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Distributed machine learning for energy trading in electric distribution system of the future

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ABSTRACT

Machine Learning (ML) has seen a great potential to solve many power system problems along with its transition into Smart Grid. Specifically, electric distribution systems have witnessed a rapid integration of distributed energy resources (DERs), including photovoltaic (PV) panels, electric vehicles (EV), and smart appliances, etc. Electricity consumers, equipped with such DERs and advanced metering/sensing/computing devices, are becoming self-interested prosumers who can behave more actively for their electric energy consumption. In this paper, the potential of distributed ML in solving the energy trading problem among prosumers of a future electric distribution system - building DC grid cell, is explored, while considering the limited computation, communication, and data privacy issues of the edge entities. A fully distributed energy trading framework based on ML is proposed to optimize the load and price prediction accuracy and energy trading efficiency. Computation resource allocation, communication schemes, ML task scheduling, as well as user sensitive data preserving issues in the distributed ML framework are addressed with consideration of all the economic and physical constraints of the electric distribution systems.

1. Introduction

Electric distribution systems have witnessed a rapid integration of distributed energy resources (DERs), including photovoltaic (PV) panels, electric vehicles (EV), and smart appliances, etc. The electric energy generation from DERs is projected to be 317,323 GW h in 2040 (D. of Energy, 2017). Among different types of DER technologies, the rooftop solar PV is seeing dominant popularity mainly because of its continuous declining in installation cost, and federal and state government incentives. For instance, in order to achieve 32 percent CO_2 reduction by 2030, a goal set by the Clean Power Plan 2015, both federal and state governments have issued different policies to promote the distributed renewable resources, such as the Renewable Energy Credits and Renewable Electricity Production Tax Credit (Anon, 2019). Although the actual installation cost varies, it was reported that residential PV systems typically sized as 6 kW have an average installation cost of 2.80 $/watt in 2017 compared to 3.92 $/watt in 2013 (Fu et al., 2017). Another noteworthy technology that flourishes at the electric distribution systems in recent years is plug-in electric vehicles (PEVs). There is a clear trend of increasing popularity of people owning and driving EVs. According to the Global EV Outlook 2020 (Global ev outlook, 2020), sales of EVs topped 2.1 million globally in 2019. After entering the commercial markets in the first half of the decade, EV sales have soared. There were only about 17,000 EVs on the world's roads in 2010, however, by 2019, that number had swelled to 7.2 million. The prosperity of the EV market is mainly dependent on three driving forces: (1) incentives from federal, state, local governments, and utility companies; (2) price drop due to peer competitions with current EV prices as low as $25,000; and (3) performance improvement of EVs brought by technological advancements which make many concerns about EV such as range anxiety no longer big issues.

The future electric distribution system customers are switching their roles from pure electricity consumers to prosumers equipped with different DERs, specifically, rooftop PVs, EVs, smart appliances, and other demand management solutions. Indeed, if properly managed, DERs of prosumers could not only bring significant benefits to the distribution system operations but also change how the retail electricity markets are cleared. Instead of purchasing electricity from the utilities at high fixed tariff or time-of-use (TOU) prices (Thumann and Woodroof, 2020) and selling excessive electricity at low feed-in tariffs via long-term power purchase agreements (PPA) (Research and Authority, 2020) back to the utilities, prosumers are exploring more flexible ways to achieve a

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win-win outcome via seeking a proper electricity price between the high TOU prices and low feed-in-tariffs for the benefits of both the buyers and the sellers. Different energy trading mechanisms and models have been proposed and analyzed (Zhou et al., 2018; Zhang et al., 2018; Abdella and Shuaib, 2018; Sousa et al., 2019; Park and Yong, 2017; Li et al., 2016a; Parag and Sovacool, 2016) in the literature, and several pilot energy trading projects have been implemented, including Piclo, Vandebron, SonnenCommunity, etc. (Zhang et al., 2017). Many of those energy trading mechanisms fall into two major categories: (1) Auction-based energy trading, which is similar to the wholesale electricity markets. A distribution system operator (DSO) is designated to securely and reliably operate the system and administrate a competitive energy trading market, while the prosumers or groups of prosumers are considered as self-interested market participants with respective economic objectives; (2) Bilateral contract-based energy trading, with the DSO only taking care of the distribution system operation, and not in charge of administrating the electricity markets. The DSO operates a platform where trading offers are posted, and handshakes are made among all the prosumers.

In this paper, a peer-to-peer energy trading framework for a direct current (DC) grid cell is proposed based on distributed ML techniques. A DC grid cell is defined as a building level DC grid penetrated by many rooftop PVs, EVs, and other DC loads of different prosumers, which is regarded as one of the future residential electricity delivery solutions. Such DC grid cells will act as building blocks to generate larger scale community grids by connecting multiple buildings, or even networks of such community grids. A DC electric power distribution system offers the ability to connect DC DERs within a grid at increased efficiency, power quality, and reliability, while minimizing the reliance on support from the local utility if adequate local resources are managed properly. However, in a smaller scale system such as a building level DC grid cell, first, it is hard to find a trusted entity to be in charge of the system operation or market clearing, second, the flexibility of DER connection/disconnection requires a plug and play operation flexibility, and third, the concerns about household privacy will increase if information is required to be submitted centrally. To enable the efficient energy trading inside such smaller systems, a fully distributed mechanism is a better option. However, challenges such as how to secure the operation of the physical system, how to guarantee the convergence of the market clearing, and what are the enabling techniques for each prosumer to participate in such energy trading remain major concerns.

The remaining of this paper is organized as follows: Section 2 summarizes the major challenges for a successful distributed energy trading solution, and detailed literature survey is conducted in exploring technologies to address those challenges; Section 3 proposes a distributed ML based peer-to-peer energy trading framework for DC grid cells, and detailed functional components are discussed; Section 4 summarizes this paper, and presents some future works.

2. Challenges and literature review

Conventional power system operation schemes relying on the coordination of a "central entity" by collecting all the system information, making decisions, and sending out control signals to each individual system component may not work effectively, nor efficiently in emerging electric distribution systems with high penetration of DERs, specifically in smaller scale building level grid cells. Thus, a fully distributed peer-to-peer energy trading framework is proposed to secure the operation of a building DC grid cell, while trying to address all the following challenges.

- Dynamic supply and demand, which are continuously fluctuating due to the integration of renewable DERs and smart building energy management solutions, make it hard to predict the system behavior, and thus hard to control its operation.
- System operation performance degradation due to increased penetration of heterogeneous system components, if all controlled centrally, will impose much heavier computation and communication burdens.
- Increased system security and privacy concerns due to the integration of many edge devices into the communication network, representing much more vulnerabilities to cyber physical attacks.
- New operation mechanism, which can guarantee the system security, economics, sustainability, as well as fairness, is highly demanded.
- Resource-constrained IoT devices have limited computation and communication capabilities for many ML approaches, which are designed for powerful centralized servers.

An extensive literature review is conducted to explore emerging technologies to help address above challenges in data analysis, communication, operation, privacy and security.

2.1. Demand and supply prediction in a distributed setting

The ability to accurately forecast future demand and supply is one of the fundamental challenges to support the efficient operation of future electric distribution systems. Electric demand forecasting can be categorized based on the prediction time period, from short-term load forecasting of seconds to hours to long-term load forecasting of months to years. The type of application decides the prediction time period. Short term load forecasting is used to control power flow, while the long-term forecasting can be used for power generation planning. Electric load forecasting has been around for more than fifty years. Earliest load forecasting approaches utilized manual data analysis with load, weather, and seasonal data (Gillies et al., 1956). Later, linear time series approaches (e.g., ARIMA, ARMA, AR, etc.) were explored for load forecasting. Starting in the eighties with the popularity of ML techniques (e.g., neural networks, support vector machines, etc.), many data-driven automated forecasting approaches have been proposed (see Hernandez et al., 2014 and reference therein). Recent load forecasting approaches have to take into consideration the renewable energy resources (e.g., wind and solar, etc.) at different locations, together with the demand, and the energy distribution has to reckon with the electricity generation uncertainty (Ahmad and Chen, 2020).

Recently, there is a strong interest in using deep learning technologies for renewable energy forecasting (Wang et al., 2019; Deng et al., 2020). These approaches either forecast the wind speed or solar irradiance. Sometimes the prediction model uses information from the weather model to improve the performance. Also, Hu et al. (2016) proposed using transfer learning on deep neural network architecture in which the hidden layers in the prediction models based on data rich wind farms are shared with prediction models for newly built wind farms to improve the prediction accuracy. Such knowledge transfer (or sharing) ML paradigm can be naturally extended to a distributed problem scenario.

Decentralized or distributed ML are natural solutions for prediction problems at the edge (e.g., household units and small island communities) of a smart grid to support system planning, operation, and control considering the integration of renewable sources (Williams and Short, 2020). It has been shown that such solutions can improve prediction accuracy (Xu et al., 2016; Rosato et al., 2019), energy savings and peak load reduction (Xu et al., 2016). While generic tools such as Apache Spark and Apache Hadoop can be used to run conventional ML algorithms in a distributed manner for forecasting purposes (Syed et al., 2020), new technologies need to be developed to integrate recent technologies in deep learning, reinforcement learning (RL), and transfer learning to provide a robust distributed framework to meet the challenges in a complex system.

2.2. ML in energy trading optimization

The energy trading among electricity consumers, suppliers, or prosumers can be modeled as a markov decision process (MDP). As a result, RL is becoming one of the most promising tools to realize optimal operation. Comparing with conventional approaches, RL has the following advantages: (1) RL is a model-free approach which learns an operation model via the interactions with the system. Hence, RL can be adopted in a wide range of systems where a variety of features of the environment may not be commonly known, such as the electric distribution system. (2) RL generates operation strategy by using learned model rather than solving a complex mixed-integer programming (MIP) and thus RL can return results quickly. And (3) RL can dynamically update the learned model with recent data.

Specifically, each DER can be modeled as an autonomous agent in RL to enable control and coordination via message interaction (Marzal et al., 2018; Rahman and Oo, 2017). Q-learning, state-action-reward-state-action (SARSA) and deep Q-learning are commonly used for model-free RL (Rummery and Niranjan, 1994). Lu et al. (2018) investigated a dynamic pricing demand response (DR) using a Q- learning in a hierarchical electricity market for both service provider's profit and customers' costs. The service provider controls the electricity demand via different price settings. Q-learning and SARSA store the expected value of each action into a Q-table and thus it works for discrete environments. Zhu et al. (Zhou et al., 2019) considered energy sharing in a residential community. They proposed a Fuzzy Q-learning method, which addresses the issue that the battery model and price model are continuous and lead to an infinite state in Q-learning. They proposed to use Fuzzy Logic to convert continuous variables to discrete variables. Chen et al. (Chen and Su, 2018a) proposed to use a deep Q-learning method to maximize the utility or economic benefit of a customer. Compared with Q-learning, Deep Q-learning is able to handle extremely large problems with leverage of deep learning techniques for model approximation. In (Chen and Su, 2018b), Chen et al. proposed an in-direct energy trading mechanism, where there is a retail energy broker in the power system. They proposed to use Q-learning to conduct buy, sell, retention, and wait operations to maximize its profit.

2.3. Edge computing in power systems

To process computation tasks in a timely manner on the grid's edge devices, edge computing is a promising technique, which provides a distributed computing paradigm by pushing computation tasks closer to nearby edge devices to address the following three major challenges faced by centralized computation paradigm (Chen and Ran, 2019): (1) Sending data to the central controller may incur additional transmission, propagation, and queuing delays from the network and cannot satisfy the real-time application requirement, especially in wireless environments. (2) Sending data from the sources to the central controller introduces scalability issues, as network access to the cloud can become a bottleneck as the number of connected devices increases (Chiang and Zhang, 2016). According to Statista's prediction result, the number of IoT devices by the year 2025 will be more than 75 billion (Department, 2016). In power systems, 800 million smart meters are expected to be installed globally by 2020 (Anon, 2015). Assuming that smart meters take one record every 15 min, this leads to about 77 billions of readings globally for one day (Jaradat et al., 2020). (3) Sending sensitive user behavior data to the central controller risks privacy concerns. Therefore, users may be wary of uploading their household information to the central controller. Since edge computing is a local computing solution, it solves the latency and scalability issues, and the data collected by the central controller could be reduced/eliminated to alleviate the privacy concern.

In addition, to accelerate the ML computation on edge devices, technology companies, such as Google, Microsoft, Nvidia, etc., all develop edge computing frameworks, such as Google IoT Edge (Cloud iot core, 2020), Azure IoT Edge (Cloud intelligence deployed locally on iot edge devices, 2020), Nvidia EGX (Nvidia egx edge computing platform, 2020), KubeEdge (Kubeedge platform, 2020), and edge computing devices such as NVIDIA Jetson TX2 (Nvidiajetsontx2, 2020), Intel neural compute stick (intel neural compute stick, 2020), Google Edge TPU (Google coral development board, 2020). The edge devices include hardware such as Pascal GPU and Google TPU for state-of-the-art ML computation acceleration. As a result, edge devices can be used to train and use a wider range of ML models to build a more secure, reliable, and intelligent power distribution strategy than the current practices in threat detection, malicious attack identification and intelligent electricity power control (Mocanu et al., 2016).

Edge computing has been utilized in many power systems applications recently. Liu et al. (2019) conducted a simulation with deep reinforcement learning in edge servers of smart grids. The experiment results show that with hourly load profiles of different practical demands including HVAC, water heating, lighting, clothes drying, freezing, and so on, the energy cost can be significantly reduced. Yang et al. (2019) proposed an efficient cooperative task offloading and resource allocation scheme in the edge computing with consideration of limited channel resource and task deadline requirement in smart grids. Chen et al. (2019) discussed applications in power distribution surveillance systems, advanced metering systems, etc.

2.4. Communication and distributed control techniques

Considering the limited communication resource in Smart Grid, the efficiency of communication and control is extremely important.

2.4.1. Communication

Advanced Metering Infrastructure (AMI) offers a sustainable solution in this regard which provides a two-way communication scheme between utilities and loads. The AMI allows service providers to collect, measure, and analyze energy usage data from advanced devices (e.g. electricity meters) through a heterogeneous communication network on request (on demand) or on a pre-defined schedule for outage management, billing, and power grid management. The typical smart grid communication network structure includes home area network (HAN), neighborhood area network (NAN), and wide area network (WAN) (Zhu et al., 2012; Emmanuel and Rayudu, 2016; Bian et al., 2019). Popular WAN communication technologies are fiber optic, powerline communications (PLCs), and wireless media using cellular, e.g., long-term evolution (LTE) and radio frequency 900Mhz. Popular NAN technologies are ZigBee and WiFi.

Narrowband Internet of Things (NB-IoT) is a promising candidate for smart grid communications. NB-IoT demands secure and reliable communications with high quality of service (QoS) requirement. On the other hand, it is difficult for license-free radio technologies to fulfill these requirements since they are very likely to suffer from interference in the crowded unlicensed band. NB-IoT works on the licensed spectrum and is designed based on existing LTE functionalities (Li et al., 2017). Currently, Mobile Edge Computing (MEC) is the widely accepted standard by telecommunication vendors (5g edge is now even closer with private mec, 2020), which enables mobile users to access IT and edge computing services in close proximity within the range of radio access networks (Mao et al., 2017; Peng et al., 2018).

There are cost-benefit trade-offs among different communication links and many design issues. Emmanuel and Rayudu (2016) provided a comprehensive comparison of different communication techniques in terms of latency, bandwidth, range, capital cost, etc. Petersen et al. (2018) discussed the processing latency and throughput under different system configurations such as different link speeds, different hardware, different messaging protocols. The wireless channel assignment issue is considered in (Yang et al., 2019). Since the smart grid uses cellular frequency for wireless communication, Kong and Song (2019) considered the interference from dynamic cellular users in the channel assignment optimization. Alam et al. (2019) jointly investigated the power and channel allocation in NAN. Both fairness and priority are considered in the proposed solution. Vukobratovic et al. (2019) dis-cussed energy optimization with price uncertainty due to limited communication opportunities.

2.4.2. Distributed control

In the emerging electric distribution systems with increased proliferation of DERs, the secure and economic operation becomes more challenging, while conventional system control architecture is expected to experience a transformation. Specifically, centralized control framework is criticized for its inability to handle potential performance degradation due to: (1) the increasingly heavy computational burden on the central controller, (2) the increasingly heavy communication burden between central controller and other system components, (3) single point of failure due to increased cyber and physical vulnerabilities, and (4) dynamic system topology and status due to plug-and-play, and uncertainties of DERs (Yazdanian and Mehrizi-Sani, 2014). Thus, decentralized or distributed control schemes are regarded as a preferable option in guiding the emerging electric distribution system operation.

Consensus based algorithm has been studied for more than two decades in various distributed control schemes of multi-agent systems (MAS) (Ren et al., 2007) via iterative information exchange between neighborhood agents (Yang et al., 2013), and has been applied in designing many power system solutions, including economic dispatch (ED) (Li et al., 2016b; Zhang and Chow, 2012; Xu et al., 2014), unit commitment (UC) (Zhang and Chow, 2011; Zhang et al., 2013), and coordinated ED and primary control (Wang et al., 2018), etc. Lagrangian relaxation (LR) based approaches, and augmented LR based approaches, such as the famous alternating direction method of multiplier (ADMM) method, are also commonly used in solving many power system problems, including DC and AC optimal power flow (OPF) problems (Boyd et al., 2011; Hong and Luo, 2017; Ghadimi et al., 2014; Loukarakis et al., 2015; Goldstein et al., 2014, 2014), state estimation (Kekatos and Giannakis, 2012; Lin, 1992; Korres, 2010), and coordinated transmission-distribution resources dispatch (Caramanis et al., 2016) etc. via different decomposition methods. Game theory-based methods are commonly used in strategic bidding in the electricity markets (Li et al., 2015; Li and Li, 2016), as well as other system operation problems (Du et al., 2014; Liang et al., 2016).

2.5. Security and privacy protection techniques

Security and privacy have a high priority in future electric distribution system. We would like to discuss emerging secure trading techniques, i.e., blockchain, and the privacy issues of smart meter.

2.5.1. Distributed Energy Trading via Blockchain

Blockchain is a distributed ledger that records transactions in a verifiable and permanent way using a peer-to-peer network (Narayanan et al., 2017). A blockchain is designed to be resistant to modification of the transaction data without relying on any trusted authorities. Recently, blockchain has been recognized as an emerging technology with great potential to fulfill security and privacy requirements in distributed energy trading (Mihaylov et al., 2014; Li et al., 2018; Gai et al., 2019; Aitzhan and Svetinovic, 2018; Li et al., 2020).

The research of using blockchain techniques in energy trading can date back to 2014, when Mihaylov et al. (2014) first proposed a digital currency paradigm, called NRG-X-Change, where consumers can trade produced energy locally in a smart grid. In NRG-X-Change, consumers are billed based on their actual usage and rewarded according to their energy provision in a distributed manner. Following Mihaylov et al. (2014); Kang et al. (2017) proposed a localized peer-to-peer energy trading model for plug-in hybrid EVs in smart grids. Li et al. (2018) further exploited the consortium blockchain techniques and proposed a secure energy trading system called "energy blockchain". To reduce transaction confirmation delays in the blockchain, they proposed a credit-based payment scheme to support fast and frequent energy trading. Lin et al. (2018) proposed an energy trading scheme, called BSeIn, where both blockchain and attribute signatures are used to authenticate users anonymously. Meanwhile, the multi-receiver encryption is applied to guarantee that only authorized users have the access to the plaintext of broadcasted messages.

In addition, trading information recorded on the blockchain also raises some privacy issues. Gai et al. (Gai et al., 2019) presented a consortium blockchain-oriented strategy to prevent users' sensitive information leakage without restricting trading functions. Considering that a blockchain stores users' pseudonyms publicly, they applied an account-mapping algorithm to hide users' pseudonyms from attackers. Aitzhan and Svetinovic (2018) implemented a token-based energy trading system that enables users to securely perform trading transactions in a decentralized manner. They used a blockchain technique with anonymous encrypted messages and multi-signatures to address the privacy and the security issues in transactions. Considering that malicious energy sellers may refuse to transfer energy to their purchaser who already completed payment, Li et al. (2020) proposed to supervise and manage the energy trading process using blockchain techniques. They used anonymous authentication to protect user data privacy and designed a timed-commitments-based scheme to guarantee the fairness of energy trading.

2.5.2. Privacy of Smart Meter

Smart meters are advanced electronic devices that record the electric energy consumption near real-time. The expected frequency of report from a smart meter could be as high as every few (1–5) minutes (Efthymiou and Kalogridis, 2010). Such detailed energy usage information might disclose the daily energy usage patterns of a household or other sensitive information, e.g., whether a specific device was in use at any given time. Therefore, many efforts have been devoted to studying and addressing the privacy issues raised by smart meters (Kalogridis et al., 2010; Molina-Markham et al., 2010; Li et al., 2010; Jawurek et al., 2011; Rastogi and Nath, 2010).

For example, considering that attackers might infer user appliance usage from a smart meter with the help of load signature libraries, Kalogridis et al. (2010) proposed home electrical power routing with rechargeable batteries and alternate power sources to "flatten" load signatures. Efthymiou and Kalogridis (2010) proposed additional protection by using a trusted escrow service, and randomizing time intervals between the setup of attributable and anonymous data profiles at the smart meter. Many works have been concentrating on aggregation-based methods for individuals' data privacy protection. For instance, Molina-Markham et al. (2010) proposed a strategy that allows a smart meter to report its billing instead of reporting its usage. In their proposed method, the smart meter provides aggregated information (e.g., neighboring consumption information) to the energy supplier, which can be also used to predict energy demand in the future. Similarly, Li et al. (2010) proposed to use neighborhood-level aggregation and cryptographic protocols to communicate with the energy supplier while protecting the privacy of individual home appliance. Jawurek et al. (2011) studied the smart energy requirements and schemes to prevent data leakage via smart metering billing. The authors introduced an additional component to integrate into smart meter, which transmits only billing data signed by the smart meter and verified by the energy supplier. Rastogi et al. (Rastogi and Nath, 2010) proposed to provide differential privacy over aggregated queries, where smart meter measurements are modeled as time-series data from multiple sources.

3. Proposed work

The goal of this proposed peer-to-peer energy trading mechanism is to build a residential energy management framework that can coordinate the operation of heterogeneous DERs and flexible loads that are all DC, in an autonomous, plug-and-play way, while is robust against cyber and physical system limitations and risks. A DC residential electricity delivery system could reduce many unnecessary AC-DC, and DC-AC conversion steps, and thus reduce the system power conversion loss and increase the system reliability with fewer mechanical failure of system components. In addition, the DC system only needs to control the voltage, which simplifies the DER integration (PV and batteries), and overall system operation. Considering the future electric distribution system is expecting increasing end to end DC components integration ranging from power generation, storage, to consumption, the DC system will see its increasing popularity in residential electricity delivery especially in the building level, and thus demands an efficient energy management framework.

In this paper, we focus on a building level grid cell, where exists homes with smart controllers and appliances, other DERs, and/or energy storage. Homes in this grid cell can directly trade energy with each other based on their respective energy generation and usage needs via a peer-to-peer mode. Fig. 1 illustrates our proposed DC grid cell peer-to-peer energy trading framework. Such a DC grid cell is expected to benefit all participants, where the seller can sell extra energy at a higher price to its neighbors than selling it to the utility company, and the buyer can get energy at a lower price from its neighbors than buying energy from the utility company.

The smart controller equipped by each home has data collection, communication, and computation capabilities and acts as the "brain" of a home. It has five modules: (1) data analysis module, (2) communication module, (3) energy operation module, (4) power control module, and (5) security and privacy module. First, the smart controllers can collect and exchange energy-related sensory data via wireless communication for initial data analysis. Second, by leveraging data from itself and its neighbors, each smart controller runs ML algorithms to learn the home's future demand and supply, utility electricity prices, and other homes' potential bidding strategies. Third, based on the ML results, the smart controller further runs RL algorithms to generate its optimal energy trading strategy. Fourth, once the local trading contracts are confirmed, the smart controllers will run a fully distributed consensus event-triggered algorithm for power routing to achieve accurate DC system load sharing and enhanced voltage regulation. The security and privacy module ensures that electricity usage, energy generation, sensory reading information is securely exchanged via data obfuscation and data poisoning. Edge computing is used to accelerate the aforementioned tasks and return results in real-time. Each smart controller will determine when and whether to participate the local energy trading asynchronously, which provides adequate flexibility for each home to choose the most economical way for energy consumption.

3.1. Load and price forecasting based on data sharing and transfer learning

Recently, Lin et al. (2020) proposed an integrated operation model with complete knowledge of distributed renewable energy generators, energy storage, and demand response from a provider perspective to predict the market price for bidding purposes. Mujeeb et al. (2019), and Kuo and Huang (2018) proposed the use of deep learning techniques for load and price forecasting using large amount of data in a smart city/-grid environment considering multiple influencing factors. Our machine learning solution utilizes limited data from within the community (e.g., real-time usage, demand, etc.) and other auxiliary data (e.g., seasonal load trend, historical market price, seasonal power generation, seasonal weather conditions, etc.) for both load and market/bidding electricity price prediction from a prosumer perspective. To ensure efficient and effective load (and/or price) forecasting for each home, pretrained deep learning forecasting model will be preloaded into the IoT devices for each home. The pretrained forecasting model is learned using historical market price and electricity usage data. Real-time usage and demand data shared by the community will be used to adapt or modify the model to ensure that the model will be effective. Furthermore, we will utilize (i) transfer learning (Pan and Yang, 2009; Weiss et al., 2016) to integrate data from different homes with similar usage behavior and (ii) distributed learning (Hu et al., 2020) to allow sharing of data (and/or model) within the community to improve the forecasting performance and sharing efficiency. Unsupervised learning (Xu and Wunsch, 2005) will be used to cluster and identify homes with similar usage behavior to share data. This process will be dynamic as usage behavior may change over time. Moreover, auxiliary data together with the individual neighbors' usage data will be used as source data for transfer learning to estimate market/bidding price for each home. One objective of the proposed method is to provide a personalized and fair bidding price for each home. One important issue to investigate is how the time granularity of the data will affect the load and price prediction performance.

3.2. Energy trading via RL

The energy trading in the proposed framework is built as a multi-agent reinforcement learning problem (Tan, 1993), where multiple smart controllers interact with each other with different operation and control goals. In this paper, we propose to use DRL for energy trading operation optimization. We plan to jointly use a home's current demand and supply situation with the previous actions of its neighbors as the DRL input. To further reduce the input state space, Mean Field Multi-Agent Reinforcement Learning (Yang et al., 2020) and neighborhood Q-learning (Shah and Xie, 2018) were proposed to solve the curse of the dimensionality, and will be leveraged in our framework.

3.3. Privacy and security via data obfuscation and data poisoning detection

To improve the accuracy of demand prediction among neighbor

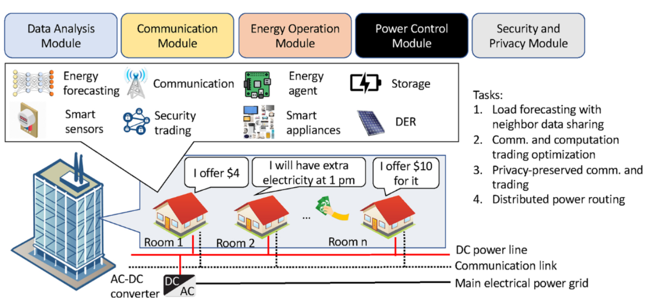

Fig. 1. A DC peer-to-peer energy trading framework.

users, our approach allows each prosumer in the community to share his/her own collected information (e.g., energy usage) with others, which may raise privacy and security issues.

3.3.1. Privacy protection via data obfuscation

As indicated in (Efthymiou and Kalogridis, 2010), the detailed energy usage information collected from smart meters might disclose the energy usage patterns or other sensitive information of a household. Such privacy concern may discourage users to share information with others. As a solution, before data sharing, we let each user obfuscate his/her own data by stochastic noise. The noise follows a derived probability distribution, which is designed to hide individual energy usage but without changing the statistical features of the whole dataset collected from the community. Thus, the impact of data obfuscation on demand prediction accuracy can be minimized.

3.3.2. Data poisoning detection and control

A malicious user may share deceptive information with other users, such that the prediction results from others are beneficial to the malicious user's own needs. To protect the data from poisoning, we first need to formulate the threat model of malicious users, i.e., what are the possible objectives of malicious users and their capability to achieve the objectives. Given the threat model, we can then design a detection algorithm that can differentiate normal obfuscated data (for privacy protection) and poisoned data. Moreover, we can carry out a sensitivity analysis to figure out how much noise can be tolerated in the machine learning model such that the prediction accuracy can be guaranteed at an acceptable level.

3.4. Processing acceleration via edge computing

Machine learning and deep learning methods have been proposed for demand/supply forecasting, operation optimization and have shown their advantages in automatic features extraction, flexibility, and superior performance, etc. However, IoT devices, e.g., smart controller of each home, is resource-constrained and has lower processing power, memory, and transmission speed. Therefore, state-of-the-art deep learning models may not be able to work efficiently in such a scenario. To address the increasing computational requirement of Smart Grid and its resource-constrained communication and computation capabilities in Smart Grid applications, we propose to use computation offloading technique. The idea is that a smart controller can wirelessly transmit data to a more powerful edge device for deep learning processing acceleration at the cost of extra communication delay. It is worth noting that the communication latency introduced by computation offloading is non-ignoble especially for smart grid applications. We propose to use a novel three-stage computation offloading scheme. That is, a smart controller can pre-process a computation task and then offload it to an edge server. The pre-processing will lead to a shorter communication time due to deep neural networks' intrinsic characteristics. This is a communication and computation trade-off and the proposed offloading scheme can dynamically adjust its offloading strategy in different network environments for latency minimization. In addition, we propose to investigate deep neural network model parallelization techniques to enable processing pipeline between smart controller and edge server.

3.5. Distributed power routing

The objective of power routing is to implement: (1) accurate load current sharing among multiple energy trading participants, and (2) system-wide voltage regulation in the DC grid cell. Droop control is conventionally employed to accomplish these goals in a communication-less and distributed manner. However, a trade-off should be made: A high droop gain improves the accuracy of load current sharing at the expense of deviated output voltages. Thus, a secondary control is proposed to address such potential deviation by correcting the voltage set points to each DC voltage source. In the literature, both centralized control and distributed control methods are adopted in the secondary level control. In recognizing the lack of central controller and the concern of privacy in the building level grid cell, as well as the design objective of the proposed energy trading framework: autonomous and plug and play, a distributed secondary control is proposed. Under existing commonly used consensus-based distributed secondary control framework, each device in the system possesses an agent that is in charge of collecting information from the neighbors over a sparse communication network and deriving the updated reference to its droop controller. It should be noted that consensus-based distributed control methods normally entail continuous information exchange among the neighboring agents to reach a consensus in a finite time, which make inefficient use of the communication bandwidth since they require the agents to communicate periodically. The chosen of initial values for the finite-time consensus distributed control may highly impact the algorithm convergence rate, and thus system stability. Furthermore, a challenge could arise for systems comprising a multitude of edge devices with limited computation capabilities, which is expected to be the case in the building grid cell. The communication network would likely suffer congestion due to such high communication demand, which will lead to degraded control performance and potential system instability. In this paper, an event-triggered distributed control is proposed to reduce the communication and computation burdens for the power routing while guaranteeing the control efficiency. In the designed event mechanism, an agent only communicates with its neighbors when certain conditions (e.g., load current sharing error, and/or voltage regulation error) is triggered after an evaluation with local measurements or estimations. The control signals derived previously will be maintained till such conditions are triggered again. That is, a fully distributed fixed time consensus event-triggered algorithm will be implemented in the secondary level together with the distributed droop control to guarantee the accurate power routing of the energy trading among different participants of the DC building grid cell.

4. Discussion and future directions

In this paper, a fully distributed framework is proposed for solving the energy trading problem of a DC grid cell in future buildings while enabling an automated, secured, efficient, and peer-to-peer energy trading. We observed that homes equipped with smart edge devices are able to process, communicate, and operate in a distributed way with recent techniques in electric distribution system, such as machine learning, edge computing, wireless communication, and blockchain. Compared with centralized energy trading solutions, distributed energy trading of a DC grid cell is expected to further increase the building electricity delivery system efficiency, power quality, and reliability, while minimizing the reliance on the main electrical power grid. In this paper, we explored the enabling techniques in addressing future power systems operation challenges. In addition, we proposed our own design skeletons to build a DC grid cell energy management solution, for which we formulated an experimental plan and would like to evaluate its effectiveness comparing with existing solutions.

As the next step, the feasibility and efficacy of the proposed peer-to-peer energy trading framework will be evaluated via numerical simulations built upon the Transactive Energy Simulation Platform (TESP), developed by Pacific Northwest National Laboratory (PNNL). It is an open-source simulation platform with transactive market and control mechanisms for the power grid (Huang et al., 2018). TESP includes multiple house data, distribution simulator, transmission simulator, building simulator with multiple transactive agents, and the communication module, i.e., Network Co-Simulation (FNCS) (Ciraci et al., 2014). New forecasting and trading operation algorithms with recent ML techniques will be developed and compared with existing approaches in terms of prediction accuracy, operation efficiency, etc. In addition, the feasibility and security of the proposed solution will be tested.

Declaration of Competing Interest

The authors report no declarations of interest.

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