smart grid technologies. In addition, LIHs tend to set one fixed temperature throughout the day, even when they

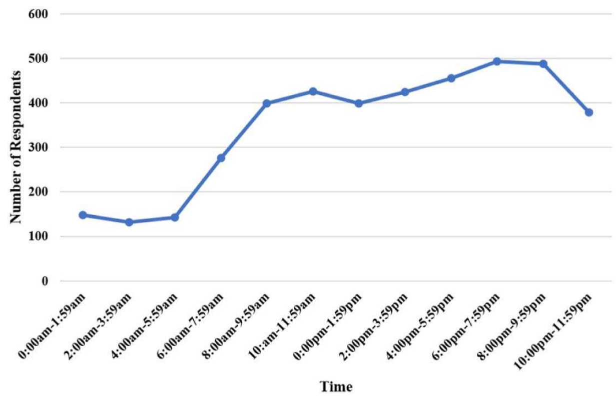

Fig. 9. *Sample of 532 N.Y. residents' weekday time of use electricity during early COVID-19, March and April 2020 [201].*

own a programmable thermostat, which might use more energy. More importantly, many LIHs are renters. As a result, renters often lack control over the type of appliances installed at home. The problem of "spilt incentives" exists, where landlords are not motivated to invest in efficient or smart appliances because tenants receive most of the benefits of installing upgraded appliances [200]. Therefore, improving energy equality and technology accessibility issues through DR among the vulnerable populations (e.g., LIHs and the elderly) is essential.

C. Impact of COVID-19 on Distribution Systems

1) Impacts on Energy Pattern: During the pandemic, the total household energy consumption increased, but the residential energy pattern also changed. For example, during the early pandemic monthly, such as March and April 2020, a study shows that home electricity use in New York areas began to increase significantly between the hours of 6:00–7:59 A.M. and leveled off at 10:00–11:59 A.M. [201] (see Fig. 9). Electricity usage continued to rise slightly until it reached peak consumption level at 6:00–7:59 P.M. and decreased after that followed by a final decrease at 10:00–12:00 A.M. Overall, the home energy pattern shows a continuous rise in electricity use during working hours (9:00 A.M.–5:00 P.M.) that would usually be a "dip" from not being at home before the pandemic. According to the U.S. Energy Information Administration (EIA), before the pandemic, overall energy demand levels in the United States generally rise throughout the day, and the on-peak hours usually occurs between 7:00 A.M. and 10:00 P.M. on weekdays. In contrast, the "off-peak" hours refer to the time when demand levels are the lowest between 10 P.M. and 7 A.M. and on weekends [202]. As mentioned earlier, this pattern is different from the load curve during the pandemic.

The peak energy hours in the early mornings have shifted to midday under work-from-home situations, with other studies reporting increases of 30% in midday consumption in the United Kingdom [203] and 23% in the United States [204]. This shift brings challenges in managing utility companies' daily load profiles and potential financial impacts to disadvantaged end-users who experienced increased energy bills while having their income impacted. Researchers need to know that different income groups have distinct energy profiles and behavioral patterns. For example, LIHs are likely to have unique stay-at-home patterns and energy practices, such as staying at home more than the higher income groups during the nonpandemic period, and peak hours-energy-use patterns that also tend to differ from those of higher income groups [197], [205].

The epidemic has a tremendous influence, but the degree and manner of impact on different locations vary because of differences in social development, customs, and urban characteristics [206]. As an example, we looked at the impact of COVID-19 on the energy pattern of Guangdong, an affluent province in China. We chose four periods (each containing five weekdays) for analysis based on the end of the Chinese New Year as the dividing point: epidemic peak period (February 3–7, 2020), epidemic mitigation period (March 9–13, 2020), previous year's same period of epidemic peak period (February 11–15, 2019), and previous year's same period of epidemic mitigation period (March 18–22, 2020). The average daily load profiles of the whole province and its 21 cities during the four periods are depicted in Fig. 10.

The little pictures in the first two rows correspond to nine cities in the Guangdong-Hong Kong-Macao Greater Bay Area. It can be seen that: 1) except for Zhaoqing, the electricity consumption in the area has recovered to 84.3%–93.3% during the epidemic mitigation period; 2) Dongguan and Zhongshan have the greatest reduction in electricity consumption due to the presence of more small and medium-sized enterprises; and 3) the electricity ratio in Zhaoqing is higher during the epidemic's peak phase than it is during the remission period. One explanation for this phenomenon is the slower return to work. Another factor is that Zhaoqing is in a population outflow region, and the epidemic surges during the spring festival when people return home. As a result of the disease isolating these people in their houses, the region's electricity consumption has increased.

Five cities in eastern Guangdong are represented by the small pictures in the third row.

1) The power ratios of the cities in eastern Guangdong were all greater than the province average during the epidemic's peak. The fundamental reason is that the eastern part of Guangdong is a population inflow area during the spring festival, and regional customs prevent local inhabitants from temporarily relocating during the epidemic's peak before the 15th day of the first month.
2) The load curves in Heyuan and Meizhou during the epidemic mitigation period have changed significantly compared to the same period in 2019, with

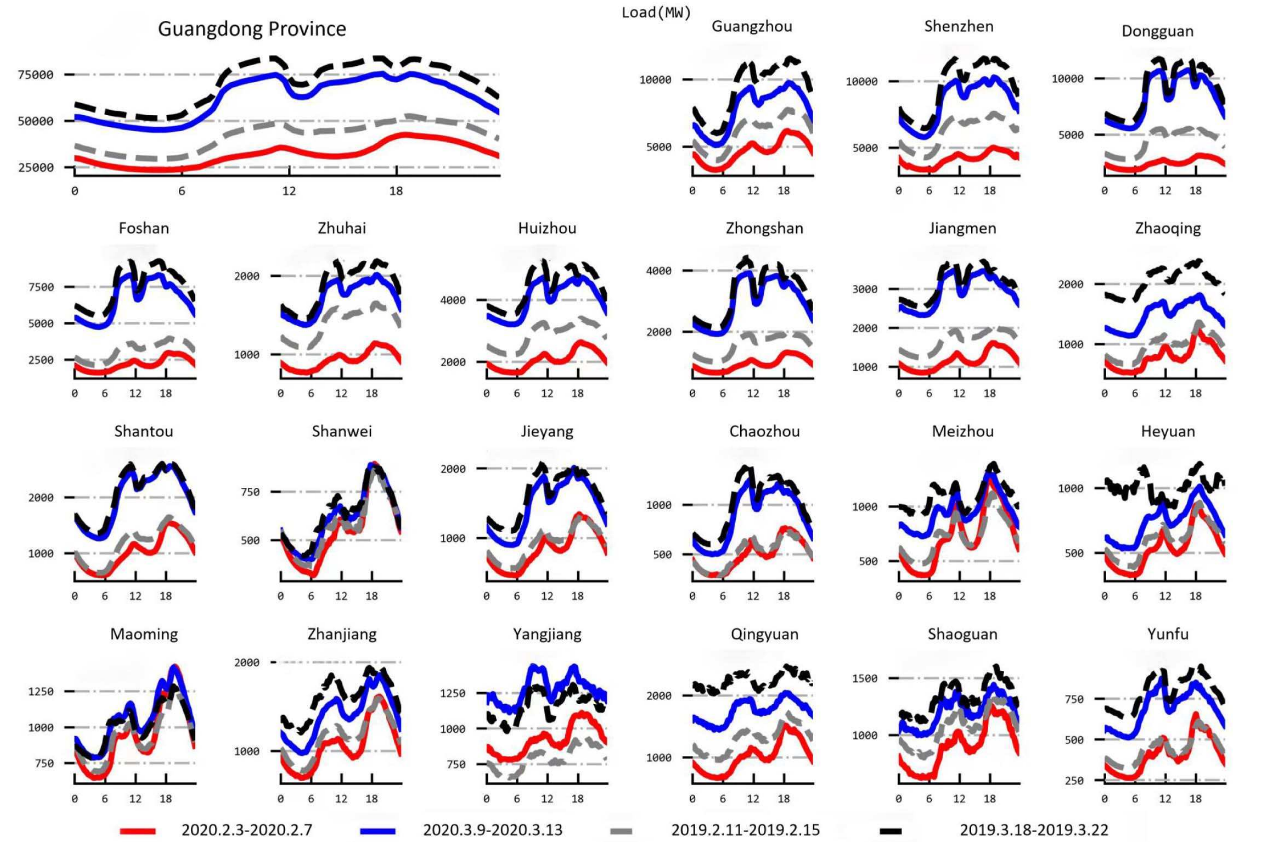

Fig. 10. *Daily load profiles of cities in Guangdong during four periods: 1) red solid line represents epidemic peak period; 2) blue solid represents epidemic mitigation period; 3) gray dashed line represents previous year's same period of epidemic peak period; and 4) black dashed line represents previous year's same period of epidemic mitigation period.*

a similar load during the daytime peak hours but a significantly lower load in the evening hours, which is expected to be since some local enterprises have not yet resumed work and fewer enterprises consume electricity in the low valley.

Another five cities in western Guangdong are represented by the small pictures in the fourth row. We found that the Qingyuan area has more small- and medium-sized firms that have recently relocated to the Pearl River Delta region, and it is not a population-moving region, resulting in a slower rate of work resumption.

2) Impacts on Energy Insecurity and Energy Medical Needs: Rising residential energy demand overall and during new peak hours may pose severe burdens for LIHs and exacerbate energy insecurity and burdens during the pandemic [207], [208]. LIHs and socially disadvantaged communities have faced long-standing energy insecurity (i.e., the lack of equal access to energy resources) and energy burdens (i.e., the inability to pay utility bills). Energy insecurity and burdens in the United States are expected to rise due to increased electricity prices, inefficient homes or appliances, and extreme weather events. On average, the median household energy burden, measured by the percentage of a household's income spent on energy bills, is approximately 3.1% across United States cities; in contrast, for LIHs, this figure is more than 2.5 times as high, at 8.1% [209]. During the early pandemic of 2020, a study showed that higher income households contributed higher electricity bills due to their larger homes or more household size. However, lower income families in New York had higher energy burdens than other higher income groups [208]. Specifically, the average monthly energy burdens were 4.01% for LIHs, 3.57% for lower medium, 2.54% for upper medium, and 1.85% for high-income households.

Extreme events have intensified energy insecurity for LIHs in many ways. For example, during the pandemic, LIHs tend to experience layoffs that challenge their ability to keep their home warm or afford the utilities. Race, age, and gender inequalities have also confounded these effects. Some LIHs who are struggling with utilities have to make tradeoffs between utility services, food, medicine, and other necessities by adopting certain unsafe behaviors, such as using ovens or burning charcoal for heat [210]. LIHs are also more likely to live in less efficient and poorer quality housing and use older, less energy-efficient appliances, and HVAC systems than higher income populations.

The energy insecurity among LIHs is exacerbated by the private rental sector, leaving renters less able to, or owners of rental properties, have little incentives to invest in efficiency improvements [197]. More importantly, a lack of quality energy infrastructure and utility services typically happens in low-income communities [211].

Energy security and affordability are also crucial for residents with complex health conditions during the pandemic, which potentially increases their need for electronic medical devices or their health that is affected by heating and cooling [210], [212]. For example, low-income populations generally are people over 65 and those with disabilities or medical needs that affect heating and cooling. A recent study found that 13% of low-income residents in New York reported that their medical conditions were affected by heating and cooling equipment use during the early COVID pandemic. In contrast, only 3% of medium- and 3% of high-income households had this situation [208]. These disadvantaged groups with medical needs are also normally suffering from high energy burdens due to the conditions of housing inefficiencies, low wages, or prioritization of other necessities [213]. Based on an epidemiological model, researchers reported that households' inability to adopt social distancing because their constraints in utility and healthcare expenditures can drastically affect the course of COVID disease outbreaks in five urban United States counties, including Allegheny, Hidalgo, Los Angeles, Philadelphia, and Oakland [214]. Health interventions combining social distancing and resource protection strategies for LIHs, such as providing sufficient utility and healthcare access, are the most effective way to limit the COVID virus spread to low-, medium-, and high-income levels. Therefore, it is critical for policymakers to pay attention to the multidimensionality of energy, housing, and healthcare access for future disasters or extreme event management.

Consequently, the bundled challenges of energy insecurity and burdens increase the likelihood of LIHs experiencing physical and mental health challenges, particularly during the COVID pandemic or other extreme events [212]. Households that experience energy insecurity and burden situations could face many potential immediate or long-term negative impacts on their housing quality, psychological stress, and overall well-being. These COVID-related challenges highlight the critical need to develop a long-term plan for reliable, equitable, and resilient energy systems to protect underserved communities.

V. CYBER–SOCIAL COUPLING IN DISTRIBUTION SYSTEMS

Fig. 11 shows the cyber–social coupling in distribution systems with a focus on electricity consumers, where the social system contains a massive number of consumers, and the cyber systems contain different networks (i.e., traditional communication networks and social networks)

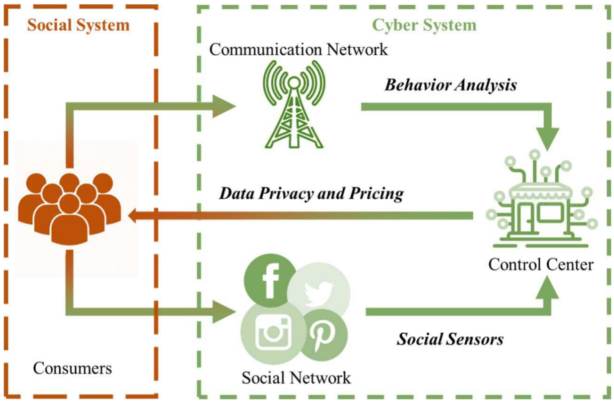

Fig. 11. *Cyber–social coupling in distribution systems.*

and distribution systems' control center. Consumers in distribution systems can generate different kinds of data in real time. These data generated from the social system can be further processed and translated into actual information in the cyber system. For example, the consumption behavior can be analyzed, and sociodemographic information of consumers can be inferred based on how much electricity they consume in different time periods. The works about behavior analysis and sociodemographics information identification were summarized in [171]. For another example, what the consumers say in social networks, called social sensors, can also be used for distribution systems management, such as outage detection. In addition, the privacy of the generated data from consumers is a significant concern that should be fully addressed. Thus, this section discusses two topics, i.e., social sensors and data privacy and pricing, which couples the social and cyber systems.

A. Social Sensors for Distribution Systems

It has been proven that the reliability of grid systems can be guaranteed by installing physical sensors. However, due to the high time costs and economic investments, it is difficult for countries or public utilities to achieve the widespread placement of physical sensors. In addition, physical sensors may be affected by cyber–physical attacks and may even be destroyed during disasters. Due to these limitations of physical sensors and the large amount of data that people generate on social media, social sensors have been regarded as another candidate method for utilities or researchers to improve the dependability of distribution systems. From the perspective of the application fields, the social-sensors-based method can be mainly classified into power outage detection and other applications.

Extremely natural disasters, such as hurricanes, earthquakes, and civil unrest, may cause a lot of damage to the city, leading to a power outage in a large area. Consumers who frequently use social media (such as Twitter, Facebook, and Instagram) may post important information related to this event during a power outage. This kind of data can be used to identify the outage first and then help utility companies or the government to take measures to tackle this problem. In [215], by using latent Dirichlet allocation, a dataset containing keywords of the outage was generated to detect four types of outages (e.g., power outages, communication outages, power-communication outages, and others). The support vector machine (SVM) was used to detect outage-related tweets. After then, a transfer learning model, bidirectional encoder representations from Transformers (BERT), was used to classify the tweets into four types above. By using social media to reinforce the capabilities and reliabilities of the smart sensor in the power grid, Baidya *et al.* [216] discussed how to use images, keywords, and geotags to identify the power outage. In [217], a novel probabilistic model with the consideration of the text, time, and posting location was proposed to detect power outages. Specifically, to improve the detection accuracy, a supervised topic model was utilized to improve the detection accuracy. Based on the keywords from tweets, Bauman *et al.* [218] focused on detecting power outages in a local area based on a few sets of relevant tweets reporting emergency events. Most importantly, Bauman *et al.* [218] gave the relationship table between the number of tweets posted and the frequency of events that occurred. Correa *et al.* [219] showed the relationship between the outage hours reported by companies and outage hours reported by users. In addition, a novel mobile application, Grid-Watch, was used to capture the data and to help people automatically detect electricity outages in [219]. In order to investigate how many phones are needed to ensure satisfying outages detection, a stochastic model was used to approximate the devices with the installation of Grid-Watch. Apart from algorithm application, in [220], hardware named GridAlert was created to monitor the outages and power consumption in Kenyan households by using local data from households. The multilayer perception (MLP) neural network and natural language processing (NLP) techniques were used in [221] to detect power outages in real time. In [222], taking the 2019 Manhattan outage as an example, quantifications of mental and behavioral responses were given by using NLP to classify the sentiment into positive, negative, and neutral and to identify six types of behavioral responses.

In fact, social sensors have many other applications that can provide inspiration in distribution systems. The first one is the disaster area location. As mentioned before, extremely natural disasters may cause a lot of damage to the city. How to locate the disaster area fast and accurately is another vital problem since the disaster will bring the opportunity to the government to rescue injured people and restore the infrastructure, especially for minimizing power outage durations and costs. In [223], an exact power outage location was detected based on the Twitter data without geotagged by using a two steps learning-based framework. The first step was to find actual outage tweets by using a probabilistic classification model. Then, in the second step, the actual outage tweets were used to extract the exact outage locations using a bidirectional LSTM deep learning neural network. A real-time natural disaster mapping was proposed in [224] without using geotags from Twitter. In order to avoid preprocessing of the tweets, available street maps and geographic information are loaded before mapping.

The second one is sentiment detection. The aim of sentiment detection is to detect the emotion of the user from the text, image, and video that they post on social media. Identifying their emotion correctly can be used to determine whether he needs help or not, especially for people who are in depression or low emotion during a power outage. This could help rescue workers provide suitable services to depressed people. The traditional sentiment detection method aims to classify the tweets into positive, negative, and neutral by only using the information of text [225]. Maynard *et al.* [226] proposed a novel sentiment detection method with the combination of text information and image information. The NLP method was used to classify the sentiment first, and locality-sensitive hashing (LSH) was used to extract emotional features from images. The sentiment detection can also be used for electricity consumers so that the retailer can figure out whether the consumers are satisfied with the current service.

The third one is air quality monitoring. Air quality plays an essential role in people's daily life. A fast and accurate air quality monitoring can allow people to prepare in advance, for example, prepare N95 masks to prevent PM2.5. In [227], an air quality trend monitor was constructed by using 93 million messages from Weibo. It was concluded that the social media-based method could provide a faster and more accurate trend than the traditional method. What is more, messages posted by Chinese people contain a large amount of firsthand information that has not been discovered. In [228], social media data from Weibo were used to construct a dynamic population map. Then, a well-developed satellite-ground-hybrid model was used to estimate population exposure to PM2.5 based on the map. Also, this kind of idea could be used in power consumption monitoring. An accurate and real-time power consumption monitoring can act as an aid in building smart city services to manage power allocation [229].

To sum up, from the research above areas, the social-sensors-based method can improve the reliability and effectiveness of system operators' decision-making, especially for the area that needs a fast and accurate response. Meanwhile, it also requires high-quality data and trustworthy information sources.

B. Data Privacy and Pricing

Governments or organizations worldwide are increasingly committed to data privacy protection. Privacy has become an emerging social concern. For example, different countries have different consumer data privacy regulations for energy consumption. The United Kingdom launched two policies in 2018, the Smart Meter Bill [230] and The

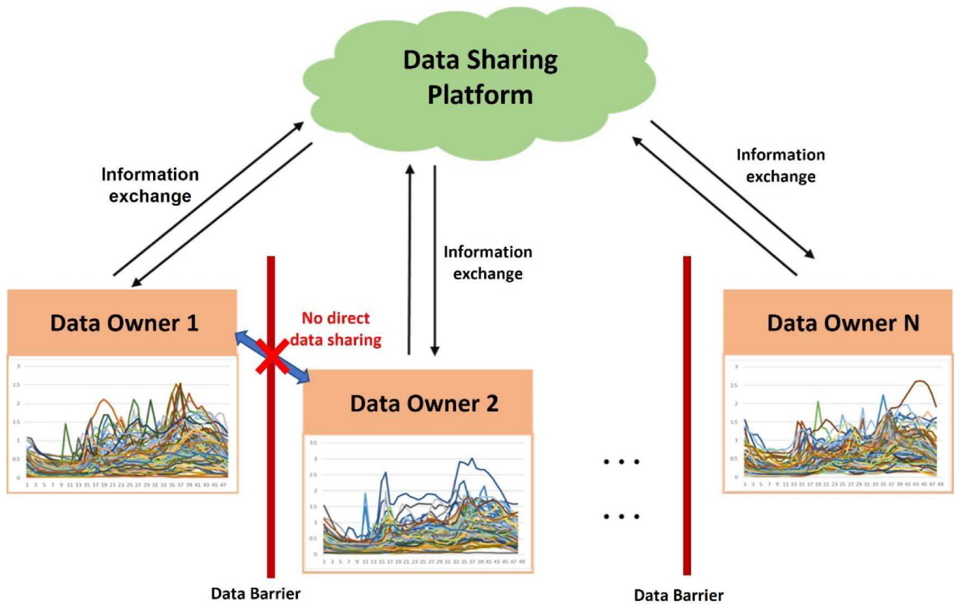

Fig. 12. ***Data barrier among data owners in distribution systems.***

Data Protection Act [231], respectively, authorizing half-hourly electricity consumption data collection and implementing general data protection regulation (GDPR) [232] to utilize consumers' data and protect data privacy at the same time. To address privacy concerns with smart grid technology, the Office of Electricity Delivery and Energy Reliability and the Federal Smart Grid Task Force have published a Voluntary Code of Conduct (VCC) for utilities and third parties in the United States [233]. Data Security Law of the Peoples' Republic of China was passed on June 10, 2021, which strictly regularizes data collection, storage, use, processing, transport, provision, and disclosure [234]. A comparative analysis of residential SM data privacy in different countries can be found in [235]. Fig. 12 shows that there is a data barrier between each two data owners. They cannot or are not willing to directly share their data with others because of the data privacy regulation, business competition, and so on. Thus, it is of vital importance to figure out how to preserve the privacy of consumers and promote secure data sharing among each other in distribution systems.

1) Data Privacy: Thanks to the widespread use of sensors such as SMs indicated above, a considerable amount of data regarding renewable energy generation, demand-side power usage, and environmental factors can be captured and transferred to data centers via the built communication network. Advanced machine learning technologies can be used to conduct optimal energy management and accurate forecasting using this aggregated copious data [236]. However, such a data-centralized method may no longer be practicable or feasible for two key reasons. The first reason is that, as urbanization accelerates and sensors, such as SMs, become more widespread, the amount of data collected will explode. The tremendous amount of raw data that must be delivered to the data center necessitates a big transmission bandwidth and high transmission speed, which could be a major difficulty for the communication network. The second factor has to do with concerns about privacy. Take SM data as an example; different retailers control SM data, and data analysis helps them better understand users' usage patterns and offer customized services [237]. These data owners may be hesitant to disclose their valuable data for fear of losing their competitiveness in the retail sector. Federated learning is offered as a possible way to address the two issues mentioned above. Multiple participants collaborate to construct a model while maintaining the data *in situ* using the federated learning framework. Instead of directly sending raw data, each participant uses local data to train models separately and transfers model parameters over secure protocols [238]. Even though raw data from many districts will not be transferred to a data center during federated learning, it is necessary to aggregate data received by sensors in the local area. To tackle this challenge, a high energy-efficient and privacy-preserving strategy for safe data aggregation was presented in [239]. The distributed federated learning approach allows for collaboration between different data owners and parallel computation while maintaining privacy. Because of the appealing qualities of federated learning, a growing number of studies are focusing on how to apply this method to the power system. For example, Wang *et al.* [240] proposed using privacy-preserving principal components analysis to extract key features from SM data and a federated learning-based neural network to identify electricity consumer characteristics. Gonçalves *et al.* [241] examined privacy-preserving collaborative forecasting methods using a federated learning system that comprises data transformation techniques, safe multiparty computation, and decomposition-based methodologies. By combining data transformation methods with the alternating direction approach of multipliers, a federated learning model was developed to increase renewable energy forecasting skills. They also addressed the asynchronous communication problem in both peer-to-peer and server–client federated learning schemes [242]. For generating renewable energy scenarios, Li *et al.* [243] combined least-squares generative adversarial networks with federated learning, and their method was shown to outperform state-of-the-art centralized systems.

In addition to preventing malevolent adversaries from stealing data, protecting private information from being inferred is another important challenge in achieving the goal of privacy preservation. Differential privacy-based approaches have been presented and are popular due to their ease of implementation [244]. Differential privacy attempts to thwart an inference attack when a single sample enters or exits a database by introducing random noise to the input data. Based on differential privacy, a privacy-preserving optimal power flow technique for distribution grids was proposed in [245]. Gai *et al.* [246] improved standard differential privacy approaches and presented a noise-based approach for a consortia blockchain-enabled neighboring energy trading system that protects members' privacy from data-mining attacks. Even while differential privacy-based approaches are useful in some situations, input data with noise may deviate from the real value, lowering the effectiveness of the model that uses these inputs. Another viable solution for privacy preservation in SMing systems is to employ renewable energy and rechargeable batteries to directly adjust consumers' actual energy consumption profiles. The use of rechargeable batteries in conjunction with renewable energy sources was studied in [247] to limit information leakage and came up with single-letter information-theoretic expressions for the least information leakage rate, while using energy storage to improve privacy will raise energy costs, which is contrary to the original purpose of storage investment, i.e., saving costs. As a result, the tradeoff between maintaining privacy and cutting costs should be carefully evaluated. Giaconi *et al.* [248] discussed the characteristics of the privacy–cost tradeoff in three scenarios: the short-horizon model, the long-horizon model, and the practical energy management strategy. The problem of determining the best privacy–cost tradeoff method was abstracted as a Markov decision process in [249] and [250], and reinforcement learning-based algorithms were used to solve it.

2) Data Pricing: The massive number of distributed data in the grids can be utilized to optimize the operation and planning of power systems with data-driven methods. For example, Bessa *et al.* [251] and Tastu *et al.* [252] have proved that distributed data can improve forecasting quality for wind and solar energy, respectively. However, as stated above, data owners are reluctant to share their data. Despite some privacy-preserving methods, such as data manipulation (such as additive noise) and federated learning, which can protect the privacy of distributed data, data owners may still be unwilling to disclose their data unless their datasets are fairly valued and paid [253]. Consequently, data markets, where data owners are incentivized to share their data through monetary compensation [254], are called for efficient data exchange as another means. In the context of smart grids, data are usually traded for improving energy forecasting accuracy, reducing uncertainty, and, thus, lowering the imbalanced costs in the energy market [255]. Consequently, data pricing in the current stage in the context of smart grids tends to be forecasting-based. For example, Gonçalves *et al.* [256] proposed an energy forecasting data market where wind agents submitted measurement data to market operators (market intermediates responsible for calculating payments, allocating payoffs, and return prediction results) and got the forecasting results instead of data from other agents. In this market, market operators made predictions based on the ordinary least-squares (OLS) regression. Buyers' payment depended on the improvement of regression accuracy. On this basis, regression markets for energy forecasting were further proposed in [257]. In regression markets, agents post regression tasks, and other agents who are willing to share their data will be monetarily rewarded based on Shapley values and related allocation [257]. Another method of payoff allocation in the regression market is based on the least absolute shrinkage and selection operator (lasso), which regularizes the useless features and selects useful ones for prediction [258]. Similarly, in [259], the economic value of PV-related data was measured as the operational cost reduction induced by forecasting improvement. Wang *et al.* [260] further defined the value of data in terms of the role of data in eliminating the impact of uncertainty on the economic interests of the data buyers. For example, the acquisition of data on electricity consumption by renewable energy providers leads to a reduction in the length of the prediction interval for probabilistic load forecasts, and this reduction can correspond to an increase in revenue for the data buyer coming to the energy market.

It has to be mentioned that data pricing models beyond the context of smart grids can also be referred to in future research, which can be divided into two categories: economics-based models and data-driven-based models. The economics-based models usually draw on traditional economics thoughts for pricing data. A classic approach for pricing goods is cost-based pricing, which considers the complete cost of a commodity (including collecting, managing, and so on) and calculates the profit as a percentage of the total cost. On account of the extremely high variety of data products, standalone cost-based pricing usually fails to measure the value of data [261].

Consequently, in data markets, the economic approach of differential pricing (i.e., setting different prices for the data of different quality/quantity) is frequently applied to price data. For example, the completeness of XML document data is used to describe its quality, and the price is determined accordingly [262]. Similarly, Shen *et al.* [263] proposed a pricing mechanism for personal data according to the measurement of information entropy. Beyond pricing data from single-dimension data quality measurement, Yu and Zhang [264] proposed a model for pricing data according to multidimension data quality measurement. In addition to the variety of data products, the demands of data consumers can be also various, and thus, data pricing can also be affected by data consumers' demands. Zheng *et al.* [265] priced mobile data considering both the accuracy of the dataset and the tolerance level of data consumers to inaccuracy. To avoid purchasing the whole dataset with probable useless parts, Koutris *et al.* [266] developed query-based data pricing, which can automatically calculate the query price according to consumers' queries and the view price set beforehand by data vendors. Willingness To Buy and Willingness To Sell from the perspective of both data consumers and data sellers are modeled in [267], bridging supply and demand during pricing data. Economics-based models usually provide general ideas for pricing data, which means that they are not limited to specific contexts and can be referred to in further research.

In comparison to traditional commodities, data-driven research can be used to investigate the potential value of data commodities and provide economic benefits. How to evaluate the value of data and determine a suitable price should examine the following two aspects from the standpoint of data-driven techniques: 1) data pricing according to its contribution to the model and 2) profit sharing. On the one hand, data are at the heart of data-driven approaches, such as machine learning, and its worth can be measured in terms of model improvement. Value-of-Information (VoI) and influence functions can be used to quantify the contribution, and reverse auctions can be used to achieve it. The VoI is defined as the extent to which provided data can aid in the elimination of uncertainty during the decision-making process [268] or the facilitation of model inference. VoI is used in healthcare systems for decision-making [269] and pricing [270]. Koh and Liang [271] investigated influence functions that can explain the contribution of individual training data, and Richardson *et al.* [272] proposed using influence functions to reward high-quality data in a crowdsourcing data gathering situation. When model owners are aware of the exact types of data required to develop the model, they can use reverse auctions to attract data contributors, such as Singla and Krause [273] proposed regret minimization techniques and reverse auctions for sensor data to create truthful incentives in crowdsourcing jobs. On the other hand, data can be valued through fair profit sharing after the economic benefits of data donation have been realized.

Table 3 Collection of Data Market-Related Literature

Context	Approaches	References
Smart Grid	Data-driven	[255] [256] [257] [258] [259] [260]
Non-Smart-Grid	Economics-based	[261] [262] [263] [264] [265] [266] [267]
	Data-driven	[268] [269] [270] [271] [272] [273] [274] [275] [276]

Gollapudi *et al.* [274] looked at utility game theory in the context of reasonable profit-sharing schemes. One profit-sharing scheme adheres to egalitarian principles, which means that all participants share the benefit equally. Other profit-sharing schemes involve a labor union game where profit is shared according to the marginal gain or marginal loss when a participant enters or exits. Ghorbani and Zou [275] presented data Shapley for establishing equitable data valuation in a machine learning context, and Jia *et al.* [276] proposed efficient algorithms for approximating the Shapley value during data pricing. Despite the fact that data-driven approaches for pricing data often need specific data-related tasks, these approaches mine and evaluate the potential value of big data.

Table 3 collates the relevant literature on different pricing methods in different contexts mentioned above. To conclude, studies on data pricing in the context of smart grids tend to be data-driven approaches, often related to forecasting tasks, while works in the context of nonsmart-grid context applied various pricing approaches, including economics-based approaches and data-driven approaches. These previous works can be further referred to and combined and, thus, design a more suitable market mechanism for smart grid data markets.

VI. OPEN RESEARCH ISSUES

Although a lot of work has been done on the intersection of cyber, physical, and social aspects of distribution systems, cyber–physical–social distribution systems are still in their infancy stage, and more work should be done for the deep fusion of cyber–physical–social systems. This section envisions three potential research directions in this area.

A. Cyber Systems Operation and Planning

1) Cyberattack Risk by Reducing Communications: As a highly sensor-driven cyber–physical system with interdependence between communication and power networks, smart grids are inevitably exposed to cyberattacks. For example, malicious attacks on sensor data transmissions can mislead the power network control algorithms, leading to catastrophic consequences, such as blackouts in a large geographic area. Under the threats of adversaries, smart grids need to maintain their functionality and availability. In the context of cybersecurity, this can be achieved by ensuring information confidentiality, integrity, and authenticity. Among these different cybersecurity aspects, ensuring communication confidentiality can keep sensor data and control command a secret to ill-intentioned parties.

This is important to prevent unauthorized profiling of the intimate details of smart grid operation and consumer lifestyle. Ensuring communication integrity can prevent control commands from being illegitimately modified in transit. Under the malicious insidious attack, the integrity of control commands can be assured as long as they are kept confidential. This is because an attacker must first learn about the system behaviors and know the original command before modifying it to gradually harm the system without being easily detected. As such, communication confidentiality is probably the most critical cybersecurity aspect of smart grids.

The risk of leaking confidential information increases with an increase in communication traffic and distance. It is an open research challenge on how to minimize the amount of information being communicated and communication distance while performing smart grid control. This can probably be achieved by shifting from a centralized control architecture to a distributed control architecture, where multiple smaller control units are tasked to make local control decisions for only a section of the smart grid in a less frequent manner. These local control units may indeed cut the risk of information eavesdropping, but the challenge remains in closing the gap in performance optimality between centralized and distributed controllers.

B. Human Behavior Modeling

1) Integrated Modeling of Cyber–Physical–Social Systems: Individual modelings of cyber, physical, and social systems are the basis of integrated modeling of distribution systems. The electromagnetic theory and the information theory lay solid foundations for modeling physical and cyber systems, respectively. Rigorous mathematical equations can be formulated, such as power flow equations for power networks and data transmission equations for wireless communication networks. However, there is no universal modeling approach for human behavior. Humans have a different way of cognition than computers, which is hard to model. In addition, humans have lower predictability, i.e., they may not make the same decision in the same situation but at different periods. It is hard to mathematically formulate human behavior, such as cyber and physical systems. Is there a way to define a behavior model that can comprehensively reflect the complex cognition and predictability of humans (such as consumers and retailers)? On this basis, is it possible to develop data-driven approaches (e.g., neural networks) to model their behavior?

Another critical issue is integrating the models of the three systems. Take DR as an example; many works in DR establish optimization models to schedule different appliances assuming that consumers are retinal. This is not the case in the real world. Even though current research from the social perspective can summarize the different influencing factors and provide some explanations according to survey data, these results cannot describe how consumers react to different signals (whether, price, and so on) and are hard to be integrated with the optimization model for DR. We call for integrated models to reflect the interactions among cyber, physical, and social systems so that the final decisions based on the integrated model are closer to the real world. There are several works on system-level modeling of cyber–physical–social systems [277], [278]. These modeling methods should be more specified for specific problems in distribution systems.

2) Human-in-the-Loop Simulation: In addition to modeling, simulation is also crucial for evaluating a decision. Since human is the most challenging part to be modeled, putting humans into the loop for simulation may better reflect humans' cognition and predictability. In fact, human-in-the-loop simulation has been widely studied for the problems outside distribution systems [279]. The design methods can be good references for designing simulations in distribution systems, such as putting consumers into the loop for peer-to-peer market simulation and putting system operators into the loop for the reliability analysis and simulation.

3) Backup Power Deployment for Cyber Systems: Due to interdependence between communication and power networks, smart grids may experience internetwork cascading failures when an initial failure propagates from one network to another network through the dependent node of a failed node. Such cascading failures may carry on for a number of cycles and may result in a complete system collapse. As such, internetwork cascading failure poses a challenge to smart grid resiliency and robustness.

The impact of internetwork cascading failures can be reduced by preventing the propagation of an initial failure. This can be achieved by installing backup power at communication nodes such that a communication node may not fail merely due to the failure of the power node that it depends on for its electricity supply. However, each backup power unit incurs a cost, and it can be too costly to install a backup power unit at each communication node. It is an open research challenge on how to optimally deploy backup power units for the smart grid communication network while maximizing its robustness and resiliency.

C. Data Supply Chain

1) Data Supply Chain Management: Traditionally, the factors of production can be divided into four main categories: land, labor, capital, and technology. In the era of the digital economy, data will become another important factor of production. Both physical and social systems in the distribution systems are generating data, while the cyber system is transmitting and analyzing data. Data are the core of future cyber–physical–social distribution systems, which involves data collection, data transmission, data storage, data mining, data trading, and so on. Is it possible to propose the concept of the data supply chain to model the whole process from data collection to data-driven decisions? Each link of the data supply chain involves various costs, such as sensor installation costs for data collection and technology development costs for data mining. Thus, each link should be carefully managed. Supply chain management has been widely studied for various commodities. Data, as a new factor of production, have distinct characteristics compared with traditional commodities. Effective modeling and fair management of the data supply chain in the distribution systems will large promote the digitalization of distribution systems.

2) Social and Technological Data Fusion: Integrating social science and engineering concepts and methods is critical to achieving effective interdisciplinary energy research; however, it is often a challenge to integrate human and physical measures and data. The first challenge arises in the fundamental research direction design. The potential of interdisciplinary and transdisciplinary research design in energy and the cyber system is clear. Still, it requires social scientists, computer scientists, and engineers to incorporate social vulnerability or more social, psychological, and behavioral measures into the broader measurement and modeling of vulnerable community resilience in the beginning stage of research design. Previous research in energy patterns, DR, and occupant behavioral analysis has often focused on technoeconomic aspects (e.g., building efficiency and electricity prices) without sufficiently integrating particular demographic groups' social, psychological, and behavioral dimensions into engineering modeling. Second, the integrated measures and data analysis are not designed fundamentally by including social, psychological, and behavioral components in the engineering's physical data; instead, they often are adding-on or *post hoc* analyses. However, the machine learning methods in big data could potentially integrate social science data. Third, human-interpretable results require that machine learning methods are informed by physical, biological, and social science understandings. More importantly, researchers should understand that big data analytics contain potentially social bias and generalization issues. For example, some forms of "big data" come from social media, or the web is likely to exclude certain groups, such as the elderly or LIHs' opinions, because they are less likely than others to participate in certain types of social media (e.g., Twitter), so analyses based on these sources have the population bias. Some applications of machine learning methods have been critiqued for reproducing certain social or ethical biases [280]. More importantly, researchers must be cautious about using big data analysis without theoretical understanding from the sciences or human behaviors will favor *ad hoc* explanations based on data that happened to be available rather than underlying causality among variables.

VII. CONCLUSION

This article provides a comprehensive review of cyber–physical–social couplings in smart distribution systems, including cyber–physical, physical–social, and cyber–social couplings. The latest developments and emerging topics, such as 5G communication, COVID-19, and data privacy, in future smart distribution systems, have been summarized and discussed. In addition, we have proposed future research directions from three aspects: human behavior modeling, cyber system operation and planning, and data supply chain. We would like to emphasize that cyber–physical–social distribution systems are an emerging and promising research area. We hope that this review can provide readers with a complete picture and deep insights into this area. ■

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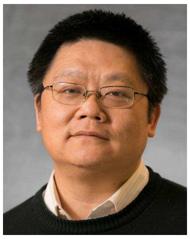

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