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Integrating plug-in electric vehicles into power grids: A comprehensive review on power interaction mode, scheduling methodology and mathematical foundation

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ABSTRACT

The vehicle-to-grid (V2G) technology is an effective and economic solution to enable the integration of electric vehicles (EVs) into power grids. As an effort to present the state of the art in relevant fields, the power interaction mode between EVs and power grids, and the scheduling methodology for the V2G implementation are overviewed comprehensively in this paper. To be specific, technical requirements, grid impacts and battery degradations regarding each power interaction mode are discussed; the operating processes of centralized and decentralized scheduling approaches are introduced and compared. More importantly, it is noted that few attentions are given to the solving algorithms of programming models used for optimizing the scheduling strategy of EVs and few works examine their feasibilities to acquire the optimal charging strategies especially for a large number of EVs. In this context, this paper also illuminates the mathematical foundation on optimization techniques for the optimal V2G strategy, and provides new insights for evaluating these models.

1. Introduction

With the increasing concern on fossil fuel shortages and environmental deteriorations, the electrification of transportation sector has attracted more and more attentions around the world [1]. EVs have been regarded as a sustainable alternative to reduce our dependence on traditional fuel sources as well as reducing our carbon footprint. At the initial stage, the development of EVs remains very slow owing to the high manufacturing costs and the severe shortage of charging facilities [2,3]. Many policies and regulations have been implemented across the world to conquer these barriers to the large scale adoption of EVs so that they might become the future vehicles. According to International Energy Agency in its report entitled “Global EV Outlook 2018”, the global EV population is projected to reach nearly 130 million by 2030 [4].

It is foreseeable that the large adoptions of EVs will bring a huge challenge to the current power system. The unmanaged loads resulting from EV charging would cause a significant negative impact on grids such as the power quality degradation and the transformer overloading. In this situation, it is inevitable to reinforce grid utilities. However, it involves a great deal of extra investments in upgrading grid utilities and deploying DGs [5]. Correspondingly, the V2G technology can provide an effective and economic solution to integrate the additional charging loads into grids friendly. Although substantial research efforts have demonstrated the potential to mitigate the adverse impact of EV charging on power grids by smart charging and/or discharging, the intelligent power interaction strategy between EVs and grids still remains an open research hotspot.

The V2G technology can achieve the bidirectional energy exchange between EVs and grids. Thus, it can store the surplus power during lower-demand periods and feeding them back to grids during higher-demand periods to achieve the balance of the supply and demand of electricity. In this situation, EVs are not only the pure electric loads, but also served as the distributed energy storage system. In consequence, the V2G mode can utilize the EV fleet to provide spinning reserve, frequency regulation and so forth for grids [6]. Moreover, EV users could benefit from rewards based on the provision of grid services [7]. However, the degradation on EV batteries would be incurred due to the discharging requirements [8]. In spite of this, the cost-benefit analysis for EVs participating in ancillary services to grids suggests that it is worth trying the V2G operation from the economic perspective, especially with the advancement of battery technology and the rapid

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Abbreviation

AC	alternating current
BEV	battery electric vehicle
DC	direct current
DG	distributed generation
EV	electric vehicle
FCEV	fuel cell electric vehicle
GA	genetic algorithm
HEV	hybrid electric vehicle
ICE	internal combustion engine
ICEV	internal combustion engine vehicle
LP	linear programming
MINP	mixed integer non-linear programming
MIP	mixed-integer programming
NP	nonlinear programming
PEV	plug-in electric vehicle
PHEV	plug-in hybrids electric vehicle
PSO	particle swarm optimization
QP	quadratic programming
SoC	state of charge
TOU	time of use
V2G	vehicle-to-grid

increase of the renewable energy [9–11].

The incorporation of EVs with grids is regarded as the efficient integration of information and energy. The key about this issue is how to build an intelligent communication link to achieve the coordinated energy exchange between EVs and grids for the win-win ecosystem. As an effort to integrate EVs into power system, the existing research efforts devote to either the centralized or decentralized methods. In centralized methods, the charging/discharging processes of EVs are directly controlled to improve the operation efficiency of grids. In decentralized methods, the charging/discharging behaviors of EV users are coordinated with an incentive strategy to follow the expectations of grids. Within the grid communication and control architecture, various objectives are adopted to obtain and implement the optimal V2G strategy, such as minimizing power losses, minimizing load variances, maximizing load factors, minimizing generation costs and so on [12–15].

In the current literature, the researchers primarily focus on the effectiveness of optimization methods employed for dealing with the EV-grid integration problem. Few papers elaborate the solution approaches in detail and examine their feasibilities to acquire the optimal charging strategies especially for a large number of EVs. As such, this paper aims at making a comprehensive review on these scheduling methodologies from a mathematical perspective, and providing a new insight to evaluate these models. The main contributions of this article can be summarized as follows:

- Different power interaction modes between EVs and grids are discussed from the perspective of power flow direction.
- Centralized and decentralized scheduling methods for EV coordinated charging/discharging are elaborated and compared.
- Mathematical foundation on the V2G optimization techniques is stated in detail.
- New insights are provided to make an overall evaluation on existing methods.

In general, this paper is organized as follows. The background is highlighted in Section 2. Section 3 introduces the power interaction modes between EVs and grids. Subsequently, two mainstreams about how to implement the V2G operation, namely centralized and decentralized method are presented and discussed respectively in Section 4. Section 5 illuminates the mathematical foundation about the optimization techniques for the solutions and conducts an overall evaluation on the models. Finally, Section 6 concludes this paper.

2. Background

2.1. PEV

According to the power sources for propulsion, EVs generally fall into three categories: HEV, BEV and FCEV. HEVs combine the conventional ICE system with the electric propulsion system to pursue

Table 1
Top 20 best-selling PEV products in global market in first half of 2018.

Ranking	Brand	Manufacturing country	Model	Capacity (kWh)	All-electric range (km)	Classification
1	Nissan	Japan	Leaf	30.0	172.0^a	BEV
2	BAIC	China	EC series	20.3/20.5	156.0^b/162.0^b	BEV
3	Tesla	America	Model 3	80.0	345.0^a	BEV
4	Toyota	Japan	Prius Prime PHEV	8.8	35.0^a	PHEV
5	BYD	China	Qin PHEV	23.0	100.0^b	PHEV
6	Tesla	America	Model S	85.0	550.0^a	BEV
7	Tesla	America	Model X	100.0	552.0^a	BEV
8	BYD	China	Song PHEV	16.9	80.0^b	PHEV
9	Renault	France	Zoe	22.0	240.0^a	BEV
10	JAC	China	iEV E/S	29.2/41.5	255.0^b/310.0^b	BEV
11	Mitsubishi	Japan	Outlander PHEV	12.0	52.0^a	PHEV
12	BYD	China	e5	43.0	305.0^b	BEV
13	BMW	Germany	i3	33.0	183.0^a	BEV
14	Roewe	China	i6 PHEV	8.0	60.0^b	PHEV
15	JMC	China	E200	29.2	252.0^b	BEV
16	Chevrolet	America	Bolt	60.0	383.0^a	BEV
17	Roewe	China	eRX5 PHEV	12.0	60.0^b	PHEV
18	Zhidou	China	D2 EV	18.0	155.0^b	BEV
19	BMW	Germany	530e	9.2	45.0^a	PHEV
20	BAIC	China	EX series	48	318.0^b	BEV

Notes to the table.
1) All-electric range is the driving range of a vehicle using only power from its electric battery pack to traverse a given driving cycle.
2) The superscript *a* indicates the all-electric range data released by the United States Environmental Protection Agency.
3) The superscript *b* indicates the all-electric range data released by Ministry of Industry and Information Technology of the People's Republic of China.

higher fuel economy. The more efficient and eco-friendly alternative of HEV is the PHEV that has a grid-chargeable battery pack. It can use either the onboard gasoline or the electricity stored in the battery pack for propulsion. Moreover, BEVs run on electricity only whereas FCEVs are driven by hydrogen fuel. Overall, only PHEVs and BEVs require to be charged from power grids for energy supply. Therefore, they belong to PEVs.

In the global PEV market, BEV has drawn more and more attention from the automotive manufacturers in recent years. As shown in **Table 1** [16], there are 13 kinds of BEV products accounting for 65% of the top 20 best-selling PEV products in the global market. It can be observed that BEVs are almost equipped with large capacity battery packs for the longer driving range. And that is exactly what makes the BEV manufacturing cost high, especially in the primary stage of BEV development. PHEVs are served as a temporary solution until more advanced EV technologies become mature in the future [17]. It can be seen that there are only 7 kinds of PHEV products with a small portion of the total. In general, the capacity of the battery packs equipped on the PHEVs is much less than BEVs, so the all-electric range of PHEV is rather short.

PEVs, both BEVs and PHEVs, are regarded as an effective way to reduce the emissions of harmful gases and relieve the dependence on fossil fuels. BEVs are known to entirely rely on the electricity stored in the onboard battery packs for propulsion. Consequently, the range anxiety is regarded to be one of the major barriers to the large-scale expansion of BEVs. However, this is not an issue for PHEVs because PHEVs can adopt their ICE as their power system when the onboard battery is exhausted. In spite of this, the all-electric range of PHEVs is also very limited. Hence, PHEVs cannot move away from a reliance on fossil fuels completely in most scenarios. In the future, it is very likely to replace the ICEVs with the BEVs with the advancement of new battery technology that has higher power and energy density in the future.

2.2. PEV charging mode

According to the charging power level of the chargers, the battery charging mode can be classified into slow and fast charging mode. Their basic characteristics for PEV charging are summarized in **Table 2**. These charging modes can be applied in different fields in accordance with their features.

The *slow charging mode* employs the AC, and it is made in different standards. In China, the home power system offers 220 V of AC, with 16 or 32 A for PEV slow charging; therefore, the charging power is either 3.52 kW or 7.04 kW. However, the charging power in America varies from 1.44 kW to 19.2 kW. It is definitely convenient to recharge PEVs by directly using the home power systems via the slow charger. Consequently, the slow charging points are the popular method for charging PEVs at residential garage or roadside parking. The problem is that, given a PEV with a 24 kWh battery, it will take about 17 h to charge it from empty to full with a charging power of 1.44 kWh. This requires the PEV users have enough free time for the charging tasks. Apart from overnight charging at home, the slow charging mode is also applicable to the circumstances in which they find the charging time in the workplace and public. This mode adopts a small rate of charging power; therefore, it consumes a rather long charging serving time.

The *fast charging mode* uses the DC instead of AC. The fast chargers provide power at up to 50 kW or more to achieve a relatively short charging time. Tesla built 120 kW supercharger stations for fast charging. The supercharger can charge Model S with a 90 kWh battery from empty to 80% in about 40 minutes. These fast charging options are more high-tech than a simple household outlet due to extremely high currents and voltages. So the fast chargers should be equipped with a tethered cable rather than the ordinary household cable. The fast charging stations aim to serve those PEVs which need to be recharged in a short amount of time. Although the less consuming time is attained for PEV charging in this situation, it may trigger extreme surges in demand and threaten the stability and security of the electric grid.

2.3. Impact of PEV uncoordinated charging on power grids

Uncoordinated charging would bring about significant negative impacts on the distribution grid due to their inflexible charging loads. Uncoordinated charging refers to the charging mode that PEVs start charging immediately when plugged into the grids, and stop charging at the moment when they are fully charged or disconnected [18]. In this situation, PEVs are only considered as a novel kind of electric load for grids. This type of charging load is projected to be huge with the rapid growth of PEVs. Due to the random time-space characteristic of PEV charging, it is extremely difficult to accurately predict and control these charging loads. If left uncontrolled, it will result in adverse influences on power quality and grid infrastructures.

The impacts of PEV charging on power quality have been investigated in substantial works [11,17,19,20]. A massive deployment of PEVs will definitely lead to the remarkable change on the power flow of distribution networks. It has been demonstrated that PEV concentration at a certain location at a given time would cause huge surges in power demand, thereby increasing the line losses and dropping the voltage. What is more, it may result in the increased risk of grid failures due to the deterioration arising from power network congestion. According to the mandatory EN50160 standard [21], voltage deviations up to 10% in low voltage grids, for 95% of the time, are acceptable for the stability of power grid. Clement-Nyns et al. conducted a research based on the radial network of the IEEE 34-node test feeder, and they found that the voltage deviations are close to 10% for a PEV penetration of 30% during the early evening periods [11]. In addition, the incremental energy losses are evaluated for different penetrations of PEVs by a comprehensive approach [17]. The results show that the energy losses will increase up to 40% during off-peak hours for a scenario with 60% of PEVs. Moreover, this kind of nonlinear loads caused by PEV charging may generate the severe harmonic pollution on the power system [19]. According to the research based on a typical 19 bus residential network, the harmonic analysis reveals that the total harmonic distortions of voltage levels will reach 45% when employing uncoordinated charging [20].

On the other hand, the large and inflexible charging loads triggered by the large-scale adoption of PEVs may also pose an additional threat on distribution transformers. At the beginning of substations construction, distribution transformers are planned and designed without the consideration of the large charging demands from PEVs. Predictably, it would increase the hot spot temperature of the

Table 2
Basic characteristics of slow and fast charging.

Feature	Type	
	Slow charging mode	Fast charging mode
Advantages	✓ Easy for charging posts installation ✓ Home charging	✓ Relatively short replenishing time
Drawbacks	λ Rather long replenishing time	λ Hard for charging posts installation λ Remarkable negative impacts on grids

transformer and accelerate the transformer ageing once the heavy PEV loads are clustered in a certain residential distribution grid [21]. Moreover, it would lead to the increased risk of transformer failure [22–24]. Taylor et al. showed that the transformer percent ageing tends to increase linearly with PHEV penetration [25]. Ghazal et al. conducted a study in the context of the National Household Travel Survey, and found that uncontrolled charging has a litter effect on the transformer life time with Level 1 (namely, 1.44 kW) whereas it will result in very high ageing rates and possibly even transformer failure at Level 2 (namely, 7.2 kW) [26]. Additionally, the uncoordinated charging behaviors would increase the burden on lines' loading [18,27,28].

2.4. PEV coordinated charging/discharging - integration of energy and information

Developing a smart charging/discharging strategy is an economic, reliable and efficient way to mitigate the negative impacts mentioned above. The key about this issue is how to build an intelligent communication link for the integration of energy and information between PEVs and grids. With smart grid technologies, PEV is not only regarded as a kind of electric load, but also served as a distributed energy storage system for power grid. In this context, PEVs are able to store the surplus power during the load-valley periods and feed power back to the grids during the load-peak periods for achieving the balance between supply and demand of electricity. Consequently, it is technically feasible to accommodate a certain penetration of PEVs for energy supply by using the coordinated charging/discharging approach.

The premise for PEV coordinated charging/discharging is to build an intelligent information platform to achieve the optimal energy management between PEVs and the grids. Fig. 1 depicts the corresponding relevance on the information and energy flow between the grid and power utilizations for PEV integration. It can be seen that the power grid is composed of generation system, transmission system, distribution system and etc. In such a conceptual framework, the system operators are important to integrate the actions of the power consumers and develop the rational strategy in generation, transmission and distribution for the supply and demand coordination of electricity. Among all the power utilizations, the power loads can fall into two types: inflexible and flexible loads. In general, the inflexible loads are not easy to be shifted such as household appliances, some commercial users and so forth. On the other hand, the flexible loads are demand-responsive and generally driven by the electricity market or system operators through the interaction with power system. In the aspect of load flexibility, PEVs can be regarded as either inflexible or flexible loads, depending entirely on their charging behaviors. Therefore, how to make the additional PEV loads flexible is the focal point for system operators especially when renewable energy resources are involved.

As stated above, the system operators should design the appropriate electricity allocation strategy on the basis of acquiring all the useful information to schedule the charging loads. The two-way communication between the system operators and PEVs or PEV aggregators should be available to achieve the information exchange. Herein, the PEV aggregators are served as the third party to exploit the business opportunities in electricity markets by managing a group of PEVs. In general, when PEVs or PEV aggregators report their buy/sell bids to the system operators, the system operators will evaluate whether their bidding strategies are validated or not, then negotiate with PEVs or PEV aggregators until a bidding agreement is achieved.

3. Power interaction mode between PEVs and power grids

The power interaction relationship between PEVs and grids could be uncoordinated or coordinated depending on the adopted charging strategy of PEVs. The uncoordinated charging mode of PEVs operates regardless of the supply and demand status of distribution networks, and is more likely to jeopardize the grid stability and reliability when a large number of PEVs are involved. The coordinated V2G mode is developed for integrating more PEVs into the existing power system. The current works for developing a smart charging/discharging system for PEVs can generally fall into unidirectional and bidirectional V2G. The unidirectional V2G mode is the so-called coordinated charging mode, and the bidirectional V2G mode is the so-called coordinated charging/discharging mode. In the uncoordinated charging mode and the unidirectional V2G mode, the energy only flows from the grid to PEVs

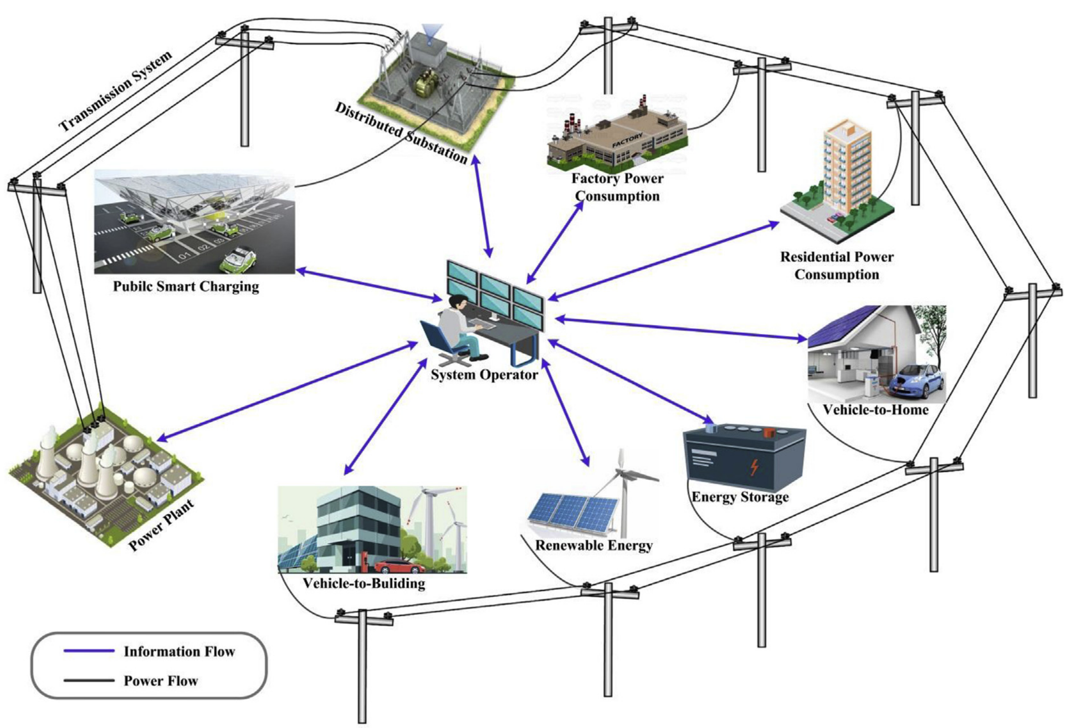

Fig. 1. Implementation framework for PEV coordinated charging/discharging.

(namely, Grid to Vehicle) whereas the energy not only flows from the grid to PEVs but also flows from PEVs to the grid in the bidirectional V2G mode. The power flow direction of three operating modes and their alternative terms are provided in **Table 3**.

The concept of Vehicle-to-Home (V2H) is a small version of V2G technology which allows a PEV to supply homes with power generated from its battery [29]. With the help of V2H technology, PEVs can be severed as a battery storage system to feed any electrical appliance where the PEV is parked. In spite of this, they don't have the capability to operate as an off-line uninterruptible power supply (UPS). Therefore, using PEVs as an off-line UPS is explored to support the smart grid and the smart home, and it is has been proved in Ref. [30]. Besides, the V2G technology can utilize PEVs to achieve the reactive power compensation so as to provide the grid with an economical in operation mode [31]. Additionally, the Vehicle-to-Vehicle (V2V) concept is developed for a local PEV community that can charge or discharge PEV battery among them [32]. It can be seen that these concepts enable PEVs act as distributed sources for the power grid within the V2G technology.

3.1. Uncoordinated charging mode

The uncoordinated charging mode refers to the conventional charging mode in a traditional power grid that PEVs start charging immediately once they are plugged in. In this case, the arbitrary plugged-in time is entirely determined by PEV users, and there are no PEV aggregators to regulate the PEV charging profile. Therefore, the charging processes of PEVs are completely dominated by their users as their own will. It has been investigated that a majority of the uncoordinated charging events occur in the home-charging situation, in which PEV users charge their vehicles as soon as they arrive home during early evening hours [33]; however, the load level of power grid is still rather high at this moment. Needless to say, the frequent PEV charging activities during this period would significantly stress the distribution system.

There are serval aspects of PEVs with the regard to the impact on distribution networks, such as vehicle pattern, vehicle penetration, vehicle load demand, plugged-in/plugged-out time, vehicle charging location, vehicle charging pattern and so forth [34]. It doesn't make significant impacts on distribution grids at low PEV penetrations [35]. Nonetheless, it is likely to result in the collapses of power grid if a high penetration level of PEVs is intensely recharged during load-peak periods. As a result, a coordinated power interaction relation between PEVs and grids should be established to tackle the charging problem of large-scale PEVs.

3.2. Coordinated V2G mode

3.2.1. Unidirectional V2G

Unidirectional V2G indicates the technical capability to modulate the charging power of PEVs to better correspond to the grid requirements with the assistance of communication technology. To that end, a smart infrastructure capable of supporting two-way information exchange between PEVs and grids is indispensable. Nowadays, a majority of PEVs have been equipped with the on-board unidirectional chargers. It is more likely to implement unidirectional V2G in the short term in comparison to bidirectional V2G.

To avoid grid congestions at rush hours, unidirectional V2G allows the third party to propel PEV users to charge their vehicles during the entire off-peak period, not just when off-peak moment starts. Therefore, the unidirectional V2G services are able to absorb the surplus power in the valley periods before PEV batteries are fully charged. Nevertheless, it is incapable of sending energy from PEV batteries back into the grid in the absence of the bidirectional power converters. Meanwhile, the extra degradation on PEV batteries would scarcely be incurred in this situation [36–38].

It has been shown that properly designed unidirectional chargers have the ability to charge PEVs with the surplus power of grids so as to mitigate the impact of large-scale PEVs charging [6]. Consequently, they can effectively support the distribution and transmission system with the active load management of PEVs. What's more, the unidirectional V2G services can help consume the abundant renewable energy sources such as solar and wind energy by the coordinated charging strategy. Although the unidirectional V2G services still face some obstacles, solutions have been in process. Additionally, unidirectional V2G would build a solid foundation to implement bidirectional V2G in the future.

3.2.2. Bidirectional V2G

Bidirectional V2G refers to the technology that allows for the reversal of electric energy stored in PEV batteries to facilitate the balance of electricity on the premise of satisfying the charging demands of PEVs. As well as the two-way communication system, this necessitates that the chargers are bidirectional so as to feed the stored energy from PEV batteries to the electric grid during the higher-demand periods. On account of its feedback function, bidirectional V2G can provide spinning reserve, frequency regulation and other ancillary services for power grid.

In bidirectional V2G, a large number of PEVs serve as a controllable fleet under a PEV aggregator. This fleet has the similar function to the distributed energy storage systems capable of providing ancillary services to the grid. Hence, the PEV discharging processes are indispensable for energy feedback. Beyond all doubt, it will lead to the extra adverse impact on the health of PEV batteries. However, these incurred costs might be offset by the benefits generated by the reasonable bidirectional V2G services [39]. In the near future, it is viable and worthwhile to implement bidirectional V2G from the economic perspective [40]. The problem is that, PEV aggregators should build an interest compensation mechanism to promote PEV users to participate in bidirectional V2G. Under such a mechanism, PEV users may benefit from rewards based on the provision of grid services and energy trading revenue.

Generally, bidirectional V2G has a greater advantage than unidirectional V2G on the integration of all kinds of resources including renewable energy and DGs. In the meantime, it is confronted with more barriers for its practical application. In the last decade, bidirectional V2G has been tested in several projects. But this technology is still in the experimental stage. A number of technical and regulatory issues need to be resolved before it can be widely and effectively used.

3.3. Comparison among different interaction modes

Table 4 lists several main characteristics among these power interaction modes in technical requirements, impacts on grids, and influences on PEV batteries and so on. The uncoordinated charging mode may cause many issues on grids when large-scale PEVs involved. The V2G technology can alleviate and even avoid these problems. In particular, bidirectional V2G can shave load peaks; however, bidirectional

Table 3
Power flow direction of three operating modes and their alternative terms.

Operating mode	Power flow direction	Alternative term
Uncoordinated charging	From grid to PEV	● Dumb charging ● Uncontrolled charging ● Conventional charging
Unidirectional V2G	From grid to PEV	● Coordinated charging ● Regulated charging ● Smart charging
Bidirectional V2G	From grid to PEV From PEV to grid	● Coordinated charging/ discharging ● Regulated charging/discharging ● Smart charging/discharging

Table 4
Characteristic analysis of different power interaction modes.

Feature	Mode		
	Uncoordinated charging mode	V2G mode	
		Unidirectional V2G	Bidirectional V2G
Technical requirements	● No information interaction ● No PEV aggregators ● No PEV coordination	● Two-way information system ● PEV aggregators ● Coordinated charging management	● Two-way information system ● Bidirectional charger ● PEV aggregators ● Coordinated charging/discharging management
Impacts on power grid	● Increases power loss ● Drops network voltage ● Elevates load peaks ● Affects grid frequency ● Overloading of lines ● Overloading of transformers	● Load-valley filling ● Voltage regulation ● Frequency regulation ● No lines overloading ● No transformers overloading	● Load-valley filling ● Load-peak shaving ● Voltage regulation ● Frequency regulation ● No lines overloading ● No transformers overloading
Influences on PEV batteries	● No extra degradation	● No extra degradation	● Cause extra degradation
Economic cost/benefits	● Increase electricity costs for power company ● Increase charging costs for PEV users	● Decrease electricity costs for power company ● Decrease charging costs for PEV users	● Decrease electricity costs for power company ● Decrease charging costs for PEV users ● Benefit from rewards on ancillary services to grids for PEV users
Feasibility	● Have widely existed	● A little difficulty	● Great difficulty

chargers are necessary for energy reversal. Meanwhile, it will cause the serious battery degradation due to the frequent charging or discharging cycles. Additionally, the V2G technology can help the power company decrease the electricity costs in generation, transmission and distributions, thereby reducing the PEV charging costs. As far as the feasibility of V2G implementation is concerned, bidirectional V2G would require significantly higher investments than unidirectional V2G on the hardware devices.

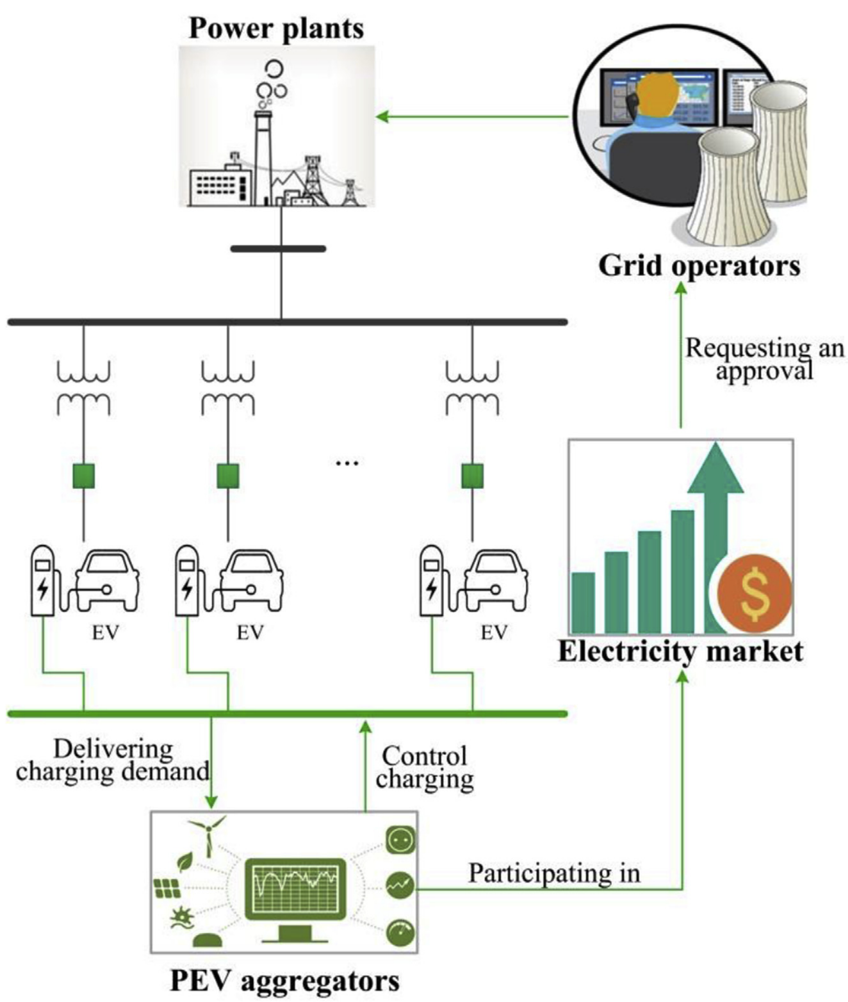

Fig. 2. General framework for centralized scheduling method.

4. Two mainstreams for V2G implementation

4.1. Centralized scheduling method

In the centralized scheduling method, PEV aggregators optimize and control PEV charging based on the grid status and PEV charging demands for a special target. Hence, the controllers should be equipped on the PEV chargers to adjust the charging rates of PEVs in this scenario. Fig. 2 shows the general process to implement centralized scheduling method for PEV coordinated charging. It can be seen that PEV aggregators are the crucial bonds to integrate PEVs in the power system and make PEVs participate in electricity markets. At first, each PEV user ought to inform the respective PEV aggregator of all the charging related information including the identity number of the plugged-in charging post, the nominal capacity of PEV batteries, the plugged-out/plugged-in time, and the plugged-out/plugged-in *SoC* of PEV batteries. Afterwards, PEV aggregators will compute the optimal charging/discharging strategy of each PEV to determine their buy/sell bids in accordance with the received charging demands and the forecasted market behaviors. Then, the bidding instruction should be at once reported to grid operators for approval ahead of schedule. And, grid operators will check whether the biding strategy is a safe and economic operation for power system. If yes, PEV aggregators can proceed to the electricity market; if not, grid operators will ask PEV aggregators to change their bidding strategies until a protocol is reached. Finally, PEV aggregators will charge each PEV in accordance with the optimal load profile of the fleet. On the other hand, PEV aggregators will check out with each PEV user by the online settlement system.

It can be seen that the PEV aggregator is responsible for a group of PEVs to exploit business opportunities in electricity markets. One of the PEV aggregator's targets is to minimize the charging costs of PEVs managed by this aggregator. In the centralized scheduling approach, the overall charging costs resulting from all PEVs are optimized in a programming model for the global optimal solution [41]. This objective function can be formulated as:

$$\min \sum_{n=1}^{N} \sum_{t=1}^{T} (P_{t,n}^{EV} \Delta t) \lambda_t^{RT} \tag{1}$$

subject to

$$P_{min,n}^{EV} \le P_{t,n}^{EV} \le P_{max,n}^{EV}, \ \ t = [\Gamma_n^s, \ \ \Gamma_n^e], \, n \in [1, \ \ N] \tag{2}$$

$$SoC_{min,n}^{EV} \le SoC_{t,n}^{EV} \le SoC_{max,n}^{EV}, \ \ t = [\Gamma_n^s, \ \ \Gamma_n^e], \, n \in [1, \ \ N] \tag{3}$$

$$\eta_n \Delta t \sum_{t=\Gamma_n^s}^{\Gamma_n^e} P_{t,n}^{EV} = (SoC_n^e - SoC_n^s) C_n, \, n \in [1, \ \ N] \tag{4}$$

where all variables, parameters and indices are defined in Section 5. Equation (2) indicates the limitations of the charging power of the n-th PEV at time t; Equation (3) indicates the limitations of the battery SoC of the n-th PEV at time t; Equation (4) indicates that the charging requirement of the n-th PEV should be satisfied.

Up till now, a general model for minimizing the total charging costs of PEVs in a centralized way is built. The charging strategies of all involved PEVs are optimized from a global perspective. The centralized model can achieve the optimal charging/discharging strategies for PEV charging scheduling. However, there are a huge amount of variables and constraints to handle when a large number of PEVs are involved in this model. Therefore, it may be difficult for the centralized scheduling method to search for the global optimal solution.

As illustrated in Fig. 2, there are three major participants in centralized approaches, namely grid operators, PEV aggregators and PEV users.[1] They have extremely different considerations in their respective position. From the view of grid operators, they focus primarily on the grid performance improvement and secondarily the total operational costs reduction. This requires that the charging time of PEVs ought to be scheduled and limited in the off-peak periods as far as possible. In this way will the power system run more safely and efficiently. However, at PEV users level, they require a more convenient and affordable recharging system. It may result in severe conflicts with grid operators on the charging periods. In this context, PEV aggregators are employed to coordinate the both sides' relation. From the PEV aggregator perspective, how to control the PEV chargers to maximize the total operational profits with the presence of satisfying the charging demands of PEV users and grid restrictions is their considered issue. On the other hand, they should design a reasonable compensation strategy to make more PEV users participate in the centralized scheduling method and provide V2G ancillary services.

Many works focus on the optimization methods to make the charging decisions on PEVs in the place of PEV aggregators. The critical issue for PEV aggregators is to develop the so-called load shifting or valley filling strategy so as to alleviate the demand pressure of power grid during the load peak hours. Originally for improving the power network quality, the model with the target of minimizing the overall load variance is presented to smooth out the fluctuation of the power load profiles while satisfying the driving demands of PEVs [42–48]. Despite all this, both the PEV charging costs and the aggregator operational profits are not taken into consideration in this sort of methods. In order to remedy these issues, the PEV aggregator in Ref. [49] provides a global optimal solution to minimize the total charging costs of all PEVs by performing charging and discharging during the day. Moreover, the aggregator operational profits are optimized in Ref. [50] to acquire the optimal dispatching strategy for the aggregator participating in the frequency regulation while satisfying the PEV driving demands. Additionally, scheduling PEVs charging properly would help in reducing the carbon emissions [51]. Consequently, the environmental impacts of PEVs participating in the V2G operation are also investigated and optimized in Ref. [52].

Conversely, the feasibility of the centralized approaches has not been paid sufficient attentions. Overall, there are two key issues, viz. the time-space characteristic of PEV charging and the execution time for the optimal solutions in the PEV charging problem. Initially, many scheduling methods for PEVs participating in the day-ahead electricity market are proposed in Refs. [53–55]. It can be observed that the execution time is not a big problem at all in the day-ahead time horizon. In spite of this, these methods are generally built on the assumption that the PEV aggregators have a full knowledge of the PEV-involved variables. Evidently, it is almost infeasible to precisely predict or collect the PEV charging demands at least one day in advance due to the stochastic driving pattern. Therefore, the real-time scheduling approaches are employed in Refs. [56–58]. In such methods, the solving time of an optimization model is crucially important when a large population of PEVs involved. As a result, some efficient algorithms such as PSO algorithm, the interior point algorithm, and GA are employed to obtain the real-time solutions. It has been proved that the solving time highly depends on the computational complexity of the applied algorithm. In consequence, the key to implement the real-time charging operation is to develop an algorithm with lower computational complexity for PEV coordination.

The centralized approaches require the PEV users to give up their charging authorities to control the PEV charging process. It can be foreseen that PEV aggregators can make a generous profit by scheduling

[1] It is worth noting that there are only two participants namely grid operators and PEV users in some works. That is because the functionalities of PEV aggregators are also performed by grid operators. Both grid operators and PEV aggregators are regarded as the energy coordinators in the PEV charging scheduling approaches.

PEVs to charge at valley hours and discharge at peak hours. The critical issue is that, this action will lead to the extra degradation on PEV batteries. Therefore, battery restricted conditions should be added into the scheduling optimization models to relieve the influences on battery lifetime as far as possible [31–59]. Nonetheless, it may still not be enough from the benefits of PEV users. On this account, the battery ageing costs for PEVs taking part in V2G should be evaluated to compensate PEV users for the extra battery degradation [60].

4.2. Decentralized scheduling method

The decentralized scheduling method refers to an incentive strategy, wherein, the charging behaviors of PEVs will be indirectly coordinated by the electricity price mechanism. In some simple situations, this only requires grid operators or PEV aggregators broadcast the price information to each PEV user so as to induce the PEV loads from high-demand hours to less congested hours. Hence, it is easy to be implemented in the short term. Fig. 3 depicts the general process to implement decentralized scheduling methods for the V2G operation. Firstly, PEV aggregators collect or forecast the PEV charging demands during each period to determine the bidding strategy. Afterwards, the bidding information will be transmitted to grid operators for approval in advance just like the centralized scheduling method. When the agreement is reached, PEV aggregators will broadcast the price to each PEV user. Consequently, each PEV user will schedule their vehicles charging as their own willingness such as reducing their charging costs.

In the decentralized scheduling approach, PEV aggregators are also employed to manage the charging of PEVs. Each PEV user will respond to the price signals according to their own willingness. And the bidding strategy will be delivered to the PEV aggregators for regulated charging. As for each PEV user, they usually strive for the minimization of their individual charging costs. In general, the objective function to minimize the charging cost of the n-th PEV can be given by Ref. [14]:

$$\min \sum_{t=1}^{T} (P_{t,n}^{EV} \Delta t) \lambda_t^{RT} \tag{5}$$

subject to

$$P_{min,n}^{EV} \le P_{t,n}^{EV} \le P_{max,n}^{EV}, \quad t = [\Gamma_n^s, \quad \Gamma_n^e] \tag{6}$$

$$SoC_{min,n}^{EV} \le SoC_{t,n}^{EV} \le SoC_{max,n}^{EV}, \quad t = [\Gamma_n^s, \quad \Gamma_n^e] \tag{7}$$

$$\eta_n \Delta t \sum_{t=\Gamma_n^s}^{\Gamma_n^e} P_{t,n}^{EV} = (SoC_n^e - SoC_n^s) C_n \tag{8}$$

It can be observed that the decentralized method allows for a distributed way to deal with the charging scheduling optimization for each PEV. The centralized model presented in Section 4.1 seems to be divided into many sub-models stated above. There are a few variables and constraints in the decentralized model. Therefore, this model is comparatively easy to be solved. Additionally, this model can also attain the optimal solution for a special PEV; however, it cannot achieve the minimization of overall charging costs for all involved PEVs. The PEV aggregator will obtain the total income by energy trading with the PEV users. The key for the PEV aggregator is how to optimize the bidding strategy electricity markets for making a profit. This issue is presented in Section 5.1.2. Herein, the concrete method is not described in this section.

As shown in Fig. 3, there are also three main participants in decentralized approaches, namely, grid operators, PEV aggregators and PEV users. From operating principle, the decentralized scheduling approach is a price-signal based method. This should presuppose that each PEV user must respond to the price signal and make an enough intelligent charging/discharging decision. Then, at the PEV aggregator level, they ought to forecast the charging demands from PEVs so as to make the bidding decision ahead of schedule; on the other hand, they ought to establish the communication network to inform PEV users of the price information. Finally, with respect to grid operators, their primary responsibility is to evaluate whether the bidding strategy of each aggregator will endanger the safe operation of power grid. In addition, they also desire the operating costs are reduced and power efficiency is improved.

Apparently, the design of TOU price strategy is the key to successfully implement the decentralized V2G approaches. Consequently, substantial research efforts exist regarding this central issue. With respect to the objectives of the energy coordinator, some authors devote to minimize the operating cost while others intend to maximize the operational profit. Nonetheless, if only considering the unilateral interest of the energy coordinator and ignoring the responding of PEV users to the price system, the generated price system may result in the failure of load shifting, thereby jeopardizing the security of power grid. Therefore, the repetitive iterations between the energy coordinator and PEV users are necessary to reach the equilibrium for satisfying the interest of both of them [14,61–63]. At each iteration, PEV users will update their optimal charging profiles according to the price signal broadcast by the energy coordinator. Afterwards, the energy coordinator will amend the price signal to guide their updates. Both the energy coordinator and PEV users search for the optimal strategy by multiple iterations. Remarkably, the iterative process converges to the optimal and unique solution only under the given conditions. At the PEV side, its implementation only requires low computation capability since each PEV will solve its individual local problem. Despite all this, a large number of iterations are still required to obtain the optimal price scheme. In consequence, the frequent bidirectional communication between the energy coordinator and PEV users will become a trouble in such methods.

As stated above, it is worthwhile to develop an advanced algorithm with a rapid convergence speed for less bidirectional communication

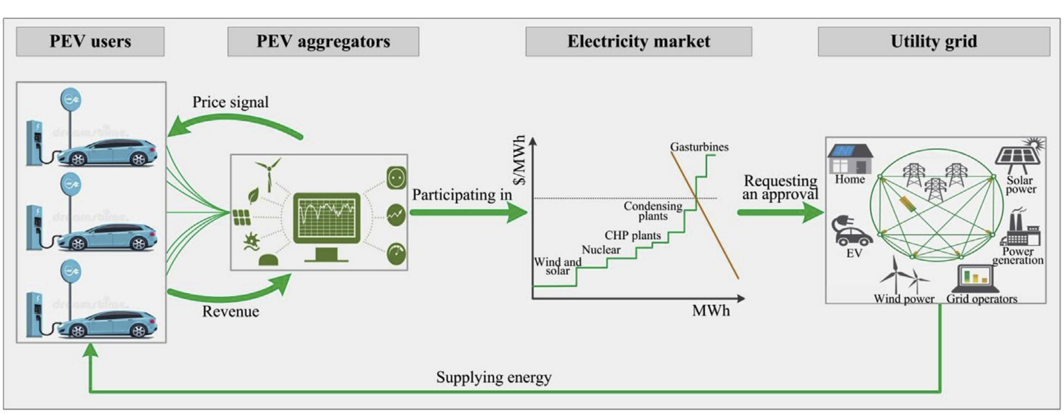

Fig. 3. General framework for decentralized scheduling method.

and computational effort. Based on this, a decentralized control method is presented to schedule PEV charging loads to achieve valley filling [64]. The iterative process in this method is able to converge within only several iterations, making it very applicable for the real-time implementation of coordinated charging. Apart from only employing the price signal, another pricing scheme is presented in Ref. [63], wherein both price and quantity information is conveyed to PEV aggregators for PEV coordination. The simulation results show that this kind of price/quantity-based approach not only has a superior performance on controlling PEV fleet charging, but also involves 24 times less information exchange than the price-only scheme. On the other hand, the research in Ref. [65] makes an improvement on the required computational effort as compared to Refs. [14,61], in which a convex optimization problem must be solved by each PEV at each iteration. Generally speaking, if the proposed methods allow for the use of cheaper communication facilities and computational devices, it will be beneficial for both grid operators and PEV users in the decentralized scheduling method.

Massive works pay great attention to the operational feasibility of the decentralized methods so as to make an improvement on the operation efficiency and power quality. In Ref. [66], a two-level optimal charging algorithm is designed to achieve both load shifting and frequency regulation. However, the load shifting algorithm is built on the basis that PEV aggregators have a full knowledge of four pieces of information: forecasted base load profile, estimated number of plugged vehicles, estimated plug-off time, and the battery *SoC* of the vehicle being charged. Obviously, it is considered impractical in real world. In addition, a more practical way for the decentralized valley-filling strategy is developed in Ref. [67]. Although it does not rely on a bi-directional communication system to collect the PEV charging information, the one-way communication is still required to broadcast the pricing scheme to PEV users. Moreover, a full decentralized controlled PEV charger is designed to mitigate the PEV charging impact on power grids [68]. There are no requirements on a centralized control center and information exchanges between the energy management system and PEV chargers. As a result, the charging scheme for PEV chargers can be effectively achieved.

The PEV users in the decentralized method preserve individual authority on the PEV charging processes according to the price scheme broadcast by the energy coordinator. However, it is possible that a part of PEV users may not be sensitive to the electricity price mechanism, or they do not receive this kind of price information at all. As a consequence, in this situation the unexpectedly plugged-in PEVs will also pose an additional stress on power system. In order to tackle this terrible scenario, in Ref. [69] a practical coordinated PEV charging approach is presented based on the worst node voltage profile. The results show that deferred plugging of vehicles will lead to the detrimental impacts on the grid, and these impacts could be encouraged by introducing higher electricity prices during the peak load hours. In addition, a non-anonymous version of the algorithm is proposed under the communication failures in Ref. [65]. This method is able to handle the PEV charging problem without successful communication. Additionally, the results indicate that the algorithm can converge to the optimal solutions of the charging problem.

4.3. Comparison between centralized and decentralized methods

Table 5 shows the main characteristics between centralized and decentralized methods. In the centralized methods, the energy coordinator is responsible to optimize the charging/discharging profile of all PEVs involved, subject to the grid constraints. With the rapid increase of PEV scale, the PEV variables required to be optimized in a centralized manner will become tremendously large. Herein, the computational complexity is remarkably high due to the curse of dimensionality, especially for the NP problem. Therefore, the computational expense for the optimal charging/discharging profile of PEVs will also sharply increase. In particular, it is a more problematic issue in the real-time scheduling operations of large-scale PEVs. On the other hand, in the decentralized scheduling method the design of electricity price mechanism is mainly done by the local grid condition and the overall charging demands of PEVs, and each PEV user solves its individual local problem according to the price scheme. Hence, there is no requirement to optimize such a large number of the PEV variables like the centralized method even if a huge mass of PEVs is involved. Nevertheless, it is observed that the repeated iterative process is necessary to search for the optimal price system in some decentralized approaches, and convergence cannot be guaranteed. Generally speaking, the decentralized approaches have a significant superiority in the aspect of computational cost and accessibility to the optimal solutions over the centralized approaches for the charging/discharging scheduling strategies of large-scale PEVs.

Theoretically speaking, the centralized scheduling approach is able to obtain an optimal solution by the unified schedule of PEVs for a special objective function. What's more, the charging/discharging processes of all PEVs are directly under the control of the energy coordinator. Consequently, the centralized method, whether in theory or technology, is capable to achieve the optimal energy management between power grid and PEV users. In contrast, the decentralized scheduling approach is a price-signal based method. In theory, the decentralized methods can provide the optimal solutions for the V2G operations. But the prerequisite is that each PEV user is enough intelligent to charging/discharge their vehicles based on the electricity price just as the energy coordinator desires. Obviously, it may be unattainable in practical applications since PEV users in the same charging situation may have different responding to the price information. Hence, the decentralized method is extremely difficult to attain the optimal V2G operations at implementation stage. In spite of this, it is an economic, effective and practical way to mitigate the negative impacts of PEV charging.

In general, the centralized solutions give more weight on grid performance and operational costs than the individual charging authority of PEV users. In addition, due to the requirement of collecting the charging information from the distributed PEVs, this involves a bidirectional communication network for information exchange. And this will cause the privacy concerns for PEV users on the PEV charging information such as the plug-in and plug-out time, the charging location. In contrast to centralized methods, the decentralized approaches allow for the individual authority on the PEV charging. As a result, it cannot ensure the overall system's optimal operation. Unfortunately it may produce some security concerns on power system when the broadcasted price system fails in shifting PEV charging loads from load peak to valley periods. However, the benefits are that, it only requires low communication and computational expenses. Moreover, it raises much less privacy concerns for PEV users.

5. Mathematical foundation

The strategy decision making for the V2G implementation is essentially a mathematical optimization problem regardless of the centralized or decentralized scheduling method. As a rule, a typical

Table 5
Comparison between centralized and decentralized methods.

Feature	Method	
	Centralized method	Decentralized method
User charging authority	Not granted	Granted
Grid security risk	Almost risk-free	Potential
User concern for privacy	Moderately concerned	Marginally concerned
Computational complexity	High	Low
Optimal solution	Global	Local

mathematical programming model is composed of three parts, viz. the objective function, the constraint conditions and the solving algorithm. The following section will illuminate the mathematical foundation on the optimization technique for the optimal V2G operation. On this basis, an overall evaluation is conducted on these models. In general, the framework of this section is illustrated in Fig. 4.

5.1. Scheduling objective function

An old Chinese saying goes, “Make the best use of everything and give full scope to the talents”. On the basis of this way of thinking, the ultimate objective for V2G implementation could be considered to integrate all the available resources (including but not limited to PEVs, energy storage devices, DGs and renewable energy sources) and fully exploit their respective advantages to fulfill the maximization of the overall energy efficiency. It is believed that in this way composite economic and environmental benefits will be improved greatly. Under the guidance of this ultimate objective, several main views on the V2G operation are summarized as follows: Technically, the PEV scheduling strategy should balance supply and demand of electrical energy in power generation, transmission and distribution. Economically, the designing strategy ought to abide by the principles of considering all multi-stakeholders, for example, the operational profits of the whole power system are maximized while the PEV charging costs are minimized. Environmentally, the carbon emissions incurred by PEVs should be reduced sharply in a coordinated charging/discharging scheduling scheme under the premise of satisfying the interest desire of multi-stakeholders.

Inspired by improving the overall energy efficiency, all kinds of methods are explored to pursue the optimal charging patterns of PEVs in the previous literature. With reference to the objective functions, many authors initially try to minimize the energy losses by employing the optimal power flow calculation [42,70,71] while other authors intend to minimize peak demands [72–74]. Another distinctive objective is to mitigate the deviation between the purchased energy in the electricity market and the consumed energy for PEV charging [75]. In other words, to achieve the electricity supply-demand balance with the flexible PEV loads is also regarded one of the valid objectives. Meanwhile, some efforts focus on the multi-objective optimization models. For instance, both the operating costs and emissions are minimized in the day-ahead coordinated charging scheduling of PEVs [76]. Another multi-objective example is to minimize both overall load variance and the charging satisfaction of PEV users regarding to energy management strategy [77]. Also, in Ref. [47] the optimal charging scheduling method is developed to minimize both electricity generation costs and carbon emissions. It can be observed that all the above objectives are designed to improve the following aspects: grid performance, economic index and environmental index.

5.1.1. Grid performance objective

5.1.1.1. Power loss minimization. The stochastic connections of large-scale PEVs not only increase the power losses, but also affect the power quality. It has been demonstrated that minimizing the distribution system losses with the additional PEVs is capable to improve the voltage profile, thereby maintaining the stability of power grid. Consequently, many works focus on the power losses minimization so as to mitigate the adverse impacts of PEV charging. In general, this kind of objective function can be defined as:

$$\min \sum_{t=1}^{T} \sum_{l=1}^{lines} R_l I_{l,t}^2 \tag{9}$$

where R_l indicates the resistance of line l; $I_{l,t}$ indicates the current of line l at time t.

Obviously, the minimization of system losses is determined by the operating schedule of PEVs. In Ref. [70] a load flow analysis is performed to assess the power losses in the residential grid topology with 34 nodes for PEV uncoordinated charging. Later, in Ref. [42] a coordinated charging method is developed to directly optimize the PEV charging current at the different nodes for losses minimization with the IEEE-node case. Although power losses, load variance and voltage regulation are improved all, it is a great trouble to consider such a complex grid topology especially when large-scale PEVs involved. Therefore, some topology independent ways are explored to decrease distribution system losses, such as flattening out the peak power,

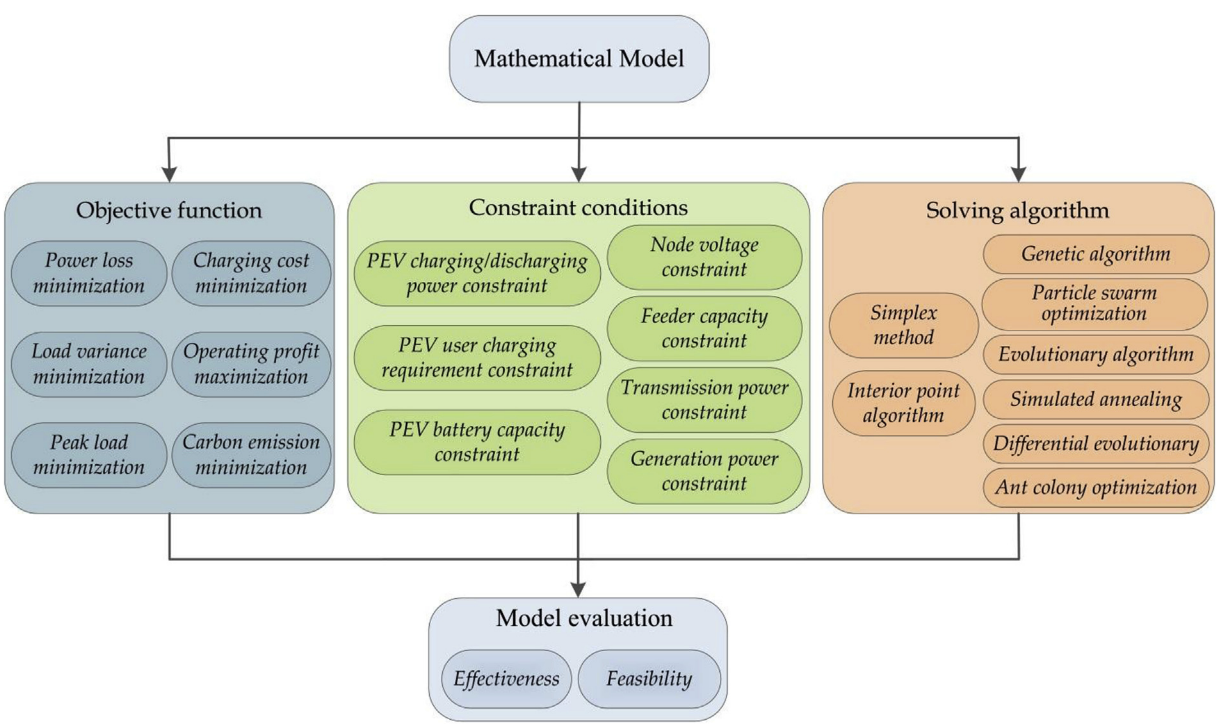

Fig. 4. General framework of mathematical modelling in V2G scheduling.

reducing the overall load variance and so on. In Ref. [78] the optimal scheduling methodology is proposed to tackle the losses minimization through peak shaving using energy storage. Moreover, the load factor and the load variance are served as the objectives to minimize system losses and improve voltage regulation [48]. Additionally, it is theoretically demonstrated that maximizing system load factor is equivalent to minimizing load variance and minimizing load variance will minimize losses approximately for practical systems. Furthermore, based on Cauchy-Schwarz inequality, the action and importance of flattening the overall load profile in reducing the network loss is analyzed and it was proved that the more flat the load curve is, the more the network loss reduces [71].

5.1.1.2. Load variance minimization. The load variance based objective function provides an alternative option for coordinated charging of PEVs regardless of the network topology. Evidently, minimizing the overall load variance will smooth out the fluctuation in the load profiles. As a result, it will inevitably reduce the system losses to a great extent. A typical objective function served as load variance minimization is given by:

$$\min \frac{1}{T}\sum_{t=1}^{T}\left(P_t^{Con}+\sum_{n=1}^{N}P_{t,n}^{EV}-\mu_T^H\right)^2 \text{ where } \mu_T^H = \frac{1}{T}\sum_{t=1}^{T}\left(P_t^{Con}+\sum_{n=1}^{N}P_{t,n}^{EV}\right) \tag{10}$$

where P_t^{Con} represents the conventional loads without PEVs at time t; $P_{t,n}^{EV}$ represents the charging power of the n-th PEV at time t; T represents the divided number of time period; N represents the number of PEVs.

In theory, the objective function using load variance concept is able to achieve load-valley filling and load-peak shaving with the PEV loads so as to improve the overall energy efficiency. There are many vital issues to be considered such as grid limits, the charging satisfaction of PEV users and the operating costs of system operators while reducing the overall load variance. In Ref. [79] the proposed charging scheduling scheme aims at minimizing the overall load variance of power grid by V2G operation while satisfying the charging requirement of all PEVs. However, the voltage issues and PEV charging costs are not mentioned. By contrast, literature [80] minimizes the load variance and charging costs by using the weighted sum method, as well as reducing the voltage drop. Likewise, Li et al. seeks to minimize the load variance and the satisfaction of all the PEV users with a weighing parameter subject to the limits on the feeder overload of power network [81]. Also in Ref. [82], the load variance and PEV charging costs are balanced by the proposing criteria. Apart from the load variance, the operating cost and pollutant treatment cost are also considered into the objective function in Ref. [83].

5.1.1.3. Peak load minimization. The peak load minimization is also one of the potential ways to effectively integrate PEVs into power system. The cost-benefit analysis has been carried out to implement the V2G operation with the peak load minimization, and it has been demonstrated that the social annual benefit is very likely larger than the total annual costs for the PEV coordination [84]. Therefore, the peak-minimizing objective is developed to reduce the peak load consumption. A simplest form of the peak load minimization is described as:

$$\min \max_{t\in\{1,2,\dots,T\}}\left\{P_t^{Con}+\sum_{n=1}^{N}P_{t,n}^{EV}-P_t^{PV}\right\} \tag{11}$$

where P_t^{PV} indicates the power supply of the photovoltaic array at time t; other variables, parameters and indices are defined as the same in equation (10).

The peak shaving strategy provides windows of opportunity to shift a part of the electricity demand to valley periods without increasing the grid capacity to the level of high peak loads. Therefore, an extensive research has devoted to minimizing the peak load for the optimal scheduling scheme of PEVs. In Ref. [85], the day-ahead scheduling method for PEV loads is proposed to minimize the system peak while satisfying the technical restrictions of the utility. Although the peak load consumption is decreased dramatically for various PEV penetrations by controlled charging, the economic benefits of PEV users are not involved. Consequently, the financial factor namely PEV charging costs are considered in Refs. [73,74,86] while reducing the peak demand. Based on minimization of peak-to-average and minimization of charging cost, a hybrid planning method is proposed to minimize the financial impacts by combining the strengths of two objectives more effectively [73]. In addition, in Ref. [74] a strategy that minimizes network peak load is compared with a strategy to minimize PEV charging costs. The results show that when PEV users make their charging decision only on electricity price, it may lead to high peaks in network load thereby high network investment costs; on the other hand, when PEV charging is controlled with the objective of minimizing peaks in network load, far less reinforcements are required. Moreover, a virtual time-of-use rate based on the load demand is proposed to encourage the PEV users to participate in peak load shaving by providing economic incentives in Ref. [86].

5.1.2. Economic objective

5.1.2.1. Charging cost minimization. The economic strategy is regarded as one of the promising solutions for PEV coordinate charging. As a consequence, the TOU scheme is usually assigned with regard to load shifting. The low prices provide an effective incentive to make PEVs be charged during less congested hours. From the PEV user perspective, the minimization of charging costs is often adopted to acquire the cost saving strategy. A most general form of the total charging cost minimization is given by:

$$\min \sum_{n=1}^{N}\sum_{t=1}^{T}(P_{t,n}^{EV}\Delta t)\lambda_t^{RT} \tag{12}$$

where $P_{t,n}^{EV}$, T and N are defined as the same in equation (2); Δt indicates the length of each time interval; λ_t^{RT} indicates the real-time price of electricity at time t.

Equation (12) aims to minimize the real-time charging costs of PEVs. The PEV aggregator will adjust the charging strategies of PEVs for cost saving. This objective function is established on the basis of a known real-time electricity price. However, this issue may be complex if considering the charging cost minimization of PEVs in a day-ahead horizon due to the uncertainty in electricity markets and charging behaviors. In Ref. [46], an optimal bidding strategy for PEV aggregators participating in electricity markets is developed. The objective is the minimization of the cost of purchased energy so as to reduce the charging costs of PEVs. The objective function can be given by:

$$\min \sum_t \lambda_t^{DA}E_t^{DA} + \sum_w \pi_w \sum_t [-\lambda_{t,w}^{RT}\Delta E_{t,w} + (Pnlty_{t,w}^{U,Up} - Pnlty_{t,w}^{U,Dn})] \tag{13}$$

where λ_t^{DA} indicates the day-ahead price of electricity at time t; E_t^{DA} indicates the day-ahead energy bidding at time t; π_w indicates the scenario w probability of occurrence; $\lambda_{t,w}^{RT}$ indicates the real-time price at time t for the scenario w; $\Delta E_{t,w}$ indicates the deviation between real-time energy consumption and day-ahead energy bid; $Pnlty_{t,w}^{U,Up}$ indicates the penalty for up uninstructed energy deviation higher than threshold; $Pnlty_{t,w}^{U,Dn}$ indicates the penalty for down uninstructed energy deviation higher than threshold.

A significant body of research has demonstrated that the charging-cost-minimizing objectives have the potential of filling the valleys in electric load profiles under a reasonable pricing scheme. However, it also takes the risks of causing another peak demand at low-price hours if PEV users only consider the reduction of their charging costs based on the pricing scheme. Literature [87] shows the PEV charging strategy, based on the price signal only, will lead to significant overloading of power system as well as severe voltage issues in power grid. Therefore, they present an optimal PEV charging strategy to minimize the charging costs, at the same time, avoid any overloading problem. However, this method may be impractical because it requires that the arrivals of PEVs during the target day are able to be predicted in advance [88]. As a result, in Ref. [89] a local scheduling optimization problem is formulated to minimize the total cost of all PEVs in the current ongoing PEV set within the local group. Also in Ref. [45], the optimal energy management for PEVs is developed to reduce their charging costs under time-varying electricity price signal while considering the stochastic arrivals and departures of PEVs. Moreover, the system load factor and PEV users' satisfaction are improved by minimizing the electricity costs required for charging [90]. It can be observed that the charging cost based objective function provides a theoretical foundation for the design of the electricity pricing mechanism from the utility perspective.

5.1.2.2. Operating profit maximization. Ordinarily, the PEV aggregator managing a fleet of PEVs participates in energy and ancillary services markets. As for the PEV aggregators, they are responsible for modulating the PEV charging level so as to maximize their profits. In general, they make an optimal bidding strategy in the day-ahead market on the basis of the PEV charging demand forecast and sell the energy for PEV charging in real-time market. On the one hand, the PEV aggregator should pay for the energy delivery at time t as

$$\lambda_t^{DA} E_t^{DA} - \lambda_t^{RT}(E_t^{DA} - E_t^{RT}) \tag{14}$$

whereλ_t^{DA}indicates the day-ahead price of electricity at time t; E_t^{DA}indicates the day-ahead energy bidding at time t; E_t^{RT}indicates the real-time energy consumption at time t.

On the other hand, they obtain the total income by energy trading with the PEV users at time t given by

$$\lambda_t^{RT} \sum_{n=1}^{N} (P_{t,n}^{EV} \Delta t) \tag{15}$$

As a result, the objective function of the total operating profit minimization is simplified to (7) when no deviations penalty and no participation in regulation market are taken into account [46].

$$\max \sum_{t=1}^{T} \left(\lambda_t^{RT} \sum_{n=1}^{N} (P_{t,n}^{EV} \Delta t) - (\lambda_t^{DA} E_t^{DA} - \lambda_t^{RT}(E_t^{DA} - E_t^{RT})) \right) \tag{16}$$

where all variables, parameters and indices are defined above.

There are extensive literature regarding the maximization of operating profits from the PEV aggregator perspective. Remarkably, as far as the PEV aggregator's benefit is concerned, the optimal operation is hardly achieved regardless of the PEV charging behaviors on cost-saving. Consequently, the PEV users with driving patterns and willingness to participate should be considered. When bidding in the electricity market, the PEV aggregators should allow for the uncertainty on PEV availability, the utility limits, their own operational risk and other issues. In existing cases, the potential of PEV aggregators in providing the regulation services has been analyzed, calculated and evaluated. In Ref. [91], a PEV-based battery storage models are proposed for power regulation by a V2G system, whereas how to maximize the PEV aggregator profit is not involved. In the later work, the coordinated dispatching method for PEVs is presented to maximize the PEV aggregator profit while regulation is performed by adjusting the PEV charging rate around a set point [6]. But the set point only varies between zero and the maximum charging power. This manifests that energy only flows from grid to vehicles. In fact, the PEV aggregators can provide the bidirectional V2G regulation to pursue more profits, wherein a PEV charges its battery for regulation-down and discharges its battery for regulation-up. However, owing to the additional battery degradation and utilizing the PEV batteries for regulation services, the PEV aggregators should compensate the PEV users by sharing a part of their profit. Furthermore, in consideration of the uncertain nature of electricity market and PEV charging behavior, stochastic programming model is employed to tackle these uncertain parameters [92]. Additionally, conditional value-at-risk measure is also adopted to maximize the PEV aggregator profit for optimal coordination of a PEV fleet [93].

5.1.3. Environmental objective

5.1.3.1. Carbon emission minimization. The environmental objective function is also employed to coordinate PEV charging so as to reduce the carbon emissions of power plants. Actually, electricity production emissions levels are highly related to the national legislation, regulatory structure, and electricity market [51]. Meanwhile, emissions deriving from the PEV usage can vary greatly depending on the region and charging time periods [52]. As a consequence, to manage PEV charging during the low-emission periods as far as possible will help the grid minimize the total carbon emissions. One representative form of the carbon emission minimization can be defined as

$$\min \sum_{t=1}^{T} \sum_{n=1}^{N} (P_{t,n}^{EV} \Delta t) MER_t \tag{17}$$

whereMER_tindicated the marginal carbon emissions rate per kWh at time t; the other symbols are defined as the same in equation (10).

The environmental impacts of PEV charging have been investigated when controlled and uncontrolled charging is taken into account respectively. It has been demonstrated that uncontrolled charging of massive PEVs may dramatically elevate the emission levels in highly carbonized power systems. On the other hand, smart charging almost doesn't result in additional carbon emissions in some specific cases; moreover, the application of bidirectional V2G technology could reduce the generator carbon emissions substantially [94]. Nevertheless, a little research focuses on the carbon emission minimization by scheduling PEV charging or discharging in an appropriate way. In Ref. [95], the total CO_2 production from both vehicles and generation units are minimized by determining the number of each EV type. However, the optimal dispatching strategy for PEV charging is not considered. In Ref. [96], an optimal scheduling for PHEV charging/discharging is presented to minimize the total fuel cost and emission for the integration of PHEVs in an electrical power system. The results show that the proposed method not only has a significant superiority over other methods in the regard of reducing total operating costs and emission, but it also increases profit, reserve and reliability.

Apart from the above objective functions, appropriate modelling of the battery degradation cost incurred in the V2G operation is necessary since that battery accounts for a remarkable portion of total vehicle cost. The battery degradation is related to the charge/discharge rate, ambient temperature, and depth of discharge. In general, it is hard to accurately weigh the battery degradation resulting from a charging event for PEVs. In Ref. [97], the battery degradation cost of PEVs is specified by a function of a charging power. Besides, the battery degradation cost is calculated into the total charging costs given by:

$$\min \sum_{n=1}^{N} \sum_{t=1}^{T} ((P_{t,n}^{EV} \Delta t) \lambda_t^{RT} + f(P_{t,n}^{EV})) \tag{18}$$

where$f(P_{t,n}^{EV})$indicates the battery degradation cost of the n-th PEV at time t under a charging power$P_{t,n}^{EV}$; and other variables, parameters and indices are defined as the same in equation (12).

5.2. Scheduling constraints

5.2.1. Constraints from PEV

5.2.1.1. PEV charging/discharging power constraint. A huge experimental results show that too high charging/discharging power will accelerate the ageing processes inside the PEV battery under the existing battery technology [98]. As for each type of PEV, there is usually an allowable charging range for the onboard charger. In order to enable a longer battery life, the charging power of the n-th PEV at time t should be limited as:

$$P^{EV}_{min,n} \le P^{EV}_{t,n} \le P^{EV}_{max,n} \tag{19}$$

where $P^{EV}_{min,n}$, $P^{EV}_{max,n}$ denote the minimum and maximum charging power of the n-th PEV, respectively.

5.2.1.2. PEV battery capacity constraint. Apparently, the battery degradation is related to the depth of discharge/charge. There is evidence that a high depth of discharge will increase the battery degradation to some extent. In addition, when the battery is overcharged, the battery wear may occur deriving from a loss of active cathode materials [99]. As a consequence, the PEV battery capacity should be restricted into a reasonable range to prevent overcharge and over discharge. For convenience, the battery SoC is introduced to indicate the ratio of the remaining capacity to the nominal capacity of the battery. Therefore, the battery SoC of the n-th PEV at time t is limited as:

$$SoC^{EV}_{min,n} \le SoC^{EV}_{t,n} \le SoC^{EV}_{max,n} \tag{20}$$

where $SoC^{EV}_{min,n}$, $SoC^{EV}_{max,n}$ are the allowable minimum and maximum SoC value of the n-th PEV, respectively.

5.2.1.3. PEV user charging requirement constraint. PEVs are served as a kind of transportation tool. The remaining driving range of a PEV is determined by the SoC of its battery pack. When a PEV user plugs his/her vehicle into the charging post, he/she has a desire that this vehicle is charged to his/her expected SoC so as to ensure his/her next journey. Consequently, as an effort to improve the charging satisfactions, the PEV user charging requirement should be satisfied by:

$$\eta_n \Delta t \sum_{t=\Gamma^s_n}^{\Gamma^e_n} P^{EV}_{t,n} = (SoC^e_n - SoC^s_n) C_n \tag{21}$$

where η_n denotes the charger efficiency of the n-th PEV; Γ^s_n, Γ^e_n denote the plugged-in and plugged-out time of the n-th PEV, respectively; SoC^e_n, SoC^s_n are the plugged-in and plugged-out SoC of the n-th PEV, respectively; C_n denotes the onboard battery capacity of the n-th PEV.

5.2.2. Constraints from grid

5.2.2.1. Node voltage constraint. In order to maintain the stability of power grid, the voltage constraints of the grids should be given by setting the upper and lower bounds. In general, it is acceptable for 95% of the time that the voltage has a ±10% deviation according to the mandatory EN50160 standard. Hence, the grid voltage at time t at node k should be limited in an allowable scope as:

$$V_{min} \le V_{t,k} \le V_{max} \tag{22}$$

where V_{min}, V_{max} denote the minimum and maximum voltage value at each node, respectively.

b. Feeder capacity constraint.

In practice, there is a maximum allowable load of each feeder of the distribution network. When PEVs are plugged into power grid, the total load capacity of each feeder should be restricted not exceeding their maximum load capacity. Consequently, the inequality constraints can be given by:

$$P^{Con}_l + \sum_{n=1}^{N} P^{EV}_{t,n} \le P_{l,max} \tag{23}$$

where P^{Con}_l denotes the conventional load without charging load via the feeder l; $P_{l,max}$ denotes the maximum load capacity supported by the feeder l.

5.2.2.2. Transmission power constraint. When considering the secure running of regional or whole grids, the transmission power between the microgrid and the main grid should be considered. Overall, the transmission power at time t cannot exceed the limits by:

$$-P_{L,max} \le P_{grid,t} \le P_{L,max} \tag{24}$$

where $P_{L,\max}$ denotes the upper limit of transmission power between the microgrid and the main power grid.

5.3. Solving algorithm

The solving process of an optimization model is usually an intractable task since it involves a bulk of variables when a large scale of PEVs joins in the V2G implementation. In addition, the established model may consist of the nonlinear objective function or the nonlinear constrain. From the mathematical point of view, the PEV scheduling models in the present literature include LP, NP, MIP and other models. Generally speaking, the LP model provides a simple and efficient approach to solve the PEV charging problem by using the traditional solving techniques, such as simplex method. Nevertheless, these traditional techniques have difficulties to deal with the NP or MIP models. Therefore, other solving techniques have been developed and used in the NP and MIP model.

In the existing works, several LP models are developed in terms of PEV scheduling [47,90,100]. These models are able to determine a global optimal solution for PEV charging in a fairly easy way, but are just limited to linear objectives and constrains. Apparently, it is not enough for a more complicated V2G system. Hence, NP and MIP models are applied to tackle the nonlinear objective functions or the nonlinear integer constrains. The QP model is the typical one of the NP models [42–44,70,79]. According to the convexity, the QP models can fall into the convex and non-convex optimization models. In general, the convex optimization model will consume a less solving time than the non-convex optimization model. The reason is that the convex programming model is able to be solved by the interior point algorithm efficiently. Moreover, there are almost no complete and robust algorithms to solve the MIP models or other non-convex models. As a result, many meta-heuristic algorithms are used to serve as an alternative option in solving the complex models.

The most popular algorithms for the optimal V2G strategy are PSO [101] and GA [102]. In Ref. [101], GA is employed on the MINP models for the PEV penetration maximization. In Ref. [102], PSO is adopted to optimize the non-linear parameters for the power consumption minimization and the PEV satisfaction maximization. Additionally, the improved GA and PSO are presented in Refs. [103–105] to search for the optimal solution in less time. Apart from GA and PSO, the metaheuristic algorithms also include evolutionary algorithm [106], simulated annealing [107], differential evolutionary [108], ant colony optimization [109] and so on. Most of them have the advantage that they require less computational time than the traditional optimization methods. In spite of this, they almost cannot ensure seeking the globally optimal solutions.

5.4. Comparison among different models

In order to integrate PEVs in power grid, various objective functions and constraints are formulated into distinct programming models from different perspectives. As shown in **Table 6**, seven representative models are selected so as to compare with each other. It can be observed that different objectives are employed in these models. It signifies that the multifarious effectiveness on either the grid performance or operational benefits is able to be achieved. On the other hand, the enormous differences with regard to the feasibility also exist depending on the structure of power system and the properties of programming models. It is evident both the effectiveness and feasibility of a model are the key factors for the V2G successful implementation. Therefore, it is valuable to make an overall evaluation for these models on the basis of effectiveness and feasibility.

Table 6
Outline and evaluation among seven typical programming models.

Model Outline				Model Evaluation	
Objective	Main constrains	Programming Model	Centralized/Decentralized	Effectiveness	Feasibility
Minimize power loss [42]	(a) Charging demand limit (b) Charging power limit (c) Voltage limit	Quadratic programming	Centralized	(a) Reduce power loss (b) Improve voltage profile	(a) High computation cost (b) Depend on grid topology
Minimize load variance [79]	(a) Battery SoC limit (b) Charging power limit (c) Charging demand limit	Quadratic programming	Centralized	(a) Fill load valley (b) Shave load peak	(a) High computation cost (b) Topology independent
Minimize system peak [85]	(a) Battery SoC limit (b) Voltage limit (c) Current limit	Mixed Integer Non-Linear Programming	Centralized	(a) Reduce load peak (b) Improve three-phase unbalance	(a) Very high computation cost (b) Depend on grid topology
Minimize PEV charging cost [90]	(a) Charging power limit (b) Battery SoC limit (c) Charging demand limit	Linear programming	Centralized	(a) Fill load valley (b) Reduce charging cost (c) Demand response	(a) Low computation cost (b) Topology independent
Maximize aggregator profits [100]	(a) Battery SoC limit (b) System load limit (c) Charging demand limit	Linear programming	Decentralized	(a) Achieve load shifting (b) Provide ancillary services (c) Reduce charging cost	(a) Low computation cost (b) Topology independent
Minimize system operating costs [110]	(a) Voltage limit (b) Current limit (c) DGs load limit (d) Charging demand limit	Mixed Integer Linear Programming	Decentralized	(a) Reduce operating costs (b) Improve voltage profile (c) Improve load unbalance	(a) Very high computation cost (b) Depend on grid topology
Minimize generation cost and carbon emissions [47]	(a) Charging demand limit (b) Charging power limit	Linear programming	Decentralized	(a) Mitigate impact of PEV charging (b) Reduce generation cost and carbon emission	(a) Low computation cost (b) Topology independent

In Table 6, the achieved effectiveness on power grid consists of reducing power losses, filling load valley, shaving load peak, improving voltage profile, improving three-phase unbalance, providing ancillary services and so on. Likewise, the achieved effectiveness on economic benefits includes PEV charging costs reduction, system operating costs reduction, aggregator operating profits increase and so on. It is deemed to be reasonable that a model considering multiple aspects is superior to the model only considering the single aspect. For example, the method proposed by Maigha et al. not only considers filling the load valley, but also minimizing PEV charging costs. This type of methods is better than the ones which only allow for filling the load valley such as in Refs. [43,48]. As for feasibility, these models can be assessed on the computation cost and whether considering the complex grid topology or not. Obviously, the topology independent models with low computation cost have a significant superiority over the models with high computation cost depending on the grid topology.

There are all kinds of mathematical descriptions to deal with the problem of integrating PEVs into power grids friendly. In general, they can be applied to the special application scenario for the V2G implementation. In the majority of existing works, the mathematical programming model is established under the conceptual operating framework with the energy and information exchange. The hypothetical framework is always perfect for their models' establishment regardless of some operating environmental issues such as the TOU price. In the coordinated V2G operation, the electricity price system plays a very important role for the PEV participation. In some regions, for example, in China and North Korea, the design and application of the TOU electricity price system is a rather crucial issue even concerned with upper-level economic reform and government policy making. More importantly, their electricity market is not mature currently and there are no electricity retailers to offer fixed prices or variable for electricity to their customers and manage the risk involved in purchasing electricity. The State Grid Corporation of China is in charge of the power generation, transmission and distribution. It can be foreseen that the grid company is more likely to become the conductor of the V2G implementation if the smart grid technology is employed in the future. Therefore, to directly improve the grid performance may be their primary target. In this sense, the grid performance index or environmental index may be taken as the objective function of the mathematical programming model.

Comparatively speaking, the electricity market environment in America and most European countries is open and flexible with fierce competition. The electricity price level will encourage more efficient use of energy, and market prices will encourage more demand response. In this situation, the PEV aggregators are allowed to exist for managing PEV charging and bargaining with electricity retailers in electricity markets to make a profit. Thus, PEV aggregators may become the energy aggregator for charging PEVs in a coordinated way. In this context, the operating cost minimization may be their major aims. As a consequence, the economic index is likely to be taken as the objective function of the mathematical description for charging scheduling optimization.

6. Conclusion

As an effort to present the relevant works for integrating PEVs into the electric grid friendly, the power interaction mode between PEVs and grids, and the mainstream methodology for the V2G implementation are overviewed comprehensively. Firstly, the power interaction mode between PEVs and grids can fall into two categories: uncoordinated charging and coordinated charging/discharging mode. The uncoordinated charging mode operates regardless of the status of the grid. In the coordinated charging/discharging mode (viz. the V2G mode), the grid operator will establish an intelligent communication link with PEV users so as to make them better response to grid requirements. In this regard, the discharging mode is allowed for PEVs to feedback the stored energy to the grid. Therefore, the incurred battery degradation cost should be taken the total charging costs into account in the charging optimization.

The operating framework for the V2G implementation is crucially important. Generally speaking, the scheduling optimization for PEV charging can be operated in a centralized or decentralized way. Due to the unified charging management of PEVs involved in this system, the centralized scheduling approach can achieve the overall optimal operation; however, it is difficult to preserve the individual charging authority of PEV users. In contrast, the decentralized scheduling approach is a price-signal based method. Each PEV user will response to price signals for determining the charging profile for their individual vehicles. In this sense, it is likely to be widely appreciated due to a higher acceptance of PEV users on charging authority; however, it is hard to attain the optimal energy management between PEVs and grids.

In essence, the acquisition of the optimal V2G strategy is ultimately to build and solve a mathematical optimization model. All kinds of objective functions are employed for coordinated charging/discharging, and LP, NP, and MIP models are developed in terms of PEV scheduling. The LP model can be solved more efficiently than the NP and MIP model. Additionally, the grid topology independent model with lower computation cost has a significant superiority over the models with high computation cost depending on the grid topology. As a consequence, it is meaningful to develop a grid topology independent model with lower computation cost for the practical implementation of V2G technology in the future.

Declarations of interest

None.

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