Decentralized Cloud-SDN Architecture in Smart Grid: A Dynamic Pricing Model

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***Abstract*—Smart grids (SG) energy management system and electric vehicle (EV) have gained considerable reputation in recent years. This has been enabled by the high growth of EVs on roads; however, this may lead to a significant impact on the power grids. In order to keep EVs far from causing peaks in power demand and to manage building energy during the day, it is important to perform an intelligent scheduling for EVs charging and discharging service and buildings areas by including different metrics, such as real-time price and demand–supply curve. In this paper, we propose a real-time dynamic pricing model for EVs charging and discharging service and building energy management, in order to reduce the peak loads. Our proposed approach uses a decentralized cloud computing architecture based on software define networking (SDN) technology and network function virtualization (NFV). We aim to schedule user's requests in a real-time way and to supervise communications between microgrids controllers, SG and user entities (i.e., EVs, electric vehicles public supply stations, advance metering infrastructure, smart meters, etc.). We formulate the problem as a linear optimization problem for EV and a global optimization problem for all microgrids. We solve the problems by using different decentralized decision algorithms. To the best of our knowledge, this is the first paper that proposes a pricing model based on decentralized Cloud-SDN architecture in order to solve all the aforementioned issues. The extensive simulations and comparisons with related works proved that our proposed pricing model optimizes the energy load during peak hours, maximizes EVs utility, and maintains the microgrid stability. The simulation is based on real electric load of the city of Toronto.**

***Index Terms*—Cloud, dynamic pricing, electric vehicle (EV), renewable energy, software define networking (SDN), vehicle-to-grid (V2G).**

I. Introduction

With the development of high energy and power density batteries, the penetration level of electric vehicle (EVs) is expected to grow rapidly. Thus, the energy required for EVs charging and discharging services is going to grow significantly on microgrids. This may lead to unpredicted peak loads and fast instability in the power grid, as most EVs are expected to be charged at peak hours (i.e., 06–09 A.M., or 4–8 P.M.) [1]. The high concentration of charging requests within a small time period may cause severe overloading in the distribution system which may lead to increased line losses and instability in the electrical system [2]. For instance, it has been estimated that the total charging energy of EVs in U.S. can reach around 18% of the U.S. summer peak at the EV saturation level of 30% [3]. In such a condition, EV users are required to pay high price for energy consumption. Thus, a fair pricing model and a smart scheduling of building energy flow including renewable energy sources may help to reduce such charging cost. Furthermore, EVs can also deliver energy to the smart grid (SG) using the discharging process (i.e., vehicle-to-grid energy, V2G).The later process can provide microgrids with the saved energy in EV batteries and contribute to minimize the operational costs inside the SG markets.

To improve the grid stability and make profit from the price variation, it is well known that the EVs charging process [grid-to-vehicle (G2V)] should be on off-peak demand period while the discharging process (V2G) would be on-peak load period. Nevertheless, it is expected that EVs will be deployed in large-scale environments; consequently, EVs need a real-time scheduling and monitoring. In this regard, a new distributed architecture based on flexible networks needs to be implemented to maintain the adequate balance between demand and supply in SG.

On the one hand, SG environment is suitable to accommodate several utilities, which can require huge data storage and processing [4]. For instance, it has been estimated that SG will generate 22 GB of data each day from its 2 million customers [5]. Also, the existing power grid in the U.S. is going through a massive transformation to make it more reliable and connected with the ability to transfer data and power in two ways [6]. Moreover, the microgrids will support an exponential growth in terms of energy demands from many devices [e.g., advance metering infrastructure (AMI), smart meters, EVs, electric vehicles public supply stations (EVPSS), etc.], located at home area networks (HANs), EV area networks (EVANs), and wide area networks. Each of these networks deploys thousands of devices that need to be managed and controlled incessantly [7]. Thus, the scheduling of all microgrid entities and minimizing the

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network management cost becomes very problematic. On the other hand, the emerging software define networking (SDN) technology can provide good opportunities for reducing the network management cost by integrating a flexible software network controller and virtualization functions (NFV). Some of existing works in the SDN area focus on data centers virtualization and cloud computing [8]. This later, with its distributed aspect and memory capacity, can offer huge computing, storage, and networks capabilities. So, there is a need to adapt cloud-based SDN technology for various SG applications.

In this work, we introduce a new SG architecture based on a decentralized cloud computing architecture for each microgrid, and a centralized SG controller located at cloud data centers. This architecture exploits SDN paradigm in order to offer to SG new options and opportunities for dealing with networks faults and communications problems even in the case of overall outages. Also, we believe that the cloud computing with its enormous data storage, computing capacity, and its distribution aspect, can help the SG to manage efficiently users' requests and solve the proposed optimization problems in a real-time manner [3].

The contributions of this paper can be summarized as follows.

1) A new dynamic pricing model, where the price is varied according to the variations of the demand–supply curve. The objective is to optimize the energy costs in the SG using V2G energy flow and renewable energy sources.
2) Renewable energy management algorithm to manage energy inside the buildings by switching the energy usage between microgrid and local renewable sources.
3) EVs charging and discharging scheduling algorithms based on two principal metrics: a) dynamic pricing and b) demand–supply curve. The objective is to ensure a well energy balancing especially on peaks hours and solve the optimization problem for EVs.
4) Centralized microgrid management algorithm. The objective is to manage and control all microgrids in different situations and solve the global optimization problem.
5) Exploration of cloud and fog computing capacities based on SDN technology. The objective is to offer EV users the best calendar (i.e., optimal reservation time) and manage all microgrid communications networks considering real-time and energy constraints.

The remainder of this paper is organized as follows. In Section II, we briefly present the related work. Section III presents the proposed architecture and motivation for Cloud-SDN enabled SG. Section IV presents the energy management model. In Section V, we formulate the real-time pricing optimization model. Section VI presents the optimal decision algorithms for energy management. The simulations results are discussed in Section VII. Finally, Section VIII concludes this paper.

II. Related Works

Several models have been proposed in the context of EVs charging/discharging and pricing scheduling (e.g., [5], [9]–[16]). A prediction-based charging strategy for EVs management is discussed in [9]. In this approach, EVs receive price information using wireless communication, and predict the market price during the charging period, in such a way that the time of charging (TOC) price is low. Different dynamic pricing policies are proposed in SG usage: distributed dynamic pricing (D2P) [10], usage-based dynamic pricing (UDP) [11], quadratic cost function (QCF) [5], and distributed demand response (D2R) [12]. In a recent work [9], Erol-Kantarci and Hussein propose an intelligent D2P mechanism for EVs charging management. Two pricing models are proposed: home price and roaming price; consequently, two types of energy services are considered: home microgrids and foreign microgrids. In this work, the real-time price is decided by microgrids using standard communication architecture for SG, where the scheduling is centralized, in such a case the management of all EVs demands become very difficult especially in peak hours. In [11], Liang *et al.* propose a UDP scheme for SG. In this work, distributed gateways are used as proxies of the utility company to timely respond the price from customers; nevertheless, the scheduling of EVs demands is performed in a centralized way inside the utility company. In [5], Park *et al.* use neural network for piecewise QCF. In such a pricing model, the grid decides the price depending on the supply power. As a result, customers may have to pay more cost, even though the total demand is low. A D2R algorithm for plug in hybrid electric vehicle (PHEV) charging in SGs is proposed in [12]. In such pricing models, the costs acquired by the customers directly depend on the demanded energy even though microgrids have excess energy to serve. Thus, clients may not be interested to consume more energy, and, thus, excess energy may be useless.

To schedule the electricity load, the utility company adopts the conventional direct load control (DLC) strategy [13] where smart switches are installed inside of houses such that the house appliances can be turned OFF during a high-demand period. The DLC enforces the customers to abandon the control of their appliances at certain conditions. Recently, in Ontario, Canada, a time-of-use (TOU) pricing strategy has been widely adopted by utility companies, e.g., Hydro One [14] and Waterloo North Hydro [15]. TOU means that the electricity unit price changes according to the time of the day. The Ontario Energy Board (OEB) divides daily and seasonal TOU periods into three categories: off-peak, midpeak, and on-peak. TOU enables the customers to view the electricity usage online and potentially influences electricity usage behavior of the customers. Though the period settings of TOU can be updated, TOU is neither truly dynamic nor related to the real-time usage. Therefore, TOU may cause some inappropriate situation.

Yet, to the best of our knowledge, there has been only limited effort to exploit the benefits of SDN for SG communications. In [17], Sgambelluri *et al.* studied the application of SDN as an alternative to multiprotocol label switching for wide area communication within the SG system. In [18], SDN was applied for developing self-configuration for substations automation, which was tested using emulation of a substation communication network. For SG, these applications are of major reputation where robustness of the communication network is a key enable for automated control.

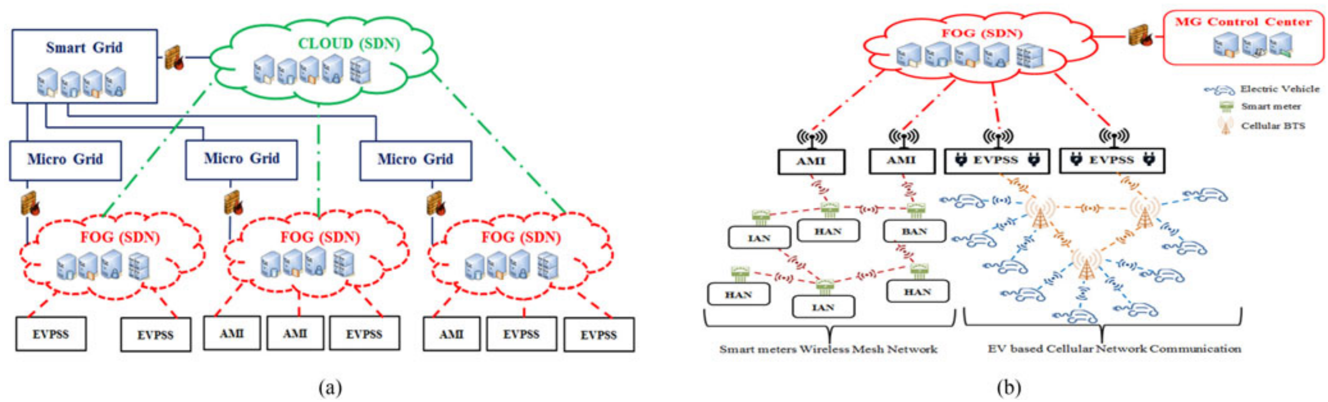

Fig. 1. Proposed Cloud-SDN and decentralized Fog-SDN architectures for SG communications: (a) Cloud-SDN architecture for microgrids communication and (b) decentralized Fog-SDN architecture for one microgrid.

III. Distributed SG Architecture Based Cloud SDN

In this section, we first describe the communication infrastructure for SG and then detail our proposed network model based on a decentralized architecture using Fog-SDN for microgrid controllers and Cloud-SDN for SG controller.

A. SG Networking Architectures

Basically, the traditional electric grid infrastructure can be divided into three major components in SG communication architecture [6]:

1) Customers layer: contains different area network as HANs, building area network (BANs), industrial area network (IAN), and EVAN. Each local network connects home, building, and industrial devices to smart meters.
2) Microgrid layer: collects the smart meters and EVPSS data from the customer layer.
3) 3) SG layer: provides long-haul communication with the utility control centers using various communication technologies and standards.

B. Motivation for Cloud-SDN Enabled SG

A communication network is the important component of SG infrastructure. With the integration of advanced technologies and applications for achieving a smarter metering of energy consumption, a huge amount of data from different building appliances and EV infrastructures will be generated for analysis, update, control, and real-time pricing methods. Thus, the management of these networks is a big challenge due to the scale. Moreover, due to heterogeneity of devices and applications from different vendors, the equipment may not be interoperable. Hence, it is very critical for electric companies to define the communications standards and find the best communication infrastructure to control and manage all customers throughout the total system considering the real-time constraint. Cloud computing based SDN is an encouraging solution for the aforementioned problems, thanks to the following advantages.

1) Cloud technology provides high computing capacity to SG utilities. In addition, with its enormous data storage, cloud can help SG to improve demand side management services and customers participation for efficient electricity usage.
2) The decentralized aspect of cloud networking using the so-called Fog-computing can be used to manage and control each microgrid in a distributed manner.
3) The SDN technology adopts standards and introduces abstraction, which provides a centralized control and management of various types of network devices and multiple vendors that are common in SG.
4) The hardware NFV through SDN solves the problem of managing different networks and reduces the energy consumption of the network equipment.
5) Programmability by operators, enterprises, independent software vendors, and users using common programming environments.

C. Proposed Network Model

As seen earlier, the traditional SG architecture contains three major components. In this regard, we need to describe the communication standards and network topologies required for information flow in a SG system for each layer.

1) Customers' Area Networks (i.e., HAN, BAN, IAN): The basic metering data flow is from sensors and electrical devices to smart meters. To do this, we use ZigBee wireless communication technology that is relatively low in power usage, data rate, complexity, and cost of deployment; it is an ideal technology for smart energy monitoring and automatic meter reading [7]. Also, ZigBee integrated SG meters can communicate with the ZigBee integrated devices and control them.

2) Smart Meters Network: In order to collect the metering data from the smart meters, we use radio frequency mesh network, where we suppose that every smart meter is equipped with a radio module and each of them routes the metering data through nearby meters as presented in Fig. 1(b). Each device acts as a signal repeater until the collected data reaches the AMI (electric network access point). The mesh network technology is used by many companies for SG metering applications due to the redundancy and high availability features of this technology.

3) EVs Mobile Network: Current cellular networks can be a good option for connecting EVs and public supply stations. The existing communications infrastructure avoids electrical companies from spending operational costs and additional time for building a dedicated communication network. Also, the cellular network technologies (e.g., 3G, 4G) enable the mobility of EVs and the deployment of EVPSS.

We suppose that an embedded mobile SIM within a cellular radio module is integrated at each EV and EVPSS to enable the communication. Many telecom operators and vendors have also agreed to put their cellular network into service of electrical companies, this can be a big challenge in terms of interoperability and privacy; we believe that the use of the SDN technology can manage and control different networks.

4) Microgrid-Based Decentralized Fog-SDN Architecture: In our proposed network architecture, we suppose that we have a number M of microgrids m, where

$$\mathbb{M} = \{1, 2, \dots, m, \dots, M\} \quad \forall\, m \in \mathbb{M}. \tag{1}$$

Each microgrid contains a number S of smart meters s, a number V of EV v, and a number E of EVPSS e, where

$$\mathbb{S} = \{1, 2, \dots, s, \dots, S\} \quad \forall\, s \in \mathbb{S} \tag{2}$$

$$\mathbb{V} = \{1, 2, \dots, ev, \dots, V\} \quad \forall\, ev \in \mathbb{V} \tag{3}$$

$$\mathbb{E} = \{1, 2, \dots, e, \dots, E\} \quad \forall\, e \in \mathbb{E}. \tag{4}$$

For each microgrid, we associate a decentralized data center (i.e., fog). A data center comprises different servers, such as database server, management server, real-time communication server, application server, and NFV and VM servers; each server provides various services for customers. Also, the data center can communicate with the microgrid control center in order to update and deliver real-time information to the company utilities (about prices for example). Hence, all communications and networks are managed and controlled using the SDN technology. Finally, the management of the fog datacenters is provided by cloud services in a centralized manner (see Fig. 1). A centralized SDN controller is implemented inside the cloud in order to manage the backhaul network.

IV. Energy Management Model

A. Energy Demand Profiling

We consider two types of demands which are given as follows.

1) Building Demands: Building demands are represented as ED_B^t including customer's devices demands $ed_{i_h}^t$, $ed_{i_l}^t$, $ed_{i_k}^t$ arriving at time interval t at each HAN, BAN, and IAN, respectively. Thus, we have

$$\mathrm{ED}_B^t = \sum_{h=1}^{H}\sum_{i=1}^{\mathrm{dev}} \mathrm{ed}_{i_h}^t + \sum_{l=1}^{L}\sum_{i=1}^{\mathrm{dev}} \mathrm{ed}_{i_l}^t + \sum_{k=1}^{K}\sum_{i=1}^{\mathrm{dev}} \mathrm{ed}_{i_k}^t \tag{5}$$

where H, L, K are the numbers of HANs, BANs, and IANs at each microgrid m, and dev is the number of devices. In our proposed model, each device has a minimum and maximum energy demand as follows:

$$ed_{i_{h,l,k}}^{\min} \le ed_{i_{h,l,k}} \le ed_{i_{h,l,k}}^{\max} \quad \forall\, i_{h,l,k} \in \text{HAN, BAN, IAN}. \tag{6}$$

2) EVs Demand: It is represented as $\mathrm{ED}_{\mathrm{EV}}^t$, the energy demand from mobile EVs, at public supply stations inside the microgrid m, depends on their available energy and battery capacity. Therefore, we consider the charging energy $\mathrm{ED}_{\mathrm{ev}_i^{\mathrm{G2V}}}^t$ of one EV ev_i^{G2V} as follows:

$$\mathrm{ED}_{\mathrm{ev}_i^{\mathrm{G2V}}}^t = \alpha_{\mathrm{ev}_i^{\mathrm{G2V}}}^t - \mathrm{soc}_{\mathrm{ev}_i^{\mathrm{G2V}}}^t \tag{7}$$

$$\text{and} \qquad \alpha_{\mathrm{ev}_i}^t \le \mathrm{cap}_{\mathrm{ev}_i} \tag{8}$$

where $\alpha_{\mathrm{ev}_i}^t$ is the predetermined target charging level of an $\mathrm{ev}_i^{\mathrm{G2V}}$, $\forall\ \mathrm{ev}_i^{\mathrm{G2V}} \in \mathbb{V}$, and $\mathrm{soc}_{\mathrm{ev}_i^{\mathrm{G2V}}}^t$ is the available energy state of charge of ev_i at time interval t. However, the condition in (8), must be respected to perform charging of an EV, where $\mathrm{cap}_{\mathrm{ev}_i}$ is the battery capacity of an ev_i.

Thus, the total energy demands $\mathrm{ED}_{\mathrm{G2V}_m}^t$ of a number V' of $\mathrm{ev}_i^{\mathrm{G2V}}$ at the microgrid m are given by

$$\mathrm{ED}_{\mathrm{G2V}_m}^t = \sum_{i=1}^{V'} \mathrm{ED}_{\mathrm{ev}_i^{\mathrm{G2V}}}^t \quad \forall\, \mathrm{ev}_i^{\mathrm{G2V}} \in \mathbb{V}. \tag{9}$$

Finally, the total energy demand of a microgrid m including all customers' devices and EVs is represented as follows:

$$\mathrm{ED}_m^t = \mathrm{ED}_B^t + \mathrm{ED}_{\mathrm{G2V}_m}^t. \tag{10}$$

And for the total SG demand ED^t

$$\mathrm{ED}^t = \sum_{j=1}^{m} \mathrm{ED}_j^t. \tag{11}$$

Remark 1: If an EV perform the charging operation at home or at building areas, its energy demand for charging will be metered by the home smart meter and the EV is considered as a device, so the energy consumption will be calculated as in (5).

B. Energy Supply Profiling

We consider that each microgrid m has renewable and nonrenewable energy sources with self-generation capacity, and provides electricity in a certain region. The energy supply sources are presented as follows.

1) Building Renewable Energy Supply: We suppose that we have a number R of building areas (HAN, BAN, and IAN) equipped with renewable energy sources as solar energy equipment, so we define a new set of building energy consumption called buildings with renewable energy denoted by $\mathbb{r}$, thus we have

$$\mathbb{r} = \{1, 2, \dots, r, \dots, R\} \quad \forall\, r \in \mathbb{r} \tag{12}$$

where

$$R < H + L + K. \tag{13}$$

The renewable energy supply for each building h, l or k is denoted by RE_r^t; this energy is used to fulfill the self-energy consumption in the same building. We suppose that the generated energy is stored used a domestic battery as Tesla wall battery [19]; this battery can be charged by the energy discharged from EVs that perform the discharging process at home denoted by $\mathrm{ES}^t_{\mathrm{ev}_r}$, so we have

$$\mathrm{soc}^t_{\mathrm{wall}_r} = \mathrm{soc}^{t-1}_{\mathrm{wall}_r} + \mathrm{RE}^t_r + \mathrm{ES}^t_{\mathrm{ev}_r} \quad \forall\, r \in \mathbb{r} \tag{14}$$

$$\text{and} \qquad 0 \le \mathrm{soc}^{t-1}_{\mathrm{wall}_r} \le \mathrm{soc}^t_{\mathrm{wall}_r} \le \mathrm{cap}_{\mathrm{wall}_r} \tag{15}$$

where $\mathrm{soc}^t_{\mathrm{wall}_r}$ and $\mathrm{cap}_{\mathrm{wall}_r}$ are, respectively, the charged level and the capacity of the wall battery at time interval t. However, the wall battery cannot be necessary sufficient to provide the total energy needed to fulfill all power demands from building devices. In this regard, we have two cases as follows.

1) If $(\mathrm{soc}^t_{\mathrm{wall}_r} > \sum_{i=1}^{\mathrm{dev}} \mathrm{ed}^t_{r_i})$, then devices of building r use the stored energy in the wall battery. The charged level of the battery will be reduced at time interval $t+1$, also the requested energy from the microgrid denoted by $\mathrm{ED}^t_{r_m}$ is null, so we have

$$\mathrm{soc}^{t+1}_{\mathrm{wall}_r} = \mathrm{soc}^t_{\mathrm{wall}_r} - \sum_{i=1}^{\mathrm{dev}} \mathrm{ed}^t_{r_i} \tag{16}$$

$$\text{and} \qquad \mathrm{soc}^{t+1}_{\mathrm{wall}_r} \ge \mathrm{soc}^t_{\mathrm{wall}_r} \ge \sum_{i=1}^{\mathrm{dev}} \mathrm{ed}^t_{r_i} > \mathrm{cap}^{\mathrm{th}}_{\mathrm{wall}_r} \tag{17}$$

$$\mathrm{ED}^t_{r_m} = 0 \tag{18}$$

where $\mathrm{cap}^{\mathrm{th}}_{\mathrm{wall}_r}$ is the predetermined minimum threshold that cannot be surpassed. We use this condition to save the reserved energy in the wall battery for emergency usage.

2) If $(\mathrm{soc}^t_{\mathrm{wall}_r} < \sum_{i=1}^{\mathrm{dev}} \mathrm{ed}^t_{r_i})$, in this case user devices of building r can use the wall battery if only it's charged level $\mathrm{soc}^t_{\mathrm{wall}_r}$ is superior to the predetermined minimum threshold $\mathrm{cap}^{\mathrm{th}}_{\mathrm{wall}_r}$.

The condition in (17) must be respected.

Therefore, the requested energy from the microgrid m denoted for one building by $\mathrm{ED}^{t+1}_{r_m}$ is not null and becomes

$$\mathrm{ED}^{t+1}_{r_m} = \sum_{i=1}^{\mathrm{dev}} \mathrm{ed}^{t+1}_{r_i} - \mathrm{soc}^{t+1}_{\mathrm{wall}_r}. \tag{19}$$

Remark 2: Taking into consideration buildings characterized by a self-renewable energy generation, the total demands of all buildings inside the microgrid m represented in (5) becomes

$$\mathrm{ED}^t_B = \sum_{h=1}^{H-R'} \sum_{i=1}^{\mathrm{dev}} \mathrm{ed}^t_{i_h} + \sum_{l=1}^{L-R''} \sum_{i=1}^{\mathrm{dev}} \mathrm{ed}^t_{i_l} + \sum_{k=1}^{K-R'''} \sum_{i=1}^{\mathrm{dev}} \mathrm{ed}^t_{i_k} + \sum_{r=1}^{R} \sum_{i=1}^{\mathrm{dev}} \mathrm{ed}^t_{i_r} \tag{20}$$

$$R = R' + R'' + R''' \tag{21}$$

where $R < (H + L + K)$. R', R'', and R''' are, respectively, the numbers of homes, buildings, and industrials area networks that have a self-renewable energy generation.

Assumption 1: Buildings with self-renewable energy generation are equipped with smart meters that can switch between the wall battery and microgrid energy usage according to conditions presented in (15) and (17).

2) EVs Discharging Energy Supply: In our proposed model, we use new industrial innovations used by cars and battery companies such as the energy flow from EVs batteries to grid or so-called V2G, where EVs located at microgrid m provide energy by discharging its batteries. An EV can perform the charging and discharging process at r buildings in order to charge the domestic battery as seen in (14) or at public supply stations EVPSS in order to provide energy to microgrid storage system. Therefore, we consider the discharging energy $\mathrm{ES}^t_{\mathrm{ev}_i^{\mathrm{V2G}}}$ of one EV $\mathrm{ev}_i^{\mathrm{V2G}}$ as follows:

$$\mathrm{ES}^t_{\mathrm{ev}_i^{\mathrm{V2G}}} = \mathrm{soc}^t_{\mathrm{ev}_i^{\mathrm{V2G}}} - \beta^t_{\mathrm{ev}_i^{\mathrm{V2G}}} \tag{22}$$

where $\beta^t_{\mathrm{ev}_i^{\mathrm{V2G}}}$ is the predetermined target discharging level of an $\mathrm{ev}_i^{\mathrm{V2G}}$, $\forall\, \mathrm{ev}_i^{\mathrm{V2G}} \in \mathbb{V}$, and $\mathrm{soc}^t_{\mathrm{ev}_i^{\mathrm{V2G}}}$ is the available energy state of charge of $\mathrm{ev}_i^{\mathrm{V2G}}$ at time interval t. The total discharging energy from V'' of $\mathrm{ev}_i^{\mathrm{V2G}}$ at public supply stations at time interval t is given by

$$\mathrm{ES}^t_{\mathrm{V2G}_m} = \sum_{i=1}^{V''} \mathrm{ES}^t_{\mathrm{ev}_i^{\mathrm{V2G}}} \quad \forall\, \mathrm{ev}_i^{V2G} \in \mathbb{V} \tag{23}$$

$$\text{and} \qquad V = V' + V'', \quad V' > V''. \tag{24}$$

3) Microgrid Energy Supply: We consider that each microgrid m has renewable $\mathrm{ES}^t_{\mathrm{RW}_m}$ and nonrenewable energy $\mathrm{ES}^t_{\mathrm{N\_RW}_m}$ sources with self-generation capacity, and provides electricity in its covered region.

Assumption 2: All microgrids can communicate with the other microgrids, and can exchange energy with one another. If a microgrid has excess energy, it can provide another microgrid that has energy deficiency.

The total energy supply of one microgrid is given by

$$\mathrm{ES}^t_m = \mathrm{ES}^t_{\mathrm{N\_RW}_m} + \mathrm{ES}^t_{\mathrm{RW}_m} + \mathrm{ES}^t_{\mathrm{V2G}_m} + \mathrm{ES}^t_{EX_{m-1}} \tag{25}$$

where $\mathrm{ES}^t_{\mathrm{V2G}_m}$ is the energy provided from discharging EVs batteries, and $\mathrm{ES}^t_{\mathrm{EX}_{m-1}}$ is the energy received from another microgrid.

V. Real-Time Pricing Optimization

A. Pricing Model Based Demand–Supply Curve Balancing

In the proposed D2P model, we aim to ensure the energy management by balancing the demand–supply curve for each microgrid m. Therefore, real-time price is subject to different constraints such as total supply, demand, and time.

Assumption 3: We assume that the real-time price of a microgrid is not affected by the pricing policy of the other microgrids. Each microgrid has its unique price according to the local demand–supply curve.

In order to characterize the demand–supply curve, we calculate the difference and the ratio between the total energy demand ED^t_m calculated in (10) and the total energy supply ES^t_m

calculated in (25) for a particular microgrid m, as follows:

$$D_m^t = \mathrm{ED}_m^t - \mathrm{ES}_m^t \tag{26}$$

$$R_m^t = \frac{\mathrm{ED}_m^t}{\mathrm{ES}_m^t}. \tag{27}$$

Each microgrid evaluates its real-time price p_m^t depending on the real-time difference and the ratio presented in (26) and (24).

Theorem: The dynamic real-time price for consuming one unit of electricity is represented as follows:

$$p_m^t = \{\tan^{-1}(e^{D_m^t}) + (\tan^{-1} R_m^t)^{10}\} + p_{\text{base}} \tag{28}$$

where p_{base} is a fixed base price. In (28), the part between brackets is the dynamic portion that changes the price according to the variation in R_m^t and D_m^t.

Proof: We know that $\lim_{x\to+\infty} e^x = +\infty$ and $\lim_{x\to-\infty} e^x = 0$, so the portion $e^{D_m^t}$ is always bounded between $[0, +\infty[\quad \forall D_m^t$. On the other hand, we have: $\lim_{x\to 0}\tan^{-1}x = 0$ and $\lim_{x\to+\infty}\tan^{-1}x = \frac{\Pi}{2}$, so the portion $(\tan^{-1}e^{D_m^t})$ is always bounded between $[0, \frac{\Pi}{2}]$, but the variance of this portion is not very important. Thus, in order to keep the balance between demand and supply effects more the real-time price, we add the second portion $(\tan^{-1}R_m^t)^{10}$ varied according to the variations in the ration R_m^t $\lim_{x\to+\infty}(\tan^{-1}x)^{10} = (\frac{\Pi}{2})^{10}$. Consequently, the proposed real-time price p_m^t is varied between $[p_{\text{base}}, \frac{\Pi}{2} + (\frac{\Pi}{2})^{10} + p_{\text{base}}]$.

Corollary: With an increase in the supply ES_m^t, the real-time price p_m^t decreases while demand ED_m^t from the customers is either fixed or decreased. On the other hand, the real-time price increases with an increase in the demand, while supply is either fixed or decreased. In this regard, we aim to vary the price value in a bounded interval in order to respect the conventional prices given by electrical companies, this is why we use exponential and arctangent functions.

B. Pricing Optimization Based Fog Management

1) For Microgrid Services: The objective of microgrid is to maximize its own utility, depending on real-time demand and supply. In this regard, we formulate the real-time price optimization, decided by each microgrid controller, as a maximization problem as follows:

$$\begin{aligned}
&\text{Maximize} \quad \sum_{t\in T} \mathrm{ED}_m^t p_m^t \\
&\text{where} \quad \mathrm{ED}_m^t = \mathrm{ED}_B^t + \mathrm{ED}_{\mathrm{G2V}_m}^t \\
&\text{subject to} \quad \sum_{t\in T} \mathrm{ED}_m^t \le \sum_{t\in T} \mathrm{ES}_m^t.
\end{aligned} \tag{29}$$

Equation (29) shows that the total demand ED_m^t to a microgrid should always be less than or equal to the total supply ES_m^t for that microgrid. In the proposed model, ES_m^t is considered as the combination of grid self-generation energy (i.e., renewable and no renewable energy), the energy from other microgrids and EVs energy which discharge their batteries at time t.

2) For Buildings With Renewable Energy: As seen earlier, buildings with renewable energy sources have the opportunity to supply local energy. Thus, their objective is to maximize the use of stored energy in the wall battery when the price is high and the demand–supply curve is not stable, so we have

$$\text{Maximize} \quad \sum_{i=1}^{\text{dev}} ed_{r_i}^t$$

$$\text{where} \quad \sum_{i=1}^{\text{dev}} \mathrm{ed}_{r_i}^t = \mathrm{ES}_{\mathrm{wall}_r}^t - \mathrm{ES}_{\mathrm{wall}_r}^{t-1}$$

$$\text{subject to} \quad \mathrm{ED}_{r_m}^t = 0 \tag{30}$$

$$\mathrm{soc}_{\mathrm{wall}_r}^{t-1} \ge \mathrm{ES}_{\mathrm{wall}_r}^t \ge \sum_{i=1}^{\text{dev}} \mathrm{ed}_{r_i}^t > \mathrm{cap}_{\mathrm{wall}_r}^{\mathrm{th}}. \tag{31}$$

Equation (30) shows that the total demand from buildings with renewable energy sources to microgrid m should be null when the demand–supply curve of that microgrid is not stable at time t, and the constraint in (31) must be respected.

3) For EVs Charging and Discharging Service: Based on the proposed network architecture (see Fig. 1), we assume that EVs can communicate with their microgrid fog platforms, in order to collect information about EVPSS state, price, etc. In our model, we assume that each EV creates own profile. The EV profile is represented as follows:

$$\begin{aligned}
&\mathrm{EV}_{\mathrm{Profile}}[\mathrm{User}_{\mathrm{Name}}, \mathrm{EV}_{\mathrm{ID}}, \mathrm{User}_{\mathrm{password}}, \mathrm{Home}_{\mathrm{Adress}}, \\
&\quad \mathrm{Battery}_{\mathrm{type}}, \mathrm{Battery}_{\mathrm{efficiency}}, \mathrm{SoC}, \mathrm{Speed}].
\end{aligned}$$

An EV may create several calendars to express several charging/discharging requests. We believe that the storage capacity inside the fog can be very beneficial, especially when the number of users increases. The EV calendars are scheduled inside the fog server for each microgrid m; then, the suitable calendar, in terms of price and scheduled time, will be sent to all EVs.

We consider two types of pricing optimizations for EVs users in the microgrid m; the sale price for charging $p_{m_{\mathrm{G2V}}}^t$, and the buying price for discharging $p_{m_{\mathrm{V2G}}}^t$. These prices are calculated as in (28), but the base price for charging is not equal to the base price for discharging, and it is decided according to different constraints like production cost, so we have

$$p_{m_{\mathrm{G2V}}}^t = \{\tan^{-1}(e^{D_m^t}) + (\tan^{-1} R_m^t)^{10}\} + p_{\text{base}}^{\mathrm{G2V}} \tag{32}$$

$$p_{m_{\mathrm{V2G}}}^t = \{\tan^{-1}(e^{D_m^t}) + (\tan^{-1} R_m^t)^{10}\} + p_{\text{base}}^{\mathrm{V2G}}. \tag{33}$$

As we can see in (9) and (23), EVs contribute on the supply–demand curve. In the one hand, EVs users aim to consume more energy when the sale price $p_{m_{\mathrm{G2V}}}^t$ is low and discharge more energy when the buying price $p_{m_{\mathrm{V2G}}}^t$ is high. Thus, the microgrid controller looks for maximizing the gain as in (29) and this by supporting more EVs that need to be charged by selecting charging calendars when the demand–supply curve is stable (i.e., $\mathrm{ED}_m^t \le \mathrm{ES}_m^t$), and minimizing the number of EVs requiring the discharging, at the same time slot interval. On the second hand, when the demand–supply curve is not stable (i.e., $\mathrm{ED}_m^t > \mathrm{ES}_m^t$), users prefer to discharge their EVs because the buying price is automatically high, and the microgrid wants to maximize the number of discharging EVs by selecting discharging calendars in order to keep the demand–supply curve more stable. Our proposed model uses EVs charging and discharging calendars in order to predict the demand–supply energy curve.

In this regard, we define our linear optimization problems for EVs charging and discharging process in different situations; 1) the demand–supply curve is stable and 2) when they are not stable, as follows.

1) If the supply demand curve is stable $(\mathrm{ED}^t_m \leq \mathrm{ES}^t_m)$

$$\begin{aligned} &\text{Maximize} \quad \sum_{i=1}^{V'} \mathrm{ED}^t_{\mathrm{ev}_i^{\mathrm{G2V}}} \, p^t_{m_{\mathrm{G2V}}} \\ &\text{where} \quad \mathrm{ED}^t_{\mathrm{ev}_i^{\mathrm{G2V}}} = \alpha^t_{\mathrm{ev}_i^{\mathrm{G2V}}} - \mathrm{soc}^t_{\mathrm{ev}_i^{\mathrm{G2V}}} \\ &\text{subject to} \quad \sum_{t\in T} \mathrm{ED}^t_m \leq \sum_{t\in T} \mathrm{ES}^t_m \quad \text{and} \\ &\alpha^t_{\mathrm{ev}_i} \leq \mathrm{cap}_{\mathrm{ev}_i}. \end{aligned} \tag{34}$$

2) If the supply demand curve is not stable $(\mathrm{ED}^t_m > \mathrm{ES}^t_m)$

$$\begin{aligned} &\text{Maximize} \quad \sum_{i=1}^{V'} \mathrm{ES}^t_{\mathrm{ev}_i^{\mathrm{V2G}}} \, p^t_{m_{\mathrm{V2G}}} \\ &\text{where} \quad \mathrm{ES}^t_{\mathrm{ev}_i^{\mathrm{V2G}}} = \mathrm{soc}^t_{\mathrm{ev}_i^{\mathrm{V2G}}} - \beta^t_{\mathrm{ev}_i^{\mathrm{V2G}}} \\ &\text{subject to} \quad \sum_{t\in T} \mathrm{ED}^t_m \leq \sum_{t\in T} \mathrm{ES}^t_m \quad \text{and} \\ &\beta^t_{\mathrm{ev}_i^{\mathrm{V2G}}} \geq \mathrm{cap}^{\mathrm{th}}_{\mathrm{ev}_i} \end{aligned} \tag{35}$$

where $\mathrm{cap}^{\mathrm{th}}_{\mathrm{ev}_i}$ is the predetermined minimum threshold that cannot be surpassed. We use this constraint to save the reserved energy in EV battery for an emergency usage.

VI. Optimal Decision Algorithms for Energy Management

In this section, we define the utility for microgrid energy management with the consumed energy from buildings and EVs, supply energy from renewable sources and discharging EVs batteries and real-time price. We discuss the decision making process for building energy management and EVs charging and discharging service by implementing algorithms to solve the optimization problems in (29), (30), (34), and (35). In order to solve the optimization problem in (29), we start by solving the problems in (30), (34), and (35).

A. Algorithm for Buildings With Renewable Energy Sources

Algorithm 1 shows the energy management inside buildings, and the switching process of energy usage between microgrid energy and the wall battery energy. The algorithm is executed inside the smart meter. The time complexity of the algorithm is $O(1)$.

B. Algorithm for EVs Charging and Discharging Management

As seen earlier, EVs may create several calendars to express several charging and discharging requests. We discuss the

Algorithm 1: Renewable Building Energy Management (RB_EM).

Input: Total supply ES^t_m, Total demand ED^t_m, $soc^t_{wall_r}$, $cap^{th}_{wall_r}$
Output: Energy demand from the micro grid $ED^t_{r_m}$.
Calculate $soc^t_{wall_r}$ as in Eq. (14) until $soc^t_{wall_r} = cap_{wall_r}$;
if $(E^t_{dem} \geq E^t_{sup})$ **then**
  if $(soc^t_{wall_r} > \sum_{i=1}^{dev} ed^t_{r_i})$ **then**
    Switch to the wall battery energy usage;
    Calculate $soc^t_{wall_r}$ as in Eq. (16);
  else /* $soc^t_{wall_r} < \sum_{i=1}^{dev} ed^t_{r_i}$ */
    while $(soc^t_{wall_r} > cap^{th}_{wall_r})$ **repeat**
      Switch to the wall battery energy usage;
      $soc^{t+1}_{wall_r} = soc^t_{wall_r} - \sum_{i=1}^{dev} ed^t_{r_i}$;
    Until $(soc^{t+1}_{wall_r} = cap^{th}_{wall_r})$;
    $ED^{t+1}_{r_m} = \sum_{i=1}^{dev} ed^{t+1}_{r_i} - soc^{t+1}_{wall_r}$;
    Request $ED^{t+1}_{r_m}$ energy from the micro grid;
  end
else
  Switch to the micro grid energy usage;
end

decision making process of EVs calendars for charging and discharging process.

The proposed algorithm (i.e., EV_OCM) aims to solve the optimization problems in (34) and (35), by taking decisions according to the available energy, distance to the charging–discharging station, and real-time price. In this regards, we define the utility function of each EV $\mathcal{U}_{\mathrm{EV}}$ depending on various parameters as follows.

$$\mathcal{U}_{\mathrm{EV}}(R^t_m, p^t_m, \mathrm{cal}^{\mathrm{t}}_{\mathrm{type}}, \mathcal{D}^{\mathrm{evpss}}_{\mathrm{m}}, \mathrm{soc}^{\mathrm{t}}_{\mathrm{ev_i}}, \mathcal{C}^{\mathcal{D}}_{\mathrm{m}}, \mathcal{Q}^{\mathcal{D}}_{\mathrm{m}}) \tag{36}$$

where, R^t_m, p^t_m, $\mathrm{cal}^t_{\mathrm{type}}$, $\mathcal{D}^{\mathrm{evpss}}_m$, $\mathrm{soc}^t_{\mathrm{ev}_i}$, $\mathcal{C}^{\mathcal{D}}_m$, and $\mathcal{Q}^{\mathcal{D}}_m$ are the demand–supply curve, price, calendar types (charging or discharging), distance to EVPSS, state of charge of ev_i battery, total cost to charge the battery, and the available energy to join the EVPSS, respectively. Therefore, the decision making process of EV charging and discharging calendars considers the global information presented in the utility function $\mathcal{U}_{\mathrm{EV}}$. We use a multiattribute decision making methodology to take the optimal decision, as explained below.

Let us consider M microgrids in particular EVs vicinity. Then, the proposed decision matrix, which is based on several decision parameters, is represented as follows:

$$\begin{pmatrix} R^t_1 & \cdots & R^t_M \\ p^t_1 & \cdots & p^t_M \\ \mathcal{D}^{\mathrm{evpss}}_1 & \cdots & \mathcal{D}^{\mathrm{evpss}}_M \\ \mathcal{C}^{\mathcal{D}}_1 & \cdots & \mathcal{C}^{\mathcal{D}}_M \\ \mathcal{Q}^{\mathcal{D}}_1 & \cdots & \mathcal{Q}^{\mathcal{D}}_M \end{pmatrix}. \tag{37}$$

Assumption 4: Due to the EVs mobility, an EV can charge and discharge its battery in any microgrid m, even if its calendar is not saved in the according microgrid fog. In this regard, communications between microgrids fog servers are authorized in order to ensure the roaming of EVs.

Algorithm 2: EV Optimal Calendar Management (EV_OCM).

Input: Total supply ES_m^t, Total demand ED_m^t, EVs charging/discharging calendars.
Output: Optimal calendar, Optimal EVPSS, Total cost $\mathcal{C}_m^{\mathcal{D}}$.
1. **For** (each $EV_{Profile}$) **do**
2. Read ($EV_{Calendars}$) at time slot t; /* EV ID, location, … */
3. **if** ($ED_m^t > ES_m^t$) **then** /*Discharging*/
4. Select discharging calendars $cal_{type}^t = discharging$;
5. Calculate utility function $\mathcal{U}_{EV}$ for discharging;
6. Calculate the total cost $\mathcal{C}_m^{\mathcal{D}}$ to discharge from each EVPSS located at each micro grid m using Eq. (37) and Eq. (38);
7. Choose the optimal cost, to maximize the utility;
8. Requests EVs to discharge their battery;
9. **else** /* ($ED_m^t < ES_m^t$) */ /* Charging */
10. Select charging calendars $cal_{type}^t = charging$;
11. Calculate utility function $\mathcal{U}_{EV}$ for charging;
12. Calculate the total cost $\mathcal{C}_m^{\mathcal{D}}$ to charge from each EVPSS located at each micro grid m using Eq. (37) and Eq. (38);
13. Choose the optimal cost, to maximize the utility;
14. Requests EVs to charge their battery;
15. **end**
16. Update the energy supply ES_m^t as in Eq. (10);
17. Update the energy demand ED_m^t as in Eq. (25);
18. Calculate prices as in Eq. (31) and Eq. (33);
19. Broadcast optimal calendars and prices to EVs users;
20. **end**

Algorithm 3: Micro Grids Energy Management (DP_DEM).

Input: ES_m^t, ED_m^t *and* p_m^t *of each micro grid* m;
Output: list of stable micro grids, list of non-stable micro grids, real time price of each micro grid m;
1. **For** ($m = 1$ *to* M) **do**
2. Receive ES_m^t, ES_m^t, p_m^t at time t;
3. Update list of stable micro grids; /* $D_m^t \geq 0$*/
4. Update list of non-stable micro grids; /* $D_m^t < 0$*/
5. **while** (list of non − stable micro grids $\neq$ null) **repeat**
6. Execute (Algorithm 1) and (Algorithm 2) for micro grid m;
7. Create virtual communications network between micro grids based SDN-Controller and NFV;
8. Request exceeded energy from stable micro grids;
9. Receive Exceeded energy;
10. Calculate energy difference D_m^t as in Eq. (26) for m;
11. **if** ($D_m^t \geq 0$) **then**
12. Remove m from list of non-stable micro grids;
13. Add m to list of stable micro grids;
14. **end**
15. **Until** (list of non − stable micro grids = null) ;
16. Calculate prices as in Eq. (28), Eq. (32) and Eq. (33);
17. Broadcast list of stable micro grids;
18. Broadcast list of non-stable micro grids;
19. Broadcast real time prices of each micro grid;
20. **end**

So, the decision instruction $\psi(\omega)$ with full information can be written as

$$\psi(\omega) = \text{argmin}\ (\omega,\ m_{\mathrm{ev}_i}\ ) \tag{38}$$

where m_{ev_i} is the selected microgrid from which ev_i charge or discharge energy, $m_{\mathrm{ev}_i} \in \mathbb{M}$ and $ev_i \in \mathbb{V}$, and ω is the set of full information parameters, i.e.,

$$\omega = \left\{R_M^t,\ p_M^t,\ \mathcal{D}_M^{\mathrm{evpss}},\ \mathcal{C}_M^{\mathcal{D}},\ \mathcal{Q}_M^{\mathcal{D}}\right\}. \tag{39}$$

We show in Algorithm 2 (i.e., EV_OCM), an optimal management of charging and discharging calendars based on the decision matrix represented in (37). The algorithm is decentralized and executed inside each microgrid fog controller. The time complexity of the algorithm is $O(n)$, where n is the number of $\mathrm{EV}_{\mathrm{Profile}}$.

C. Algorithm for Microgrid Energy Management

The objective of each microgrid m is to maintain the stability of the demand–supply curve, and determine a real-time price of energy. Therefore, we have a global maximization problem represented in (29), where each microgrid always looks to maximize its utility. In this regards, we propose a centralized algorithm (DP_DEM) to manage and control all microgrids in different situations. Also, it uses SDN and NFV technologies to supervise the communication networks between microgrids, and control the data flow in order to maintain the total SG demand–supply curve, by maximizing the number of stable microgrids. The algorithm is executed inside the SG cloud controller, as a centralized master algorithm based on the proposed architecture. The time complexity of the algorithm is $O(M)$, where M is the number of microgrids.

VII. Performance Evaluation

A. Simulation Settings

We implement extensive simulations to evaluate the performance of the proposed dynamic pricing model based on a decentralized Cloud-SDN architecture. We use simulation of urban mobility (SUMO) to implement EVs mobility and MATLAB/Simulink to execute the proposed energy management algorithms. We consider a real electric load in the city of Toronto, divided into 05 microgrids and managed using SG controller. We examine the energy load (i.e., EV charging and discharging, renewable energy supply, building consumption) during a day (24 h) starting from 12:00 A.M. The day is evenly divided into 288 intervals. Each interval has a length of 5 min. For EVs mobility modeling, we consider a scenario of ten roads that allow access to a city having area of 10 km $\times$ 10 km where EVPSSs are placed randomly. All vehicles are traveling with speeds that cannot exceed 60 km/h. Table I shows the parameters used for simulation.

B. Performance Metrics

In order to evaluate our proposed model, we use different metric as follows.

1) *Dynamic real-time price:* the price is calculated as in (28) for buildings energy consumption and as in (32) and (33) for EVs charging and discharging, respectively.
2) *Demand–supply curve:* is the principal metric used to inspect the performance of the proposed model, especially

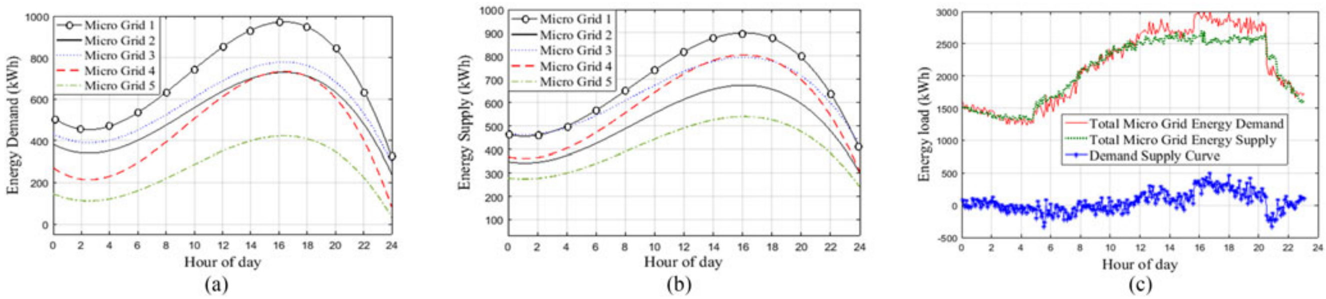

Fig. 2. Real-time supply and demand for microgrids and total supply–demand curve. (a) Real-time energy demand for microgrids. (b) Real-time energy supply for microgrids. (c) Total energy supply–demand curve.

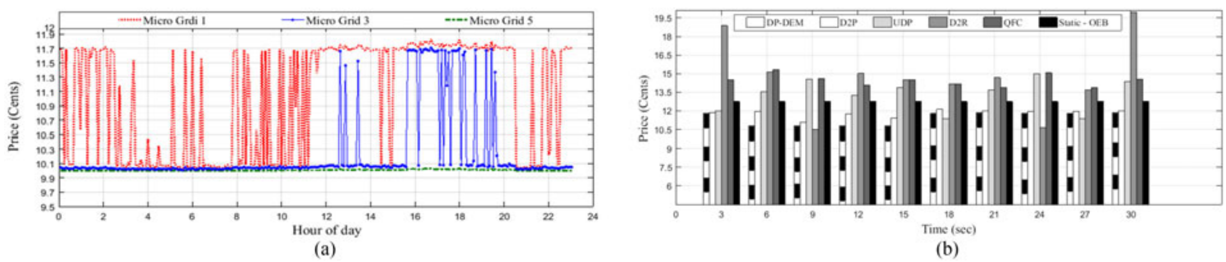

Fig. 3. Impact of energy load on the proposed pricing policy and price comparaison. (a) Energy load impact on price for three heterogeneous energy microgrid. (b) Comparison of proposed real-time price with related works.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Number of EVs	1000
Initial EV SoC for charging	[1–40 kW]
Initial EV SoC for discharging	[30–50 kW]
Wall Battery capacity	[20–80 kWh]
EV Battery capacity	60 kWh [21]
$\mathrm{cap}^{\mathrm{th}}_{\mathrm{wall}_r}$, $\mathrm{cap}_{\mathrm{ev}_i}$	20%
$p^{\mathrm{G2V}}_{\mathrm{base}}$	10 cent [6]
$p^{\mathrm{V2G}}_{\mathrm{base}}$	5 cent [6]

during peak hours. The demand–supply curve is evaluated from (26) and (27).

3) *Charging delay:* is the sum of the fog provider response time, time to travel to the selected EVPSS, the waiting time in the queue, and the service time.

4) *EV charging cost:* is consistently related to the real-time price and distance to the charging station of the selected microgrid. It is calculated as in (38).

5) *Utility for EV charging:* EV_OCM algorithm takes decisions based on the decision matrix proposed in (37). We calculate the utility for EV as charging cost using D2P [10], D2R [12], UDP [11], QFC [5], and the proposed pricing model DP-DEM. Thus, we denote the utility function as follows:

$$\mathcal{U}_{\mathrm{EV}}\left(\mathrm{ED}^t,\, p^t, \mathcal{D}_m^{\mathrm{evpss}}\right) = \begin{cases} \mathrm{ED}^t\left(p^t_{\mathrm{D2P}} - p^t\right) \\ \mathrm{ED}^t\left(p^t_{\mathrm{D2R}} - p^t\right) \\ \mathrm{ED}^t\left(p^t_{\mathrm{UDP}} - p^t\right) \\ \mathrm{ED}^t\left(p^t_{\mathrm{QFC}} - p^t\right) \end{cases} \quad (40)$$

where p^t_{D2P} p^t_{D2R}, p^t_{UDP}, and p^t_{QFC} denote the real-time prices obtained using D2P, D2R, UDP, and QFC pricing policy, respectively.

C. Results and Comparison With Exiting Works

In order to keep our simulation scenarios more realistic, we use a real load consumption, Fig. 2(a) and (b) shows the energy consumption and the energy supply, respectively, for each microgrid, simulated by scaling the real energy load in Toronto city by a factor of 1/1500 and divided into 05 microgrids. Fig. 2(c) shows the total energy demand, the total energy supply for all microgrids, and the demand–supply curve including the charging and the discharging load of EVs.

We can see that the demand–supply curve is not stable from [12:00 P.M. to 08:00 P.M.].

To evaluate the impact of the proposed dynamic pricing policy, we compare the price over different microgrids situations in Fig. 3(a). For microgrid 1, the curve is not stable; we can observe different energy peaks during a day, consequently the price is varied according to the variations in the energy load. For microgrid 3, we have two peaks, midpeak period [12:00 P.M. to 14:00 P.M.] and evening-peak period [17:00 P.M. to 20:00 P.M.]. We can see that the price is high (11, 7 cents) compared with other periods (10, 00 cents). Finally, the price for microgrid 5 is stable because the demand–supply curve of the microgrid is regular during all the day. In Fig. 3(b), we compare our proposed price policy DP-DEM with existing works, UDP, D2R, QFC, and static pricing policy from OEB [20].

In simulation, we assume that each microgrid calculates the real-time price every 3 s interval. We can see that with the implementation of DP-DEM, the cost to consume energy is less

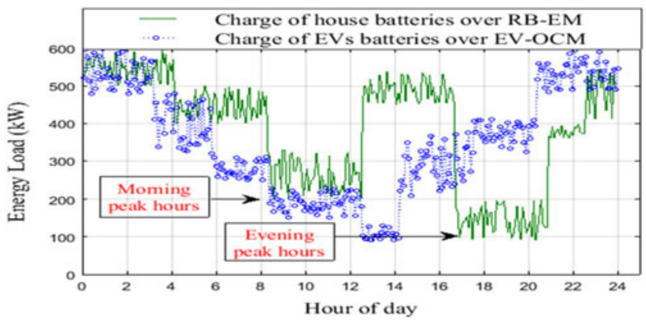

Fig. 4. Charge of ten house batteries and ten EVs batteries.

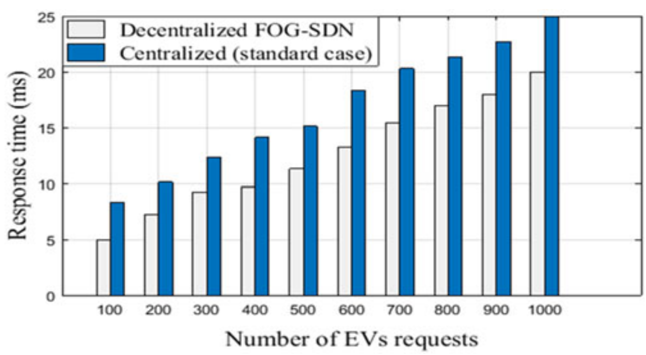

Fig. 5. Variation of response time with the number of EVs requests.

than that with the other pricing policies; the proposed distributed pricing policy gives better result than the centralized one. In the proposed scenario, we see that a reasonable pricing policy, using the proposed pricing equations, is also maintained compared with D2R price policy for example.

Fig. 4 shows the charge that is held at ten house batteries (we selected ten house of a no stable microgrid). We run simulations using RB_EM algorithm. We can observe that the charge energy in house batteries' (represented by the green plot) decrease during morning peak hours and evening peak hours, this is due because the total demand–supply curve is not stable so, and according to our proposed pricing policy the price of one unit of energy increase, as results house devices use the house battery energy. However, we can see that from 12:30 P.M. and from 20:30 P.M. the charge level of the house batteries increases, this is because the demand–supply curve is stable so the price decrease, so the proposed scheme make profit of this situation and start charging the house batteries.

In order to specify why it is useful to use Cloud-SDN architecture in the SG environment, we present in Fig. 5 the implementation of decentralized Fog-SDN architecture for microgrids, where we use response time as a performance metric (This is the time it takes for the first response to come after processing of a dataset). We implement two scenarios as follows: 1) centralized standard scenario without using SDN technology and 2) decentralized scenario using Fog-SDN technology.

For all simulation tests, the topology shown in Fig. 1 was used where a finite number (1000) of EVs submit their requests for charging. We have 03 data centers (i.e., each microgrid has its data center); the data centers contain different scheduling servers (i.e., represented as virtual machines VMs with 2 giga octet (GO) capacity in our simulation parameters). In order to evaluate the effectiveness of the proposed scheduling scheme based on a decentralized Fog-SDN architecture, we evaluate the proposed architecture using ns-2. Fig. 5 shows the response time of end users (EVs requests) waiting for scheduling charging/discharging demands from the grid. When the number of EVs requests is increased, the proposed Fog-SDN approach yields a lower response time compared to the approach making use of the traditional centralized core network infrastructure. The lower response time is because when the centralized core network is used, services need to be accessed far away from remote sites that reduce the overload on the core. In the proposed decentralized scheme, the services are immediately available from the fog computing resources, thereby minimizing the response time.

The performances of our proposed algorithms (i.e., DP-DEM, EV-OCM, and RB-EM) are shown in Fig. 6. In Fig. 6(a), we evaluate the execution of the optimal EVs calendars management algorithm during peak hours. We can observe that the number of discharging EVs is higher than the charging EVs; this is because the demand–supply curve is not stable and the EV-OCM selects discharging calendars in order to maximize the utility function $\mathcal{U}_{\mathrm{EV}}$ for discharging by choosing the optimal cost. Also, the price in that period is high and EVs users profit to maximize their gain by discharging the EV battery. Fig. 6(b) shows the utility function for the discharging delay for the same number of EVs in Fig. 6(a). We can see that the delay with EV-OCM algorithm is less than that with the utility function that uses D2P pricing policy, especially during peak hours. This is because the calendars scheduling helps microgrid controller to predict the energy load and the EVPSS state at time t. On the other hand, the proposed decentralized architecture based on SDN networking and fog computing, reduces the response time by controlling all network entities (i.e., EVs, EVPSS, AMI, ...).

In Fig. 6(c), we evaluate the price variation during a day, and compare the DP-DEM scheduling policy with the D2P scheduling. First, we can see that our price is less than that of D2P price during all the day including peak hours and nonpeak hours. Second, we see that with the proposed DP-DEM, we have two peaks during a day at 02:00 P.M. (midpeak hours) and at 08:00 P.M. (evening peak hours); however, the price is reduced from (11.4 cents) to (10.05 cents) when the DP-DEM sends notifications to all microgrids controllers located at the data centers to execute the EV-OCM algorithm (at 02:00 P.M.). Thus, the utility for discharging EVs is maximized as seen in Fig. 6(a) and (b). Also, at evening peak hours, DP-DEM sends notifications to all microgrids to execute the RB-EM algorithm in order to manage the energy inside the buildings and switches to the use of energy from the wall battery. DP-DEM scheduling can help each microgrid to reduce the price, especially during peak hours, by keeping the demand–supply curve stable compared with the D2P scheduling.

The total charging cost for EVs is shown in Fig. 7(a) using DP-DEM (proposed), D2P, UDP, D2R, and QCF pricing poli-

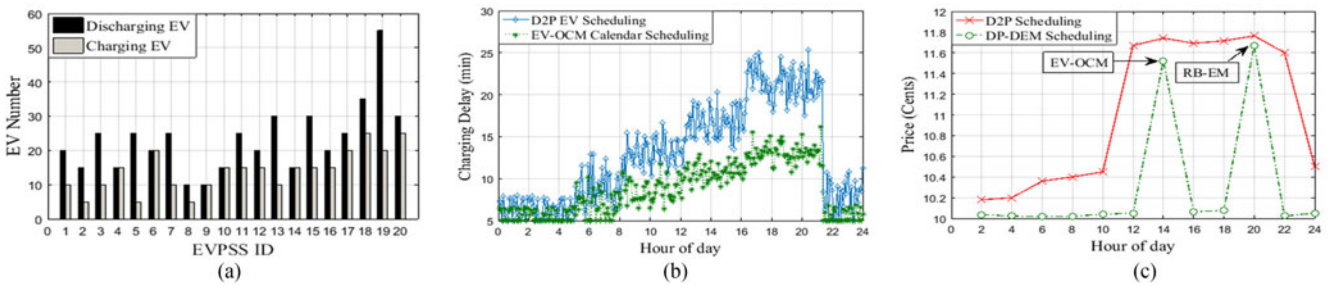

Fig. 6. EVs prices optimization and comparison during a day over DP-DEM, and charging delay over EV-OCM scheduling. (a) EVs number in peak hours over EV-OCM. (b) Delay for discharging the EVs battery. (c) Price variation and comparison during a day.

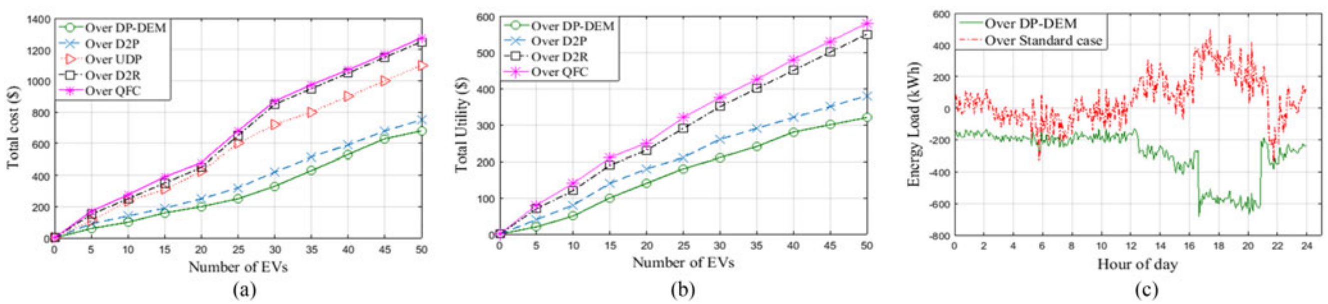

Fig. 7. EVs charging cost and utility comparison, and demand–supply curve comparaison. (a) Total cost for the required energy from EVs. (b) Utility comparison for EVs while charging. (c) Demand–supply curve stabilization.

cies. Based on the energy requests from each EV, we see that with the increase in the number of EVs, DP-DEM outperforms D2P, D2R, UDP, and QCF scenarios. In Fig. 7(b), we compare the utility of EVs while charging. Using the proposed dynamic pricing policy DP-DEM, the utility of EVs increases compared to that of D2P, D2R, and QFC. This is because DP-DEM algorithm supervises all microgrids energy flow and decides when sending notifications to each microgrid to execute EV-OCM, in order to maximize the EV charging and discharging utility and minimize the cost. Finally, we evaluate in Fig. 7(c) the demand–supply curve state during a day over the proposed scheduling. We can observe a significant stabilization of the demand–supply curve compared to the standard case; an important energy saving (600 kWh) is obtained during evening peak hours. Thus, our proposed model is capable to regulate the total demand curve.

VIII. Conclusion

In this paper, we proposed a D2P model for EVs charging and discharging scheduling and building energy management in SG, which considers real-time and energy demand constraints. The model is based on a decentralized Cloud-SDN communication architecture. We used a linear optimization approach to achieve the price decision process, maintain the demand–supply curve stable, and ensure more grid efficiency. Also, we use a multiattribute decision making methodology to take optimal decisions aiming to maximize the utility for SG users. We solved the optimization problems by using two distributed algorithms; one for EV charging and discharging calendar, and the second for managing building renewable energy. We implemented a centralized algorithm in order to manage all microgrids. Our algorithms aim to ensure the balance between the charging and discharging requests of EVs and balancing energy usage between grid energy and renewable energy. We used dynamic pricing equations to incite users to consume their energy when the price is optimal for the SG and for users. As proved in simulations and comparisons with four other works, using real electric load in the city of Toronto, the proposed decentralized Cloud-SDN architecture can be useful for SG applications. Furthermore, the proposed pricing policy based on Cloud-SDN architecture can also improve the grid stability, especially in peak hours.

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