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Review on Scheduling, Clustering, and Forecasting Strategies for Controlling Electric Vehicle Charging: Challenges and Recommendations

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ABSTRACT The usage and adoption of electric vehicles (EVs) have increased rapidly in the 21st century due to the shifting of the global energy demand away from fossil fuels. The market penetration of EVs brings new challenges to the usual operations of the power system. Uncontrolled EV charging impacts the local distribution grid in terms of its voltage profile, power loss, grid unbalance, and reduction of transformer life, as well as harmonic distortion. Multiple research studies have addressed these problems by proposing various EV charging control methods. This manuscript comprehensively reviews EV control charging strategies using real-world data. This review classifies the EV control charging strategies into scheduling, clustering, and forecasting strategies. The models of EV control charging strategies are highlighted to compare and evaluate the techniques used in EV charging, enabling the identification of the advantages and disadvantages of the different methods applied. A summary of the methods and techniques for these EV charging strategies is presented based on machine learning and probabilities approaches. This research paper indicates many factors and challenges in the development of EV charging control in next-generation smart grid applications and provides potential recommendations. A report on the guidelines for future studies on this research topic is provided to enhance the comparability of the various results and findings. Accordingly, all the highlighted insights of this paper serve to further the increasing effort towards the development of advanced EV charging methods and demand-side management (DSM) for future smart grid applications.

INDEX TERMS Electric vehicle charging, scheduling, clustering, forecasting, probabilities, machine learning.

I. INTRODUCTION

Shifting the global energy demand away from fossil fuels requires fuel-based automobiles to be replaced by EVs. Since the number of electric vehicles is expected to rise, given the potentially massive number of vehicles involved, a reliable control of EV charging will be essential for its successful penetration into the power system [1]. To comprehend the impact of EV penetration in the electrical grid, Rezaei *et al.* [2] investigated the effect of EV charging in terms of the stability and reliability of the power system. Andrew and Qiu [3], Schuller *et al.* [4] analyzed the economic and environmental issues brought about by the integration of renewable energy sources (RES), specifically the incorporation of EVs. Uncontrolled electric vehicle charging leads to large load variations in the electrical grid and impacts the power quality of the distribution grid [5]–[9]. This, in turn, leads to significant adverse effects on the existing power systems, which include high load peaks, increased energy consumption, and power quality degradation. Godina *et al.* [10] investigated

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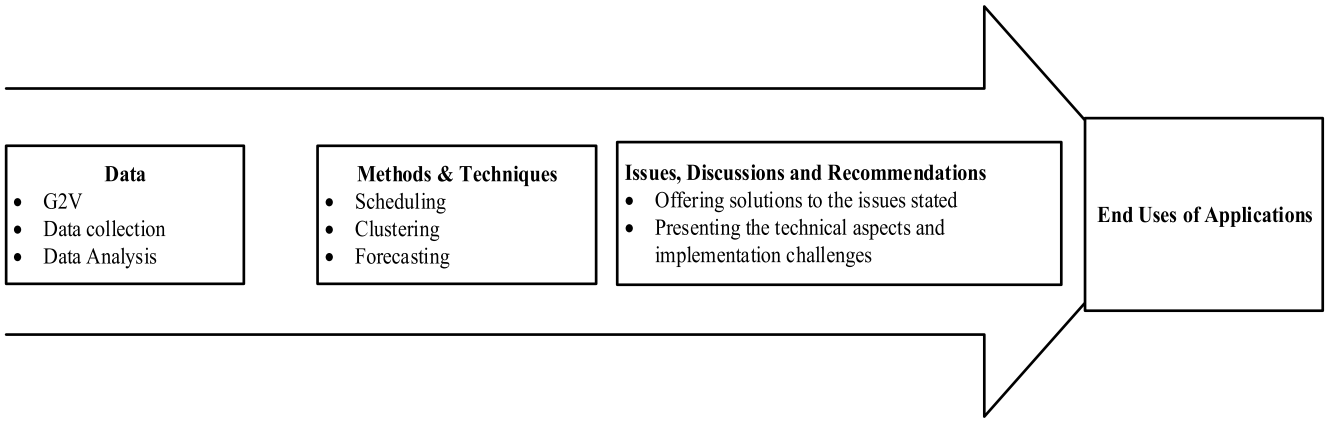

FIGURE 1. The core structure of this review.

the impacts of uncontrolled EV charging on the distribution network, which may lead to the power demand and line current exceeding the distribution transformer ratings, as well as the distributed voltage dropping outside the required levels.

Scheduling, clustering, and forecasting are widely used strategies to control the penetration of high EV charging. The main objectives of these strategies are to minimize the impact of charging on the electricity distribution. In particular for scheduling strategies, Harris and Webbe [11] investigated the effects of EV charging at the consumer level. Electric vehicle charging coordination is intended to maintain the stability of the electricity network by ensuring the balance between the power supply and energy demand of electricity [12]. Moreover, scheduling EVs is a valuable technique to shift the grid demand and mitigate over generation and night peak problems [13].

Clustering strategies have been applied on EVs charging to find the most common and recurrent load profiles. The EV charging clustering strategy is used to identify groups of similar charging objects in a multivariate dataset collected from the field. By clustering these datasets across the year, month, or week, important patterns associated with different types of consumption during the year, month, or week can be distinguished. The work in [14] discussed the issues of EV charging patterns and classified them into the following three categories: home, work, and other. Typically, each category contains a distinct load profile. For example, the work category exhibits an early morning peak, which includes EV charging at schools, colleges, or workplaces. The home category covers an afternoon time, indicating EV charging in residential locations. The last category of other comprises EV charging at leisure locations and shopping malls.

In the case of forecasting strategies, fault prevention and network stability are critically dependent on the forecasting of the daily demand [15]. The accuracy of the EV charging forecast is essential to utility development and decision-making. The enactment of a highly accurate forecasting model will not only advance the prediction precision for optimal dispatching but will also support the development of EV charging and encourage manufactures to promote the use of EVs. Consequently, further research devoted to forecasting strategies is greatly needed [16], [17].

Previous studies have revealed some particular approaches to control EV charging; however, each approach has shortcomings in terms of performance efficiency and a lack of functioning capability in real applications. Additionally, a lack of flexibility to operate in different operating environments and high computation costs are the other concerns that make implementing a controlling process very difficult. Scholars and researchers have conducted extensive research to develop precise EV control charging strategies. However, the issues in modeling an efficient approach are not resolved yet. Further, the potential risks in EV control charging strategies have not been identified. Thus, this review fills this research gap by exploring different existing approaches and addressing the key issues and challenges of EV control charging strategies

This review paper includes information on energy systems from research reports, published legislation, and critical databases from academic sources. This paper encapsulates practical categories, such as EV charging strategies and observations relating to modeling techniques. It includes a review of strategies, in particular the methodologies and techniques associated with controlling EV charging within electricity distribution networks, as shown in Fig. 1. The classification of these methods is divided into probability and artificial intelligence methods. The main contributions of this paper include the following:

1) This research paper addresses the key issues and challenges of EV charging by investigating different existing methodologies of scheduling, clustering, and forecasting strategies.
2) The highlights of this paper will help power system operators to decide on an appropriate method and identify challenges.
3) The review identifies many issues and challenges involved in controlling EV charging, which could encourage further research on how to overcome these challenges.

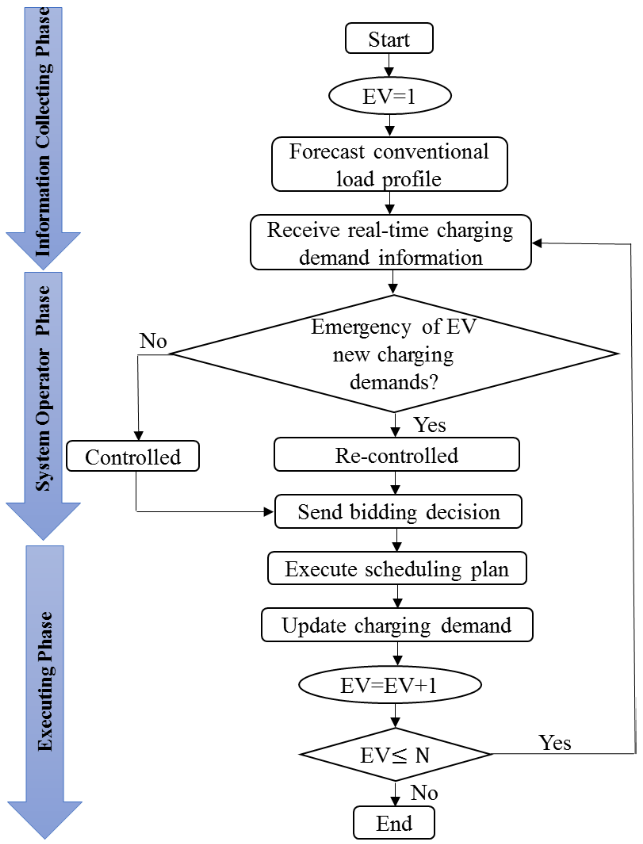

FIGURE 2. The core structure of this review.

4) Last, this paper proposes a new framework of guidelines for EV charging control to be applied in smart grid applications.

The paper is organized as follows: A summary of generic framework-based real-world data for the most recent EV charging strategies is presented in Section 2. Section 3 introduces a generic framework for controlling electric vehicle (EV) charging, while Section 4 describes the methods and techniques of EV charging strategies. Section 5 presents the challenges and recommendations and, finally, concluding remarks are made in Section 6.

II. GENERIC FRAMEWORK OF EV CHARGING STRATEGIES

This section describes the generic framework of EV charging strategies. Fig. 2 illustrates the control processes of EV charging, which include the following three main phases: the information collecting phase, the system operator phase, and execution. During the first phase, the system operator predicts the conventional DSM and receives the charging request signal via the communication system implemented at the charging spots. Then, in the system operator phase, the charging patterns are generated according to the charging plan equipped at the last spatial-temporal slot. In the execution phase, the charging decision is sent to the charging posts by a communication system. After that, the charging posts execute the charging strategy instructions.

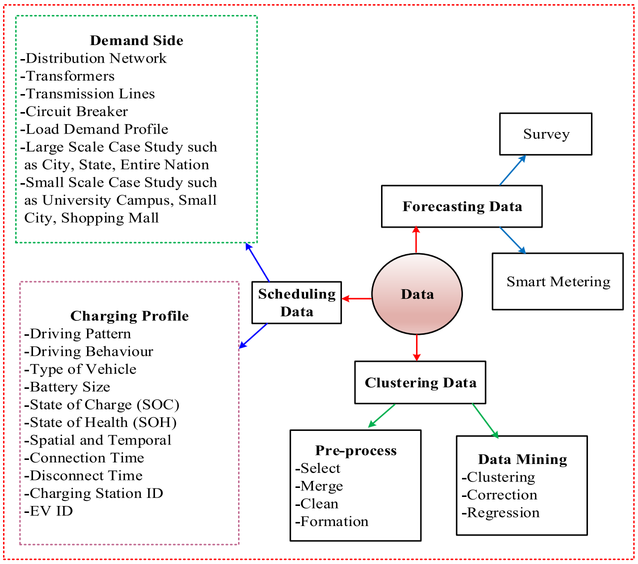

FIGURE 3. Data sources of EV charging strategies.

A. INFORMATION COLLECTING PHASE OF EV CHARGING STRATEGIES

This phase describes the sources, methods, and ways of collecting the data for the three main methodologies (scheduling, clustering and forecasting). A summary of real-world data for the most recent EV charging strategies is presented in Fig. 3. The EV charging strategies data are divided into the following three groups: scheduling data, clustering data, and forecasting data.

The grid to vehicle (G2V) data are used as the input to the scheduling strategy. Furthermore, the scheduling data are implemented according to two categories: demand-side and charging profile information. For example, in [18], the researchers presented baseline load profiles data of charging EVs for regular household usage to obtain the optimal charging schedule. In [19], a 24-hour load demand profile of a residential network and the low-voltage network topology were used as the input data for a smart charging schedule for EVs. In [20], Han *et al.* proposed a model that can deal with different charging profiles data to control the charging schedules of all EVs subscribing to predetermined payment schemes.

The clustering data that is used as the input to the clustering strategies consists of data mining and a preprocess. The preprocessing model consists of the modules of select, merge, clean, and formation, while the data mining model comprises the modules of clustering, correlation, and regression [21], [22]. A data mining model was developed to investigate the characteristics of the electric vehicle charging demand in a geographical area [97].

In the forecasting that is used as the input to forecasting strategies, the data are survey data and smart metering data. For example, a probabilistic method is presented in [23], which proposed two different datasets illustrated in the National Travel Survey (NTS), i.e., the mileage data of EV charging profiles and residential smart meters.

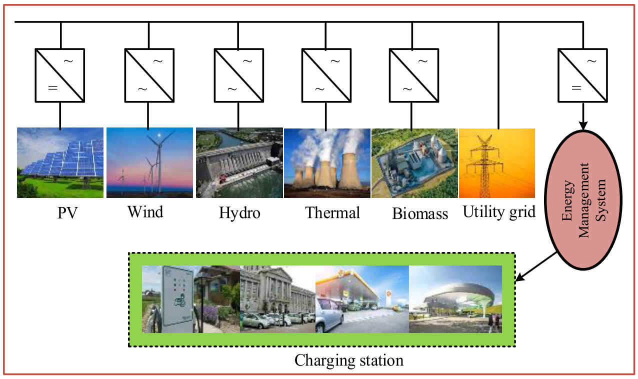

FIGURE 4. Generic framework of the system operator phase of EV charging strategies.

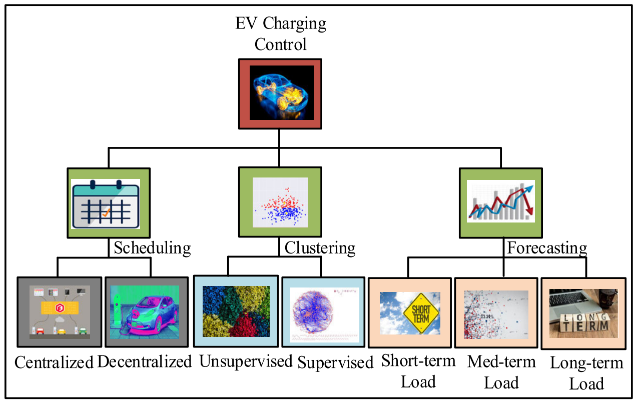

FIGURE 5. The control strategies for EV charging.

B. SYSTEM OPERATOR PHASE OF EV CHARGING STRATEGIES

To simplify the operator phase of EV charging strategies and manage the optimum load profiles with respect to the formulated EV charging problem, the following three generic modeling approaches are used in the literature:

i. Mathematical optimization: linear programming, quadratic programming, dynamic programming, and mixed integer linear programming.

Meta-heuristic

ii. optimization: genetic algorithm, particle swarm optimization, and evolutionary algorithms.

iii. Heuristic optimization: ANN, Markov process, and the technique for the order of preference by similarity to the ideal solution.

The framework for controlling EV charging is depicted in Fig. 4. Based on the figure, the framework shows that the energy management system plays an important role in controlling the energy flow between EV charging and the accumulated power captured from various sources, such as photovoltaic (PV), wind, hydro, thermal, and biomass energy sources.

The conventional techniques to charge electric vehicles can be either fast or slow battery charging types [24]. The charging power rating is inversely proportionate to their charging time, with a higher charging power rating being analogous to a shorter charging time for the same charge capacity battery. EV chargers can be grouped into level 1, level 2 and level 3, referring to the power rating. Level 1 and level 2 are implemented with onboard chargers, while level 3 is used for an off-board charger. In Level 1, the typical EV battery for a plug-in hybrid vehicle (PHEV) is 16 kWh. In level 2, the typical capacity for the battery electric vehicle (BEV) of a sedan is 24 kWh. In level 3, the typical capacity for the battery electric bus (BEB) is 250 kWh. Usable data was obtained from 115 charges and the mean charging efficiency was found to be 85.7%. With slow charging at a charging power of 3 kW, it takes approximately 6 to 8 hours for a typical EV battery to reach full capacity. Overnight charging typically uses slow charging. Fast charging is typically defined as any charging scheme that works faster than slow charging. The utility must accommodate both slow and fast charging requirements as the market penetration of EVs increases. The increasing penetration of EVs may affect the power system stability and security [25].

Therefore, scheduling, clustering, and forecasting strategies of EV charging offer solutions for the issues that arise from EV charging. These control strategies consider both the real-time status of the power grid and the demand of EV charging, thus improving the power grid stability and efficiency, reducing the grid operating cost, and avoiding peak loading [26]–[28]. EV batteries are potential storage options for intermittent supply and can be featured in scheduling, clustering, and forecasting schemes as a factor to seamlessly match the load consumption [16], [29]. The key to effectively control charging requires communication between the electric vehicles, the electric vehicle supply equipment (EVSE), the regional power grid, and the control center. EV control charging requires a communication system that has the ability to send and receive information with a bidirectional flow.

C. EXECUTION PHASE OF EV CHARGING STRATEGIES

The charging strategies will be executed in this phase according to their charging plan. A charging model produces the optimal charging profile of each EV with the optimal performance, which is then executed by the power grid at the appropriate spatial-temporal slot.

III. CONTROL STRATEGIES OF EV CHARGING

This section presents the core work of this paper, as shown in Fig. 5. It illustrates the scheduling, clustering and forecasting control methods. Furthermore, this manuscript discusses the process variables, data transformation strategies, and modeling methods of the EV charging strategies.

A. SCHEDULING STRATEGIES OF EV CHARGING

Proper scheduling of EV charging can maintain the stability of the power grid and ensure the equilibrium between the electricity supply and demand. It also enables grid-to-vehicle and vehicle-to-grid services through coordinated scheduling [30]. Shojaabadi *et al.* [31] comprehensively exhibited

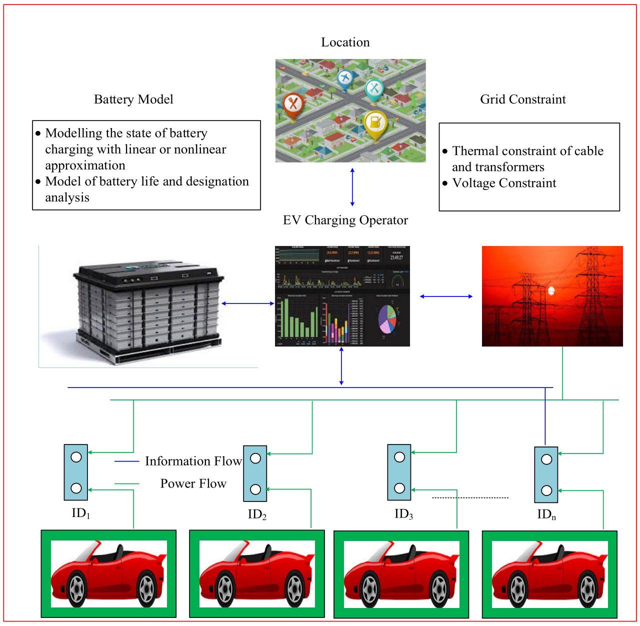

FIGURE 6. **Diagram of centralized scheduling for EV charging.**

the merits of an appropriate EV charging or discharging schedule. The coordination between the electric vehicle's owner and system operators increases the EV penetration levels to enable effective vehicle-to-grid (V2G) services and EV charging scheduling [32]. There are two main types of EV charging scheduling strategies, as follows: (1) centralized scheduling and (2) decentralized scheduling.

1) CENTRALIZED AND DECENTRALIZED SCHEDULING OF EV CHARGING

A central strategy is responsible for managing and controlling the EV charging demand by controlling the charging process of each EV directly. In the central approach, communication with EV users is established by the EV aggregator in a way that minimizes the energy charging cost. The EV aggregator collects charging data from the EVs and the electrical grid to solve optimization problems and to arrange the charging pattern for each EV directly. A centralized scheduling strategy utilizes historical and statistical data to study the charging time, the capacity of the grid, and the charging rate. The literature asserts that centralized charging requires a universal plan set by the central controller. Quan-Do *et al.* [33] proposed serving EV parking lot users by utilizing a centralized charging controller that considered the size of the battery pack, the state of the charge (SOC), and the power system conditions. The main goal of the abovementioned study was to minimize the peak loads on the grid and satisfy driver expectations. In a decentralized case, EV users behave strategically and seek to minimize their charging costs individually. Each EV user will then decide when to charge individually. Furthermore, the charging power and time are chosen according to the parameters and the associated optimization criteria of the EV users.

In this decentralized approach, each EV formulates its own bids, and the aggregator simply has the role of aggregating these bids. In [34], as an example, Wu and Sioshansi presented a two-stage stochastic optimization model with balance constraints to provide the optimal profit of an aggregator. A Monte Carlo-based sample-average approximation technique is applied to solve the resulting optimization problem efficiently. The work in [35] presented the concept of a price-based decentralized control scheme, wherein electric vehicles communicate their load demands iteratively, depending on a pricing pattern. In [36], Wu *et al.* proposed a decentralized structure that applied a price pattern to inspire electric vehicle users to manage their EV charging.

2) CENTRALIZED SCHEDULING METHODS AND TECHNIQUES

Each electric vehicle owner should communicate with the electric system operator using a centralized approach to arrange the charging scheme for each electric vehicle directly. Several examples of control strategies for the charging demand and charging processes can be found in [37]–[43]. On the other hand, two-stage stochastic programming is another method that has been applied for centralized approaches to electric vehicle charging demand. The stochastic programming approach establishes an appropriate tool to make decisions under uncertainty [44]. A scenario tree is another technique used to visualize the probability of uncertain data, which consists of decision point nodes and branches. The nodes represent possible solutions to the problem, while a branch represents a transition between scenarios [45]. An example of a two-stage stochastic method is a centrally administered control model for a high-voltage and quick charging station [34], [46]. The study presented in [47] implemented a scenario-based stochastic model for a renewable energy microgrid in the presence of electric vehicles to solve the optimal scheduling problem over one day. Moreover, if an electric vehicle is added to the V2G process or an electric vehicle is unpredictably cut off from the grid, the mathematical model will be transformed according to these updated inputs. Subsequently, the rescheduling will be directed in the coordinated operation center [48]. Fig. 6 represents a typical model of centralized scheduling for EV charging.

Two-stage stochastic programming is one of the best approaches for modeling problems that involve uncertainty in decision-making. The model presented in [49] assigns Boolean variables to the first stage to denote the availability of charging points at parking lot spaces. The second stage makes a recourse judgment to designate EV drivers to their favored parking lot spaces based on their walking propensity, thereby maximizing access to the conventional charging network. In [50], the first stage is presented to formulate the number of charging stations in the chosen parking lots. A recourse decision is made in the second stage to assign the electric vehicle owners to one of their selected parking lots depending on their willingness to walk. In this context, the predicted admission of electric vehicle owners to the public charging grid is maximized. A two-stage stochastic programming model has also been developed to find the optimal locations to exchange EV battery packs in battery exchange stations [51]. Hosseini and MirHassani [52] proposed a two-stage stochastic program to trace permanent and movable charging stations to increase the served traffic flows. The station-control approach is expressed as a stochastic two-stage optimization problem, which reduces the anticipated charge station-operation costs over a fixed period. The first stage describes the present time interval (the next minute) for (here/now) electric vehicle charging. The second stage describes the balance of the model horizon. The model assumes that the electric vehicle charging demand and the energy prices are known for stage 1, but that these are undefined for stage 2 [34], [46], [53]. In [54], Graber *et al.* proposed a framework based on a centralized double-layer smart charging management strategy to optimize the charging energy of electric vehicles and to direct the electric vehicles to the proper charging stations.

The most important advantage of the centralized strategy is the reduction of power fluctuations. For example, in [55], Zheng *et al.* proposed a schedule for electric vehicle charging demand based on a centralized charging approach to achieve a reduction in power fluctuations. A genetic algorithm (GA) was employed to obtain the stochastic feature parameters of the aggregation model. In [56], the scholars proposed a model of V2G technology as a strategy for peak load shaving and valley filling. Moreover, a centralized approach can be applied to optimize the swapping of electric vehicle batteries [57]. Nguyen *et al.* [58] presented an optimization method to regulate the V2G power to deal with the intermittency in RES. In [59], the researchers proposed a scheduling strategy for electric vehicles integrated with wind generation utilities to achieve balance in the power system. The most classic algorithm employed to choose areas where EVs will be guided for charging is the Floyd algorithm (shortest way algorithm), shown in Equation (1) [60]. The shortest way from point v to point v' including the vertex N is considered, which includes a subway from V to N and a subway from N to v'. Each subway can only contain intermediate vertices in $\{1,\ldots, N-1\}$ and must be as short as possible. Namely, they have the lengths of d_{vN}^{N-1} and $d_{Nv'}^{N-1}$. Thus, the route has a length of $d_{vN}^{N-1} + d_{Nv'}^{N-1}$. Combining the two cases, the following equation is obtained from [40], [61]:

$$d_{vv'}^{N} = mim\left\{d_{vv'}^{N-1}, d_{vN}^{N-1} + d_{Nv'}^{N-1}\right\} \tag{1}$$

The optimal solution of the centralized charging strategy based on real optimal charging is proposed in [30] by applying four steps, as illustrated in Fig. 7. In the first step, the total loads with EV penetration is calculated by employing uncoordinated charging with a reasonable searching interval of the supplying power (Pc), which should be optimized.

$$P_U(EV_k) = P_{T-uc}^{max}(EV_k) \tag{2}$$

$$P_L(EV_k) = P_{Con}^{max} \tag{3}$$

where $P_U(EV_k)$ is the power of the upper boundary, $P_{T-uc}^{max}(EV_k)$ is the total value of the maximum power with uncontrolled charging, $P_L(EV_k)$ is the power of the lower boundary, and P_{Con}^{max} is the maximum power of the conventional load profile.

In the second step, an initial value of Pc is chosen by using the dichotomy method, namely, as follows:

$$P_c = \frac{P_U(EV_k) + P_L(EV_k)}{2} \tag{4}$$

In the third step, the EV charging loads are scheduled with the given Pc. In the fourth step, the search interval is successively halved until its length is short enough.

However, for a large number of electric vehicles, optimizing and controlling the electric vehicle charging demand by using centralized approaches is computationally expensive [62]. In addition, the scalability issue is the main drawback of centralized control—the high computational complexity of the centralized control algorithms become a burden inhibiting the efficient and prompt operations of the system as the number of EVs increases. Although the centralized scheduling approach delivers a straightforward manner to regulate electric vehicle charging demands, it is not applicable for large-scale numbers of electric vehicles, as it requires massive computational energy and an advanced communication system. Shortcomings have also been stated concerning the information confidentiality of electric vehicle owners, as their charging behavior and data would be composed in one location, increasing the threat of exposure to malicious cyber-attacks.

3) DECENTRALIZED SCHEDULING METHODS AND TECHNIQUES

In the decentralized control architecture, each individual EV creates its own charging schedule based on the local load. Unlike the centralized control architecture, an operator is not needed, and this allows each individual vehicle to minimize its charging cost [63]. In this case, the decentralized charging can be improved by carrying out a number of algorithms, such as the genetic algorithm (GA) [64], the neural network (NN) [65], [66], the Markov decision process (MDP) [67], and a multiagent system [68].

The case study outlined in [69] examined a prototype implementation of a decentralized system for scheduling the charging of electric vehicles by using the GA. The model reported in [70] is decentralized based on the artificial bee colony algorithm and is chosen for operation in a small-scale power network, as shown in Fig. 8. The authors presented an aggregated charging technique based on multiagent Markov decision processes, which accounts for the uncertainty in the renewable energy supply and coordinates the charging processes of several EVs.

The study conducted in [63] proposed a decentralized electric vehicle charging schedule, using broadcast control signals and asynchronous computation to converge on

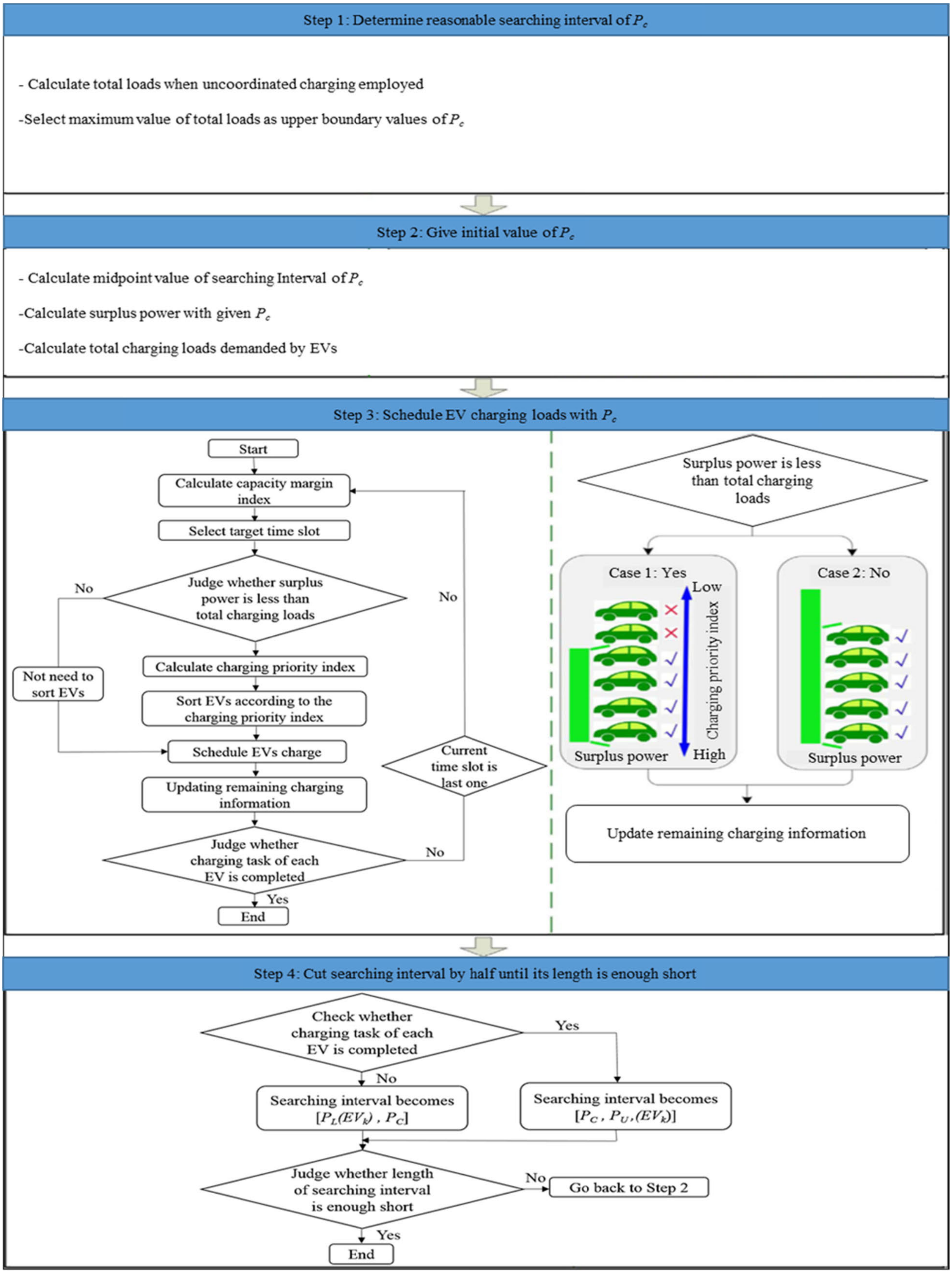

FIGURE 7. Calculation process to search for the optimal solutions by Model (k) [30].

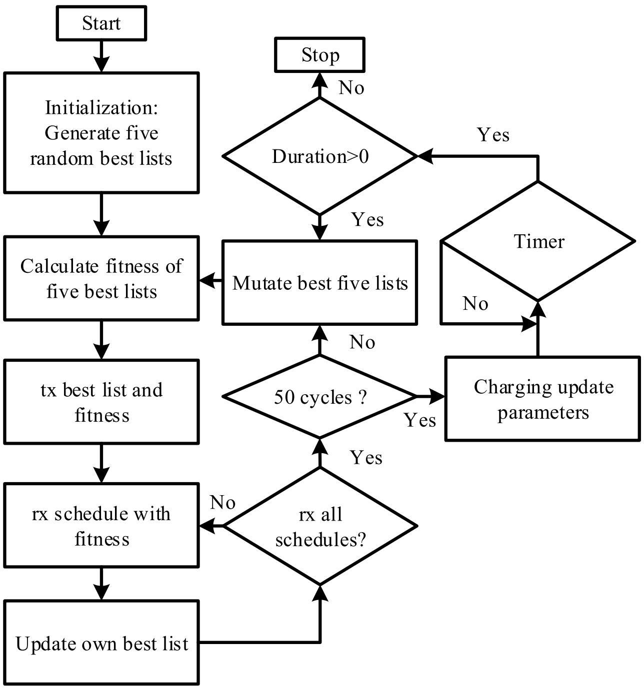

FIGURE 8. Flow chart of the genetic algorithm (rx=receive, tx=transmit) [69].

an optimal valley-filling charging demand. A decentralized strategy was presented in [35], [71] to create a timetable of electric vehicle charging loads by using game theory. In [72], [73], and [74], the authors proposed a decentralized EV charging method to optimize load demand based on the energy price, which required iterative interactions between the EVs and the market. The Stochastic Dual Dynamic Programming (SDDP) algorithm is used to define the optimal charging profile for minimizing the household daily operation costs with respect to EV charge scheduling [72]. A pricing pattern is formulated as two-stage stochastic programs that convey the price and quantity information to the load aggregator and compare it to a simpler price only scheme [74]. In [75], a decentralized control strategy was developed based on a multiagent system algorithm that involves data interactions between neighboring agents. Fig. 9 presents a typical model of decentralized scheduling for EV charging.

The main advantage of decentralized charging is the possibility to minimize the communications infrastructure cost. Although the decentralized strategies for scheduling EV charging require minimal computational resources, some of the strategies require higher communication burdens and, due to a lack of worldwide information, it is difficult for distributed control strategies to reach global optimal solutions.

To some extent, the decentralized strategy can obtain the optimization targets asymptotically with reduced data computations. For example, in [76], the Frank–Wolfe algorithm was applied to solve a general convex quadratic optimization problem.

A summary of the outcomes obtained by different centralized and decentralized studies is presented for the

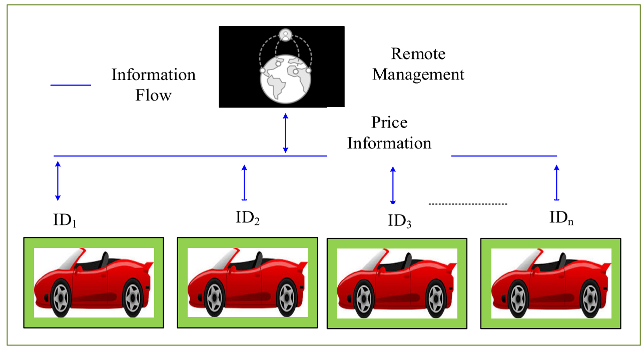

FIGURE 9. Diagram of decentralized scheduling for EV charging.

convenience of the reader in Tables 1 and 2. It can be seen that there is remarkable inconsistency between the probabilities methods in Table 1 and the artificial intelligence methods in Table 2 in terms of their optimization abilities, which are also reported in the tables.

4) POTENTIAL BENEFITS AND RISKS OF SCHEDULING EVs

A summary of the potential benefits and risks of scheduling EV charging is given as follows:

A. Potential Benefits

i. Better utilization of network capacity;
ii. Economic saving;
iii. Reduction of peak and overall demand;
iv. Market participation.

B. Potential Risks

i. Needs a primary communications infrastructure across the grid;
ii. Requires a third party to manage the EV charging rates;
iii. Security issues; Exploitation of private information for public commercial purposes.

B. CLUSTERING STRATEGIES OF EV CHARGING

The load profile curves can be analyzed based on EV charging data to gain an enhanced observation of the EV charging performance and energy demand patterns as well as to clarify the potential energy efficiency, which can help grid operators to manage the consumption demand. The strategy of clustering is used to analyze the curves of the EV charging load. Clustering can be defined as an unsupervised method of data mining, which can be used to group the related daily load profiles into similar clusters. Furthermore, clustering algorithms can be used to create load profiles that cluster consumer behaviors based on their similarities.

1) DATA FOR CLUSTERING OF EV CHARGING

The clustering method discovers unknown dataset patterns by separating the dataset into subgroups [77]. The analysis of the daily EV charging demand involves applying clustering strategies to group related profiles into the same subgroups, thus revealing the most typical load profiles [78]. The required EV cluster for dataset collection is usually operated with temporal, spatial, or spatial-temporal datasets.

TABLE 1. **Probabilistic methods of scheduling strategies.**

Number	Centralized/ Decentralized	Method Brief Summary	RES	Data	Region	Software	Findings
[47]	Centralized	The aggregator model for EV charging involved a parking lot integrated with a renewable energy sources microgrid (RMG)	Wind	The capacity of the parking lot is 200 vehicles.	-	MATLAB function/ARIMA model	The cost of the RMG equipped with the parking lot is minimized.
[48]	Centralized	The proposed model is formulating by using the even trigged scheduling approach	-	The number of EVs involved is 200	China	--	Improve the security and the operation efficiency of the power grid
[34]	Centralized	This work introduced the L-shaped and sample-average approximation method	PV	The data are acquired by the geographical information system (GIS) of the Ohio region	Central-Ohio region,, U.S.	-	Minimized the impacts of the EV charging load on the distribution transformer
[72]	Decentralized	A coordinated model is presented to control EV charging integrated with households	-	EV charging time, final desired charging and initial charge data	-	-	Minimizing the household cost of purchasing energy from the power system

The temporal resolution of the data points directly affects the resolution of the resulting typical load profile. Typically, 48 data points, one taken every half hour, or 96 data points, one taken every 15 minutes, are common resolutions. For example, in [79], the EV dataset was organized using MATLAB software into three time series, as follows: an hourly energy time series, a daily peak energy time series, and a monthly energy time series. The resulting data were formatted to the correlation module. The data preprocessing procedure is presented in Fig. 10. In [80], Shepero and Munkhammar presented data mapping to cluster the buildings into the following three groups: residential, workplace, and other. Recently, a number of studies have used clustering approaches for EV charging demand to determine load profiles with mutual characteristics. Several case studies have been presented to cover the following two types of geographical scale: small-scale grids, such as islands, residential buildings, shopping malls, and universities, and large-scale grids, such as cities, states, and entire nations. Regarding spatial EV models, Fraile-Ardanuy *et al.* [81] used global positioning system (GPS) data from a taxi fleet to develop a spatial EV charging model. The authors of [82] employed a Markov chain traffic model to develop a spatial-temporal model for EV charging in urban areas.

2) CLUSTERING METHODS AND TECHNIQUES

Several methods have been applied for clustering the EV charging demand, such as Markov-inspired stochastic, k-means, self-organizing maps (SOM), and Markov chain methods. In [83], a statistical analysis of the data was used to feed into a Markov-inspired stochastic model used in the simulation, as shown in Fig. 11, where the three-state model was based on the state probabilities, and Pt(S) denotes the probability that a transition to state S will occur at time t. The authors proposed the Markov chain to be used along with RES

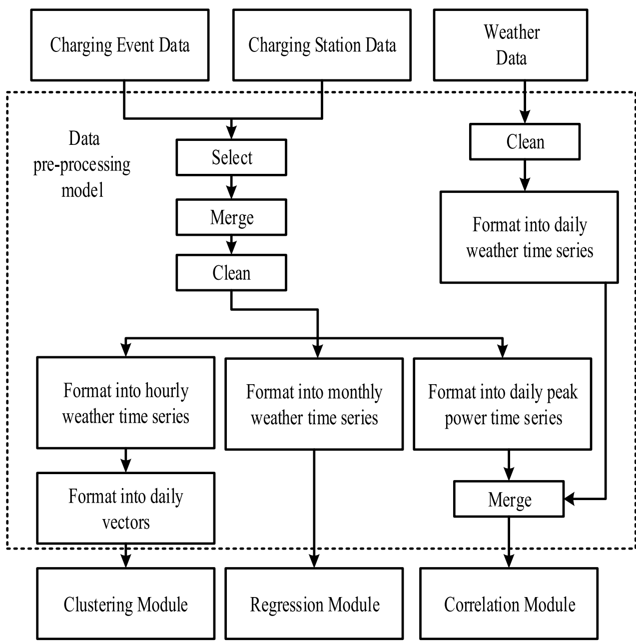

FIGURE 10. **Data preprocessing of a temporal model [79].**

TABLE 2. Artificial intelligence (AI) methods of scheduling strategies.

Number	AI Approach	Centralized/ Decentralized	Model	Method brief summary	Data	Region	Software	Finding
[66]	Supervised	Decentralized	(ESNA+ CMA) and (NN-A+CMA)	Proposed generic framework of an NN-based controller	The data are collected from the national household transportation survey (NHTS)	Texas, U.S.	-	Control the peak consumption
[65]	Supervised	Decentralized	Scaled conjugated gradient (SCG)	The authors used a supervised feed-forward Multilayer NN.	4 × 288 samples of data in a 10-minute time interval from the smart meter	California, U.S.	GridLAB-d and MATLAB	The proposed method can be applied to schedule the charging and discharging of EVs
[64]	Supervised	Centralized	M/M/∞ model	Genetic algorithm is applied for the minimization of multi-attribute utility function and daily scheduling of EVs	Metered data collector	Serbia	MATLAB/Genetic algorithm with integer variables	The decision maker attitude towards risk can be incorporated, with the structure of the individual utility function.
[70]	Supervised	Centralized	Dynamic constraint satisfaction problems (DCSP)	The researchers presented an artificial bee colony (ABC) algorithm enhanced with mating strategies borrowed from GA	Database	-	C++ programming language	It was optimized to make the best use of the contracted power in the charging station

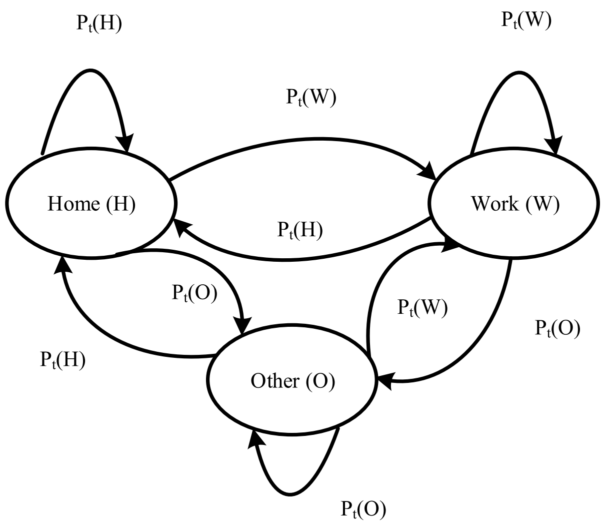

FIGURE 11. Illustration of the stochastic model for a vehicle based on state likelihood [83].

models to estimate the spatial-temporal synergy potentials between the two technologies.

The study presented in [84] employed k-means programming on over 1000 customers to ascertain usage patterns, and those datasets were sampled within a 48-hour window. However, that analysis was significantly skewed by differences between weekend and weekday charging patterns. Since the initial assignment of the predefined cluster affects the final clustering outcome when utilizing a k-means clustering approach, the application of the k-means clustering algorithm categorizes the EV user behavior, and may apply supervised learning and unsupervised learning approaches to provide additional classifications [85]. The main objective of k-means models is to decrease the variation inside the cluster. However, finding the optimal number of clusters is recognized as the main challenge that might require inspection and intervention. In [86], the k value with the largest validity index was chosen after determining the optimum cluster amount, performing k-means clustering with the training dataset for a k range from approximately 10% to 100% of the number of unique occurrences in the training dataset. Various studies in the literature applied the SOM algorithm, which can provide automatic clustering; meanwhile, [87], [88] used the SOM algorithm to cluster different load profiles.

A number of models can be used for clustering strategies, such as decision tree and support vector machines (SVM) [89]–[92]. Xydas *et al.* [15] presented a model

TABLE 3. Probabilistic methods of clustering strategies.

Number	Spatial, Temporal, or Spatial-Temporal	Brief Summary of Method	RES	Data	Region	Software	Findings
[83]	Spatial	Presents a stochastic model based on the Markov algorithm to cluster EV charging locations	-	The data collected during the "Test-en-elbil" project	Denmark	-	The cost of the RMG integrated with the parking lot is minimized
[82]	Spatial-temporal	This study introduces an urban road-network model based on a Markov chain traffic model to describe the EV arrival rate at specific fast-charging stations.	-	The data were collected from CCTV	Korea	--	EV charging power demand can be calculated using traffic data
[80]	Spatial-temporal	The model is introduced to be integrated with RES models to quantify the spatial-temporal synergy potential between EVs and RES in cities	PV	Extracts parking lot data from maps and clusters them into types	City of Uppsala, Sweden	-	Classified whether EVs could be allowed to charge at all charging locations in the city or in only home locations
[79]	Temporal	The EV dataset is organized into the following three-time series using a MATLAB script: an hourly, a daily, and a monthly energy time series	-	The EV dataset is collected according to the connection time, disconnection time, energy drawn, charging station ID, and charger type	UK	MATLAB/Data analysis toolbox	The model was applied on a dataset of real charging events from three counties in the UK, and their ''risk level" index was calculated

framework containing two parts of a dataset, i.e., training and testing. The support vector machine's objective is to provide a model that expects the target values of the test data. Various traffic situation modes resulted from the analysis of historical traffic and meteorological data. In this context, the charging behavior of electric vehicles was classified by applying the decision tree algorithm. To establish the relationship between the formed clusters of traffic patterns and influential factors, Arias and Bae [93] used a decision tree as a classification method to predict the responses to the data.

Although the SVM algorithm can efficiently handle high-dimensional data and has great flexibility in modeling different sources of data, it requires complex computations for large-scale EV charging data. Decision tree methods take advantage of the flexibility, extensibility, and resilience of distributed control systems. Moreover, decision tree methods have been considered to be the most suitable tool for the dispatch problem. Among the major disadvantages of decision tree analysis is its inherent limitations [94]. A number of algorithms have been proposed to obtain the optimal number of clusters. For example, in [79], the algorithm of the Davies–Bouldin criterion was applied to obtain the optimal number of clusters. A summary of different methods is presented for the convenience of the reader in Tables 3 and 4. It can be seen that there is a significant difference between the probabilities methods in Table 3 and the artificial intelligence methods in Table 4 in terms of the clustering ability of the models with diverse datasets, which are reported in Table 4.

3) POTENTIAL BENEFITS AND RISKS OF CLUSTERING EVs

A summary of the potential benefits and risks for clustering EV charging is given as follows:

A. Potential Benefits

i. The clustering strategy research aims to explain the effects of EV penetration on the quality of the power system;
ii. These strategies provide a quick and efficient way to solve the location problem of charging stations;
iii. They also minimize the total operating costs by assigning the charging station to the selected charging demand cluster.

B. Potential Risks

i. A threat for clustering security and reliability;
ii. The clustering research has shown that different clusters may reveal considerably different load profiles; hence, using the same clustering model over these different clusters may not be the most appropriate approach.

TABLE 4. Artificial intelligence (AI) methods of clustering strategies.

Number	Spatial, Temporal, or Spatial-Temporal	Brief Summary of Method	Data	Region	Software	Findings
[93]	Spatial-temporal	Proposes a cluster of EV charging to classify traffic patterns and a relational analysis to recognize significant factors; a decision tree algorithm is applied to establish the classification criteria	Used historical real-world traffic data and weather data	South Korea	MATLAB/ MapReduce function/ fitctree function	The historical data handling processes contain a cluster analysis to classify the traffic patterns in each cluster, as well as a relational analysis to identify the influential factors affecting the traffic patterns
[85]	Spatial	Uses the unsupervised learning algorithm of k-means clustering to categorize EV user behavior	200 EV charging stations installed in public parking structures	Santa Monica, U.S.	--	Labeling the dataset becomes an automatic process and eliminates the need to perform clustering every time a new user joins the charging network
[87]	Spatial-temporal	This work applies a machine learning approach based on self-organizing maps (SOM) to model the driving and charging behaviors of EV users and to cluster the collected vehicle samples	8300 Nissan Leaf and Chevrolet Volt EVs	Shanghai, China	-	The key findings of this work show that the charging demand in the daytime is significant, potentially overlapping with the peak energy demand from non-EV loads

C. FORECASTING STRATEGIES OF EV CHARGING

Most of the research works in the literature aim towards the association of usage patterns and predictions of EV charging demand. In this context, the forecasting strategies in the EV charging pattern can be grouped into the following types: (1) charging load prediction and (2) charging pattern identification. From the data mining perspective, such categories can be referred to as predictive and descriptive analytics, respectively [16].

According to the time horizon, the EV charging forecasting load is grouped into the following three main categories: short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF). STLF is required to predict the load demand from a few hours to one week. STLF plays an important role in power system optimization and next-day operation commitment. Furthermore, STLF is used to maintain the stability of the power system and to minimize the energy cost for EV charging. MTLF is applied to forecast the load of EV charging from one week to one year in advance. MTLF is essential for power system planning, where an accurate MTLF is crucial to plan maintenance operations and EV charge switching. LTLF is required to predict the load demand of EVs from one year to many years in advance. LTLF has an important impact on the decisions regarding investments in infrastructure and new generation units [15], [95].

1) DATA FOR FORECASTING EV CHARGING

Most of the studies that applied EV charging demand forecasting strategies acquired datasets by using a transportation survey on the EV user's behavior based on annual averages [96]. However, the collection of such survey data may be difficult and impractical. Therefore, smart meter installations at building or stations can provide an extensive amount of data, which is collected from termination points, e.g., every 15 minutes, which could be applied for EV charging forecasting strategies. Recent studies have examined different ways to use calendar information from smart meters, such as holiday, weekday, weekend, and daily data [97], [98].

Moreover, a load consumption graph has also been used for EV charging demand forecasting strategies, where the load consumption graph can be applied to enhance the energy management system and strengthen the resourcefulness of the proposed approach. This will help to overcome energy supply shortages on the vendor side and avoid inconveniences for the user as well. The load consumption graph includes arbitrary load forecasting samples from charging stations in different regions directed to the user. These samples help to predict the peak hour demand as well as the number of customers expected during a specific time of the day [99], [100].

2) FORECASTING METHODS AND TECHNIQUES

EV load forecasting is influenced by fluctuating factors, such as the driving and travel patterns of each EV owner. These patterns must be considered to approximate the charging demand. The stochastic nature of the EV charging demand factors forces the use of advanced forecasting techniques that are able to decipher all the patterns [101].

A Markov chain is a sequentially formed stochastic method that satisfies the Markov attribute [102]. The Markov algorithm can be applied to model electric vehicle travels and the electric vehicle charging demand by following the events in a

TABLE 5. **Probabilistic methods of forecasting strategies.**

Number	STLF, MTLF, or LTLF	Brief Summary of Method	RES	Data	Region	Software	Findings
[23]	MTLF	Urban, rural and generic networks are presented to study the peak load of the distribution network integrated with the EV charging load	-	Smart meters are used to record 85,000 EVs and their charging events	UK	IPSA 2	The distribution grids are not a homogeneous group with various capabilities to accommodate EVs
[50]	MTLF	Presents a model of two-stage stochastic programming to examine the growth of EV charging loads	-	Case 1: 1% and 2% for BEVs and PHEVs, respectively, for market share. Case 2: 2% and 3% for BEVs and PHEVs, respectively, for market share	Detroit midtown area in Michigan, U.S.	Python 2.7 using Gurobi 6.5.1 software	Improving the accessibility to charge EVs
[105]	LTLF	This method distributes the charging times so that all flexible EVs do not start charging at the same moment	-	The data were obtained from a detailed Swedish National Travel Survey named RES0506	Sweden	-	Specifying a potential for load shifting with flexible EV chargers
[102]	STLF	This method proposed a generic model that can be tailored to different places with different driving habits	-	Implements the local charging characteristics of customer behavior	Vienna		Accurate model at specific locations
[67]	STLF	This dynamic programming model is proposed to optimally charge EVs	PV	Global positioning system (GPS) data of each single EV obtained over 183 days	Denmark	Statistical software package R	Shows that the costs associated with running the vehicle are decreased significantly when the charging strategy is determined by the proposed optimization model

stochastic process [103]. The Markov chain has been demonstrated to be a useful instrument to optimize the states and phases during charging events at each time step [104], [105].

Markov analysis has the advantage of being an analytical method, which means that the reliability parameters for the system are calculated in effect by a formula. This has the considerable advantages of speed and accuracy when applied in forecasting strategies for EV charging. Iversen *et al.* [67] used a hidden Markov model that allowed the forecasting of additional states not directly observed in the data. In fact, a hidden Markov model can estimate these states so that the waiting time in each state matches what is actually observed in the data.

Recently, various studies have considered artificial network algorithms as the forecasting method for EV charging demand applications [106]. For example, in [107], the electric bus (EB) power consumption forecast design picks similar days using a wavelet neural network (WNN), which can improve the prediction accuracy and provide a reference for EB operation optimization. The electric bus (EB) power consumption forecast guarantees an optimal EB dispatch, which dramatically affects the reductions in EB charging station operating costs. The artificial neural network (ANN) algorithm used charging data to forecast the energy demand of EV charging and load management [65], as shown in Fig. 12.

In [108], the proposed method is mainly used for short-term load forecasting for large-scale EV charging demand to present the impacts on the power system network, discharging and charging control approaches, and charging infrastructure development. In this case, machine learning (ML) models are mostly preferred over probabilistic models, because of their adept functionality and superiority in representing complex nonlinear problems, such as individual forecasting for the demand load of EV charging. Furthermore, in a typical ML structure, the models are tested on the existing dataset before being used in real forecasting applications. Several traditional optimization algorithms have been used to select the parameters for EV charge forecasting, such as genetic algorithms, particle swarm optimizations, and ant colony algorithms [109]. Although the above algorithms have their own advantages, they also have corresponding shortcomings. For example, a genetic algorithm cannot guarantee the convergence to the best fit and can easily fall into the local optimum, which leads to a decrease in the prediction accuracy [110]. In Particle swarm optimization, premature

TABLE 6. Artificial intelligence (AI) methods of forecasting strategies.

Number	STLF, MTLF, or LTLF	AI Approach	Main Objective (Scheduling, Clustering, or Forecasting)	Model Type	Brief Summary of Method	Data	Region	Findings
[107]	SLTF	Supervised	Scheduling and forecasting	Wavelet neural network (WNN) forecast	The proposed study introduces the network analysis for fast charging	Actual survey data	Baoding, China	The prediction accuracy is improved
[108]	MLTF	Supervised	Scheduling and forecasting	Wavelet neural network (WNN)	The model is presented to predict EV charging by using historical EV charging loads	The station has 14 charging piles and 14 electric buses for 35 days	Guangdong, China	Provides a scientific basis for large-scale electric bus charging stations distributing a power load in a rational and orderly manner
[106]	LTLF	Unsupervised	Forecasting	Markov decision process	Studies the demand response strategy-based ML	The GPS data from 17 different conventional cars	City of Winnipeg, Manitoba, Canada	The results reveal average savings of 88% and 87% in the summer and winter, respectively

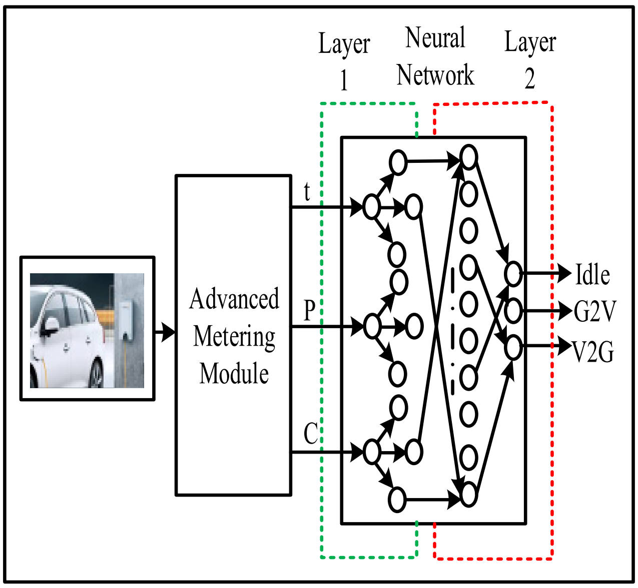

FIGURE 12. Energy demand forecasting for EV charging using an artificial neural network (ANN) [65].

convergence will occur in different situations [111]. The lion algorithm is a social behavior-based bionic algorithm. In [109], the optimal solution was proposed through territorial lion breeding patterns. In this approach, the process includes the following four main steps: population initialization, mating and mutation, territorial defense, and territorial takeover.

A summary of the results obtained by different probabilities and artificial studies is presented for the reader's convenience in Tables 5 and 6. In a typical machine learning framework, the models are trained, validated, and tested on the available dataset before being used in a real forecasting application.

3) POTENTIAL BENEFITS AND RISKS OF FORECASTING EVs

A summary of the potential benefits and risks for forecasting EV charging is given as follows:

A. Potential Benefits

i. Increased predictive capabilities to obtain a demand and supply balance;
ii. A precise estimate of the EV charging demand is essential for the purpose of setting tariffs;
iii. The forecasting strategy is necessary to predict the energy demand for the operation and planning of power systems.

B. Potential Risks

i. Data security issues;
ii. Forecasting models are developed based on big data technologies. It requires high-resolution data which may not available.

IV. ISSUES, DISCUSSION, AND RECOMMENDATIONS

This study identified many significant drawbacks by analyzing the methods and techniques presented in many EV charging studies. The following section provides these related issues and separates the major fundamentals of the previous studies into the following two categories: operational aspects and implementation challenges. The final part of the section provides a report on guidelines for future studies on this research topic. This guideline aims to enhance the comparability of the various results and findings.

A. OPERATIONAL ASPECTS

As described previously in Section 4, most of the EV charging scheduling methods studied in the literature utilize centralized control. In this context, because the number of electric vehicles penetrating the power network has increased, centralized control strategies face some challenges and the problems of reduced system scalability, high computational time, and high instability.

Therefore, the recent research has focused more on decentralized strategies. However, decentralized strategies require continuous accessibility of a two-way communication network between the communication system of the EVs and their synchronization, leading to increased system costs. Furthermore, the costs of upgrading these communication networks need to be optimized. Applying a hybrid control system that includes centralized and decentralized strategies in two level managements is recommended—level 1 is occupied by the centralized control system, while level 2 comprises the decentralized management operator. A hybrid centralized-decentralized EV charging control method is suggested to offer flexible charging choices for customers. In this charging scheme, EV owners can either assign the charging tasks to the system controller or individually choose the charging profiles based on their own preferences.

This study reviewed many clustering studies. The most important observations included that these studies applied diverse clustering techniques on diverse data criteria and evaluated the performance with diverse validity indices. Furthermore, these studies did not present a vision regarding the dependency of the outcomes on the model variables and validity indices, which leads to a major challenge for the process assessments among the outcomes achieved by the diverse clustering research. Using statistical measures with the model variables is suggested to evaluate the changeability of the validity indices to overcome the assessment challenges.

Based on previous discussion, one of the most significant problems of forecasting the EV charging load is that that EV load is considered an unpredictable load. In this content, the variation and magnitude of the EV demand directly impact the accuracy of the predictions. A large number of research studies that have examined the impression of the EV demand scale on the prediction precision have shown that forecasting a large-scale EV demand is more challenging compared to forecasting a small-scale EV demand. In this case, STLF can be significantly more accurate than MTLF or LTLF.

B. THE CHALLENGES OF CONTROL CHARGING IMPLEMENTATIONS

A fundamental problem with many of the reviewed studies is their limited designs of realistic models for electric vehicle arrival/departure times. The question raised in this case is whether or not the proposed strategies for electric vehicle charging can be applied in real life.

The operator management center is required to communicate between the EVSE and the power system operator. Thus, reliable communication links, protected protocols, and a secure network are essential. Nevertheless, there are very significant challenges in the communication systems related to ensuring compatibility among the diverse mechanisms and providing smooth and secure data broadcasting. Therefore, issues concerning the increased infrastructure, maintenance budgets, and functioning are also raised.

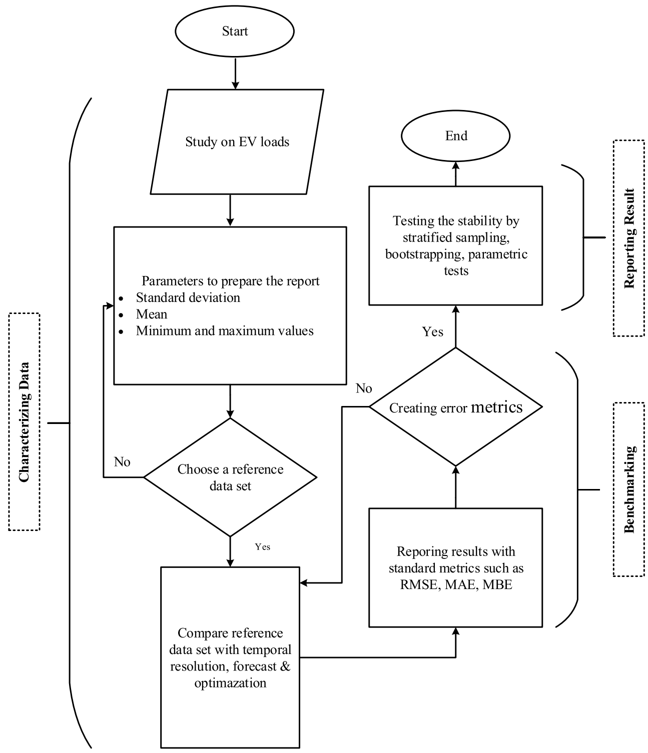

FIGURE 13. Proposed analysis guideline for future EV charging studies.

C. SUGGESTED ANALYTICAL FRAMEWORK FOR FUTURE STUDIES

There was no benchmark or framework set to compare the research in this area. Therefore, it was quite complicated to determine which methods provide the best results. Furthermore, the different EV charging control studies work on managing diverse kinds of applications and the optimization purposes may differ among the research works. Thus, while new research may provide valuable outcomes, it is difficult to verify the actual achievement due to the absence of a set analysis benchmarks or frameworks. Therefore, the following guideline framework, shown in Fig. 13, is presented to minimize some of these discrepancy problems among the research works and make their comparison and analysis easier:

1) CHARACTERIZE THE EV LOAD PROFILE DATA

Describe different types of EV loads based on the size of the batteries and the standard deviation. To this end, establishing an accurate and reasonable load profile model of EV charging is of great importance for the planning, operation, and scheduling of a power system. By considering a series of different EV load profiles, the distribution management system can take uncertainty into account when making decisions, such as the safe operation of the distribution network, optimal economic trade, and cooperative scheduling strategies.

2) BENCHMARKING

Choose a reference dataset commonly used in the literature (for example, Commission of Energy Regulator (CER) Smart Meter Trial, NOBEL field trial). Apply the methodology to the reference dataset in addition to the available unique dataset. Choose data characteristics, such as temporal resolution, forecast and optimization horizon, and analyzed appliance types, that are consistent with the reference dataset.

3) REPORTING RESULTS

Use conventional performance metrics to compare with the previous studies. Customize the error metrics for particular end-use applications (this can be used to prevent problems related to the use of conventional error metrics). Apply statistical measures to test the stability of the results.

V. CONCLUSION

Most methods discussed in this paper used real-world datasets of EV driving and charging patterns according to scheduling, clustering, and forecasting EV charging demands. These collections of data are practical, since they are based on real-world datasets. The use of real-world data avoids the need to make assumptions about the stochastic nature of the vehicle use and can minimize the uncertainties associated with a simulated charging demand.

The methods investigated in this manuscript have generated useful results in addressing the inherent challenges of applying the strategies of scheduling, clustering, and forecasting for EV charging. Considering the versatility of the methods investigated in this paper, potential enhancements can be obtained by integrating them for specific applications. According to the literature, artificial intelligence models have been the preferred approach for many researchers, as they perform better than other probabilistic models. Furthermore, new models, such as unsupervised machine learning models, offer promising supplementary improvements for EV control charging strategies.

This extensive review addresses the solutions, opportunities, prospects, and optimizations to minimize the impacts of EV charging on power system networks by applying numerous powerful methods. These methods are selected based on their suitability, practicability, and tractability. Extensive research is still needed to address customer privacy issues, as well as secure and reliable communication system cost management. Furthermore, control charging analyses based on DSM have not been presented in detail for remote area applications. These particular areas require further examination and should be studied in detail to achieve the optimal energy efficient operation of the power systems.

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