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Review

An Overview of Modeling Approaches Applied to Aggregation-Based Fleet Management and Integration of Plug-in Electric Vehicles †

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Abstract: The design and implementation of management policies for plug-in electric vehicles (PEVs) need to be supported by a holistic understanding of the functional processes, their complex interactions, and their response to various changes. Models developed to represent different functional processes and systems are seen as useful tools to support the related studies for different stakeholders in a tangible way. This paper presents an overview of modeling approaches applied to support aggregation-based management and integration of PEVs from the perspective of fleet operators and grid operators, respectively. We start by explaining a structured modeling approach, i.e., a flexible combination of process models and system models, applied to different management and integration studies. A state-of-the-art overview of modeling approaches applied to represent several key processes, such as charging management, and key systems, such as the PEV fleet, is then presented, along with a detailed description of different approaches. Finally, we discuss several considerations that need to be well understood during the modeling process in order to assist modelers and model users in the appropriate decisions of using existing, or developing their own, solutions for further applications.

Keywords: aggregation-based; modeling approaches; integration; fleet; plug-in electric vehicle

1. Introduction

As a special kind of distributed energy resource (DER), a plug-in electric vehicle (PEV) is a dynamically configurable mobile energy storage unit, with its spatial-temporal load profile primarily determined by its drivers. According to [1], the worldwide sales of PEVs for Q1-2016 reached 180,500, which is 42% higher compared to the same period in 2015. This rapid increase of PEVs is primarily due to its particularly noteworthy link to renewable energy. On the one hand, PEVs can substantially contribute to a reduction in CO_2 emissions if the vehicles are powered by electricity produced from renewable sources [2]. On the other hand, intelligent charging and discharging of PEVs may help mitigate renewable generation intermittency by taking advantage of the energy storage capability of PEVs [3,4]. Moreover, providing ancillary services may enable additional revenue streams to PEV owners that help reduce the cost difference between gasoline vehicles and PEVs [5–7].

Aggregating PEVs into a PEV fleet (PEVF) is currently one of the most widely recognized approaches for exploiting the synthesized value of PEVs [8–11]. This approach is also referred to as a virtual power plant and aggregation-based management/integration approach. In comparison to operating a PEV individually, the development of a community/company/national fleet could: (1) offer a more cost-effective charging management of PEVs by taking advantage of the central intelligence of fleet operators (FOs) (such as optimal charging of PEVs in a certain period considering electricity price variation and capacity limitation of charging infrastructure); (2) offer add-on services to PEV owners (such as energy-efficient PEV routing and range maximization); (3) acquire additional value streams by meeting special requirements (such as the minimum size of the bid) of the energy/ancillary service market; (4) lower the cost of PEVs' purchases; and (5) support better planning of PEV infrastructure. The new aggregation-based entities could be independent or integrated in an existing business function of energy suppliers or grid operators (GOs).

The design and implementation of management and integration policies for aggregation-based PEVs need to be informed by a holistic understanding of involved systems (e.g., PEVF system, power system and energy market), various functional processes (e.g., scheduling and control), as well as their complex interactions. Such models, developed to represent systems and functional processes, are useful tools to support the actions of different stakeholders. However, the inherent complexity of different systems and processes, the ambiguous dependencies between them, and the very high diversity of modeling perspectives, pose significant challenges to modelers and model users who are in this field. Such complexity and diversity can be briefly explained by Figure 1, where integration and management of PEVs are performed in a market-based environment, for example the Nord Pool Spot serving Scandinavia [12]. Although the involved stakeholders are few, namely GOs (i.e., transmission system operators and distribution system operators) and FOs, as depicted in Figure 1, the related issues and the angles from which the investigations are established can be many. Taking the FOs as an example, the related functional processes can include, for example, energy procurement from the electricity market following different time frames; selling flexibility as ancillary services that must comply with the corresponding technical requirements; and charging management of PEVs from the phase of scheduling to real-time dispatch. The related disciplines vary from technical to economic. The related considerations vary at both temporal (e.g., real time to long term) and spatial scales (e.g., distribution system to transmission system). The same concerns over complexity are valid for the GOs when they perform various tasks, such as requesting different kinds of ancillary services, ensuring the energy plans comply with grid constraints and validating the technical performance such as through metering, etc.

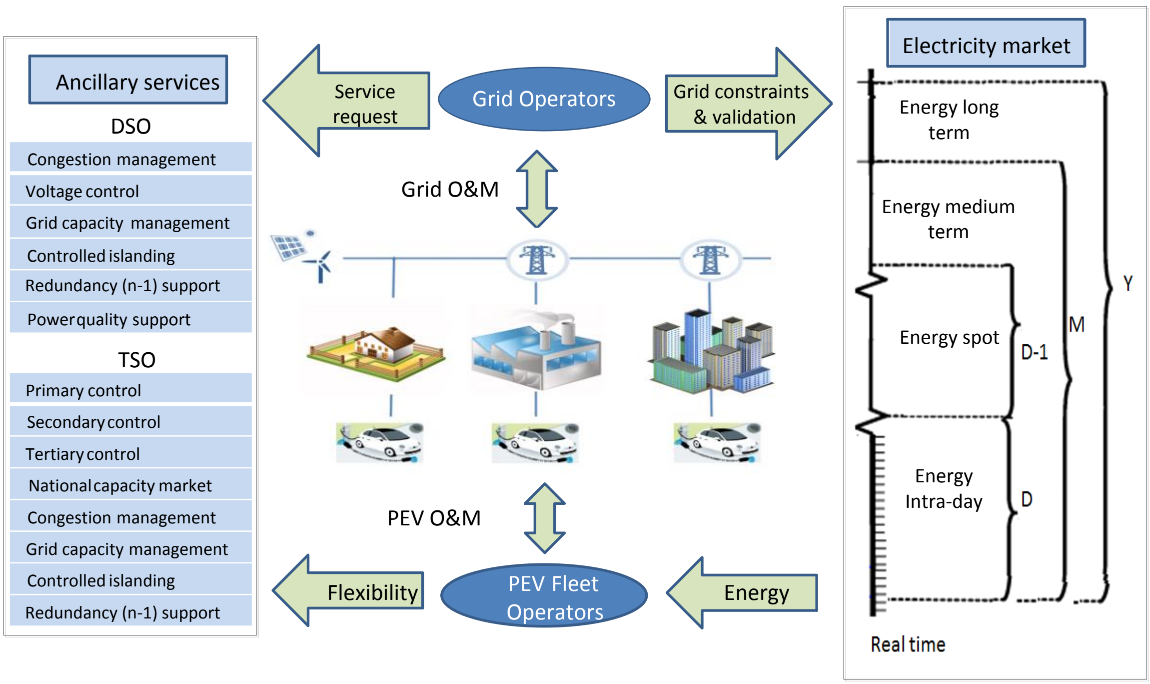

Figure 1. A schematic overview of integration and management of plug-in electric vehicles (PEVs) in a market-based environment.

This paper presents a review of key aspects included in various models developed to investigate aggregation-based PEV management and integration. This paper has two major contributions: (1) a structured approach is proposed to model the systems and the processes related to PEVFs, enabling a flexible combination of models and modeling approaches for various applications; (2) a state-of-the-art overview of modeling approaches concerning both macroscopic and microscopic aspects. In addition, several important issues that need to be considered during the modeling process are discussed, in order to assist modelers and model users in the proper choice of existing models or the development of their own solutions for further applications.

2. Structure of Modeling Aggregation-Based PEVF

A model-based representation of a PEVF can be developed from many different angles. In this paper, we categorize the relevant models into two basic groups, i.e., process models (PMs) and system models (SMs), which are explained in this section. In most studies, the two groups need to be combined in different structures in order to establish a study for supporting design and implementation of management and integration policies. Figure 2 presents an abstracted overview of PMs and SMs with two layers of abstraction for each group.

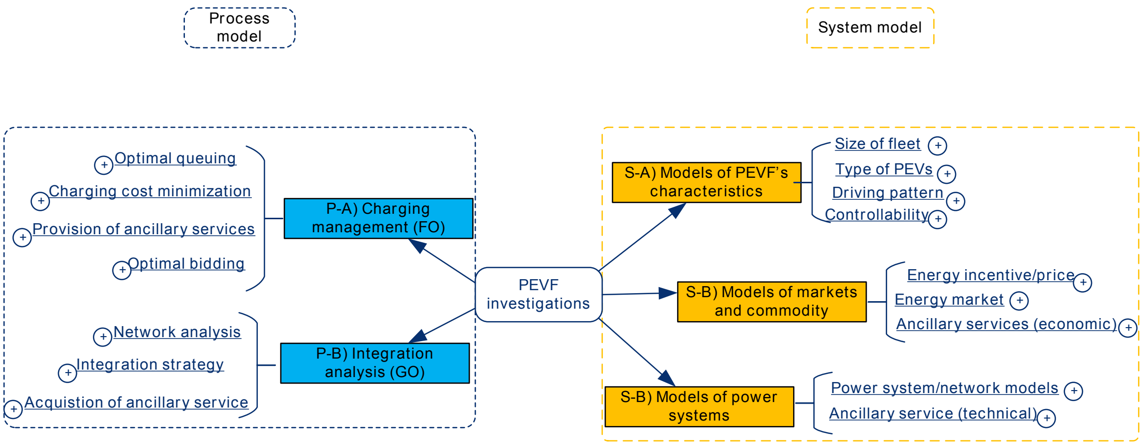

Figure 2. An abstracted overview of process models vs. system models (⊕ denotes further extension is possible).

2.1. System Models

System models are built to represent static and dynamic features of a system. In most of the studies related to PEVFs, there are three primary-level systems that can be identified, i.e., PEVF's characteristics, markets and commodities, and the power system. Among the three, SMs of a PEVF are essential, while the other two SMs can be added to enhance the context of the related studies.

System models developed to represent a PEVF usually contain a number of characteristics, such as size of the fleet, type of PEVs, battery information and controllability. Each feature can be modeled with further details. For instance, when the controllability is to be modeled, there is a number of options that can be considered at the fleet level where different control algorithms, such as direct and indirect control, can be modeled [13]. At the individual PEV level, the options can also vary from on/off control [14], modulation [15], and vehicle-to-grid [16]. Regarding the types of PEVs, there is also a variety of features of individual PEVs that can be modeled as either parameters or variables, such as driving range, battery information, and charging power.

With respect to modeling the power market and related commodities in a PEVF study, the modelers can select to model incentives/prices or the framework and mechanisms of markets for both energy and ancillary services, as well as the variety of products offered by the two markets [17]. The fundamental difference between the modeling approaches is whether the PEVF is a price-taker or a price-maker in the market setup. Currently, because of the relatively low penetration of PEVs in power markets, the "price-taker" assumption is generally accepted in the majority of studies [18,19]. When the influence of PEVs on the electricity market prices is under consideration, then studies can be performed from the perspective of energy planning [20].

Similar to market models, power system models provide another kind of envelope to the PEVF-related studies that are often structured from the grid integration perspective. The two groups of power system models include system (often including network, generation and demand as well as power system operation schemes) or network models, used for examining the grid impact, and ancillary service models that target more on finding solutions or developing better integration strategies.

2.2. Process Models

Process models, in this context, refer to actions that are modelled in order to achieve a particular functional need which can also be understood as the objective of modeling. The PMs illustrated in Figure 2 contain some high-level functional needs, such as charging management and integration analysis, which can have a strong dependency of the time scale. One schematic function-based example, adapted from [21], is shown in Figure 3 to illustrate various functional needs between different stages. The time-related decomposition describes the functional needs of each stakeholder at five stages, namely planning, operational planning, scheduling, operation, and settlement. These stages model a logical sequence based on the assumption that each stage is based on the completion of the previous stage to simplify the illustration. In practice, the five stages are usually organized as a closed loop with information exchanged among them on a regular basis.

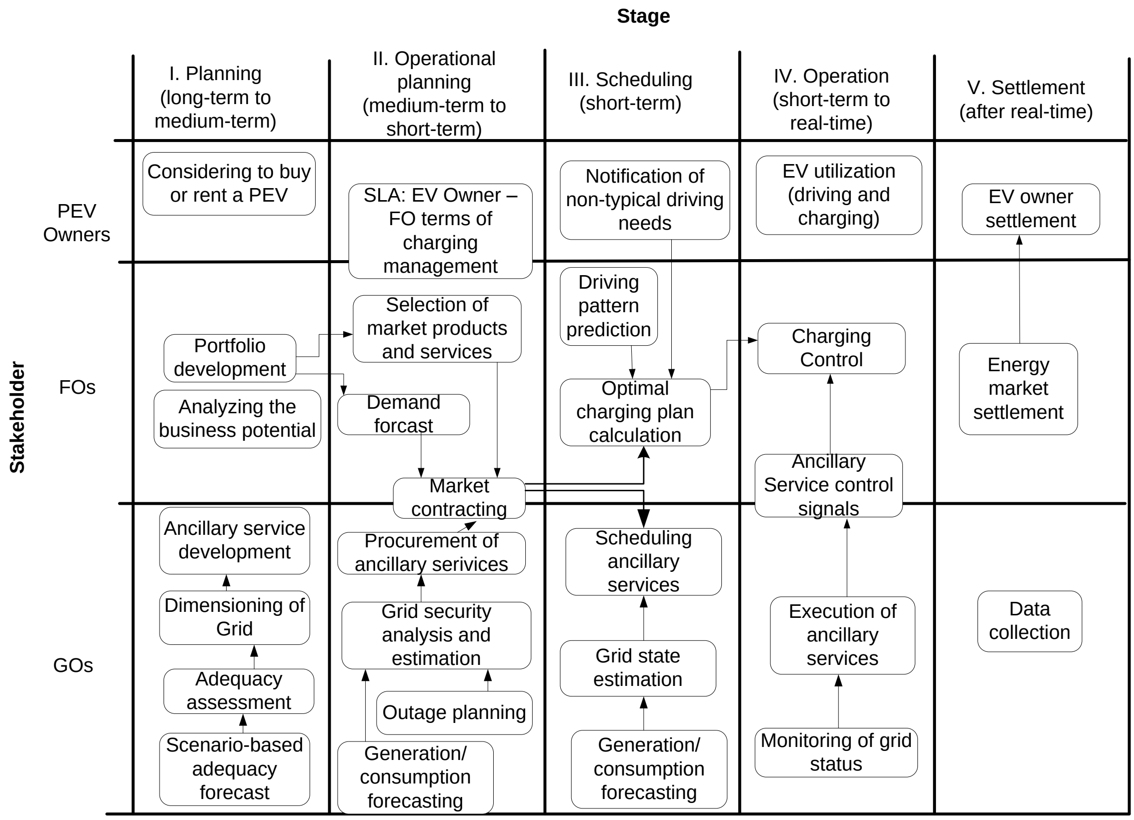

Figure 3. Schematic diagram of stage-based functional processes for EV owners, FOs, and grid operators (GOs) (adapted from [21]).

Starting from the final stage, settlement refers to the aftermath of the process: recordings (measurements, sent commands, etc.) of executed operations are consolidated and financial responsibility is allocated. The stage of operation refers to the process of executing actions on real-time, based on triggers according to the schedules made at the earlier stage. For executions that require manual intervention, triggering is not necessarily immediately translated to an action. For instance, the activation of manual frequency restoration reserve from the GO's perspective is done by sending activation signals up to 15 min before the real-time response [22]. The scheduling stage can, in time, be closely coupled with operation (e.g., charging scheduling with a 5 min resolution) or extend hours or days ahead of it [23], typically depending on the time frame of the electricity market. At this stage, available resources are best known based on market transactions, which are agreed at the stage of operational planning. In comparison to the scheduling stage, operational planning handles uncertainties over longer time horizons (i.e., from medium-term to short-term) by recursively updating the related information/forecasts and performing bidding/offering actions in different markets. For FOs, the markets can be both the energy market and the ancillary service market, wherein optimal product/service portfolios and trading strategies are developed to maximize their revenues. For GOs, the ancillary service market is the place where they can acquire resources for maintaining reliable grid operation; meanwhile, a continuous update of the energy production/consumption plans is given to the GOs by market platforms to support their operational planning. Finally, the first stage planning has been distinguished from operational planning and aims at exploring the opportunities or addressing the uncertainties associated with PEVs' management and integration at a more strategic level. Unlike the other stages where the analyses and decisions are made on a regular basis, the analyses made at this stage can have long intervals in between.

2.3. Combined Models Driven by Different Views of GOs and FOs

Modeling a complicated process of aggregation-based PEVs in many studies requires a combination of PMs and SMs. The structure of the model is defined by the objectives of the processes and the systems that are involved. Different views of GOs and FOs, as well as their business structure can result in different problem formulations [24].

For FOs, the general objective is to create a profitable business by developing competitive products or services. Typically, aggregation-based studies performed by FOs aim at ensuring the energy requirement of PEVs are met at a minimum cost by recurrently executing a number of functional processes, e.g., charging-demand forecast, energy procurement, charging scheduling, and settlement. When additional value streams, such as ancillary services, are taken into account, the studies performed by FOs then have to consider both the technical requirements and the economic potential for that service that they expect to provide; therefore, modeling these requirements and the associated economic potential become necessary.

For GOs, the objective is to ensure secure and reliable grid operations. In the field of modeling aggregation-based PEVF, this means the network impacts of a PEVF have to be well understood, and minimized if the impacts are negative or maximized if the impacts are positive. Therefore, power system models are always needed to support the impact assessment, proactively dimensioning the grid for better accommodation of PEVs, and strategic decisions that would consider using the flexibility of PEVs as alternatives to conventional grid planning and operational solutions.

2.4. An Illustrative Example of Combing System Models and Process Models

This subsection demonstrates an example concerning the ancillary services between FOs and GOs, wherein a number of interactive processes are involved in different stages. Each process may require more than one PM and SM at a certain level of detail. For instance, from the FO's perspective, the provision of ancillary services needs six further PMs in different stages, which, among others, include demand forecasting and market product selection; these PMs are shown in Figure 4. Furthermore, as the dashed arrow indicates, the process of demand forecasting of a PEVF at the stage of operational planning needs the SM of a PEVF's characteristics, which includes the size of the fleet, the types of PEVs, the driving pattern, and the controllability information.

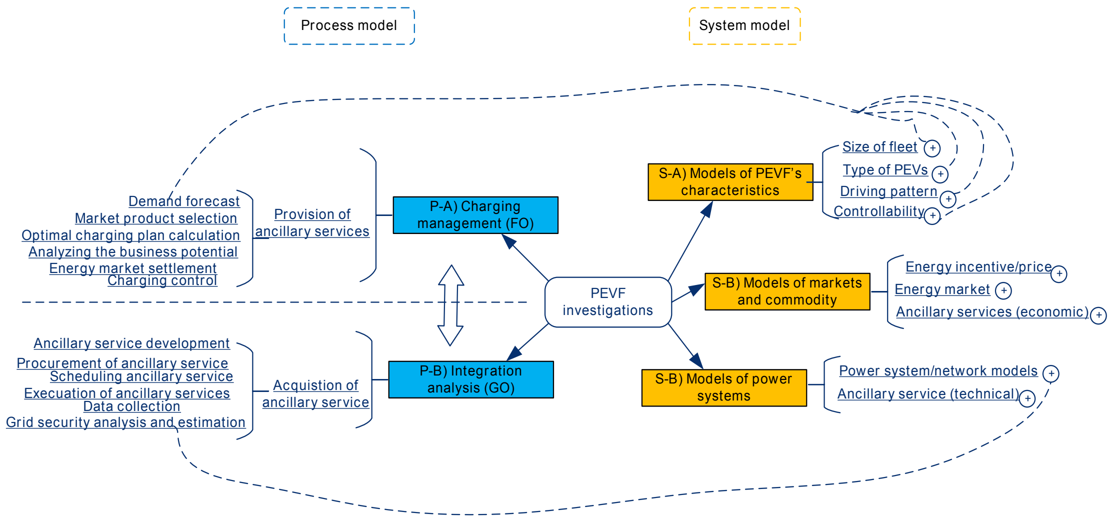

Figure 4. Process models and system models combined for ancillary services coordination between FOs and GOs.

At the same stage, when GOs would like to acquire the ancillary service, six PMs are also needed to reach the purpose as listed in different stages in Figure 3. These PMs are shown in Figure 4, including ancillary service development, procurement of ancillary service, etc. Similarly, as the arrow indicates, the grid security analysis and estimation process needs the support of the power system/network models.

It is noted that FOs and GOs interact with each other during most of the stages, such as in stage II operational planning, where FOs and GOs reach an agreement via the market contracting process. Furthermore, in Stage IV, GOs send the ancillary service activation signals to FOs via the ancillary service control signals process. These interactions are shown by the wide double arrow in Figure 4. Moreover, SMs of ancillary services (economic) become the third necessity when the process of contracting coordinates the ancillary services exchange between FOs and GOs. During services provision, if the FOs perform charging management through scheduling and control to realize the contract, the GOs only need to send the ancillary service signals to the FOs when the services need to be activated. Typically, when such a process involving multiple actors is to be modeled, an agent-based approach can be utilized to model the information flow and the process of decision-making by the different actors.

3. Methods Applied to Model the Key System Models and Processes

The task of modeling a group of PEVs can be carried out from either the microscopic or macroscopic perspective, or sometimes a combination of the two, resulting in different modeling approaches of a PEVF and its related applications. Taking SMs as an example, an aggregation model which aims at representing the grouped behavior of a large number of PEVs may choose a statistical representation of the aggregated driving needs; therefore, the requirements of routing and charging of an individual PEV is not necessary to be elaborated. The difference between microscopic and macroscopic aspects can also be found when the processes are modeled, which is also reflected by the example shown in Figure 3.

If the process of charging is under investigation, a transient-dynamic continuous model that models the dependency between current and voltage electrical equivalent circuits simulate the charging dynamics at a time scale from sub-seconds to minutes, thus supporting the analysis related to power management of PEVs. When discrete-time/steady state models are applied, in most cases the corresponding analysis is related to the energy management of PEVs at a time scale from minutes to an hour; therefore, the fast transient dynamics caused by different real-time charging schemes (e.g., constant voltage and constant current) are neglected. From the computational perspective, models developed with microscopic properties are more appropriate for analyzing problems that have a limited number of properties but are orientated towards capturing a high level of detail, such as controlling a relatively small number of PEVs that are connected along one low voltage feeder. On the contrary, macroscopic models are developed to analyze the behavior of a large number of PEVs and their interactions with other systems, e.g., market and power systems, which also involve a large number of systems and processes. In this section, different modeling methods considering these various modeling aspects are comprehensively reviewed.

3.1. Models of an Individual PEV Characteristics

A single PEV is the fundamental element of a PEVF. The approaches used to model the characteristics of a single PEV can usually contribute a lot to the PEVF modeling, especially with respect to the PEV battery and its dynamic characteristics during charging and discharging. Several reviews, such as [25–27], have categorized PEV battery models into three groups, namely (1) electrochemical models; (2) equivalent electric circuit (EEC) models; and (3) mathematical models that model the dynamic flow of charge.

In general, these models are derived from an understanding of a battery's chemical processes and are more appropriate for investigations carried out from the battery or battery management (such as lifetime estimation) perspective. Therefore, detailed battery models are only occasionally applied in modelling the aggregated behavior of a PEVF when a continuous time scale analysis is needed or the detailed impact analysis to the PEV battery needs to be investigated. In [28], a model which captures the current and temperature dynamics of an EV battery is proposed, and in [29] two battery equivalent models are compared. Such models can be combined with inverter-charger models, to describe the behavior of the two main components of a PEV. A simplified representation is used in [30] to validate the services provision of a number of PEVs, where their power response to a control signal is modelled as a time delay; in [31] a first-order response is assumed. Among the three groups of PEV battery models, EEC models can often meet such needs better than the other two groups due to a reasonable tradeoff between accuracy and granularity. Further, the EEC model of a battery can include the inverter models of PEV chargers, therefore providing detailed transient dynamics for the charging and discharging process.

Considering the high-level need of PEV management is often based on the charging management, a further abstracted mathematical model based on the discrete time energy balance (DTEB), described in Equations (1)–(6), has been applied in many studies [15,32,33]:

$$E_t = E_0 + \sum_{k=1}^{k=t} \left\{ \Delta E_{c,k} \cdot u_{1,k} - \Delta E_{d,k} \cdot u_{2,k} - E_{d,k} \cdot u_{3,k} \right\}, \ \forall\, t \in [1 \ldots N], \tag{1}$$

$$\delta_{\min} \cdot E_{\text{nom}} \le E_t \le \delta_{\max} \cdot E_{\text{nom}}, \ \forall\, t \in [1 \ldots N], \tag{2}$$

$$E_{d,\, t+1} \cdot u_{3,\, t+1} \le E_t, \ \forall\, t \in [1 \ldots N], \tag{3}$$

$$0 \le \Delta E_{c,t} \le P_{c,\max} \cdot \eta_c \cdot \Delta t, \ \forall\, t \in [1 \ldots N], \tag{4}$$

$$0 \le \Delta E_{d,t} \le \frac{P_{d,\max}}{\eta_d} \cdot \Delta t, \ \forall\, t \in [1 \ldots N], \tag{5}$$

$$u_{1,t} + u_{2,t} + u_{3,t} = 1 \ \forall\, t \in [1 \ldots N], \tag{6}$$

where the charging period is divided into N time intervals, t denotes the time step, and Δt the duration of each interval. The charging and discharging efficiency of the battery charger are represented by parameters η_c and η_d, whereas parameters $P_{c,\max}$ and $P_{d,\max}$ denote the maximum charging and discharging power, respectively. Parameters E_{nom} and E_0 represent the nominal energy capacity and the initial energy of the battery in a charging period. $\Delta E_{c,t}$, $\Delta E_{d,k}$ and $E_{d,k}$ represent the energy charged into and discharged from the battery during a time step and the energy demanded by driving, respectively; the three statuses are indicated by the binary variables $u_{1,t}$, $u_{2,t}$ and $u_{3,t}$. The parameters δ_{min} and δ_{max} applied in Equation (3) denote the recommended range of the state of charge (SOC).

The DTEB of a PEV battery can also be formulated in many other ways, such as in [34,35], where SOC is dynamically calculated to represent the energy status of the PEV, or in [36] the battery degradation factor is included in the cost function when an optimal schedule of charging is under concern. However, the basic idea of these models is the same. Given that the parameters can be found from the specifications of the PEV, DTEB is used to represent the energy status variation of the PEV over time, for different processes (from planning to operation). Since the three time-dependent variables $\Delta E_{c,t}$, $\Delta E_{d,k}$, and $E_{d,k}$ relate the energy variation of the PEV to the processes of charging, discharging, and driving, DTEB easily enables the creation of combined models wherein various optimal charging management strategies and driving behaviors can be included to model the dynamic energy characteristics of the PEV.

3.2. Aggregation Models for PEVF Representation

Based on a combination of PMs and SMs, the aggregation models are developed to mainly support decisions that are made at different stages by FOs and GOs. One of the most important characteristics is the size the controlled fleet of an aggregator. Although there are models developed to forecast the market size of PEVs [37], the size of the fleet, as well as the capacity of the PEVF, are often randomly selected due to the lack of practical information.

The most basic and straightforward approach is to use a DTEB model for each individual PEV of a portfolio and, thus, represent them on an aggregate level [33,38,39]. In [38], where optimal bidding was cast as a two-stage stochastic linear programming problem and multiple scenarios were used to represent the uncertainty (driving pattern). The problem with such approaches is scalability, because optimization problems become intractable when the PEVF is large. Moreover, in practice, this approach might be limited by the unavailability of information, e.g., scenarios for the individual driving patterns based on historical data.

An aggregation model that is often used is a virtual battery, or else referred to as lumped battery model, which clusters the PEVs and represents them as one battery [35,40,41]. By using such a model, probabilistic driving patterns can be applied, as described in more detail in Section 3.3, and typically the battery's parameters are set equal to the mean values of individual batteries' parameters. These works neglect the dynamic phenomena associated with charging and discharging and consider that the PEVs are always in a steady state and DTEB equations are used to describe the evolution of the virtual battery's energy content. Such models are appropriate for optimization problems but not for impact assessment on the grid on a short time-scale (e.g., for power quality studies or dynamic frequency studies).

If the load dynamics are important but still an aggregate representation of the PEVs is required (mainly for computational reasons), then dynamic aggregate models must be used. In [42], an EEC virtual battery model was developed and applied to analyze the impact of vehicle to grid (V2G) to load frequency control (LFC) in Western Denmark, and the parameters of the virtual battery (such as energy capacity) were derived deterministically based on simple assumptions that 50% of PEVs in the fleet is always available for delivering V2G. In [43] a PEVF is used to simultaneously offer primary and secondary frequency control. The dynamic response of a single PEV is represented as a first-order transfer function and a participation factor for each PEV is used to indicate its availability for primary control. On an aggregate level, an average participation factor is calculated (where a probability distribution function of the estimated SOC is used) and an hourly index is used to represent the aggregate hourly availability; an average transfer function constant is used for the loads' dynamics. In [44] a similar, but more advanced, method is used to aggregate PEVs on a bus level, to be used for more detailed studies including the distribution network characteristics. In a similar manner, in [31] the response of a PEVF consists of a time delay (corresponding to communication delays) and a first-order delay, both having the average values of the population's parameters.

Another aggregation model was introduced in [45]. Starting from a first-order model for describing the energy content evolution of a PEV as in [46], then a charging requirement index was introduced, as the ratio of the required charging time at full capacity over the user-defined remaining time for charging. Then the authors used the concept of state bins used in characterizing the dynamics of thermal loads [47] to partition the domain of this index into bins and derive a non-linear model to describe the aggregate dynamics.

Another approach that can be used for representing the aggregated flexibility more precisely is Minkowski summation [48–50]. Constraint sets for the charging rate and the battery storage volume of PEVs are represented as polytopes in high-dimensional Euclidean space. Minkowski summation, formed by adding together the vector of each polytope, is derived to represent the aggregated flexibility in a more generic, mathematical manner. As shown in Figure 5, the flexibility of the two PEV batteries (IC_1 and IC_2), represented by their constraints, can be summed together to form the representation of the aggregated flexibility [49]. This modular approach supports both visualization of aggregated flexibility of PEVs and applications that use the aggregated flexibility to power system operations through charging management [51]. However, compared to using the lumped battery approach, the computational cost of Minkowski summation can be very high.

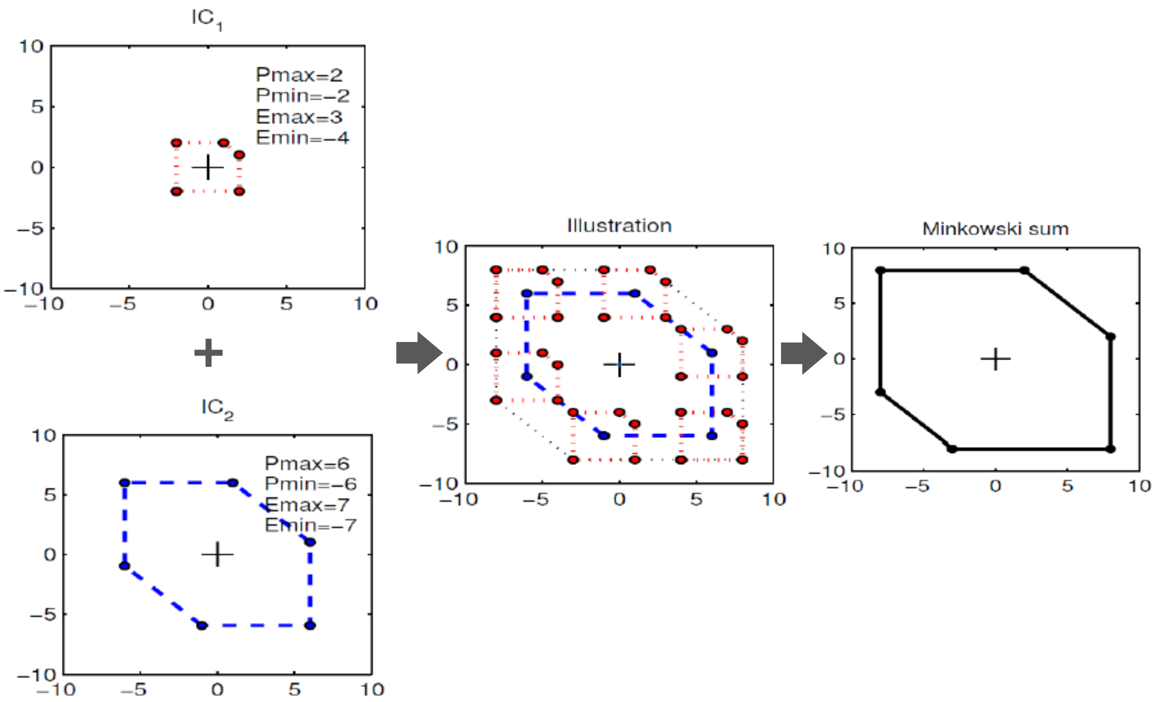

Figure 5. Minkowski summation of two resource polytopes for a two-sample horizon (*P* and *E* refer to power and energy limitations, respectively) (adapted from [49]).

3.3. Driving Pattern Modeling

Driving information is the essential part of estimating the energy demand and the flexibility of a PEVF. Today, the driving information is either modeled based on data collected from gasoline cars [32,52] or based on real measured PEV data [53]. In case there is little data available, Monte Carlo methods are applied to populate the collected data according to the needs [54] or, as in [34], a stochastically-generated driving pattern is applied to dynamically represent the average SOC of the PEVF. From the FO's perspective, key driving information of its fleet includes: (1) the number of vehicles arrived at the charging destinations; (2) energy status (e.g., SOC) of the vehicles arrived at the charging destinations; (3) the number of vehicles departing from the charging destinations; and (4) the number of vehicles connected to the grid [35]. The last two information items can be also modelled as one, i.e., the available duration of charging, to further simplify the representation [40,55,56].

Due to the stochasticity of driving, parametric stochastic models are often used to represent the probability distribution of the information related to driving and charging. Markov chain models [57,58], as probabilistic, stochastic modelling approaches, are currently widely used to model the transition dynamics among driving, parking, and charging. An example from [58] is given in Figure 6 to illustrate the basic idea of a Markov chain model, wherein four different event states (i.e., *M*-driving, *R*-parking in residential area, *C*-parking in commercial area, and *I*-parking in industrial area) are considered as cyclostationary properties. The corresponding probability functions can be derived based on historical data, if possible; therefore, different kinds of distribution exist. For instance, the dynamic process of a vehicle arriving and leaving a parking lot is described as a Poisson process in [34,59], is assumed to be uniformly-distributed in [33], is presented as a truncated Gaussian distribution in [40,59], and is also represented exponentially for testing its practicality [60]. These parametric models require a further process of parameterization in order to find the corresponding parameters.

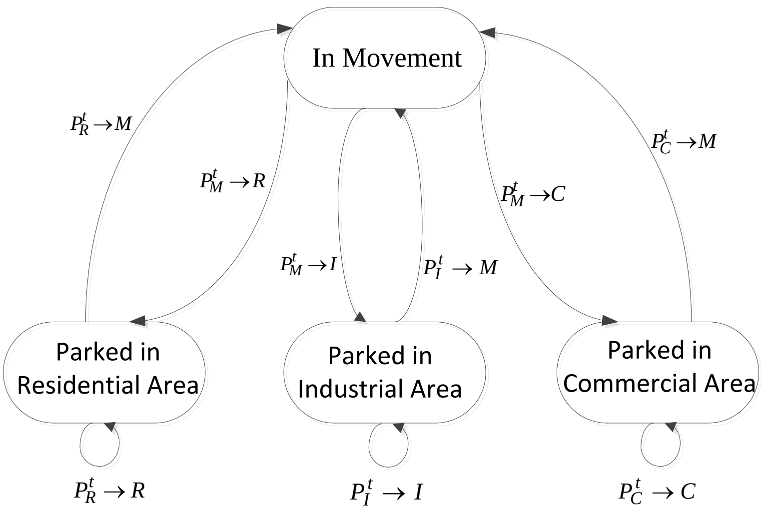

Figure 6. An example of discrete state and discrete time of a Markov chain model for modelling the driving pattern of a plug-in electric vehicle fleet (PEVF).

In contrast to parametric stochastic models, non-parametric approaches have also been developed to represent the dynamics of the driving and charging of a group of PEVs. These approaches vary from histogram-based or non-parametric bootstrapping representations of PEVs' temporal charging durations [61,62] to a fuzzy neural network model [53]. Compared to the parametric models, which assume a finite set of parameters and, thus, complexity is bounded, non-parametric models can often be defined by assuming the information function has a non-fixed dimension. This allows more flexibility during the modelling process; however, the associated complexity can also increase dramatically.

3.4. PEVs in an Aggregator's Portfolio with other Flexibility Sources

The synergistic value achieved via aggregating a group of PEVs with diversified characteristics can be extended when other flexible sources are added into the portfolio. In [63], a large population of PEVs and domestic heat pumps (HPs) are represented by a lumped PEV model and a lumped HP model respectively, and controlled together to offer LFC. The lumped model of PEVs takes into account the number of PEVs that enter or leave the controlled portfolio and is updated every 30 s, enabling a straightforward dynamic representation of the aggregated flexibility. The change of the total power consumption after HPs begin to start/stop heating is approximated by a normal distribution function that emulates the heat demand. During control, the flexibility of PEVs is utilized according to the SOC of each PEV, i.e., a PEV with a high SOC is preferred to be discharged first and a PEV with a low SOC is preferred to be charged first; a similar approach is applied to control the HPs.

This approach developed for modelling and controlling a large number of PEVs is also applied in other works, such as [64,65]. In [64], the flexibility of PEVs, thermostatically-controlled loads (TCLs) and a co-generation plant in an urban area are coordinated by an aggregator to provide LFC through receding-horizon optimization, while considering both operational constraints of energy networks and dynamic behavior of appliances. A more generic representation of the aggregate dynamic behavior of a number of TCLs is given by using a differential equation. In [65], an aggregator's portfolio including PEVs and controllable loads, together with a microgrid, are managed in real-time to provide automatic generation control service to the TSO. The controllability of PEVs is extended by combining different types of charging infrastructures that include slow charging, fast charging, and battery swapping.

3.5. Modeling the Related Systems: Energy Markets and the Power System

Charging management strategies are often modelled to represent the interactions between a PEVF and related systems, i.e., the energy market and power system. When describing these systems, there are considerations of treating their granularity in different ways.

Considering the power system, there are essentially two dimensions that have to be considered when modeling a power system, i.e., space and time. When considering the space factor in a power system model, three levels of granularity can be selected: (1) Lumped models that provide a single set of outputs for the entire system. This can be understood as a single bus system with load/generators modeled to simulate the system behavior w.r.t load curves or frequency signals [42]; (2) Zonal models that provide outputs for homogeneous subareas of a total area. Often, these models include the information of multi-machines and demand in each zone, and also the network features that connect the zones together [66]. Such models can be used to represent both transmission and distribution systems; and (3) Nodal models that provide a more detailed outlook of the power system within a zone area, often with detailed network information. The nodal models can also be applied to represent either transmission or distribution systems. However, when a nodal system is applied to the PEVF-related studies, the objective is often to provide a more detailed understanding of the impacts on a specific network [67–69]. Typically, if the modeled nodal system has a voltage level above 0.4 kV, the PEVs have to be modeled using aggregate models.

When considering time in modeling a power system, the granularity level differs from application to application. The process example given in Figure 3 already, to certain degree, illustrates how time discretization can be relevant in most PEVF applications. However, for some fast power system applications (up to a few seconds), such as spinning reserve, primary frequency control, power quality, etc., the time step in the power systems simulation models has to be very small, implying the need of modeling the system dynamics at high detail. If the PEVF is used in such analyses, or to provide such kinds of services, the corresponding models of the PEVF have to adapt to the time requirements and the corresponding dynamics can be modeled using EEC-based models, which can include the transient dynamics of PEV chargers [68,70].

Considering the power market, when the interaction between the PEVF and the power market is modeled as a process, such as bidding, the granularity of a market model can also be treated in different ways: (1) As a price signal that assumes the time-series electricity prices are known ahead either as fixed prices or forecastable. In most of the studies that use price signals, the developed strategies assume the PEVFs are price-takers; (2) Lumped market models that model the market framework and certain level of price dynamics. For instance in [33], the relationship between the electricity spot price and the load is assumed to be linear, implying the charging scheduling of the PEVF could impact the electricity price; and (3) Detailed market models usually include both bidding and market clearing in order to represent how the electricity prices are derived while considering the uncertainty factors such as price and volume. A typical approach applied to model a detailed bidding process is to use game theory, as in [71], which models the different risk-averse bidding strategies.

3.6. Charging Management Strategies

Since the driving needs determine the expected amount of energy consumption which has to be met by executing a control process through charging management, when modeling the PEVF, the controllability of the individual PEVs is a very important factor that has to be considered. At the PEV level, two categorizations exist: on/off control vs. continuous modulation and unidirectional vs. bidirectional charging. At the aggregator level, it is purely dependent on which type of charging management strategy is used by the aggregator. The review given in [72] presented a good overview of how different charging management strategies can be modeled and implemented, as seen in Figure 7. When the process of charging management is included in the PEVF model, it would, to a large degree, affect the dynamic characteristics of the PEVF.

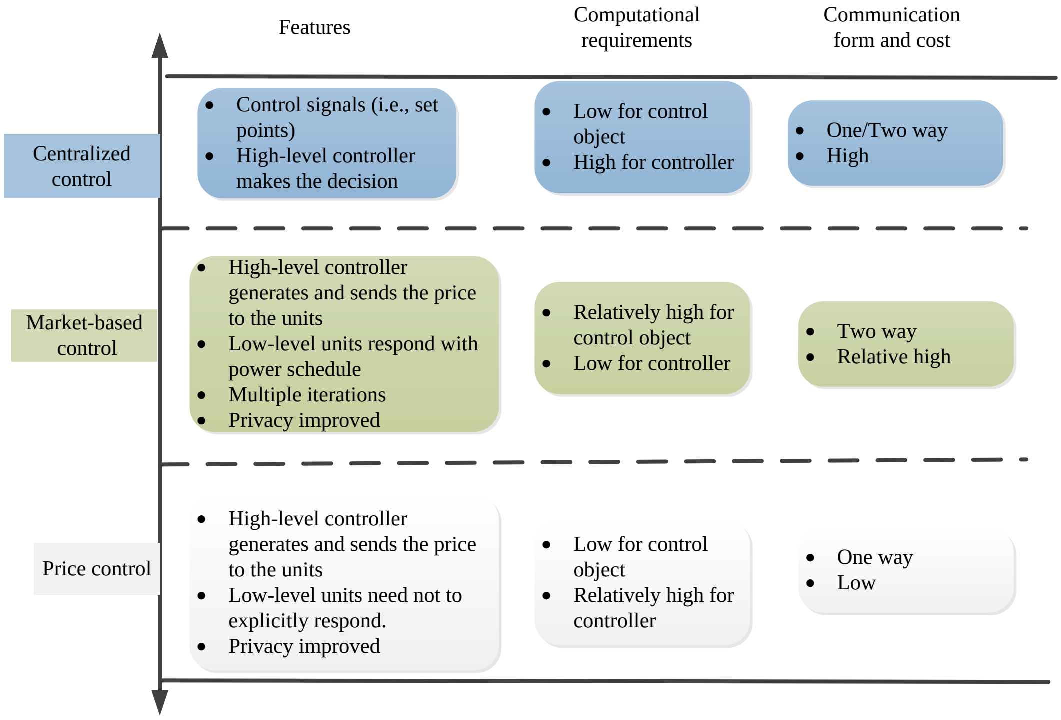

Figure 7. Overview of charging management strategies (adapted from [72]).

Charging management as a high-level process can cover both charging scheduling and charging control. Depending on the perspective (FOs or GOs), the process of charging management can be formulated as different optimization problems. Mathematically, these problems are modeled and solved using different approaches, such as linear programming, quadratic programming, dynamic programming, mixed-integer programming, nonlinear programming, stochastic programming, robust optimization, heuristic and meta-heuristic algorithms, and model predictive control, which have been intensively reviewed by several articles [72,73]. In this part, we only briefly review the objectives of different charging strategies and elaborate on what additional constraints (with respect to SMs) need to be considered when modeling the charging strategies based on the basic characteristics of the PEVF.

(1) Optimal queueing: Except for battery swapping, charging a PEV to the expected energy level can be heavily time-consuming in many occasions. Given the assumption that the charging infrastructure has limited capability, either temporal (i.e., one charging station) or spatial (i.e., more than one charging stations that are geographically distributed), or both, queues might occur

at charging stations. Optimal solutions to this issue, as in [58,74], are developed to ensure PEVs are charged to their expected levels of SOC as much as possible by charging them sequentially in a given period, which typically considers the stochastic pattern of arrival and departure of PEVs. This problem is also sometimes known as optimal routing, when the spatial influence, such as the distance between charging stations [75,76] and traffic jams, are modeled [77]. In addition to including the driving needs and the basic characteristics of the PEVF, the formulation of optimal queueing or routing often takes into account the capacity of charging infrastructures as additional constraints. The corresponding objectives also cover one or more of the following: shortest path, minimum energy consumption during driving and waiting, shortest waiting time, etc., which complement the fundamental needs of charging, i.e., energy. The solutions derived by optimal queueing or routing can be used not only by FOs to manage the charging of their PEVF, but can also be used for charging infrastructure planning in relation to both sizing and siting [78].

(2) Charging cost minimization: As one of the fundamental and essential objectives that a FO wants to achieve, cost minimization often refers to the operational cost of charging the PEVF. If the electricity is bought from the wholesale market, then the cost minimization implies the FOs needs to come up with optimal bidding strategies that can ensure the operational cost is minimized while considering both the uncertainty of market prices and the uncertainty of energy consumption [35,79]. If the electricity price is already known ahead of time (e.g., dynamic tariff), for achieving the same objective, only the intermittency of charging needs to be considered [35,55,56]. In some cases, additional cost items, such as the cost for battery life reduction [33], is also included in the objective, incurring the need of having additional considerations to represent the cost formulation and the related control scheme.

(3) Profit maximization can be formulated by FOs who aim at maximizing the profit of using PEVs to provide one or more ancillary services. In contrast to charging cost minimization, profit maximization is based on the assumptions that the flexibility of PEVs is managed to meet the technical requirements of ancillary services. Typically, this process is combined with cost minimization because trading energy and trading ancillary services are closely related to each other, such as in [40,61], where the day-ahead energy trading is combined with regulation services and manual reserves, respectively. Additional constraints in such groups of problems are usually about market regulations and bidding strategies that would result in optimal schedules of the PEVF.

(4) Minimization of negative impacts: When PEVs are passively connected to a power system, this new form of intermittent demand may result in a number of issues, such as network congestion [67,80,81]. Both FOs and GOs intend to minimize the corresponding negative impacts as much as possible by either controlling the charging of PEVs at the phase of operation directly or setting charging limits (temporal and spatial) to the PEVs. Such problems often require additional constraints (network operational requirements) and other kinds of generation/load models in order to model the negative impacts from the PEVs and to find the corresponding solutions.

(5) Maximization of the technical flexibility of the PEVF: With properly-designed charging management strategies, the flexibility of the PEVF can be used to address various kinds of power system challenges, such as frequency support and congestion management. In contrast to profit maximization, which considers the provision of ancillary services from the economic perspective, the models that fall into this category are built from the technical perspective and used for assessing the technical benefits. The optimality part of this work is on maximizing the flexibility utilization to meet the technical requirements of ancillary services, especially control-wise (reaction time and ramp rate), while considering the intermittency of the PEVs. In [66] the PEVs are controlled to offer primary, secondary, and tertiary reserves using a hierarchical model predictive control (MPC) structure. In [82], congestion management is modeled as a service offered by the FOs to optimally allocate the charging flexibility of the PEVF. Additional constraints are, therefore, mainly modeled from the power system side (e.g., modeling the variation of frequency signals and network performance) for formulating the system context of ancillary services.

Most of the optimization problems, in practice, also have to deal with multi-objectives. When multiple-objective-oriented charging management strategies are modeled, SMs of different market commodities and different power systems are often both included. For instance, Moradijoz, M. et al. [83] formulated an ambitious multi-objective optimization algorithm using a heuristic technique to maximize V2G revenue and to improve grid reliability by minimizing the system disruption cost, as well as reducing the power losses. In [84] the power purchase cost, emission cost, and operational cost of a distribution grid with a large number of PEVs are minimized.

4. Discussion and Concluding Remarks

As a complicated task, fleet management can be modeled from different perspectives. To reduce the level of diversity, this paper classifies them into two types of models, i.e., process models and system models. The former are action representations, whereas the latter describe features and principles. With a flexible combination of the two types of models, different models can be developed for studying the integration and management of PEVs. This paper reviewed the current state-of-the-art modeling approaches applied to modeling several key SMs and PMs.

Currently, the majority of studies use a lumped battery model to represent the aggregated characteristics of PEVs. When the applications of the model are discrete-time based, the lumped battery is often modelled as DTEB-based mathematical models that use a difference equation together with a number of constraints to represent the dynamic energy balance and thresholds of the fleet's power and energy. Depending on how the driving pattern is represented and how the forecasting is done, the dynamic status of the lumped battery can be either modeled stochastically or in a deterministic manner. The reason for the majority to select this approach to model the aggregated behavior is mainly due to the convenience of extending the mathematical formulation towards various kinds of charging management strategies. For the cases when a PEVF is controlled to provide fast ancillary services which require continuous time simulations, an EEC-based PEVF model is chosen due to the possibility of modeling the transient dynamics of PEV chargers and batteries.

When the models of the PEVF are applied to a specific context, i.e., either the power system or the market, the granularity of the two SMs are treated in different ways. The challenge to integrated modeling is to understand the objectives and capture the advantages of different approaches while overcoming some of their limitations, possibly through the development of hybrid models. Models of charging management are already developed in different ways to show how this challenge can be addressed in different ways. However, most of the models are built from the research perspective and the purpose is, therefore, often for knowledge development/conceptualization. From the application perspective, this implies that the majority of aggregation-based models are more appropriate for long-term planning. When more in-field information is collected over time, and the business models for the PEVF become clearer, it can be perceived that the effectiveness of different models will be tested and validated.

Finally, it is clear that there are many approaches available for supporting the investigations of management and integration of PEVs. The related models are often developed based on a consideration of issues across multiple disciplines (e.g., the power system and markets), integration of processes and models, and spatial and temporal scales. Moreover, these three types of integration are not mutually exclusive. A modeling framework that can achieve an appropriate combination of SMs and PMs in order to reach a good compromise between representing individual systems/processes in detail and representing the range of the over systems/process would facilitate the work of model development. Further development of generic/taxonomized approaches that can represent the dynamics (or flexibility) of populations through time and across geographic areas, theoretically, is another important research element. This will facilitate the development of various PEVF applications that rely on optimization and allow for synergy maximization among various flexibility resources.

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