Stochastic energy modeling with consideration of electrical vehicles and renewable energy resources-A review

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Energy crisis and global warming due to fossil fuel implementation in the energy production sector and in the transportation sector have stimulated global trends to employ the electric vehicles (EVs) in the transportation sector and renewable energy sources (RESs) in the power generation. Coordinated charging of EVs can bring some benefits by itself such as voltage and frequency regulation, spinning reserve, load leveling, peak shaving, RESs support, GHG emission saving and so on. But implementation of this scenario with uncoordinated EV charging which can impose a huge amount of excess load on the grid. In this regard, EVs coordinated energy scheduling is inevitable. This paper comprehensively reviewed the pros and cons of integrating EVs to the grid and recent investigations in EV energy scheduling especially ones that focused on stochastic energy scheduling. Moreover, with knowing this fact that, microgrid with the presence of different distributed generation (DG) such as RESs and a diverse storage system such as EVs would have an important role in the future smart grid, thus, this paper aims to illustrate further research opportunities in this particular field. Also, different types of uncertain variables in recent studies and mathematical methods for optimizing the relevant objective functions of EVs charging are reviewed inclusively. Finally, future trends and investigation occasions in this field of study are discussed.

keywords: *Stochastic Optimization, Electric Vehicles, Renewable Energy Sources, Microgrid, Heuristic Optimization.*

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1. INTRODUCTION

Energy is crucial for global success, economic growth, and social development. Although these factors need to more energy demand and with more than 80% share of fossil fuels in energy resources, it causes more greenhouse gas (GHG) emission. The energy sector produces about 66% of GHG and more than 80% of CO_2 emission. Moreover, the three energy sectors, which have the biggest contribution of CO_2 emission, are power generation with 39%, an industry with 26% and transport with 20% [1, 2]. In this regard two promising solution for less GHG emission in energy sectors could be implementing renewable energy resources (RESs) versus fossil fuel power plants in power generation and also plug-in hybrid electric vehicle (PHEV) or electric vehicle (EV[1]) versus conventional internal combustion vehicles (ICVs) in transport sector. So with using these two factors together, GHG emission of more than 60% of the energy sector can be enhanced [1, 3]. With many promising improvements in battery technologies (higher efficiency and lower cost) and the growing number of vehicle manufactories, which produce EVs, it seems this kind of modern vehicle becomes more affordable, tangible and absorbs more social attention and interest [4]. EV can interact with power grid in two ways, charging power flow from grid to EV (in this case EV act as a load or a storage device) and discharging power flow from vehicle to grid (in this case EV act as a source of electric power), so EV can interact with grid unidirectional or bidirectional and this interaction brings a vehicle-to-grid (V2G) concept by itself, this concept was introduced by willet Kempton [5]. V2G could bring so many applications like voltage regulation, frequency regulation, load leveling, peak shaving, reactive power support, and renewable energy support. Zhao and et al. [6], have investigated the economic and environmental impact of electric trucks instead of conventional trucks with consideration of V2G regulation services and results show significant GHG

[1] In this paper for simplicity any kind of electric vehicle is called EV.

emission saving and additional revenue. Also, the smart public transportation network has been investigated by [7] which it's smart network structure includes the distribution network with PV systems and has electrical bus stations to charge electric vehicles and electric buses. Two applications of V2G, valley filling, and load variance minimization have been considered in [8]. Nevertheless, using EVs instead of ICVs bring so many troubles because they can be charged as soon as they plug-in to the grid and investigations show that departure time of vehicles from work to home is almost in the power grid peak time and with this uncoordinated and stochastic charging theme a huge amount of load will be imposed to the grid. Some studies had investigated the effect of EVs on the power system, especially in the power distribution system. An analysis of EV impacts on the power distribution system has been investigated in [9]. The results of this study show excess peak load and power loss problems due to coinciding EV charging and daily peak load. So it is important to control EV charging time and the way that they are going to be charged. In this regard, controlled smart energy charging or coordinated charge scheduling seems to be a good solution [8, 10]. In order to control the operation of a system, which can include RESs and EVs, two types of energy scheduling can be used; deterministic and stochastic. In deterministic terms different kinds of uncertainties such as wind speed variation, solar radiation, departure time of vehicles, the usage time of each EV and etc. are neglected and a firm and definite scheduling are presented [11]. On the other hand, in stochastic energy scheduling, various type of uncertainty can be implemented and results of these studies are more accurate and realistic than deterministic energy scheduling because of considering uncertainties which exist in the real condition. Intermittency of wind speed and stochastic behavior of EV owners have been modeled in [12] in order to achieve optimal power flow. For the diverse type of V2G advantages, different objective functions have to be optimized with consideration of network, RESs, EVs and other operational constraints. Some of these objective functions are operational cost minimization, GHG emission minimization, profit maximization, and RES usage maximization. Also, in some studies, a multi-objective scheme by considering a number of objective functions together have been investigated. These optimization problems can be solved by different methods that divided into two main segments: conventional methods and heuristic methods. Conventional methods include linear programming (LP), quadratic programming (QP), dynamic programming (DP) and etc. which these methods are usually based on repetitive search algorithms that begin with a solution which is repetitively enhanced according to some deterministic rules [13, 14]. Heuristic methods are based on search algorithms and they are used when conventional methods too slow or fail to find the exact solution and some of them as follows: ant colony optimization, evolutionary computation, particle swarm optimization, and genetic algorithms [13]. Some studies deal with different issues in the integration of EVs to the grid. A comprehensive study focused on different types of V2G technologies and their relevant challenges and opportunities [15]. Diverse services of V2G, challenges, optimization objectives, constraints, and algorithms have been thoroughly discussed in [16]. Prerequisites of charging system infrastructure of EVs and different types of charging levels and related optimization targets and methods have been investigated in a recent study by Rahman et al. [17]. Few attentions were given to different types of EVs charging especially stochastic energy scheduling of EVs. In recent studies, due to the stochastic nature of EV behaviors and uncertainty of RESs, stochastic EV energy scheduling has been paid more attention. Thus, this study aims to have an inclusive review of challenges and opportunities in integrating of EVs and power grid with focus on EVs energy scheduling particularly stochastic EV scheduling and related optimization methods and uncertain variables in recent investigations. The remainder of this paper is organized as follows: in Section 2 a review of energy scheduling which includes V2G concept and its benefits and different studies in integrating RESs with EVs is covered. Also, two types of scheduling (deterministic and stochastic) and related uncertain variables are reviewed. The main focus of this paper is dedicated to this subsection and recent articles about energy scheduling in microgrids and trends in this field are brought at the end of this section. In Section 3, computational methods in optimization of energy scheduling problem with RESs and EVs have been mentioned and relevant articles reviewed. At the end of this article (Section 4), future trends and a conclusion of this review have been discussed.

2. ENERGY SCHEDULING

A. Smart charging of EVs

As mentioned in the previous section, EVs bring by itself some pressure on the power grid and it could be worse when we know major of these EV owners reach at home almost at the same time and the EVs are connected to the grid in the peak load of the grid. So an enormous load is imposed on the power grid. A load producing model for PHEV home-charging and residential load pattern have been proposed in [18] and the results of this study show that in uncontrolled and unidirectional energy scheduling for PHEVs, most charging occurs in the afternoon and 33% of peak load is relevant to the PHEVs. Thus, a promising solution to declining the peak load would be scheduling the excess load due to EVs. The significance of energy scheduling is about to more efficient and economical use of energy, and it means efficient usage of energy sources, lower operation cost, lower peak load, and GHG emission saving. In this regard, by implementing RESs and EVs and its benefits such as peak shaving, ancillary services and energy planning, and scheduling is vital, not only for preventing excessive load due to EVs charging but also for the better usage of RESs and saving their energy and use them at appropriate times. For better load flattening and reducing the EV aggregator costs, two demand response (DR) algorithm by using copula (as a data estimator) have been proposed in [19]. Demand Response intends to adjust electricity consumption in response to the electricity market situation. This is usually done to reduced peak consumption, which reduces the spot prices in the short term and declines long-term investment in electricity generation [20]. Fig. 1 states DR program which contains price-based DR programs and incentive-based DR programs. The price-based DR programs are related to the voluntary program and incentive-based DR programs associated with both voluntary and mandatory programs [21]. Another benefit of EV integration to the grid regarding energy scheduling is improving power grid reliability. Some studies focus on reliability assessment of EV integration to the grid. Wang and et al. [22] have investigated the impact of EV integration into a residential distribution system and results show that enhancement in system adequacy indices by using smart energy scheduling. EVs energy scheduling on large scale has some prerequisite such as two ways communication services, aggregators, efficient battery technology, charge facilities and etc. An EV aggregator is an intermediate layer between a system operator and EV owners

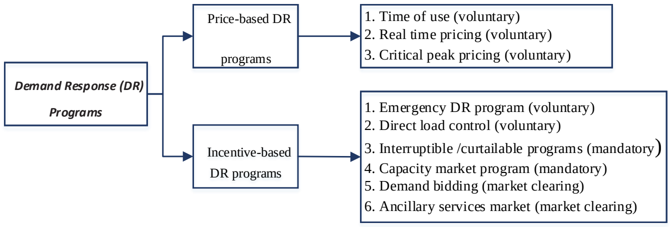

Fig. 1. Types of DR program [21].

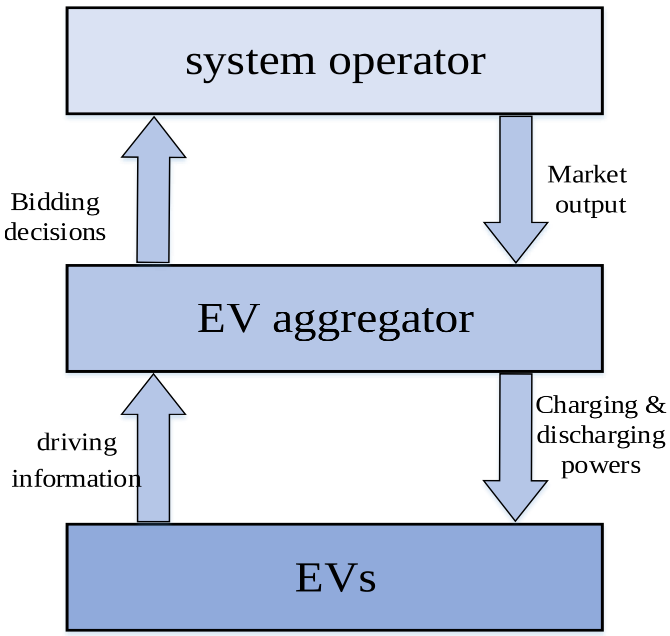

Fig. 2. The relationship between EVs, aggregator and the system operator [25].

[23]. In other word, the aggregator is responsible for managing the EVs charging. In the day-ahead energy market, the aggregators decide the bidding strategy instead of each EV solely. By considering the driving information of the EVs, the aggregator determines the bidding strategy and sends it to the system operator [24] and [25]. From the system operator viewpoint, the aggregator is seen as a large source of generation or load, which could provide ancillary services such as spinning and regulating reserve [26]. In order to clarify the subject, this concept represented in Fig. 2 [25]. Aggregators have to deal with EV owners and up-stream operators via two ways communication structure using much data such as online electricity prices, EV information (departure time, SOC and etc.), grid constraints and so on [27].

The presented model in [28], indicates that participation of local aggregators in the residential sector, with smart buildings and smart parking lots, could have higher income for local aggregators and less energy not charged for EVs. As mentioned before, coordinated and smart charging scheme should be used for EV energy scheduling to prevent imposing excess peak load to the grid and also using V2G privilege. Coordinated charging can be centralized for instance in a parking lot [29] or battery charging stations or decentralized for instance parking lot of each home and for each vehicle we should schedule the energy flow and relevant data of these vehicles gathered by an aggregator which interacts with other aggregators or network via a communication system. In order to have a comparison between centralized and decentralized intelligent energy scheduling approaches, in computation time, Karfopoulos and et al. [30] examined a decentralized multi-agent EV management approach that using a hierarchical architecture with intermediate aggregation layer via a respective centralized approach. This study indicates that, as we increase the number of EVs, the computation time of distributed approach is almost constant, but in centralized approach, computation time is a polynomial function of EV numbers. A centralized coordinated strategy for minimizing operation cost with the moving window optimization model is investigated in [31]. This study shows that the proposed model has a lower operating cost than uncoordinated one in different window sizes. On the other hand, the decentralized parking lot which is, more available, has a long charging time; however, for the development of electric vehicles, it is required to install the fast-charging stations that the electric vehicles batteries are charged on 15 minutes. But the main disadvantage is high power demand that should be imposed on the grid [32]. A smart EV energy scheduling with aggregator concept consideration and reserve scheduling (imbalance reserve for overcoming the forecasting error, reliability reserve for the overcome probability of unit outage) has been investigated in [33]. This study has two objective functions that might be minimized, the sum of the costs and total energy expected not supplied, that is a multi-objective optimization, and finally, a fuzzy decision maker applied to this problem for catching the best compromising solution. Effect of EV integration with the electricity grid in 3 different kinds of network (i.e., urban, rural and generic) has been investigated in [34] and results show that urban network is endangered when EV penetration is 60% , generic network and rural network are endangered with 40% and 15% of EV penetration, respectively. That shows the sensitivity of the rural network to EV penetration level and also with an increase in EV penetration, electricity load increases and consequently, the minimum experienced voltage reduces. Moeini-Aghtaie and et al. has modeled a two-stage energy scheduling [35]. In the first stage, the EV charging cost is considered as the objective function and in the second stage, the optimal charging plans for three different scenarios of EV owner preferences and system operator perspectives have been considered. Finally, a fuzzy multi-criteria decision making has been implemented for robust optimal planning.

A.1. V2G concept and services

Since the battery capacity of each EV is ignorable compared to the grid capacity, the V2G concept aims to gather a group of EVs to interact power between the EV groups and the power grid, effectively. V2G controls and manages power flow between the power grid and EV batteries via communication services to achieve the desired advantages [36]. This concept can be expanded in various ways, in [28] regard to vehicles, buildings, storages systems, RESs, and the electrical grid, 18 different kinds of energy exchange such as V2G, G2V, V2V, E2V, E2B and etc. have been proposed and aggregators are in charge of energy management. For meeting the V2G requisites, some factors have to be considered in the current power grid such as an aggregative architecture, high power home-charging, automatic generation control, lower percent call for V2G and vehicle degradation [37]. V2G divided into two types in case of power flow, unidirectional and bidirectional. In the former one, the charging rate of EVs is controlled and a single power flow just allowed and has some advantages such as voltage regulation and spinning reserve [38, 39]. Later one is bidirectional, which allows twodirection power flow and brings by it selves more flexibility and diverse advantages for the power grid and even for EV owners such as voltage regulation, frequency regulation, load leveling, peak shaving, reactive power support and renewable energy support [16]. In recent studies, so many authors have focused on V2G benefits. Three kinds of scenarios for EV charging has been proposed in [40], first of all an uncontrolled scheme shows increasing in afternoon peak load, and second, smart charging of EVs (unidirectional), shows a good accommodating with PV generation and reduce the ramps, and the last one is V2G scheme (bidirectional) that shows a good combination of PV generation and EV for saving solar energy and using this energy for peak shaving. An EV modeling in order to analyze the impact of V2G on the national energy system of Denmark has been investigated in [41]. This study has shown that V2G can increase power system reliability, decrease CO_2 emission and better using of wind power generation. The battery capacity of EVs has been used as a spinning reserve for frequency control and an autonomous V2G control for smoothing the intermittency of RESs has been proposed in [42]. Applications of EVs to frequency regulation in multi-area power system are studied in [43]. With concerning the V2G concept, EVs in [44] are participating in the energy market and they are used for ancillary service (system regulation) and with consideration of three different scenarios results show the effect of the proposed model in reducing the costs and better applying optimization in a competitive market for an energy supplier. One of the V2G benefits for the power grid is reliability improvement and some studies have been done in this area. Four cases for assessing EVs charging impact on power system reliability have been investigated in [45]. The results showed that in unmanaged EV charging time of being in at-risk level doubled compared to without the presence of EV and in the V2G scenario this criterion is well improved. Also, in some investigations, EVs with different battery capacity are used, for example, there are three types of vehicles in [7] that are varied in terms of application and battery capacity; however, all of them can improve the power quality of the grid.

A.2. Integration of EVs with RESs

Since RESs are so intermittent and have lots of uncertainty due to climate conditions such as wind speed and solar radiation, they need storage systems to save their energy and use it at the appropriate time. On the other hand, EVs are an appealing option for using them as a storage system because aggregated EVS has huge storage capacity and most of the time, they are in the park and are not used. In this regard, integrating RESs and EVs is a promising solution not just for charging the EVs, but also for peak load reduction, ancillary services, and GHG emission saving and enhancement in RESs usage. Thus, in recent years so many researches projects have been investigated to show the impact of integrating RESs and EVs [46–49]. Using RESs and EVs and smart energy scheduling in a smart grid can reduce operation cost and GHG emission [50]. For meeting the increasing electrical demand, distributed energy resources (DERs) could be a reasonable solution to integrating with future smart grids. In [51], energy scheduling has been optimized with a single objective approach that the network in this study is a micro-grid include RESs generation and EVs as a load. A multi-objective algorithm for optimal sizing and RESs allocation and for an EV parking lot has been developed in [52, 53]. In order to compare the profits of the smart distribution company in [21], different modes are considered. In these modes, the number of EVs and strategy of charging as well as the amount of supplied renewable energies are varied. Also, most of this literature has focused on wind power, solar power or combination of these and in the diverse scale of penetration. A local PV production with two scales of power generation (less than and more than electric load) in an isolated energy system, which contains EVs, have been utilized for meeting a part-electric demand of this energy system [54]. The results have shown that the effectiveness of the proposed model on better using of RESs and lower charging energy cost. Different PV and EV penetration under three scenarios, which include an uncontrolled scheme, a smart charging scheme, and a V2G based scheme, have been utilized in [40]. A rooftop photovoltaic system and distributed generator installed in a parking lot, and also are connected to the grid, have used for EV charging in [55]. A new probability distribution model which contains three variable PV power production, EV home-charging and household power consumption in two different levels, household, and aggregator (multiple households), has been developed [56]. Wang and et al. [57], implemented EVs as a power plant to participate in unit commitment with the presence of large-scale wind farms. High penetration of wind energy with the integration of EVs has been considered in the stochastic model for unit commitment in [58]. EVs can reduce the operating cost of the grid by using their battery capacities to capturing the RESs energy. Impact of EVs on Denmark national energy system with consideration of a different range of wind power generation (0 to 100% electricity demand) has been analyzed in [41]. In some studies, RESs are modeled as a negative load; for instance, in [59] wind power is given a negative load in the electric grid that changes with time. To obtain optimal power flow intermittency of wind speed and stochastic behavior of EV owners have been modeled in [12]. To meet EVs scheduling problem regarding the time and space domain of EVs and also the presence of wind power, a bi-layer optimization has been suggested [60]. Impact of three different parameters as electricity price, EVs penetration and EVs load location have been analyzed and improving in the economics of power grid and benefits for EV owners have been shown in results. In this literature, authors achieved these results by scheduling charging and discharging of EVS not just temporally but spatially scheduling also have been considered. Romero-Ruiz in [61] used a combination of wind power and solar power for meeting 25% of network demand (80% and 20% respectively) and some uncertain parameters are taken into account like as power generated by wind turbines and PVs, power demand and behavior of EV owners in congestion procedure participation. Uncertainties of wind speed and solar radiation are modeled by Weibull distribution function and bimodal distribution function, respectively [28]. Also, in [32], wind speed is modeled by Weibull distribution, but solar irradiation data is obtained from PVGIS (Photovoltaic Geographical Information System). A distributed EV coordination method has been implemented in [8] to improve synergy between RESs (solar and wind power) and EVs to increase RES and EV penetration in the power grid without extra network investment. EVs act as a reserve capacity for solar and wind power generation by using an integrated scheduling and EVs participation in ancillary service program [62]. Another study has focused on an energy resource management model for a micro-grid by contemplating of practical constraints, EV owner's satisfaction, spinning reserve requisites and renewable power (wind and solar) forecasting error [63]. In [21], a new bi-level model is developed. Uncertain parameters are: the time interval of EV presence in the parking lot, initial SOC of EVs, planned Wind and PV, in order to obtain operational scheduling of the smart energy system. In this paper, two-level are considered that the upper-level is considering the smart distribution company view and the lower-level is intending the parking operation perspective which solver for obtaining the objective function to consider two levels.

B. Energy scheduling in microgrids

A new growing trend in the power system is replacing the conventional large power systems with large centralized generators to some smaller distributed generation (DG) which connected to the distribution system with nonconventional and renewable sources. It means DGs which have been used as a back-up for the electricity grid, now trend of DG functions is going to change and they are acting as a primary source of the electric grid in the form of microgrid [64, 65]. Microgrid is a concept that uses DERs which is near to the customer site and they are a promising solution for meeting the electrical and thermal demand with accentuating on reliability and power quality. EVs can be used in a large scale with high penetration but in recent study implanting EVs in microgrids have been paying more attention because of an increasing trend on microgrid and microturbines such as micro wind turbines and small scale of PV panels. Four main reasons for increased attention to the micro-grids are energy loss reduction, reliability improvement, enhancement of energy management and benefits to the main grid. Fig. 3 shows a typical microgrid. Liang and et al. [66], have investigated a comprehensive review of stochastic modeling and optimization and key features of microgrids. As energy supply in microgrids limited in the inside of the microgrids, RESs such as wind and solar could have a large penetration in total generation portfolio. Since a microgrid is self-limited and self-balanced, one of the important objects that might be optimized is operating costs with consideration of reliability, by decreasing the uncertainty and intermittency of the RESs in the microgrid [67]. A single objective approach for energy scheduling in microgrid has been investigated in [51]. This study has different objective functions that are investigated separately, such as squared voltage deviation, power losses minimization, security margin, energy cost, and load leveling. These objective functions are compared with considering bus energy loads, electricity price, EV loads, data centers, storages and RESs generation. In [68], a two-stage operating strategy with consideration of wind farm, PV panels and pump-storage hybrid system in microgrids has been proposed. The aim of this study is to maximize the profit of RESs with frequency based pricing. Demand-side management (DSM) in a commercial building microgrid with solar generation, stationary battery energy storage system (BESS) and EV with V2G capability has been investigated in [69]. A two-stage stochastic DSM for modeling the stochastic nature of EV demands and availability, solar generation and load have been suggested and results show that a moderate number of EVs reduce the operational cost of the system. Various types of RESs have been contained in a microgrid (such as PV, WT, and fuel cell (FC) and micro-turbine and battery storages); also a stochastic smart charging framework has been suggested to investigate the impact of EV charging on optimal operation of this microgrid [70]. Two EV functions for peak shaving and load curve modification have been used in a microgrid by a simultaneous scheduling of EVs and responsive load to minimize operation cost and emissions [71].

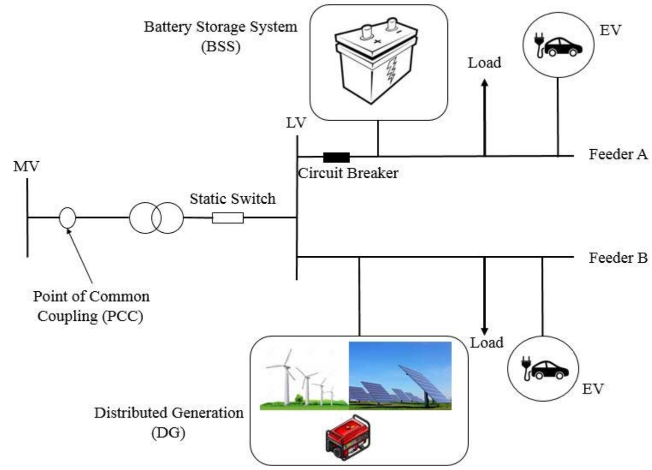

Fig. 3. Typical microgrid configuration.

C. Types of scheduling

C.1. Deterministic

A deterministic model has no stochastic elements and the entire input and output relation of the model are conclusively determined. If the input data of an optimization problem are fixed and certainly determined, its optimal solution (decision) is achieved by solving the problem and it has the best outcome [72]. As it can be seen in Fig. 4, deterministic optimization methods do not deal with uncertain variables (such as wind speed, solar radiation, EVs behavior). Since there are a lot of uncertainties in a real-world situation and specifically in EV energy scheduling problems, such as EVs driving pattern, diverse temporal and spatial EV charging pattern and so on, in the literature in this field, deterministic scheduling has been implemented much less than stochastic one. In this regard, trends in energy scheduling with the presence of EVs and RESs are using stochastic programming due to stochastic and uncertain variables. Fig. 5 illustrates this fact by considering relevant statics from the two most valid references (IEEE, Science direct) in this field. However, some of the investigations used a deterministic approach to assume perfect knowledge of the uncertainties of the system. Although in the first step a deterministic demand-side management (DSM) (assuming perfect knowledge of uncertainties) has been suggested in [69], a two-stage stochastic method implemented to meet stochastic nature of EVs availability, EV charging demand, solar generation and loads. A multi-objective energy scheduling with a two-stage method which contains a deterministic mixed-integer linear programming (MILP) and particle swarm optimization (PSO) without any uncertainty consideration has been used in [11]. Some deterministic problems are attained from stochastic ones by replacing the random variables of the considered stochastic processes by their expected or forecasted values. Some studies suggested stochastic programming methods and compared the results to relevant deterministic approach and indicated the effectiveness of stochastic methods. In [73], a stochastic dynamic programming method has been suggested to reduce the operation cost of the charging stations and their impact on the distribution grid and optimal power dispatch schedule. The results of this method are compared to the relevant deterministic dynamic programming with consideration of perfect anticipation of RESs output and charging demands.

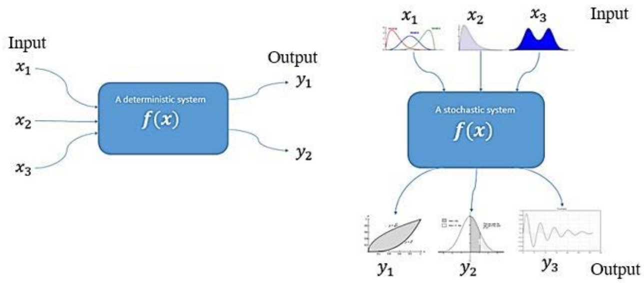

Fig. 4. Deterministic versus stochastic system modeling.

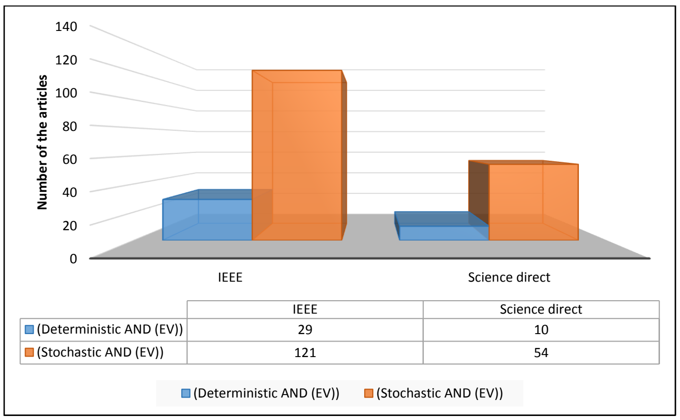

Fig. 5. Search results of stochastic and deterministic electric vehicle modeling in IEEEexplore and ScienceDirect (2015-2016).

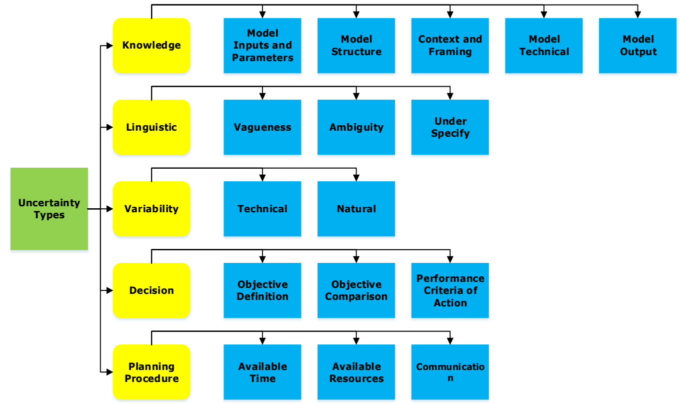

Fig. 6. Uncertainty types [75].

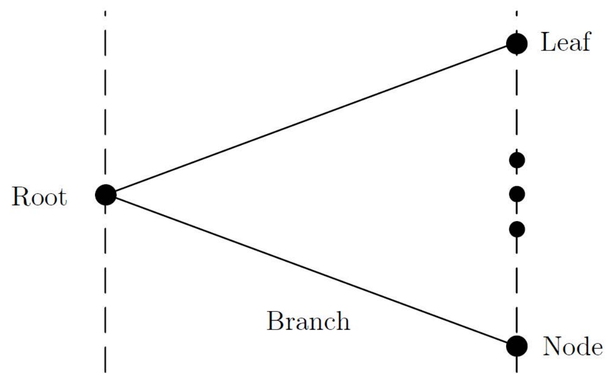

Fig. 7. Scenario tree for a two-stage stochastic problem [72].

C.2. Stochastic

A stochastic model has one or more stochastic elements. The system having stochastic element is generally not solved analytically and, moreover, there are several cases for which it is difficult to build an intuitive perspective. In the case of simulating a stochastic model, a random number is normally generated by some method, such a simulation is called the Monte-Carlo method or Monte-Carlo simulation [74]. This method is used in [32] to simulate the electrical vehicle arrivals. In the electricity market specifically in such grids with intermittent renewable energy sources, electric vehicles, stochastic planning, and scheduling can be a good solution to meet stochastic behavior and related uncertainties of these elements. That is why a major part of this study dedicated to stochastic energy scheduling. Different types of uncertainties are shown in Fig. 6.

The expected value of perfect information (EVPI) and value of the stochastic solutions (VSS) are used to assess the interest of using stochastic programming [72]. However, it can be validated by using actual real-world outcomes. Authors in [69] validated the stochastic method with real solar generation, loads, battery energy storage system (BESS) and EV data using average sample approximation. Stochastic programming is used to formulate and solve problems with uncertain parameters, thus, in the stochastic programming context, each uncertain parameter is modeled as a random variable [72]. Since in stochastic programming, a set of uncertain input is considered, defining an objective function for decision making is the main problem. In this regard, maximizing the expected value of the objective function or limiting the variance of this objective are two promising solutions to accurate modeling the stochastic problems. This solution is not best for each data set, but it is the best for the whole input sets overall. To sufficiently define a stochastic process, it is important to generate a sufficient number of scenarios so that these scenarios cover the possible set of stochastic inputs. To obtain this, a huge number of diverse scenarios must produce which cause a lot of computational costs. Thus, a proper procedure is needed for scenario reduction which comprehensively investigated in [72]. In stochastic programming due to the amount of information we have and a number of stages which is needed for problem formulation two categories are considered:

- Two-stage problems: in the first stage (here-and-now), decisions are made before the realization of the stochastic process and in the second stage (wait and see) decisions are made after knowing the actual realization of the stochastic process (Fig. 7). In the second stage, uncertain data formulated by relevant scenarios. The decision-making process is as follows:

1. Decisions x are made.
2. Stochastic process λ is realized as $\lambda(\omega)$.
3. Decisions $y(x.\omega)$ are made.

λ is a stochastic process that contains a set of possible realization $(\lambda_\Omega = \{\lambda(1), \ldots, \lambda(N_\Omega)\})$, ω is scenario index and each realization is $\lambda(\omega)$ associated with a probability $\pi(\omega)$ defined as :

$$\pi(\omega) = P(\omega | \lambda = \lambda(\omega)). \text{ where } \sum_{\omega \in \Omega} \pi(\omega) = 1 \tag{1}$$

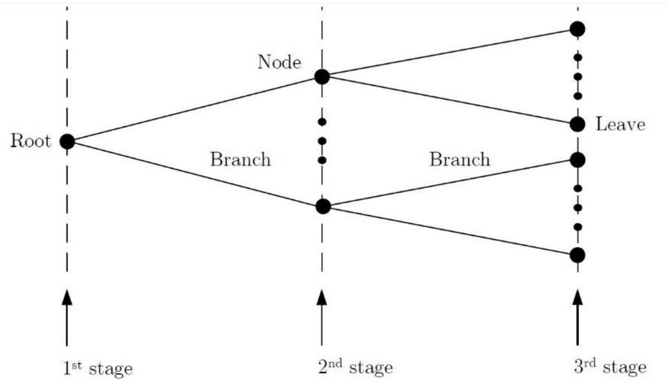

Fig. 8. Scenario tree for a multi-stage stochastic problem [72].

General formulation of two-stage stochastic optimization problem is as below:

$$\text{Minimize}\ _x Z = C^{\mathrm{T}} x + \varepsilon\{Q(\omega)\} \tag{2}$$

$$\text{subject to} \qquad Ax = b \tag{3}$$

$$x \in X \tag{4}$$

where:

$$Q(\omega) = \text{Minimize}_{y(\omega)} \quad q(\omega)^T y(\omega) \tag{5}$$

$$\text{subject to} \qquad T(\omega)x + W(\omega)y(\omega) = h(\omega) \tag{6}$$

$$y(\omega) \in Y, \quad \forall y(\omega) \in \Omega \tag{7}$$

where x and $y(\omega)$ are the first and second-stage decision variable vector, respectively, and $c, Q(\omega), b, h(\omega), A, T(\omega), W(\omega)$ are known vectors and matrices of appropriate size, and N_Ω is number of scenarios.

- Multi-stage problems: an r-stage decision making process is as follow

1. Decisions x^1 are made.
2. Stochastic process λ^1 is realized as $\lambda^1(\omega^1)$.
3. Decisions $x^2(x^1.\omega^1)$ are made.
4. Stochastic process λ^2 is realized as $\lambda^2(\omega^2)$.
5. Decisions $x^2(x^1.\omega^1.x^2.\omega^2)$ are made.

...

2r-2. Stochastic process λ^{r-1} is realized as $\lambda^{r-1}(\omega^{r-1})$.
2r-1. Decisions $x^r(x^1.\omega^1.\ldots.x^{r-1}.\omega^{r-1})$.

Fig. 8 illustrates the structure of multi-stage stochastic optimization and for preventing from elaborate long-formulation of that the details of this formulation can be found in [72].

Due to uncertain data modeling of stochastic scheduling, the trend to use this method in EV and RES scheduling has been increased in recent investigations. A two-stage stochastic energy scheduling model is proposed in [67]. At the first stage, an optimal day-ahead transaction obtains and in second-stage real-time operations consider the presence of wind and solar power variability. In this study authors consider 10 scenarios for wind and 10 scenarios for solar and compare the stochastic results with the deterministic results. The deterministic approach, in this

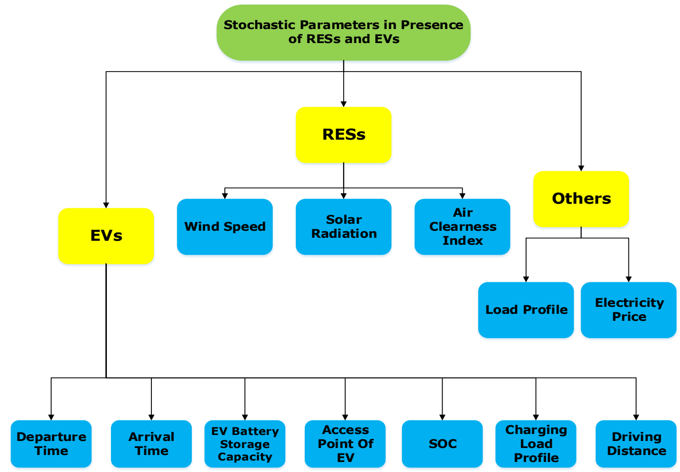

Fig. 9. Stochastic parameters considered in literature with the presence of RESs and EVs.

case, is one of the stochastic scenarios and the results indicate that ΔSOC at the end of a day for EVs in the stochastic approach is lower than a deterministic one. ΔSOC at the end of a day for EVs is better to be almost zero. A new two-stage stochastic-probabilistic energy and reserve smart scheduling model, with EVs and wind as a renewable energy resource, with consideration of wind, electric load, total available capacity, required the state of charge and available power for one hour in each electric vehicle have been introduced in [33]. The EVs are modeled as a stochastic storage capacity with consideration of the aggregator concept. Variety of the uncertain parameter has been considered in recent studies in RESs and EVs scheduling which is shown below in Fig. 9.

One of the most important parameters is the behavior of the driver or the arrival time of the EVs. For this purpose, in [32], the distribution functions to obtain this time is used. $ta_h(x)$ indicates the arrival time of two consecutive electrical vehicles which represent in Eq. (8) by an exponential distribution. In this distribution, λ is the average arrival time or time of between two arrivals which in Eq. (8) λ_h is represented for each hour. In the next step, the Monte Carlo method is used and a list of random numbers is constructed in the range of [0, 1], which is related to x in Eq. (8) and thus represent the arrival time of the next EV.

$$\mathrm{ta}_h(x) = 1 - e^{-\lambda_h x} \tag{8}$$

Also Due to the stochastic nature of the arrival time and departure time of each EV, authors in [30] used normal distribution function to simulate these characteristics and an exponential probability function for EV traveled distances. Authors in [28], to designate the wind and solar uncertainty, has used a Weibull distribution function for wind speed and bimodal distribution function for solar radiation. By these probability functions, the authors defined different scenarios for wind speed (s) and solar radiation (r) and accordingly r*s different scenarios for RESs and stochastically examined the effect of RESs uncertainty on income. The total income in the stochastic approach is less than a deterministic approach and it is due to the output power of RESs and it is closer to reality situation by consideration of uncertainty. Impacts of a large-scale penetration of EVs have been assessed in [58] with a stochastic security-constraint unit commitment (SCUC) method in the case of wind uncertainties, load forecasting errors, number of EVs in the aggregated fleets and power system outage. Four cases that include two deterministic solutions, grid controlled and consumer controlled, and two stochastic solutions, grid controlled and consumer controlled, have been utilized for validating the proposed method. In [59], authors for optimization of the EVs charging divided the EVs to the different groups by their time that EV can wait for charging (flexibility) and then sort them from least flexibility to higher flexibility. Because of the random flexibility of EVs, the utility will deal stochastically with EVs in each group and any of these EVs could start charging with probability p. In [57], authors have used different normal distribution functions for modeling the energy consumption per Km, EV traveling time and daily traveling distance. In this study, SOC is modeled stochastically with normal distribution function and EV battery capacity for different EV groups is modeled from normal and gamma probability functions. Copula method has been used for optimal prediction of the EV loads as non-controllable loads, then for next day hourly demand, a stochastic model with consideration of selected scenarios have been implemented in [19]. Uncertainties of wind speed and solar radiation and market electricity price in [68] have been modeled with the scenario-based stochastic model. A stochastic model based on queueing theory for EVs electricity demand, charging schema and arrival pattern prediction have been proposed in [76]. This study has used different probability functions for uncertainty consideration of EVs electricity demand, arrival time, traveling distance and etc. based on real information. For depicting the stochastic nature of the EVs arrival time, authors of [77] have used a chi-square distribution function. This stochastic energy scheduling shows a huge improvement in power load variance. Authors in [78] have proposed a scenario-based stochastic optimization framework for maximizing profit of the smart distribution company (SDC) with consideration of high wind and EV penetration. In this study EV batteries and battery energy storages (BES) have been implemented to manage the instability of wind farms. The power output of wind farms considered as a stochastic variable in this article and modeled with a zero mean normal distribution function. The result of this article shows that with a combination of demand response and battery energy storages as energy management, SDC profit will be increased. Dynamic economic and environmental dispatches with the integration of EVs, with consideration of stochastic nature of driver charging behavior and uncertainty of load profile, have been investigated in [79]. For minimizing the total cost of the system for unit commitment with consideration of DERs such as wind turbines and EVs, a TLBO algorithm has been used [80]. In this study for addressing the uncertainty and stochastic nature of the wind, a Weibull probability distribution function has been used and the results show that in respect of wind turbines, EVs and emergency demand response programs in the unit commitment the total cost has been reduced. Two scenarios for EV charging (off-peak charging and stochastic charging load) for the participation of the EVs in unit commitment under unit commitment electric vehicles (UCEV) concept have been considered in [81]. A normal distribution function has been implemented to generate the stochastic charging load profiles (5 scenarios of charging have been generated in this study). The results show that the stochastic behavior of the charging load will increase the operating costs and off-peak charging has a lower operation cost; however, the stochastic charging load is more realistic than off-peak scenario. Table 1 demonstrate different aspects of recent studies in EVs stochastic optimization. These considered characteristics are different stochastic variables with their PDFs, investigated objective and problem types in case of optimization method and relevant solver and used the software. Some studies used Monte-Carlo simulation (MSC) in order to cope with uncertain variables numerically. By using this method, different types of parameters such as EV charging profile, driving pattern of EVs, load profile and etc. are generated usually based on real data history or probability function of data. A Monte-Carlo simulation has been used for making an artificial history of components fault for reliability assessment [22]. This artificial history stochastically has made by values that obtain from the analytical approach from real information. Also, SOC and access point of EVs have been created randomly. A study has used real data charging and discharging of EVs, so the stochastic nature of EV charging (i.e., temporal and spatial) have been considered by itself [34]. This article has implemented Monte-Carlo simulation to make load and EV charging profile population. Energy price in studies are constant or variant by time, thus in the majority of studies the price is assumed to be deterministic but in [44] by using Hang's method (HM) prices of energy in each time has been shown by a PDF and CDF. Also, a Monte-Carlo simulation has been used for generating a group of driving patterns and then GAMS/SCENRED is used for clustering the EV fleets into the three driving pattern groups instead of all 100000 driving pattern scenarios. Monte-Carlo simulation has been used for assessing the system reliability and this new method is based on the stochastic nature of the EV owner behavior, RES generation and availability of the system elements [45]. The normal distribution function is used for arrival time and driving distance of EVs, Weibull distribution function is used for the departure time of EVS and wind speed modeling and beta distribution function for clearness index modeling in relation to solar irradiation.

3. COMPUTATIONAL SCHEDULING METHODS

As mentioned before, the integration of EVs to the power grid brings by itself some benefits and services such as voltage regulation, spinning reserve, load shifting, peak load shaving, and load leveling. In this regard, some objective function has been defined, for instance, cost minimization, GHG emission saving, profit maximization, RESs support, and power loss minimization. Fig. 10 shows the summary and relation between the V2G types, services, optimization objectives and constraints [16]. In Fig. 10, each V2G services shown by a specific color and any of the objective functions tag with its' relevant services color, then connected to the related and considered constraints which are used in the recent investigations. These objective functions can be solved by different methods which depend on the type of objective function and relevant constraints. Mainly optimization methods divided into two groups: conventional methods and heuristic methods which are comprehensively reviewed in the following sections. Four indicators have to be used to determine the appropriate optimization method which include input parameters, type of energy sources, merits and demerits [82].

A. Conventional methods

Conventional methods are based on iterative search algorithms that begin with a deterministic solution and improve the solution due to following some deterministic rules to the best answer. These kinds of methods can handle problems with equalities and inequalities. The appropriate method for a problem depends on the size and type of problem [13]. Some of the conventional methods are as below:

Table 1. Stochastic variables, objectives and problem types of recent stochastic investigation with EVs and RESs
*Stochastic variables with relevant PDF; ** Problem types with related software and solving method

Ref	Stochastic Variable*	Objective	Problem Type**
[18]	PHEV load House-hold electricity consumption	PHEV home charging pattern estimation	
[19]	Controlled Uncontrolled Load	Load flattening	NLP (GAMS)
[22]	SOC EV access point (uniform)	Reliability assessment	
[30]	Plugin and departure time (normal)	Charging Cost Minimization Virtual Cost Cost of Deviating, Load Variance	Continuous Linear Problem (Brand New Heuristic Method) The quadratic problem (Hybrid PSO) (JADE)
[33]	Wind forecasting error (Rayleigh) Total available capacity(normal) Required state of charge(normal) Available power for one hour in electric vehicles(normal) Load forecasting error(normal)	Cost of Energy Market Reserve Market Total Expected Energy Not Supplied	MILP
[44]	Electricity Price (Normal)	Cost of the Day-ahead energy market Welfare of participating in Ancillary Services	LP(GAMS)
[45]	Wind speed (Weibull) Departure time (Weibull) Arrival time and driving distance of EVs (Normal)	Reliability Assessment and Risk Management	
[55]	Solar Radiation (Weibull)	Maximizing the Intelligent Parking Lot Revenue	MILP (Cplex)(GAMS)
[57]	SOC (Normal) Traveling Time (Gamma)	Virtual Power Plant of EVs for UC	
[58]	Wind error (Weibull) Energy consumption forecasting error	Minimizing Grid Operation Cost	Main (Non-Convex, Non-Deterministic Polynomial-Time Hard), MIP Main Problem LP Sub-problems(CPLEX 12.1)
[59]	Selecting groups for charge and selecting each EV for charging (uniform) Net Load Forecast Error (Normal) Estimate the number of EVs which would start charging (Binominal)	Flatten the Overall Load	Quadratic problem
[68]	Wind speed (Weibull) Solar radiation (Weibull) Electricity price (Weibull)	The optimal hourly contractual agreement Profit Maximization	GAMS (Cplex)
[76]	EV charging demand Arrival time (poison) Charging duration (lognormal) Daytime charge request (exponential) Nighttime charge request (lognormal)	EV, PHEV Load Forecasting	
[77]	EV including V2G (Bernoulli) SOC (Uniform) Arrival time(chi-square)	Minimizing Power Load Variance	Quadratic problem
[78]	Wind (Normal)	Profit Maximization	MINLP
[79]	Charging profile of EVs (normal)	Minimizing the Total Operational Cost	NLP (SL-TLBO)

- Linear programming: Objective function and relevant constraints must be linear.
- Quadratic and concave Programming: Objective function is quadratic and constraints are linear.
- Dynamic programming
- Non-linear programming
- Integer programming
- Binary programming

One of the main characteristics of this method is that they work with some definite problems which they should have a certain type of objective function and can be expressible with certain formats. Thus, their application is limited by some restricted problems. Also, since these functions work with some deterministic rules, they might obtain wrong solutions when the considered problem has not just one global, but also one or several local optima [13]. However, in some studies, conventional methods have been implemented to the optimization problem and a global optimum solution achieved for EVs energy schedule. Many studies in EV scheduling, which used conventional methods, implemented mixed-integer linear or nonlinear programming, in order to address nonlinear variables such as charging/discharging state of EVs which are binary variables. In order to use MILP form, [33] have been linearized reliability with the integration of PEV aggregation model. Because of the stochastic nature of EV owner's behavior and mobility of V2G, the problem is a non-deterministic, non-convex, polynomial-time hard (NP-hard) problem and authors have used mixed integer programming to minimize the operation cost of the grid [58]. A MINLP problem has been used in [78] to obtain the maximum profit of the smart distribution company (SDC) and because of the complications in solving the nonlinear problems, the optimization problem has been separated into a master problem and sub-problem by

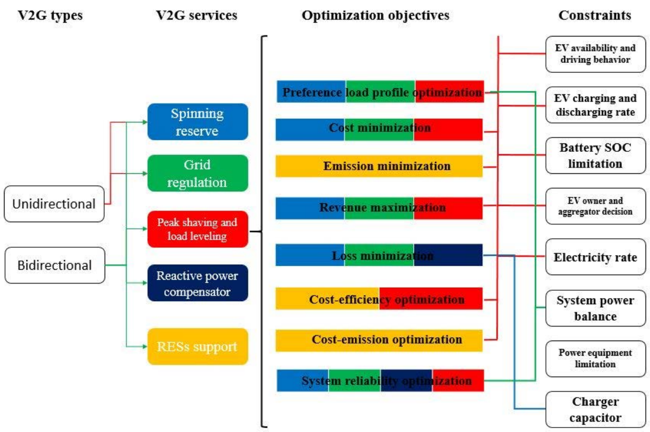

Fig. 10. V2G services and relevant objective functions and constraints.

using the Benders decomposition method. The optimization problem based on moving window scheme is formulated as a binary linear programming problem for diverse EV charging profile in each step and solved with the OPTimization Interface (OPTI) toolbox [31]. In the proposed method in [83], to reduce the computing time and complexity, the problem is divided by some sub-problems that one of them is power flow equations. A MILP problem has been implemented in [84] for addressing the effect of large penetration of EVs on the generation side in the unit commitment. For obtaining the global optimum solution (for objective function) and meeting the binary nature of EV charging and discharging status, authors in [55] have applied a MILP solving method. Dynamic programming based optimization problem for EV energy scheduling (a day, a week and three months scheduling time), in a local isolated grid with RES production, has been proposed in [54]. Also, an aggregate battery model has been implemented in this study and the model and the results compared to a heuristic optimization algorithm. The results show that the effectiveness of the proposed model on better using of RESs and lower charging energy cost. An open-source linear optimization model that is called EVLS (electric vehicle linear static model) has been used in [40] for simulating the EV power interaction and meeting the technical and behavioral constraints with energy market consideration. Stochastic linear programming for reducing the costs and maximizing the V2G benefits, as an ancillary service, has been used in [44] and results show the effectiveness of the proposed stochastic method.

B. Heuristic algorithms

As mentioned before, the conventional method used some deterministic rules, but some other methods are different, one of them is a Monte-Carlo search. A large number of guesses for decision variables are made and relevant values for considered objective function are determined. With a huge number of guesses, this approach finally reaches to the global optimum or at least determined regions within which it is likely or unlikely to be found [13]. Heuristic search methods and heuristic optimization techniques also incorporate stochastic elements. Unlike Monte-Carlo search, however, they have mechanisms that drive the search towards promising regions of the opportunity space. The main common feature of all heuristic optimization (HO) methods is that they start with some initial solution, iteratively produce new solutions by some generation rule and evaluate these new solutions, and eventually report the best solution found during the search process [13]. Some heuristic algorithms as follow:

- Ant colony optimization
- Evolutionary computation
- Particle swarm optimization (PSO)
- Genetic algorithms (GA)
- Simulated annealing (SA)
- Artificial bee colony (ABC)
- Teaching-learning based optimization (TLBO)

The most popular heuristic methods which are used for EV energy scheduling are a genetic algorithm (GA) and particle swarm optimization (PSO) as it can be sawed in Table 2. The genetic algorithm is inspired by the concept of natural selection and genetics [85]. GA search for a global optimum solution within an iterative process [86]. However, PSO depends on memorial computation and find the optimum within some random solutions and improve the solution by updating the generations [11]. This method is modeled based on population and social behavior of birds' groups [85]. PSO has the advantage where it requires lesser computational time and memory. A GA optimization method has been used in [87], for solving a multi-objective problem (mixed-integer programming (MIP)) that is formulated to reach optimal sizing and location for DG units with the presence of EVs. Authors in [81] have applied two different GA algorithms (GAH, GAD) for examining the EV charging in the unit commitment under UCEV concept. With consideration of EVs in a unit commitment by introducing UC-PEV structure, authors in [88] have used synthetic GA-LR for minimizing the total operating cost. Particle swarm optimization (PSO) method has been used for minimizing fuel cost and GHG emission saving with consideration of RESs, EVs, and thermal units in [89]. Some studies have used different types of PSO to optimize EV scheduling problems [30, 50]. For minimizing the total cost of unit commitment with consideration of EVs and effects of carbon emission trading on generation schedule an improved particle swarm optimization (IPSO) algorithm has been utilized in [90]. For minimizing cost and GHG emission in [50] both binary and integer PSO have been implemented. Binary PSO is found out the optimal state of generation units and integer PSO for obtaining the optimal number of EVs. Other types of heuristic algorithms (except GA and PSO) also have been used to optimize objective functions that are related to EV energy scheduling and planning in recent investigations. Authors in [80], have utilized teaching-learning based optimization (TLBO) algorithm to obtain the minimum cost of the whole system in case of unit commitment with the presence of DERs such as wind turbines as an RES and EVs and emergency demand response program (EDRP). Real time DRP is considered for coordination of an energy nexus considering PEVs in [91]. In order to attain the optimal location and sizing of EV parking lots in the distribution, a multi-objective problem using an artificial bee colony (ABC) and Firefly (FF) algorithm has been used in [92]. Table 2 shows the trend of using diverse algorithms for V2G and EVs charging scheduling optimization in recent studies.

4. CONCLUSION AND FUTURE TRENDS

EVs are an inevitable part of future smart grids and combination of EVs and RESs is a promising solution for solving energy crises such as fossil fuel shortage and global warming problems. So Societies are more moving toward renewable sources and electric vehicles. Power grid can benefit from the V2G capability of

Table 2. Optimization methods which used in recent studies

Conventional		Heuristic	
LP	[31], [40], [44], [93]	**GA**	[86],[87], [81], [88], [94], [95], [96], [97], [32]
MILP	[33],[58], [78], [84], [55], [11], [98]	**PSO**	[89], [30], [90], [50], [99], [100], [101], [96], [11]
Dynamic programing	[54]	**Others**	ABC [92], [46], [52], [12]
			Ant Colony [101], [102]
			θ-krill herd [70]
			TLBO [80]

EVs such as load leveling, peak shaving, spinning reserve, and voltage and frequency regulation. Electric vehicles are charged in a coordinated and uncoordinated manner. If they are charged uncoordinatedly, EVs imposing a huge amount of excess load to the grid. So coordinated EV charging is a prerequisite for future smart charging. In this regard, to model the stochastic nature of real smart grid and uncertain variables and using different services of EVs, stochastic coordinated charging theme better to be used. In addition to charging methods, charging stations are divided into two centralized and decentralized categories. Coordinated charging can be centralized for instance in a parking lot or battery charging stations or decentralized, for instance, parking lot of each home and for each vehicle and generally, centralized stations are more profitable and minimize the operation cost. The integration of EVs and RESs together in the microgrid has been investigated in this study. This paper represents to be more focus in order to optimally deal with a future smart grid which contains many DGs such as RESs, Storage devices such as EVs and their relevant stochastic variables should be considered. Also, most of this literature has focused on wind power, solar power or a combination of these sources. Energy system models are considered either deterministic or stochastic. A deterministic model has no stochastic elements and the entire input and output relation of the model are conclusively determined but a stochastic model has one or more stochastic elements and the system having stochastic element is generally not solved analytically. In other word, for considering the stochastic phenomena, the distribution functions are used. For example, authors used normal distribution function or an exponential probability function for EV traveled distances or used a Weibull distribution function for wind speed and bimodal distribution function for solar radiation. This study presented a comprehensive review of a recent investigation of stochastic energy scheduling with consideration of EVs and RESs. As it is shown in the article, the tendency of using stochastic energy scheduling is because of more realistic modeling of the uncertain variables, due to uncertainty in EV behaviors and RES stochastic natures. In this regard in optimization problems, due to size and type of problems, diverse kind of objective functions and constraints should be solved. Regard to results of this study in conventional methods MILP and in heuristic methods, GA and PSO have been used the most. The fact of the matter is that stochastic EV scheduling problems have so many difficulties and non-linear parameters due to different parameters and uncertainties in a real situation and the power grid, so heuristic method seems to be promising methods to find the global optimum with logical computational time and feasible answer. For solving related objective functions of stochastic modeling heuristic methods is an appropriate option. On the other hand, to address the stochastic variables, few studies implemented robust optimization, IGDT or machine learning methods. These mentioned approaches seem to be more comprehensive than stochastic optimization problems. And this is because they are more flexible and thorough in uncertainty modeling in compare to stochastic optimization. Thus, there are many vacant seats for further investigation in EV scheduling and uncertainty modeling to optimally deal with future smart grid whether with stochastic optimization method or with other approaches.

REFERENCES

1. "The way forward," www.IEA.org, 2014.
2. Y. Noorollahi, R. Itoi, H. Yousefi, M. Mohammadi, and a. A. Farhadi, "Modeling for diversifying electricity supply by maximizing renewable energy use in Ebino City Southern Japan," no. 34, pp. 371–84, 2017.
3. M. Mohammadi, Y. Noorollahi, and B. Mohammadi-ivatloo, "Demand response participation in renewable energy hubs," in Operation, Planning, and Analysis of Energy Storage Systems in Smart Energy Hubs, Springer International Publishing, pp. 116–129, 2018.
4. B. Diouf and R. Pode, "Potential of lithium-ion batteries in renewable energy," Renewable Energy, vol. 76, pp. 375-380, 2015.
5. W. Kempton and S. E. Letendre, "Electric vehicles as a new power source for electric utilities," Transportation Research Part D: Transport and Environment, vol. 2, no. 3, pp. 157-175, 1997.
6. Y. Zhao, M. Noori, and O. Tatari, "Vehicle to grid regulation services of electric delivery trucks: Economic and environmental benefit analysis," Applied Energy, vol. 170, pp. 161-175, 2016.
7. P.K.S.M. Bhaskar Naik, "Smart public transportation network expansion and its interaction with the grid," Electrical Power and Energy Systems , vol. 105 , pp. 365–380, 2019.
8. E. L. Karfopoulos and N. Hatziargyriou, "Distributed coordination of electric vehicles providing V2G services," IEEE TRANSACTIONS ON POWER SYSTEMS, vol. 1, 2015.
9. S. Shafiee, M. Fotuhi-Firuzabad, and M. Rastegar, "Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems," IEEE TRANSACTIONS ON SMART GRID, vol. 4, pp. 1351-1360, 2013.
10. H.N. Nguyen, C. Zhang, and A.M.A. Mahmud, "Optimal coordination of G2V and V2G to support power grids with high penetration of renewable energy," IEEE TRANSACTIONS ON TRANSPORTATION ELECTRIFICATION, 2015.
11. J. Soares, M.A.F. Ghazvini, Z.Valel, and P.D.M. Oliveira, "A multi-objective model for the day-ahead energy resource scheduling of a smart grid with high penetration of sensitive loads," Applied Energy, vol. 162, pp. 1074-1088, 2016.
12. H. Jadhav and R. Roy, "Stochastic optimal power flow incorporating offshore wind farm and electric vehicles," Electrical Power and Energy Systems, vol. 69, pp. 173-187, 2015.
13. D. maringer, "Heuristic optimization," in portfolio management with heuristic optimization, Springer, pp. 38-76, 2005.
14. M. Mohammadi, Y. Noorollahi, and a. B. Mohammadi-Ivatloo, "An introduction to smart energy systems and definition of smart energy hubs," in Operation, Planning, and Analysis of Energy Storage Systems in Smart Energy Hubs, Cham: Springer, pp. 1-21, 2018.
15. C. Liu, K.T. Chau, D. Wu, and S. Gao, "Opportunities and challenges of

Vehicle-to-Home, Vehicle-to-Vehicle, and Vehicle-to-Grid technologies," IEEE TRANSACTIONS ON SMART GRID, vol. 101, no. 11, pp. 2409-2427, 2013.
16. K.M. Tan, V.K. Ramachandaramurthy, and J.Y. Yong, "Integration of electric vehicles in smart grid :A review on vehicle to grid technologies and optimization techniques," Renewable and Sustainable Energy Reviews, vol. 53, pp. 720-732, 2016.
17. I. Rahman, P.M. Vasant, B.S.M. Singh, M.A.A. Wadud, and N. Adnan, "Review of recent trends inoptimization techniques for plug-in hybrid, and elecrtic vehicle for charging infrustructures," Renewable and Sustainable Energy Reviews, vol. 58, pp. 1039-1047, 2016.
18. P. Grahn, J. Munkhammar, J. Widén, K. Alvehag, and L. Söder, "PHEV home-charging model based on residential activity patterns," IEEE TRANSACTIONS ON POWER SYSTEMS, vol. 28, pp. 2507-2515, 2013.
19. V.T. Bina and D. Ahmadi, "Stochastic modeling for scheduling the charging demand of EV in distribution systems using copulas," Electrical Power and Energy Systems, vol. 71, pp. 15-25, 2015.
20. S. Nolan, M. O'Malley, and M.T. Devine, "The impacts of demand response participation in capacity markets," Applied Energy , vol. 250, p. 444–451, 2019.
21. M. Bagher Sadati, "Operational scheduling of a smart distribution system considering electric vehicles parking lot: A bi-level approach," International Journal of Electrical Power & Energy Systems, vol. 105, pp. 159-178, 2019.
22. Z. Wang, R. Yang, L. Wang, and J. Tan, "Reliability assessment of integrated residential distribution and PHEV systems using Monte Carlo simulation," IEEE Power & Energy Society General Meeting, 2013.
23. M. Alipour, B. Mohammadi-Ivatloo, M. Moradi-Dalvand, and K. Zare, "Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets," Energy, vol. 118, pp. 1168-1179, 2017.
24. A. Nazarloo, M.R. Feyzi, M. sabahiorcid, and M.B.B. Sharifian, "Energy management of electric vehicles aggregator using a new multi-objective algorithm," Journal of Energy Management and Technology (JEMT), vol. 2, no. 2, pp. 20-30, 2018.
25. R.S.A. Luis Baringo, "A stochastic robust optimization approach for the bidding strategy of an electric vehicle aggregator," Electric Power Systems Research , vol. 146, pp. 362–370, 2017.
26. R.J. Bessa and M.A. Matos, "The role of an aggregator agent for EV in the electricity market," in 7th Mediterranean Conference and Exhibition on Power Generation, Transmission, Distribution and Energy Conversion, Agia Napa, Cyprus, 2010.
27. P. Aliasghari, B. Mohammadi-Ivatloo, M. Alipour, M. Abapour, and K. Zare, "Optimal scheduling of plug-in electric vehicles and renewable micro-grid in energy and reserve markets considering demand response program," Journal of Cleaner Production, vol. 186, pp. 293-303, 2018.
28. M.H. Amirioun and A. Kazemi, "A new model based on optimal scheduling of combined energy exchange modes for aggregation of electric vehicles in a residential complex," Energy, vol. 69, pp. 186-198, 2014.
29. M. Ghahramani, M. Nazari-Heris, K. Zare, and B. Mohammadi-Ivatloo, " Energy management of electric vehicles parking in a power distribution network using robust optimization method," Journal of Energy Management and Technology, vol. 2, no. 3, pp. 22-30, 2018.
30. E.L. Karfopoulos and N.D. Hatziargyriou, "A multi-agent system for controlled charging of a large population of electric vehicles," IEEE TRANSACTIONS ON POWER SYSTEMS, vol. 28, 2013.
31. C. Ma, J. Rautiainen, D. Dahlhaus, A. Lakshman, J.C. Toebermann, and M. Braun, "Online optimal charging strategy for Electric Vehicles," Energy Procedia, 9th International Renewable Energy Storage Conference, pp. 173–181, 2015.
32. A. Domínguez-Navarro∗, "Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems," Electrical Power and Energy Systems, vol. 105, pp. 46–58, 2019.
33. A. Khazali and M. Kalantar, "A stochastic–probabilistic energy and reserve market clearing scheme for smart power systems with plug-in electrical vehicles," Energy conversion and management, vol. 105, pp. 1046-1058, 2015.
34. M. Neaimeh, R. Wardle, A.M. Jenkins, J. Yi, G. Hill, P.F. Lyons, Y. Hübner, P.T. Blythe, and P.C. Taylor, "A probabilistic approach to combining smart meter and electric vehicle charging data to investigate distribution network impacts," Applied Energy, 2015.
35. M. Moeini-Aghtaie, A. Abbaspour, and M. Fotuhi-Firuzabad, "Online multi-criteria framework for charging management of PHEVs," IEEE Transactions on Vehicular Technology, 2014.
36. M. Mohammadi, Y. Noorollahi, and B. Mohammadi-Ivatloo, "Impacts of energy storage technologies and renewable energy sources on energy hub systems," in Operation, Planning, and Analysis of Energy Storage Systems in Smart Energy Hubs, Springer publishing International, pp. 22-53, 2018.
37. A. Ahmadian, M. Sedghi, B. Mohammadi-ivatloo, A. Elkamel, M.A. Golkar, and M. Fowler, "Cost-benefit analysis of V2G implementation in distribution networks considering PEVs battery degradation," IEEE Transactions on Sustainable Energy, vol. 9, no. 2, pp. 961-970, 2018.
38. R. Romo and O. Micheloud, "Power quality of actual grids with plug-in electric vehicles in presence of renewables and micr-grids," Renewable and Sustainable Energy Reviews, vol. 46, pp. 189-200, 2015.
39. C. Guille and G. Gross, "A conceptual framework for the vehicle-to-grid (V2G) implementation," Energy Policy, vol. 37, no. 11, pp. 4379-4390, 2009.
40. F. Fattori, N. Anglani, and G. Muliere, "Combining photovoltaic energy with electric vehicles, smart charging and vehicle-to-grid," Solar Energy, vol. 110, pp. 438-451, 2014.
41. H. Lund and W. Kempton, "Integration of renewable energy into the transport and electricity sectors through V2G," Energy Policy, vol. 36, pp. 3578-3587, 2008.
42. Y. Ota, H. Taniguchi, T. Nakajima, K.M. Liyanage, J. Baba, and A. Yokoyama, "Autonomous distributed V2G (Vehicle-to-Grid) satisfying scheduled charging," IEEE TRANSACTIONS ON SMART GRID, vol. 3, 2012.
43. A. Oshnoei, M.T. Hagh, R. Khezri, and B. Mohammadi-Ivatloo, "Application of IPSO and fuzzy logic methods in electrical vehicles for efficient frequency control of multi-area power systems," in 2017 Iranian Conference on Electrical Engineering (ICEE), Tehran, 2017.
44. M. Panto, "Exploitation of electric-drive vehicles in electricity markets," IEEE TRANSACTIONS ON POWER SYSTEMS, vol. 27, pp. 682-694, 2012.
45. H. Hashemi-Dezaki, M. Hamzeh, H. Askarian-Abyaneh, and H. Haeri-Khiavi, "Risk management of smart grids based on managed charging of PHEVs and vehicle-to-grid strategy using Monte Carlo simulation," Energy Conversion and Management, vol. 100, pp. 262-276, 2015.
46. C. Rathore and R. Roy, "Impact of wind uncertainty, plug-in-electric vehicles and demand response program on transmission network expansion planning," Electrical Power and Energy Systems, vol. 75, pp. 59-73, 2016.
47. A. Rabiee, M. Sadeghi, J. Aghaeic, and A. Heidari, "Optimal operation of microgrids through simultaneous scheduling of electrical vehicles and responsive loads considering wind and PV units uncertainties," Renewable and Sustainable Energy Reviews, vol. 57, pp. 721-739, 2016.
48. V.N. Coelho, I.M. Coelho, B.N. Coelho, M.W. Cohen, A.J. Reis, S.M. Silva, M.J. Souza, P.J. Fleming, and F.G.G. Aes, "Multi-objective energy storage power dispatching using plug-in vehicles in a smart-microgrid," Renewable Energy, vol. 89, pp. 730-742, 2016.
49. E. Karan, S. Asadi and L. Ntaimo, "A stochastic optimization approach to reduce greenhouse gas emissions from buildings and transportation," Energy, vol. 106, pp. 367-377, 2016.
50. A.Y. Saber and G.K. Venayagamoorthy, "Plug-in vehicles and renewable energy sources for cost and emission reductions," IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, vol. 58, 2011.
51. S. Khormali and F. Mottola, "Single-objective approaches for microgrid scheduling in the presence of plug-in vehicle fleets and datacenters," IEEE, 2015.
52. A. El-Zonkoly, "Intelligent energy management of optimally located

renewable energy systems incorporating PHEV," Energy Conversion and Management, vol. 84, pp. 427-435, 2014.
53. M. Mohammadi, Y. Noorollahi, B. Mohammadi-ivatloo, and A.H. Yousefi, "Energy hub: from a model to a concept–A review," Renewable and Sustainable Energy Reviews, vol. 80, pp. 1512–27, 2017.
54. B. Skugor and J. Deur, "Dynamic programming-based optimisation of charging an electric vehicle fleet system represented by an aggregate battery model," Energy, pp. 1-10, 2015.
55. M. Honarmanda, A. Zakariazadeh, and S. Jadid, "Self-scheduling of electric vehicles in an intelligent parking lot using stochastic optimization," Journal of the Franklin Institute, vol. 352, pp. 449-467, 2015.
56. J. Munkhammar, J. Widén, and J. Rydén, "On a probability distribution model combining household power consumption, electric vehicle home-charging and photovoltaic power production," Applied Energy, vol. 142, pp. 135-143, 2015.
57. M. Wang, Y. Mu, H.E. Jia, P. Zeng, J. Wu, and W. Sheng, "An efficient power plant model of electric vehicles for unit commitment of large scale wind farms," Energy Procedia, vol. 75, pp. 1059-1064, 2015.
58. M.E. Khodayar, L. Wu, and M. Shahidehpour, "Hourly coordination of electric vehicle operation and volatile wind power generation in SCUC," IEEE TRANSACTIONS ON SMART GRID, vol. 3, pp. 1271-1279, 2012.
59. A. Bilh, N. Kshirasagar, and E. Shatshat, "An adaptive charging algorithm for electric vehicles in smart grids," IEEE Vehicular Technology Conference (VTC Spring), pp. 1-7, 2015.
60. L. He, J. Yang, J. Yan, Y. Tang, and H. He, "A bi-layer optimization based temporal and spatial scheduling for large-scale electric vehicles," Applied Energy, vol. 168, pp. 179-192, 2016.
61. G. Romero-Ruiz, J. Pérez-Ruiz, S. Martin, J. Aguado, and S.D.l. Torre, "Probabilistic congestion management using EVs in a smart grid with intermittent renewable generation," Electric Power Systems Research, vol. 137, pp. 155-162, 2016.
62. A. Zakariazadeh, S. Jadid, and P. Siano, "Integrated operation of electric vehicles and renewable generation in a smart distribution system," Energy Conversion and Management, vol. 89, pp. 99-110, 2015.
63. M. Honarmand, A. Zakariazadeh, and S. Jadid, "Integrated scheduling of renewable generation and electric vehiclesparking lot in a smart micro grid," Energy Conversion and Management, vol. 86, pp. 745-755, 2014.
64. A. Banerji, D. Sen, A.K. Bera, D. Ray, D. Paul, A. Bhakat, and S. K. Biswas, "Microgrid: A review," in Global Humanitarian Technology Conference: South Asia Satellite (GHTC-SAS), IEEE, Trivandrum, 2013.
65. Y. Noorollahi, M.S. Shabbir, A.F. Siddiqi, L.K. Ilyashenko, and A.E. Ahmadi, "Review of two decades geothermal energy development in Iran, benefits, challenges, and future policy," Geothermics, vol. 77, pp. 257–266, 2019.
66. H. Liang and W. Zhuang, "Stochastic modeling and optimization in a microgrid: A survey," Energies, vol. 7, pp. 2027-2050, 2014.
67. W. Su, J. Wang, and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources," IEEE TRANSACTIONS ON SMART GRID, 2013.
68. M.Z. Oskouei and A.S. Yazdankhah, "Scenario-based stochastic optimal operation of wind, photovoltaic, pump-storage hybrid system in frequency-based pricing," Energy Conversion and Management, vol. 105, pp. 1105-1114, 2015.
69. Y. Wang, B. Wang, C.C. Chu, H. Pota, and R. Gadh, "Energy management for a commercial building microgrid with stationary and mobile battery storage," Energy and Buildings, vol. 116, pp. 141-150, 2016.
70. A. Kavousi-Fard, A. Abunasri, A. Zare, and R. Hoseinzadeh, "Impact of plug-in hybrid electric vehicles charging demand on the optimal energy management of renewable micro-grids," Energy, vol. 78, pp. 904-915, 2014.
71. A. Rabiee, M. Sadeghi, J. Aghaeic, and A. Heidari, "Optimal operation of microgrids through simultaneous scheduling of electrical vehicles and responsive loads considering wind and PV units uncertainties," Renewable and Sustainable Energy Reviews, vol. 57, pp. 721-739, 2016.
72. A.J. Conejo, M. Carrión and J.M. Morales, "Stochastic programming fundamentals," in Decision Making Under Uncertainty in Electricity markets, New York, Springer, pp. 27-62, 2010.
73. Y.T. Liao and C.N. Lu, "Dispatch of EV charging station energy resources for sustainable mobility," IEEE Transactions on Transportation Electrification, vol. 1, no. 1, pp. 86-93, 2015.
74. M. Mohammadi, Y. Noorollahi, B. Mohammadi-ivatloo, H. yousefi, and S. Jalilinasrabady, "Optimal scheduling of energy hubs in the presence of uncertainty-A review," Journal of Energy Management and Technology (JEMT), vol. 1, no. 1, pp. 1-17, 2017.
75. A. Mirakyan and R.D. Guio, "Modelling and uncertainties in integrated energy planning," Renewable and Sustainable Energy Reviews, vol. 46, pp. 62-69, 2015.
76. M. Alizadeh, A. Scaglione, J. Davies, and K.S. Kurani, "A scalable stochastic model for the electricity demand of electric and plug-in hybrid vehicles," IEEE TRANSACTIONS ON SMART GRID, vol. 2, pp. 848-560, 2014.
77. L. Jian, Y. Zheng, X. Xiao, and C.C. Chan, "Optimal scheduling for vehicle-to-grid operation with stochastic connection of plug-in electric vehicles to smart grid," Applied Energy, vol. 146, pp. 150-161, 2015.
78. A. Ghasemi, S.S. Mortazavi, and E. Mashhour, "Hourly demand response and battery energy storage for imbalance reduction of smart distribution company embedded with electric vehicles and wind farms," Renewable Energy, vol. 85, pp. 124-136, 2016.
79. Z. YANG, K. LI, Q. NIU, Y. XUE, and A. FOLEY, "A self-learning TLBO based dynamic economic/environmental dispatch considering multiple plug-in electric vehicle loads," Journal Power System Clean Energy, vol. 2, no. 4, pp. 298-307, 2014.
80. M. Govardhan and R. Roy, "Economic analysis of unit commitment with distributed energy resources," Electrical Power and Energy Systems, vol. 71, pp. 1-14, 2015.
81. L. Zhang, Q. Niu, Z. Yang, and K. Li, "Integration of electric vehicles charging in unit commitment," International Journal of Computer Science and Electronics Engineering, vol. 3, no. 1, pp. 22-27, 2015.
82. N. Taghizadegan Kalantari, "Bibliographic review and comparison of optimal sizing methods for hybrid renewable energy systems," Journal of Energy Management and Technology (JEMT), vol. 2, no. 2, pp. 66-79, 2018.
83. A. Zakariazadeh, S. Jadid, and P. Siano, "Integrated operation of electric vehicles and renewable generation in a smart distribution system," Energy Conversion and Management, vol. 89, pp. 99-110, 2015.
84. D. Madzharov, E. Delarue, and W. D'haeseleer, "Integrating electric vehicles as flexible load in unit commitment modeling," Energy, vol. 65, pp. 285-294, 2014.
85. M. Nazari-Herisa, "A comprehensive review of heuristic optimization algorithms for optimal combined heat and power dispatch from economic and environmental perspectives," Renewable and Sustainable Energy Reviews, vol. 81, pp. 2128–2143, 2018.
86. M. Ghofrani, A. Arabali, and M. Etezadi-Amoli, "Electric drive vehicle to grid synergies with large scale wind resources," in IEEE Power and Energy Society General Meeting, San Diego, CA, 2012.
87. M. F. Shaaban, Y. M. Atwa and E. F. El-Saadany, "PEVs Modeling and Impacts Mitigation in Distribution Networks," IEEE TRANSACTIONS ON POWER SYSTEMS, vol. 1, 2012.
88. E. Talebizadeh, M. Rashidinejad, and A. Abdollahi, "Evaluation of plug-in electric vehicles impact on cost-based unit commitment," Journal of Power Sources, 2013.
89. U.K. Debnath, I. Ahmad, D. Habibi, and A.Y. Saber, "Energy storage model with gridable vehicles for economic load dispatch in the smart grid," Electrical Power and Energy Systems, vol. 64, pp. 1017-1024, 2015.
90. N. Zhang, Z. Hu, D. Dai, S. Dang, M. Yao, and Y. Zhou, "Unit commitment model in smart grid environment considering carbon emissions trading," IEEE TRANSACTIONS ON SMART GRID, vol. 1, 2015.
91. F. Jabari, H. Jabari, B. Mohammadi-ivatloo, and J. Ghafouri, "Optimal short-term coordination of water-heat-power nexus incorporating plug-in electric vehicles and real-time demand response programs," Energy, 2019.
92. A. El-Zonkoly and L.D.S. Coelho, "Optimal allocation, sizing of PHEV

parking lots in distribution system," Electrical Power and Energy Systems, vol. 67, pp. 472-477, 2015.
93. Y. Zheng, Z.Y. Dong, Y. Xu, K. Meng, J.H. Zhao, and J. Qiu, "Electric vehicle battery charging/swap stations in distribution systems: comparison study and optimal planning," IEEE Transactions on Power Systems , vol. 29, no. 1, pp. 221-229, 2014.
94. J. Tong, T. Zhao, X. Yang, and J. Zhang, "Intelligent charging strategy for PHEVs in parking stations based on multi-objective optimization in smart grid," in Transportation Electrification Asia-Pacific (ITEC Asia-Pacific), IEEE Conference and Expo, Beijing, 2014.
95. F. Fazelpour, M. Vafaeipour, O. Rahbari, and M.A. Rosen, "Intelligent optimization to integrate a plug-in hybrid electric vehicle smart parking lot with renewable energy resources and enhance grid characteristics," Energy Conversion and Management, vol. 77, pp. 250-261, 2014.
96. W. Su and M.Y. Chow, "Computational intelligence-based energy management for a large-scale PHEV/PEV enabled municipal parking deck," Applied Energy, vol. 96, no. smart grid, pp. 171-182, 2012.
97. M. Ghofrani, A. Arabali, M. Etezadi-Amoli, and M.S. Fadali, "Smart scheduling and cost-benefit analysis of grid-enabled electric vehicles for wind power integration," IEEE TRANSACTIONS ON SMART GRID, 2014.
98. Z. Luo, Z. Hu, Y. Song, Z. Xu, and H. Lu, "Optimal coordination of plug-in electric vehicles in power grids with cost-benefit analysis—part I: Enabling techniques," IEEE TRANSACTIONS ON POWER SYSTEMS, vol. 28, no. 4, pp. 3546-3555, 2013.
99. W. Su and M.Y. Chow, "Performance evaluation of a PHEV parking station using Particle Swarm Optimization," in 2011 IEEE Power and Energy Society General Meeting , San Diego, CA, 2011.
100. A.Y. Saber and G.K. Venayagamoorthy, "Optimization of vehicle-to-grid scheduling in constrained parking lots," in 2009 IEEE Power & Energy Society General Meeting, Calgary, AB , 2009.
101. T. Ghanbarzadeh, S. Goleijani, and M.P. Moghaddam, "Reliability constrained unit commitment with electric vehicle to grid using hybrid particle swarm optimization and ant colony optimization," in 2011 IEEE Power and Energy Society General Meeting, San Diego, CA , 2011.
102. S. Yang, M. Wu, X. Yao, and J. Jiang, "Load modeling and identification based on ant colony algorithms for EV charging stations," IEEE Transactions on Power Systems , vol. 30, no. 4, pp. 1997-2003, 2015.
103. C. Quinn, D. Zimmerle, and T.H. Bradley, "An evaluation of state-of-charge limitations and actuation signal energy content on plug-in hybrid electric vehicle, Vehicle-to-Grid reliability, and economics," IEEE TRANSACTIONS ON SMART GRID, vol. 3, 2012.