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# Control Strategies for Smart Charging of Electric Vehicles from a Grid Perspective: A Review

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**ABSTRACT**
Electric vehicles have emerged as an alternative way to reduce fossil fuel consumption, which is the cause of increasing environmental, economical and geopolitical problems. This paper reviews the strategies for charging electric vehicles smartly from the viewpoint of the grid. These strategies are classified into three categories. The strategies at the component level discuss the necessary aspects of batteries, their charging methods, and chargers for smart charging purposes. The strategies on the system level are discussed under the heads of unidirectional and bidirectional power flow strategies. Unidirectional power flow strategies manage the power flow from the grid to electric vehicles for their charging. The bidirectional power flow strategies, apart from charging the electric vehicles, also use their battery storage for grid support. Also, the strategies that can be deployed at the operational level are discussed. These strategies, on the one hand, tend to alleviate the stressful impacts of increasing the load of charging the electric vehicles on the grid, and on the other hand, use the energy storage capability of the electric vehicles for grid support.

**INDEX TERMS** Electric Vehicles, Smart Charging, Power Flow Control of Electric Vehicles, Centralized Control, Decentralized Control

## I. INTRODUCTION

Fossil fuels have been the main source of energy throughout the growth of human civilization. Increasing industrialization, technological advancements, and machine dependent lifestyle over the past few decades have stressed fossil fuels to a dangerous level. This has resulted in various environmental, economical and geopolitical problems. The greenhouse gas emissions have increased to a hazardous level. The prices of fossil fuels are increasing and becoming more and more shaky. Above all, the demand for fossil fuels, especially oil, has resulted in terrible peace-related problems, leading to the usage of oil as an economic weapon and the instability of oil-producing countries. So, naturally, the trend has shifted towards the use of alternative sources to meet human needs [1], [2]. The usage of Electric Vehicles (EVs) is one of the attractive options for this purpose.

The usage of EVs reduces oil consumption, resulting in less greenhouse gas emissions. Also, the noise pollution is reduced. It reduces oil imports of a country, resulting in an improved economy. The cost per kilometer for an electric drive is less than that of an internal combustion engine. So, energy is used more efficiently. The energy stored in the batteries of EVs can be used to support the grid in terms of voltage and frequency regulation, peak load shaving, and tracking of Renewable Energy Sources (RESs). As a result, the number of EVs is increasing continuously [3]–[5].

From the grid perspective, EVs act as a load while charging. Studies have shown that the environmental, economical and grid-related benefits of EVs can be achieved if they are charged smartly with respect to the grid. If not charged smartly, a fleet of EVs may increase the peak load. This results in increased power demand, higher transmission losses, heating of transmission equipment, and ultimately high costs [6], [7]. With deregulated electricity markets, EVs should be charged smartly. Otherwise, they are of no economic benefit to the owner [8]–[10]. An EV powered by a coal-based power plant produces more pollution than an ordinary fossil fuel-based vehicle [11]. In short, EVs would do more harm than good if not charged smartly [12].

This paper reviews smart charging strategies of EVs from the grid perspective. The aim is to reduce the burden of adding an extra load of vehicle charging to the grid, as well as to use the storage capacity of the battery for grid support. The strategies are described under three major categories.

In Section II, component-based strategies are discussed. In Section III, strategies at the system level are described. In Section IV, strategies at the operational level are described. Finally, in Section V, the conclusions of the whole discussion are drawn, and an outlook is presented.

## II. STRATEGIES AT THE COMPONENT LEVEL

No matter how smart the charging strategies are, nothing can be gained if the EVs are not able to cope with these strategies. Therefore, the components of the EVs should be able to comply with the smart charging strategies. This section discusses different aspects of the batteries, their charging methods, and chargers that are essential for smart charging.

From the grid perspective, batteries should have high efficiency, high energy density, high charging and discharging power, and smooth charging and discharging characteristics. High efficiency reduces energy losses. High energy density imparts flexibility of storage. High charging and discharging power make it possible to charge the battery rapidly during off-peak hours and deliver large amounts of power to the grid when required. Smooth charging and discharging characteristics are desirable for maintaining good power quality [13].

Initially, lead-acid batteries were used, but these were dropped due to low energy density and environmental hazards. Then came the Nickel batteries with higher energy densities as compared to the lead-acid batteries. But these batteries have low efficiency, high self-discharge, and memory effect. Nowadays, lithium-ion batteries are used. These batteries have relatively high energy and power density and are capable of fast charging. Research is going on to improve the batteries from the grid and customer perspective [14], [15].

There are different ways to charge the battery. The most common method is constant voltage charging. In this method, the voltage is kept constant during the charging. The current is very high at the start and gradually falls to a very small value. The problem with this method is that it requires very high power at the start. The constant current method maintains a constant current during charging by changing the charging voltage. This method requires a complex method of monitoring temperature, voltage, and time to determine the cut-off. A better choice is the constant current constant voltage method. In this method, initially the battery is charged at constant current (battery voltage rises), and when the voltage reaches a predefined value, the charging method is shifted to constant voltage (now the current falls). This method is used for fast charging [16].

Instead of providing continuous voltage or current, these may be provided in the form of pulses. The width of the pulse is adjusted to meet the charging rate. A certain rest period is provided between the pulses to allow the chemical reaction to keep pace with the charging, thus avoiding the gas formation. This effect is strengthened by providing negative pulses. The selection of an appropriate charging method depends on local conditions like battery characteristics, charging circuits, driving routine, and grid constraints [14].

Charging is done through specialized power electronic circuits called chargers, which may be built inside the vehicle (on board) or outside (off board). On-board chargers are small, of low power rating, and used for slow charging. Off-board chargers are bigger in size, of high-power rating, and usually used for fast charging. These chargers use different control techniques to implement different charging processes and special circuits to lessen the grid impact of vehicle electrification. Typical examples include filters to reduce harmonics and snubbers to reduce inductive voltage spikes. The choice of a charger depends on the battery charging characteristics, driving schedule, and grid constraints [17].

## III. STRATEGIES AT SYSTEM LEVEL

This section discusses the strategies that can be opted for on the system level for charging the EVs smartly from the grid frame of reference. Such strategies can be categorized into unidirectional and bidirectional power flow strategies as described below.

### *A. UNIDIRECTIONAL POWER FLOW STRATEGIES*

These strategies treat EVs as loads taking electricity from the grid and charging the EVs. They are broadly classified into centralized and decentralized strategies [11], [18]. Some examples are as follows.

#### 1) Centralized Strategies

A central unit controls the charging of each EV. Centralized (also known as direct) strategies are simple to implement but involve high computational effort, extensive communications, and large delays. Also, there are issues of data privacy and hacking. So, these strategies are not appropriate for large systems [11], [18]. Some of the commonly used strategies are discussed below.

**A Simple Strategy for a Charging Station**

In a simple charging strategy, a centralized communication system inputs some data each time a new EV arrives, such as the arrival and departure times of the EV, the state of charge (SoC) of each battery, the capacity of the battery, and the extent to which the battery should be charged. This data is used to formulate an optimization problem to minimize the power losses under the constraint of charging the battery to the desired SoC within the given time schedule without exceeding the maximum power limit of the charging station. In this way, optimized charging schedules and charging rates are determined. Such a non-linear optimization problem can be solved by sequential quadratic optimization [19], [20].

**Fuzzy Logic-Based Strategy**

The fuzzy logic technique uses linguistic variables to define a system, which are the words of a natural language, e.g., the linguistic variable for an air conditioning system may be defined as “temperature". Each linguistic variable is decomposed into various terms, e.g., cold, warm, etc., to qualify it. These variables are then quantified using membership functions, e.g., a numerical value is assigned to “cold" temperature. This process is called fuzzification. The interaction of these variables is assessed through different rules by an inference engine, e.g., if the temperature is warm, a command for cooling should be issued. Defuzzification of these assessments determines the output [21], [22].

Fuzzy logic based charging controller can be used to ensure a minimum network voltage while charging the EVs.The required input linguistic variables are the minimum bus voltage (obtained by power flow solution), SoC of the batteries (provided by the communication system between the EV and the battery), and electricity price (provided by the utility). These inputs are fuzzified and assessed through knowledge-based rules by the inference engine to provide fuzzy charging levels. Defuzzification of these fuzzy charging levels results in crisp charging levels of the batteries. If these charging levels are maintained, the network voltage does not fall below a minimum value (usually 0.9 p.u.). For example, charging levels are reduced at peak load when the system is more vulnerable to voltage drop [23], [24].

As this algorithm is based on linguistic variables and general rules of system behaviour, it can be easily extended. As an example, the Vehicle to Grid (V2G) option may be added by introducing a "discharge" linguistic variable, which can be used to control the discharge of batteries for the grid support if surplus storage is available [24], [25].

**Valley Filling Algorithm**

The off-peak hours appear as a valley in the load profile of a network. Stress on the grid caused by the charging of EVs can be reduced by charging the EVs during the off-peak hours. Such a strategy is known as the valley-filling algorithm, which can be carried out in the following steps [26]–[28].

1) In the first step, the total charging power required by the EVs at each time step is estimated. This can be done by developing some stochastic models based on historically available data. Then the surplus power at the $k^{th}$ time step ($P_{surp}^{k}$) is calculated as

$$P_{surp}^{k} = P_{conv}^{max} - P_{conv}^{k} \quad (1)$$

where ($P_{conv}^{max}$) is the maximum conventional load and ($P_{conv}^{k}$) is the conventional load at the kth time step. After that, the capacity margin index at the kth time step *($CM^{k}$)* is calculated as

$$CM^{k} = \frac{P_{surp}^{k}}{P_{demand}^{k}} \quad (2)$$

Where ($P_{demand}^{k}$) is the charging power demanded by the EVs at the $k^{th}$ time step and is equal to the sum of the charging powers of all the EVs connected at that time step. The time slot with the highest capacity margin is selected to charge the EVs. This ensures that the deepest point of the so-called load valley is filled first.

2) The charging priority index at the $k^{th}$ time step for the $n^{th}$ EV ($CP^{k}$) is calculated as

$$CP_{n}^{k} = \begin{cases} \frac{E_{n}^{k}}{(T_{n}^{k} \times \Delta t) P_{n}}, \text{if } I_{n}^{s} \leq k \leq I_{n}^{e} \\ 0, \text{else} \end{cases} \quad (3)$$

where $E_{n}^{k}$ is the remaining charging energy required at the $k^{th}$ time step for the $n^{th}$ EV, $T^{k}$ is the remaining number of time intervals at the $k^{th}$ time step for the $n^{th}$ EV, $\Delta t$ is the duration of one time slot, and $P_{n}$ is the power of the charger of the $n^{th}$ EV. Moreover, $I_{n}^{s}$ and $I_{n}^{e}$ denote the serial number of the time step of the connection and disconnection of the EV, respectively. The EV with a higher charging priority index means it has a high priority for charging in a given time slot, and vice versa. It can be seen that the EVs that are more discharged and/or have less charging time are given high priority. If the surplus power is enough to charge all the EVs in the selected time slot, all the EVs are connected. Otherwise, EVs are connected according to their charging priority.

3) The charging energy required and the time left for each EV are determined. If all the vehicles have zero charging energy required and/or the end of the time is reached, the program is terminated. Otherwise, the next iteration begins with the first step.

It should be noted that the calculations of ($P_{surp}^{k}$) use ($P_{conv}^{max}$). This ensures that the valleys are filled no higher than the peak value of the conventional load. The underlying assumption is that the EVs can be charged by using the energy available in the gaps between ($P_{conv}^{max}$) and ($P_{conv}^{k}$) But if some vehicles remain uncharged at the end of the cycle, a value higher than ($P_{conv}^{max}$) The value should be used. The lower this value, the lower the stress on the grid. One way to optimize this value is the dichotomy method as described in [29].

***B. DECENTRALIZED STRATEGIES***

In decentralized (also known as indirect, local, or distributed) strategies, each part of the system, particularly EVs, takes part in decision-making. So, computations and communications are reduced as compared to the centralized strategies. This makes these strategies attractive for large fleets of EVs [11], [18]. Some of the strategies are discussed below

**Offline Heuristic or Rule-Based Strategy**

The algorithm of such a control strategy determines the hours with the lowest electricity price and the charging power patterns to charge the battery in that particular time span without exceeding the load limit of the house. Specific case studies for price and peak load reduction by using this algorithm can be found in [20] and [30]. This algorithm is mostly used for simple systems and does not take into account the charging of all the vehicles in a particular network [20]. It has a high computational time, especially for complex systems [24]. It is a decentralized control and does not take into account the charging of all the vehicles in a particular network [20], [31].

A typical offline heuristic algorithm takes into account the daily load profile of a house, total power allowed by the utility, energy prices, and the arrival and departure hours of EVs. Analytical relations are used for the calculations of the battery parameters, e.g., SoC, voltage, current, etc.

First of all, the time duration for which the EV is available for charging is determined by the arrival and departure times. This time duration is sampled into time slots of equal length. The power available for charging the EV is calculated considering the power allowed by the utility and the losses of the charger. Different charging powers can be set for the EVs. Then the time slots are sorted in ascending order of the energy prices. The time slot with the lowest energy price is selected for charging the EV. Then the current SoC of the EV is determined using analytical expressions. If the current SoC exceeds the desired SoC, the algorithm terminates. Otherwise, the voltage and the current are determined from the analytical expressions of the battery. If the battery current exceeds the nominal current, the battery is charged at the nominal current. Otherwise, the battery charges at the calculated current. Afterwards, the SoC is calculated, and the algorithm starts at the next time slot with the next lowest price. In this way, the charging is done at the lowest priced time slots. So, the charging price is minimized, and the peak load is avoided to the maximum extent [30].

**A Price-Based Routing Mechanism for Charging Stations**

Charging patterns of EVs are randomly distributed in temporal and spatial domains. This puts a non-uniform stress on charging stations. For example, a charging station at a particular site may be more loaded at a particular time than the other one. This leads to inefficient service of charging stations, high power losses, and congestion situations from the grid point of view, as well as inconvenience for the customers [32].

To avoid all these, a routing strategy can be employed. When the vehicle arrival rate at a particular charging station exceeds a specified limit, an increased price is offered by the charging station. This will encourage the customers to go to a nearby station, thus increasing the uniformity of load distribution. For each diverted vehicle, a penalty is imposed on the charging station as well. This is done to ensure the best efforts of the charging station to satisfy the customers. With this vehicle diversion, a communication system is designed to communicate between the vehicles and charging stations about the available locations and prices. A game theoretic model is developed where the operator of charging stations acts as one player (leader) and EVs act as another set of players, which respond to the former player (followers). Each player opts for certain actions (called "'strategies" in game theory) which result in certain outcomes (called "payoffs" in game theory). The strategy of the leader, i.e., operator of the charging stations, is to offer prices to earn maximum profit (leader payoff) by maximizing the number of customers and minimizing the diversions, keeping in view the grid constraints. In response to the leader, the followers, i.e., EVs, opt for a strategy of picking those charging stations where charging is least expensive (follower payoff) [33], [34].

**Multi-Agent System-Based Strategy**

A multi-agent system can be used for charging a large number of EVs (in the range of millions) in a decentralized manner. This strategy considers the EV charging system as a set of autonomous agents. An agent is an entity (physical or virtual) that senses its environment and reacts in a predefined manner to attain certain goals. In a multi-agent system, various agents interact with one another following certain rules to achieve specialized goals. A properly designed multi-agent system is robust (i.e., tolerant to faults) and modular (i.e., new agents can be added for enhanced abilities) [35], [36].

In a typical implementation, the system can be classified into three agents, namely charging stations, responsive EVs, and unresponsive EVs. Responsive EVs are those that can adjust their charging schedules in accordance with external constraints, e.g., energy prices, voltage limitations, etc. Unresponsive EVs have rigid charging schedules. The algorithm is carried out in the following steps [11].

1) In the 1st step, the arrival of a new EV is monitored. If there is a new EV, its charging is planned by referring to the 3rd step. If it is the first time step of the algorithm cycle (usually one day), the forecasting is done by executing the 2nd step.

2) In the 2nd step, the forecasting of renewable energy generation and the demand of unresponsive EVs is made. This can be based on previously available data. The conventional load (i.e. without EVs) profile comes from the distribution grid operator. Then the total power demand on conventional resources at each time step for each feeder is given by:

$$\begin{aligned}&\mathit{Scheduled\ Responsive\ EV\ Load}\\&+\mathit{Forecasted\ Unresponsive\ EV\ Load}\\&+\mathit{Forecasted\ Conventional\ Load}\\&-\mathit{Forecasted\ Renewable\ Energy\ Generation}\end{aligned}$$

and the virtual energy price for each time step for each feeder is given by:

$$\frac{\mathit{Power\ Demand}}{\mathit{Power\ Rating\ of\ the\ Feeder}}\times \mathit{Profit\ Factor}$$

Profit factor can be linear, quadratic, or any other function, depending on revenue targets. It should be noted that this price is a virtual price and does not reflect the actual utility price. It can be seen that the virtual price increases with the demanded power. Such a pricing strategy encourages the EVs to charge at low price time steps, which are the time steps of off-peak loads and/or high renewable energy generation.

3) The 3rd step decides the charging schedule of each responsive EV on first come first serve basis. The objective is to minimize the product of the instantaneous charging power demand of the EV and virtual cost at that time step over the specified duration of charging.

The constraint is that the sum of the instantaneous charging power demand of the EV in the specified duration should be equal to the desired charging capacity i.e. the particular EV should be charged to the desired capacity in the available duration. Moreover, the instantaneous charging power demand of the EV should not exceed the nominal power rating of the charging station.

After the EV is scheduled, the power demand and energy price for each time step and each feeder are calculated again, as done in the second step. If such an update of energy prices is not done, each new incoming EV will prefer to get charged at the lowest energy price points. If this is allowed to go on, the load at these points will continue to increase, and hence the stress caused by these points on the grid will increase as well. In the worst case, these valley points may become the peak load points. Moreover, such sequential updates would incentivize the early-coming responsive vehicles.

4) After scheduling each responsive EV, the network is continuously monitored. This can be done by having measurements in real time or performing a power flow analysis. If all the measurements, e.g., voltages, thermal limits, etc., are within the specified limits, the monitoring is continued until the end of the algorithm cycle is reached, and the algorithm starts again from the first step.

Meanwhile, if some new EV comes to the grid, its schedule is determined as stated above. In case something wrong happens resulting in unacceptable variations of the voltages or thermal limits, etc., the previously determined power demand and charging schedules are nullified. This may be the result of some unexpected change in production or demand. The remaining charging power demands of all the vehicles are determined. The charging station determines the power required to be rescheduled to solve the problem. Each responsive EV is rescheduled again. After rescheduling a vehicle, network conditions are monitored. If the problem is solved, no further EV is rescheduled. Otherwise, rescheduling of the next EV is done. This continues until the rescheduled power is zero or there is no EV left. As such, a condition is not the fault of the customer, no extra charges are applied for rescheduling. Some algorithms calculate the schedules at each time step to avoid such network problems, but this gives a high computational load to the algorithm.

### *C. BIDIRECTIONAL POWER FLOW STRATEGIES*

Due to the presence of batteries, EVs act as spatially and temporally distributed energy storage. The idea of bidirectional power flow strategies is to use this available storage from the grid perspective, along with charging the EVs. The power of batteries can be used for maintaining the frequency and voltage, i.e., regulating the active and reactive power flow, preventing the line losses and transformer stress by providing local generation, providing the spinning reserve, harmonic filtering, tracking the RESs, and peak load shaving. But this is done at the cost of complex control techniques, changes in network operation and structure, high computational effort, large communication overhead, and complex fault protection. Moreover, the battery degradation is enhanced due to the increased number of charge/discharge cycles. As a result, the economic analysis of a particular charging strategy is essential. The bidirectional power flow strategies can be broadly classified into individual-based strategies and aggregator-based strategies [37], [38].

#### 1) Individual-Based Strategies

These are very simple strategies that deal with each EV on an individual basis. When an EV is connected to the grid, the owner enters the final SoC and departure time. The load curve of the house and the electricity price curve are also made available. Such curves are based on measured or estimated values. The controller allocates the charging and discharging time slots based on the fact that the EV should be charged in low price hours and discharged at high price hours, provided that the EV is charged to the desired level at the end of the charging period and the SoC limitations of the battery are not violated [8], [39].

#### 2) Aggregator-Based Strategies

The storage capacity of a single EV is very small from the grid's point of view. Using EVs individually for grid regulation is complex in terms of control, exhaustive in terms of communication, and less economical in terms of storage capacity and flexibility. So, many EVs are grouped and controlled as a whole. This is the essence of aggregator-based strategies [2], [40]. Some examples are as follows [40], [41].

**Strategies Based on Load Frequency Control Signal**

First of all, the current SoC of each EV is measured. Then the required SoC for the scheduled driving routine is estimated, keeping in view the charging routine, battery capacity, and system efficiency provided by the vehicle owner. If the required SoC is below the current SoC, it means the vehicle has surplus energy, and it can participate in V2G operation. Otherwise, the vehicle is to be charged [42].

In the second step, the participating power of the aggregator is determined by a multi-objective optimization problem to maximize the profits earned by V2G operation and minimize the tracking error of the load frequency control signal. The constraints are that the current SoC of each vehicle should not go below the SoC required for the driving demand during the up frequency regulation and above the maximum SoC limit during the down frequency regulation.

In the next step, the aggregator's participating power is allocated to each EV, which is to be charged or discharged. The objective is to minimize the change in the SoC of each EV under the constraints that the sum of individual vehicle allocated powers is equal to the participating power of the aggregator without exceeding the maximum charging/discharging power rating and without violating the SoC limitations of each battery [40], [43].

**Strategies Based on Integration of Renewable Energy Sources**

Probability density functions of driving and charging routines are determined based on available statistical data, and hence, a stochastic model for the power requirement of EVs is determined. Similarly, the available data for solar irradiance and wind speed, along with the respective plant capacities, help to model the output power of RESs. Network operators provide load and frequency regulation data on the basis of which respective forecasts can be made. Frequency regulation data is an indication of the grid power requirement as a positive or negative reserve.

When a new EV arrives, its SoC is measured, and the owner is prompted to input the charging duration. After that, the grid power, power from RESs, and frequency regulation data are estimated. This data is fed to a controller, which determines the charging priorities. High priority means high charging power and vice versa. As different EVs have different arrival times, SoC and charging durations, different charging/discharging powers are assigned to these. For example, a vehicle with low initial SoC and a small charging duration requires high charging power, and it is unable to contribute to V2G operation. On the other hand, a vehicle with a high initial SoC and a long charging duration requires less charging power and can wait for off-peak and high renewable energy production times. It can be discharged during peak load times for grid contribution. Such vehicles are incentivized economically by dynamic pricing [**?**], [44], [45].

**Strategies Based on Peak Load Reduction**

Each registered EV owner is identified with a unique radio frequency identification tag. Whenever an authorized EV enters a charging station, the owner is prompted to specify its final SoC and departure time. The technical details, such as system efficiency, battery type, etc., can be extracted from the tag.

Based on this information, the charging time of the EV is estimated. If the charging time exceeds the departure time, the owner is prompted. The electricity price curve is fed to the controller, which is regularly updated based on available electricity market data. The price curve is quantized into a number of small intervals (usually 15 minutes) during which the price is assumed to be constant. Based on the charging time and electricity price, the cheapest time intervals are selected. In this way, the cheapest possible charging and peak load reduction are ensured.

If the owner allows for V2G operation, the time intervals with the highest price are determined for discharging under the constraint that the EV achieves its desired SoC at the moment of departure, and SoC limitations are not violated. Optimization of charging/discharging of EVs for the electricity price implicitly implies the optimization with respect to load demand [6], [46].

## IV. STRATEGIES AT OPERATIONAL LEVEL

The above-mentioned control strategies involve EVs either at the component level or system level. Strategies can be developed at the operational level that can manage the charging of the EVs from a managerial point of view. A few are discussed below.

1) The discharged battery bank can be swapped with the charged one. This strategy adds enormous flexibility to EV scheduling but comes with cost, infrastructure, and regulation problems [14], [47].

2) The routes of EVs in a particular area are optimized and allocated efficiently to the available charging stations. This balances the load on charging stations and enables predictive modelling of charging behaviour. However, this approach is limited to a particular area and requires high computational effort for route modelling [48], [49].

3) EVs charged by an aggregator can be scheduled to share the energy stored in the batteries among themselves. EVs being charged in the homes can be used to provide electricity for the home during peak loads or faults, etc. This is called vehicle-to-home (V2H) operation [50].

4) Apart from the batteries, alternative energy storage systems, e.g., ultracapacitors and hydrogen-based energy storage systems, are under investigation [51], [52].

5) Apart from the physical connection for charging, electromagnetic phenomena can be used to charge the EVs in a wireless manner. This strategy has the advantages of safety and durability, but it has low efficiency and high power losses [53], [54].

## V. CONCLUSIONS

The stress on fossil fuels has continuously increased over the past few decades, resulting in various environmental, economical and geopolitical problems. Electric vehicles can be used to reduce this stress if charged smartly. If not charged smartly, the vehicle electrification will be more harmful than beneficial. This paper discusses the strategies for smart charging of electric vehicles from the grid perspective. This means that the discussion on one hand is on the ways to reduce the burden on the power grid when an additional load of electric vehicles is added, and on the other hand, to use the energy storage capabilities of electric vehicles for grid support. As the first step, the selection of components for smart charging is discussed. Batteries, their charging methods, and chargers of different types are described. Then the strategies on the system level are discussed, which can be broadly classified into unidirectional and bidirectional power flow strategies. Unidirectional power flow strategies charge the electric vehicles from the grid, whereas the bidirectional power flow strategies not only charge the electric vehicles from the grid but also discharge them to support the grid when needed. Unidirectional power flow strategies are further classified based on centralized and decentralized strategies. Centralized strategies manage the charging of electric vehicles from a central control unit, whereas in decentralized strategies, the intelligence is distributed among the various components of the whole system, particularly the electric vehicles. The bidirectional power flow strategies can be split into individual and aggregator-based strategies. Individual-based strategies consider each electric vehicle on an individual level, whereas aggregator-based strategies consider a fleet of electric vehicles. Since the storage capacity of a single electric vehicle is small for the grid, the aggregator-based strategies are practically useful. In the end, some new ideas like battery swapping, route optimization, battery energy sharing, vehicle to home concept, usage of alternative energy storages and inductive charging are discussed.

A next step can be to gather the research work done so far on these new ideas and to discuss their practical applicability. Various optimization techniques like genetic algorithm, particle swarm algorithm, interior point method, and bi-level programming, etc., which are usually used to implement these charging strategies, can be studied and compared as an extension of the present discussion. Moreover, the strategies outlined here can be used to improve the situation of electric vehicles in different case studies to bring pleasant effects for the grid integration of vehicle electrification.

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