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Charging Schemes for Plug-In Hybrid Electric Vehicles in Smart Grid: A Survey

PENG-YONG KONG[1], (Senior Member, IEEE), AND GEORGE K. KARAGIANNIDIS[2], (Fellow, IEEE)
[1]Electrical and Computer Engineering Department, Khalifa University of Science, Technology and Research, P.O. Box 127788, Abu Dhabi, United Arab Emirates
[2]Electrical and Computer Engineering Department, Aristotle University of Thessaloniki, 54636 Thessaloniki, Greece

Corresponding author: P.-Y. Kong (pengyong.kong@kustar.ac.ae)

ABSTRACT Plug-in hybrid electric vehicles (PHEVs) have emerged as an important tool in reducing greenhouse gas emissions, due to their lower dependency on fossil fuel. Since, for cost efficiency, PHEVs have a limited battery capacity, they must be recharged often and especially after trips. Thus, efficient battery charging plays an important role on the success of PHEVs commercial adoption. This paper surveys the state-of-the-art of existing PHEV battery charging schemes. We classify these schemes into four classes, namely, *uncontrolled*, *indirectly controlled*, *smart*, and *bidirectional* charging, and review various existing techniques within each class. For uncontrolled charging, existing studies focus on evaluating the impact of adding variable charging load on the smart grid. Various indirectly controlled charging schemes have been proposed to control energy prices, in order to indirectly influence the charging operations. Smart charging schemes can directly control a rich set of charging parameters to achieve various performance objectives, such as minimizing power loss, maximizing operator's profit, ensuring fairness, and so on. Finally, bidirectional charging allows a PHEV to discharge energy into smart grid, such that the vehicle can act as a mobile energy source to further stabilize the grid, which is partially supplied by intermittent renewable energy sources. This survey provides a comprehensive one-stop introductory reference to quickly learn about the key features and technical challenges, addressed by existing PHEV battery charging schemes in smart grid.

INDEX TERMS Plug-in hybrid electric vehicles, uncontrolled charging, indirectly-controlled charging, smart charging, bidirectional charging, smart grid.

I. INTRODUCTION

At the Paris Climate Conference in December 2015, a total of 195 countries have adopted the first ever universal and legally binding climate change agreement [1]. This agreement sets out a worldwide action plan to put the mankind on track, to limit global warming to well below 2°C above the pre-industrial levels. This ambitious plan requires a significant reduction in greenhouse gas emissions, starting from 2020. According to the International Energy Agency, the long-term concentration of greenhouse gases in the atmosphere must be limited to about 450 parts per million of carbon-dioxide equivalent [2].

Currently, a large portion of emitted greenhouse gas comes from the internal combustion engines of motor vehicles. According to [3], motor vehicles contribute about 16% of the global man-made carbon dioxide emissions. In addition to the greenhouse gas, by burning fossil fuel, internal combustion engines release harmful pollutants that can significantly degrade the air quality and threaten our health. These harmful pollutants and greenhouse gas emissions can be drastically reduced if the use of internal combustion engine can be avoided. In this context, plug-in hybrid electric vehicles (PHEV) can offer a solution. Each PHEV is equipped both a battery driven electric motor and an internal combustion engine, and thus, it can significantly reduce its dependency on the environment-polluting combustion engine [4].

Technically, a PHEV is an advanced combination of a conventional hybrid electric vehicle (HEV) and an all-electric vehicle (EV).[1] Both PHEV and HEV have an electric motor in addition to the internal combustion engine. In a HEV, the battery that drives the electric motor can only be charged[2] from capturing energy, using regenerative braking that

[1]In the literature, all-electric vehicle (EV) is also called plug-in electric vehicle (PEV). For consistency, we use only the term EV in this paper to represent both EV and PEV.

[2]Strictly speaking, a depleted battery is recharged to restore its energy. For simplicity but without loss of generality, we use the terms "recharge" and "charge" interchangeably without differentiating them.

converts kinetic energy into electricity. The battery in a HEV cannot be charged from an external energy source. As a more advanced alternative to HEV, PHEV has a built-in adaptor to connect to the electrical grid for battery charging. This plug-in charging capability in PHEV is also a defining feature of EV. Compared to an EV, that depends solely on its battery driven electric motor, PHEV can eliminate the problem of range anxiety, because its combustion engine can work as a backup when the battery is depleted, giving PHEVs a driving-range comparable to that of a conventional vehicle.

A detailed comparison between HEV, EV and PHEV has been presented in [5]. In summary, compared to HEV, PHEV has a better performance in terms of fuel economy (fuel consumed per travel distance), emission reduction, cost saving (monetary cost per travel distance) and charging flexibility. In addition to alleviating the range anxiety, PHEV has an advantage over EV in terms of fueling flexibility, since PHEV can be fueled at any traditional gas station as well as being charged at home or a public charging station. Despite PHEV's overall superior characteristics, the difference in popularity between PHEV and EV is not obvious in some geographical regions, such as the United Kingdom and Japan [6]. Furthermore, in some countries, such as Norway and Denmark, EV is much more popular than PHEV, probably due to government policies and incentives, in terms of tax reduction, tax exemption, legal limits on pollutant emission by transportation vehicles, etc. We expect that, over a long time, i.e., beyond 2050, EVs will globally and decisively overtake PHEVs as the vehicles of choice, if battery technology can mature to support a drive range of 315 miles (500 km) and a battery lifetime of 125,000 miles [7]. This is a result of EV's zero pollution and greenhouse gas emission at the location of use. Although the various technical aspects of battery charging discussed in this paper are applicable to both EV and PHEV, we use only the term PHEV hereafter, to represent both, depending on context, due to PHEV's fueling flexibility, which is much needed at the current stage of electric vehicles proliferation.

PHEVs have been formally defined by the United States of America (USA) government as a vehicle that [8]:

- has an electric motor in addition to a conventional combustion engine;
- draws motive power from a battery with a capacity of at least 4 kWh;
- can be recharged from an external source of electricity for motive power; and
- is a light-, medium-, or heavy-duty motor vehicle or non-road vehicle.

The Institute of Electrical and Electronics Engineers (IEEE) has a similar PHEV definition, but with an addition requirement [9]. According to IEEE, PHEV is a vehicle that has an all-electric range (AER) of at least 10 miles, where AER is the distance to be driven solely by an electric motor, without using the vehicle's internal combustion engine.

The PHEV definitions given above imply that the vehicles may use a mix of electric motor and combustion engine for motive power during a trip. Depending on which motive power is mainly used, PHEV operation can be classified into two modes, namely charge depleting (CD) and charge sustaining (CS). In CD mode, PHEV disables its internal combustion engine and draws propulsion energy entirely from the battery, until it reaches a threshold state-of-charge (SOC), where SOC is a quantity that measures the percentage of remaining charge in the battery. The threshold SOC indicates the minimum amount of energy that must be stored in the battery at all times. Upon reaching the minimum SOC, PHEV switches to operate in CS mode and the combustion engine provides energy to propel the vehicle as well as to maintain battery charge above but near to the minimum SOC. PHEVs can drastically reduce fossil fuel consumptions and greenhouse gas emissions by avoiding the CS mode. For better fuel efficiency, a third mode, called charge blended (CB), has been advocated [10]–[12]. In CB mode, electric motor and internal combustion engine are optimally and dynamically employed during a drive cycle, so that they are able to operate longer using the most efficient setting, while achieves an overall reduction in greenhouse gas emissions.

TABLE 1. PHEV battery requirements by vehicle classes.

Vehicle class	Energy consumption per mile (kWh/mile)	PHEV-30 (kWh)	PHEV-40 (kWh)
Compact sedan	0.26	7.8	10.4
Mid-size sedan	0.30	9.0	12.0
Mid-size SUV	0.38	11.4	15.2
Full-size SUV	0.46	13.8	27.6

By avoiding CS and CB modes, the greenhouse gas emissions can be eliminated and therefore, we may speculate that a larger battery capacity is better. However, the authors in [13] have shown that the cost and energy efficiency brought by a larger battery capacity reaches an asymptotic value, and thus, an infinitely large capacity is not necessary. Depending on the types of the vehicles, [14] has shown that the battery capacity should be about 11.6 kWh for a passenger car to cover a distance of 40 miles at a speed of about 25-30 mph, without using internal combustion engine. This is a reasonable battery size because a typical USA passenger vehicle travels an average of less than 30 miles each day [15]. A similar PHEV battery size requirement has been reported in [16] and presented in Table 1. This table covers several types of vehicles and PHEV-x is a PHEV with AER equals x miles.

Regardless of the actual battery capacity, as trips are performed and batteries are discharged, the SOC drops. Due to the limited capacity, the depleted battery must be recharged regularly to maintain its SOC within a desired range, which is defined by the minimum SOC and full capacity. Typically, it is desirable to keep a high SOC at the beginning of a trip to minimize the total energy cost as well as to achieve a longer AER, although a high SOC results in a faster battery degradation [17].

From the perspective of product marketing, a vehicle's SOC can be restored in two ways: (a) battery swapping, and (b) battery recharging. In battery swapping method, PHEV

TABLE 2. Types of PHEV charging options.

Charging options	Amperage (amp)	Voltage (volt)	Power (kW)
Level 1 charging 1-phase slow charging	12 to 16	120	1.3 to 1.9
Level 2 charging 3-phase slow and fast charging	up to 80	240	up to 19.2
Level 3 charging 3-phase fast charging	up to 80	480	up to 130

driver exchanges the depleted battery for a fully charged one at a service station [18]–[20]. This approach has zero waiting time for battery charging and allows the service provider to reap the benefits from lower energy price for charging during off-peak hours. This negligible time needed in restoring SOC is the biggest advantage in comparison to the second method, i.e., battery recharging that requires the drivers to plug their PHEVs into electric outlets for a charging period. Despite the benefit of zero waiting time, battery swapping has yet to become popular due to three major challenges, namely huge upfront cost for system deployment, limited AER for each battery, and difficulties in ensuring identical performance among all exchangeable batteries. The huge cost is due to the need to keep sufficient stocks of charged batteries at each charging station. Hereafter, in view of the lack of current popularity, we focus on the battery recharging methods in this paper.

The battery in a PHEV can be recharged by simply plugging into an electric outlet, that can be found at homes, workplaces, parking facilities or dedicated charging stations. The time needed to fully restore a battery's charge depends on the battery's SOC, the battery's capacity, and the outlet's output power. Specifically, the charging time equals the difference between battery capacity and SOC, divided by the charging power. With reference to Table 1, the charging time for a fully depleted battery can range from 5 minutes to 20 hours, depending on the types of charging options used. These options vary from country to country, depending on the power source and plug capacity standards, which have been standardized by several organizations such as the IEEE, the Society of Automotive Engineers (SAE), etc. As shown in Table 2 for the SAE-compliant charging equipment, charging options can be classified into slow charging and fast charging, with different power ratings [5], [21], [22].

- *Level 1 AC charging:* Almost all PHEVs come with a level 1 charging cord. One end of the cord is a standard connector that can be plugged directed to a wall outlet at home. The other end is a SAE J1772 standard connector that plugs into the vehicle's J1772 charge port [23]. Therefore, there is no need for additional charging equipment. Level 1 charging can be provided, by using an on-board charger, up to 1.9 kW through 120 V single-phase AC.
- *Level 2 AC charging:* This charging option uses the same SAE J1772-compliant charging cord as in level 1, but offers up to 19.2 kW output power by using an on-board charger. Level 2 charging is available to premises that are supplied with 3-phase AC at 208 or 240 V, and requires dedicated electric circuit to support a higher current up to 80 amp. This option is suitable for charging at home, as well as at public charging facilities, although residential level 2 charging operates at a lower current (about 30 amp) and a lower power of 7.2 kW, as compared to the public ones. Level 2 is preferred over level 1 for its shorter charging time.
- *Level 3 AC charging:* This is a new charging option which is being developed by SAE to supply up to 130 kW for very rapid restoration of SOC, using 3-phase AC at 480 V and high current. This 3-phase power distribution is common at commercial and industrial locations. To support the high output power, level 3 chargers are much larger in size and heavier in weight, compared to level 1 and level 2 chargers. Also, level 3 chargers require dedicated cooling equipment for high-power electronics. As a result, level 3 chargers are not installed on-board, but they are located externally (off-board). It is likely that SAE J1772 connector will not be suitable for this option.

Slow charging can be conveniently supported by the typical wall outlets at home but it takes an overnight to complete charging. Therefore, slow charging is also called residential charging or overnight charging. Fast charging is useful to rapidly restore SOC partially or in-full, during the day time to complete a trip that is longer than the vehicle's AER. While Table 2 is comprehensive, it covers only AC but not DC charging. As an emerging option, high power DC offers faster and more efficient charging compared to AC, but requires significant investment in new infrastructure. We focus on AC charging in this paper hereafter, although many of the surveyed literature does not clearly specify the use of AC or DC.

Each plugged-in PHEV is a variable load added to the electrical grid. Several industrial standards, such as the IEC1000-3-2, require each PHEV charger to drawn current from the grid with a low distortion in order to minimize the impact on the power quality [24]. However, these standards do not cover the aggregated effect from a fleet of PHEVs. When a large number of PHEVs are charged simultaneously, the additional electric load may cause a number of problems to the grid, in terms of excessive voltage deviations, thermal overloads, elevated power losses, increased aging of transformers and lines, degraded power quality, power outages, etc [25]–[27]. These problems and challenges can be broadly classified into three groups as follows:

- *Deterioration of power quality:* This type of problems affect power quality, which is measured in terms of harmonics, power factor, voltage deviation, frequency shift, etc [28]. A larger amplitude at a higher harmonics, a lower power factor, a voltage deviation beyond limit, and an excessive frequency drift from a target value, are indications of a lower power quality. In general, a lower

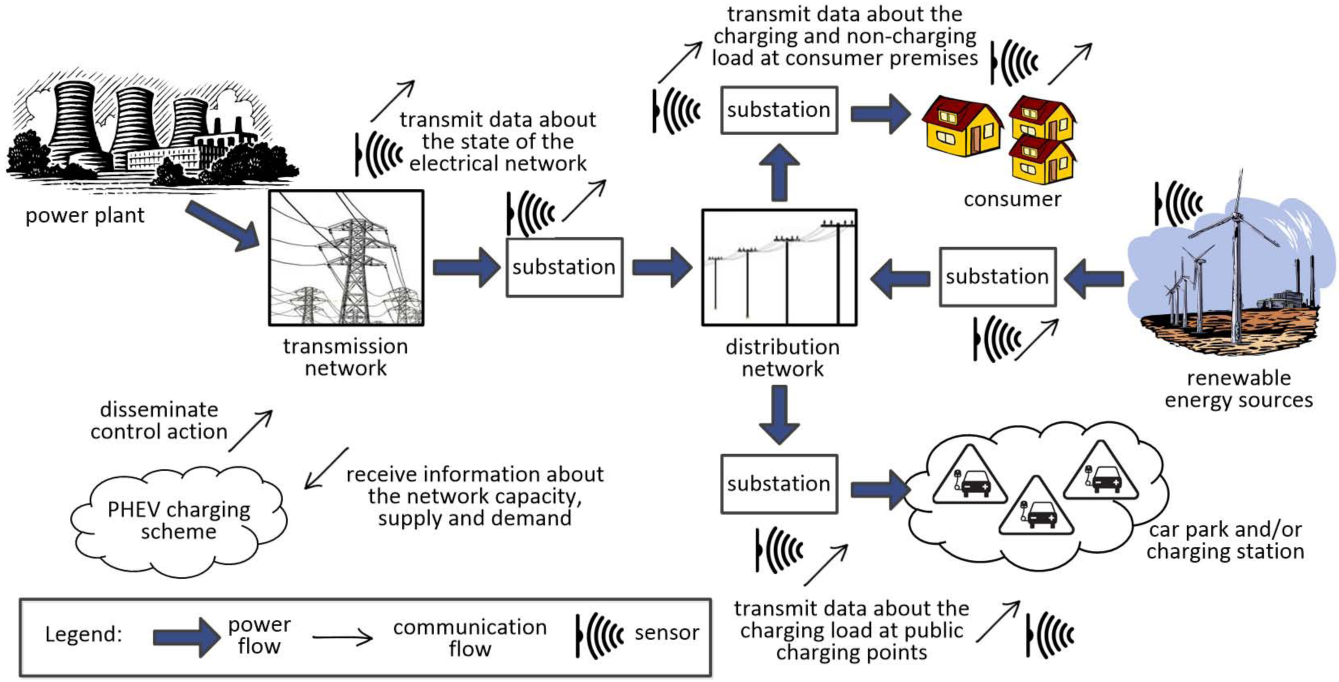

FIGURE 1. Intelligent PHEV charging schemes require support from communication networks. The integration of analog electrical network and digital communication network is the foundation of smart grid.

quality will not immediately disrupt the electrical grid, but it is an indicator for an upcoming serious issue, if no corrective action is taken. Although there is no disruption, a lower power quality may still affect operation of electrical loads. For example, lower voltage may cause malfunctions to home appliances.

- *Instability of electrical network:* This type of problems destabilize and disrupt the electrical networks, leading to power outages, blackouts, etc. When it happens, part of the electrical network will loss the power supply. Practically, preventing network disruption is one of the most important tasks for the grid operators.
- *Degradation of operation efficiency:* This type of problems do not affect the grid's functionality but its efficiency. Higher transmission losses lead to a lower revenue and profit. Consistent thermal overloads speed up equipment aging and thus, require a higher monetary investment for equipment replacement.

From the above, it is desirable to ensure *power quality*, *network stability* and *operation efficiency* of electrical grid. All the three classes of technical problems must be overcome in order to support an increasing PHEV popularity and penetration. In May 2016, there are more than 1.5 million electric passenger cars worldwide [29], but this figure probably represents less than 1% of total passenger cars globally. According to [7], the light-duty PHEV penetration level is expected to reach over 50% by 2050.

In a simplistic way, most of the electrical grid problems which are caused by PHEV charging, is a result of a mismatch between power supply and demand (load). To ensure stability in the grid, the power demand needs to be closely matched with the supply all the times. This matching is difficult to achieve in a dynamic scenario like PHEV charging, where the load is unpredictable and can vary greatly between different hours within a day. This problem is further complicated by the introduction of renewable energy sources, such as solar and wind power into the grid [30]. The output powers of wind turbines are highly variable and intermittent. In the presence of random supply and time-varying demand, intelligent schemes must be designed to coordinate charging at individual PHEVs, such that the instantaneous aggregated load is closely matched to the instantaneous grid capacity. As illustrated in Fig. 1, these intelligent charging schemes require extensive support from communication networks in order to:

- Perform *in situ* and continuous monitoring of the electrical grid and collect data to determine the grid's physical *capacity*.
- Collect and analyze sensor data as well as plug-in requests to determine the real-time power *demand*.
- Collect and process information to determine the accurate power *supply*, available at different parts of an electrical grid.
- Transmit the collected data and information to the executor of intelligent charging schemes.
- Disseminate the control actions as determined by the intelligent charging schemes, to respective actuators.

The dependency on communication networks is well addressed by the concept of smart grid, which adopts and integrates advanced information and communication technologies into the traditional electrical grid [31]–[33].

Smart grid uses digital communication network to supervise and control analog electrical network. Despite the importance of communication networks, there is no agreement in the research community on which particular technology to use in smart grid. There exists a wide range of potential candidates, such as optical fibers, wireless sensor networks, Wi-Fi, WiMAX, satellite communications, etc. Generally, it is believed that different segments of an electrical network as well as different smart grid applications, require different types of communication networks, leading to a highly heterogeneous communication system. For example, transmission network that covers a large geographical area needs a communication technology with large coverage. Also, an application that provides protection to electrical networks needs a communication technology that can offer small delay with high reliability. These communication requirements for the smart grid have been specified in [34] by the Department of Energy, USA. Furthermore, the authors in [35] have provided a brief overview on different communication technologies that are applicable to PHEV charging stations. These technologies include power line communications (PLC), IEEE 802.15.4 (Zigbee), ZWave, and cellular networks. Among these communication technologies, [36] has further proposed a Zigbee based platform to test the various parameters for a PHEV charging station.

Technically, we may treat the intelligent charging schemes as algorithms that run within, and become an integrated part of a smart grid. With accurate and timely information, these charging schemes can rapidly adapt to time-varying conditions for better power quality, optimal operation efficiency, and minimal disruption. As such, the combination of charging schemes and smart grid plays an important role in supporting a further proliferation of PHEVs.

There exists in the literature, a plethora of PHEV charging schemes. In general, these charging schemes determine which vehicle that is plugged-in at which location, has to be charged at which time using which charging profile, so that a certain performance objective can be achieved. For clarity, charging profile is defined as the charging set-point, energy or power as a function of time. We classify these existing charging schemes into four classes, namely uncontrolled, indirectly-controlled, smart and bidirectional charging. The last three classes are collectively called controlled charging. This paper reviews the state-of-the-art of these charging schemes. It aims to serve as an one-stop reference point for new researchers to quickly learn about the key features and technical challenges addressed by existing charging schemes. Our approach is to relate and compare various schemes in terms of their performance objectives and detailed mechanisms. As far as we know, there is no existing survey that covers all types of PHEV charging schemes. The surveys in [37] and [38] have focused only on controlled charging, but the detailed simulation framework uncovered from surveying uncontrolled charging schemes is a valuable reference, even in guiding evaluation requirements for future controlled charging schemes.

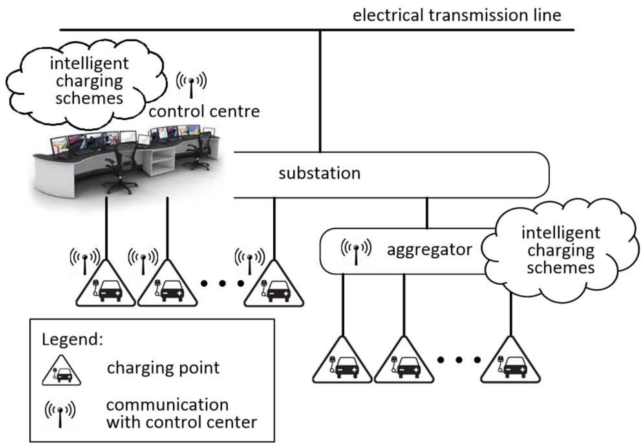

FIGURE 2. PHEV charging schemes are implemented at control center or aggregator.

The rest of this paper is organized as follows. Section II presents a taxonomy for existing PHEV charging schemes. The four classes of charging schemes are surveyed in detailed in Section III, IV, V, and VI, respectively. Section VII discusses some open issues that still require significant attentions from our research community. This paper ends with a summary and some concluding remarks in Section VIII.

II. TAXONOMY

PHEV charging schemes are implemented by the smart grid operators at an aggregator, or a control center, which is located at a transformer or substation. As illustrated in Fig. 2, an aggregator is an entity that combines a fleet of PHEVs and works as the interface between the vehicles and different smart grid entities. The aggregator acts as a proxy between the PHEVs and the smart grid as well as the electricity market, so that the operator needs not directly deal with a large number of vehicles. Such a two-tier hierarchical architecture ensures scalability of the charging infrastructure in supporting a growing PHEV population. Despite the importance of aggregator, most of the existing charging schemes are applicable with and without it. This is especially true when the proposed scheme is evaluated only for a small number of PHEVs. We use the terms aggregator and operator interchangeably hereafter, except in Section VI, where aggregator becomes a necessity for a class of charging schemes.

As mentioned above and illustrated in Fig. 3, PHEV charging schemes can be classified into *uncontrolled* and *controlled* charging. In the literature, uncontrolled and controlled charging are also called uncoordinated and coordinated charging, respectively. Here, coordination refers to the alignment of charging instances and parameters among PHEVs. Therefore, uncontrolled charging makes no attempt to organize and schedule the requests from the PHEVs, but serves them as they arrive. As such, in uncontrolled charging, the batteries start to charge immediately when they are plugged-in, or after a user-specified delay. Uncontrolled charging is reasonable in a scenario where the grid operator

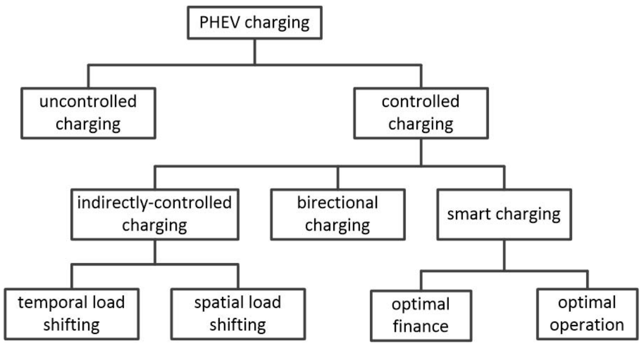

FIGURE 3. **PHEV charging schemes classification.**

does not have the essential information to control the charging profiles, for the purpose of optimizing smart grid stability, operation efficiency and power quality.

Although uncontrolled charging is very simple, it directly exposes the smart grid to volatility and randomness in charging load, which are highly dependent on the driver's behaviors. Consider a scenario during the morning rush hours, where everybody arrives at the company car park at about the same time. In this case, the charging load depends on randomness in the arrival times and promptness in plugging into an electric outlet. Apart from the randomness, the charging load coincides with the daily on-peak hours of the smart grid. The excessive variable load can bring to the grid some severe problems, such as frequency drift, voltage drop, power outage, thermal overload, etc. This justifies the idea of controlled charging, such that not all the plugged-in vehicle are rigidly served immediately upon plug-in.

In controlled charging, the operator organizes the charging moments and parameters to prevent the grid from experiencing unacceptable power quality and suffering disruptive destabilization, at the same time of fulfilling driver's charging demands, and satisfying monetary or operational performance objectives. These objectives can be summarized as follows:

- *Financial performance objectives:* This type of objectives aim to gain direct financial returns. For example, minimizing operator cost, minimizing power losses, maximizing operator profit, maximizing electrical network utilization, etc.
- *Operational performance objectives:* This type of objectives result in an improved power system efficiency. For example, flattening the load curves on main substation transformers, avoiding thermal overload, achieving fairness in charging opportunities among PHEVs, etc.

While operational objectives are not directly related to revenue and profit, they help in saving capital expenditure and investment by reducing aging of transformers and transmission lines, and deferring infrastructure upgrade. This is achieved as the dedicated management and coordination can optimize the charging set-point to reduce aging and will allow the existing electrical network to support a larger PHEV population. While the upgrade of transformers and transmission lines can be delayed, the financial benefit may be partially offset by the need to invest in advanced communication technologies to monitor time-varying conditions in the electrical network and to coordinate charging operations among different PHEVs.

Depending on the types of control parameters, controlled charging can be further classified into indirectly-controlled charging, smart charging and bidirectional charging. In indirectly-controlled charging, the schemes do not control directly the charging parameters, such as charger's power, charging time, charging duration, etc. Instead, these schemes control some out-of-system parameters, that will affect indirectly the charging operation. For example, a scheme may control the energy price that will influence the charging decision of individual drivers in achieving the goal of avoiding grid overload.

Different from indirectly-controlled charging, smart charging schemes control directly the charging parameters. For example, some schemes control the output of electric outlets or the set-point of chargers so that the power can be varied from location to location, as well as from time to time. In this case, a PHEV is not necessarily to be charged all the time when it is plugged-in, because it does not draw any energy from the smart grid when the outlet power is set to zero. Hence, smart charging can effectively turn each PHEV battery into a flexible load, that will impose a demand only if doing so does not risk disrupting the smart grid or violating the power quality requirements.

The benefits of flexible load have been further exploited in bidirectional charging, which is the same as smart charging except one point. Specifically, bidirectional charging supports the vehicle-to-grid (V2G) concept, which allows PHEV batteries to discharge their energy into the smart grid [39]. In bidirectional charging, each PHEV is both a flexible load and a mobile energy source, although there is no obvious difference in other aspects, as compared to smart charging. The benefits of using PHEV batteries as energy sources have been studied in [40]–[42]. Simply, with the bidirectional power flow, PHEV battery can help in further stabilizing the smart grid by returning energy to fill the demand gap, when there is an excessive electricity load. The capability of returning energy to the grid can also help in supporting a greater scale integration of renewable energy into the smart grid. Since renewable sources are intermittent in nature, bidirectional charging allows PHEV to discharge to make up the shortfall in power supply, when the renewable energy is suddenly unavailable.

A. SUMMARY

PHEVs are treated as different types of loads, depending on the charging schemes, as follows:

- *Rigid load:* Each PHEV is an inflexible load in uncontrolled charging.
- *Flexible load:* Each PHEV is a controllable flexible load in indirectly controlled charging and smart charging.

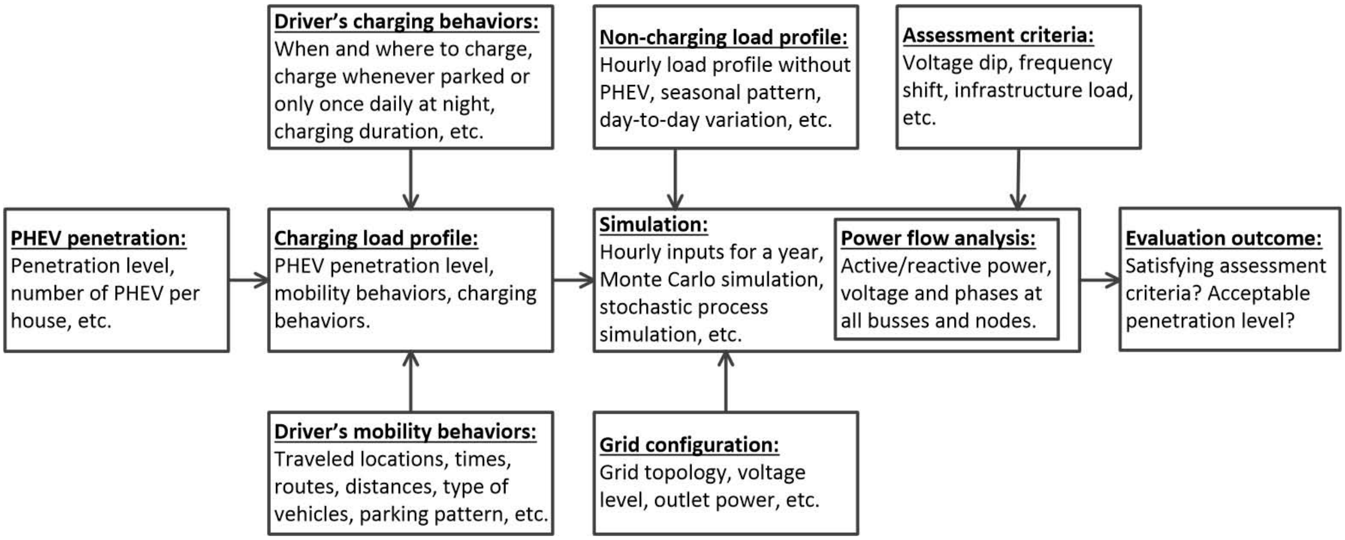

FIGURE 4. Evaluation framework for impact assessment of uncontrolled charging.

- *Mobile storage:* In bidirectional charging, each PHEV is a flexible load when it is charged but an energy source when it is discharged.

Regardless of the sub-classification, all types of controlled charging schemes are practically intelligent demand-supply management schemes for the smart grid. They are designed to match as close as possible time-varying demand and random supply. The objectives are to achieve financial or operational gain, avoiding unacceptable power quality and preventing electrical network disruption, at the same time of fulfilling all driver's charging demands. Different classes of controlled charging schemes are unique in their choice of control actions. These schemes depend heavily on the advanced communication capabilities of the smart grid, to acquire knowledge about the current load and demand states, and to disseminate control decisions.

III. UNCONTROLLED CHARGING

In uncontrolled charging, a vehicle is charged immediately upon plug-in or after a user-specified delay, without any control from the operator. The delay is introduced to give the vehicle owner the possibility of charging their vehicles by using off-peak electricity tariffs. Also, it is normally assumed that once a charging starts, it continues until the battery is full, or the vehicle is used, whichever occurs first.

Due to the lack of control, the research on uncontrolled charging has focused on studying and analyzing the impact of attaching a PHEVs population to the electrical grid [43]–[46]. In general, all the studies have tried to investigate if a certain PHEV penetration level can be supported, or to identify the maximum supportable PHEV penetration level. Despite the similarity in objectives, the existing studies are diverse in assumptions and evaluation settings. These settings can be organized within a common framework as illustrated in Fig. 4. Following the evaluation framework, each impact analysis requires a number of inputs, such as existing (non-charging) load profile, charging load profile, grid configuration, and assessment criteria.

A. NON-CHARGING LOAD PROFILE

In the common framework, non-charging load profile measures the total electricity demand in the absence of PHEVs. The difference between non-charging load and smart grid capacity quantifies the amount of PHEV charging load that can be supported. The non-charging load is provided in terms of load curves of various time scales. For a simple case, the curve shows how the load varies over the time within a day, and 365 copies of the same curve are concatenated to form the load profile for a year, where one year is the typical duration for an impact evaluation. This simple way of modeling non-charging load may not be ideal because in reality, load curves may be different from one day to another day. For a better accuracy, [47]–[50] have formed a set of daily load curves based on recorded measurements, and uniform randomly select a load curve from the set to represent each day in a year. However, this method is not perfectly accurate, because it does not take into consideration the different probabilities between weekdays and weekends.

To capture the fact that weekday occurs more frequently than weekend, the authors in [51] have proposed a non-uniform selection from a set of daily load curves. First of all, 8,760 data points of hourly load are collected for a year. These measurements are normalized in multiple stages such that the weekly peak load is first represented as a percentage of the annual peak load and then, the daily peak load is represented as a percentage of the weekly peak load. Finally, the hourly peak load is represented as a percentage of the daily peak load. This process will produce 365 daily load curves, each has 24 normalized hourly data points. These daily load curves are then grouped into six clusters using principle component analysis, such that all members in a group are more similar to each other, compared to a member from another group. Specifically, several clustering algorithms such as k-mean, fuzzy c-mean and hierarchical clustering have been tested, and fuzzy c-mean has been found to yield the best clustering results. Given the clustering, an average daily load curve is constructed for each cluster, and a probability mass function (PMF) is subsequently formed indicating the chances of occurrence for each cluster. The PMF is used to pick one of the 6 average daily curves to represent each day in a year.

In addition to the effect of different days of a week, non-charging load may also be affected by the different months of a year, especially in countries with distinctive four seasons. As presented in [47], the daily load curves have a seasonal pattern where the energy consumption is the highest in winter due to heating requirements. This seasonal effect has also been accounted for in the non-charging load model in [52].

There exists some works that differentiate residential load from commercial and industrial load [51], [54]. Commercial and industrial loads are classified based on the associated economic activities. For example, energy consumed by shopping malls and restaurants is considered as commercial load, and consumption data is collected only for weekdays. On the other side, energy consumed by factories and mills is considered as industrial load. The authors in [55] have discovered that, compared to residential load, commercial load has a lower variability from day to day, but industrial load exhibits an opposite characteristic. The larger variation in industrial load is due to the fact that most industrial activities use small size motors, with an intermittent mode of operation during the day. To the best of our knowledge, we have not discovered any published work that uses a separate industrial load curve. Both [51] and [54] have used a single daily load curve for commercial load.

B. CHARGING LOAD PROFILE

Providing an accurate charging load profile is a challenge because the load depends on PHEV penetration levels and driver's behaviors, where the behaviors are human nature which are difficult to model precisely. The driver behaviors can be further classified into mobility behavior and charging behavior.

- *Mobility behaviors* describe the PHEV's traveled locations, times, routes, distances, type of vehicles, etc. These behaviors affect the charging load through their influence on daily traveled distance, visited location, home arrival time, battery SOC, parking availability, etc.
- *Charging behaviors* describe the user's seeking of charging opportunity. These behaviors affect the frequency of charging (once a day at night, or whenever there is a chance), charging location (at home, work or car park), charging duration, etc.

Some drivers may charge their vehicles whenever they are parked and there are available electric outlets. In this case, a vehicle may be charged several times in a day and the charging duration is the interval between two consecutive trips [48], [56]. On the other hand, some drivers may charge their vehicles only once a day at night after arriving home following the final trip, and the charging duration covers the time until the first trip in the next day [57], [58]. According to [59], most of the drivers are expected to adopt the slow overnight charging options, and only 10% of PHEV drivers charge their vehicles multiple times in a day. These charging behaviors affect the load through the driver's selections of when and where to charge, as well as the charging duration and the battery's *initial SOC*. Here, initial SOC is defined as the SOC value right before charging starts.

Although there is no argument that driver's mobility and charging behaviors have an impact on the charging load, there is no common agreement in the literature on how to account for these behaviors in calculating the load. In a simple way, these behaviors imply that charging load profiles can be different at different locations, instead of uniformly distributed over the electrical grid. Specifically, the load size should be different at home, workplace and shopping mall, at a given time. The authors in [53] have produced three different daily load profiles, for residential, office and commercial areas, respectively through simulations. For commercial load profile, the simulation parameters are configured based on shopper traffic volume. However, not all the simulation parameters have been clearly justified.

The authors in [54] have used demographical data from a Swedish travel survey to determine the charging load size at work, home and shopping areas. The demographical data includes number of workplaces, vehicle density and number of employees, etc., for an area. As an example, the load size at home at night is determined by multiplying the expected number of employees living in an area with the expected fraction of vehicles travel to home. The number of employees in the area is calculated as the total number of employees surveyed multiplied by a proration factor, where the factor is given by the number of household in the area divided by the total number of households surveyed.

Considering each PHEV as a mobile load that can be added to a static grid topology, the authors in [48] have proposed a Markov chain model to determine the location where the load is added to the grid. The model consists of four states, namely *in movement*, *parked in a residential area*, *parked in a commercial area*, and *parked in an industrial area*; representing the condition that a vehicle is in. The probability of being in a particular state depends on the transition probability matrix of the Markov chain, where the matrix has been empirically constructed using the mobility data collected from drivers in Portugal. The model assumes that the driver plugs-in the vehicle whenever it is parked, and therefore, a load is added to the corresponding location in the smart grid as indicated by the type of parked location. Specifically, when the Markov chain model decides that the vehicle is in the state of *parked in a residential area*, a corresponding charging load is attached to one of the buses which have been configured as ''residential''.

In [48], each PHEV is represented by a Markov chain, which is discrete-time in nature and the state transition occurs once every 30 minutes. As the simulation progresses, the location of each PHEV changes from time to time and thus, the charging load varies from location to location. At any location, the load size introduced by each PHEV is defined as the difference between battery capacity and its initial SOC. Identical to [60]–[62], [48] has assumed that the initial SOC is a random variable following a truncated normal distribution. In different works, the initial SOC has been assumed to follow a log-normal distribution [60], [63]. In a few cases, the initial SOC has taken some deterministic values, such as 0% in [47] and 30% in [64]. The use of deterministic values for initial SOC without justification is not realistic, because it does not consider the randomness in driver's behaviors.

As a more accurate way to model the initial SOC, the authors in [51] have determined the value as a function of trip distance, vehicle type, and the SOC before the trip begins. As indicated in Table 1, vehicle type is an important parameter in the function because it affects the energy consumption to complete a trip. In [51], the initial SOC is a random variable because the trip distance is a random variable, with its probability density function (PDF) determined using some recorded measurements of driver's mobility behaviors. Unfortunately, the function in [51] does not capture the dependency between trip duration and the energy consumption during the trip. Specifically, the model does not enforce a logical fact that a longer travel duration will lead to a lower SOC after the trip. This dependency between trip duration and energy consumption that has been overlooked in [51], has been included in the Markov chain model in [65] based on vehicle mobility data collected in Sweden.

Recall that, in [48], all parked PHEVs are assumed plugged-in for charging. This may not be the reality, because some drivers may decide not to charge the vehicle if its SOC remains high and the parking duration is short. This decision may involve subjective judgment, which vary from person to person. For example, 30 minutes parking duration may be considered short by a driver, but the opposite by another driver. This subjective decision making process has been emulated in a fuzzy logic model proposed in [56]. With the fuzzy system to model each driver and all drives make independent decision, the charging load at each location can be calculated more accurately, because the number of plugged-in vehicles does not necessarily equal to the number of parked vehicles.

It is reasonable that the charging load at a location depends on the number of plugged-in vehicles at that location. When there are multiple vehicles plugged-in at a car park or a charging station, the authors in [62] have proposed a model to compute the aggregated charging load at that location. This model assumes that PHEVs arrive to a location following a Poisson arrival process, and their initial SOC is a random variable following the truncated normal distribution, as described earlier. Hence, the aggregated charging load is a function of two random processes. In [62], the PDF of aggregated load is determined and refined dynamically throughout a simulation. Specifically, a load PDF obtained in a current simulation stage, is used to determine the parameters for the Poisson arrival process and the truncated normal distribution, to be used in the next simulation stage. Theses parameters are determined using a genetic algorithm such that the difference between the theoretical load PDF and the observed one is minimized. These parameters, that appear in the forms of the vehicle arrival rate and the bounds in initial SOC, are useful to evaluate the impact of uncontrolled charging, with self-improving accuracy. However, a large number of data points are needed to construct a truthful PDF at each simulation stage, and it is not clear if sufficient data points are available at each stage.

The use of Poisson arrival process in [62] to model PHEV arrivals has also been adopted by [66] and [67]. However, [47] has used a different method, where the number of plugged-in vehicles in a given period is determined by analyzing the probability of making a trip in that period, such that a parked vehicle is considered plugged-in. The authors in [47] have not mentioned how the probability distribution can be determined. On the other hand, the authors in [57] have analyzed the mobility behaviors of some German full-time employees to determine a PDF for the time that vehicles complete their final trip of a day. Based on this PDF, the number of plugged-in vehicles in a given time period is assumed equals to the number of vehicles that have completed their final trip of a day in the same period.

C. GRID CONFIGURATION

As another input to the evaluation framework, different smart grid configurations have been considered in the literature. Here, grid configuration describes the grid topology, voltage level, power rating of charging outlets, etc. Due to its simplicity, single line radiant network topologies are often used in the literature [47], [49], [68], [69]. In [68] and [69], the evaluations have simulated an IEEE 37-node residential feeder network. The network size is reduced to only 34 nodes in [47] and [49]. Also, the authors in [68] have considered the location distribution of the houses and the number of PHEVs per house, but the authors in [47] have allowed only a maximum of one PHEV at each house.

A larger network with two-level hierarchy has been considered in [70], where an IEEE 31-bus network represents a 23 kV distribution system. Out of 31 buses, 22 of them are further modeled by an IEEE 53-node system each, where every 53-node system represents a 415 V feeder network in a densely populated residential area. Compared to the approximately 1,000 users in [70], the authors in [71] have adopted a large-scale distribution network within an urban area with more than 6,000 low-voltage residential users. Instead of focusing only on residential areas, [71] has also used a grid topology that covers a medium-voltage industrial and a low-voltage residential area with over 61,000 users. As shown in Table 2, another aspect in grid configuration is the output power of the charging outlets. In [47], [49], [68], and [70], all the outlets have a same power of 4 kW considering only the slow charging option. To evaluate the impact of fast charging

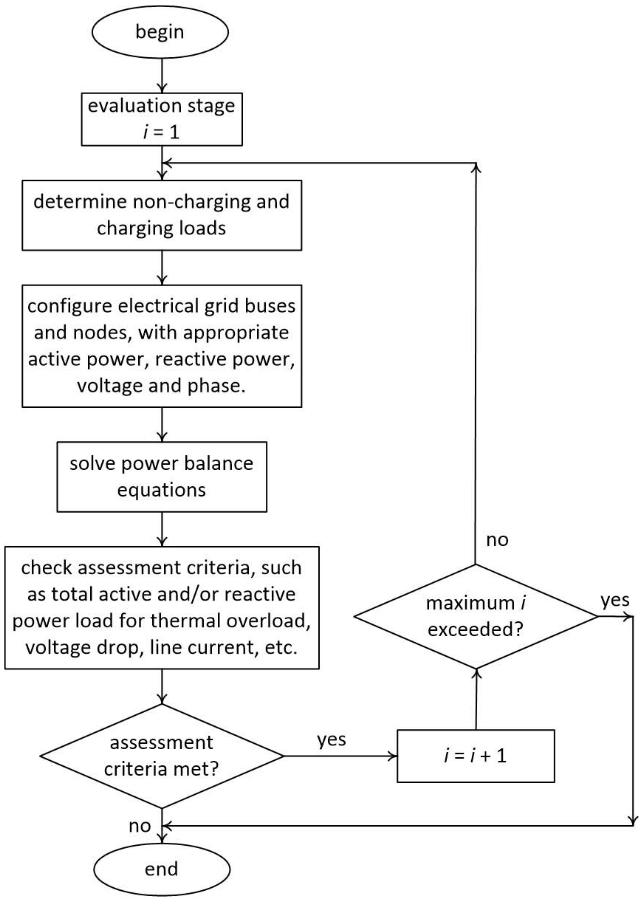

FIGURE 5. Assessment flow chart for uncontrolled charging with power flow analysis.

options, the cases of two outlet powers have been studied in [56], [69], and [72], and the cases of three outlet powers have been examined in [17] and [71].

D. ASSESSMENT

With the various inputs entered into the evaluation framework, power flow analysis is performed, where the non-charging load and charging load are used to configure the active and reactive power at each node or bus on the grid. As illustrated in Fig. 5, the power flow analysis determines the voltage and phase at buses and nodes, as well as the current in transmission lines. One power flow analysis is needed for each set of inputs, and there are often 8,760 sets of hourly inputs to evaluate the performance over a simulated one year period. These hourly data sets can be produced through Monte Carlo methods which assume statistical independence between two successive hours [51], or through time-progress stochastic process modeling that does not assume time independence [48], [65].

Although there is a consensus that uncontrolled charging imposes an upper limit in the PHEV penetration, the actual value of the upper limit differs from one publication to another. For example, [68] has shown that the supportable penetration level is 30%, but the same limit reported by [47] is only 20%. While the results in [47] and [68] have not considered infrastructure upgrade, [71] has reported that 60% penetration level can be supported with a corresponding 40% increase in power losses during off-peak hours, and a marginally higher capital investment for new infrastructure. But, it is not clear what is the quantity of this ‘‘marginally higher’’ investment. On the other hand, where the electrical grid is reconfigurable by opening and closing some circuit breakers, 70% to 100% penetration levels have been reported in [54] as suppotable. The differences in reported findings are due to the variation in evaluation settings, which include grid topology and grid capacity, as well as the selection of assessment criteria. Specifically, [68] has assessed the tolerable penetration level by observing the percentage of transformer load such that it does not exceed 100%. Using a different criterion, [47] and [71] have assessed the acceptable penetration through maximum voltage deviation which is set to 5% and 10%, respectively. The assessment criteria in [54] is both 10% maximum voltage deviation combined with thermal limits at transformers and transmission lines. Generally, higher supportable penetration levels are found in studies that assume PHEV charging at home in the night. This highlights the fact that most of the spare grid capacity is available only at off-peak hours.

E. SUMMARY

Based on the survey above, it seems that it is difficult to compare and reuse most of the results from the rich set of existing studies on uncontrolled charging. This is due to the lack of common evaluation settings, and the fact that results have been obtained through simulations. There is a large number of simulation parameters, but not all the parameters have been considered in each evaluation and study. Furthermore, a small difference in simulation configuration can lead to a large variation in results, or can even challenge the results reproducibility. In some cases, important parameters have not even been specified. Specifically, the transmission line impedances have a significant effect on the power losses and voltage deviation at each node and bus on a grid topology. But, these impedances have not been stated or vaguely mentioned in most cases. There is a need to establish some standardized simulation platforms and use-case scenarios for the purpose of synchronizing research efforts in the community. With a consistent evaluation framework, platform and scenarios, results from different parties can be cross-verified and redundant works can be avoided, leading to more rapid progress in the knowledge discovery process. This standardized evaluation framework is not only useful for studying uncontrolled charging, but will have significant benefits in understanding and designing future controlled charging schemes.

Simulations can be excessively computational expensive in some cases, and analytical results can be helpful in obtaining quick results for system wide planning. The lack of analytical result can be attributed to the complex nature of power balance equations that are needed in power flow analysis. It will

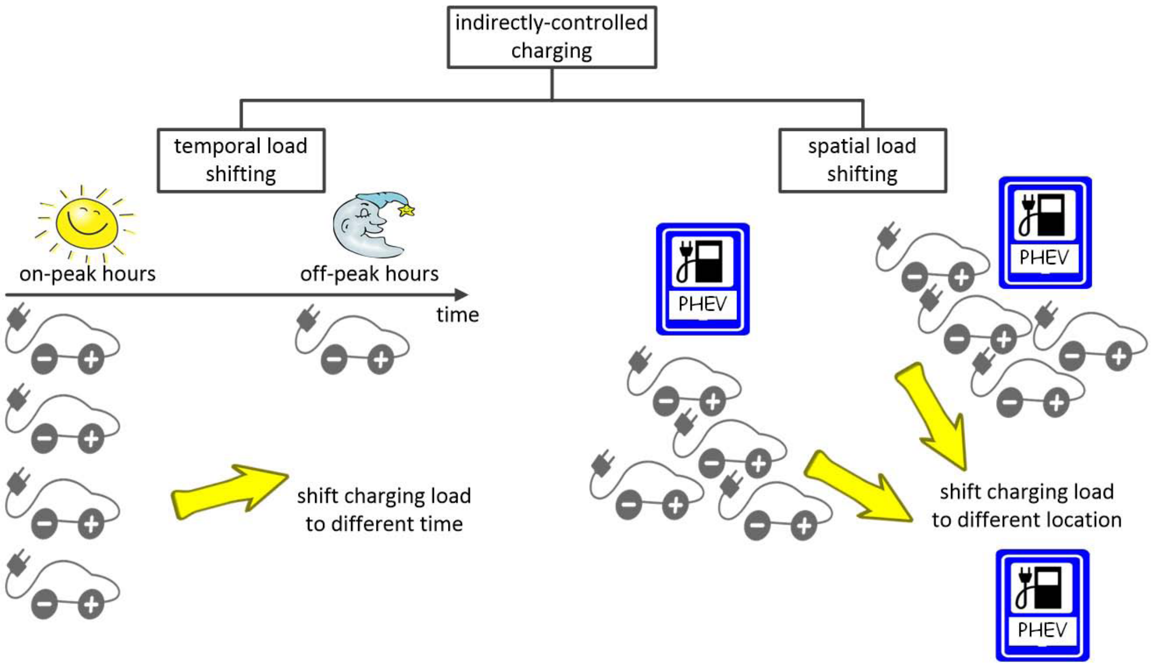

FIGURE 6. Classification of price-based indirectly-controlled charging schemes.

be beneficial if some forms of linear approximations such as the one in [73], can be applied in power flow analysis to derive useful closed-form expressions to characterize system level performance metrics.

IV. INDIRECTLY-CONTROLLED CHARGING

Indirectly-controlled charging schemes manipulate out-of-system parameters, such as energy price and charging cost that affect the charging operation. Through this indirect control of charging, the schemes aim to maintain grid stability, power quality and operation efficiency while supporting an increasing penetration of PHEVs. It is expected that increasing energy price during on-peak hours can shift some charging load to off-peak hours, when spare grid capacity is available, and thus preventing grid overload. As illustrated in Fig. 6, the charging schemes that shift the load in time domain by controlling prices are called *temporal load shifting* schemes. There exists another class of indirectly-controlled schemes, which are called *spatial load shifting* schemes. These schemes control the prices in order to shift spatially the charging load from an overloaded location to other non-congested locations.

A. TEMPORAL LOAD SHIFTING

According to [74], if electricity is dynamically priced depending on the time-of-day, PHEV charging load can be shifted to late night hours when other demands for electricity are low. Assuming that all users are attracted to the lower price and their energy consumption will be shifted to the off-peak hours as long as the grid can support the load, the on-peak demand will increase only by less than 10% of what is originally expected without the dynamic pricing.

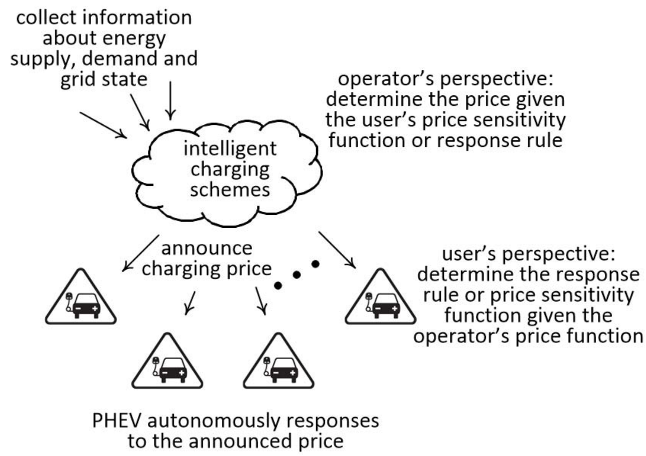

FIGURE 7. Different perspectives in price-based indirectly controlled charging schemes.

The effectiveness of controlling PHEV charging through the adjustment of energy price, depends on the price difference between the regular electricity price and the off-peak tariff. This relation has been studied in [75] in the context of motivating users to switch from uncontrolled to controlled charging. It has been found that, in order to motive a change, there is a minimum requirement in the price difference between schemes. The required price difference is user dependent and is a function of the user's price sensitivity. A bigger price difference is needed to motivate a user who is less price-sensitive. However, [75] has not provided any detail for the price sensitivity functions.

In a case where the user price sensitivity functions are known, charging schemes can be designed to influence the charging decision of individual PHEVs [32], [76], [77].

This is possible assuming the drivers are rational in the sense that they want to pay the lowest price to satisfy their individual charging demands. As illustrated in Fig. 7, the charging scheme will determine an appropriate price while satisfying its performance objective, such as maximizing operator profit, minimizing power losses, etc. The price will then be announced to PHEVs, which will autonomously response to the price. The scheme's objective can be achieved if the PHEV responses are indeed in accordance to the known price sensitivity functions.

In [78], the price sensitivity function is defined as a generic function with a negative derivative. As such, an increased price will lead to a lower charging demand. Given such a function definition, the authors have formulated an optimization problem that can be solved using dynamic programming to find the price that maximizes the operator's revenue, subject to technical limitations of the electrical grid. This work is unique in the sense that it proposes to set two prices, one for local drivers, and another one for visiting drivers. The price for visitors is higher than that for locals. The authors have argued that this differential pricing is necessary to avoid local users from being charged unfairly high when visitors compete for charging opportunity during peak hours. This is not a very strong argument because when there is a congestion at a particular spatial-temporal point, the visitors should be given a higher priority so that they can return home instead of abandoning their vehicles to walk home, while locals are already close to home. Penalizing visitors may amplify range anxiety and will not help the proliferation of PHEVs.

Following the same model as in Fig. 7, instead of deriving a scheme to dynamically find the optimal price, some works have assumed that the price will change according to a known function. For example, it is common to assume that the operator will set a price which is an increasing convex function of the aggregated charging load [79], [80]. In this case, focus of the research is no longer in setting the price, but in setting rules to govern the autonomous behavior among PHEVs. We call this rule the *response rule*, and it is equivalent to the user's price sensitivity function mentioned above. The common rule for all PHEVs rule is necessary to avoid a chaos, because the action of a PHEV may alter the aggregated load and thus, affect the price that will be effective on all PHEVs. In the literature, this kind of charging schemes that define response rule, are known as scheme with user's perspective, as compared to operator's perspective [81].

From a user's perspective, [82] has applied flow control theory from communication networking for PHEV charging control. In this scheme, the aggregated load is a combined result of all autonomous responses. Due to the autonomy, the price may take a few iterations to stabilize. For example, after a price is announced, the aggregated load may result in a new price which is considered low (high) to most of the PHEVs. Thus, a higher (lower) price will be announced in a new iteration. The process continue until the new price attracts only a statistical stationary collective response from the PHEV population. It has been shown that, given the convex price function and rational driver behaviors, charging price and charging demand will both converge to some desired values that can be controlled by assigning different weights to different drivers. In this context, the weight can be used to differentiate PHEVs such that a higher paying PHEV is given a larger weight to receive more charging energy in average.

The above idea in [82] has been extended in [83] to take into account the case where the number of PHEVs is time-varying. Assuming charging is performed only at home, the number of PHEVs is a random variable because their arrival times in a certain day are random variables. The authors in [83] have derived a response rule that helps individual PHEV to decide its charging start time so that the charging process can be completed by a desired deadline, at the minimum cost. The rule is player's strategy within a game theory framework, where the players are the individual PHEVs. A very similar problem and a solution to [83] have been presented in [84]. Apart from the fine mathematical details in deriving probability distribution functions for various random variables, the basic difference between [83] and [84] is in the definition of the price function. In [83], the price is a convex function of total load. But, in [84], the price is a function of total-load-to-power-generator-output-ratio. This normalized aggregated load in [83] is indeed a more accurate representation of loading conditions.

In a different scheme which is on user's perspective, the price function is unknown *a priori* but it can be predicted [85]. Assuming that dynamic prices are regularly received at charging points (outlets), the authors have used the k-nearest-neighbors (KNN) algorithm to predict an upcoming price based on previous prices. KNN is a simple classification algorithm that does not require complex model fitting operation, which is otherwise commonly required in time-series based methods. The authors have divided the price range into a number of non-overlapping segments, where each segment is considered a class. Then, the KNN algorithm is continuously trained on the classification using some immediate data points within a moving time window. After the training, the next price is predicted using just two most recent prices. The scheme has proposed a very simple response rule, where the predicted price is compared against a threshold value. If the predicted price is above the threshold, the PHEV will not start its charging. However, there is no mention on how to pick an optimal value for the threshold.

The authors in [86] have proposed a scheme that covers both operator's perspective and user's perspective. Assuming that the energy cost is a convex function of total charging demand, the operator will set price to minimize cost while fulling all demands by their respective deadlines. The determined price implies a desired charging load profile. To enforce the load profile, the scheme further derives an optimal response rule that must be followed by all PHEVs.

Similar to [86], the charging scheme proposed in [87] covers both the operator's and user's perspectives. In [87], the objective is to flatten the aggregated load profile.

Also, compared to [86], this scheme has not derived an optimal response rule for the PHEVs, but has imposed requirements on how the individual PHEVs should response to an announced price. At each price setting moment, the scheme takes into consideration technical limitations of the grid in terms of the maximum charging output at each charger, and PHEV's charging deadline. After receiving the price, each vehicle autonomously determines their own charging profiles, and inform the operator about the decision. Upon receiving the reported charging profiles, the operator updates the price to guide the PHEV's behaviors. The authors show through analysis that this iterative scheme is guaranteed to converge, regardless of the maximum charging powers and charging deadlines of individual PHEVs. The analysis also shows that the flatness of the load profile is optimal at the convergence. The problem settings and iterative solution framework of [87] are similar to [82], with [87] has taken into consideration physical limitations in price setting.

A dual perspective problem similar to [87] has been solved in [88] using game theory. In [88], the objective is to determine the appropriate price to flatten aggregated load profile and minimize cost. Since all PHEVs will response to a same price by autonomously choosing their own charging profiles, the PHEVs are effectively interacting with each other through the average charging profile of the entire population. For a very large (infinite) population, the effect of each individual PHEV on the average charging profile is negligible. Thus, the average charging strategy seen by every PHEV is identical. Following the Nash certainty equivalent principle, a collection of individual charging profiles is a Nash equilibrium if: (a) each of the individual charging profile is optimal with respect to a commonly observed charging profile, and (b) the average of individual charging profiles is equal to the commonly observed charging profile. Exploiting this principle, the operator will set price using any increasing function of the total charging and non-charging loads. The authors in [88] have shown that, using such a price function at the operator can ensure load profile flattening. At each individual user, the response function will find the local charging profile to minimize the individual charging cost plus the sum square of deviation from the average charging profile of the entire PHEV population. The authors have shown results that load profile is indeed flatten. However, to implement such a scheme, the operator needs to collect in each iteration, all individual charging profiles to compute the average profile before announcing it with a new price. We are not sure how this can be done efficiently through a practical communication network.

In the literature, mathematical functions, such as concave function [89] and linearly decreasing function [89]–[91] have been used to describe user's price sensitivity. As described above, such functions are useful in developing model-based pricing schemes [78] and in facilitating performance analysis [82]. However, these functions may not be a very accurate representation of the actual user behaviors. For example, it is hard to believe that in reality, a driver's desire to charge their vehicles decreases linearly with an increasing electricity price regardless all other factors. The absence of suitable and simple mathematical functions is partly due to the complexity in human behaviors. Different drivers may react very differently to a price change, and may adapt too quickly to a changing environment, beyond the representation of a simple universal mathematical expression.

When there is no mathematical function that can accurately describe user's price sensitivity for model-based schemes, dynamic price adjustment scheme can still be developed based on observation or measurement. In [89], a regression scheme, namely additive-increase-multiplicative-decrease (AIMD) has been proposed to adjust the charging cost at a charging station in a timely manner in response to the difference between a desired vehicle arrival rate and a measured value. Here, an arrived vehicle is one that demands charging. The proposed AIMD scheme will linearly increase the price to slowly decrease the charging demand when the vehicle arrive at a faster than desired rate. On the other hand, the price will be exponentially decreased when the vehicle arrival rate is too high.

B. SPATIAL LOAD SHIFTING

Comparing [89] to [88], we notice that, in additional to shifting of charging load to off-peak hours, [89] can also shift load spatially from one location (charging station) to another location. Spatial shifting of load is justifiable considering the case where different stations have different capacities, and a lower cost can be offered by the station with a larger capacity to attract more drivers or customers. Regarding the spatial load shifting scheme in [89], the performance objective is to minimize the vehicle's waiting time to reach an available charging outlet. The authors in [89] have assumed that vehicles arrive according to a Poisson arrival process and the charging durations are exponentially distributed random variables. Therefore, the simple M/M/1 queueing model can be used to determine the waiting time at each charging station. In the queueing model, waiting time at each station is a function of vehicle arrival rate. As such, [89] has proposed to differentiate the prices among stations to control the arrival rate at each station to achieve its performance objective through shifting of load to different locations.

For a different performance objective, the authors in [92] have proposed a scheme to control the charging prices at difference stations as a mechanism to guide the dispatch of a large electric taxi fleet. By optimally dispatching the right number of taxis to different areas after taking into consideration the respective area's grid capacity, the service quality and operating efficiency of taxi system can be improved. The assumption is that the proportion of taxis serving an area is statically the same as the proportion of taxis at the charging stations in that area. Since taxi drivers are cost-sensitive revenue seekers, the number of taxis at a charging station can be increased by lowering the station's price. In [92], the price at each station is determined using a Stackelberg (leader-follower) game model, which consists of 2 stages. In the first stage, the single service provider that controls all the charging stations, acts as the leader, and announces the prices and waiting times at each station. The waiting time here is determined using a different method than that in [89], and it is inversely proportional to the number of idle charging outlets. In the second stage, all the electric taxis act as followers by responding autonomously to the announced price in such a way that individual cost is minimized. In this game, different players in the second stage interact with each other through the waiting time. Specifically, an action of one driver may affect the decision of the other drivers through the changes in waiting time.

In [89] and [92], the prices for different stations are controlled centrally by a single service provider. In a competitive market place, different charging stations may be operated by different service providers. These providers may adjust their prices competitively to maximize individual profit. This competition among multiple charging stations have been formulated as a Bertrand's oligopoly game in [90]. In such a game, the aggregated charging load is considered fixed despite the changes in price, and charging stations compete by setting their individual prices to attract the right amount of load to maximize profit. In this model, different charging stations interact with each other through the constant total demand where a cheaper price at a competing station will lower the charging load at other stations. In [90], when a PHEV needs to charge its battery, it obtains location information of all its near-by charging stations and sends charging request to them. Upon receiving the request, each station responses with its individual charging price which is determined by using the Bertrand's non-cooperative oligopoly game model. The vehicle selects the best charging station after assessing all the received prices and the travel distance to the stations. Here, travel distance is considered because it is a cost to the driver. It is not reasonable to drive a long distance to a charging station that offers only a negligibly lower price.

A similar problem of competitive charging price setting in [90] has been formulated as a supermodular game in [93], where such a game has a guaranteed equilibrium even for pure strategy. Through the game theoretic model, each charging station set and announce its price periodically. The price is determined to maximize the station's profit, where relevant physical constraints such as the transmission line capacity, the number of charging outlets at a station, the energy cost from grid and renewable source, and the number of potential customers are taken into account. Here, the customer numbers at each station are affected by prices announced by different stations, where a driver will select the station that offers the lowest cost after considering the travel cost to the station. Compared to [90], the game model in [93] has considered more parameters in a realistic smart grid system. However, the authors in [93] have assumed that the station selection by a PHEV has no impact on other PHEVs. This may not be true because PHEVs will suffer from a longer waiting time if all vehicles select a same station, and a driver must wait for its turn when all charging outlets are occupied. In practice, a driver may avoid a cheaper charging station for shorter waiting time. Such a dependency between drivers through waiting time has been described earlier in this subsection for [89] and [92].

Similar to [89] and [92], the dependency between PHEVs has been considered in [91] through the formulation of waiting time as a function of charging prices of all stations. In [91], the competitive price setting problem has been formulated as a 2-stage Stackelberg game, where the stations are the leaders and the PHEVs are the followers. This Stackelberg game is different from the one in [92] in the sense that all stations in [92] are centrally control without non-cooperative competition among them. In the first stage in [91], the charging stations determine and announce their charging prices to maximize individual profit. In the second stage, PHEVs select their respective charging stations, taking into account the price, travel distance and waiting time. The 2-stage Stackelberg game always has an equilibrium which depends on the charging station's capacity and the price difference between the stations.

In addition to dynamic control of charging price, spatial load shifting can also be achieved through network planning. In a significantly different approach, the authors in [94] have formulated a planning problem to minimize system level power losses by optimizing the number of charging outlets that are installed at different parking areas. The planning problem would install fewer outlets at an area that suffers from higher power losses and receives less PHEV visitations. The problem formulation has taken into consideration the typical charging profiles of PHEVs, and the statical characteristics of vehicles that appear at different parking areas.

C. SUMMARY

Indirectly-controlled charging schemes play an important role in exploring the use of dynamic electricity pricing, e.g., differential day-night pricing, real-time pricing, etc., to meet the growing PHEV charging needs while preventing grid overload. Accurate price setting to shift charging load requires an accurate understanding of the user's price sensitivity. Unfortunately, existing works have adopted simple mathematical functions for price sensitivity for tractability in performance analysis and optimal control development. The accuracy of these price sensitivity functions should be verified. Accurate price sensitivity function must be used, or the research may remain academic in nature.

Compared to the literature for uncontrolled charging that depends on detailed power flow analysis to verify the impact of charging load on smart grid, the competitive pricing research has not focused on power flow analysis. As such, the actual impact of such price-based charging schemes on the smart grid may need further investigation.

In spatial load shifting, existing game theoretic schemes have used waiting time for a charging outlet as a metric to influence the distribution of PHEVs among different charging stations. The formulation of these waiting times have not taken into account the difference between fast and

TABLE 3. Smart charging schemes.

Optimal Finance			
Performance Objective	Scheme	Control Variable	Solution Technique
Minimize power losses	Min. losses subject to voltage deviation and charger output power [47], [49]	Charging start time	Iterative quadratic programming
	Max. load factor or min. load variation [95]	Charging profile	Convex optimization
	Min. cost subject to voltage deviation and total load [96]	Charging profile	Use loss sensitivity as criterion in selecting charger with the least loss
Maximize profit	Max. profit and fulfill demand subject to technical limits of grid [97]	Charging profile	Multi-stage mixed integer liner programming
	Max. profit considering traced-based mobility [98]	Charging profile	Mixed integer linear programming + heuristic
	Max. profit from offering regulation to grid operator [99]	Charging set point	Linear programming
	Min. cost from day-ahead wholesale price plus real-time dynamic dispatch [100]	Charging time	Linear programming solved by heuristic
	Min. cost from day-ahead wholesale with market coordination among aggregators [101]	Charging time	Linear programming + Lagrangian relaxation
	Min. cost to charge a fleet of taxis and private cars [102]	Charging profile	Quadratic programming
	Max. utilization subject to available energy supply [103]	Which PHEV to charge	Heuristic
	Max. utilization subject to energy electrical network's technical limits [104]	Charging power	Linear programming
Optimal Operation			
Performance Objective	Scheme	Control Variable	Solution Technique
Minimize load variation	Min. load difference between two successive time intervals [105]	Charging profile	Genetic algorithm
	Min. load deviation from a constant ideal load level [106]	Charging time, power and duration	Quadratic programming
Maximize fairness	Equality in charging opportunity [107]	One unit of energy per PHEV per unit time	Heuristic
	Min. deviation from average SOC [108]	PEHV decides its own charging profile	Heuristic
	Equality and necessity [109]	Charging profile	Semi Markov Decision Process
	Avoid overload and achieve fairness [110]	Charging time	Packetization of charging demand for probabilistic requests

slow charging, which will significantly affect the overall performance.

V. SMART CHARGING

Compared to indirectly-controlled charging that can only control out-of-system parameters, smart charging controls directly a set of charging parameters, such as output powers at different chargers, charging time patterns, etc. The control can be flexibly applied to only a subset of the vehicles in different ways, but not necessarily to all vehicles in a homogeneous way. With an increased flexibility in control, [47] and [68] have shown that smart charging can support a significantly higher PHEV penetration, compared to uncontrolled charging.

Smart charging schemes are often developed through the formulation of constrained optimization problems, where the constraints are to keep power quality within acceptable limits, to prevent disruptive grid destabilization, and to satisfy all charging demands. In these formulations, the controllable actions are the optimization variables. Other non-controllable parameters are information that must be collected from or provided by the smart grid. As introduced earlier in Section II, there is a diverse set of performance objectives, such as minimizing power losses, minimizing cost, maximizing profit, improving voltage regulation, etc, which can be classified into operational or financial objectives. In this section, as summarized in Table 3, we organize the surveyed smart charging schemes according to their performance objectives, and group them into *optimal finance* and *optimal operation*.

A. OPTIMAL FINANCE

Different chargers at different locations suffer from different power losses, depending on the characteristics of the eletrical network. These characteristics include the length of the cables between the charger and the substation, as well as the cable impedance. The lost power cannot be sold to the user and cannot be used to perform works. Therefore, power losses affect operator's revenue and profit.

In [47] and [49], a scheme has been proposed to minimize power losses, while maintaining the voltage deviation at each bus within an acceptable limit and keeping the output powers at all chargers below their maximum ratings. In this scheme, all PHEVs are assumed to have been plugged-in at the beginning of a time period and must be fully charged at the end of the given period. This problem is formulated as a quadratic programming constrained optimization where optimization variables are the charging start times for vehicles. This is not a conventional quadratic programming problem, but an iterative algorithm where each iteration involves solving the power balance equations to provide initial values to the quadratic programming problem in the subsequent iteration. The iteration will continue until a convergence is achieved in the power flow analysis. The evaluation results have shown that minimizing power losses in the electrical network will also minimize voltage irregularity.

Similar to [47] and [49], the authors in [95] have aimed to minimize power losses and improve voltage regulation. In contrary to [47] and [49] which control charging start times, the authors in [95] have proposed to control the output powers at chargers. Also, the scheme in [95] has not directly used transmission line losses as the minimization objective. Instead, the authors have discovered that loss minimization can be achieved by maximizing load factor, or minimizing load variance. This finding is true independent of grid topology if the maximum base load energy is small enough and the sum of the energy required for all PHEVs is large enough. The use of load factor or load variance has the benefit of ensuring convexity in the performance objective function for optimization. The convexity allows a faster finding of the optimal control action, and the use of commercially available optimization tool. Therefore, the authors in [95] have claimed that the proposed scheme is suitable for real-time power dispatch in support of PHEV charging control.

Minimization of power losses is also an objective of [96]. However, achieving the minimum losses is not the ultimate objective, and it is only a part of the performance objective function to minimize the operator's cost. The scheme wants to minimize power losses while keeping voltage within an acceptable limit and ensuring total power demand can be adequately supported by existing infrastructure. This is achieved by controlling which plugged-in PHEVs to be charged at what time in a discrete time model, after taking into consideration the randomness in driver's charging behaviors, time-dependent energy prices and transmission line losses. As described earlier, chargers at different locations suffer from different losses. Therefore, [96] has used loss sensitivity to select the PHEV that contributes the least to system losses, and to begin charging that particular vehicle as soon as possible. The loss sensitivity quantifies the changes in power losses with respect to changes in the charger's load. In practice, loss sensitivity is computed by temporarily increasing the loads at each charger by a small amount of 5%. From this small load perturbation, it is then possible to determine the loss sensitivity due to load changes at each candidate charger from its Jacobian matrix of power flow. Simulation results show that the proposed scheme can support a much higher (63%) PHEV penetration compared to that (32%) of uncontrolled charging.

A problem similar to [96] has been formulated in [97] to directly maximize operator's profit for a system that has multiple parking areas sharing a single distribution transformer. Here, the profit comes from a difference between the wholesale power price and the retail price, multiplied by the aggregated charging load. The hourly prices are exogenously known day-ahead. There is a penalty on profit if the operator cannot fulfill all the charging demands within a give time horizon. The network limitations, such as power limits at the charging points, the parking areas and the distribution transformer, are considered as constraints. This constrained optimization problem has a finite horizon with a fixed number of discrete time intervals. The control variables are the charging powers at each charging points, which can only be changed at the beginning of each time interval. The optimization problem can be solved centrally through a mixed integer liner programming. However, the authors have argued that solving such a problem centrally is not scalable in the case of a very large PHEV population. Hence, they have further proposed to use distributed sub-gradient method, to decompose the mixed integer linear programming problem into multiple sub-problems, one for each parking area. Specifically, through Lagrangian relaxation, the constraint on the shared transformer is added as a penalty term to the original optimization objective function. With a local scope of a parking area, the new optimization problem has a much smaller number of variables, and thus can be solved more efficiently. Also, multiple copies of the local optimization can be solved in parallel, one for each parking area.

Maximizing profit is also the objective of the charging scheme proposed in [98], for a single parking area. The profit is calculated in the same way as in [97], but without penalty for missing demand deadline. Instead, charging deadlines are hard constraints. The authors have observed that visitors to the parking area can be classified into regular and irregular. Regular PHEVs travel daily between their homes and works, following a typical mobility pattern every weekday. Irregular PHEVs represent visitors from other places on short non-routine journeys. With such an observation, the authors have proposed a scheme consists of two layers, namely routine layer and correction layer. The routine layer analyzes the mobility traces of individual regular PHEVs to identify their average arrival and departure times from the parking areas. These times become constraints of a mixed-integer linear programming problem. Other constraints include the grid's technical limitations. Given the day-ahead power price, the optimization problem has been solved using CPLEX to determine a rough charging profile for each PHEV, ahead of time. At real time, when the actual arrival and departure times differ from their expected values, the correction layer will modify the charging profile using heuristic, which unfortunately has not be clearly described. Also, the correction layer is responsible in real-time handling of the charging demand of irregular PHEVs. The authors claim that the main novelty is in the use of actual mobility traces of regular PHEVs in controlling their charging profiles at a parking area.

Another profit maximization charging scheme has been proposed in [99]. However, different from [98] that makes a profit from charging PHEVs, the profit in [99] is obtained from offering voltage regulation service to the smart grid while charging a fleet of PHEVs. The offer of regulation service by PHEVs is a key feature of V2G which will be discussed more extensively in Section VI. The uniqueness of [99] is in providing such regulation service without bidirectional charging. The authors have considered the inclusion of renewable energy sources, such as wind and solar generators, which may inject intermittently power into the electrical grid. Since the battery capacity of a single PHEV is too small to have an impact on the grid, an aggregator must exist to combine a group of PHEVs in an area. The aggregator can make a profit when it is requested by the grid operator to regulate up or down the voltage. The regulation is achieved by setting a proper preferred operating point (POP) for each PHEV. In [99], the POP equals to the charging set-point, which defines the average, maximum and minimum charging powers at each outlet. An optimization problem has been formulated to maximize the profit by choosing the optimal charging set-points for all PHEVs. The constraints are limits as indicated by the maximum and minimum aggregated power required to properly regulate the voltage. The optimization has been solved using linear programming. The results show that it is feasible to offer regulation service without bidirectional power flow. However, this study has not taken into consideration the grid's technical limitation, such as thermal loading, and maximum charger output.

Profit can be maximized by minimizing cost. Thus, the authors in [100] have proposed to minimize the total energy cost purchased to fulfill all the charging demand. It is assumed that the operator can buy energy from day-ahead market at wholesale price, and from current market at retail price, where retail price is generally higher than wholesale price. To exploit the lower wholesale price, the authors propose a two-layer scheme, where the first layer buys energy from the day-ahead market to serve a fraction of the PHEV population, and the second layer uses the real-time market to serve the rest of the population as well as to adapt to deviation in the actual demand from the expected value which has been determined in the first layer using statistical data. This two-layer approach is conceptually similar to that in [98]. In [100], the first layer is designed as a scheduler that controls charging time to minimize energy cost, in the view of the constraints imposed by individual PHEV service demands, and grid limitations. The paper considers three types of charging levels, similar to those in Table 2. Although this first layer problem has been presented as a constrained optimization, it is not solved using mixed integer linear programming. Instead, a heuristic has been used to allocate the lowest price charging time slots to each PHEVs, at a fixed power depending on the outlet's charging level. This is different from most of the other smart charging schemes, which allow any charging power as long as it does not exceed the maximum rating. We believe that this fixed power allocation considered by [100] is closer to reality compared to other works. The second layer is designed as a dispatcher that uses a heuristic to distribute the purchased energy to PHEVs, following as close as possible the outcomes from the first layer.

A system model and problem definition similar to [100] has been adopted in [101]. They both have considered buying energy from the day-ahead market to service a group of PHEVs at minimum cost, but [101] has further dealt with the existence of multiple co-located aggregators. In [101], the aggregator is called fleet operator (FO), where each FO is responsible for a fleet of PHEVs, with them the FO has entered into a contract. In this system model, there are three main components, namely grid operator, FO and the PHEVs. The authors have provided a detailed description on the processes that govern the interactions among the three components. Specifically, each FO needs to first determine the optimal charging profiles for its own group of PHEVs. This is a constrained optimization problem solved using linear programming, where the constrains are drivers' demands to be fully charged before departure. Based on the optimal profiles, hourly energy consumption can be determined. All FOs will submit their consumption estimates to a virtual market. The market formulates another optimization to allocate actual consumptions to minimize the sum square of deviation from the optimal consumption. The constrain for this second optimization is the capacity limits of the grid. This second optimization is solved using Lagrangrian relaxation method, and the Lagrange multiples are used as shadow prices. If the shadow price is greater than zero, all FO will add their respective shadow prices to the day-ahead market price, and repeat the optimization to compute their energy consumptions. The iterative process ends when all shadow prices are not greater than zero. Although this paper has not provided details for real-time dispatch such as those given in [100], the results here show a significant (45%) reduction in charging cost.

For the objective to minimize cost needed in charging a fleet of 50 PHEVs, made up by an equal number of taxis and private cars, the scheme in [102] has used wind generated power to offset part of the energy cost. In this scheme, the main novelty is in the use of a detailed battery model to account for the charging efficiency. For a less efficient battery, the energy acquired by the battery is less than the energy drawn from the electrical grid. The detailed battery model suggests that the internal battery power is a non-linear function of the external charging power, and internal power is often lower than external power. Through a simple Taylor series expansion, the authors have approximated the non-linear relation using a quadratic function, where the coefficient of the quadratic term depends on the battery model. Then, an optimization problem is formulated to minimize the energy cost by controlling the charging power and charging time for every plugged-in PHEV over a period of time. The optimization is solved using quadratic programming, and the results are compared to that of another optimization formulation that assumes a simple linear relation between internal and external powers. The results indicate that the performance difference between the quadratic and linear models is only about 2%. The authors have stated that this small difference in performance does not justify the increased complexity in using quadratic programming. The authors have also concluded that a linear battery model is good enough.

Smart grid operators can maximize their return-on-investment on the infrastructure by maximizing its utilization, where utilization is generally calculated as the demand-to-supply ratio which must be kept below unity to avoid overload. The authors in [103] have proposed a heuristic charging scheme to maximize average utilization. The scheme treats PHEV charging problem like a transmission scheduling problem in communication networks, where each power supply and charging demand is represented by a token. These tokens are kept in two separate queues, one for supply and the other for demand. A supply token is removed from its queue when the power it represents starts to flow. Demand tokens are removed from the queue to match the supply as close as possible while guaranteeing that utilization is below unity at all times. The difference between supply and demand indicates the amount of wasted energy. Each matched demand token is used to guide on which PHEV charging requests to be actually performed in correspondence to the supply. When the demand tokens are removed from the queue in a first-in-first-out manner, there is a need to decide which supply token, the demand token should first attempt to match to. In making this decision, the scheme has tried the following four policies: (a) in the increasing order of supply end time, (b) in the decreasing order of the amount of energy that is left in the supply token, (c) select a supply token uniform randomly, and (d) in the increasing order of supply token's current utilization. Evaluation results show that regardless of the policy, a high utilization above 0.95 can be achieved with a very large (> 2 million) PHEV population.

Energy network utilization can be maximized by maximizing the amount of energy delivered all PHEVs within a time period. A charging scheme has been proposed in [104] to maximize the total energy delivered by controlling the charging power at each plugged-in PHEVs. The constraints are the grid limitations, which include charger's maximum output power, tolerable voltage deviation and maximum thermal loading. The authors have assumed a specific energy network topology and configuration, and perform power flow analysis to find the voltage drop and thermal loading at each bus in the presence of only residential (non-charging) load. Given this baseline setting, further power flow analysis is performed to identify the impact of adding extra power load at a charging outlet. This helps in quantifying the voltage and thermal loading sensitivities in response to varying charging load. This sensitivity parameters is conceptually similar to the loss sensitivity introduced earlier in [96], but differs in practice. The authors in [104] have discovered that both voltage and thermal loading sensitivities are approximately linear. Therefore, the constrained optimization becomes a simple linear programming problem. Apart from the linear approximation, one of the main novelties in this scheme is the inclusion in constraint, a limit in variation in charging power between two consecutive time steps. This constraint is practically important because rapid and large variation in charging power is harmful to battery.

B. OPTIMAL OPERATION

Flattening the combined charging and non-charging load profile plays an important in improving power quality, network stability and operational efficiency of the electrical grid. The authors in [105] have proposed a scheme to flatten load profile at a transformer, while taking into consideration the technical limitations of the grid. These limitations include maximum charging power, acceptable voltage deviation, maximum current and maximum thermal loading. They serve as the constraints to an optimization, where the objective function is the sum square of the difference in load at the transformer, between two consecutive hours. The control variables are the charging profiles at all outlets. The feasibility of charging profiles are verified through power flow analysis on a specific grid topology and configuration. Also, a charging profile is feasible only if there is PHEV plugged-in to the respective outlet. The authors have established the chances of plug-in at an outlet by analyzing the statistical data from a mobility survey carried out in the city of Madrid in Spain. For a large number of charging outlets, the solution space is too large to be efficiently handled as a conventional optimization. Therefore, the authors have adopted a meta-heuristic method, specifically genetic algorithm to search for the optimal solution. In this genetic algorithm, each gen in a chromosome defines the charging power at a specific outlet. Simulation results show that the load profile can indeed be flatten. Since the charging profiles are based on statistical mobility data, we feel that it has no ability to adjust to real-time deviation from the expected behaviors, where such ability has been designed into [100] presented earlier.

Another load flattening PHEV charging scheme has been proposed in [106]. In this scheme, the objective is to flatten the load profile at the same time of minimizing the peak load. The authors have considered a system model where an electrical grid supports 100-200 homes, and each home has a charging outlet. Two types of control strategies are considered, namely local and global strategies. In the local strategy, a home control unit manages the charging profile for its own vehicle, in the presence of non-charging load from home appliances. The scheme first determine an ideal load profile, which is a flat line of the average load over the entire time horizon within which the vehicle must be completely charged. Then, the performance objective can be achieved by minimizing the sum square of difference between the scheduled and ideal loads, over all time steps within the horizon. The control variables are charging time and power. The optimization is constrained by transmission line capacity, and the need to fulfill the charging demand. This optimization has been solved using a quadratic programming. Different from this local strategy, the global strategy does not require the home control unit to manage the charging. Instead, the home control unit simply submits the charging demand and local load profile to a control center. At the center, the optimization is identical to that of the local one, but with a larger number of control variables. The same quadratic programming is applied to solve the global optimization. As expected, results show that the global strategy can lead to a flatter load profile, due to the global view on the system.

With limited capacity in a residential distribution network, the electricity supply may not fulfill all charging demands at some instances. When such a congestion occurs, it is necessary to ensure fairness in charging opportunity among all the vehicles. To be fair, each vehicle should receive an entitled share of the available energy drawn from the smart grid. From the operator's perspective, it is more efficient to avoid chargers at a remote location because of their higher power losses due to their longer distance from the substation. In order to ensure fairness, [107] has proposed a scheme that will allocate at least one unit of energy per control interval to each plugged-in vehicle, regardless of their power losses. In a separate work, [108] has shown that a distributed charging control can lead to a better fairness compared to a centralized scheme, where the fairness is measured in terms of the deviation from the average SOC among all vehicles at the time they leave for their respective trips. In this distributed scheme, each vehicle can decide on its own charging profile based on a pre-defined probability distribution. The distribution function is created through interaction with a central controller that provides the vehicle with predictions about the future energy consumption in the grid.

Instead of considering only fairness in energy share, the authors in [109] have also considered the relative importance of charging to a particular vehicle. Specifically, a PHEV with a SOC which is high enough to meet its daily need, should not compete equally with another vehicle that has a much lower SOC, that is insufficient for its next trip. The authors terms this consideration as *discouraging fairness* because it acts to discourage a high SOC vehicle to compete equally with a low SOC vehicle, for an universal fairness. Here, the universal fairness means all PHEVs have at least enough energy for their next trips. In [109], an entropy-weighted combination of charging fairness and discouraging fairness has been used as the objective function in a dynamic optimization problem. The optimization problem is formulated as a Semi Markov Decision Process, and solved using the neuro-dynamic programming. The use of dynamic programming allows the scheme to learn from the charging process, sufficient information that characterizes the system features and parameters, which are not deterministic. The system parameters include PHEV number, locations, arrivals and electricity demand. These parameters are regulated adaptively to meet the PHEV charging requirements even if the daily PHEV mobility and demand on electricity are unknown *a priori*.

For the purpose of avoiding congestion in energy distribution networks and achieving fairness in charging opportunities, the authors in [110] have proposed to adopt the idea of medium access control protocol from wireless communication networks, to manage PHEV charging. The paper assumes a fleet of PHEVs share a single transformer, and all vehicles will be charged using level 2 fast charging. Due to the much higher output power at each outlet for fast charging, the transformer can be severely overloaded when many vehicles are charged simultaneously. Since fast charging requires much shorter time than the entire over-night parking time, the charging durations should be carefully scheduled to avoid overloading without affecting the desire to get all vehicles fully charged by the next morning. To schedule the charging time, each PHEV will first divide its charging demand into multiple small units, analogues to data packets in communication networks. For example, 4 hours of level 2 charging is broken into 48 packets, each is for just 5 minutes. Then, for each packet, its PHEV will send a charging request to the transformer in a probabilistic manner. Says, there are three levels of transmission probabilities, namely P_1, P_2 and P_3, such that $P_1 > P_2 > P_3$. Further assume that the vehicle will first attempt to send its request using probability P_2. If the request is received and granted by the transformer, the vehicle will send its subsequent request at a higher probability P_1. If the request is not granted, the vehicle will retransmit the same request at a lower probability P_2. With such a transmission probability adaption performed independently at all PHEVs, the authors have shown results to confirm that grid overloading can be avoided and charging opportunities are fairly distributed among all plugged-in vehicles.

Without significant deviation in performance objectives, there are existing smart charging schemes such as [99] and [102], that have considered the adoption of renewable energy in their system models. Integration of renewable energy into smart grid is an important but challenging topic, due to the energy's intermittent nature and highly variable output powers. The issue of renewable energy integration is more extensively addressed by bidirectional charging, and the survey of relevant schemes is presented in Section VI.

C. SUMMARY

With the flexibility in choosing control parameters, various smart charging schemes have been proposed for different performance objectives, and system constraints. Thus, in general, most smart charging schemes have been formulated as constrained optimization problems. For such problems, the performance objectives are to maximize financial rewards or to optimize operation efficiency. The main constraint is to fulfill the charging demand for all plugged-in PHEVs. The other system constraints should include technical limitations of the electrical grid, expectations on power quality and conditions to prevent network disruptions. Most of the existing scheme have considered the maximum charger power as a constraint. However, other technical limits of the grid and requirements on power quality have not been consistently considered in all existing works. Despite largely different objectives and constraints, most optimization problems share a common control variable, which is the charging profiles of individual PHEVs, where each profile defines charging set-point, time, energy and/or power. Most of the optimization problems are solved numerically using different types of dynamic programming techniques, as well as heuristic algorithms.

TABLE 4. Bidirectional charging schemes.

Scheme	Performance Objective	Ancillary Service	Renewable Energy	Battery Degradation	Solution Technique
[122]	Min. cost of charging a fleet of PHEVs	Frequency regulation	Wind	Not considered	Sequential quadratic programming
[123], [124]	Min. cost of charging all PHEVs in a parking area	Regulation services	Solar	Not considered	Fuzzy logic
[125]	Min. combined cost of charging and parking PHEVs in a parking area	Reactive power compensation	Not considered	Not considered	Multi-objective optimization
[126]	Min. combined cost of charging all PEHVs in a parking area and missing their departure deadlines	Not considered	Not considered	Considered	Mixed integer linear programming
[127]	Min. cost of charging a huge PHEV population	Not considered	Not considered	Considered	Two-level convex optimizaton
[128]	Min. cost and carbon emission	Spinning reserve	Wind and solar	Not considered	Particle swarm optimization
[129]	Min. combined cost of charging and battery degradation	Frequency regulation	Not considered	Considered	Particle swarm optimization
[130]	Min. combined cost of charging PHEVs and operating HVACs	Not considered	Not considered	Not considered	Constrained optimization
[131]	Min. power losses and tap changer usage	Not considered	Combined heat and power unit	Not considered	Time correlated optimal power flow
[132]	Flatten load profile	Voltage regulation	Not considered	Not considered	Fuzzy logic
[133]	Complete charging by plug-out time	Frequency regulation	Generic renewable sources with random outputs	Not considered	Heuristic

VI. BIDIRECTIONAL CHARGING

Recall that bidirectional charging is different from smart charging because the former supports V2G which allows PHEVs to discharge energy to the smart grid. Supplying the electrical grid with energy from PHEVs is feasible because the vehicles are parked for an estimated 90-95% of their total lifetimes, and more than 90% of all vehicles are not driven even during on-peak travel hours. In general, both bidirectional and smart charging schemes can be similar in terms of their performance objectives and control mechanisms, with bidirectional charging has the additional control in the direction of energy flow. In most of the cases, the performance objectives are to minimize cost or maximize profit at operator, aggregator and/or PHEVs, by controlling the charging and discharging profiles at individual PHEVs. The constraints are to fulfill the driver's charging demands and to satisfy the grid's technical limitations. On top of the similarities, bidirectional charging is set apart from smart charging by addressing three issues, namely (a) provide ancillary services, (b) support large scale adoption of renewable energy sources into smart grid, and (c) account for battery degradation. As summarized in Table 4, we organize this section to focus on schemes that address fully or partly these three issues.

The amount of energy each PHEV can discharge to smart grid depends on the user's mobility behaviors. Through analysis of mobility data, the authors in [57] have shown that each vehicle may contribute about 2.6 kW for up to 15 minutes upon request, with a 47% depth of battery discharge. While each PHEV may contribute only a small amount of energy to the smart grid in a non-continuous manner, a fleet of PHEVs may work collectively in providing a sustainable and continuous energy flow. To facilitate this collective effort, an aggregator is needed to bind and control a significant number of PHEVs within a region, so that their combined energy flow is smoothen over time. The authors in [111] have defined the roles of an aggregator for V2G, and describe its operation in electricity market. According to [111], the operator is expected to manage the charging of a fleet of PHEVs, to smoothen the aggregated load and charging profiles. Hence, aggregator can shield the operator from large variation in supply and demand introduced by any single PHEV. As such, aggregator plays an critical role and becomes a necessity in bidirectional charging. In the increasing presence of PHEVs and bidirectional charging, recent literature has equated the role of an aggregator to virtual power plant, which is a model that manages some geographically dispersed electricity generations and demands, as if they are a single entity [112]–[114].

Through an aggregator, a fleet of PHEVs can be contracted and paid by the grid operator to provide ancillary services, which include spinning reserves and regulation services [39], [115]. Spinning reserves are the idle sources that can dispatch power to the grid within 10 minutes of a request. These are the services which are generally paid to be immediately available, but they do not generate power unless requested. Compared to spinning reserves that are only on standby, regulation service are under real-time control of the operator. Regulation services are used to prevent excessive voltage deviation and to keep the grid frequency as close to a target, e.g., 50 or 60 Hz as possible. The frequency needs to be regulated because the extend of a frequency shift indicates a corresponding gap between supply and demand. These ancillary services are expanded functionalities offered by PHEVs through smart grid, and they are made possible by bidirectional charging. The ancillary services allow smart grid to rapidly self-regulate and heal, to improve system

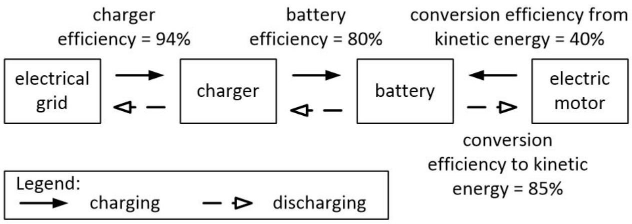

FIGURE 8. Charging-discharging cycles add to accumulated energy losses because battery efficiency is not perfect [119].

reliability and security, and to more efficiently manage energy delivery and consumption.

The success of PHEV in reducing greenhouse gas emission depends on the cleanliness of electricity source that is used to charge the battery [116]. Therefore, it is ideal if clean renewable energy can be used to charge PHEVs. Since renewable energy is also wanted to partially power up the smart grid independent of PHEVs, the energy's intermittent nature and highly variable output powers can impose severe risk to the grid operation. Through bidirectional charging, PHEVs can collectively act as a reservoir in filling the gap between uncertain supply and random demand. By ensuring such a closer match between supply and load profiles, bidirectional charging supports both a higher PHEV penetration and a wider renewable energy integration into smart grid [117], [118].

Providing ancillary services and adopting renewable energy sources require frequent and deep charging-discharging cycles of PHEV battery. Such cycles can rapidly degrade the battery [17], [120]. In addition to unwanted battery degradation, each charging-discharging cycle will also add to an accumulated energy losses. This is because, as illustrated in Fig. 8, the battery efficiency is less than 100%. As such, the amount of energy needed to restore a give SOC after discharging, will be larger than the amount of energy draw from the battery. The battery degradation and energy losses are amplified when energy is required from the battery to supply for non-productive reactive power. In view of the problem, the authors in [121] have shown that it is possible to configure a charger system to avoid the discharging energy from battery to provide reactive power, when the DC link capacitor is enough to fully supply the required reactive power for level 1 slow charging.

A. MINIMIZING COST

The authors in [122] have considered a power system at West Denmark, where wind turbines contribute 27% of the total electricity output. In such a system, PHEVs are needed to provide regulation service through load frequency control. In [122], the system model assumes individual PHEV can buy and sell power from the day-ahead market. Therefore, every PHEV can act to minimize its own charging cost by establishing a charging-discharging profile based on the day-ahead price. For each PHEV, a local optimization has been formulated to minimize its total cost over a finite time horizon, subject to maximum input and output powers at the charger and the need to keep battery SOC within a range of 0.2 to 0.8. The range is justified to leave some spare capacity to provide for regulation services. Also, each PHEV battery must be fully charged before starting a journey, and the SOC gap will be filled by energy from real-time market. The vehicle departure time is a statistical average obtained from analyzing past mobility data. The authors have indicated that this optimization has been solved using sequential quadratic programming. However, we have noticed that the objective function is indeed a linear function, that sums a time series of charging-discharging powers multiplied by their respective price. Thus, there is probably no need of quadratic programming, but linear programming. Nevertheless, results form the paper show that the scheme can bring about a very significant financial benefit. Specifically, while fulfilling all charging demands for driving needs, the PHEV owners can still collectively make a profit. If this is true, it means owning a PHEV can help in generating income. Although there is no detail in how frequency regulation can be performed in the formulated optimization, results show that it leads to a significant reduction in power deviation from a planned value. The scheme has not accounted for the cost of battery degradation arises from frequent charging-discharging cycles.

Consider a workplace parking area which is equipped with a photovoltaic farm to partially supply its energy requirement, a scheme has been proposed in [123] to minimize the total cost to charge all the parked PHEVs by theirs respective deadlines. The cost is incurred in purchasing energy from the electrical grid when the solar generated output is not sufficient. Also, when the grid load is too high, the PHEVs may return energy to the grid to make money to partially offset the total cost. The impact of these two way power flows on the grid are governed by the power balance equations, which are highly non-linear. To avoid solving these non-linear equations in optimization, the proposed scheme uses a fuzzy logic controller to decide which PHEV to be charged or discharged at what power at current decision step. Fuzzy logic is used here for its ability to deal with decision rule in linguistic form. For example, the linguistic rule may be written as "a PHEV with high SOC can be charged later". The controller divides all PHEVs into five classes based on their SOC and parking durations. The classification is used to prioritize the charging service and to select the proper charging power. For example, the highest priority class has low SOC and short deadline, and thus requires immediate charging at high power and is not allowed to discharge. In making dispatch decision, the controller considers this priority classes, as well as two other factors, namely the current energy price and the grid loading. There is not specification on how the regulation service are implemented, but results show that the scheme can successfully maintain voltage deviation within limits at the same time of reducing charging cost. The scheme has not considered the effect of charging-discharging cycles on battery health.

The work in [123] has been extended in [124] to include statistical and forecasting models. These models account for the various uncertainties in the system, such as the solar power outputs, the PHEVs arrival times, and the amounts of energy available in PHEV batteries upon their arrivals. While still considering PHEV charging at parking lots similar to [123], the authors in [125] have developed a scheme to minimize the total (charging and parking) cost and the insufficiency in reactive power supply. The scheme has formulated a multi-objective optimization problem to determine the best charging profile with reactive power compensation at each charging outlets. The optimization problem has been solved using a normalized normal constraint method with Lagrangian.

Still considering charging PHEVs at a parking area under the supervision of an aggregator, the authors in [126] allow a PHEV to use its stored energy to charge another PHEV via the aggregator, bypassing the grid. This type of direct energy exchange between vehicles is called vehicle-to-vehicle (V2V) to differentiate itself from V2G. In [126], V2V is in addition to permit a PHEV to discharge energy to grid to make a profit. Similar to many existing works, [126] assumes the aggregator can buy and sell energy with prices quoted in the day-ahead market. Considering this pricing information together with the arrival and departure times of each PHEVs, the aggregator aims to minimize a cost function that consists of three components. The first component is the net cost of buying and selling energy to the grid. The second component is the cost of missing service requirement, when PHEVs are not fully charged at their departures. The third component is the cost of operating V2V. The authors state that the V2V cost is due to control and energy conversion activities, without giving much detail. We feel that the cost is most likely a result of inefficiency as depicted in Fig. 8. In operating V2V, the scheme considers the effect of charging-discharging cycles on battery health. To preserve battery lifetime, the scheme will not discharge the battery SOC below a threshold, which is set at 0.7. This is a rather high minimum SOC threshold compared to existing literature. The paper has done a sensitivity analysis to show that lowering the threshold can further lower the total cost, but not significantly. Specifically, when threshold is set to 0, such that the battery is allowed to fully discharge, the cost will be reduced further by only 5%. Yet, this cost reduction has not taken into account a further loss in battery lifetime. In this scheme, the control variables are the charging and discharging time, charging power and direction of energy flow, subject to grid's limitations. This constrained optimization problem has been solved using mixed integer linear programming. Unfortunately, this work has not considered the use of renewable energy and provision of ancillary services.

Without specific consideration on renewable energy sources, the authors in [127] have proposed a scheme to minimize charging cost by controlling the charging powers at each PHEVs and the charging load within each 1-hour interval. The scheme aims to support a huge populations of PHEVs and thus, argues that a single centralized scheme is not scalable. Therefore, [127] has formulated a global and a local optimization problems. The global optimization accounts for the total number of PHEVs to be charged within a day, based on the statistical characteristics of vehicle arrivals. On the other hand, multiple copies of local optimizations at different aggregators can collectively handle a larger number of vehicles with dynamic and random arrivals. The local optimization has considered the effect of battery degradation by adding a cost for battery lifetime reduction, where the cost is a quadratic function of the amount of energy exchanged. The problems have been solved as convex optimization.

Instead of focusing solely on cost, the authors in [128] have proposed to simultaneously minimize the cost and carbon emission by controlling the charging schedules and powers at all plugged-in PHEVs. The optimization problem formulation has taken into consideration the need to provide spinning reserves as well as the adoption of wind and solar generated energy sources. The problem has been solved using particle swarm optimization technique. The same technique has also been used in [129] to find the optimal charging and discharging profiles for each PHEVs in minimizing cost. The cost here include the charging cost and battery degradation cost. In [129], the battery degradation cost is a function of battery capacity, battery lifetime at a given discharge depth and the amount of energy discharged. While the scheme does provide ancillary service in the form of frequency regulation, it has not considered renewable energy. The model in [129] is unique in the sense that significant effort has been invested in accurately estimating charging load using a fuzzy logic method, that accounts for random driver behaviors and statistical distribution of different vehicle types.

In a typical household, thermostatically controlled appliances, such as refrigerator, electric water heater, and the heating, ventilation, and air-conditioning (HVAC) system, collectively account for more than half of total residential energy consumption. Therefore, electric bill can be reduced if these appliances are powered by PHEVs' batteries. The work in [130] has looked into the interaction between PHEV, HVAC and grid, within a residential area that has a number of households. In the literature, using PHEV battery to supply energy to a premise or building is termed Vehicle-to-Building (V2B), to differentiate itself from V2G. In this work, an optimization has been defined to minimize cost while jointly satisfying energy demand of PHEV and HVAC. The vehicles must be fully charged within their respective parking durations, where the arrival and departure times are statistical average determined from mobility survey. The HVACs must be supplied with required energy to keep the temperature at a preferred value, with an acceptable deviation limits. The preferred temperatures differ for different households. The optimization cost function is a sum of energy cost and discomfort cost, where the discomfort cost is a linear function of temperature deviation from its preferred value. The energy cost depends on the price of buying and selling energy in the day-ahead market, where the buying and selling prices are assumed equal at a time, but change hourly. The vehicles are allowed to sell excess energy to the grid, as long as the travel requirements can be satisfied, battery SOC is within acceptable range and grid's technical limitations are not violated. The optimization considers a time slotted model, where control decision is made at every 1-hour interval based on the energy pricing information and electricity demand. The control action decides how much energy should be bought from the grid at each time slot; and how to allocate and schedule the energy usage; and to exchange energy between PHEVs and HVAC. This is indeed a constrained optimization, but it has not considered usage of renewable energy, nor cost of battery degradation. In order to preserve battery health, the authors simply maintain SOC within a prescribed range as mentioned above. Also, there is no mention of offering of ancillary services to the grid, apart from allowing PHEV discharging to fill the demand gap. Nevertheless, results show that a very significant (65%) cost saving can be achieved, where a higher saving is obtained when the average PHEV travel distance is shorter. This is reasonable because a shorter distance leads to more energy remains in PHEV, ready to be sold back to grid for a profit.

B. OTHER THAN MINIMIZING COST

Compared to the majority of works that have focused on minimizing cost, the authors in [131] have wanted to minimize power losses and to avoid usage of tap-changers. The paper states without giving further explanation that, avoiding the use of tap-changer is to prevent overusing control assets. We believe frequency use of tap-changer can expedite its wear-and-tear and shorten its lifetime, because it is an electromechanical device designed to control voltage with mechanical movement. The paper assumes a small radiant network with combined heat and power (CHP) units, in addition to houses, where each house has an PHEV on top of residential (non-charging) load. A time coordinated optimal power flow formulation has been presented, where each time step solves an optimal power flow problem with parameters time-correlated to the previous time step. At each time step, the cost function is a weighted of the power losses and the magnitudes of tap-changer movements. The control variables are the charging and discharging powers at each PHEVs, as well as the movements at tap-changers. The results show that V2G can significantly reduce power losses, and the largest reduction comes from controlling PHEVs that are located farthest from the main energy supply point. This is reasonable because PHEVs help is supplying energy locally to avoid the long distance between supply and demand, and thus to reduce losses. The results also show that there is little impact on the losses, which are caused by PHEVs that are located close to the main supply point. Therefore, controlling PHEVs far-away from the main supply point with increased computation, is more worthwhile. This paper has not considered ancillary services and battery degradation.

The authors in [132] have considered a radiant energy distribution network with three feeders and 12 buses. A total of 3 charging stations are attached to the farthest bus from the

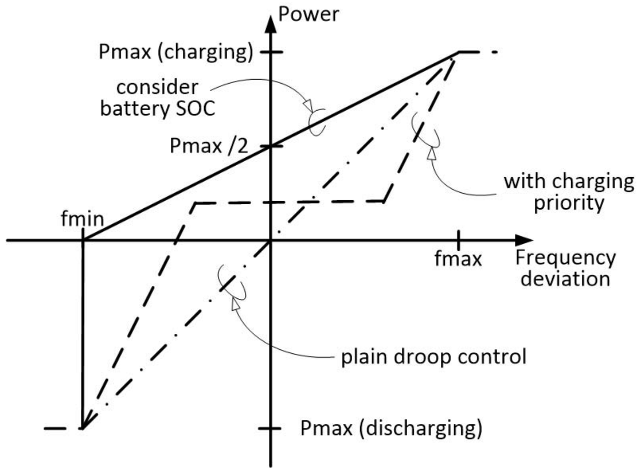

FIGURE 9. Response functions for droop control.

slack bus, and each charging station has 150 charging outlets. Says, the bus where charging stations are connected to is called the connection bus. In the presence of time-varying loading, the authors want to flatten the load profile at the connection bus, at the same time of providing ancillary service to maintain the connection bus voltage within an acceptable limit. For this purpose, the authors have designed a fuzzy logic controller to control the aggregated power flow at the connection bus. The power flow can be positive or negative. A positive (negative) value means energy flows from (to) the connection bus to (from) the aggregator to charge (discharge) the PHEVs. In deciding the power flow, the controller takes into consideration of three inputs: (a) energy available from all plugged-in PHEVs, (b) voltage at connection bus, and (c) required ancillary service duration. Fuzzy membership functions have been presented for each of the three inputs. The basic principle of the controller's fuzzy inference engine is that PHEVs will be discharged if their energy availability is high and the bus voltage is low. On the other hand, the PHEVs should be charged if the bus voltage is high. After finding the desired aggregated power flow, the scheme will divide the flow among the three charging stations, proportional to the aggregated available energy at each station. At each station, the share of power flow is further distributed among the plugged-in PHEVs under its care. The allocated power flow is then used to determined the charging current at each outlet. The paper shows that the scheme can indeed flatten the load profile, and the voltage is kept within limits. However, the paper has not taken into consideration integration of renewable energy and battery degradation due to charging-discharging cycles. According to our understanding, in this paper, the term ''power flow'' means apparent power, which depends on both active and reactive powers. Also, each battery has been modeled as a P-Q (but not P-V) bus which is connected to the connection bus. Yet, the authors have assumed that power factor is unity. Then, it is not clear what is providing for the required reactive power at each PHEV.

A large scale integration of renewable energy sources into smart grid can exploit the load frequency control capability of bidirectional charging to perform frequency regulation. The authors in [133] have proposed a scheme to satisfy PHEV charging schedules at the same time of offering such ancillary services. The scheme is autonomous and distributed because each charging outlet will made its own control decision depending on the locally measured frequency and individual charging demand. The charging demand is to fully restore PHEV's SOC by a plug-out time, which is stated by the driver at the time of plug-in. The frequency regulation is achieved through a unique droop control. As illustrated in Fig. 9, droop control involves altering the magnitude and direction of power flow in response to changes in frequency deviation. Generally, when a frequency becomes higher compared to a target value, more energy should be drawn from the grid to charge PHEVs. In a different work, droop control can be designed to offer priority to charging PHEV instead of keeping frequency deviation at zero [134]. The droop control in [133] is different from that in [134] in the sense that [133] has taken into account the battery SOC and charging deadline in setting the charging power. In addition to changing the droop control response function, the maximum charging power in [133] is also dependent on battery SOC, which the authors have assumed can be obtained accurately. Despite the dependency on battery SOC, the scheme has not taken into account the effect of such control on battery degradation and lifetime. Results have shown that frequency deviations can be maintained within a desired range in the presence of fluctuation in renewable energy outputs. Here, the authors have not specified any particular type of renewable energy, and have modeled the fluctuation in renewable power outputs as a normally distributed random variable.

C. SUMMARY

Bidirectional charging adds flexibility to smart grid in supporting a higher PHEV penetration, and a greater renewable energy adoption. Bidirectional charging requires PHEVs to function as energy source from time to time to fill the gap between random demand and uncertain supply. This requirement amplifies the range anxiety problem, where drivers are concerned by the potential of emptying the battery before reaching the destination. A larger battery capacity may help in reducing the range anxiety. But, the high cost of a larger battery, coupled with the rapid battery degradation and significant energy losses due to frequent and deep charging-discharging will make the benefit of bidirectional charging less obvious to individual PHEV owners. As such, instead of imposing further requirements on PHEVs, the success of bidirectional charging, so as V2G concept will depend largely on the ability of aggregator in efficiently binding a huge number of small mobile energy storages, taking into consideration imperfect efficiency. Thus, aggregator is not optional, but one of the most critical elements in bidirectional charging.

VII. RESEARCH CHALLENGES

In this section, we discuss some open research issues that deserve further attention from the research community.

A. STANDARDIZED EVALUATION MODEL

Simulation is a very power tool in studying PHEV charging schemes because it avoids the need to develop physical test system and thus, speeding up invention and reducing cost. There is a large number of existing works evaluating the impact of PHEV charging schemes on the smart grid through simulations. However, these rich set of existing results are not easily reusable due to the lack of commonality in evaluation settings, simulation platforms and use-case scenarios. Reusability and reproducibility of published research results are important in ensuring efficient deployment of research resources. Most effort should not be wasted to repeat similar studies and evaluations, that have been completed by the research community. Standardization of evaluation model is an important step toward optimal sharing and exploitation of common results. It is ideal if various simulation and evaluation programs can be made open-source and freely accessible.

In standardizing an evaluation model, the following issues need to be considered:

- *Mode of simulation:* The simulation platform must integrate both power and communication networks for realistic evaluations. Currently, power-focused evaluations rely mainly on Monte Carlo simulations and power flow analysis that examine stationary statistics of a grid. On the other hand, communication network research have depended on random-event-driven simulations, using OPNET, NS2, Qualnet, OMNET++, etc, which are capable of finding the worst case performance in the presence of unsynchronized time events. These events are not synchronized because each event is an outcome of a multi-stage process, and each stage alone is a random process. For example, sending a data packet from a wireless sensor to an aggregator involve stages, such as random channel fading, random noise and interference, random transmission delay, etc. There exist some efforts that partly combine hardware to a computer simulation, to more accurately capture interaction between power and communication networks [135]. We need to decide on the mode of simulation, and believe that random-event-driven simulation should form the basis. This is because it can avoid the use of hardware for wide-spread adoption, and it can detect extreme conditions due to uncoordinated events.
- *Simulation platform:* There are existing tools in MATLAB, such as MATPOWER [136] that are open-source and are very useful in analyzing power flow for a given electrical grid topology. However, there is no commonly adopted platform for power-focused Monte Carlo simulations, where various papers seem to have their own proprietary simulation and tool implementations. For communication network related research, OPNET and Qualnet are commercial tools that users must

pay for. Open-source tool, such as NS2 and OMNET++ have efficient simulation engines that are well maintained by volunteers. We need to decide a common platform to combine the details of both power and communication networks.

- *Simulation framework:* Performance of a proposed scheme depends on many factors, such as non-charging load, driving behaviors, charging behaviors, grid topology, etc., as discussed earlier in Section III. A comprehensive simulation framework is needed to integrate all these necessary factors and components into a single simulation platform. For this purpose, we suggest to adopt the framework presented in Fig. 4, with the enrichment of communication network components.

B. THEORY OF PHEV CHARGING

Power flow analysis is necessary in evaluating the impact of uncontrolled charging load on the grid. The same analysis is also needed in assessing the effectiveness of various controlled charging schemes. Unfortunately, power flow analysis involves a set of power balance equations that are highly nonlinear, and can only be solved numerically. Consequently, there is a lack of analytical results and theories for PHEV charging. We need to develop a set of common theories and analytical results, possibly through some approximations such as the linear approximation proposed in [73], to facilitate network planning and performance trade-off in a cost efficient manner. With such theories, system level performance and dimensioning can be done quickly without computationally expensive simulations. While the biggest challenge is in linearizing the power balance equations through approximation, other linear approximations such as those for the nodal sensitivity in [104] and for internal-external battery power in [102], may help in enriching the theory for rapid network planning.

C. INTEGRATION WITH COMMUNICATION NETWORKS

The importance of communication networks in controlled charging scheme has been introduced earlier in [35] and [36], as well as been illustrated in Fig. 1. This dependency on communication has been specifically stated in some schemes, such as [98], [99], and [106]. While there is no doubt about its importance, these schemes have simply assumed communication related issues will be solved separated by other works, or the communication networks are perfect. For example, [112] has proposed a system architect for virtual power plant that depends on bidirectional charging. As a critical module in the architecture, the authors have identified various communication requirements and have suggested some information process flows. However, the authors have also stated that they expect real-time data can be obtained from existing utilities supervisory, control and data acquisition (SCADA) system; and have not proposed any method to fulfil the communication requirements. In the literature, most of the existing charging schemes have not mentioned how an efficient information exchange can be supported by a realistic communication network.

In reality, due to PHEV's mobility, we except wireless communication networks will be used for controlled charging schemes, but wireless communication channels are far from perfect. Given the unreliable nature of wireless links and limited communication bandwidth, it is important to consider the effect of radio propagation impairments, such as channel fading, path loss, etc., on the performance of charging control and grid stability. We see the following emerging research areas:

- *Minimize dependency of charging control on high-speed communications:* It is useful to develop a charging scheme that has minimum dependency on communications, and such communication is not too expensive or unavailable. In order to achieve this objective, we may move control decision as close as possible to the PHEVs. A good example of this approach is the method proposed in [133] that has the individual charging outlets making their own decisions locally. This approach allows rapid response to sudden changes without much reliance on communications. In such an approach, there is still a need to coordinate the local decision makers with a center controller, although such a communication will happen at a much lower rate and consume significantly less bandwidth. The drawback of such a method is the loss of global optimality where excessive power flow from one local decision point cannot be directed timely to another local decision point which is underpower. We believe that specially designed communication schemes are required to support such a distributed decision making model. Different communications QoS are needed for local and global decision makers. The local decision maker needs data packets to be received with minimum delay and can probably tolerate a higher level of packet losses, as compared to the global decision maker which expects very reliable transmissions for a potential higher delay. One important aspect in such a communication scheme is the number of local decision makers that can be supported by each global decision maker, in view of the QoS requirements. The work in [137] has related analytically packet delay and transmission reliability to the number of smart meters that can be supported in a cluster. Such findings can be exploited in this research for controlled charging schemes
- *Minimize impact of communication errors on charging control:* Communication errors has a big impact on load management. For example, [138] has considered load control through dynamic pricing and shown that communication errors can impose a lower limit in price update interval and an upper limit in price update quantum. When communication errors cannot be eliminated with a finite financial resource, we should consider minimizing their impact on charging control at an acceptable cost. A proper objective function should be defined to include both the charging related performance metrics and the cost; as well as impact of reducing

communication errors. Such an objective function can facilitate a managed trade-off between fulfilling charging demand and tolerating communication errors.

- *Customized communication system architecture:* PHEVs are new types of mobile intelligent power consumption devices in smart grid, and emerging green transportation vehicles. These vehicles require a powerful, automated and intelligent energy service network over a wide area so that they will not face an excessive risk of energy deficiency. For such an energy service network, the network infrastructure and the communications demands of various terminals, devices and monitoring systems, should be studied. The communication system architecture should be adapted to interactive user services scenarios and intelligent monitoring of energy operations, by means of new technologies, e.g. Internet of Things (IoT). A novel design of different networking schemes in access networks and backbone transmission networks should be investigated in order to meet the multi-scene and multi-operation interaction requirements. Furthermore, the networking schemes should provide efficient technical support to implement intelligent, cross-regional, and interactive energy services to electric vehicle users. The communication system architecture should facilitate the development and test of smart charging algorithms and other capabilities of the future smart grid, such as remote monitoring of PHEVs.

D. EXPLOITATION OF BIG DATA ANALYTIC

Electricity market operators and charging service providers rely on forecasting tools that provide short, medium and long-term estimation on non-charging and charging loads. Detailed stochastic modelings of driver's charging and mobility behaviors have helped in accurately predicting the charging load. However, in the existing literature, these forecasts are based on traditional statistical analysis. With the rapid growth in smart mobile devices, sensor networks, social media, and Internet technologies, a large volume of unconventional data have become available in real-time. Big data analytic should be used to exploit useful values from these real-time data to further enhance charging efficiency and grid stability [139], [140]. The research challenges are in the followings:

- *Efficient use of big data:* We need to first establish a quantitative metric to measure the benefits of big data exploitations. Generally, we need to know the reward of knowing more accurately and quickly, the characteristics of some random behaviors in charging process. Then, we need to find out the cost of achieving such improvement in accuracy and timeliness. This will require us to identify the types of raw data that are needed to estimate mobility behaviors, charging behaviors, demand profiles, and supply profiles. After knowing the benefits and cost, we can optimize the data size and time-scale, for real-time estimation and data exploitation.
- *Alleviate range anxiety:* Range anxiety is a real issue. In fear of becoming stranded, PHEV owners often plug into public stations to top-up their batteries, and at peak times, rather than find themselves out of fuel on a highway. By harnessing big data, potentially in the future, charging stations can be more strategically installed to alleviate the concern, placing less stress on peak-time power grids. However, current technologies that estimate how much longer a battery will last, still provide inaccurate measurements, because they use computer models that rely heavily on the driver's recent behavior and do not account for other factors. Therefore, a big challenge is the development of new software that uses a big data approach to gather information from multiple sources in order to very accurately estimate electric vehicle range. The driver should need only to provide a destination address or GPS coordinates, and the software could combine historical data along with predictive data-variables such as traffic data, road surface characteristics, tire pressure rates and even weather, to determine how much longer a driver can go before the batteries are flatted out. This big data based software should be an effective tool for providing information to drivers based on information on PHEV use. More specifically, by providing directions to charging stations and equipment. If the location of a PHEV is known, suitable charging stations can be identified. Together with the collection of information from charging stations, including its future schedule, this means that drivers can be directed to the charging station with the shortest waiting time when the level of charge in their PHEV is running low. The directions in this case are provided by the car navigation system. By applying statistical analysis and prediction functions to location and speed information from a large number of vehicles, it could be possible to identify which roads are congested or to estimate how long it will take to reach the charging station. Furthermore, the availability of accurate arrival time predictions improves the convenience of PHEV use because it allows the use of charging outlets to be scheduled and drivers to be informed of how long they will need to wait before their vehicles can start charging.
- *Support new use-case scenarios:* With the rapid development of technology and fast moving consumer appetite, new usage scenarios for PHEV are expected to appear from time to time. Typically, new use-cases have limited historical data to refer to, and may depend on big data analytic to identify indirect data to boost confidence level, in new charging scheme design. For example, self-driving and autonomous PHEVs may experience rapid grow in near future, and there is competition among a few potential deployment strategies. One question is about allowing these self-driving PHEVs be controlled centrally all the times, or be autonomous most of the times. These are new deployment scenarios because, as compared to human-driven PHEVs, self-driving PHEVs

may have more predictable routes and battery SOC. However, the extend of this predictability is not known. There is limited data that we can refer to in developing joint optimization of route planing and charging scheduling. For such optimization of a new use-case, big data analytic may help in closing the gap by identifying and extracting the most relevant indirect data.

VIII. CONCLUSIONS

We have classified PHEV charging schemes into four classes, and reviewed various existing schemes within each class. The review has discovered that there are several open research challenges that deserve attentions. It is necessary to standardize the evaluation model for charging scheme evaluations. This standardization is to ensure reproducibility and reusability of published research results. Reusable results in public domain can ensure efficient deployment of research resources. There is a need to develop some general analytical results and theories for PHEV charging to facilitate system level performance planning and trade-off in an cost efficient manner. Such theories are expected to reduce the need of expensive computation in performance evaluations. There is also a need to consider a realistic communication network model in charging scheme designs and evaluations. Without such consideration, the charging schemes that assume ideal communication system may not work in practice. Finally, the research of charging scheme should exploit emerging big data technologies to take advantage of the vast unconventional real-time data to establish a more accurate forecast on variable load, renewable power output, and driver's behaviors.

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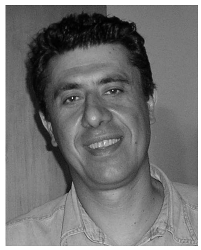
PENG-YONG KONG (M'03–SM'12) received the B.Eng. degree (Hons.) in electrical and electronic engineering from the Universiti Sains Malaysia and the Ph.D. degree in electrical and computer engineering from the National University of Singapore. He was an Adjunct Assistant Professor with the Electrical and Computer Engineering Department, National University of Singapore, concurrent to the appointment of Research Scientist with the Institute for Infocomm Research, Agency for Science, Technology and Research, Singapore. He was an Engineer with the Intel Malaysia. He is currently an Associate Professor with the Electrical and Computer Engineering Department, Khalifa University of Science, Technology and Research, Abu Dhabi, United Arab Emirates. His research interests are in the broad area of wireless networking and wireless network protocols.



GEORGE K. KARAGIANNIDIS (M'96–SM'03–F'14) was born in Pithagorion, Samos, Greece. He received the University Diploma and Ph.D. degrees in electrical and computer engineering from the University of Patras in 1987 and 1999, respectively. From 2000 to 2004, he was a Senior Researcher with the Institute for Space Applications and Remote Sensing, National Observatory of Athens, Greece. In 2004, he joined the Faculty of Aristotle University of Thessaloniki, Greece, where he is currently a Professor with the Electrical and Computer Engineering Department and the Director of the Digital Telecommunications Systems and Networks Laboratory. He is also a Honorary Professor with South West Jiaotong University, Chengdu, China.

His research interests are in the broad area of digital communications systems and signal processing, with an emphasis on wireless communications, optical wireless communications, wireless power transfer and applications, molecular communications, communications and robotics, and wireless security.

He is the author or co-author of over 400 technical papers published in scientific journals and presented at international conferences. He is also the author of the Greek edition of a book on Telecommunications Systems and co-author of the book *Advanced Optical Wireless Communications Systems* (Cambridge Publications, 2012).

Dr. Karagiannidis has been involved as a General Chair, Technical Program Chair, and member of Technical Program Committees in several IEEE and non-IEEE conferences. He was an Editor of the IEEE Transactions on Communications, a Senior Editor of the IEEE Communications Letters, an Editor of the *EURASIP Journal of Wireless Communications and Networks* and several times a Guest Editor of the IEEE Selected Areas in Communications. From 2012 to 2015, he was the Editor-in-Chief of the IEEE Communications Letters.

He is one of the highly cited authors across all areas of Electrical Engineering, recognized as 2015 and 2016 Thomson Reuters highly cited researcher.