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Review and classification

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OPTIMIZATION AND CONTROL METHODS FOR SMART CHARGING OF ELECTRIC VEHICLES FACILITATED BY FLEET OPERATOR: REVIEW AND CLASSIFICATION

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ABSTRACT

Electric vehicles (EV) can become integral parts of a smart grid, since they are capable of providing valuable services to power systems other than just consuming power. As an important solution to balance the intermittent renewable energy resources, such as wind power and PVs, EVs can absorb the energy during the period of high electricity penetration and feed the electricity back into the grid when the demand is high or in situations of insufficient electricity generation. However, the extra loads created by increasing EVs may have adverse impacts on grid. These factors will bring new challenges to the utility system operator; accordingly, smart charging of EVs is needed. This paper presents a review and classification of methods for smart charging of EVs found in the literature. The study is mainly executed from the control theory perspectives. Firstly, service dependent aggregation and the facilitator EV fleet operator are introduced. Secondly, control architectures and their integrations in term of electricity market and distribution grid are discussed. Then, data analysis of EVs including a battery model and driving pattern is presented. Further discussion is given on mathematical modelling and control of smart charging of EVs. Finally, the paper discusses and proposes future research directions in the area.

1   INTRODUCTION

EVs are commonly recognized as smart grid assets in addition to their primary transport function. They can be utilized to balance power fluctuations caused by the high penetration of intermittent renewable energy sources [1], [2]. However, a large scale application of EVs also mean new loads to electric utilities, and undesirable peaks may exist in the distribution network when recharging the battery [2]. All these factors bring new challenges to the system operator. As a result, smart charging (including power to vehicle and vehicle to grid (V2G)) solutions are needed which can make EV an asset to the grid rather than a mere traditional load and make the grid more flexible.

Much research has been done to address the above challenges. The purpose of this study is to give a review and classification of the control strategies used for smart charging of EV fleets. From the literature, it is summarized and concluded that a new business entity, namely the EV fleet operator (FO) has been widely proposed capturing the new business opportunities by providing the multiple services of EVs and then by this contributing to the challenges solving of power distribution system operator. Alternatively names for an EV FO are used such as EV virtual power plant, EV aggregator, EV charging service provider or EV service provider (EVSP). The new entities [3], [4] could be independent or integrated in an existing business function of the energy supplier or distribution system operator.

In principle, two types of control architectures are used by FOs when aiming at the above objectives, named centralized and decentralized control. Centralized control means electric vehicles can be aggregated and controlled by FO directly, while the decentralized control usually is implemented in the form of price signal, i.e. the individual EV optimizes the charging based on the electricity price information made available to them either from EV FO or the utility. A comprehensive discussion and comparison on these architectures can be found in [5], [6]. From the discussions in [5]-[7], it can be shortly summarized that for a centralized charging the decisions are made on the system-level and therefore can give better results such as ensuring the safety of the distribution network; however, the cost of communication infrastructure would be high for centralized charging. For a decentralized charging, one of main advantages is the possibility to minimize the communications infrastructure cost [8], however, the solution may or may not be optimal, depending on the information sharing and methods used to make the charging scheme.

The paper is organized as follows: The control objectives are discussed in Section 2. Section 3, 4 describes the role and control architectures of EV FO. The battery model and driving patterns of EVs are briefly discussed in section 5. Some commonly used algorithms in the centralized and decentralized control of smart charging of EVs are presented in Section 6 and 7, respectively. Section 8 concludes the paper with some suggestions for future research.

2   SERVICE DEPENDENT AGGREGATION

In [9], Lopes et al. shortly summarized that a large deployment of EVs will involve the following studies: 1) Evaluation of the impacts that battery charging may have on system operation; 2) Identification of adequate operational management and control strategies regarding batteries' charging periods; 3) Identification of the best strategies to be adopted in order to use preferentially renewable energy sources (RES) to charge EVs; 4) Assessment of the EV potential to participate in the provision of power system services, including reserves provision and power delivery, within a vehicle to grid (V2G) concept. Inspired by this summary, we will first review four kinds of goals when investigating in smart charging of an EV fleet. In addition, we also see these four objectives as four types of opportunities and products that can be captured by FOs and then provided to other actors in a smart grid context.

2.1   Providing ancillary services to the transmission system operator (TSO)

Kempton et al. [10], [11] analysed the potential profits of V2G support by comparing it to existing ancillary services and found that participating regulation power market appears to be most promising and offers a substantial earning potential to EV owners. Rotering and Ilic [12] took into account vehicle to grid as a mean of generating additional profits by participating in the ancillary service markets. Based on the data of the independent system operator of California, provision of regulating power substantially improves plug-in hybrid electric vehicle economics and the daily profits amount to $ 1.71, including the cost of driving. Han et al. [13] proposed an FO that manages EVs to provide frequency regulation services, the cost arising from the battery charging and the revenue obtained during the participation is investigated. The problem is formulated as an optimization problem and dynamic programming is used to generate the charging control profile. Divya et al. [14] carried out a study investigating the feasibility of integrating EVs in the Danish electricity network which is characterized by high wind power penetration. They found that EVs have the potential to assist in integrating more wind power in 2025 when the EV penetration levels would be significant enough to have an impact on the power systems. Tuffner and Meyer [15] explored two different charging schemes: V2G Half and V2G Full to handle the entire additional energy imbalance imposed by adding 10GW of additional wind to the Northwest Power Pool. The result indicates that the proposed frequency based charging strategy can meet the new balancing requirements. However, this also depends on the charging station availability (residential and public charging station), the economics of the implementation and a viable and compelling business model. All these results indicate that it is reasonable and profitable to participate in the electricity market and provide ancillary service to the grid.

2.2   Providing services to renewable energy source (RES) supplier

Lopes et al. [16] investigated the dynamic behaviour of an isolated distribution grid when wind power and electric vehicles are presented. The objective is to quantify the amount of intermittent RES that can be safely integrated into the electric power system with the utilization of EVs' storage capacity. Another study [17] by the

same author analyse two tasks. The first part of the work studied the maximum share of EVs on the low voltage networks without violating the system's technical restrictions. The second part focused on the prevention of wasting renewable energy surplus when charging the EVs. The results indicate that the grid can allocate higher penetration of EVs with a smart charging strategy compared with a dumb charging and that the EVs have the capability to store energy and discharge to grid later into the system. In this way, the RES can be utilized more. Lund and Kempton [18] investigated the impact of using V2G technology to integrate the sustainable energy system. Two national energy systems are modelled; one for Denmark including combined heat and power (CHP), the other is a similarly sized country without CHP. The model (EnergyPLAN) integrates energy for electricity, transport and heat, includes hourly fluctuations in human needs and the environment (wind resource and weather-driven need for heat) The results indicated that adding EVs and V2G to these national energy systems allows integration of much higher levels of wind electricity without excess electric production, and also greatly reduces national CO_2 emissions.

2.3   Minimizing charging cost

An electricity market is presumed and is ideally suited for the application of optimal charging control; this is because the various hourly market prices can bring benefits for EVs if they are scheduled to charge in the period of lower prices. Within this scope, most the work [19] [20], [21] assume that the EV FO manages the electricity market participation of an EV fleet and presents a framework for optimal charging or discharging of the EVs. In addition, the electricity price of the day-ahead spot market and the regulation market and the driving patterns of the EV fleet are usually assumed to be known by the FO who is assumed to be the price-taker in the electricity market in studies. However, Kristoffersen et al. [22] also investigated the possibilities of EV management where the FO has a significant market share and can affect electricity prices by changing the load through charging and discharging. Besides studying the optimal charging from an EV fleet perspective, research in [12], [23] showed how dynamic programming can be utilized by the individual EV controller to make an optimal charging schedule taking into account the electricity market price. In [24], an intelligent charging method is proposed which responds to TOU price and minimize the charging cost.

2.4   Providing ancillary services to distribution system operator (DSO)

It is assumed that the distribution network has the capacity to allocate new loads when achieving the objectives discussed above. With the objective of avoiding grid bottlenecks, the purpose of the smart charging is to solve the potential grid congestion problem. Many investigations has been performed studying the impact of EVs on grid, which can be dated back to the early 1980s [25]. In [26], the authors gave a review and outlook about the impact of EVs on distribution networks. Sundstrom and Binding [27] considered the power grid on the Danish island of Bornholm, where the grid of the isolated island is used to study the impact of EVs and the potential profit to be made of grid services. The focus of the paper is on proposing a method for planning the individual charging schedules of a large EV fleet as well

as respecting the constraints in the low-voltage distribution grid. The impact of EVs on the electricity grid is studied in [28], where the focus is on the Vermont power grid. They assume a dual-tariff, nightly charging scheme, and conclude that enough transport capacity is available in the power grid. Lopes et al. [29] studied the potential impact on a low-voltage distribution grid. Smart charging behaviour is here considered to maximize the density of EV deployment into the grid, i.e., to reach the maximally tolerable number of EVs and meanwhile maintaining grid constraints. Kristien et al. [30] investigated the impact of charging EVs on a residential distribution grid and illustrated the results of coordinated and uncoordinated charging. Without coordination of the charging, the power consumption on a local scale can lead to grid problems. While the coordination of the charging can reduce the power losses, power quality is improved to a level which is similar to the case where no EVs are present.

2.5   Analysis of the research framework and the goals of smart charging

Several questions would naturally arise after reviewing the four goals described in 2.1 to 2.4, e.g., whether some goals can be integrated when making the optimal charging schedules of an EV fleet, what are the relationships between these four goals. In [12], the authors took into account vehicle to grid as a mean of generating additional profits by participating in the ancillary service markets and integrated it with the goal of minimizing the charging cost of the EV. The result indicated that the combined goals substantially improve EV economics. Sundstorm and Binding [27] considered the distribution grid congestion issue when minimizing the charging cost of an EV fleet. It is observed that multi-goals study is already performed, however, a systematic way of understanding the relationships between the described goals is missing.

In general, relationships between goals can be described as [31]:

- Independence: the goals do not affect each other.
- Cooperation: achieving one goal makes it easier to achieve the other.
- Competition: one goal can be achieved only at the expense of the other.
- Interference/Coordination: one goal must be achieved in a way that takes the other goal into account.

We use these four relationships as guideline and analyse the relationships between the four goals of smart charging. Table 1 presents the results.

Table 1: Relationships between the four goals discussed above

	Providing services to RES supplier	*Providing ancillary services to TSO*	*Minimizing charging cost*	*Providing ancillary services to DSO*
Providing services to RES supplier	N.A.	Cooperation	Cooperation	Coordination
Providing ancillary services to TSO	Cooperation	N.A.	Cooperation	Coordination
Minimizing charging cost	Cooperation	Cooperation	N.A.	Coordination
Providing ancillary services to DSO	Coordination	Coordination	Coordination	N.A.

It is shown in table 1 that the first three goals needed to be coordinated with the last one, and this coordination is usually called congestion management in distribution network and the topic has recently attracted many researches. Besides, table 1 shows that the first three objectives can be well integrated when generating the optimal schedule of EV fleets. With this qualitative analysis, it is beneficial for the FO to make global optimal schedules.

3   INTRODUCTION OF FO IN THE CONTEXT OF SMART GRIDS

From previous discussion, despite some services like minimizing charging cost could be done by individual EV, in most cases, these services can be practical in place only provided by a large fleet of EV. As shortly mentioned above, FO is widely proposed to aggregate the large penetration of EVs in the near future (FO used in the Edison project: http://www.edison-net.dk/). Firstly, the roles of the FOs are summarized from the literature; then we show the relationships between the FOs and other actors in a smart grid context; further discussion is made on the communication standard used for implementing the charging schedules.

3.1   Role of FOs

Tomas et al. [4] proposed two new electricity market agents: the EV charging manager and the EV aggregator/FO which are in charge of developing charging infrastructure and providing charging services, respectively; based on this, the authors

proposed a regulatory framework for charging EVs. Similar concept is introduced in [32], where the concept of EV service provider (EVSP) is discussed. In [32], the EVSP has two functions: one is responsible for installing and operating the charging equipment, another is supplying electricity to the EVs. In term of the feasibility of applying the FO concept, Bessa and Matos [3] gave a literature review regarding the economic and technical management of an aggregation agent for electric vehicles. The reviewed papers are organized into three technical categories: electricity market and EV technical and economic issues; aggregation agent concept, role and business model; algorithms for EV management as a load/resource.

It is observed that the main difference between the proposed solutions of FO lies on whether the FO has twofold functions or sole function, i.e., some studies assumed that a FO functions as both charging equipment supplier and charging service provider, others only refer FO as the charging service provider. Although various differences exist in the details of the proposed FO concepts, they are assumed to achieve the same goals in this study, regardless the ownership of the charging equipment:

- Guarantee driving needs of the EV owners with optimal management of EV charging;

- Provide ancillary services to power system operators with optimal allocation of EV fleet resources.

3.2   Service relationships between FOs and other actors in a smart grid

Figure 1 illustrates the relationships between FOs and other actors in a smart grid by showing the services that FOs can provide to them.
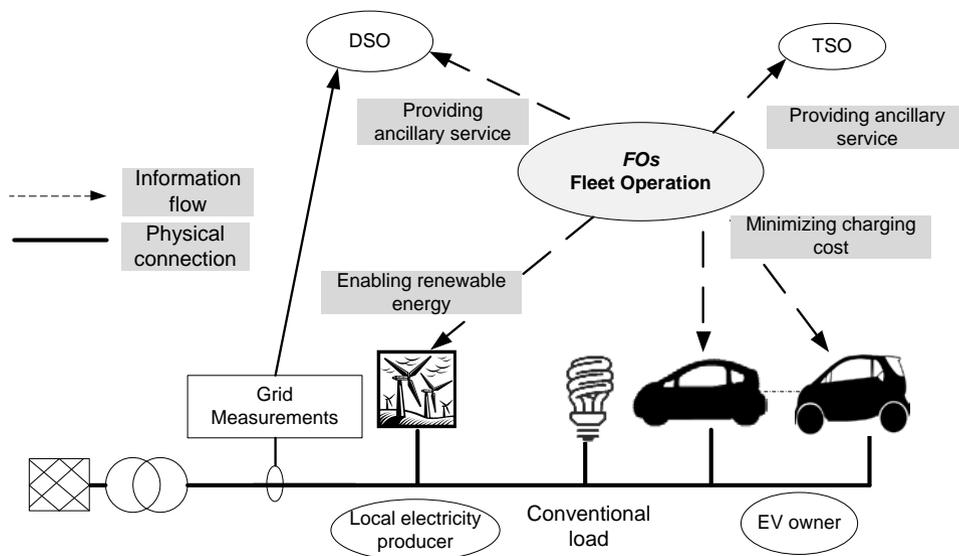

Figure 1: *The services relationships between FO and other actors in a smart grid.*

Note that the relationship between FOs and EVs is a slightly more complex. From one perspective, FOs need to attract the participation of EVs and then have the ability to provide services to other actors in the smart grid; from another perspective, FOs can provide the service of minimizing charging cost to EVs which help the EV owner to save money. Therefore, FO may need to consider many factors rather than purely make benefits when providing services to EVs.

3.3   Implementing the charging services/schedule provided by FOs

With the purpose of illustrating how the charging schedule is implemented, this section discusses the relevant communication standard for integrating EVs into the distribution grid. For example, the studies in [12], [13], [19], [22] focus on generating the optimal charging schedule instead of implementing it. These parts are supplemented by the works in [33], [34], [35], [36], [37]. It is noted that the purpose is to provide the relevant/widely used communication standard which can support the EV smart charging rather than comparing the various communication standards. Su et al. [33] presented an overview of EVs from the perspectives: 1) charging infrastructure (society of automotive engineers standard) and Plug-in Hybrid Electric Vehicles (PHEVs)/Plug-In Electric Vehicles (PEVs) batteries, 2) communication requirements. In European area, studies in [34], [35], [36], [37] recommended the IEC standards which are illustrated in figure 2. The objectives of all the studies [34], [35], [36], [37] are the realization of a standardized communication interface, the vehicle to grid communication interface. The standardization will make it possible for users of EVs to have easy access to EV charging equipment (EVSE) and related service throughout Europe. EVSE refers to all the devices installed for the delivery of power from the electrical supply point to the EV. EVSE supports the smart charging functions. The decision can be made on the EV level or on the FOs level. The IEC 15118 is the most recommended communication standard in the work [34], [35], [36], [37] and demonstrated in details in [34], [35] by showing the sequence diagram of a charging process between the EVSE and the EVs. For the communication between the EVSE and the FOs, it is recommended that IEC 61850 can fulfil the functions.
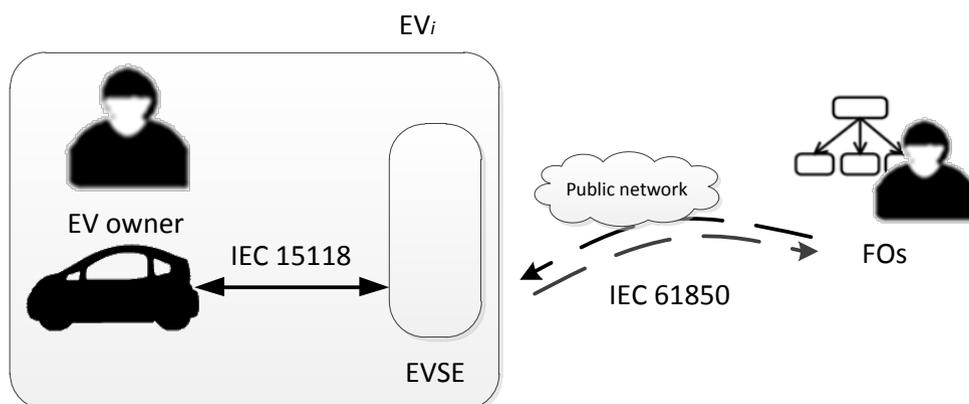

Figure 2: Relevant ICT standards support the EV smart charging in the context of smart grids.

In general, we define EV*i* as the combination of the EVSE and the EV as well as holding the intelligence endowed by the EV owner (illustrated in the figure 2). With this background, for the next parts of this paper, we will review the control architectures, the algorithms which are used by FOs in the literature and the communication part will be ignored.

4   CONTROL ARCHITECTURES AND THEIR INTEGRATION

4.1   Centralized charging control of EV FO

Battery Model
- Modeling the state of charging of the battery with linear or nonlinear approximation
- life time assessing model, battery degration analysis

Driving Pattern
- Forecasting driving requirement of EV owner
- Location prediction of Evs
- Normal vehicle's historical data are used
- Normal distribution, Monte-Carlo based method

Grid Contraint
- Thermal constraint of cable and transformers
- Voltage constraint

Electricity Market
- Day-ahead market
- Regulation power market
- Other reserve market

EV FO

FO operation

Control Signal →

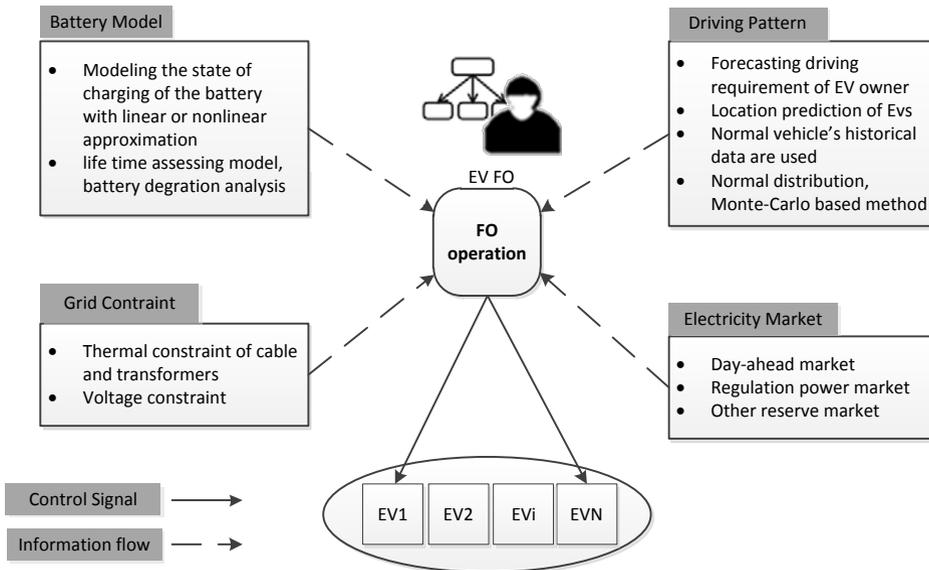Information flow – →

EV1   EV2   EVi   EVN

Figure 3: Primary inputs and output of EV FO.

Figure 3 mainly depicts the four inputs when making the control strategies. In this context, FO obtains all the relevant information including the EV battery model, the EV driving patterns, the grid constraint and the electricity price and centrally makes the charging schedule for each EV. In contrast, some EV owners want to generate the charging schedule by themselves, this is called decentralized control. However in the context of decentralized charging, the FO still needs to coordinate the grid constraints with the EV owners and this coordination is usually implemented by using price signal. In the following section, we will present two methods of implementing decentralized charging control as well as respecting to the grid constraint.

4.2   Decentralized charging management of EV FO

The scheme of the information flow in decentralized charging control is presented in figure 4.
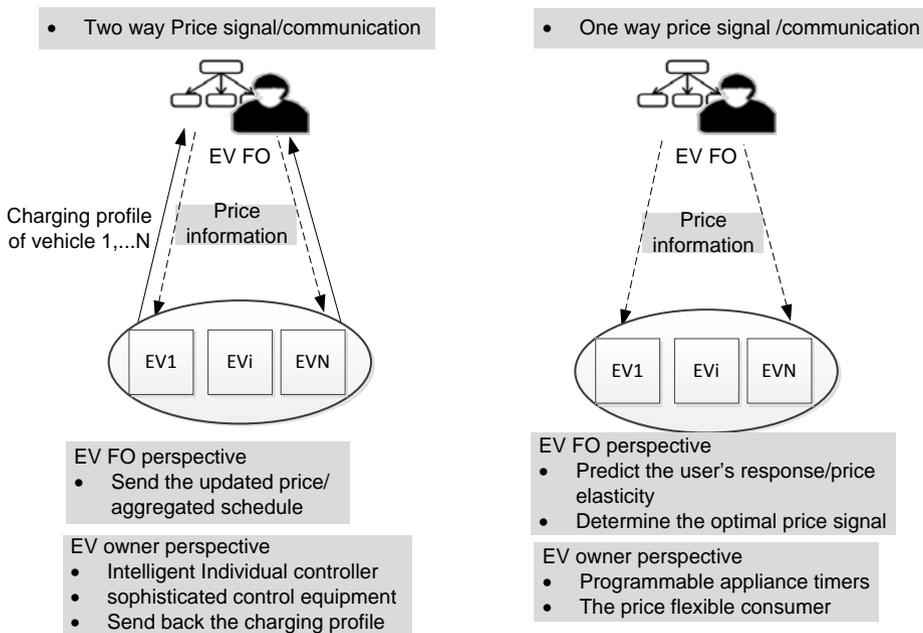
Figure 4: *Schematic view of the information flow between the FO and the EVs.*

In figure 4, two kinds of price signals are presented. For the left figure, i.e., two way price signal, this is also used such as game theory, valley filling. The basic idea is that EVs update their charging profiles independently given the price signal; the FO guides their updates by altering the price signal. Several iterations are required for the implementation. For the right figure, we call it one way price signal method; this method requires FO to predict the users' response to the prices. The price signal can be designed simply as time-of-use price or more dynamic prices.

4.3   Comparison between control strategies

Table 2 compares the two control methods based on literature review. We first clarify the terminologies used in this study: centralized control and decentralized control are regarded as architectures, which mean the charging schedule decision is made either in upper FO level or local EV controller level. Direct control means that FO sends the control signal to the EVs and the EVs executes the charging schedule.

Price control means that the FO coordinate their requirements (distribution grid constraints) by sending electricity price to the EV controller and the EV controller takes the decision to generate the charging schedule. This is indirect control for the FO because the FO is only specifying a constraint (the price) for the charging schedule and not the charging schedule itself.

Table 2: Comparison between direct control and price control strategy

| | Control Methods | |
	Direct control	Price control
Features of the control method	• Control signals (i.e., set points) • High level controller makes the decision	• Price incentive • Consumer make decision
Advantages	• High certainty • Better optimal results	• Privacy improved • Less communication cost
Disadvantages	• Inflexible • High communication cost • High computation requirement	• Lower certainty • Better knowledge on customer's response to price required

5   DATA ANALYSIS OF BATTERY MODEL, DRIVING PATTERN

5.1   Battery model

Basically, there are two ways to model the charging characteristics of the EV, i.e., the battery model. One is an individual battery pack model, another is aggregated (characterize the state of charge of an EV fleet in one model). For simplicity, most of the studies considered EV as a battery pack when investigating the optimal charging and discharging problem. Currently, most battery model studies [38] [39] [40] focus on three different characteristics:

- The first and most commonly used model is termed as a performance or a charge model and focuses on modelling the state of charge of the battery, which is the single most important quantity in system assessments.

- The second type of model is the voltage model, which is employed to model the terminal voltage so that it can be used in more detailed modelling of the battery management system and the more detailed calculation of the losses in the battery.

- The third type of model is the lifetime model used for assessing the impact of a particular operating scheme on the expected lifetime of the battery.

We give further discussion on the first model, usually, linear and nonlinear approximation are used to characterize the state of charge of the battery. Linear approximation are utilized in works [19], [20], [21] to approach the charging behaviour of an EV battery. Rotering and Ilic [12] considered a nonlinear battery model. The

studies [20], [21] has shown that violations of the battery boundaries when applying the charging schedule based on the linear approximation are relatively small, i.e., less than 2% of the usable capacity. The benefit of using a nonlinear approximation does not justify the increase in computation time.

5.2 Driving pattern

The analysis of driving pattern can be divided into two main directions:

- Utilization of EVs, in other words, a typical user daily life means that at any point during the day an EV could possibly be in the garage, in an employer's parking lot, in a store parking lot or on the road. This means that the aggregator needs to characterize/predict the driving pattern of EVs.

- Location of EVs when charging and how many of them will be charged at a time, since such driving patterns produce an impact on the distribution gird.

In most papers [19], [20], [21] the authors assume that the aggregator know the users' driving patterns. There are few studies on investigating the driving pattern issue. Kristoffersen et al. [22] investigated the method to construct driving patterns with the historic data in Danish case. By clustering the survey data on the vehicle fleet in Western Denmark (January 2006-December 2007), a representative driving patterns for each vehicle user are constructed. S. Shahidinejad et al. [41] developed a daily duty cycle which provides a complete data set for optimization of energy requirements of users and furthermore, this information can also be used to analyse the impact of daytime charging by a fleet of plug-in electric vehicles on the electric utility grid that may create a peak demand during the day to be met by the local utility grid. Normally, intra city or short term driving patterns are largely predictable due to fixed working hours and fixed business schedules and routes.

6 MATHEMATICAL MODELING AND CONTROL: CENTRALIZED CONTROL

In this section, we will present algorithms often used for the centralized control. Linear programming, quadratic programming, dynamic programming and stochastic programming will be shown for the discussion through an extensive literature review. Further, a qualitative comparison among the four algorithms will be presented in the end of this section.

6.1 Linear programming (LP)

Sundstrom and Binding [20], [21] used linear approximation to characterize the state of charge of a battery and formulate the charging process for an EV fleet into a linear programming based optimization problem:

$$\min t_s c^T P_b \tag{1}$$

Subject to

$$\begin{cases} A_s P_b \geq b_s \\ A_g P_b \geq b_g \\ A_b P_b \geq b_b \\ b_l \leq P_b \leq b_u \end{cases} \qquad (2)$$

With the time slot t_s, cost vector c, the charging power P_b, the stopover inequality constraints (A_s, b_s), the generation inequality constraints (A_g, b_g), the battery inequality constraints (A_b, b_b), and the upper and lower bounds (b_u, b_l). The solution of this linear optimization problem is the optimal charging profile while minimizing the charging cost of EV fleet.

6.2   Quadratic programming (QP)

A nonlinear approximation (quadratic formulation) of the battery charging model is also studied in [20], [21]. The results showed that the number of constraints is higher and increases faster with a growing fleet in the quadratic formulation than in the linear formulation, the difference in calculation time increase with increasing fleet size. An example is conducted for comparison and the result indicated that calculating time using the quadratic formulation is 819 times the calculation time using the linear formulation. But the result difference does not justify the benefits of using quadratic formulation. Another example of using quadratic programming method was introduced by Kristien et al. [30] who formulated the power loss problem caused by large penetration of EVs in the grid into a sequential quadratic optimization problem. The objective is to minimize the power losses which are treated as a reformulation of the nonlinear power flow equations. The charging power obtained by the quadratic programming cannot be larger than the maximum power of the charger P_{max}. The batteries must be fully charged at the end of cycle, so the energy which flows to the batteries must equal the capacity of the batteries C_{max}.

x_n is zero if there is no EV connected and is one if there is an EV connected at node n. The above problem specification can be represented as follow:

$$\min \sum_{t=1}^{t_{max}} \sum_{l=1}^{lines} R_l . l_{l,t}^2$$

Subject to

$$\begin{cases} \forall t, \forall n \in \{nodes\}: 0 \leq P_{n,t} \leq P_{max} \\ \forall n \in \{nodes\}: \sum_{t=1}^{t_{max}} P_{n,t}.\Delta t . x_n = C_{max} \\ x_n \in 0,1 \end{cases} \qquad (3)$$

The quadratic programming techniques are applied using both deterministic and stochastic methods in Kristien's paper. The input variables in both cases are the daily/hourly load profile. In the deterministic case, the load profiles are static. In the stochastic case, the load profile are transformed into probability density func-

tions, which means that the fixed input parameters are converted into random input variables with normal distributions assumed at each node. The details of stochastic case are presented in the following section.

6.3   Dynamic programming (DP)

Dynamic programming is widely used in many papers [12], [13], [23], [30] with different purposes. We introduce the work in [12]. In the paper, a specific control strategy is denoted by

$$\pi = \{u_0, u_1, \dots u_k, \dots, u_{N-1}\}$$

Where u_k is the control variable denotes a dimensionless and discrete representation of P_k. P_k corresponds to the purchased power flow. The total cost of a whole charging sequence, J^π is then given as below:

$$J_0^\pi(x_0) = J_N(x_N) + \sum_{k=1}^{N-1} l_k(x_k, u_k, k)$$

J_N means cost of the final step, $l_k(.)$ denotes the cost-to-go for all other steps, N denotes the total number of time intervals. The objective is to find the optimal control variables which can minimize the total cost. The detailed mathematic formula of cost of final step and cost-to-go are not presented here. The purpose of the function used for calculation of cost of final step is ensuring that the battery is fully recharged before the first trip of the following morning. For the function of cost-to-go, the electricity price, regulating-up price and regulating-down price are considered.

This is a classical dynamic programming formulation and the optimal trajectory is calculated starting with the cost of the last state and going backwards through time until the first state's optimal cost $J_0^0(x_0)$ is given by the algorithm. Concerning the computing time of dynamic programming, the results in [30] show that the difference of the charging profiles for the QP and DP technique are negligible, however, considering the computational time and storage requirements, the storage requirements are heavier for the DP technique compared to the QP technique, hence, the computational time for DP technique is longer.

6.4   Stochastic programming

Most of the current researches [12], [19], [21] assume that the load profiles, initial state of charge, driving pattern, grid conditions and electricity price are known and determined to the FO, however, this is certainly not the case in the reality. It is therefore necessary to put efforts on stochastic approach to reduce the risks, and some works have been done recently [30], [42], [43], [44], [45].

A stochastic approach for calculation of the daily load profiles is considered in [30] when minimizing the power loss problem. A sample average approximation method [46] is utilized to formulate the random inputs and the lower bound estimate principle is used to estimate the optimal value. It is noted that the model is the same as presented in equation (3) of this section (section 6.2). The uncertainties of

these parameters can be described in terms of probability density functions. In that way, the fixed input parameters are converted into random input variables with normal distributions assumed at each node. N independent samples of the random input variable ω^j, the daily load profile, are selected. Following equation (4) gives the estimation for the stochastic optimum $\hat{v}_n$. The function $g(P_{n,t}, \omega^j)$ gives the power losses and $P_{n,t}$ is the power rate of the charger for all the EVs and time steps. $\hat{f}_N$ is a sample-average approximation of the objective of the stochastic programming problem:

$$\hat{v}_n = \min\left\{ \hat{f}_N(P_{n,t}) \equiv \frac{1}{N}\sum_{j=1}^{N} g(P_{n,t}, \omega^j) \right\} \tag{4}$$

The mean value of the power losses, $E(\hat{v}_n)$, is a lower bound for the real optimal value of the stochastic programming problem, v^*, as shown in the below:

$$E(\hat{v}_n) \le v^*$$

$E(\hat{v}_n)$ can be estimated by generating M independent samples $\omega^{i,j}$ of the random input variable each of size N. M optimization runs are performed in which the non-linear power flow equations are solved by using the backward-forward sweep method. The optimal values of M samples constitute a normal distribution:

$$\hat{v}_n^j = \min\left\{ \hat{f}_N(P_{n,t}) := \frac{1}{N}\sum_{i=1}^{N} g(P_{n,t}, \omega^{i,j}) \right\}, j = 1,...,M.$$

$\hat{v}_n^j$ is the mean optimal value of the problem for each of the M samples. $L_{N,M}$ is an unbiased estimator of $E(\hat{v}_n)$. Simulations indicate that in this type of problem, the lower bound converges to the real optimal value when N is sufficiently high:

$$L_{N,M} = \frac{1}{M}\sum_{j=1}^{M} \hat{v}_n^j.$$

A forecasting model for the daily load file for the next 24 hours is required at first, then the daily profile of the available set are varied by a normal distribution function. The standard deviation σ is determined in such a way that 99.7% of the samples vary at maximum 5% or 25% of the average. In general, the simulation results indicated that the difference between the power losses of the stochastic and the deterministic optimum is rather small.

Other studies such as Fluhr et al. [42] use Monte-Carlo method to generate the probability distributions of the driven travel paths for one week with the survey "Mobility in Germany" (MIG), because the original data MIG only provide one day driving behavior; studies in [43], [44], [45] use normal distribution and Poisson distribution to investigate the probabilistic distribution of plugin time and initial state of charge of EVs.

6.5   A summary of the presented algorithms with three types of criteria

In table 3, we mainly summarize the information of the presented algorithms in term of the computation time, the certainty of performance, and the applicability. The summary aggregates the comparisons described in the literatures in term of computation time and performance of the presented algorithms. Besides, the applicability of the presented algorithms is summarized from two perspectives.

	Computation time	*Certainty of Performance*	*Applicability in general*	*Applications to EV charging*
Linear programming *Used in: [19], [20], [21].*	Generally, it is the fastest.	Results in [19], [20], [21] showed that the performance is excellent in term of finding the optimal solution.	1) The objective function is linear, and the set of constraints is specified using only linear equalities and inequalities. 2) Standard model, easy for implementation.	Minimize charging cost of EVs.
Quadratic programming *Used in: [20], [21], [30].*	Ref. [20] showed that the calculation time using the QP is 819 times than the one using LP for a fleet of 50 vehicles.	Ref. [20] showed that the difference between using LP and QP is minor. Therefore, the benefit of using the QP does not justify the increase in computation time.	1) The objective function has quadratic terms, while the feasible set must be specified with linear equalities and inequalities. 2) Standard model, easy for implementation.	1) Minimize charging cost of EVs. 2) Minimize power losses of power systems.
Dynamic programming *Used in: [12], [13],[23], [30].*	Ref. [30] indicated that the computational time for DP is slower compared to QP.	Ref. [30] showed that the difference between the charging profile of using QP and DP is negligible, although the QP gave more accurate results.	1) Studies the case in which the optimization strategy is based on splitting the problem (EV charging schedule) into smaller subproblems (multi-time slots). 2) No standard model, difficulty increases for complex problem. 3) Give global optimal result.	1) Minimize charging cost of EVs. 2) Minimize power losses of power systems. 3) Maximize profit of providing regulation services.
Stochastic programming *Used in: [30], [42], [43], [44], [45].*	The computation time is longer generally because more scenarios are considered.	The simulation results in [30] indicated that the difference between the power losses of the stochastic and the deterministic optimum is rather small.	Studies the case in which some of the constraints or parameters (Load profile, driving pattern etc.) depend on random variables.	1) Minimize charging cost of EVs. 2) Minimize power losses of power systems. 3) Maximize profit of providing regulation services.

7   MATHEMATICAL MODELING AND CONTROL: DECENTRALIZED CONTROL

Compared to centralized control, the decentralized control is a relative new application to EV fleet control, but still a lot of efforts have been done considering the amount of the articles.

7.1   Two way price signal- Price and power negotiation

As discussed in section 3, the following papers [7], [47] [48] [49] [50] [51] are chosen to further illustrate the two way price signal control method. Considering the similarities of the papers, we will discuss and present the papers in the following: the detailed formulas are given in the first paper with the purpose of facilitating reader's understanding. In paper [7], decentralized charging control of large population of electric vehicles is formulated as a class of finite-horizon dynamic games. Within this game, the control objective is to minimize electricity generation costs by establishing an EV charging schedule that fills the overnight demand valley. Moreover, the paper establishes a sufficient condition under which the system converges to the unique Nash equilibrium.

The key formulas are listed below:

$$x_{t+1}^n = x_t^n + \frac{\alpha^n}{\beta^n} u_t^n, t = 0, ..., T-1$$

Where x^n is the state of charge of EV_n , α^n and β^n means the charging efficiency and battery size of EV_n, and u^n represents the local control variable. The purpose of the study is to find the set of feasible full charging controls, which are described below:

$$\omega^n := \left\{ u^n \equiv (u_0^n, ..., u_{T-1}^n); s.t. u_t^n \geq 0, x_T^n = 1 \right\}$$

Where the final constraint on x_T^n requires that all EVs are fully charged by the end of the interval. The cost function of agent n, denoted by $J^n(u)$ is used as criteria and specified as:

$$J^n(u) := \sum_{t=0}^{T-1} \left\{ p(r_t) u_t^n + \delta (u_t^n - avg(u_t))^2 \right\}$$

Where each agent's optimal charging strategy must achieve a trade-off between the total electricity cost $p(r)u^n$ and the cost incurred in deviating from the average behaviour of the EV population $(u^n-avg(u))^2$. With these criteria and certain conditions, the theorem about the existence of the Nash equilibrium is presented in the paper.

The proposed algorithm ensures convergence to a flat, or optimally valley filling aggregate charging profile. However, in both papers [47], [48], all EVs are required to participated the negotiation at the same time, and implement the schedules they

commit to. In a more realistic scenario, EVs may join the negotiation at different time, not necessarily known to the FO beforehand. Furthermore, the approach is suitable to today's system or those mainly comprised of conventional demand, this limits the cycling required in thermal plants; however the response to intermittent generation will be of more interest. During periods of intermittent (renewable) generation (RG), the price is unlikely to be directly related to demand, as RG typically has lower or zero marginal cost.

Zhong Fan [50] applied the concept of congestion pricing in Internet traffic control and showed that price information is very useful to regulate user demand and consequently balance the network load. Individual users adapt to the price signals to maximize their own benefits. User preference is modelled as a willingness to pay parameter which will influence both individual charging rate/cost and overall system behaviour, because, the unit price of energy in a time slot is a function of the aggregate demand in the paper. Charging power is allocated according to fair pay principle which is economically efficient and the mechanism ensure the system stable under arbitrary network topologies. However, the approach is not compatible with current market structure since in Zhong Fan's paper, iterative convergence is required. Besides, the assumption that price is a function of demand, with a fixed constant of proportionality is quite weak, because reductions in demand won't necessarily lead to corresponding reductions in price. Moreover, only the EV load is considered in the paper, it is arguable to inquiry the conventional load. As mentioned by the authors in the paper, the proposed model is also a kind of game theory.

In short conclusion, both papers [49] [50] made a good effort in trying to use game theory to formulate the complex decision making process for future energy traders, especially the FO. In the future smart grids, the distributed generation resources (DER) are most likely to be integrated via market-based mechanisms; therefore game theory will be a very useful tool to study the dual impacts between DERs and the markets.

7.2   One-way price signal-Price and demand elasticity

By using one-way price signal, we mean that the EVs controller do not need to propose and submit their charging profile to the EV FO, instead the FOs will anticipate their response to the dynamic price. The dynamic price ranges from simple time-of-use electricity rate [52] [53] to more varying hourly prices [54] [55]. Both studies [52] [53] suggested that the TOU rates can be properly designed to reduce the peak demand as EVs penetrate the vehicle market. However, it is also noted in [52] that the extent to which properly designed rates could assist in maintaining grid reliability will remain open until empirically tested EV owner's price responsiveness through experiment pilots are known.

Both studies [54] [55] investigated the price elasticity of electricity consumers and these are also the key issues in one-way price signal approach. Details in [55] is presented. In the model [55], the marginal utility function of loads is realized by the following parametric stochastic process:

$$r(t) = \begin{cases} \beta - \delta(t-\alpha), & \alpha \le t \le \alpha + \gamma; \\ 0, & \text{otherwise.} \end{cases}$$

where $\alpha, \beta, \gamma, \delta$ are random variables that describes the different characteristics of utility function as follows:

a) α stands for the time slot that a task is initially requested, which also reflects the task distribution;

b) β is the initial marginal utility, which stands for the magnitude of the marginal utility.

c) γ is the tolerable delay, which determines the maximum delay that a user can tolerate to finish a task;

d) δ means the utility decay rate, which represents the cost of inconvenience by the delay.

Under this model, the scheduling of each individual task is now a random event whose probability distribution is controlled by the stochastic process $r(t)$. The aggregated demand curve can be estimated through expectation with respect to the distribution of $r(t)$. Note that some assumptions have been made before, such as the time period of the scheduling is divided into T time slots, the total M individual tasks $m: m=1,..., M$ of different appliances that are to be initialized by all the users within the scheduling period, and each task will consumer x_m kWh energy. Furthermore, it is assumed that each task can be completed within one time slot; therefore, tasks that have duration longer than one time slot will be decomposed into multiple tasks that are considered independently.

In general, one can see that within decentralized control, no significant computing resources are required and the communication infrastructure is also simplified compare to centralized control.

8   CONCLUSION AND RECOMMENDATIONS

8.1   Conclusion and discussions

As a conclusion, it is learned from this study that:

- Control objectives of aggregating a large penetration of EVs are essential for the starting of generating EVs' schedules.
- Linear approximation of state of charge of battery (EV) is acceptable when doing the smart charging study.
- Linear programming is suitable for the smart charging study of EV fleet and individual EV.
- Price signal can be well designed and utilized to coordinate the charging profiles of EVs.

The following benefits of present study can be identified:

- ▪ The study outlines a foundation for future improvements in term of smart charging from a control theory perspective.

- ▪ The advantage and disadvantage of centralized and decentralized control are discussed, which gives a basis for comparing available methods for future developments.

- ▪ Details modelling method and algorithms are illustrated by showing the key formulas and compared in term of their performance, calculation time etc.

However, it should be observed and emphasized that the above discussion did not consider the real time operations, i.e., there is no continuous monitoring and assessment of the state of dynamic system and therefore lack of the appropriate response in abnormal situations. This means that new procedures considering the dynamic behaviour of EV fleet and distribution networks should be developed as well.

8.2   Recommendations on future research directions in the area

Based on the discussions in the present study, future research directions are outlined below:

1) Coordinate the multi-goals of smart charging of EVs

Recently, the trend in smart charging of EVs is to integrate the interests of EV owners, ancillary services required by the transmission system operator as well as respecting the hard constraint imposed by the distribution system operator. Research in [9] [21] aim to coordinate these multiple objectives centrally. Alternatively, some studies [56] used a price signal/market approach to coordinate the multiple objectives.

2) Integrating the control method

Although most research assumed either centralized control or decentralized control methods when starting the study, this is indeed an important decision which should be taken in the earlier stage. From our perspective, three issues shall be investigated thoroughly.

- ▪ Depending on the aggregation goals, this is due to different goals have various requirement on EVs in term of response time etc.

- ▪ Depending on the EV consumer's participation, such as some consumers do not like their EVs to be controlled by FOs, under such circumstance, price incentives are a suitable method.

- ▪ Depending on the business model, we means whether the economic benefits of optimal charging of EVs can justify the cost of communication infrastructure in all cases; this will be an important consideration when choosing the control method.

Studies in [57], [58] compared the centralized control and decentralized control method when utilizing them to make an optimal plan which can optimal delivery

energy to EVs as well as avoiding grid congestions. They outlined the advantages and disadvantages of both strategies. Figure 5 illustrates the structures of integrating control strategies in a smart grid environment especially considering the congestion management in distribution networks. The argument for proposing this integration relies on the fact that this system architecture is comprehensive for the solution of integrating EVs into the power distribution systems.
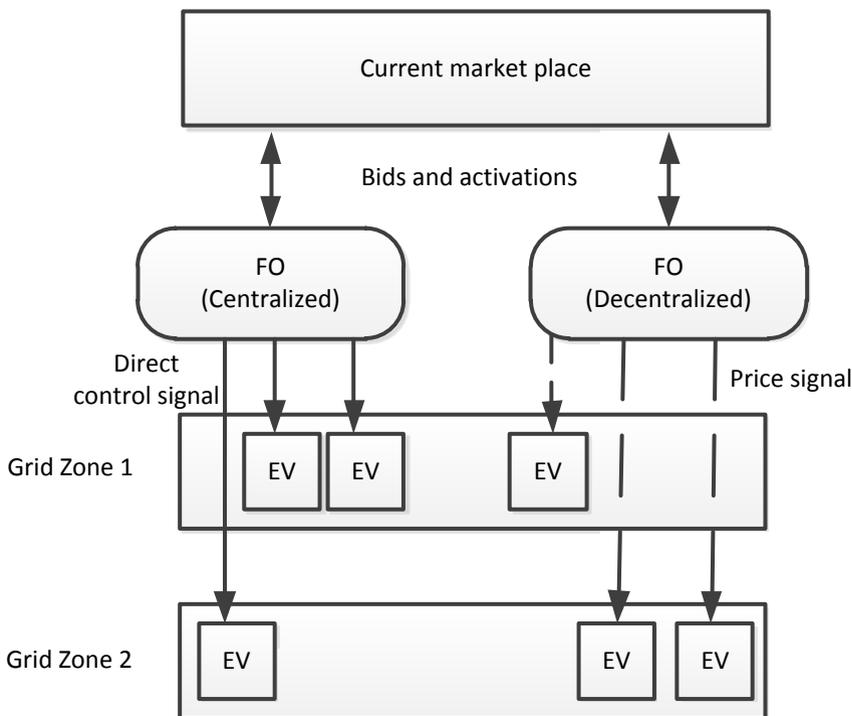

Figure 5: Integrating control method considering grid congestion management.

3) A multi-agent systems based realization of smart charging of EVs

It is observed that when implementing both control strategies of smart charging of EVs, especially decentralized control method, multi-agents system based technology is very suitable to design a coordinated and collaborative system for an intelligent charging network of EVs. In the multi-agent systems, different interests of various actors shown in figure 1 can be presented and coordinated by using smart charging method. By using multi-agent systems technology, one can model the optimizations and the negotiations happened in the smart charging of EVs. In [58], [59], the authors modelled the smart charging of EVs using multi-agent systems technology.

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