3. Recognition of Electric Vehicles Charging Patterns with Machine Learning Techniques

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3.1. Introduction

In recent years, to supply some parts of the required energy, reduce fossil fuel usage, and decrease CO2 emission, the utilization of Renewable Energy Sources (RESs) is highly attracted [1]. The presence of Distributed Energy Resources (DERs), including RESs and Electric Vehicles (EVs), has changed the planning and operation of power systems dramatically [2]. Traditional power systems have been transformed into modern ones by increasing the penetration of DERs. Modern smart grids are becoming more reliant on smaller and decentralized generations than the conventional power systems powered by a limited number of large and centralized generation units.

The most popular categorization of EVs included: hybrid EVs, plug-in EVs, and plug-in hybrid EVs. They are considered as the essential components of future smart grids because of environmental concerns, which led to the gradual disposal of conventional gas and diesel vehicles [3], [4]. In addition to environmental issues, due to the rising price of fossil fuels, EVs may also provide economic benefits to the users. Although the use of EVs has many advantages, increasing the number of these vehicles will be resulted in the energy demand increments and has become a new challenge for the grid operators to handle the electricity grid's balance.

Preserving the modern power grid's stability and resiliency requires proper coordination of RESs and EVs [5]. An uncontrolled EV charging pattern might wreak havoc on power distribution networks. There have been various studies on EVs' integration into smart grids. Generally, the researches around EVs and their impacts on energy systems are divided into three main domains:

- EVs charging behaviors;
- Allocation of the EV charging stations;
- Coordination of the integration of the EVs with RESs.

The scope of this chapter is to use the Machine Learning (ML) techniques to investigate and analyze EVs' charging behavior. Firstly, an unsupervised learning method, i.e., K-means, is utilized in order to cluster the charging patterns of the EVs. The primary contribution of this chapter is to consider items that have not been well addressed in prior work. The most popular items for investigating the EVs charging behaviors are: start time, stay duration, and energy demand. Other items which might have significant effects on the classification of the EVs are traffic patterns and weather that will be addressed in this chapter. Finally, a supervised learning method, i.e., K-NN, is utilized for further classification of the dataset of the EVs.

This chapter aims to provide readers with a better knowledge of EV charging habits. Hence, researchers who want to improve the planning of smart charging infrastructure and exploitation of smart charging technologies, can benefit from the results of this research. Figure 3.1 illustrated a graphical abstract that highlights various parts of this chapter.

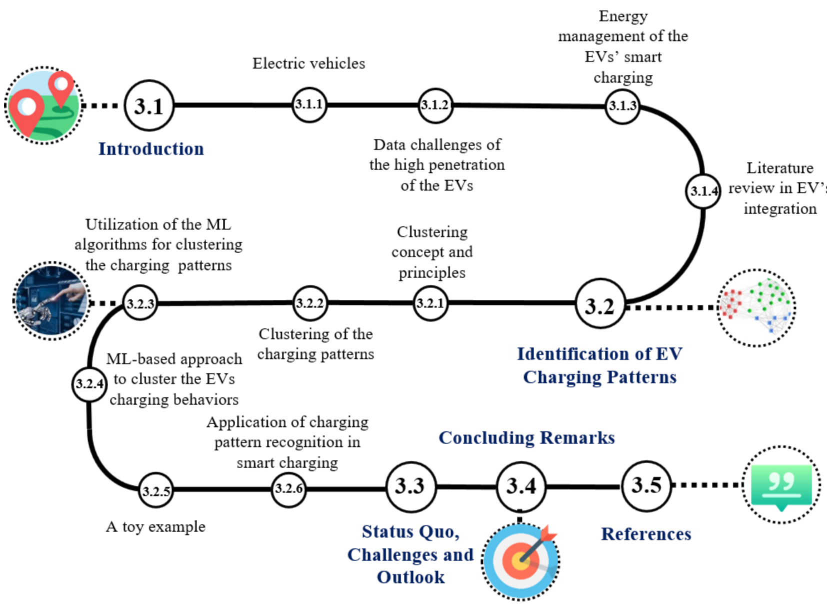

Fig. 3.1. Graphical abstract

3.1.1. Electric vehicles

Environmental issues, resource depletion, and energy dependence have given rise to changing the structure of transportation and replacing EVs [6]. Various estimations have been considered for the penetration level of EVs. As an instance, there are approximately 32 million EVs currently in the UK, and it's predicted that more than 112 million of them will be in 2050 [7].

Currently, there are different types of EVs around the world, considering the manufacturing technology. But, generally, they can be divided into five groups: Battery Electric Vehicles (BEVs), Plug-In Hybrid Electric Vehicles (PHEVs) [8], Hybrid Electric Vehicles (HEVs), Fuel Cell Electric Vehicles (FCEVs) [9], and Extended-range EVs (ER-EVs) [10].

3.1.1.1. Taxonomy of EVs

BEVs are powered entirely by electricity. Therefore, BEVs are referred to as full-electric vehicles. BEVs neither have an internal combustion engine nor use any liquid fuel. Instead, BEVs usually use large battery packs to provide the vehicle with enough propel. BEVs have much larger batteries and kilowatt-hour (kWh) outputs than comparable HEVs and PHEVs, because they rely solely on electricity. In addition, BEVs often cost more than other types of EVs due to different battery technologies. BEVs require a charge to be driven. This can be accomplished via a home charger or a fast-charging station or by recovering energy through regenerative braking [11].

Moreover, a conventional combustible engine, in collaboration with an electric engine powered by a pluggable external electric source, propel PHEVs. They are comparable to HEVs in this regard. PHEVs often contain larger battery packs and more powerful electric motors than HEVs, because their electric system conducts a lot of heavy lifting while driving. This means that PHEVs can be moved fully on electricity with the internal combustion engine turned off. Driving a PHEV is comparable to driving an HEV because the vehicle will automatically recharge the battery and depending on the conditions, switch between internal combustion and electric power. In contrast, PHEVs may be filled up with both fossil fuel and electricity. A PHEV can run solely on gasoline if all of the battery charge is used up. Vice versa, it can run exclusively on the battery charge if all of the fuel is used up [12]. As a result, PHEVs could be able to store sufficient power from the network to cut gasoline usage considerably under normal driving circumstances [13].

HEVs are propelled by a combination of an internal combustion engine and an electric motor which also reduces fuel consumption. Unlike PHEVs, HEVs are not grid-connected. Instead, the produced power from the vehicle's combustion engine and brakes are used to charge the electric motor's battery. HEVs are the most like classic internal combustion engine vehicles to drive because they can only be refueled with traditional fuels (usually petrol). Through regenerative braking, HEV technology charges the battery automatically [14]. When the conditions are right, it turns on the electric motor system, so drivers don't have to keep an eye on the charge or plug their cars into outlets.

On the flip side, FCEVs are similar to BEVs in that they solely utilize electricity to drive, but their energy storage is considerably different. FCEVs have an electric engine that runs on a mixture of compressed oxygen and hydrogen from the air. Unlike BEVs which store electrical energy from a charging station, FCEVs generate their electrical charge via a chemical reaction utilizing hydrogen. As a result, FCEVs can now be filled with hydrogen and do not need to be charged from the grid [15]. Because the only waste generated by this procedure is water, it can be considered environmentally friendly. However, most of the hydrogen used in this EV type is extracted from natural gas [10].

ER-EVs are very similar to the BEV category in terms of design. However, the ER-EVs also come with a backup combustion engine that can charge the vehicle's batteries if necessary. Unlike those embedded in PHEVs and HEVs, this type of engine is solely utilized for charging, and for this reason, it is not connected to the vehicle's wheels. An ER-EV has an auxiliary power unit (also known as a range extender) that extends the vehicle's range. The majority of range extenders are small internal combustion engines that power an electric generator, which provides power to the electric batteries and motor. When the ER-EV's small range extender motor runs, CO_2 is produced, but not when the ER-EV runs on electric power. As a result, an ER-EV will produce substantially less CO_2 over its lifetime than a vehicle powered by an internal combustion engine [16].

These types of EVs are illustrated in Figure 3.2.

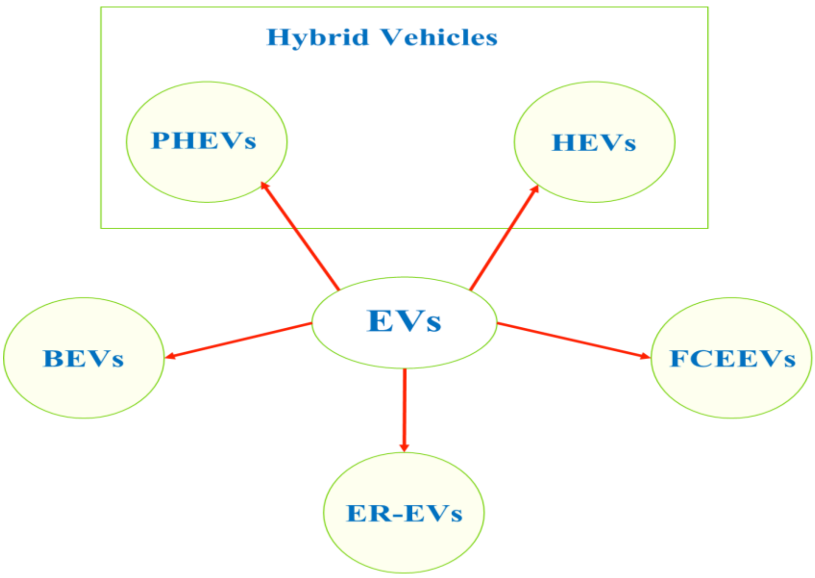

Fig. 3.2. Five types of EVs

3.1.1.2. EV integration's benefits

What all types of EVs have in common is that they are charged with electricity, and it is possible to use the stored energy for driving up to a certain distance. EVs' integration with the power grid has various benefits. It is believed that the large penetration of EVs may assist in minimizing greenhouse gases emission, and they can be regarded as the pioneers in offering a pure form of transportation [6]. Also, EVs can enhance the integration of RESs. Increased size (or capacity) of the Energy Storage System (ESS) is required for the large-scale integration of RES [8]. As a result, EVs may also be used as storage devices to overcome the problems of RESs [10].

What made EVs special is their ability to exchange electricity with the power grid in Vehicle-to-X operation modes, such as unidirectional control of Vehicles (V1G), Vehicle-to-Grid (V2G), Grid-to-Vehicle (G2V), Vehicle-to-Home (V2H), and Vehicle-to-Building (V2B). As we are currently heading toward EVs to reduce greenhouse gas emissions, these functions of EVs may also operate as a dynamic-natured ESS, delivering stored energy in their batteries back to the power network. Besides, because EVs spend so much time parked [17], they may be utilized as ESSs without causing drivers any difficulty.

Furthermore, EVs can be utilized to establish the balance between generation and consumption while preserving the stability and quality of the grid [18]. Also, EVs can offer several possible ancillary services to the grid, including frequency regulation, load leveling, spinning reserve, voltage regulation, and congestion reduction at transmission and distribution feeders [9], [19]. EVs can also improve energy efficiency [8] and engage in energy trading, providing an income stream for drivers and aggregators to offset the battery degradation caused by V2G participation [20].

3.1.1.3. Challenges and problems of EVs high penetration

Despite the aforementioned benefits from EVs, the high penetration of EVs also poses some problems for power system operators due to the high-power needs and caused negative impacts on the power grid. The electrical network will be strained as a result of the load generated by EV charging at different charging stations. This could bring negative impacts such as voltage deviation, transformer saturation, power loss, voltage regulation problems, and voltage fluctuation [21]–[23]. When the number of EVs grows, so does the overall load demand, while the voltage constantly decreases. Therefore, in the case of the high penetration of EVs, voltage boundaries are violated, affecting the power network security. Also, due to the existence of power electronic equipment, charging an EV can cause power quality difficulties, such as harmonics and voltage imbalance [24], [25]. For instance, voltage profile problems are more likely to occur in radial networks, especially if peak demand periods overlap with EV charging periods [8]. To address this problem, a high-quality filter is used to connect the charger to the power grid, preventing harmonics from affecting the grid as well as a motor connected to the vehicle [26].

Furthermore, un-coordinated EV charging behavior can result in extra deterioration and instability in power distribution networks [6]. When EVs are charged in large numbers simultaneously (dumb charging, uncoordinated charging), the demand for electricity rises, producing an imbalance in the power grid [27]. Besides, it is difficult to expand charging station capacity to meet the increasingly changing demands due to the implications of the power constraints.

Moreover, EVs' high penetration also causes challenges with the quality of distribution network, such as off-nominal frequency problems, network congestion, and three-phase voltage imbalance. Because EVs are single-phase mobile loads, they may be plugged into at any of the three phases of distribution networks at any time. It may result in a situation that one phase's electrical components, such as overhead line, power supply cable, or transformer, are severely loaded while the other phases are not. Unbalanced three-phase loads can result in various power quality problems, including transformer failures, equipment failure, and relay malfunction [19].

Two of the large-scale EVs integration major problems are grid overloading and load forecasting. Overloading the grid may lead to voltage control problems, voltage fluctuations, increased peak demand, decreased reliability and efficiency, and increased temperature of the lines. Large-scale EVs integration also has a significant impact on load forecasting. All of these difficulties impact the system's overall efficiency, which is incompatible with the development of EVs and EVs' charging stations [23]. In the electrical distribution system, load forecasting is critical for estimating how much electricity is generated by calculating peak demand and baseload. However, since introducing EVs and charging stations, the complexity of load forecasting has been increased because estimating the changing loads was a challenging problem [28]. Researchers suggested various solutions to overcome these types of problems. For instance, State of Charge (SoC) levels and Battery Management System (BMS) can be utilized using the Internet of Things (IoT), which could result in more accurate load forecasting [23].

EVs' charging time and traffic congestion management at charging stations are also among the EVs' high penetration problems. The majority of EVs require a long time to charge, which is inconvenient [29]. Because of the pressure on the grid and physical space restrictions, the straightforward approach of expanding charging stations to enhance charging capacity for overcoming the issue of longer charging time is ineffective [30]. As a result, scientists have concentrated on creating smart scheduling algorithms that employ modeling and optimization to control the demand for public charging [31], [32]. Energy management of EVs' charging significantly influences the wholesale power market, emphasizing the need to know charging behavior [33].

Another issue that has constantly challenged power system operators is the uncertainty in RESs and EVs. Charging operations for EVs are carried out in a highly distributed and dynamic context, with uncertainties arising from charging time, charging station availability, EV arrivals, and energy costs. Moreover, because EVs are very spatially and temporally unpredictable, it is challenging to manage EVs as new loads while preserving grid reliability and security [22], [30], [34], [35]. Based on the optimization procedure's objective, these uncertainties will impact decisions about when, where, and how much to charge an EV. Furthermore, there are additional uncertainties in power systems, including the electrical grid's status, the generation of RESs, network congestion, availability of charging station, and the quantity of EVs accessible to deliver V2G services [21].

A summary of the mentioned challenges and problems due to the high penetration of EVs is given in Table 3.1.

Table 3.1. EVs high penetration challenges

Challenges and Problems	Effects	References
The strain on the electrical network	Voltage deviation, transformer saturation, power loss, voltage regulation problems, and voltage fluctuation	[21]–[23]
Violation of voltage boundaries	Negatively affecting the power network security	[24], [25]
Voltage profile problems in radial networks	The affected grid, as well as the motor connected to the EV, cause harmonics	[8], [26]
Uncoordinated charging / dumb (non-smart) charging	Extra deterioration and instability in power distribution networks	[6], [27]
The strain on the power electronic equipment	Power quality difficulties such as harmonics and voltage imbalance	[24], [25]
Distribution network quality, such as network congestion, off-nominal frequency problems, and three-phase voltage imbalance	One phase electrical components, such as overhead line, power supply cable, or transformer, are severely loaded while other phases are not. Unbalanced three-phase loads can result in various power quality problems, including transformer failures, equipment failure, and relay malfunction	[19]
Grid overloading	Voltage control problems, increased peak demand, decreased reliability and efficiency, and increased temperature of the lines	[23]

Table 3.1. EVs high penetration challenges (*continued*)

Challenges and Problems	Effects	References
Load forecasting	Load forecasting has grown more complex because calculating changing loads was a challenging problem	[23], [28]
Prolonged EVs' charging time and difficulties in traffic congestion management at charging stations	Because of the pressure on the grid and physical space restrictions, the straightforward approach of expanding charging stations to enhance charging capacity for overcoming the issue of longer charging time is ineffective. This problem also has some negative effects on the wholesale power market	[29]–[33]
Uncertainties, including the electrical grid's status, the generation of RESs, availability of charging station, EV arrivals, energy costs, network congestion, and the quantity of EVs accessible to deliver V2G services	These uncertainties will impact decisions about when, where, and how much to charge an EV. Also, it is challenging to manage EVs as new loads while preserving grid reliability and security	[21], [22], [30], [34], [35]

So far, data challenges have not been addressed, which is one of the most important challenges of the high penetration of EVs. Due to the high importance of this matter, data challenges caused by the large-scale usage of EVs, as well as the solutions to deal with these problems, will be presented in the following.

3.1.2. Data challenges of the high penetration of the EVs

The big data problem is defined by the massive volume of data created by devices, EVs, buildings, the power grid, and many other connected objects and increasing data transmission speeds [36]. Smart grid and EVs, among many other sectors linked with the IoT, face this problem since they are both producers and consumers (i.e., prosumers) of extensive data. Moreover, travel records and information obtained through sensors embedded in vehicles are among the data generated by EVs. Users' driving behaviors, battery charge rates, acceleration, location, tire pressure, battery security data via a BMS, and grid charge management data via charging stations are all examples of data that EVs create and store continually. Smart gadgets and wearables are also carried by drivers, which add to the data collected on the road [37].

Also, some parts of EV data are from a variety of sources, including batteries and onboard chargers. Onboard electronic control units and BMS provide the majority of EV data. Most charging/discharging decisions are based on the SoC of EV batteries. SoC data and how an EV battery is functioning are displayed in BMS logs [36]. In addition to the data directly collected from EVs, drivers can also voluntarily contribute to collecting driving patterns and charging habits information. Furthermore, trip information, including start and end times of journeys, charger connect and detach times, and battery SoC may be readily gathered.

Various types of data have been employed, such as road traffic density, distribution of charging stations, and EV ownership. However, as cities get smarter such data will grow in bulk, and mining them alongside EV data will provide further challenges for smart grids. Generally, EV data can be classified as shown in Figure 3.3.

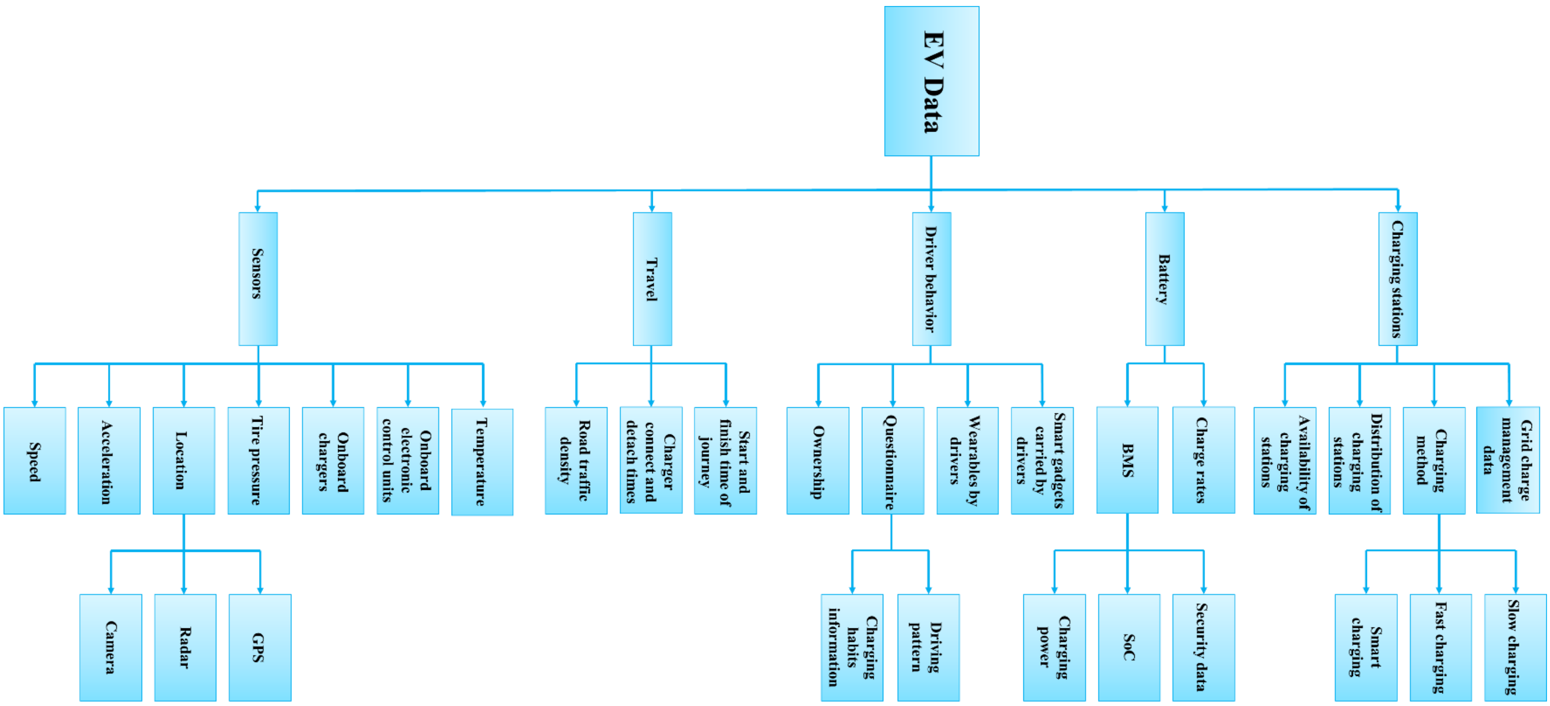

Fig. 3.3. EV data

However, there is no consensus on how much data a connected EV might create daily; some estimates put the maximum limit at 32 terabytes [38]. Millions of EVs expected to be on the road over the next decade will lead to the generation of a massive amount of data, which is challenging to be handled. Because the data acquired from EVs is diverse and large in volume, standard statistical methods for building a model (to study and analyze the EV problems) may not be effective.

Data science should be widely employed today to address a variety of EV-related issues. EVs' data is produced from multiple mentioned sources, including EV charging stations, vehicles, and road sensors. Moreover, the industry is increasingly providing private data to researchers, paving the way for developing high-quality data-driven research. Therefore, on the one hand, data-driven approaches to EV analysis are required. On the other hand, various new research issues cannot be solved using existing techniques. Management of Smart charging stations, which includes expanding, suspending, and reallocating charging stations, is an example of these issues [39].

In this section, several EV-related big data challenges were mentioned. Once these challenges are overcome using data analysis techniques and data-driven methods, there is a chance to go toward more intelligent approaches such as smart charging to handle large-scale integration of EVs. Addressing energy efficiency issues, developing policies for allocating charging stations, assessing the capability of power distribution networks to manage increased charging loads, and estimating the market value for the services offered by EVs (i.e., V2G opportunities) are among other advantages of this phenomenon [36].

3.1.3. Energy management of the EVs' smart charging

It's important to figure out when the EV should be charged and when it should be utilized as energy storage during peak load times to offload the energy grid. It's also crucial to managing the EV battery to meet the demands of both the driver and the energy grid [8], [39]. There are two main strategies in this regard: 1) Dumb (non-smart) Charging; 2) Smart Charging [8], [40], [41].

EVs start charging as soon as they are connected to the charging station in the dumb charging scenario. The time it takes to connect does not have a fixed value; instead, it is determined by the normal distribution of return following transportations [8].

The smart charging scenario is about automatically managed charging, necessitates installing intelligent vehicle controllers that also control the EVs' charging. This is set in conjunction with smart controllers placed on the load and production units. Charging pursues the load demand curve, and in the following, EVs are charged during off-peak hours. Thus, EV charging rates increase as grid demand decreases. To put it another way, this is a case concerning valley filling.

In other words, smart charging refers to adjusting the charging cycle of EVs to the power system's circumstances, as well as the demands of EV drivers. This makes it easier to integrate EVs while fulfilling mobility requirements. As a result, smart charging is a method for optimizing the charging process depending on the local RES availability, the constraints of the distribution grid, and users' priorities [42].

Smart charging stations should determine the quantity of energy provided to each plug-in EV during each period, as restricted by the power distribution networks and energy storage systems. Thus, energy management is essential for coordinating EV transit and charging at central smart charging points. In order to deliver high-quality services and maintain the power grid's stability simultaneously, energy consumption for each journey, the timing of each charge, and the capacity of each charging station should be addressed [22]. Furthermore, smart charging facilities should be able to cooperate with the intermittent behavior of the RESs, including solar panels or wind turbines, which might cause uncertainties and problems to smart charging scheduling.

3.1.3.1. Concepts and applications

Smart charging is commonly considered in the smart grid environment and offers a degree of control over the process of charging [43]. Smart charging generates charging schedules for each EV, with the goal of effectively and equitably allocating charging capabilities across a number of EVs. However, practically EV charging methods use charging profiles like constant voltage and/or current [44]. Therefore, to prevent gaps between charging plans and actual EV power usage, smart charging should take charging profiles into account. Besides, smart charging includes different pricing and technical charging options. Also, at a larger penetration level and for the delivery of ancillary services, as well as real-time balancing, more advanced smart charging techniques (i.e., direct control techniques) would be required as a long-term solution [45].

Moreover, charging point operators, EV drivers, and the other components of the EV market behave independently of the electricity market in the non-smart charging strategies. Against dumb charging, smart charging requires strong coordination between the electricity market and electric mobility to satisfy EVs' integration requirements in the power grid while maintaining its flexibility. To put it another way, smart charging is the process of charging an EV managed by two-way communications among multiple actors to optimize grid management, customer needs, and energy generations, such as RESs with concerning limitations, costs of the system, security, and reliability.

There are a variety of smart charging mechanisms. Some of the most important forms are as follows [19], [42]:

1- Unidirectional control of vehicles (V1G): Allows to increase or decrease the charging rate. In this mechanism, vehicles or charging infrastructure alter their charging speed;

2- Bidirectional vehicle-to-grid (V2G): Permits the EV to deliver services to the grid in the discharging mode. In fact, in this case, the smart grid manages EV charging while it is possible to return power to the grid.
3- Vehicle-to-Building (V2B) and Vehicle-to-Home (V2H): They are additional types of two-way charging in which EVs are utilized as a residential backup power generation during electricity outages. In addition, in this method, EVs can also be used to increase the self-consumption of energy produced on-site. In other words, vehicles will serve as backup power sources for homes or buildings in this scenario.

However, among the various forms of smart charging, the V2G method is the most welcomed and used [19], [23], [41], [42], [46]–[48]. Smart charging enabled by the V2G method controls EV loads. It involves consumer reaction to pricing signals, as well as automatic responses to control signals reacting to network/market circumstances, or the combination of them. This could be done while taking into account the customer's desire for EV availability. However, it entails delaying certain charging cycles or regulating power in response to certain restrictions, such as connection capacity, user demands, and real-time local energy generation.

Furthermore, smart charging of EVs has many advantages and applications, such as network congestion management, minimizing grid infrastructure investments, ancillary service provision, and peak shaving. It also reduces the impact of EVs' load, allowing more solar and wind power to be used for providing flexibility.

Moreover, EVs could modify their charging patterns using smart charging to fill load valleys, reduce peak load, and assist the real-time grid's balancing by changing their charge levels. Using EVs as a flexible resource through smart charging techniques could minimize the demand for carbon-intensive fossil fuel power plants to balance renewables [49]. Besides, the prolonged charging time challenge can be solved using a smart charging approach in which the smart grid collects real-time data about loads at different charging stations and passes it on to each EV. Thus, it makes it possible for EVs to develop charging strategies (i.e., the optimum charging station along the route to the destination) [31], [50].

In addition, existing parking lots are being transformed into smart charging parking lots with internet access for slot booking and traffic information at parking locations [51]. In fact, smart charging may be used to quickly pre-book charging station spaces and monitor the status of available slots. This method makes load forecasting more efficient and would ease the communication with the RESs, whether at home, at the workplace, in a parking lot, at a shopping center, or a charging station [52]. Besides, distribution system operators (DSOs) may profit from the smart charging of EVs in a variety of ways. For instance, it can assist in managing capacity constraints via demand response or serve as a balancing resource to accommodate DERs within a distribution system [53]. Smart charging also decreases the costs of strengthening local power networks and diminishes the load peaks.

On top of those, reducing RES curtailment, enhancing RESs integration (in system operation and long-term expansion planning), improving local utilization of RESs, cutting peak loads, avoiding high investments due to the peak demands, and mitigating grid reinforcement needs are among other applications of EVs' smart charging.

A framework for designing a smart charging system for integrating the EV-RES system into the grid is illustrated in Figure 3.4 [19].

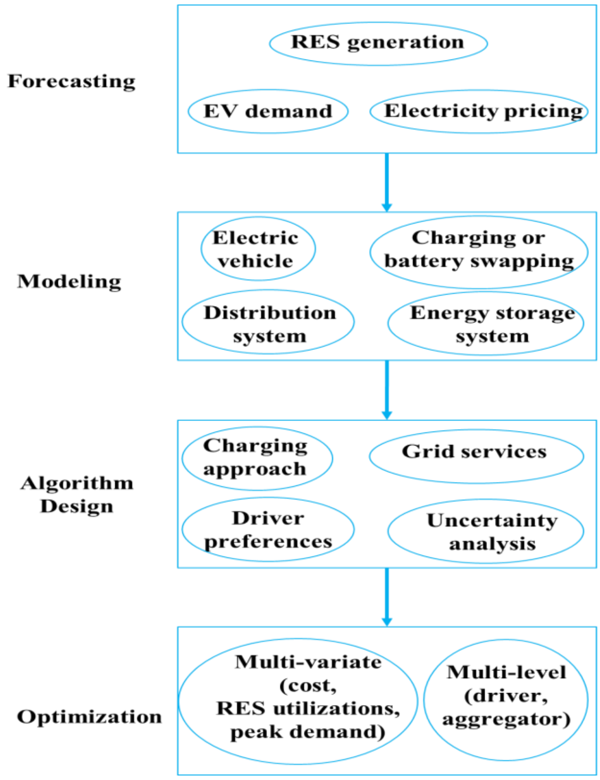

Fig. 3.4. A framework for a smart charging system [19]

3.1.3.2. Challenges and opportunities

To allow the implementation of energy management of EVs' smart charging, intelligent sharing of information, standardized communication protocols, information of connected EVs and charging stations utilizing smart meters and intelligent infrastructures are required. Some of the key factors to enable the deployment of smart charging are as follows [45]:

1- *Charging infrastructure:* Charging infrastructure development necessitates large expenditures. Since there are currently few economic models for private investment at the moment, governments should catalyze the installation of charging stations either in private or public areas. Furthermore, a key challenge is figuring out how to effectively charge, collect, and aggregate the EV load on the grid. This would influence critical choices in the developing charging infrastructures, such as the location of charging stations, which technology to employ, and how to mix slow smart chargers with fast smart chargers in order to satisfy consumers' urgent requirements.
2- *Definition of stakeholders' function and responsibilities:* A utility, energy supplier, e-mobility organization, or even a firm specializing in demand response services may regulate charging a fleet of EVs to unlock the potential of V2G use cases and smart charging plans.
3- *Regulation design of EV's integration with grid:* Smart charging and V2G technologies will not be fully implemented without the right incentives in the form of dynamic price signals, and without the possibility to stack money from different revenue streams, respectively. This requires the existence of well-functioning energy markets. However, competitive wholesale markets, retail markets, and emerging EV markets are not always in place. Even if such markets exist, their structure needs to be evolved, and regulations should be modified to enhance the motivation for the evaluation of services provided by EVs.
4- *Communication protocol:* Communication protocols should be established to optimize the system and allow information sharing across all participants.
5- *Artificial intelligence and big data methods:* Artificial intelligence (AI) and big data advancements could help smart charging systems provide better services. Smart charging capabilities would be enhanced by ICT developments, such as data management and analytics from drivers, charging habits, and charging stations. Besides, data analytics and digital technologies will make it feasible to fix mobile demand and power supply patterns as closely as possible, and determine the best sites for charging stations.

The introduction of big data analytics and ML has had significant impacts on current scientific problems. For example, it has transformed natural language processing, picture, audio, and video recognition. In particular, it can be seen that the focus has been changed to use data-driven techniques to tackle the EV smart charging challenge. Algorithms of ML could be trained and learned trends and patterns through previous data of charging load and user behavior [6], [54]. ML-based scheduling, forecasting, and clustering strategies are widely deployed to handle high EV penetration and enhance smart charging deployment. These solutions are primarily designed to reduce the impact of EV charging on electricity distribution.

The goal of the EV charging schedule is to keep the electricity network stable by ensuring that the power generation and energy consumption of electricity are balanced. In addition, scheduling EVs' charging is a practical approach to shift the demand, reduce extra-generation problems, and diminish peak challenges [55].

When it comes to forecasting techniques, network stability and fault prevention are highly dependent on daily demand forecasts. As a result, the accuracy of the EV charging forecast is critical for utility and decision-makers. Moreover, implementing an exact forecasting model would support the development of EV charging, improve prediction precision for optimal dispatching, and motivate manufacturers to promote EV usage.

Furthermore, to identify the most frequent load patterns, clustering methods were applied to EV smart charging. In a multivariate dataset gathered from the field, the clustering of EV charging is employed to find clusters of identical charging items. Important patterns linked with distinct forms of demand over the course of a year, month, or week could be recognized by clustering these statistics across that interval [56].

3.1.4. Literature review on EV integration

There have been various studies on EVs' integration into smart grids. Generally, the researches around EVs and their impacts on energy systems could be divided into three main domains:

- EVs charging behaviors;
- Allocation of the EV charging stations;
- Coordination of the integration of the EVs with RESs.

In this context, EVs penetration in California was modeled using the regulated and optimized charging options [57]. Based on this study, the authors concluded that in smart charging mode, EVs charging is managed that has resulted in just a 1.3% increase in peak demand, compared to an 11% increase in an uncontrolled charging manner. Similarly, researchers in [58] claimed that switching from uncontrolled charging mode to schedule charging mode could decrease the peak load increment from 19% to 0-6% when EVs integrate into the grid. They also suggested that charging can avoid increasing peak demand if it would happen only at off-peak hours.

Moreover, according to [59], if DSOs do not recognize shortages in their grids, the grid infrastructures may limit the high penetration of EVs in residential and private regions. Thus, they should integrate smart charging, taking into account not just time limits but also location constraints. Besides, the impact of local EV penetration on peak load of the German power grid in the presence and absence of smart charging is investigated in [60]. Results showed that with utilizing time-of-use tariffs and the V1G method, the peak demand could diminish by 16%.

A summary of the current existing standards for grid integration, EV charging, and safety is discussed in [61]. Besides, the EV charging infrastructures, such as the power, control, and communication infrastructure, are presented, and the effects of EV integration on different aspects of power systems are also examined. In addition, the authors of [62] investigated the EV integration with power systems based on their relevance to different players in the electricity market, including DSOs, generation companies, EV aggregators, and drivers using classification and scheduling methods. [63] have presented the Distributed Resource Allocation (DRA) strategy for EV integration into the power grid based on the concept of output agreement. It also recommended an appropriate charging method for each grid-connected EV to meet grid objectives and EV drivers' economic and social interests.

Furthermore, V2G's idea, structure, benefits, difficulties, and optimization techniques are discussed in [64]. In addition, the authors examined the advantages, services, and potential hurdles of using V2G technology, as well as different V2G optimization approaches and new insights into V2G technology possibilities. Ref. [65] investigated the interactions among charging, on-road power management, and battery-degradation mitigation of EVs to overcome the energy management challenges of EVs in a smart-grid environment. Besides, [66] investigates how EVs might help smart cities to establish sustainable energy as a service business model. According to this research, EVs are valuable assets for a sustainable energy future since EV batteries provide the potential to store electricity generated from RESs.

In addition to such researches, many practical projects for integrating EVs with the power grid are being carried out worldwide. For instance, San Diego Gas & Electric (SDG&E) has started an EV-grid integration pilot project that aims to improve grid stability by making fleets of EVs available as dispatchable DERs [67]. The company used an app to match customers' preferences with dynamic pricing.

Nuvve[1] is another V2G technology pioneer. Since 2009, Nuvve has provided a wide range of power system services, such as frequency and supply reserve capacity, in several energy markets in Pennsylvania, Jersey, and Maryland in the United States [68]. Customers just have to give information about their SoC status and whether or not they utilize EV. This is the program that determines whether power should be returned to the grid or another service should be provided. Besides,

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[1] Nuvve is a publicly-traded company accelerating transportation electrification through its proprietary V2G technology and offering charging and grid services.

Nuvve recently has announced plans to deploy 1500 smart chargers with V2G capabilities in the United Kingdom. Moreover, this company, along with the other EV-grid integration pioneers including, Enel[2], Insero[3], Nissan[4], and Mitsubishi[5], took part in the Danish parker project aiming to use smart charging technology and depend on the collaboration among the power and automotive industries to shows the EVs' capability for supporting power systems based on the RESs [69]. The project demonstrates that V2G can play a major role in boosting vehicle income and providing grid flexibility. However, there are still some practical issues to be overcome, such as uncertainty regarding battery deterioration, communication standards, and consumer awareness of the V2G system.

3.2. Identification of EV Charging Patterns

To build a powerful model for analyzing the utilization of EV smart chargers, it's essential to study EV owners' charging behavior to validate the underlying dataset and understand regularities and patterns in the dataset [70]. EVs may adopt different charging patterns than others in order to overcome obstacles in using the charging infrastructure, such as long charging periods. Therefore, understanding what elements contribute to this charging behavior can aid in the development of methods to promote a more efficient charging system [71].

Moreover, the preferred charging patterns of customers should be considered when predicting the implications of new demand on the grid constraint. By examining consumers' preferred charging times, it is feasible to estimate how the extra electricity consumption will be distributed all over the day. Furthermore, by monitoring consumer preferences, it is possible to determine the electricity consumption on each EV charging station at a specific time of day. As a result, analyzing the charging patterns of EVs is critical for precisely calculating the additional grid constraint posed by EVs and establishing a roadmap for future energy regulations [72].

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[2] Enel (Ente Nazionale per L'energia Elettrica) is an Italian multinational manufacturer and distributor of electricity and gas.

[3] Insero is a company that wants to create sustainable growth and development within the energy, information technology, and EVs in Denmark's local area.

[4] The Nissan Motor Company is a Japanese multinational automobile manufacturer headquartered in Nishi-ku, Yokohama, Japan.

[5] Mitsubishi Motors Corporation is a Japanese multinational automotive manufacturer headquartered in Minato, Tokyo, Japan.

Besides, it is critical to understand consumers' different EV charging patterns to provide sufficient EVs infrastructures. In other words, consumers' electricity consumption patterns have an impact on peak electricity demand, which is a key factor in determining the amount of power capacity required. Exploring EV charging patterns is essential not just for policymakers and suppliers but also for EV manufacturers because these charging infrastructures are a surefire way to attract new EV purchasers [73].

EV charging patterns could be quantified based on daily driving patterns and individual activity schedules [74]. In other words, a charging pattern is a representation of a customer's preferred charging time, location, and EV charging station type. Customers' charging patterns contain information including the average daily trip, types of destinations, driving motives, preferred charging times of a day, and charging stations. Charging patterns analysis included recognizing electricity consumption by the time of a day and investigating the desire to utilize public and residential EV charging stations [73].

In addition, different charging patterns, including single charge, multi-charge, and deferrable or partial charge with configurable energy demands, will add uncertainty to EV charging schedules while also providing flexibility [22]. Many factors influence EV charging behaviors, including travel patterns, energy usage, and charging infrastructure facilities. The EV usage behaviors and seasonal fluctuations have a significant impact on the charging frequency [75].

Vehicles will have multiple options for recharging during the day, taking into account the mobility pattern of each EV [32]. The time and location of charging for EVs depend on the EV type, its SoC, geographical area, and the availability of the charging station. Individual EVs have predictable charging patterns. However, depending on the business models, charging patterns of shared and commercial cars (for instance, taxi and other vehicle fleets) may be less predictable. Also, electric bus charging patterns are dependent on the charging station location.

Furthermore, new functionalities such as remote maintenance and management of charging stations will be enabled through data analytics and data management of charging patterns [45]. The distribution network operator could utilize the EV charging pattern as a guideline when developing future networks. In addition, charging patterns could also be utilized in load aggregation, clustering, forecasting, and direct load control strategies [74].

Two methods of EV charging pattern recognition are charging load prediction and charging pattern identification. Predictive and descriptive analytics are the terms used in data mining to describe these two types of analytics. In addition, many studies focus on consumer classification and clustering in order to improve usage predictions and demand balancing. Data mining algorithms like K-means clustering, self-organizing maps, and neural networks are commonly used in this case [76].

3.2.1. Clustering concept and principles

Clustering is a technique for grouping unlabeled data into clusters based on similarities between observations. The precision of this procedure is determined by the data characteristics (e.g., similarities between instances in the clustering technique). In other words, the higher the similarity, the more accurate the statistical procedure [77].

3.2.1.1. Concept of the clustering

Clustering is one of the most common unsupervised learning methods. One of its goals is to reduce supervised learning's preprocessing noise. Clustering is the division of a collection of observations into clusters, each comprising items similar to one another but dissimilar to those in other clusters. In fact, clustering is the accumulation of data into groups of similar patterns [78]–[80].

Clustering is a basic method to perform supervised learning such as linear regression for each divided model resulting from unsupervised learning methods such as k-means. The K-means algorithm has been frequently employed because of its easy algorithmic design, quick clustering speed, and good clustering result [81]. In addition, clustering algorithms are used for various applications, including the prediction by regression and improving the efficiency of recommender systems [77].

3.2.1.2. Principles of the clustering

In data mining, clustering analysis is a critical analytical algorithm. By using static classification, clustering divides similar objects into different groups or subsets, ensuring that the member objects in the same cluster have identical attributes [81], [82]. Cluster analysis of data also enables the detection of patterns and the reduction of data dimensionality [79].

Moreover, clustering analysis is a representative unsupervised learning method that classifies n items based on various predictor values observed for each object into clusters with similar characteristics and evaluates the links between clusters by finding the cluster features [83].

3.2.2. Clustering of the charging patterns

Clustering- as an unsupervised strategy- has been widely used for assessing load profiles to identify EVs with similar consumption patterns [84], [85]. Clustering algorithms have been applied to EV charging in order to identify the most prevalent and recurrent load profiles. The EV charging clustering approach finds groups of similar charging items in a multivariate dataset obtained from the field. The load profiles can be examined based on EV charging data to acquire a better understanding of the EV charging performance and energy demand patterns as well as to clarify the potential energy flexibility. It can assist grid operators in managing demand for electricity. The EV charging load curves are analyzed using the clustering approach. Clustering the charging patterns could be referred to as an unsupervised technic of data mining strategy that groups linked daily load profiles into separate groups. Clustering algorithms could also be utilized to develop load profiles that categorize EV charging behaviors into groups based on their commonalities [56].

Clustering algorithms are frequently employed to model energy usage because of two main reasons. Firstly, clustering is frequently utilized to analyze data and increase the prediction accuracy of energy models. Secondly, stable clusters can be utilized to organize, target, and interpret observed subjects if they are reproducible with respect to non-essential changes. However, clustering approaches are well recognized to be extremely sensitive to the algorithms and variables used. This can lead to erroneous assessments of predictive accuracy and misinterpretation of clusters in policymaking [86].

The goal of EV clustering is to find discrete clusters that capture some aspect of EVs' uniqueness [84]. By dividing the dataset into subgroups, the clustering process uncovers previously discovered dataset patterns [87]. For example, the daily EV charging demand analysis reveals the most common load profiles using clustering algorithms to put related profiles into the same subgroups [88]. The required dataset collection for EV clustering is usually operated with temporal and spatial datasets, or a combination of them. The resolution of the generated typical load profile is directly affected by the temporal resolution of the data points [56].

In the literature on energy consumption, clustering approaches have been used extensively. For example, clustering has been used by various researchers to extract similar groups from large datasets. Examples include looking for groups of energy consumers with the same load or generation profiles, and buildings [86]. Important patterns related to distinct forms of consumption can be differentiated by clustering the datasets across the year, month, or week [56]. In the case of EV charging patterns, finding patterns allows a better understanding and visualization of fleet utilization. Furthermore, the prediction problem's computation will be simplified if a set of common profiles is discovered. Thus, rather than estimating individual requirements, the number of vehicles in each cluster should be predicted [79].

Figure 3.5 depicts clustering in the context of EV charging patterns. Only two input features are used to group the objects in this simple example. We can observe four distinct charging behavior clusters based on the entrance time to the station and weekdays.

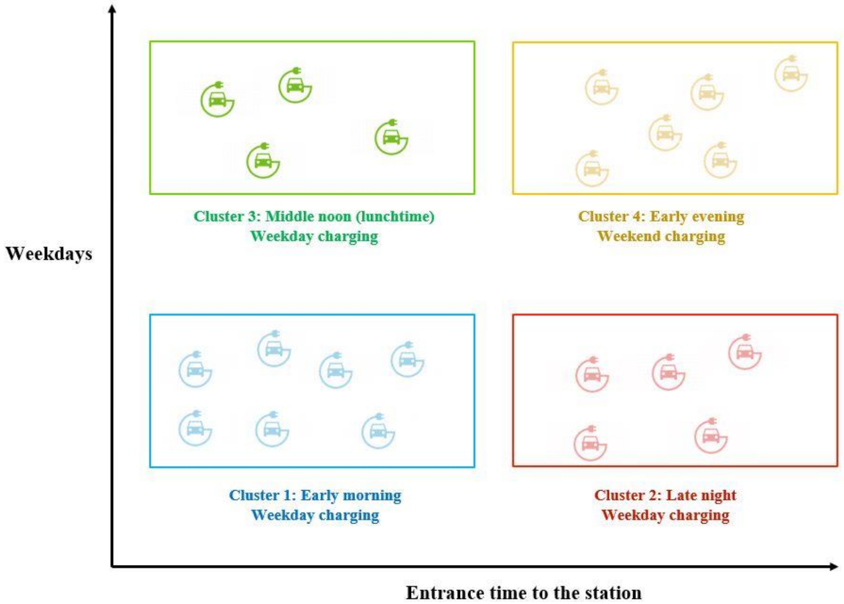

Fig. 3.5. Example of EV charging patterns clustering

There are numerous advantages to clustering EV charging patterns. For example, the clustering approach seeks to explain the consequences of EV adoption on power system quality. These solutions offer a quick and efficient solution to the problem of charging station allocation. They also reduce overall operating costs by assigning the charging station to a selected charging demand cluster. However, some research gaps still exist regarding the clustering of EV charging patterns which may lead to potential risks for power system operators. For instance, the security and reliability aspects of clustering have not been addressed appropriately. In addition, according to the clustering research, various clusters can disclose different load profiles, therefore using the same clustering model to all of them may not be the best method [6].

3.2.3. Utilization of ML algorithms for clustering the charging patterns

Since the introduction of big data analytics and ML techniques, the focus has moved to use data-driven methods to overcome EV charging problems. An ML solution has three main advantages, including speed, generalizability, and scalability [89]. ML algorithms could be trained and learned trends and patterns using the historical data of the charging stations, as well as users' behavioral data.

AI and ML methods could be used to cluster and classify driver actions and forecast EV charging behavior [81]. ML allows computer systems to learn from their experiences without the requirement for explicit programming. ML algorithms utilize various datasets for training themselves. The models learn to recognize the dataset's trends and patterns over time. The models can produce accurate predictions and so provide predictive analytics after successful learning.

ML algorithms can be classified into the following categories based on the types of variables to be predicted (the response variable). On one hand, if the response variable is continuous, the problem would be a regression problem. On the other hand, the problem is considered as a classification problem if the response variable is categorical [6]. ML algorithms are also divided into two main categories based on their applications: Unsupervised learning and Supervised learning.

3.2.3.1. Unsupervised learning

The training dataset for unsupervised learning, solely consists of inputs, with no labeled outputs. Labeling the data is considered a time-consuming and expensive process in many practical applications. The purpose of ML models is to discover structures or patterns in the data. Cluster analysis is an instance of unsupervised learning in which the ML model seeks out the groups of objects that share some common characteristics. To identify the clusters of EV behavioral patterns, unsupervised learning can be used.

For instance, K-means clustering, Kernel Density Estimation (KDE), and Gaussian mixture model (GMM) are widely used in EV charging clustering as unsupervised learning methods. These methods are briefly introduced in the following:

- K-means clustering: Individual data points create k clusters in K-means clustering. First, each point is assigned to one of the k center points at random. Following that, using updated center calculations, the data points are transferred to the nearest center. It is necessary to know how many clusters there are; otherwise, a method should be employed for calculating it (such as the elbow approach as one of the best methods). The K-means clustering algorithm is simple, but it is sensitive to outliers and starting assignments [90]. Nevertheless, the K-means algorithm is one of the most widely used clustering techniques.

- Kernel Density Estimation: In parametric estimation approaches, the form of the probability density function (PDF) should be supposed. When this is not achievable, a continuous random variable's PDF could be estimated by Kernel functions utilizing nonparametric estimation. Kernel functions should have a value of one for the region under the curve of the function. They also should be nonnegative and symmetrical. For example, Diffusion-based KDE and Gaussian KDE are two popular kernels for KDE [91].
- Gaussian mixture model: The GMM could be considered as a probabilistic learning model which considers several normal distributions in the dataset to represent normally distributed sub-populations. Although GMMs are primarily employed for unsupervised learning, supervised learning versions are also available. Prior knowledge of the sub-populations is not necessary for an unsupervised model.

3.2.3.2. Supervised learning

Labeled training datasets could train ML models in supervised learning. The input variables and the response variables are included in the dataset. The model repetitively learns the connection among the input and response variables using the optimization of a specified objective function.

A dataset comprising the vehicle's entrance time, name of the city, and vehicle's leaving time might be an example of supervised learning regarding EV charging patterns. The ML model would learn the association among the entrance time and name of the city as the inputs and the leaving time as the response variable, if the aim is to forecast the leaving time. The scope of this chapter does not contain a thorough examination of all supervised learning methods. However, some of the most commonly utilized algorithms for predicting EV behaviors are [6]:

- Support Vector Machine (SVM): SVM is primarily utilized to solve classification issues. However, it may also be utilized for regression problems. In that scenario, the technique is known as support vector regression. The optimum hyperplane that maximizes the margin between the various categories is used by the SVM to separate the classes. The inputs could be mapped to high-dimensional feature spaces[6] that could be linearly separable using Kernels including polynomial, linear, and radial basis functions [92]. However, the lengthy training period is one of the SVM's major drawbacks. As a result, the SVM may be unsuitable for larger datasets.

- Decision Tree (DT): Both classification and regression problems can be solved with a DT. DTs use split points from the input features to break down difficult decisions into a series of more straightforward decisions. A decision node is a location where decisions are made. The leaf nodes are the sites where no additional splitting takes place. The average value of entire the components in the leaf node is used to predict regression problems. The set of projected classes is known as the leaf nodes in classification problems [93].
- K-Nearest Neighbor (K-NN): Although K-NN may be utilized for regression and classification, but it is best known for classification. The K-NN does not require a separate training time. It is also known as a type of lazy learning method. A distance metric, commonly Euclidean distance, is utilized to discover the *k* closest neighbors of a new data point. Then it is given to the class with the greatest number of neighbors [94].

3.2.4. ML-based approach to cluster the EVs charging behaviors

One possible approach for easing the stress of EV charging on the power grid is to predict EV charging behavior. EV consumers can be categorized into regular and irregular users. Regular users' charging patterns are predictable, whereas irregular users' charging patterns are unpredictable. As a result, it is helpful to model normal users' charging behavior, while irregular users' charging behavior will increase the prediction error.

Initially, the behavior of the EVs is clustered to examine the EVs' charging behavior. The following considerations mainly considered while choosing variables as the basis for EV behavior clustering:

1- EVs have the most impact on the grid considering charging start time, charging end time, and charging demand.
2- The charging time is roughly proportional to the amount of charge.
3- Some users charge predictably, while others do not.

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[6] High-dimensional spaces are used to model datasets with a large number of properties. A dataset can be represented directly in a space spanned by its features. Each record is represented as a point in space, and its location determined by the values of its attributes [95].

4- Weather affects road traffic congestion, and eventually, both of them influence the driving behavior of EV owners.
5- Weather will also affect the EVs' energy consumptions and thus their charging demands.

In this work, K-Means clustering and K-NN algorithms are utilized to categorize the EVs charging behavior. The procedures for the clustering and classification of the EV charging patterns are shown in Figure 3.6.

Fig. 3.6. Procedures for the clustering and classification of the EV charging patterns

3.2.4.1. Pre-Processing

Data should be preprocessed before being clustered. The low-quality data in the raw data collection could be inspected and eliminated. For example, users with fewer than three records are deleted since they are unhelpful in determining behavior patterns. Weather data are also mapped to the proper time of charging events.

A linear normalization approach is used to normalize data, as illustrated in (3.1).

$$X^{*} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3.1}$$

3.2.4.2. EV's charging behavior clustering using K-means algorithm

K-means is considered an unsupervised learning technique, meaning there are no labels on the data to be processed. It separates data points into k clusters, where each object belonging to the cluster corresponds to its nearest mean. The 'means' is the representation of the mean of the data objects in the cluster, and 'k' specifies the number of clusters. The algorithm assigns each point to the cluster corresponding to its nearest mean (the cluster center) and utilizes it as the clustering standard. This algorithm analyzes the historical charging data and generates assumptions of EV behavior for EV charging schedules.

The distance between vectors can be calculated using a variety of approaches. The most common method of measuring distance in the K-means algorithm is Euclidean distance, as formulated in (3.2).

$$dict(x_i, y_i) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3.2}$$

where, x_i and y_i are two points in an n-dimensional Euclidean space. Here, the mean and standard deviation of entrance and leaving times, the Pearson correlation coefficient between staying time and EV charging demand, and the Pearson correlation coefficient between weather attribute values and EV charging demand are used as the clustering criteria.

The initial cluster centers of the K-means method are randomly chosen from a pool of n data objects. The distances between the objects and cluster centers are then determined, and the associated objects are re-divided according to the minimum distances. In the end, each cluster's mean is recalculated to become a new cluster center. The cluster center for the k^{th} iteration is updated as follows:

$$Center_k = \frac{1}{|C_k|}\sum_{x_i \in C_k} x_i \tag{3.3}$$

where $|C_k|$ denotes the number of data points in the k^{th} cluster, and center k denotes a vector with D characteristics, as shown below:

$$Center_k = (Center_{k,1},\ Center_{k,2}, ..., Center_{k,D}) \tag{3.4}$$

Furthermore, to redistribute the clusters and update the cluster centers, the K-means algorithm requires constant iteration. The group centroid locations are changed when all user group tags are updated based on the EVs who belong to, as demonstrated in the following equation:

$$\mu_j = \frac{\sum_{i=1}^{m} I\{c^i = j\}x^i}{\sum_{i=1}^{m} I\{c^i = j\}} \tag{3.5}$$

There are k centroids $\mu_j \in R^6, j \in [1, k]$. After clustering and before classification, the data results are normalized, and the user record is imported into the same tuple structure as the clustering centroids, as follows:

$$\mu = (\bar{t}_{arrival}, \bar{t}_{departure}, \sigma_{arrival}, \sigma_{departure}, cor1, cor2) \tag{3.6}$$

where $cor1$ and $cor2$ are the Pearson correlation coefficient among staying time and EV energy demand, and the Pearson correlation coefficient between weather attribute values and EV charging demand, respectively.

The complete steps for K-means-based EV charging patterns clustering are shown in Algorithm 3.1.

Algorithm 3.1: EV charging behavior clustering using K-means algorithm

1: Generate K random numbers and corresponding K cluster centroids;

2: For each instance:

3: Classify each object with minimum distance;

4: Repeat

5: Update the centroid;

6: Reassign the instances to clusters;

7: Until no update.

However, in the K-means algorithm, determining the optimal number of clusters is always a challenge. There are several options for dealing with this issue. For instance, the elbow algorithm, which employs the Sum of Squared Errors (SSE) approach, might be used to determine the most efficient number of clusters. The SSE rapidly decreases as the cluster number approaches the optimal number of clusters. However, SSE would continue to drop when the number of clusters exceeds the optimum cluster number. Meanwhile, the rate of the reduction of the SSE slows down. Therefore, the optimum K value can be better identified by plotting the curve of the K value on the SSE (K-SSE) and determining the inflection point on the way down.

3.2.4.3. K-NN classification for EV charging behavior

There is a need to classify the behavior of new EV users after clustering the data using the K-means approach in order to manage and improve their charging behavior. However, re-clustering the entire dataset is inefficient if new data is entered. So, based on the results of the K-means clustering algorithm, the K-Nearest Neighbors (K-NN) algorithm could be applied to characterize the behavior of new EV user.

K-NN is a supervised learning approach for classifying new data by calculating the distance between new data points and previously marked data points. All of the selected neighbors are accurately classified using the K-NN method. It is a distance-based approach that determines the category of new data based on the category of its closest neighbors, such as when the distance between data points is calculated using the Euclidean method. Then, the new data is assigned to a group that has the least distance from that group's training data. However, the selection of k values is not governed by any specific rule. In general, a lower value is preferable based on the sample distribution, and an appropriate k value can be found via cross-validation.

The complete steps for K-NN-based EV charging patterns classification are shown in Algorithm 3.2.

Algorithm 3.2: EV charging behavior classification using K-NN algorithm

1: Calculating the distance between the labelled objects and the chosen objects;

2: Sorting the distance in ascending order;

3: Choose K objects with minimum distance from the selected objects;

4: Classify the objects that are repeated most often in the first k objects.

The ratio of the K-nearest training sample marker to the input marker can be used to calculate the training error rate (ER). The ER is calculated as (3.7):

$$ER = \frac{1}{k \sum_{x_i \in N_k(x)} I(y_i \neq c_j)} = 1 - \frac{1}{k \sum_{x_i \in N_k(x)} I(y_i = c_j)} \tag{3.7}$$

Furthermore, the following coefficient in the training set could be maximized by selecting the proper *K* value:

$$\alpha_k = Max\left\{\frac{1}{k \sum_{x_i \in N_k(x)} I(y_i = c_j)}\right\} \tag{3.8}$$

in which, α_k is the coefficient to find the nearest neighbors to the k^{th} cluster center in the K-means approach.

3.2.5. A toy example

The ML-based clustering algorithm processes the historical data of EV users and divides their behaviors into three groups, as shown in Figure 3.7. Three of the six features in the tuple are used for visualization: start time, end time, and weather correlation. The three possible categories can be cold weather, normal weather, and hot weather. User behavior is labeled using human intelligence following the clustering. According to the results of the simulation, it could be concluded that red and blue colored users have charged in cooler climates, indicating that their charging behavior is more regular and predictable. Therefore, such users will be able to collaborate in the centralized scheduling of the power network. In contrast, orange-colored users have more inefficient charging behaviors in hotter times. Therefore, it is not helpful for these users to participate in the centralized scheduling of the power network.

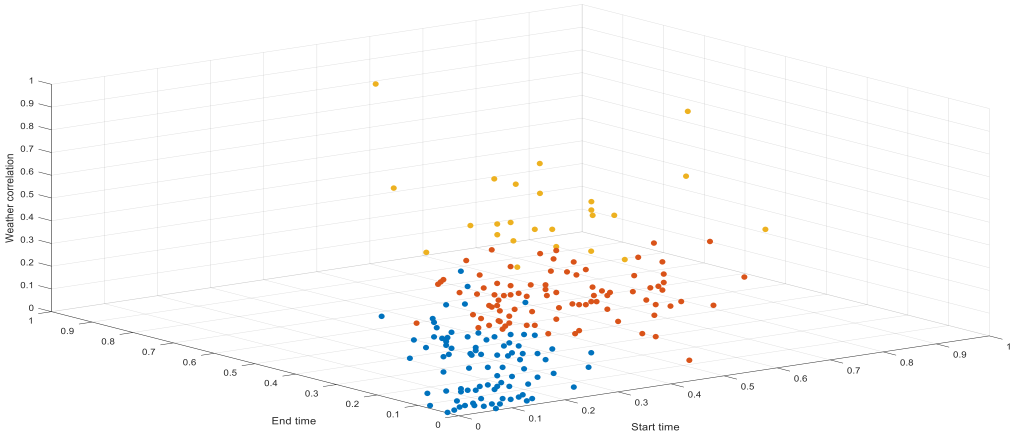

Fig. 3.7. EV user charging behaviors

3.2.6. Application of charging pattern recognition in smart charging

Smart charging reduces EV-induced load peaks and flattens the load profile to make integration of RESs at the system levels and the local levels easier over shorter period scales. To be specific, adjusting and clustering the charging patterns of EVs parked in parking lots for the majority of time (90-95% of time) could help with peak shaving, ancillary services, and backup power [45].

Clustering approaches are also applied to EV smart charging in order to determine the most common load patterns. The EV charging clustering technique is utilized to find the clusters with identical charging items using a multivariate dataset. EVs can change their own charging patterns using smart charging to flatten peak load, fill up demand valleys, and assist the real-time balancing of the grid by altering charging and discharging levels. Furthermore, using EVs as a flexible source through smart charging technologies could lessen the requirement for investment in power plants that produce a vast amount of CO2 to balance fluctuations in renewable generations.

Furthermore, advancements in information and communications technology, such as data management and analytics from users, charging stations, and charging patterns could improve smart charging functionality and optimize grid service presentation.

3.3. Status Quo, Challenges and Outlook

In this chapter, definitions of EVs and a general taxonomy of them were provided. Then, the EVs integration methods (V1G, V2G, G2V, V2H, and V2B) with the electricity network were introduced. In the following, general challenges and problems of EV integration were introduced. However, data challenges of the high penetration of the EVs were investigated as a separate section. A general classification of EV data was also proposed in this section.

Moreover, various aspects of the EVs' smart charging energy management were discussed, such as concepts, applications, challenges, and opportunities. A framework for designing a smart charging system for integrating the EV-RES system into the grid was also presented. Next, some of the recent literature on EV integration and practical EV projects were examined to demonstrate the current situation of EV's employment around the globe.

Afterward, various benefits, reasons, and methods of EV charging patterns identification were presented in the second section. Then, general concepts and principles of clustering methods were discussed, and charging pattern clustering advantages were addressed. Next, different types of ML algorithms for clustering the charging patterns were presented and discussed in detail, including unsupervised learning and supervised learning.

Furthermore, different types of ML algorithms for clustering the charging patterns were presented and discussed in detail, including unsupervised learning and supervised learning. In addition, the proposed ML-based approach to cluster the EVs charging behaviors was introduced, and the related formulations of the K-means and K-NN algorithms were presented. Also, a toy example was provided in order to demonstrate the practicality and effectiveness of the proposed method. Eventually, the application of charging pattern recognition in smart charging was also discussed briefly.

There are several research gaps that could be filled in future research. Some of the important future research outlooks from the authors' point of view are presented as follows:

- The lack of a labeled data set posed a problem for this research. Further evaluation could be conducted using a properly labeled dataset to verify whether the promising results and training method are sound.
- Deep learning and reinforcement learning are subsets of ML that utilize artificial neural networks. These methods, unlike ML models, contain a large amount of composition of learned functions. Therefore, using deep and reinforcement learning, which could result in better efficiency, should be considered in future works.
- Further studies should be conducted to identify the applications of the clustering methods to analyze the behavior of drivers and the relevant aspects.

3.4. Concluding Remarks

The goal of this chapter was to look into and examine the charging behaviors of EVs. In this chapter, an unsupervised learning method, i.e., K-means, was utilized in order to cluster the charging patterns of the EVs. The main contribution of this chapter was to consider items that have not been appropriately considered in the previous literature. The most popular items for investigating the EVs charging behaviors are: start time, stay duration, and energy demand. Other items which might have significant effects on the classification of the EVs are traffic patterns and weather that have been addressed in this chapter. Finally, a supervised learning method, i.e., K-NN, was also utilized for further classification of the new dataset of the EVs.

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