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Distributed Holistic Framework for Smart City Infrastructures: Tale of Interdependent Electrified Transportation Network and Power Grid

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ABSTRACT Plug-in Electric Vehicles (PEVs) play a pivotal role in transportation electrification. The flexible nature of PEVs' charging demand can be utilized for reducing charging cost as well as optimizing the operating cost of power and transportation networks. Utilizing charging flexibility of geographically spread PEVs requires design and implementation of efficient optimization algorithms. There is a synergy between electro mobility (e-Mobility) infrastructures (including charging stations) and PEVs. In this paper, we introduce a holistic framework to model interdependent nature of power systems and electrified transportation networks, enhance the operational performance of these systems as a network-of-networks, and explain the required information exchange via coupling agents (e.g., PEVs and charging stations). We develop a holistic framework that enables distributed coordination of interdependent networks through the IoT lens. To this end, we propose to use a fully distributed *consensus+innovations* approach. This iterative algorithm achieves a distributed solution of the decision making for each agent through local computations and limited communication with other neighboring agents that are influential in that specific decision. For instance, the optimal routing decision of a PEV involves a different set of agents as compared with the optimal charging strategy of the same PEV. The exogenous information from an external network/agent can affect internal operation of the other agents. For instance, having some information about traffic congestion at the transportation networks changes the decision of PEVs to charge their battery at another location. Our approach constitutes solving an iterative problem, which utilizes communication at the smart city layer, as a network of infrastructures, including power grid and electrified transportation network, that enables fully distributed coordination of agents. Fully distributed decision making enables scalability of the solution and plug-and-play capability, as well as increasing the information privacy of PEVs by only requiring limited local information exchange with neighboring agents. We investigate a detailed application of our framework for interdependent power systems and electrified transportation networks. To this end, we first identify the functionalities, constraints, objectives, and decision variables of each network. Then, we investigate the interdependent interactions among these networks and their corresponding agents.

INDEX TERMS Consensus+innovations, distributed processing, smart city, interdependent infrastructures, electrified transportation networks, smart mobility, power systems, electric vehicles, cooperative charging, optimality conditions.

I. INTRODUCTION

A. MOTIVATION

From the to Interdependent Smart City Infrastructures to the Internet-of-Things: Ever-increasing Internet of Things (IoT) technologies provide a platform for efficient communication and decision making of heterogeneous agents, e.g. smart electricity meters, autonomous vehicles, and smart appliances. Smart cities are considered as notable examples of the urban IoT due to their architecture and integration of various networks [1], [2]. The concept of smart cities is emerged to pave the road towards sustainable urban development. Smart cities

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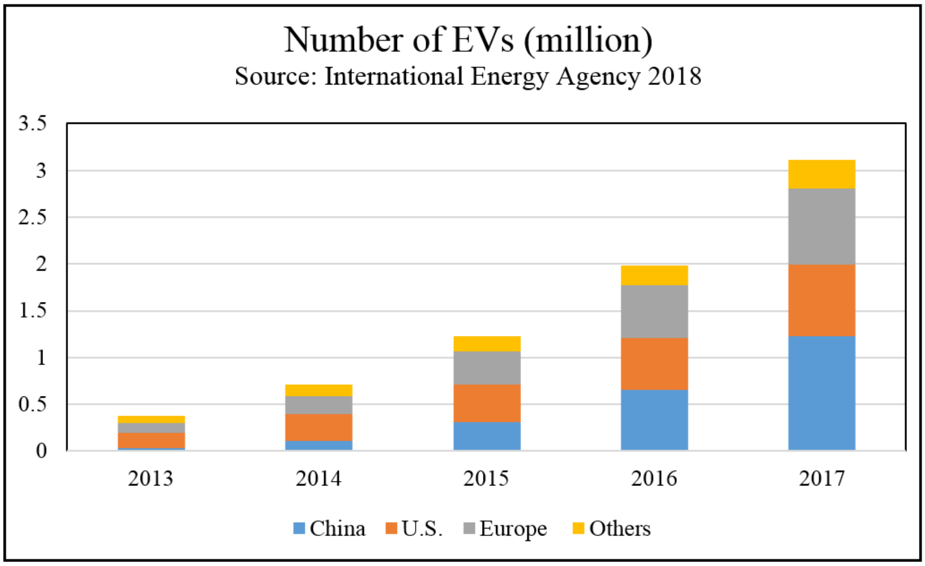

FIGURE 1. Growing number of EVs from 2013-2017.

aim at increasing the intelligence among various networks to enhance the operation of urban infrastructures, such as energy systems, transportation networks, communication networks, and water networks [3]. Multidisciplinary approaches are required to implement smart city as a combination of these networks [4]. Major challenges of future cities have increased by the high rate of urbanization. These challenges include satisfying the increasing energy demand, reducing the green house gas emissions, improving the social welfare, and decreasing the dependence on fossil fuel resources [5]. Emerging technologies are deployed to upgrade current networks from centrally-operating independent systems to more decentralized, intelligent, interdependently-operating, and autonomous systems. There is a crucial need to investigate these interdependencies (e.g., the bidirectional effect of power systems and electrified transportation networks) and develop efficient algorithms that capture the mutual effect of these networks.

From the Internet-of-Things to Interdependent Power Grids and Electrified Transportation Networks: Smart mobility is one of the key elements of smart cities. It leads to increasing penetration of new technologies, including electric vehicles, autonomous vehicles, and intelligent traffic cameras. The growing number of vehicles introduces new challenges for the transportation networks, including traffic congestion and air pollution [6]. In order to enable efficient traffic management, Vehicle to Infrastructure (V2I) communication technologies have been integrated to provide real-time communication among vehicles and transportation agents [7]. This will effectively help reducing traffic using smart route optimization. Electric vehicle (EV) is among the pivotal solutions in the transition towards smart mobility [8]. EVs not only can contribute to reducing the air pollutions, but also can help managing the traffic congestion more effectively as they can potentially recharge their battery at a wider range of locations as compared with fuel-based vehicles. Further, both charging stations and EVs are acting as coupling agents considering their effect on the operation of power systems (charging demand) and transportation network (traffic congestion). Reducing traffic congestion in transportation network is considered as one of the main goals of smart cities [9]. Based on 2018 Global EV Outlook of International Energy Agency (IEA), there is a 50% expansion of total number of EVs as compared with 2016. Figure 1 illustrates detailed contribution of various regions to this increasing trend.

IEA defined two scenarios for the projection of EVs penetration till 2030, IEA's New Policies Scenario and EV30@30 Scenario. Considering these scenarios, the expected number of EVs is 125 million (IEA's New Policies Scenario) and 220 million (EV30@30 Scenario) by 2030 [10]. We used the historical data for the total number of vehicles from 1960 to 2014 [11]–[14] to predict the expected number of vehicles by 2030. According to our prediction results, the expected number of vehicles by 2030 is 3.73 billion. Considering the two scenarios of transportation electrification defined by IEA [10] and our prediction of total vehicles, EVs will cover from 3.34% to 5.89% of the total vehicles worldwide by 2030. Growing penetration of EVs requires further analysis in terms of impacts on power system operation and transportation networks. Further, integration of fast charging stations introduces new challenges by increasing peak load demand and subsequently affecting electricity price. Tesla has installed 2,478 fast charging spots in 357 charging stations with a maximum charging rate of 120 kW [15]. Each of these fast charging stations accommodate one to 12 electric vehicles. As of August 2018, these stations increased to 1,342 Tesla supercharger (fast charging) stations, providing 11,013 charging spots for plugin EVs (PEVs) [16]. Spatiotemporal flexibility of PEVs enables

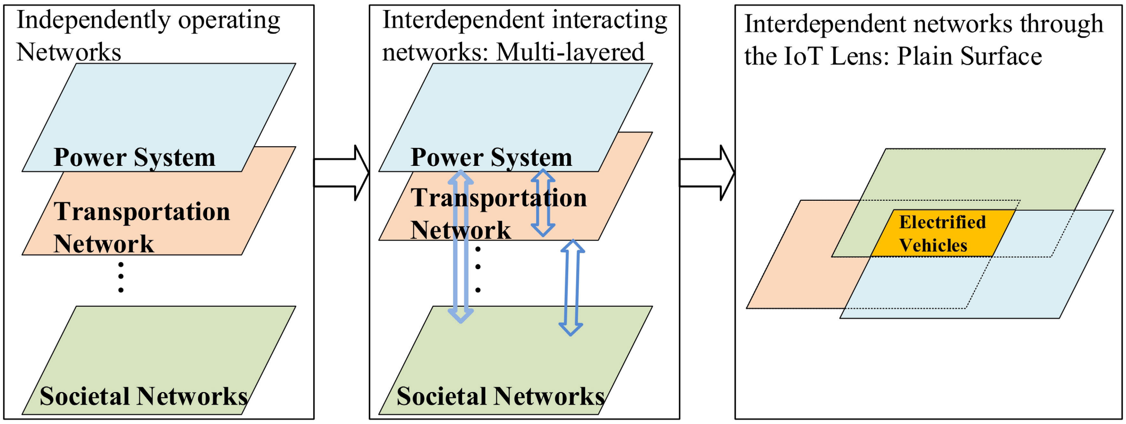

FIGURE 2. Transition from independent layered networks to the agent-based distributed framework from the IoT lens.

their potential contribution to: 1) traffic management by leveraging their flexibility to charge different location/time and reduce traffic network congestion [17], [18]; 2) power system operation by operating as mobile and flexible storage units [19]–[22]. Using distributed renewable generations as environmental-friendly energy resources makes PEVs as promising solutions to reduce dependence on fossil fuels and reduce the air pollution [23], [24]. The spatiotemporal nature of PEVs charging demand can facilitate peer-to-peer (P2P) energy trading. It also enables distributed computations instead of centralized decision making [25]. According to [26], machine-to-machine (M2M) communication infrastructures pave the road towards autonomous networking as an influential step towards the IoT without human intervention.

The interdependent representation of PEV charge scheduling problem constitutes several layers of complexity and involves multiple networks. The ultimate goal of this paper is to provide a thorough vision towards leveraging the interdependence of power and transportation networks while taking advantage of PEVs as coupling agents. We motivate this work on developing distributed solutions for interdependent networks from the IoT lens based on three major steps as shown in Fig. 2:

1) From independently operating the networks to cooperative coordination of interdependent networks
2) From the multi-layered networks towards the Internet-of-Things framework with distributed heterogeneous agents
3) From the Internet-of-Things framework to electrified transportation networks and smart power grids

B. RELATED WORKS

Previous studies used several terms to describe coupling among power systems and electrified transportation networks, including coupled, interdependent, joint, and interconnected networks/infrastructures. We first provide an overview of smart cities concept. Using this concept, we explain interdependencies between power systems and transportation networks. We then elaborate on studies on transportation electrification with emphasis on the collaborative nature of interdependent power and transportation networks. We also provide a comprehensive literature on decentralized/distributed/hierarchical algorithms for optimal charge coordination of PEVs and optimal power flow problem.

The IoT is an emerging paradigm recognized as a platform including networks of devices communicating with each other [27]. The IoT is enabled by more connectivity among distributed agents and entities using communication technologies, e.g., wireless sensor network [28], [29] and 5G mobile technologies [30]. In this study, we aim at investigating the interdependencies of power systems and transportation networks in an IoT-based smart city context. This allows for implementing a fully distributed multi-agent based platform at each network while exchanging limited information with agents from other networks. A big picture of interdependent power and transportation networks as subsets of IoT-based smart cities in represented in Fig. 3.

In the literature, electrified transportation networks often have been studied based on accommodation of PEVs charging demand into smart power grids. PEVs operate as spatiotemporally flexible demands to facilitate integration of stochastic renewable resources [19], [31]–[33]. In [31], simultaneous operation of PEV charging stations and distributed renewable resources is used to obtain loss reduction in power distribution systems. According to [32], optimal operation of PEV charging stations and vehicle to grid (V2G) application can enhance the grid operation and pave the road for deploying more renewable resources. Further, in [33] a decentralized method is proposed for joint integration of charging stations as well as solar generations.

In addition to demand flexibility of PEVs, given the V2G technologies, they can inject power to the grid [34], [35]. Charging infrastructures are the key to enabling transportation electrification [20], [36]. In [37], intelligent charging methods for PEV charging have been studies. A smart PEV

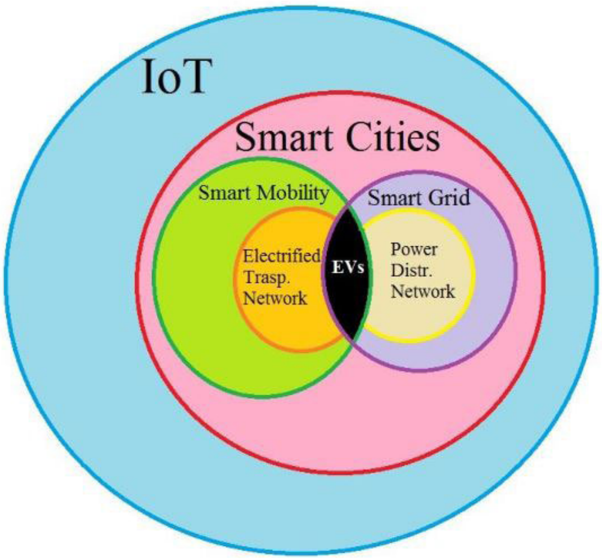

FIGURE 3. General framework of the interdependent power and transportation networks in the IoT environment.

charge scheduling method is proposed in [38] to optimize electricity demand while satisfying the needs of PEV drivers. Chung *et al.* [39] investigated the required infrastructure for smart charging. It consists of a charge scheduling algorithm, a mobile application as user-interface, V2G technology, and a remote communication hardware [39].

A strategy for increasing the penetration of PEVs into power distribution networks has been proposed in [40]. Interaction of PEVs and power grids can be optimized by developing smart charging methods [41]. Further, the effect of transition from fossil fuel-based mobility to an electrified platform on power systems is important due to the increasing electric consumption caused by PEV charging demand [42], and its potentially detrimental effect on distribution grids [22], [43]–[45]. Flexibility of PEVs' charging demand can be leveraged to improve power system operation [20], [46]. This includes loss minimization [47], voltage profile control [48], frequency regulation [49], [50], transformer aging risk minimization [21], overloading prevention of power distribution transformers [51], precipitating in ancillary services [52], [53], and congestion management [54]. In [54] a comprehensive method is proposed for expansion planning of urban electrified transportation networks. This approach finds the optimal investment strategy for both power distribution network and transportation network in terms of the optimal sites and sizes of new roads, charging infrastructures, power distribution lines, and distributed generation units [54]. In addition to the contribution of EVs to grid operation services, the historical load demand of PEVs can be exploited to improve the operation of smart grid [55]. For instance, in [56] conventional load demand and PEV charge demand are predicted in a decoupled fashion to capture different seasonal patterns. This led to considerable improvement in the accuracy of demand forecasting methods, and hence reduced the mismatch between day-ahead and near-real-time schedule of generation units [56].

Some of the studies in the literature require new agents or entities to capture the interdependencies among power and transportation networks. For instance, Alizadeh et al. [57] proposed a new entity (charging network operator) to enhance the PEV charge optimization problem. Although in a idealistic framework this entity facilitates the modeling and investigation of coupled power and transportation networks, is requires further investigation from both implementation point of view and policy-making perspective. One of the important features of our holistic framework, as compared with the previous studies, is to leverage the current entities by enabling inter-network communication and enhancing their operation, i.e., our framework does not need new stakeholders/entities to enable the implementation of distributed decision making. It only needs communication capability with neighboring agents.

Previous studies have considered traffic conditions in the optimal charge scheduling of PEVs [18], [58]–[71]. Sun *et al.* proposed a supervised predictive approach for energy management of PHEVs using traffic flow information [58]. In order to analyze the performance of the proposed framework, they considered three scenarios: 1) ignoring traffic information in the model, 2) considering static traffic flow, and 3) considering dynamic traffic flow [58]. In [59], mobile charging stations are introduced to provide charging service at various locations upon request [59]. Cui *et al.* developed a novel formulation that minimizes the total traveled distance while considering various constrained enforced by charging station, traffic management system, and power systems [59]. An improved routing method in proposed in [18], referred to as Charging Station Strategy-Vehicle Powertrain Connected Routing Optimization (CSS-VPCRO). The main goal of CSS-VPCRO is to capture the interdependence of electric power grids and electrified transportation networks. According to [60], for multi-modal transportation-electrification, PEVs are considered as the coupling agents in the infrastructures that formed a *transportation-electricity nexus*. Lam *et al.* [61], [62] coined the notion of Vehicular energy networks (VEN) that thoroughly accommodates systems and decision parameters of power systems and transportation networks. A hybrid dynamic model is proposed In [72], a hybrid model of transportation electrification is proposed. Further, simultaneous charging and routing strategy for autonomous vehicles is developed in [63] by taking into account vehicle requirements, renewable generations, logistic requests, and the corresponding transportation network. A hierarchical control architecture is proposed in [64] to enable optimal energy management of PHEVs. This architecture used traffic light information (broadcast via vehicle to infrastructure (V2I) platform) and the status of neighboring vehicles' using vehicle to vehicle (V2V) communication. Open source simulation tools and their application for transportation electrification have been studies in [73].

Coupled power systems and transportation networks have also been studies from a market perspective [68]. Alizadeh *et al.* proposed a collaborative algorithm with two non-profit entities, each representing one of the coupled networks in the market. These entities share information to jointly find the optimal charge schedules, price signals, and road tolls [68]. They have also proposed an optimal routing method for PEVs considering the drivers' preferences, traffic information, and electricity price signals [69].

C. CONTRIBUTION

In order to thoroughly identify the contributions of this study, we explain our contributions of the proposed holistic framework, as well as advantages of using fully distributed multi-layer algorithm for the IoT purpose in two thrusts: algorithm-wise and application-wise reasons and typical motivations for using distributed algorithms as follows:

- Algorithm-wise Advantages
    1) Distributed algorithms allows for adding/removing some agents from the optimization problem in an efficient fashion. This feature is referred to as plug-and-play capability. For instance, deploying more PEVs on the roads will affect the optimization problem of transportation and power network operators. Distributed solutions accommodate the new agents with less required modification as compared with centrally operated solutions.
    2) Distributed algorithms decompose a large-scale optimization problem into several small-scale problems with less number of decision variables and constraints. This leads to reducing computational complexity.
    3) We ensure the feasibility of the solution for each agent at all iterations. This translates into robustness to the communication failure.
    4) Each agent in the distributed IoT environment only requires limited information exchange with neighboring agents. This preserves the privacy of agents as the critical decision making factors may not be shared.
    5) Distributed nature of computations reduces the run-time.
    6) Agents are able to serve as active players; i.e., they are not enforced to follow the automated signals, such as price signal and routing decision signals.
- Application-wise Contributions: Enabling Real-time Decision Making and Heterogeneous Communication For Real-World Decision Making Scenarios in Electrified Transportation Networks and Power Grids
    1) Taking into account the various types of interactions and exogenous information exchange among interdependent networks will not only increase the size of optimization problems, it will also have a noticeable impact on managing several networks from a policy perspective. It is caused by some reasons including having a large-scale network of networks with independent stake-holders who aim at optimization their objectives. Our holistic agent-based solution to this network-of-networks problem, however, addresses this concern by introducing inter- and intra-network communications. This allows for optimizing the internal goals of each network operator while taking into account the exogenous information from other influential networks. For instance, power system operator can still continue optimizing the demand-supply balance problem while using the expected PEV charging demand as an exogenous input from PEV charging station aggregators. This not only is not diverging from the primary objective of power system operator, but also enables more accurate demand estimation which increases the feasibility of obtained solution.
    2) From a network-of-networks perspective, using fully distributed approaches at each network (e.g., power and transportation networks) enables isolated operation at critical events. For instance, in case of line outage in power distribution network, our distributed algorithm enables local operation of the affected areas using distributed energy resources (e.g., distributed renewable resources, demand side management, and V2G) which enables the uninterrupted operation of the corresponding charging stations which are geographically located in that specific area. This will address one major concern of PEV owners for not having charging source during power outages.
    3) PEVs are major components of electrified transportation networks. As PEVs are mobile loads, a fully distributed framework can facilitate their integration in both power system model and transportation network, especially flexibility of PEVs charging demand can be modeled as mobile energy storage for congestion management in power distribution system.
    4) Prior works on interdependent electrified transportation and power networks [18], [60], [71], [74]–[77] have proposed centralized algorithms to solve the coupled optimization problem in a synchronized fashion, i.e., they assume that each network optimizes its own problem and at the same time they share the required signals with other networks as exogenous input. Although centralized solutions often find the globally-optimum solution, they are not capable of accommodating different agents at each network have their spatiotemporally-varying constraints; i.e., it is more realistic to solve the problem in multiple layers in a synchronized manner while sharing information among these layers in a

asynchronized manner. In our framework, we propose to bridge this gap by defining an IoT-based communications with different time-scales, which is comparatively more realistic than formulating the optimal operation of coupled networks as a centralized problem. This also allows for multiple layers of information exchange that is explained in the next application-wise motivation.

5) Although we propose to enable information exchange among heterogeneous agents, our framework considers various time-scales of various networks and infrastructures. For instance, distribution network operator may consider a 1-hour time resolution for solving the optimal power flow problem and calculating the price signals. PEV aggregator, however, can consider a different time-scale, e.g., 15-minute interval to update the aggregate PEV demand.
6) Our framework does not need to define new entities or stakeholders to capture interdependencies. Previous approaches, however, have defined new entities (e.g., charging network operator defied by Alizadeh *et al.* [57]) to enable optimal interdependent operation of power and transportation networks. Introducing new stakeholders, on one hand, facilitates the overall problem by covering the gray area in which multiple networks have benefits and prefer to optimize their goal rather than considering the external objectives and constraints of other networks. On the other hand, it increases the complexity of network-of-networks framework from a policy making viewpoint.
7) In terms of communication infrastructure, there are both available communication platforms as current assets, as well as emerging communication networks such as 5G systems which are capable offering per-link data rates of increased by $100\times$, as well as increasing data rate roughly $1000\times$ as compared with 4G [78].

The proposed framework referred to as **H**olistic **A**gent-based **D**istributed algorithm for **I**oT-based interdependent networks, referred to as $\mathcal{HADI}$. It mainly includes three networks. The proposed framework is expandable to other networks and infrastructures as subsets of smart cities,

- Power distribution system managed by distribution network operator (DNO)
- Charging coordination network managed by PEV aggregators who optimize the operation of charging stations
- Transportation network that includes two layers:
  - Parking management systems
  - Traffic management systems [6]

We elaborately investigate the objectives, constraints and stakeholders of these networks. To this end, we first provide a list of all agents, classify them, and identify their corresponding goals. We then present a generic formulation for any arbitrary optimization problem with certain structure. This general solution can be adjusted considering objectives and constraints of heterogeneous agents in smart cities environment. We also explain an agent-based *consensus+innovations* method to solve the formulated optimization problem in a distributed fashion. Several applications benefited from *consensus+innovations* algorithms, including but not limited to distributed energy management in power grids [79], [80], distributed inference for the IoT [29], distributed sensing in networked systems [81], distributed charge coordination of PEVs [82], distributed economic dispatch [83], and distributed coordination of microgrids [84]. This framework demonstrated the second stage of the transition from independent operation towards the IoT presented in Fig. 2. According to this figure, conventionally, each of the networks are finding their optimal operating point without directly communication information with other interconnected networks. In the next stage, we demonstrate multi-layered decision making structure, i.e., each network considers some input information from other interdependent networks while solving its optimization problem. The ultimate goal is to enable fully distributed decision making with exogenous information sharing capability among heterogeneous agents. Although distributed optimization algorithms introduce above-mentioned algorithm-wise and application-wise contributions and advantages, there are some requirements and system limitations for deploying these algorithms. For instance, one of our assumptions is having a connected communication graph, i.e., each agent needs to at least be connected with one of the agents in the same network to reach an optimal decision using local information exchange, i.e., by inferring information about network using limited information from its neighbors.

D. ORGANIZATION

The rest of this paper is structured as follows: Section II provides more details of the proposed framework by elaborately explaining the current practice and future technologies. Section III provides detailed definition of agents in our distributed framework and its features. Section VI is devoted to problem formulation and explaining the distributed algorithm for smart cities applications. Section VII provides detailed convergence analysis of the proposed distributed algorithm. In order to demonstrate some of the advantages and capabilities of our holistic distributed solution, we provide case study of distributed charge scheduling for PEVs in Section VIII, followed by conclusions in Section XI.

II. DESCRIPTION OF THE PROPOSED FRAMEWORK

In this section we first explain more details of the proposed framework. To this end, we provide the current challenges with available methods that have been briefly introduced in the previous section as well as advantages of our framework that bridges the gap between theoretical models and real world networks. We then elaborate on the interaction among layers and required infrastructures for

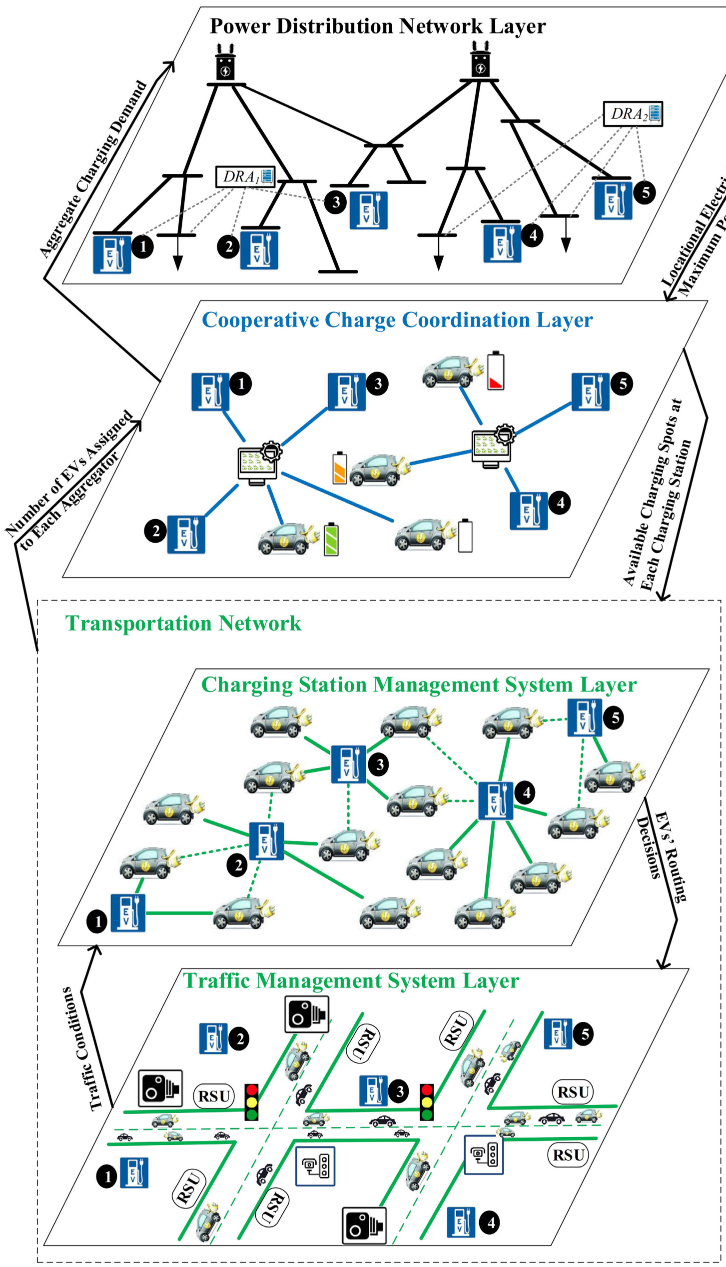

FIGURE 4. General framework of the proposed holistic agent-based distributed framework for interdependent power and transportation networks.

enabling such information exchange. Ultimately, we provide the applications of distributed agent-based structure to the IoT paradigm.

A. CHALLENGES AND SOLUTIONS

In order to identify the motivations for a holistic distributed framework, we need to first list the challenges with the current independently/centrally-operating settings. In the current methods for optimizing the operation of power distribution networks and electrified transportation networks, the provided solutions are loosely coupled.

1) DECENTRALIZED/DISTRIBUTED ALGORITHMS FOR INDEPENDENT OPERATION OF POWER NETWORK LAYER AND CHARGE SCHEDULING LAYER

First group of methods that tackled the independent operation of each layer in a distributed/decentralized fashion to deal with the complexity of the solutions. These solutions, however, do not capture the interdependencies sufficiently.

Distributed algorithms proposed to solve the optimal power flow optimization problem to find the optimal generation level while considering grid constraints [79], [85]–[87]. These studies used various distributed/decentralized techniques, including decomposition theory such as Lagrangian

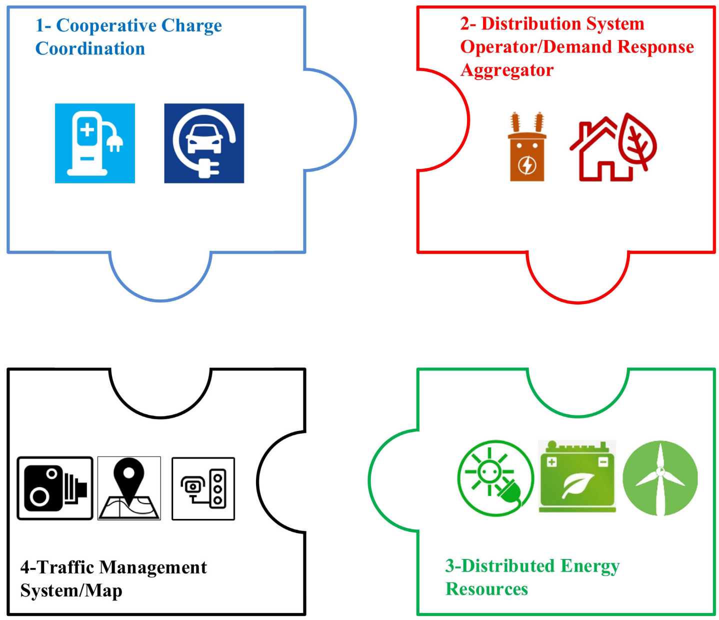

FIGURE 5. Four pieces of the IoT puzzle for interdependent power systems and transportation networks.

Relaxation [88]–[94], auxiliary problem principle [95], alternating direction method of multipliers [96], distributed consensus-based algorithms [83], [97]–[100]. Specifically, consensus-based methods attracted extensive attention for various powers system related applications, such as optimal power management [79], [84], and economic dispatch problem [97].

Previous works focused on deploying cooperative and non-cooperative solutions to solve charge coordination of EVs. To this end, several approached have been proposed, including [101], fully distributed *consensus+innovations* algorithm [102], [103], consensus-based distributed charging control [104], distributed consensus-based charge scheduling [105], hierarchical charge scheduling using Dantzig-Wolfe decomposition [106], the alternating direction method of multipliers [107], mean field game theory [108].

2) CENTRALIZED ALGORITHMS FOR INTERDEPENDENT OPERATION OF POWER SYSTEMS AND ELECTRIFIED TRANSPORTATION NETWORKS

Second group of methods considered the coupling among these networks such as [18], [60], [71], [74]–[76]. This class, however, deployed centralized solutions which increases the complexity of the model from optimization and computational burden perspectives, as well as policy making perspective. Such models have to take the decision variables and constraints of all stakeholders from both networks in a single model. This raises two major challenges: 1) increasing the number of decision variables and constraint directly enlarges the size of optimization problems which makes it hard-to-solve as compared with the independent optimization problems of each network; 2) complicating the operators' roles at each network due to combining various objectives from different stakeholders and various networks, i.e., the questions of *Who is solving this large-scale optimization problem?* and *Who is gaining benefit from solving this problem?* will be more crucial after merging the optimization problems of multiple stakeholders from multiple networks, including but not limited to power system operator, transportation network operator, and EV drivers. Based on the four pieces of the Internet-of-Things requirement puzzle, represented at Fig. 5, in the context of power distribution system and electrified transportation network.

3) OUR SOLUTION: HOLISTIC AGENT-BASED DISTRIBUTED OPTIMIZATION OF INTERDEPENDENT NETWORKS THROUGH THE IOT LENS

The first stage of our proposed solution is mostly based on the current practice in terms of available communication infrastructure. It deals with the challenges raised by deploying each of the above-mentioned methods by developing a network-of-networks-based multi-layer platform, in which each layer operates in a fully-distributed fashion while sharing/broadcasting/receiving limited information with/to/from some other layers. In our framework, some of the networks may be segregated into more than one layer to address the objective of different stakeholders. A general schematic overview of the proposed framework is provided in Fig. 4.

The second stage of our solution provides a futuristic framework considering the increasing intelligence and emerging widespread M2M communications enabled by 5G technology. In this framework, we model each element at any network as a heterogeneous agent with communication capabilities. Depending on their goals and decision

TABLE 1. Comparing the related literature with our study (✓:considered; ×: not considered).

Approach \ Aspect	Optimization Structure	1. Coordinated Charging	2. DSO/DR Aggregator	3. DERs	4. Traffic
Our proposed approach	Fully Distributed	✓	✓	✓	✓
Ma *et al.* [109]	Distributed	✓	×	×	×
Amini *et al.* [106]	Hierarchical	✓	×	×	×
Mohammadi *et al.* [82], [103], [109], [110]	Fully Distributed	✓	×	×	✓
[111]–[116]	Distributed	✓	✓	×	×
[117]–[119]	Decentralized	✓	✓	×	×
[21], [120]–[122]	Centralized	✓	✓	×	×
Zhang *et al.* [33]	Decentralized	✓	✓	✓	×
[31], [123]	Centralized	✓	✓	✓	×
[18], [22], [71]	Centralized	✓	✓	×	✓
[60], [75]	Centralized	×	✓	×	✓
[58], [59], [61], [69], [76]	Centralized	✓	×	×	✓
G. Vaya *et al.* [124]	Decentralized	✓	×	×	✓
Wei *et al.* [74]	Centralized	✓	✓	✓	✓

making criteria, a cluster of agents may choose to cooperate with each other to reach a consensus towards a common goal. This is the pivotal contribution of pour framework that enables spatiotemporal plug-and-play capability, i.e., at any time and at any location, an agent can decide which other agents and entities to communicate/cooperate with. In our knowledge, this study is the first of its kind that provides a holistic model for interdependent power and electrified transportation networks while enabling distributed decision making. For instance, an EV driver plans to find the optimal route from current location, loc_1 to the destination loc_2. This trip lasts from time t_1 to t_2 and the battery state of charge of EV reduces from SOC_1 to SOC_2. The EV driver may decide to choose one of the following options depending on time limitations, state of the charge, traffic conditions, and charging price:

Charge scheduling-specific alternatives:

- charge at origin
- charge on the way at a cheaper charging station
- charge at destination at a cheaper charging station

Optimal route planning-specific alternatives:

- choose a shorter and less congested route including highway with toll road
- choose a less congested but longer route
- choose the optimal distance but congested road

III. DEFINITION OF AGENTS AND THEIR CORRESPONDING FEATURES

In this section we identify various agents in the proposed framework, their objectives and constraints, and the time-scale at which each agent is operating. To this end we investigate the agents in three major categories: power system-specific agents, transportation network-specific agents, and coupling agents. These agents can count as one of the following categories: *passive* such as traffic lights, *active decision maker* such as EV charging station aggregators, and *active sensor* such as EV charging stations, based on their functionality. A passive agent only receives commands, which can be basically the output decisions of active agents based on the local optimization at each iteration, and change its state based on the received command, e.g., traffic lights are basically passive agents that are responsible to switch between two status (red and green) for traffic management purposes. Another set of passive agents are the ones who are responsible for recording data and communicating raw data to the intelligent agents, such as conventional traffic cameras, here referred to as *passive* traffic cameras. Active decision maker agents are the ones who not only receive or fetch the data from other sources and agents, but also use the received data to solve an optimization problem and send the proper command signals to other agents. Sensor agents are the agents that are collecting/receiving data at one layer, and communicate it to other agents at another layer. These agents help us using the current infrastructures with minimum hardware requirements and communication platform. EV charging stations are consummate examples of sensor agents that indirectly enable communication between power distribution network layer and charge coordination layer. Table 2 summarized agents from various networks and their features.

A. POWER SYSTEM-SPECIFIC AGENTS

1) Distribution System Operator: This agent is responsible for maintaining reliable operation of power distribution networks by optimizing the available resources and satisfying the physical constraints of the grid. It mainly manages the power delivery from transmission networks to the customers.
2) Demand Response Aggregator: This agent offers demand response services with two main objectives: reducing the electric load demand of the customers, and maximizing its benefit by saving energy. As a commercial entity, it offers load reduction services to wholesale energy market. The interaction of demand response aggregator and utilities can be modeled as a non-cooperative game (see for example [125]).
3) Distributed Energy Resources (DERs) Agent: This agent potentially covers a wide range of technologies

TABLE 2. Agents and their features.

Agent \ Feature	Active/Passive	Physical/Virtual	Power/Transportation/Coupling
Electric Vehicle (EV)	Active	Physical	Coupling
EV Charging Station	Active	Physical	Coupling
Demand Response Aggregator	Active	Virtual	Power
Distributed Energy Resources	Active	Physical	Power
Transformer Agents	Active	Physical	Power
Distribution System Operator Agent	Active	Physical	Power
Intelligent Traffic Cameras	Active	Physical	Transportation
Passive Traffic Cameras	Passive	Physical	Transportation
Road Side Units	Passive	Physical	Transportation
Traffic Lights	Passive	Physical	Transportation
Toll Road Pricing Agent	Active	Virtual	Transportation

and resources, including energy storage units and renewable energy resources (e.g., PV panels). Its main task is to optimize the internal operation of the corresponding resource and to maximize the benefit of the DER owner.

4) Transformer Agents: This agent is responsible for communicating the transformer's situation to other entities. In the intelligent distribution system, a smart transformer agent at the main substation of each feeder is capable of conducting optimal power flow with respect to the transformer loading constraint as well as the expected load demand.

B. TRANSPORTATION NETWORK-SPECIFIC AGENTS

1) Intelligent Traffic Cameras: These cameras are capable of monitoring the vehicles, local decision making, sharing traffic situation with other agents, and broadcasting command signals to traffic lights to manage congestion.
2) Passive Traffic Cameras: These cameras are only capable of monitoring the traffic situation and sharing it with decision making entities. The main difference of these cameras ad intelligent traffic cameras is lack of decision making capability.
3) Road Side Units: Road Side Units (RSUs) are equipped with communication capability. They communicate with on-board units (installed on the vehicles) to monitor traffic situation, such as location ad speed of the vehicles.
4) Traffic Lights: Traffic lights are mainly scheduled to follow a certain schedule. They are equipped with a remotely controllable device which can be managed through the control signals from active/decision maker agents, such as intelligent traffic cameras.
5) Toll Road Pricing Agents

C. COUPLING AGENTS

These agents interact with both power system-specific and transportation network-specific agents.

1) Electric vehicle (EV): EVs are one of the major coupling agents. The coupling is caused by their optimal routing decisions that affect the congestion in transportation networks, as well as their spatiotemporal charging decisions that affect both the load demand in power systems and traffic condition of transportation networks. Potential objectives, internal constraints, and external limitation of EVs are listed as follows:
Goals:
   - Finding their optimal route
   - Reducing their charging cost
   - Leverage the flexibility of their load demand in terms of time and location (spatiotemporal flexibility) to reduce energy cost

   Constraints:
   Internal Constraints:
   - Charging rate
   - Minimum state-of-charge
   - Time limits to arrive destination
   - Duration of stay at charging station

   External constraints:
   - Limits enforced by power network agents (e.g., hourly demand limit and locational marginal price variations due to line congestion)
   - Limits enforced by transportation network agents (e.g., traffic conditions and traffic congestion pricing)
2) Charging station agent[1]: Charging stations play a pivotal role in modelling the interdependency among power systems and transportation networks. First, they communicate with power distribution system operator,

[1]There are various types of charging stations that can enable communication. For instance, Eaton offers the following four models with different functionality:
A series: Single phase, no communication, proper for residential uncontrolled applications, upto 7.4 kW charging capacity.
X series: Single/Three Phase, communication and building management system integration capability, proper for controlled charging at the residential level, upto 7.4 kW charging capacity.
S series: Single/Three phase, intelligent load management and communication capability; offers the features of X series as well as enabling UDP (the standard protocol for integrating a device into other operating systems, such as a smart home system) and OCPP (the standard protocol that is used if several charging stations are networked together), two options for the charging capacity: 7.4 kW or 22 kW.
xChargeIn M series: integrator (master) for networking a number of **S series** equipped with Online communication.

demand response aggregator, and other entities to optimize their cost of energy. Second, they try to find the optimal strategy to attract more EVs. After EVs plugged in their batteries, charging station agent need to make sure to satisfy all EVs energy needs while maximizing its own benefit. Note that charging station agent can also participate in demand side management programs leveraging its flexibility based on the plugged in EVs, i.e., the optimal decision to charge or not to charge EVs at each timestep can vary based on the market signals, load demand, and availability of other distributed energy resources. Potential objectives, internal constraints, and external limitation of charging station agents are listed as follows:

Goals:

- Maximizing their profit by offering optimal price signals to EV agents
- Meeting all EVs' charging demand expectations
- Leveraging the flexibility of EV load demand to increase their profit
- Providing ancillary services/demand side management to power systems

Constraints:

Internal Constraints:

- Maximum capacity in terms of charging spots
- Maximum capacity in terms of total hourly power demand

External constraints:

- Limits enforced by power network agents (e.g., line congestion limits)
- Limits of transportation network agents (e.g., traffic conditions that affect the time for EVs to arrive charging stations)

IV. GENERAL PROBLEM FORMULATION

Formulate the centralized optimization problem, shown in (1). Let Ω_{agents}, Ω_{ineq}, and Ω_{eq} denote sets of all agents, inequality constraints, and equality constraint, respectively.

$$\underset{d_k}{\text{minimize}} \sum_{k \in \Omega_{\text{agents}}} f_k(x_k) \tag{1a}$$

$$\text{s.t. } g_j(x) \leq 0; \quad (: \mu_j) \quad j \in \Omega_{ineq} \tag{1b}$$

$$h_j(x) = 0; \quad (: \lambda_j) \quad j \in \Omega_{eq} \tag{1c}$$

where $f_k(\cdot)$ and x_k denote the objective function and variable(s) of agent k in the network, respectively. Depending on the problem definition, agent can represent a wide range of physical or virtual entities, including power distribution network bus, microgrid operator, demand response aggregator, and charging station aggregator. Functions $g_j(\cdot)$ and $h_j(\cdot)$ denote corresponding functions of inequality and equality constraints, respectively.

V. OPTIMALITY CONDITIONS

Formulate the $\mathfrak{Lagrangian}$ for the optimization problem in (1), as shown in (2).

$$\begin{aligned}\mathfrak{L} = & \sum_{k \in \Omega_{\text{agents}}} f_k(x_k) \\ & + \sum_{j \in \Omega_{ineq}} \mu_j g_j(x) \\ & + \sum_{j \in \Omega_{eq}} \lambda_j h_j(x).\end{aligned}$$

Derive the first order optimality conditions, as provided in (2).

$$\begin{cases} \dfrac{\partial \mathcal{L}}{\partial x_k} = 0, & \forall k \in \Omega_{\text{agents}} \\ \dfrac{\partial \mathcal{L}}{\partial \mu_j} \leq 0, & \forall j \in \Omega_{ineq} \\ \dfrac{\partial \mathcal{L}}{\partial \lambda_j} = 0, & \forall j \in \Omega_{eq}. \end{cases} \tag{2}$$

VI. *CONSENSUS+INNOVATIONS* BASED DISTRIBUTED ALGORITHM

A. DISTRIBUTED DECISION-MAKING: GENERAL DISTRIBUTED UPDATE RULE

Distributed iterative approach for a generic optimization problem is followed to solve the first order optimality conditions in (2). The iterative model only needs information exchange between physically-connected agents at each iteration. Let Ω_i denote the neighboring set of agent i. Let $y_i(k) = [x_i(k), \mu_j(k), \lambda_j(k)], j \in \Omega_i$ denote the variable associated with agent i at iteration k. The general format of the local updates which is performed by all agents at each iteration is shown in (3).

$$y_i(k+1) = \mathbb{P}[y_i(k) + \rho_i s_i(y_j(k))]_{\mathcal{F}}, \quad j \in \Omega_i \tag{3}$$

where $s_i(\cdot)$ reflects the first order optimality constraints related to agent i, and ρ_i denotes the vector of tuning parameters. Further, $\mathbb{P}$ is the projection operator to project x_i onto its determined feasible space, denoted by $\mathcal{F}$.

Note that, $s_i(y_j(k))$ only depends on the iterates $y_j(k)$ of neighboring nodes j in the physical neighborhood of i. Hence, a distributed implementation of (3) is possible.

The projection operator settings, tuning parameters, and corresponding constraints varies based on the network objectives, constraints, and decision making variables. We later elaborate on each network's optimization problem as well as network-oriented distributed algorithm that is tailored for each network.

The **M series** serves as a master device in online or offline charging systems and manages the connected vehicles via individual charging stations of the **S series**. A charging system can consist of one **M series** master station and up to 15 **S series** charging stations.
Source: http://www.eaton.eu/Europe/Electrical/ProductsServices/Residential/xChargeIn/index.htm

B. AGENT-BASED DISTRIBUTED ALGORITHM

Here we present a more detailed formulation of Consensus+ Innovation based distributed algorithm at the intra-network layer. Let inter-agent communication graph to be connected.

Agent i updates its local variables, i.e., variables that are directly corresponding to this agent (y_i). Let k represent iteration counter. The corresponding variables of agent i are updated using (4).

$$y_i(k+1) = \mathbb{P}[y_i(k) + \rho_i^{\mathcal{C}} \overbrace{s_i(y_j(k))}^{\text{neighborhood consensus}} + \rho_i^{\mathcal{I}} \underbrace{s_i(y_i(k))}_{\text{local innovation}}]_{\mathcal{F}}, \quad j \in \Omega_i \tag{4}$$

where $\rho_i^{\mathcal{C}}$ denotes positive tuning parameters corresponding to consensus among agent i and its neighboring agents $j \in \omega_i$. Further, $\rho_i^{\mathcal{I}}$ is the tuning parameter for the local innovation term. In (4), the first and second terms represent the neighborhood *consensus* and local *innovation* respectively.

Consequently, the update rules for the all variables at the intra-network optimization of network $\mathcal{N}$ in a dense form is provided by (5)

$$\begin{aligned} X_{\mathcal{N}}(k+1) &= \widetilde{x}_{\mathcal{N}}(k) - A_{\mathcal{N}}\widetilde{x}_{\mathcal{N}}(k) + C_{\mathcal{N}} \\ \widetilde{x}_{\mathcal{N}}(k+1) &= \mathbb{P}\left[X_{\mathcal{N}}(k+1)\right]_{\mathcal{F}} \end{aligned} \tag{5}$$

where $X_{\mathcal{N}}$ is the vector of the stacked variables, i.e., y_i, for all agents, and $\mathbb{P}$ is the projection operator which ensures that the Lagrange Multipliers for the inequality constraints stay positive and the box constrained variables stay within the given bound. Further, $\mathcal{F}$ represents the feasible space spanned by positiveness and box constraints. Hence, $\widetilde{x}$ is the vector of the stacked projected variables.

VII. CONVERGENCE ANALYSIS

This section presents a formal proof that any limit point of the proposed algorithm in (5) is optimal solution of optimization problem in (1). Moreover, it introduces a sufficient condition for convergence of the proposed algorithm.

In the following Theorem, we first show that a fixed point of the proposed iterative scheme necessarily satisfies the optimality conditions (2) of the original optimization problem.

Theorem 1: Let X^* be a fixed point of the proposed algorithm defined by (5). Then, $X^\star$ satisfies all of the optimality conditions of the original problem (2).

Proof: To prove this theorem, we verify the claim that $X^\star$ fulfills all of the first order optimality conditions. Note that $X^\star$ is the vector of stacked variables.

Claim 1: $X^\star$ fulfills the optimality conditions which enforce the positivity of the Lagrangian multipliers associated with the inequality constraints, i.e., $\mu_j^\star \geq 0$.

Verification by contradiction: Let us assume on the contrary that in $X^\star$ one of the multiplier variables, say $\mu_j^\star$, is negative. Now, note that, evaluating (4) at $X^\star$ results in a non-negative value for μ_j due to the projection of μ_j into the set of positive reals. This contradicts the fact that X^* is a fixed point of (2).

Claim 2: $X^\star$ satisfies the optimality conditions associated with the inequality constraints, $\frac{\partial \mathcal{L}}{\partial \mu_j} \leq 0$.

Verification by contradiction: Let us assume that $X^\star$ does not fulfill $\frac{\partial \mathcal{L}}{\partial \mu_j} \leq 0$ for all j, i.e., there exists j such that $\frac{\partial \mathcal{L}}{\partial \mu_j}(X^\star) > 0$. This implies that the value of the innovation term in (4) is negative when evaluated at $X^\star$. Also, note that, based on the claim 1, $\mu_j^\star \geq 0$. Therefore, evaluating (4) for the inequality constraints at $X^\star$ results in a value greater than $\mu_j^\star$ which contradicts the fact that X^* is a fixed point of (4). Similar arguments can be used to prove that $X^\star$ fulfills the KKT conditions corresponding to the equality constraints, $\frac{\partial \mathcal{L}}{\partial \lambda_j} = 0, \quad \forall j \in \Omega_{eq}$.

Claim 3: $X^\star$ satisfies the optimality conditions associated with the complementary slackness condition, i.e., for all $j \in \Omega_{ineq}$, we have $\mu_j^\star \cdot \left(g_j(x^\star)\right) = 0$.

Verification by contradiction: Let us assume on the contrary that X^* does not satisfy the above complementary slackness condition, i.e., there exists a value for j such that both $\mu_j^\star$ and $g_j(x^\star)$ are non-zero. Hence, according to the claims 1 and 2, we must have, $\mu_j^\star > 0$ and $g_j(x^\star) < 0$, respectively. Now, note that evaluating (4) at $X^\star$, results in a value less than $\mu_j^\star$, which clearly contradicts the fact that X^* is a fixed point of (4).

We now discuss the consequences of Theorem 1. To this end, note that, since the proposed iterative scheme (5) involves continuous transformations of the updates, it follows that, if (5) converges, the limit point is necessarily a fixed point of the iterative mapping. Since, by Theorem 1, any fixed point of (5) solves the first order optimality conditions (2), we may conclude that, if (5) converges, it necessarily converges to a solution of the first order optimality conditions (2). This immediately leads to the following optimality of limit points of the proposed scheme.

Theorem 2: Assume that the original optimization problem (1) has a feasible solution that lies in the interior of the corresponding constraint set. Further, suppose the proposed algorithm introduced by (5) converges to a point $X^\star$. Then X^* constitutes an optimal solution of the original problem (1).

Proof: By Theorem 1 and the above remarks, $X^\star$ satisfies the optimality conditions (2). Since the original optimization problem is a convex problem and, by assumption, is strictly feasible, it follows that the primal variables ($x_i^\star$) in X^* constitute an optimal solution to the original problem (1).

Consequently, we note that Theorems 1 and 2 guarantee that any fixed point of the proposed distributed algorithm constitutes an optimal solution to the original problem, and, if the scheme achieves convergence, the limit point is necessarily an optimal solution of the original problem. Finally, we note, that whether the scheme converges or not depends on several design factors, in particular, the tuning parameters $\rho_i^{\mathcal{C}}$ and $\rho_i^{\mathcal{I}}$.

VIII. CASE STUDY: DISTRIBUTED CHARGE COORDINATION OF PLUG-IN ELECTRIC VEHICLES CONSIDERING POWER DISTRIBUTION TRANSFORMERS LIMITS

In order to illustrate the effectiveness of the proposed distributed solution, we provide simulation results for a fully distributed algorithm to find the optimal charge schedule of the PEVs with Power constraints. We refer to this problem as PEV-CCP, i.e., PEVs' Cooperative Charging with Power constraints. We further refer to our distributed solution as the $\mathcal{CI}-\mathcal{DPEVCCP}$, i.e., *consensus+innovations* based Distributed PEV Coordinated Charging with Power constraints. This problem takes into account the power distribution systems limits that originate from features of charging station, such as nominal capacity of on-site transformer, and enables modeling charging load of PEVs on power distribution systems. Further, this distributed solution enables plug-and-play and valley-filling features. Using an iterative communication between neighboring agents, $\mathcal{CI}-\mathcal{DPEVCCP}$ distributes computation among PEVs.

A. PROBLEM FORMULATION

The objective of PEV-CCP problem is to find cost-optimal charge schedules of a fleet of PEVs, meet their mobility requirements, and satisfy power distribution systems constraints [82], [110]. The PEV-CCP formulation is provided by

$$\min_{\mathbf{d}_v,\mathbf{D}} c_1\mathbf{D}^\top\cdot\mathbf{D}+c_2^\top\cdot\mathbf{D} \tag{6}$$

$$\text{s.t. } \mathbf{D}=\sum_{v\in V}\mathbf{d}_v \tag{7}$$

$$\mathbf{D}\le\mathbf{P}_{\max} \tag{8}$$

$$A\cdot\mathbf{d}_v\le e_v \quad \forall v\in\{1,\cdots,V\} \tag{9}$$

$$\underline{d}_v\le\mathbf{d}_v\le\overline{d}_v\ \forall v\in\{1,\cdots,V\} \tag{10}$$

where $\mathbf{d}_v$ represents charging schedule of PEV v at a given time horizon $[0,T]$, $\mathbf{d}_v\in\mathbb{R}^{T\times1}$; and $\mathbf{D}$ is aggregate charging demand over a given time horizon $[0,T]$, $\mathbf{D}\in\mathbb{R}^{T\times1}$. Matrix A and vector e_v denote the PEVs energy constraint for vehicle v. Coefficient $c_1\in\mathbb{R}$ and vector $c_2\in\mathbb{R}^{1\times T}$ represent the electricity tariff values.

The upper and lower limits on charging power of an individual PEV v are denoted b $\underline{d}_v$ and $\overline{d}_v$ respectively; and V is the total number of PEVs.

$$\mathbf{d}_v(k+1)=\mathbb{P}[\mathbf{d}_v(k)+\delta_k\left(\frac{\mathbf{D}_v(k)}{V}-\mathbf{d}_v(k)\right) -\eta_k\left(\lambda_v(k)\right)]_{\mathcal{F}}, \tag{11}$$

where δ_k and η_k denote positive tuning parameters. $\mathcal{F}$ is the feasible space spanned by equations (9) and (10). The projection operators enforce feasibility of updated variables.

B. DISTRIBUTED CHARGE COORDINATION APPROACH

Each PEV v updates its local variables that are associated with its decision making, i.e., $\mathbf{d}_v$, $\mathbf{D}_v$, and λ_v. iven the iteration counter k, the update for Lagrange multipliers λ_v is

$$\lambda_v(k+1)=\mathbb{P}\Bigg[\lambda_v(k)-\beta_k\overbrace{\left(\sum_{w\in\Omega_v}(\lambda_v(k)-\lambda_w(k))\right)}^{\text{neighborhood consensus}} -\alpha_k\underbrace{\left(\frac{\mathbf{D}_v(k)}{V}-\mathbf{d}_v(k)\right)}_{\text{local innovation}}\Bigg]_{[c_2,\infty)}. \tag{12}$$

where positive tuning parameters are represented by α_k and β_k. $\mathbb{P}$ is the projection operator to ensure that our solution satisfies $\lambda_v\ge c_2$. In (12), the first term represents the link between the Lagrange multipliers of neighboring PEVs. This term also guarantees the convergence of λ's to a *consensus*. The second term referred to as *innovation*, ensures the accuracy of each PEV's estimate of the total charging load ($\mathbf{D}$). If agent v's charging demand passes its expected proportion of total charging demand ($\mathbf{D}_v(k)/V$), then the *innovation* term's value increases $\lambda_v(k+1)$.

We use the update rule in (13) to find the value of $\mathbf{D}_v$ at each iteration.

$$\begin{aligned}\mathbf{D}_v(k+1)&=\mathbb{P}\left[\mathbf{D}_v(k)-\frac{1}{2c_1}\frac{\partial\mathfrak{L}}{\partial\mathbf{D}_v(k)}\right]_{(-\infty,\mathbf{P}_{\max}]}\\&=\mathbb{P}\left[\frac{\lambda_v(k)-c_2}{2c_1}\right]_{(-\infty,\mathbf{P}_{\max}]}.\end{aligned} \tag{13}$$

The following update rule is used for PEVs' charging schedules:

$$\mathbf{d}_v(k+1)=\mathbb{P}[\mathbf{d}_v(k)+\delta_k\left(\frac{\mathbf{D}_v(k)}{V}-\mathbf{d}_v(k)\right) -\eta_k\left(\lambda_v(k)\right)]_{\mathcal{F}}, \tag{14}$$

where δ_k and η_k denote positive tuning parameters. $\mathcal{F}$ is the feasible space spanned by equations (9) and (10). The projection operators enforce feasibility of updated variables.

C. MANAGING THE PEVS CHARGING DEMAND USING THEIR SPATIOTEMPORAL FLEXIBILITY

In order to manage the charge demand of the PEV fleet while meeting power constraints of power distribution transformers, charging stations can reduce the total charging rate of the PEVs. To compensate the energy reduction at a specific charging station, we assume that PEVs are also solving their own optimization problem to choose the optimal charging station. Let $\alpha_{e,i}$ denote the energy reduction required at charging

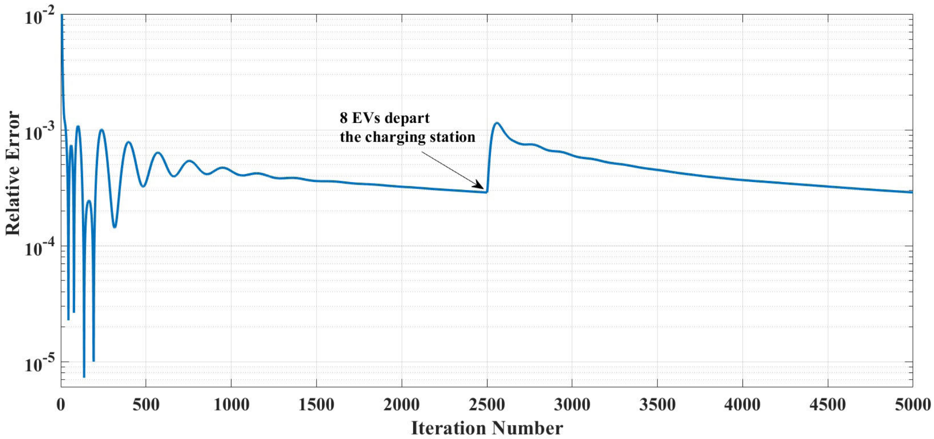

FIGURE 6. Relative distance from optimal load.

station i to achieve a feasible solution that satisfies power constraints. Note that increasing $\alpha_{e,i}$ at one charging station means less flexibility for other charging stations. In future work, we will focus on developing a coordination algorithm among multiple charging stations and finding an equilibrium among charging stations.

$$\min_{\mathbf{d}_v,\mathbf{D}} c_1\mathbf{D}^\top \cdot \mathbf{D} + c_2^\top \cdot \mathbf{D} + M.c_3^\top \cdot \alpha_{e,i} \cdot [e_1; \cdots ; e_V]^\top \tag{15}$$

$$\text{s.t. } \mathbf{D} = \sum_{v\in V} \mathbf{d}_v \tag{16}$$

$$\mathbf{D} \leq \mathbf{P}_{\max} \tag{17}$$

$$A \cdot \mathbf{d}_v \leq (1-\alpha_{e,i})e_v \quad \forall v \in \{1, \cdots, V\} \tag{18}$$

$$\underline{d}_v \leq \mathbf{d}_v \leq \overline{d}_v \quad \forall v \in \{1, \cdots, V\} \tag{19}$$

where M is a relatively big number to penalize the objective function (total charging cost) in case of deviating from the expected charging demand of PEVs. Further, c_3 is a vector with the same size as c_3. In this study, we assume all PEVs contribute equally to charging demand reduction, i. e., $c_3 = [\mathbf{1}]_{T\times 1}$.

D. ILLUSTRATIVE EXAMPLE

In order to show the effectiveness of the proposed $\mathcal{CI}-\mathcal{DPEVCCP}$, we use a simulation setup with 20 PEVs, with maximum power limit of 3.5kW, efficiency of 0.9, minimum state of charge of 0.2, and battery capacity, C_v, of either 16kWh or 24kWh. The maximum charging power of charging station assumed to be 25kW. More detailed specifications are provided in [103].

In the iterative approach the time-varying tuning parameters at iteration k are updated using $\frac{\nabla}{k^{\mathcal{O}}}$. According to [126], it can be shown that the above update rule for the tuning parameters guarantees the convergence of the *consensus+innovations* iterations. Note the update in (12) is an instance of such algorithms. Values of tuning parameters for the presented case study are presented in Table 3. We consider cold start, i.e., initial values of all variables are zero at the first iteration. Detailed formulation of first order optimality conditions is provided in [110].

TABLE 3. Tuning parameter values [110].

Parameter	α	β	γ	δ
∇	10.0222	0.1080	0.0080	0.0192
$\mathcal{O}$	0.1600	0.0001	0.0320	0.0010

In order to evaluate the effectiveness of the proposed $\mathcal{CI}-\mathcal{DPEVCCP}$ algorithm, we find the relative distance of the objective function (f) from the optimal solution of the centralized solution (f^*). Let ζ denote the value of this relative distance. We have:

$$\zeta = \left|f - f^*\right| / f^*.$$

Figure 6 represents the relative error of the objective function over 2500 iterations with 20 EVs, as well as tracking capability of our algorithm after 8 EVs leave the charging station.

Figure 6 represents the relative error of the objective function over 5000 iterations. Note that the first 2500 iterations show the day-ahead scheduling, while the second 2500 iterations show the real-time rescheduling after a change in total number of vehicles in the charging station. According to this figure, the relative error values converge to a value between 10^{-4} and 10^{-3} after almost 1500 iterations in the day-ahead scheduling and after almost 500 iterations in the real-time rescheduling. The reason for faster convergence and less oscillations in the real-time rescheduling is the starting point. Oscillations illustrated in this figure are correlated with the values of tuning parameters. In order to reduce the oscillations, we can adjust the tuning parameters. Note that based on the maximum power limit, that limits the feasible space, this solution may require a larger number of iterations to converge. Further, note that the obtained solution at each iteration is feasible.

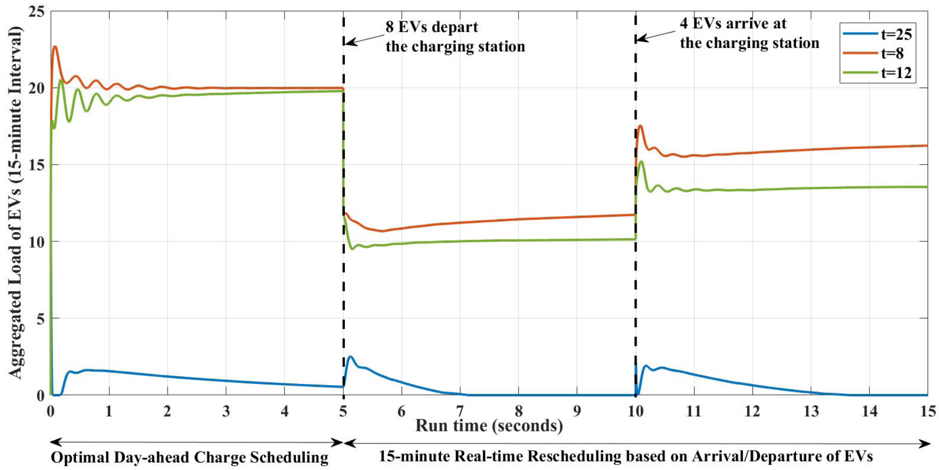

FIGURE 7. Real-time tracking capability of the proposed algorithm in response to arrival/departure of PEVs.

TABLE 4. Effect of mobility pattern on reaching feasible solution.

Scenario	$\mathbf{P}_{\max}$	e reduction (%)	Power mismatch ($\mathbf{D} - \mathbf{P}_{\max}$)	Total charging cost	ζ (relative distance)
1	25	0	-0.0206	2.8756e+5	3e-4
2	24	0	-0.0312	2.8769e+5	3e-4
3	23	0	-0.0286	2.8787e+5	3e-4
4	22	0	-0.0080	2.8816e+5	2e-4
5	21	0	0.0055	2.8857e+5	2e-4
6	20	0	0.0334	2.8914e+5	2e-4
7	19	0	0.1211	2.8993e+5	1e-4
8	15	0	1.1155 (infeasible)	2.9842e+5	0.0123
9	10	0	2.8301 (infeasible)	3.3541e+5	0.0014

Figure 7, illustrates two scenarios for three selected time intervals: first eight PEVs leave the charging station and then four PEVs arrive at the charging station during the real-time operation. In this scenario, the maximum power limit is 20kW. The required time to conduct each iteration is 1.96 milliseconds, i.e., given the fact that real-time rescheduling takes about 1000 iterations, each PEV can update its schedule in about two seconds after a change occurs in the problem setting (e.g., departure/arrival of some PEVs). This figure also implies faster convergence rate for the execution of proposed algorithm in the real-time operation setting as compared with the day-ahead scheduling. This is mainly due to using a more realistic initial point derived from day ahead operation.

IX. ENABLING FEASIBLE SOLUTION BY MANAGING MOBILITY PATTERNS

In order to evaluate the effect of mobility patterns on the charging demand of the fleet, we have analyzed 9 scenarios with different power constraints, as well as different values of the b parameter that corresponds to the mobility patterns. Smaller value of this parameter represents less charging demand. This can be caused either by charging the PEVs at different locations, or reducing the expected charge demand at this charging station. Further, this represents the interdependence among electrified transportation networks (value of parameter b) and power systems (maximum power limit $\mathbf{P}_{\max}$), i.e., feasibility of charge coordination problem can be enabled by leveraging the spatiotemporal flexibility of PEVs to change a different charging station or partly charge their battery at a different time.

According to the results shown in Table 4, by reducing the maximum power limit of the whole fleet, total charging cost increases. For instance, the total charging cost value is steadily increasing from scenario 1 to scenario 7. At some point, the obtained solution is not feasible. In order to deal with this infeasibility, we leverage the flexibility from the mobility viewpoint, i.e., we reduce the value of b parameter which is coupled with the mobility pattern of PEVs. In order to obtain optimal values for the charge reduction, we use the formulation in Section V.C which is devoted to the spatiotemporal flexibility of PEVs. The results of optimal reduction and charging costs are provide in Table 5.

According to the results of Tables 5 and 4, expected charge demand reduction only happens in scenarios 8 and 9 that there is no feasible solution. For the other scenarios with a feasible solution, the proposed formulation in (15) -(19) finds an almost-zero value for the optimal reduction. This does not only help the proposed algorithm to obtain a feasible solution, but also distributes the stress on power distribution feeders by motivating PEVs to charge at different locations, i.e., instead

TABLE 5. Effect of spatiotemporal flexibility on reaching feasible solution.

Scenario	$\mathbf{P}_{\max}$	e reduction (%)	Total charging cost
1	25	1.5766e-12	2.8757e+05
2	24	5.2055e-10	2.8769e+05
3	23	6.6465e-10	2.8788e+05
4	22	2.3856e-11	2.8816e+05
5	21	4.5215e-11	2.8857e+05
6	20	3.8629e-10	2.8914e+05
7	19	2.2797e-11	2.8993e+05
8	15	5.18	2.8227e+05
9	10	26.99	2.4324e+05

of fully-charging the battery at one lcoation, PEVs partly charge their battery in more than one location which leads to more flat energy demand over different loadpoints/feeders in power distribution systems.

X. POTENTIAL OPTIMIZATION, LEARNING, AND CONTROL PROBLEMS IN THE CONTEXT OF INTERDEPENDENT NETWORKS

In this section, we briefly introduce some of the potential optimization and control problems in the context of interdependent networks. To this end, we start with the simultaneous integration of electric vehicles and renewable resources into power distribution networks. Due to stochastic nature of renewable resources, as well as uncertainty of driver behaviour, it is imperative to develop efficient stochastic optimization algorithms to ensure load-generation balance in power networks, data-driven techniques to model the behaviours of electric vehicle drivers, and control techniques to manage power system operation while integrating these emerging resources.

From the intelligent transportation perspective, a fleet of electrified vehicles can contribute to traffic management leveraging their spatiotemporal flexibility. This flexibility caused by geographically distributed charging stations, commercial or residential, i.e., electric vehicles can postpone their charging or connect their battery at a different location. This can significantly be leveraged in traffic management by motivating a number of EVs to a certain area with lower traffic and avoid congestion in transportation network.

Electrified public transportation networks require advanced control algorithms to manage power consumption. Due to high capacity of the batteries, as well as repeating charging schedule for the fleet, electric buses which are deployed at certain times need to be charged at specific times. These buses however can be charge at different location to avoid peak demand at power distribution network. This can be formulated as an optimization problem to benefit both public transportation authorities, as well as power grid operator.

XI. CONCLUSION

We developed *consensus+innovations*-based holistic agent-based distributed algorithm and framework for the IoT-based interdependent networks. Our solution enables distributed coordination of agents in the network-of-networks, such as smart city infrastructures. To this end, we propose a fully distributed *consensus+innovations* approach. Our distributed iterative algorithm achieves a distributed solution of decision making for each agent through local computations and limited communication with other neighboring agents that are influential in that specific decision. For instance, the optimal routing decision of a PEV involves a different set of agents as compared with optimal charging strategy of the same PEV. The exogenous information from an external network/agent can affect internal operation of the other agents. For instance, having some information about traffic congestion at the transportation networks changes the decision of electric vehicles (EVs) to charge their battery at another location. Our approach constitutes solving an iterative problem, which utilizes communication at the smart city layer, as a network of different infrastructures that enables fully distributed coordination of agents, plug-and-play capability, and scalability of solution algorithm for future expansion of each network.

As a use case of our proposed holistic framework, we provide simulation results on the distributed charge scheduling of plug-in electric vehicles (PEVs). Owing to spatiotemporal flexibility of PEVs' charging demand, they lend themselves as promising solutions to improve the performance of both power systems, by leveraging their electricity demand flexibility, and transportation networks, by leveraging their degrees of freedom to charge at various locations. In this use case, we present our proposed fully distributed *consensus+innovations*-based algorithm to solve the PEVs' cooperative charge scheduling problem that aims at minimizing charging cost while satisfying each PEV's constraints. Our method considers uncertain driving behavior of each PEV driver by taking into account various scenarios for PEVs' driving pattern. The simulation results verify the convergence of our distributed solution to the optimal value obtained by centralized solution with acceptable accuracy. We also highlighted the plug-and-play capability of our distributed algorithm for real-time rescheduling applications.

According to simulation results and theoretical proofs for convergence of our novel distributed algorithm to the optimal solution, distributed algorithms are more efficient in terms of scalability as well as run-time, i.e., by increasing the total number of agents, run-time of distributed algorithm does not change significantly. Centralized methods, however, are not scalable due to increasing number of decision variables with having more agents. Although distributed solution lends itself as a promising alternative to centralized solution, it requires advanced communication infrastructure to enable local information exchange. Fully distributed *consensus+innovations* algorithm for optimal operation of interdependent networks paves the way for future researchers to implement agent-based models while integrating heterogeneous agents in the IoT environment.

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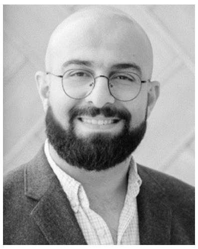

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