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Electric Vehicles Beyond Energy Storage and Modern Power Networks: Challenges and Applications

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ABSTRACT Electric vehicles (EVs) have been increasingly experiencing sales growth, and it is still not clear how to handle the associated impacts of a substantial integration of EVs against the power network performance and electricity deregulated market. Power networks development moves slowly compared to EVs, so it is hard to harmonize the two systems. Also, the associated cost required to modernize electric networks to accommodate the EVs additional loading is so huge that it makes it impractical. An electric network would suffer from many performances and quality-related problems if a significant number of EVs are not taken into account. Thus, it is vital to calculate at a reasonable accuracy the additional capacity to which the network would take. Also, the modeling of these EVs in terms of charge/discharge procedure (central or distributed) is essential to enable the optimization and compute potential impacts. The electricity market has to interface with the bidirectional supply nature of the EVs, so they become economically feasible. A business model that incorporates market structure and standards is selected in harmony with the charge/discharge model for best outcomes. Some approaches, algorithms, and schemes are deemed necessary to mitigate the effects of having EVs in the network. This paper presents a comprehensive review categorically on the recent advances and past research developments of EV paradigm over the last two decades. The main intent of this paper is to provide an application-focused survey, where every category and subcategory herein is thoroughly and independently investigated.

INDEX TERMS Business model, central charging model, distributed charging model, electric vehicle, power network.

I. INTRODUCTION

The CO_2 emission, fossil fuel depletion, and capability to balance the electric grid stability make transportation sector shift to electric vehicles (EV) or plug-in hybrid electric vehicles (PHEV) [1]–[3]. However, the EVs are being developed at a slow pace due to the battery high cost and lack of charging infrastructure [1], [4]. Thus, governments in many countries adopted some policies, such as tax exemption financial subsidies, to boost the EVs purchase rate [5]. Also, many automobile manufacturers have started developing their production lines to include this emerging technology [6]–[8]. The EV expected market growth in conjunction with the policy incentives and technology advancement will result in a significant growth in EV market, which in turn would impact electric networks adversely [1], [9]. Seemingly, the question arises: how would the additional loading caused by EVs be accommodated by existing electric networks?

Uncoordinated charging of EVs would elevate load peaking at rush hours, or even create new load peaking at different times [10], [11]. Hence, a straight solution is to invest in reinforcing the electric grids so as to accommodate the additional EVs load. Nevertheless, the resources required for such an investment is so huge that the whole proposal might be turned out economically infeasible [12], [13]. Several concepts were proposed to formulate so-called coordinated charging that is a cost-effective solution dealing with the EVs load peaking.

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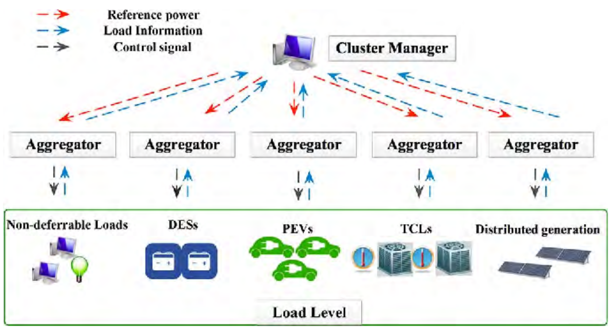

FIGURE 1. Hierarchical control schematic [19].

Smart charging and its derivative could shift the peak loading to off-peak hours [14]–[16].

Basically, the charging/discharging techniques in smart grids can be classified as follows [17]–[20]:

- Centralized and decentralized techniques: A central controller is adopted in the centralized strategy where the global optimal solution is achieved, but at a high cost. The computation requirements and the signaling overhead for information collection are so huge that it might render it impractical. On the other hand, the decentralized strategy adopts a local iterative-based controlling decisions by EVs. Of course, iterative information is exchange with lesser complexity compared to the centralized strategy.
- Dumb charging: It's an uncontrolled charging mode in which EV is plugged with no delay or incentives. Basically, EVs are freely charged at will and it lasts till battery is fully charged or unplugged. Moreover, the electricity cost is fixed, so users receive no economic incentives to coordinate their charging timings in order to minimize coincidence factor and peak hour loading of load profiles.
- Multiple tariffs: It is similar to the previous approach except that price is not fixed throughout the day for EVs charging to manage electricity demand whereby prices during valley hours are low, whilst the prices during peak hours expensive. That being said, this approach is not an active strategy, as it relies on users' willingness to adhere to the regulation, so one expects that only part of EVs would shift to valley hours.
- Smart charging: The EVs charging requests are handled by a hierarchical control structure (see, e.g., Fig. 1) headed by an aggregator who is in control of all EVs charging rates. This active management system is in operation only when the electric grid is in normal conditions. Typically, aggregators group the EVs charging requests to grasp business opportunity in the electricity market where they tend to buy energy during valley hours to reduce the energy price to their respective clients. Hence, this ensures efficiency in resource utilization of the overall system. Also, aggregators' market behavior aid to prevent network overloading and excessive voltage drops, alleviating the need to enforce existing network. EV users acceptance of smart charging is critical to widely adopt such technique, especially from the user economic perspective.
- Vehicle-to-Grid (V2G): V2G is simply an extension to the smart charging approach in which the charging direction is a two-way street for a grid to which EVs can inject power. The load controllability and the storage capacity both help providing peak power to flatten the energy demand through the course of the day. However, there are several downsides that adversely impact this approach, such as battery degradation due to cyclic charge/discharge operation. Thus, the economic incentives planned for this approach must be higher than its counterpart in smart charging to account for battery deterioration.

There are several differences between the liquid-fuel vehicles and the electric vehicles, like the rather high capital cost of the EVs and the ancillary services provided by the EVs. These ancillary services are not easy to quantify, which brings business models into picture. The EVs capital cost as well as the battery cost are the main obstacles to adopt them widely, so governments employ incentive policies to promote EVs. Apart from effectiveness of these policies, the business model of oil-filled vehicles is that an operator purchases a vehicle that is used for transportation, and the operator pays for fuel and maintenance. On the contrary, EVs' interaction is much different from liquid-fueled vehicles, and many business models are presented in the literature.

Studies are being held to investigate the impacts of potential EVs' rise in transportation market. Electric networks need more power capacity to supply additional EVs load, and the interconnection between the grid and the EVs raises concerns about harmful impacts against the electric networks. The issues associated with the EVs grid interconnection are inferred from extensive researches in the literature: system equipment overloads, harmonics, voltage drop, system losses, stability issues, and phase unbalance [21].

Power system planning should account for additional EVs loading for future substations, whereas it should find cost-effective solutions for existing substations rather than adopting costly retrofittings. These solutions range from simple optimization tactics to compounded coordinated charging/optimization procedures. Ultimately, they boil down to utilizing available resources (energy) effectively and efficiently to avert such adverse impacts. Also, V2G process requires systematic ways to coordinate power flow and financial transactions between EV users and power networks in deregulated power markets. The evaluation process of EVs on electric networks starts with quantifying the anticipated capacity of bidirectional power flow in order to have a base line before selecting suitable charging model. The power flow is controlled through modeling the charge/discharge process, whereas the financial transactions are governed via a business model concept. A centralized charging model is one option in opposition to a distributed model. The selection of the two models rely on many factors, like the system scale and the

TABLE 1. Society of automotive engineers charging levels [21].

Charging Level	Charging Rate	Charging Time	Remark
AC Level 1	120 V, 1.4 kW (12 A) 120 V, 1.9 kW (16 A)	PHEV: 7h (SOC-0 % to full)	On-board Charger
AC Level 2	240 V, up to 19.2 kW (80 A)	**For 3.3 kW charger**: PHEV: 3h (SOC-0 % to full) **For 7 kW charger**: PHEV: 1.5h (SOC-0 % to full) **For 20 kW charger**: PHEV: 22 min (SOC-0 % to full)	On-board Charger
AC Level 3	> 20 kW, single phase and three-phase	To be determined	To be determined
DC Level 1	200-450 V_{DC}, up to 36 kW (80 A)	**For 20 kW charger**: PHEV: 22min (SOC-0 % to 80 %)	Off-board Charger
DC Level 2	200-450 V_{DC}, up to 90 kW (200 A)	**For 45 kW charger**: PHEV: 10 min (SOC-0 % to 80 %)	Off-board Charger
DC Level 3	200-600 V_{DC}, up to 240 kW (400 A)	**For 45 kW charger**: PHEV: 10 min (SOC-0 % to 80 %)	Off-board Charger

existing power network infrastructure conditions. Optimization techniques are a good choice that help achieve resource efficient utilization. The charge/discharge model has to be formulated in adherence with the business model so as not to have any contradictions among these two models. The business model involves not only regulations and standards of monetary transactions, but also the market structure within which power networks operate. The whole modeling procedures of the V2G capacity, charge/discharge, and business model are interlinked to each other and a slight deviation might influence the inter-system effectiveness, which in turn would affect the grid impact profiles. Society of Automotive Engineers (SAE) has formulated charging standard for EVs that consists of both AC-based chargers and DC-based chargers. The AC chargers are on-board chargers that usually reside in residential and commercial areas, while DC chargers are off-board chargers that are subsations dedicated for EVs charging [22]. In accordance with the standard, there are there levels of charging rates for both AC chargers and DC chargers as illustrated in Table 1. Note that the level 3 charger for both AC and DC are not yet finalized, and they are promising in terms of charging duration reduction [21].

A thorough application-based review of the V2G charge/discharge approaches, business models, and the technical impacts attributed to V2G grid integration over the past decade is addressed. This paper is organized as follows: Section II discusses the charge/discharge scheme in which V2G capacity is assessed prior to addressing central/distributed scheme characteristics. Business models are discussed to integrate V2G into energy markets in Section III. Section IV, addresses the adverse issues accompanying EV-to-power-grid integration are addressed with some proposed solutions. Conclusion is in Section V.

II. CHARGING/DISCHARGING SCHEME

In all the literature, there has been no comprehensive strategy to represent charging/discharging dispatch procedure for EVs; this strategy needs to consider both the network operational requirements as well as the drivers preferences. Basically, the merge between the two aspects results in different dispatching patterns, so one needs to assess the relative importance of each requirement upon determining a dispatch mode of EVs.

The V2G concept is formed by a group of EVs that are controlled by an aggregator, and hence this EVs fleet functions as a storage system. The EVs fleet exchange power with electric networks for charging the EVs and discharging to the grid loads, and the whole process is controlled by communication signals traversing throughout the system in both directions. An aggregator is the focal point of the system who interfaces the EVs to the electric grids as shown in Fig. 2. Essentially, the quantitative assessment of V2G capacity (i.e., charging/discharging power ranges) ahead of time forms the basis to which V2G is based [23]. Charge/discharge capacity is evaluated prior to formulating a strategy to coordinate the V2G process. The coordination strategy could be central, distributed, or a combination of the two to set-up the suitable procedure that does not violate any of a grid constraints. The charging/discharging concept, techniques, and types were reviewed extensively in [24].

A. V2G CAPACITY EVALUATION

Researchers have done extensive work in doing the capacity evaluation, some of which forecasted the V2G capacity based on a single EV charging demand forecast. Basically, the capacity provided in this scheme and the particular EV that serves a timely demand are all valid questions that are addressed in algorithms in the literature [25]. In [26], a basic methodology was formulated to forecast the V2G capacity from an individual EV charging demand estimate. Three factors limit the V2G capacity-namely, current-carrying capacity of the circuit interconnecting EVs to a grid, EV stored energy, and EV power electronics rating. Often, the power electronics rating is much higher than the other two factors,

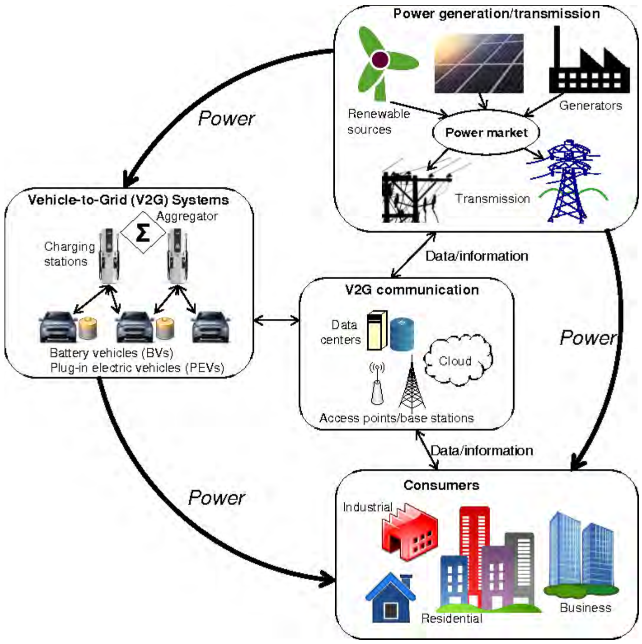

FIGURE 2. V2G architecture [23].

so it is excluded from analysis. Moreover, the V2G capacity is as large as the lowest rating of these three factors. The underlying assumption was that the aggregator, whose main task is to collect enough number of EVs to build up large capacity that can influence the network operation [27], has accurate information on EVs driving patterns, so an optimal V2G charging scheduling is achieved [28].

EVs data can be acquired at different levels to estimate the available capacity for dispatching. Authors in [29] used roll-up approach whereby timely data of each EV is compiled at three levels: EV charging point level, bus level, and microgrid level. The final stage conveys the maximum capacity that can be dispatched. Furthermore, some algorithms were based on a precise estimate of EVs charging demand, like [30] that presumes that every single EV can be estimated exactly in terms of charging demand and the V2G capacity of each EV can be computed. Unlike other approaches in the literature that consider capacity assessment for a group of EVs at fixed instant of times, this algorithm uses real-time dynamic smart charging scheduling to assess V2G capacity of EVs connected to a building. Aggregate methods, also, compute V2G capacity at any interval of time, but none of them considers dynamic scheduling for capacity calculation.

There are two constraints on which this algorithm bases its estimate. First, maximum and continuous V2G power that is confined to the EVs' power electronics rating. The EV's battery has a higher rating than its power electronic components, so the battery part is ignored in this algorithm computation. Seemingly, it is vital to take this point into consideration to determine an aggregate power of a group of EVs. Second, V2G energy availability is an auxiliary service that is ensured after securing the primary function of EVs: chargeability and drivability (i.e., ability to charge EV to proper SOC and ability to drive). EV's scheduling algorithm would ensure the EV chargeability to required SOC prior to departure and drivability factors, so such an algorithm forms the cornerstone of V2G capacity estimation.

The algorithm was tested in three case studies resulting in many interesting findings. Several parameters, such as contracted capacity, EV battery capacity, EV arrival and departure time, and load demand were studied to evaluate the algorithm performance, and it was found that such parameters have unique impacts on V2G capacity estimation. SOC alone may not be the best choice for accurate capacity estimation, and then other parameters could be employed to obtain precise V2G capacity. An algorithm presented in [31] did this by combining SOC and open circuit voltage (OCV) and developing a table that contains preliminary values of SOC-OCV and a corresponding capacity of EV batteries. This table and the capacity are updated successively in accordance with previous readings till required values are met. It turned out that the estimate error of SOC is high, but the capacity estimate error did not exceed 3 % in the implemented case. The real-time capacity forecasting tactic optimizes EV energy for usage without compromising the prime function of EV users. Renewable energy integration comes into play in [32], where EVs flexibility was assessed on the basis of renewable energy increase consumption due to the coordinated EVs charging. This work is only restricted to unidirectional EVs charging and requires accurate EVs charging demand.

A price-based charging technique is considered in which electricity price varies with the load peaks. In [33] an aggregator could exploit the electricity and reserve markets by bidding strategy to maximize its profit. Presumably, the aggregator has the EVs charging demand known at least a day ahead of time. Social and human factors can influence the capacity evaluation in different ways, such as EV drivers' inclination to charge EVs fully (i.e., full SOC) and the drivers' tendency to deplete most of battery capacity. These factors had not been considered in previous models as per [34], so the authors incorporated such aspects in their proposed capacity evaluation model. The model was tested on University of Queensland parking area, which proved that the willingness of EV users could introduce different results from other models that do not account for human factors. A critical review was made for on-board capacity estimation techniques in [35] that are electrochemical-based models, incremental capacity analysis and differential voltage analysis models, aging prediction-based models, and estimated electromotive force methods. Despite the inherent differences among these techniques, they all use same principle for the capacity estimate, which is the relationship between amp-hour charge/discharge reading and the voltage-based SOC readings, which in turn are analyzed relative to the initial and end points of the measured amp-hour throughput. The main challenge of the reviewed techniques is to detect the capacity loss for each user over the battery lifetime to optimize the operation process for lower costs. This note was highlighted in [36] for the incremental capacity analysis and differential voltage analysis methods for on-board capacity estimation and SOC. The proposed method was evaluated for battery aging for different cells, which indicated that desirable estimated were achieved at relatively low errors.

The stochastic nature of EVs charging demand is a function of many variables that would influence it differently, such as weather condition, drivers' travel pattern, social factors, etc. Moreover, the EVs demand forecast is difficult even for EVs' users, so the assumption of acquiring EVs charging demand accurately in [26], [28], [32], [37], [38] is rather strong. Also, it is prohibitively computationally expensive to assess V2G capacity and schedule V2G power for all EVs independently and simultaneously for the whole V2G fleet. Alternatively, stochastic estimation could provide acceptable capacity estimates under some reasonable assumptions to ease on the capacity evaluation process. A blend of EVs and renewable resources was assessed in [39], where the probabilistic nature of renewable resource generation was the driver for estimating the available V2G capacity using power flow analysis. The main obstacles in finding aggregate power capacity according to [40] lie in the probability of both EVs availability and EVs connectivity. The EVs availability probability is solely driven by the drivers' behavior, whereas the EVs connectivity probability depends on availability of charging points at charging stations and the driver connectivity-related behavior; both random variables were modeled in the paper for a fleet of EVs.

The EVs mobility was modeled using so-called trip chaining, and the driving patterns were based on statistical figures from conducted surveys in Singapore. Also, an availability probability table was prepared to keep track on EVs availability taking into consideration the EV reliability as well as the traffic congestion indices. A case study in Singapore was presented to test previous models whereby EVs availability is estimated with the aid of probabilities assigned for each possible trip. Moreover, plug-in points in charging stations are linked to each EV to obtain the availability probability table, thereby mapping infrastructure with varying connection points availability. Consequently, average power capacity is estimated using the availability probability table and the power capacity. The outcomes showed there is a direct relationship between the driving pattern and the EVs availability in the grid. The maximum availability was noticed to be at homes and offices, so they can be utilized for providing maximum capacity to V2G process. The stochastic nature of EVs is complicated further if integrated with distributed generators and renewable sources, and therefore the sophisticated stochastic model is a valid requirement. In [41], authors devised a two-stage dispatching model to tackle this issue. The first stage produces dispatch decisions for the next 24-hours, and the second stage determines the EVs charge/discharge profile for each scenario. The simulation showed that the underlying model can efficiently produce at a good accuracy the grid production and consumption rates including the EVs figures.

It is not practical to use individual EV charging demand techniques with large-scale V2G fleet due to computational problems that render it infeasible. Instead, aggregate models do not need an individual EV charging demand estimation, nor capacity assessment. These models are used to evaluate V2G capacity for large-scale EVs. Queuing theory was used to evaluate the parking lot charging station V2G capacity [42]. The underlying system is considered as time-invariant system, so a single time interval was used for such a proposal. A probabilistic model proposed in [43] assumes that V2G capacity is proportional to the number of EVs plugged into the network. The V2G fleet capacity is a function of both EVs rated charging/discharging power and EVs' SOC. Also, EVs that are fully charged are not subject to further charging, whilst EVs with low SOCs cannot be further discharged. Therefore, one can infer that the V2G fleet capacity cannot be estimated precisely in accordance with the number of EVs connected to the network. The driver behavior is essential in estimating the probability distribution model of the V2G capacity, so the drivers' lifestyle and EVs' behavior sampling govern the modeling process. The authors in [30] devised an algorithm that computes aggregator real-time scheduled capacity that is constrained by drivers travelling demand, battery life, and SOCs. The first two factors set the upper-limit of EVs capacity, while the last one sets the lower-limit.

Charge/discharge scheduling might change the EV battery status, which in turn would change the V2G capacity. For instance, the charging power scheduled during low-tariff intervals may result in a huge number of EVs that are fully charged so that the charging capacity during forthcoming intervals would adversely be impacted and vice versa. Thus, the charge/discharge scheduling shall be considered for evaluating the V2G capacity; smart charging could be the answer to overcome the mentioned issue. In [44], the impact of V2G fleet that participates in a ramp market on power systems is investigated. A Markov process estimated the V2G capacity of the EVs under the assumption that such a capacity is not affected by V2G fleet charge/discharge scheduling.

Aggregate queuing network model introduced in [45] along with smart charging technique is used to evaluate large-scale EVs' V2G capacity such that the V2G capacity was accomplished in real-time operation. The model can estimate deficit power as well as excess power, which aids setting up regulation contracts between an aggregator and a grid operator to facilitate transactions in a given business model. Nonetheless, the exponential distribution was used to model the duration of EVs' charge/discharge process, but this may not reflect the actual situation. This is attributed to the interdependence between EV population affecting their related behavior. Also, the memoryless assumption is not practical since the exponential distribution is time-invariant, while it is not for actual systems.

The proposed approaches for computing V2G capacity suffer from many shortcomings. The contribution of [12] tackles such limitations differently. A V2G aggregate model puts

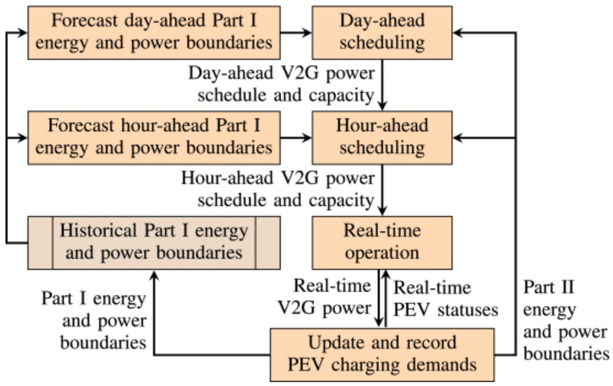

FIGURE 3. Framework of V2G capacity evaluation [12].

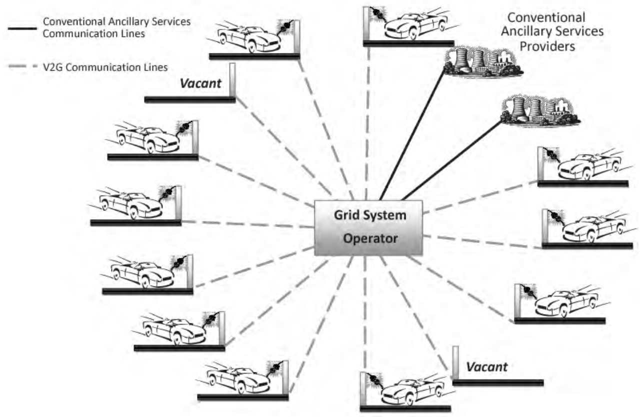

FIGURE 4. Direct V2G system architecture without using aggregators [49].

constraints on energy and power of the whole EVs population size. The model makes use of several aggregate variables of the V2G fleet rather than the individual charging approach, so the forecasting process is significantly lessened. Also, a quantitative assessment of the capacity of a large-scale V2G fleet improves the efficiency of computation, avoiding an expensive calculation algorithm. The availability of V2G capacity data ahead of time is achieved in the proposed approach, and therefore a real-time operation is accurately estimated.

The methodology followed of this approach is simply to replace the random individual demand of each EV by a single smooth aggregate model that relaxes generating timely forecasts of aggregate power and energy boundaries of the entire V2G fleet. These boundaries are computed at two stages as follows:

- New EV arrivals, not yet engaged in real-time charge/discharge operation, are evaluated in terms of aggregate energy and power boundaries.
- EVs that are already connected to grid are evaluated in terms of aggregate energy and power boundaries.

A storage-like aggregat model (SLAM) was formulated in [46] to represent energy and power constraints of the whole EV population. Also the paper designed a heuristic-based charging technique that relies on EVs charging demand laxity-SOC to enhance the SLAM modeling accuracy. The paper was extended in [12] whose outline of the V2G capacity assessment is illustrated in Fig. 3. Prior to the capacity evaluation process, the EV new arrivals power boundaries are forecasted, and the connected EVs power boundaries are updated accordingly. After that, the total of power and energy boundaries of the two stages are added to evaluate V2G capacity and set power schedule subsequently.

Fundamentally, real-time V2G capacity estimation is made possible through a heuristic smart charging tactic called Laxity-SOC-based, whereby EVs are segregated into groups based on their associated Laxity-SOC values, thereby increasing computational efficiency. Dynamic scheduling for EVs is the proposed algorithm to estimate V2G capacity [30], where real-time EV data of scheduling is used in conjunction with the building energy management system that forecasts a building demand without EVs and predicts the load profile of connected EVs to the building to obtain theV2G capacity estimate. Moreover, the model ensures that EVs are charged to desired level of SOC before departure while the V2G capacity is being estimated. The algorithm tested three scenarios on residential, commercial, and office buildings in Singapore to prove its effectiveness. The results showed that the V2G capacity is uniquely affected by several factors, such as arrival and departure times, contracted capacity, battery capacity, and load demand. Also, it was found that the proposed algorithm is superior to the fixed minimum SOC limited estimation method and estimated plug-in probability in terms of estimate accuracy that do not get impacted by the time precedes EVs departure. High-rise buildings can be a source of distributed energy storage system that would provide many services to their surroundings. The model in [47] proved the effectiveness of exploiting available V2G capacity for peak-shaving in a case study.

B. V2G CHARGE/DISCHARGE CENTRALIZED MODEL

A centralized charge/discharge approach uses a central controller, where a global optimal solution is reached at an aggregator level upon gathering all required data pertaining to the EVs power requirements. Nevertheless, the associated cost with such an approach is so huge that it can be considered prohibitive, thereby impeding its implementations. The EVs can communicate their electric-related parameters like SOC, maximum batter capacity, and charging rate to an aggregator, who in turn makes a contract with an Independent System Operator (ISO) based on its power needs. After that, ISOs decide fair power shares for each aggregator using an energy management system. At last, the aggregator executes an optimization technique so as to grant each EV user its anticipated energy share [48]. The aggregator role can be fulfilled by an ISO instead [49]. The same reference presented the advantages and disadvantages of the two approaches and their corresponding layuts are shown in Fig. 4 and Fig. 5.

The computation requirements and the signaling overhead for information collection are so huge that it might render it impractical. Also, the communication protocol being

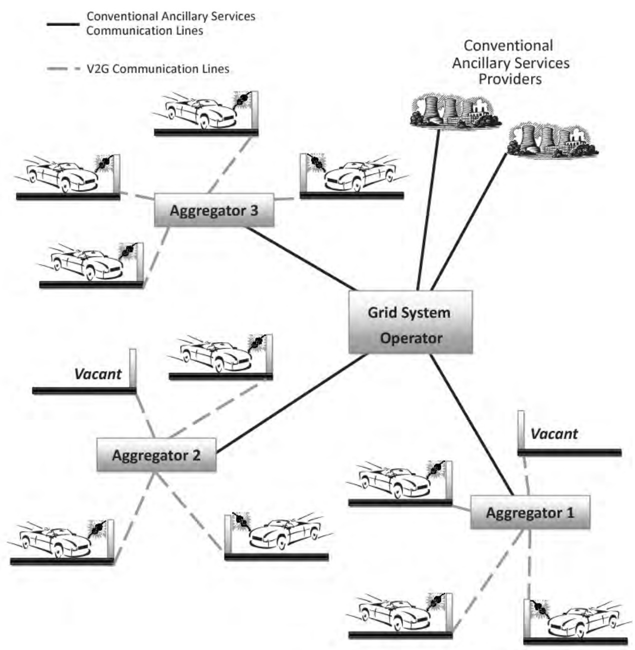

FIGURE 5. Indirect V2G system architecture with aggregators [49].

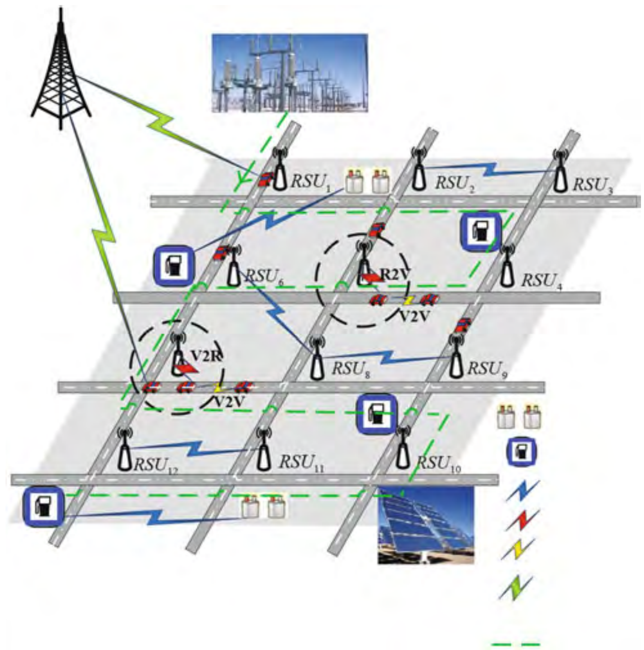

FIGURE 6. The VANET-Enhanced smart grid architecture [50].

utilized to exchange real-time data is vital for reliable central controlled V2G. The literature addresses and resolves the central V2G controller at the power system level in which the EVs residing in different areas are assumed to be ready for charging process, which might not be the case. The authors in [50] confront these issues differently to come up with an enhanced centralized V2G charge/discharge model. Real-time vehicular data is important to generate accurate models that tackle EV mobility and its effect against power capacity and availability. Most of the current works depend on cellular networks and Wi-Fi networks to exchange vehicular data on the move. There are many shortcomings, however, that render such tactics impractical.

First, EVs location could be inaccurate if the network is overwhelmingly dense, which would impact the computational process adversely. Second, the mentioned networks are not specifically designed for vehicular communication purposes, so a bulk of vehicular data exchanging is costly and congestion-oriented, especially in dense vehicular areas. Hence, the so-called Vehicular ad-hoc network (VANET) supports real-time communication between mobile EVs and communication units for real-time EV mobility data and charging/discharging decision without suffering from the drawbacks of the above mentioned systems. Furthermore, the model considers the V2G controller from the EV perspective. The vehicle mobility is highly important in modeling the centralized system so as to maximize the overall charging energy. The architecture of VANET is depicted in Fig. 6 that comprises a power distribution system, a traffic server, charging stations, EVs, and road-side units (RSU). The power distribution system provides energy to the whole network through feeders. Also, the charging stations provide fast-charging scheme for all EVs. Furthermore, centralized and distributed charging modes were addressed altogether in the same source for a review that described up-to-date techniques in both approaches. Also, it offered a comparison between centralized charging model and the distributed charging model, including static and mobility-aware modes. These modes apply to both charging models, where the former excludes the mobility pattern of EVs, while the latter accounts for such a pattern.

The uncertainty of EVs charging on electric systems is inevitable, as it relies on drivers' arrival pattern and daily driving habits. The uncertainty related to EV drivers' behavior, such as time distribution, energy consumption each user spends in a trip, and economic as well as social attributes that contribute towards a model that computes EVs charging demands as the probabilistic agent-model in [51] states. The model combines social, technical, and economic variables to compute EV charging demand as shown in Fig. 7. Also, the paper formulated a benchmark to compare different case studies like different cities or zones in the same city, so zones with high density of EVs can be easily located. A simpler approach is to compute the capacity margin available and prioritize the EVs to be charged first as in [52]. The strategy formulated in the reference is to propose an efficient approach that generates optimal solutions that meet the EVs charging demand as well as alleviate adverse impacts on power system networks. Moreover, the computational requirements are moderate compared to other centralized strategies, which is attributed to an easy technique using two indices to prioritize EVs charging demand-namely, capacity margin index and charging priority index. The basic strategy format is to quantitatively analyze the load profiles and the EVs charging demand using the two indices, and the EVs charging load

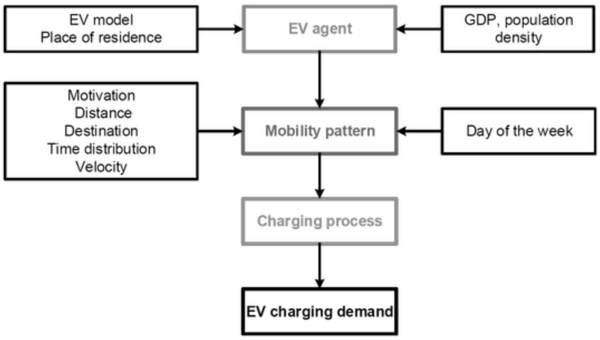

FIGURE 7. Basic scheme of EV charging demand parameters [51].

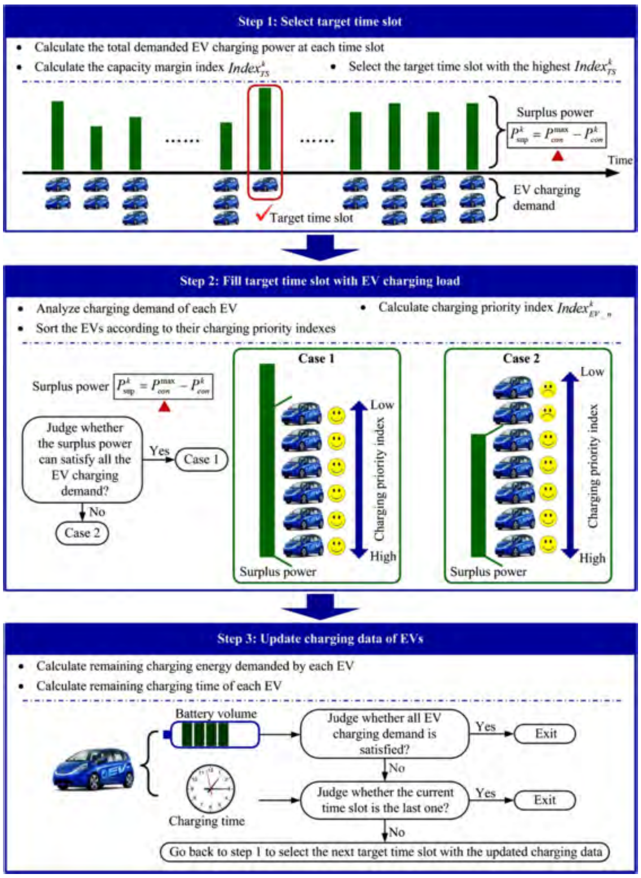

FIGURE 8. EV charging method using valley-filling approach [52].

demand is scheduled during low demand hours (valley hours) to utilize surplus power at proper period of times, which is shown in Fig. 8. The approach was verified in a case study held in China that showed its effectiveness as well as its efficiency.

On the contrary, [53] assumes the determinism of the EV behavior (e.g., arrival/departure time and charging characteristics) in which so-called large scale charging facility is capable of handling large amount of EVs simultaneously by setting right policy considering energy consumed, overall charging power capacity, and the arrival/departure pattern. The algorithm showed a superior performance compared to other off-line algorithms.

Limited resources raise many concerns related to service reliability and continuity, and V2G is no exception. Besides, the uncertainty and dynamics associated of EVs mobility make the V2G system so much complex so that only optimization techniques can manage power flow between EVs and the grid, or vice versa. Thus, the optimization techniques came into picture to utilizing available power margin efficiently. The centralized control models usually use certain algorithms to represent the process, which include: linear programming, quadratic programming, dynamic programming, mixed-integer linear programming, mixed-integer nonlinear programming, stochastic programming, robust optimization, heuristic and meta-heuristic algorithm, and model predictive control [17]. Traditionally, optimal power dispatch is determined using unit commitment concept, which they can be applied to V2G system. It has been known that linear programming (LP) and quadratic programming (QP) are widely used for unit commitment optimization techniques [54]. Mathematically, these techniques determine the best solutions for the optimization problem, but they are limited to simple and linear problems. Hence, nonlinear programming and mixed integer nonlinear programming were employed for more complicated problems, but they tend to underperform with uncertainty, and they lack of efficient computations.

Other techniques used for optimization purposes are priority list technique and Lagrangian Relaxation technique. The former is mostly heuristic, while the latter is difficult to get feasible solutions, so they cannot be used effectively for the V2G system [17]. That being said, the most popular methods for V2G system optimization are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) [55]. GA is defined as an iteration method used to search for a global optimal solution within a time limit, while PSO is a memory-oriented computational algorithm searching for a global optimal solution in a population of random solutions. The advantage of PSO is the requirement of a lesser computational timing and memory [55], [56].

Authors in [57] utilized GA to optimize V2G scheduling so as to minimize electric network load variance, which is contributing towards network stability. In [58], the optimization algorithm varies the charging rate around a set point that is determined based on the cost-versus-revenue ratio to optimize the charging rate point called the preferred operating point (POP). The reference addresses two approaches used to select POP: heuristic smart charging algorithm and optimal selection algorithm. The smart charging algorithm employs so-called price-based technique and load-based technique. The load-based tactic is preferred, as it includes the effect of renewable generation sources, thereby enhancing the system performance. The optimal selection algorithm, on the other hand, imposes aggregators as interface between EVs and utilities, so the V2G asset optimization is done by the aggregator to maximize profit, which in turn leads to maximizing the EVs charging rate as well as providing regulation service to electric networks. This practice ensures optimality achievement compared to suboptimality of smart charging techniques. These algorithms were applied to the Pacific Northwest system case study, which revealed that only the optimal algorithm provide benefits to all parties: utilities, customers, and aggregators.

In addition to EVs random mobility, authors in [59] incorporates time of use (TOU) pricing policy to so-called state-dependent policy (i.e., timely battery energy level and optimal battery level) to formulate an energy minimization function for optimal cost-based V2G modeling. The paper uses stochastic inventory theory to optimize energy delivery problem, where the EVs' SOC resembles the inventory stock level. The reference proved that the state-dependent policy is truly optimal through real data gathered from Canadian utilities. Optimization techniques produce good results for V2G as seen before, but the V2G performance can be enhanced further by integrating such tactics together or with heuristic strategies for optimal results. This was experienced in [60] that combined PSO, GA, and the author proposed dynamic crossover and adaptive mutation techniques. These combinations were compared to an approach that is based on spot pricing of energy market for optimal charging priority technique along with a battery swapping technology for EVs. These comparisons were conducted on IEEE 30-bus test system indicating that the combined strategy of PSO and GA outperformed all other strategies in terms of charging costs and power quality aspects. Operation cost is linked to emissions, as certain precautions are applied to minimize anti-environmental emissions. The cost-emission optimal mix was the topic analyzed in [61] in which a number of EVs in parking lots were utilized using unit commitment concept to balance the cost-emission equation, leading to enhanced profit and reliability of the whole system. EDISON project described in details in [62] modeled an optimization technique for cost minimization and charging prediction.

The previous papers assume that the EVs connectivity to charging stations is certain. That is, the stochastic nature is related to drivers' daily travel, but the plug-in process is not uncertain. Queuing theory was employed in [63] to account for such uncertainty and integrates it with a price-based model that presents incentives/penalties to optimize the EVs charging/discharging penetration rate. The EVs' charging stations were modeled as multiqueued system, where each station represents a queue. Markov chain is another stochastic tool that could help modeling V2G random driving pattern and the end-user price preferences [64]. The stochastic process explains the EV users' behavior that can be modeled as inhomogeneous Markov chain, which is solved recursively using stochastic dynamic programming technique. Consequently, the results address issues pertaining to V2G schemes and availability of EVs. The optimal charging policy is then selected in accordance with electricity price, EV usage, and risk aversion of EV users. The central charging control introduces many applications which V2G can provide. The centralized optimization modeling in [65] offers a model that uses time coordinated optimal power flow (TCOPF) formulation to utilize the V2G concept and on-load transformer

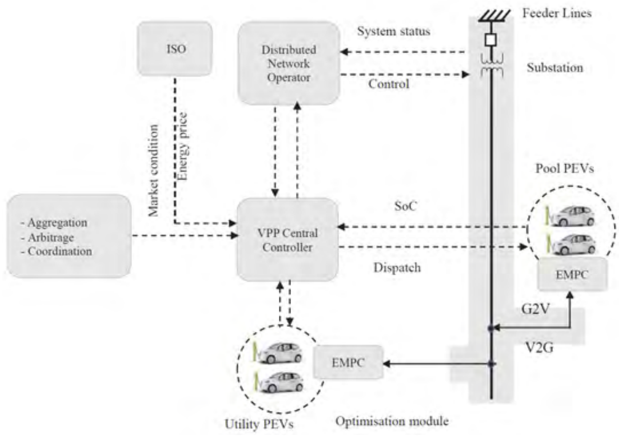

FIGURE 9. Bi-directional model of PEVs and their interactions with the grid [11].

tap-changer (OLTC) to influence system losses. Also, the residential loads can put constraints on the maximum charging rate of each EV as stated in [66]. However, the capability to control load side allows EVs to vary their charging rates accordingly. This is orchestrated by an aggregator to safeguard the grid variable constraints while maintaining the process. The algorithm employs linear programming approach, so the involved computations are not intense, thereby simplifying its integration into coordinated charging schemes. Of course, several factors (e.g., environmental) can be added for more accurate results, but rather complex modeling. For instance, [51] integrates travel pattern model, energy consumption model, and historical records of temperature values in one model that produces optimal results for EV charging allocation.

C. V2G CHARGE/DISCHARGE DISTRIBUTED MODEL

EVs are equipped with some computational capabilities, so the charge/discharge decision is taken by both EV users and an aggregator. In contrast to the centralized approach, EVs communicate only their energy requirements to the aggregator to decide on an optimal charging schedule [67]. The advantages of de-centralized charging/discharging techniques over the centralized one are significant, so authors exploited such an approach to come up with optimal results. The differences between the centralized and the distributed schemes are discussed at two charging aspects: unidirectional and bidirectional [24]. The same paper discussed the advantage and the disadvantages of the two schemes of the two charging types along with their applications; this layout is depicted in Fig. 10. The so-called estimation distribution algorithm (EDA) is employed to account for a large PHEV penetration that would otherwise have harmed the network. The energy consumption management of local households to which EVs are connected aid reducing peak loading as in [11]. The model in [68] compares a centralized technique "Equal Share" concept to uncontrolled charging and de-centralized charging techniques. The former measures power at the distribution transformer side to allot equal power

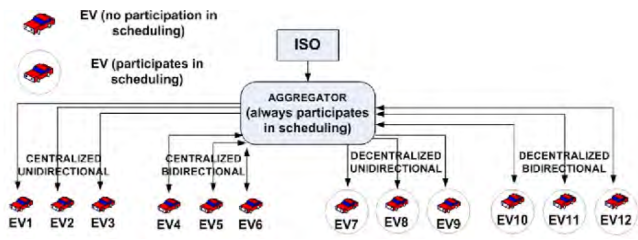

FIGURE 10. Charge scheduling process system view [24].

share to all EVs, while the latter uses a local voltage signal to determine whether the network load is high (EVs shall not be charged) or low (EVs can be charged). The results inferred from this study indicated that both centralized and distributed methods provide improved performance over the uncontrolled approach. Actually, the centralized technique offered 3-6 times as many EVs to be connected to the grid as in the uncontrolled approach, while it is 3-4 times in distributed approach as many EVs as in uncontrolled case.

Also, [69] offers a sensitivity analysis comparison between a local control charging technique (LCC) and a centralized control charging (CCC). Furthermore, the paper claimed that the two approaches can have roughly close performance level in terms of energy supplied to EVs; however, the LCC is claimed to have a superior performance provided that a set of expected household load-related sensitivity measures are calculated for several scenarios. Scalability is a major constraint to promoting centralized charging approach, so distributed charging strategies to overcome this limiting factor in accordance with [69], [70]. Importantly, the economic aspects of shifting from centralized to de-centralized models are case-sensitive, so the fact of the matter is that detailed analyzes is required. The authors in [71] investigates the economic and its corresponding technical aspects of selecting centralized or de-centralized option.

The charging revenue is the parameter for which the reference opts, so anticipated new peaks arise under TOU pricing basis. Hence, the reference proposed a technique to reduce the peak-valley difference whereby an aggregator has incentives to exploit such a difference to maximize profits and minimize user-related costs. Regarding the decentralized approach, on the other hand, so-called rolling-update pricing technique was suggested for individual users to overcome the TOU new peaks issue. Price-based techniques can be combined with renewable sources for enhanced performance. The renewable production rate and the network demand forecast at short-term allow the distributed price-based charging control to allocate EV loads during off-peak (valley) hours with a priority to hours that have surplus renewable energy production and exploit the V2G process to minimize the system loading as elaborated in [72]. The technique given in [73] offers a two-level optimization algorithm that achieve valley-filling and frequency regulation services using the distributed modeling. In addition, individual and collective efforts can contribute to shift load peaks as presented in [74] that offers two approaches for valley-filling purpose. cooperative and noncooperative techniques were developed in the source to handle the load peak issue, where the former is into reducing a user charging cost, while the latter is more into optimizing the overall charging cost. Most of the literature works assume idealism in the customers behavior, communication infrastructure integrity, and knowledge about the system parameters, which might not be the case most of the time. The game theory was conceptualized in [75] to suit a decentralized charging system for EVs to avoid these assumptions and prepare a more realistic model that mimics the actual situation. The decentralized charging approach utilized so-called Nash Folk technique to coordinate game-based charging mechanism. The mutual benefit of EV users and electric network are the focus of [76] that used analytical hierarchy process to govern the dispatch process. The model was tested on IEEE Reliability Test System, which was proven effective. The infrastructure needed to serve EVs was elaborated in a case study in Beijing [77] that emphasized the significance of fast charging stations in the general layout of other charging station types. In fact, the radius to which the fast charging station extends is vital in founding new stations provided that the EV users satisfaction is met.

III. BUSINESS MODEL

A. BUSINESS MODEL SYNOPSIS

The models dealing with V2G charge/discharge process analyze the feasibility of the scheme from a technical perspective, but only a few look at economic factors (business model) that requires extensive assumptions [48]. These assumptions cause a highly volatile revenue such that the electricity market becomes unstable. Also, policies set to govern EVs market growth may complement cost reduction of renewable energy sources that are tied to EVs through the V2G process [78]. Recent R&D of storage batteries paved a rout towards a cost-effective energy source [78]. Often, many business models focus on a single aggregator profit performance, but only few consider full-scale grid profit maximization. Authors in [79], however, concentrated on maximizing the aggregator total profits, considering the possibility of inter-aggregator energy trading to exploit any energy trading between aggregators. The reference developed distributed optimization heuristics to overcome the computational complexities arose from the nonconvexity nature of the formulated EVs charging problem, which was proven successful after testing it in a case study. Renewable energy sources go hand in hand with EVs because of the interrelated services provided mutually. The authors in [80] reviewed business model concept of V2G in terms of renewable energy source solely. Many business model topics were reviewed intensively in [81].

Cloud computing finds its way into many applications in different industries because of the features given by the technology. Interestingly, authors in [82] designed a business model that made use of the cloud computing technology in which it helped finding nearest charging station with minimum waiting time cost. The model, also, provided service to all stakeholders involved like aggregators and charging vendors. Uncertainty associated with EV integration introduces financial risks that might put a business model in jeopardy. A risk averse optimization strategy was devised in [83] to enable smart charging management of EVs. Moreover, it evaluated technical, social, and commercial uncertainties in energy market to generate a bidding strategy for smart charging that act as an aggregator for managing financial risks caused by the mentioned uncertainties.

Specifically, a closed system like building-integrated energy system can economically benefit from EVs integration, as utilities are tuned optimally so as to incur revenue and keep the system stable through EVs integration as explained in [84]. Authors presented in [48] a thorough view of EVs business model at different aspects ranging from industry perspective and charging/discharging process to EVs integration to electric grids forming V2G services. The source is rich of global perspectives of EVs integration and the impact against proposed business models, and it presented several case studies at different location of the world to explore the business model shape at different energy market global wise. Beside technical attributes of V2G, [85] addressed the importance of sociotechnical attributes of it in the published researches that span the period between 2015 and 2017. Particularly, market segments, complexity of EV drivers' motivation, and any other human/social-related aspects did not receive proper attention in the literature, which could result in bias results. Social and human factors are equally important as technical aspects, so no unforeseen results catch us by surprise.

B. BUSINESS MODELS AND ECONOMIC EVALUATION

In [48], the authors presented a V2G model that accounts for revenues associated with the scheduled charging/discharging process that is overseen by an aggregator. There are many proposed models and standards that govern the bi-directional communication and power exchanges between vehicles and the grid. These business models range from a simple model like "EVs as Appliance" that offers no connectivity service to the grid, through "EVs charging as a Service" and "EV Battery and Charging as a Package Service" where the former lumps EVs management and cost into a single package with a monthly fee payment, while the latter is similar to the former one except that an EV battery is owned by the service provider, resulting into more expensive monthly payments, to an advanced model "Paying the Owner for Providing Grid Services" in which V2G requirements are fulfilled. Also, the reference introduced many integration project examples in which economic integration is illustrated in each example to compare these approaches. The technology described for these projects cover two main topics: software and hardware components that manage all required computational requirements and the communication protocols that are used to exchange data among entities.

Pricing-based strategies(valley-filling) are usually utilized successfully for mitigating harsh impacts resulted from a high EV penetration rate. Likewise, business models can employ the same concept to minimize charging schedule cost, which in turn raises profit margin. The valley-filling technique was the core of [74] that had two mechanisms to achieve the valley-filling strategy: noncooperative and cooperative. The former assumes that an aggregator is in control of all EVs parameters, while the latter assumes that each EV can schedule its own charging power without cooperating with other EVs. The cooperative scenario adopts a rolling optimization tactic to schedule EVs charging power according to charging price function. On the other hand, the noncooperative scenario employs a charging guide approach to help EV drivers specify their charging power schedule and do the cost-minimization process. Basically, the results showed that both approaches indicated provide incentives for aggregators or EV drivers to shift their charging schedules to valley hours. Moreover, the authors in [86] introduced a price-based optimization formulation in which linear programming as well as quadratic programming are used to minimize charging costs. The Danish network was set as an appealing example for such an approach because of several reasons listed in the paper, one of them is the substantial difference between power surplus and power deficit during a day, which supports the price-based approach. Basically, the paid price is composed of a twofold set: availability fixed payment and activation flexible payment. The study concluded that there is an inverse relationship between number of participants and the flexible cost the customers incur. Later, the model in [11] was developed under the assumption that the grid aggregator already is aware of the grid constraints. The model (see, e.g., Fig. 9) assumes the central controller (CC) accumulates the contributions of distributed energy resources (DER) and coordinate EVs charge/discharge process.

Furthermore, the CC can fetch data from optimization module planted in the EVs so as to select appropriate charge/discharge schedule for each set of EVs,and authors in [58], [87] explored the possibility of meeting users' requirements during the charging planning stage. In other words, there are many available connections that are cheaper than the full power connection point, so users have the option to select the proper channel. Furthermore, a central price predictor based on the market status can be used to influence the V2G behavior through different techniques, such as forward charging, backward charging, and other market-related pricing that rely on the timely power price. An objective function of cost minimization was formulated in [63] to manage the charging/discharging process. Importantly, the market price is so much volatile so that the charging scheduling could get impacted adversely at certain instants of time. This emphasizes the importance of considering such price variations into the proposed charging models. The proposed V2G optimization model in [59] takes this point into consideration along with the driving pattern of the EV fleet; the aggregator centrally is in control of the entire process.

Energy markets are governed by same principles that regulate all markets, such as supply-and-demand law. Often, a single EV cannot accommodate power demand at certain instants of time, so a sufficient number of EVs has to be dedicated to participating in the market so as to support frequency regulation; participate in spinning reserve service; or otherwise. Each application entails different participation rules and a minimum power capacity as outlined by [88]. The reference tackled the communication issue of the model by introducing so-called coalition server that facilitates the information exchanging among EVs and provide an abstract about their related information. There were many coalition formation strategies that were put under simulation testing for a comparison purpose. Furthermore, [89], [90] emphasized on the importance of a mediating party to facilitate the communication between the EVs and ISO, who is in charge of frequency regulation, to make such an aggregation scheme feasible. Basically, there are two main stakeholders for which the V2G ancillary service transactions are transferred-namely, the grid system operator and the EV owner. The EVs are suitable for frequency regulation because of their rather short ramp-up time and negligible costs during idle times [90]. The grid system operator is concerned about availability and reliability of the V2G service, and the EV owner is more concerned about the return on investment.

The aggregator role can be performed by an external entity to the grid system operator, or it can be fulfilled by the grid system operator. Apart from that, the reference claims that there is an inverse proportionality between the reliability-availability requirements and the revenue gained from utilization of EVs in the V2G scheme due to the fact that the aggregator needs to cumulate more EVs to meet these requirements, which in turn affects the revenue share of each EV. This aggregating scheme was conceptualized in [7], where the V2G mode is not considered. Instead, preferred operating point (POP) supplies the reserve in a range between zero and the maximum charging power of EVs. There were two optimization algorithms were addressed: a one-day ahead of time algorithm that operates in a normal energy trading and frequency regulation and another algorithm that manages EV charging process in accordance with the trading outcomes. The former optimizes charging rates and periods to reduce costs, and the latter enhances profit from selling regulating power. The authors used artificial EVs time series and actual market data to assess the algorithms, which resulted in a significant cost reduction for several fleet structures. Typically, V2G has a fixed price for injected energy into a grid, which imposes a certain number of hours for EVs to be available for V2G process, thereby raising concerns of EV users about contract terms. Also, the uncertainty of EVs availability introduces some ambiguity about the profitability of V2G process that can manifest as a reduction in the net profit since the contracted price is high. Consequently, EV users see a high cost for utilizing EVs, which in turn affects the V2G process badly.

The frequency regulation is a process that prevents any power-related violations to electric grids. The computed gross revenue ranges from \$1000 to \$5000, based on a market sample price in 2002, depending on the driving habits. After that, authors in [28] extended the work to cover V2G concept in a case study conducted for California energy market. The paper addressed the basic concepts of V2G and its capacity, power market, generation regulation control, and EV economic calculations. The revenue relies on the service to which EVs provide. For instance, energy revenue is simply calculated from the energy dispatched price, while spinning reserve and regulation services include different variables in the revenue equation. It turned out that V2G is not suitable for bulk power applications due to the fact that EVs are not economically feasible compared to conventional generation schemes. That being said, the most profitable scheme is to utilize V2G in spinning reserve and frequency regulation. Nevertheless, the local electric network would saturate if only three percent of local cars shift to V2G process. The previous reference was extended in [13], where electric grid source was compared to EV fleet source to shed lights on pros and cons of each scenario. The electric grid has a high capital cost and a low production cost, whilst it's quite the opposite for the EV fleet case. The reference, also, covered the implementation procedure, business model and the transition process towards EVs application.

In [91], a single-level EV was used to support frequency regulation in energy market, which was proven a valuable source for ancillary services. These findings were confirmed in [88] in which the short response of an EV fleet is of a great advantage that can be exploited to provide ancillary service. The estimated revenue was in a range of \$1200 to \$2400 under the assumption that each EV participates in a 15-h duration a day on average and the set price is double the normal market price. The frequency regulation was the main ancillary service considered in [92] that examined a business model at several EV SOCs in different time during a day in the German electricity market. The revenue incurred at current market conditions was lower than investment costs, thereby rendering the case infeasible. Instead, it would be profitable to charge EV batteries immediately.

A study in [93] included a fleet of 50 EVs in which each EV contributes only for four hours a day. The estimated revenue per an EV is only \$40 per year, while [88] uses substantially optimistic assumptions with regard to the set price and EVs availability, which resulted in exaggerated revenue ranging between \$1200 to \$2400 a vehicle. Nevertheless, the two studies were held in different markets under different conditions which leads to inconclusive results [92]. The communication architecture that governs the EVs and the system operator plays a major roles in setting the economic feasibility of the provided ancillary services [94]. The paper compared two communication architectures: deterministic and aggerative. The former sets a direct communication line between EVs and a system operator, while the latter has an aggregator as an intermediary between the EVs and the system operator. The deterministic architecture limits the bidding process only to the EVs that are in the charging station, as the system operator is fully aware about all available EVs. Conversely, the aggregator places bids all the time under the assumption that the statistically available EVs' number is enough in the aggregative architecture. The final outcome revealed that the aggregative approach improved the EVs reliability and availability factors, which in turn rendered the EVs ancillary services feasible at the cost of reducing the collected revenue per EV.

Aside from the previous studies about EVs' profitability, these studies had many impractical assumptions [48]. A large-scale deployment of EVs only justify adopting a new control architecture between EVs in distribution networks. This might not be reachable in the near future, so the whole researches might not be realized in long time. Moreover, charging manufacturers have no intention to penetrate emerging EV market because they lack of large-scale production and they focus on short-term objective. The downside here is that these manufacturers don't utilize charging optimization algorithms, as they have no incentives to do so. The deployment of EVs, however, is attractive for utilities, as it spares them investment costs. Unfortunately, it was found that many industry key players invest in EV batteries just to capture knowledge and expertise that are to be used in other industries. Of course, this would delay the realization of EVs adoption in electric networks.

Electricity market as many other markets has uncertainties at different levels, one of them is bidding prices of deploying V2G into grids. Authors in [79] accounted for uncertainty of ancillary service prices and their associated deployment signals. Fuzzy sets were employed to model such uncertainties whereby a fuzzy linear program for an EV aggregator was formulated to coordinate the provision of ancillary services. Simulation outcomes revealed that because of the fuzzy optimization technique, the aggregator profit rose and the profit error (difference between actual profit and expected profit) did really decrease. Also, the fuzzy optimization compared to deterministic optimization, improved the final SOC of EVs a bit and reduced subtly the average peak load resulted from EV adoption. Unlike many researches, the authors in [83] presented a complete communication layout of all concerned stakeholders involved in the V2G process to efficiently manage and monitor charge/discharge process and ancillary service provision in a model that strives to maximize net profit value and meet the grid energy requirements. The EV users underlying driving assumptions play an important role in setting the profit value and ensuring the benefit of the model. Many papers consider simple assumptions for driving patterns, but this model considered more realistic assumptions that resemble actual drivers' behavior, which means more accurate estimate of incurred profit per user based on optimization of charging schedule. The authors conducted several case studies that presented net profit values because of the model proposed.

C. POLICIES AND REGULATIONS

State of art business models along with pilot projects were reviewed in [95] for V2G service in smart grids. The pilot projects indicated that the value from consumer perspective is related to lower energy consumption and lower bill prices, whilst it is more concerned with reducing demand load peaks and improving system reliability from system operator viewpoint. Essentially, an EVs aggregator should be employed in smart grids so as to turn a business model profitable by integrating many smart grid services with enough EV users to reach break-even point. The authors in [96] commented on the policy issue of V2G in the Nordic region and the need to set appropriate policies and standardized regulations pertaining to aggregators, distribution system operator (DSO) positions, and electricity markets to boost the EV market for V2G process. Socio-cultural factors shall be studied quantitatively and qualitatively for enhanced understanding of hidden aspects that influence a business model in different ways. The authors in [97] highlighted the criticality of common standards and policies between manufacturers to help the growth of EVs deployment. EVs usage as flexible loads in a day-ahead market is not profitable as the authors in [98] claim. A case study held in Denmark showed that the EVs should participate in ancillary service provision to incentiveze the use of the V2G service.

A successful business model is a combination of proper blend of policies, experts' judgment of dominating factors, and impeding barriers. A roadmap was created in [99] to have a better understanding of opportunities of the emerging EVs smart charging technology within emerging environmental conditions so as to bring forth suitable business models. Moreover, the authors listed main conclusions about the business models to be devised. Researchers agreed that there should be a balance between hardware and software sides of the battery chargers for the sake of proper business model. Standards and policies must be there beforehand to facilitate a wide-spread deployment of EV charging, especially fast DC chargers. Generally, the viewed business models agree and disagree on certain points, but they intend to develop a business model that suits the EV charging at large-scale deployment level.

Apart from the cost issues of V2G implementation, lack of standardization of hardware and software composing the V2G system is one of the major barriers against adopting EVs at large scale. Different approaches followed by Asian and European/American manufacturers deter many players from engaging into this industry, resulting in limited scalability of a business model. Consequently, it mandates a large pool of EV users of that business model to be profitable, which might not be possible at this stage of the V2G technology. The authors in [99] investigated previous pointes in forming a business model guideline to be implemented in Swiss market so that key players are convinced to penetrate this market and turn it profitable. Briefly, the reference suggested a three-stage model to implement the V2G. A closed charging environment with limited number of EV users is the first stage, as it might not be feasible to integrate with other systems due to the lack of standardization. Supposedly, the EV users would gradually gets higher and then technology would become mature enough to make standardized protocols and procedures, making a flexible business model a must. The three-stage roadmap

TABLE 2. Services of electric vehicles in vehicle-to-grid system.

Service Type	Characteristic
Energy Supply Service	Fixed charging price Low return on investment Low availability of EVs Long-time requirement of EVs connectivity Low power network reliability High battery degradation effect
Ancillary service: peak shaving regulations spinning reserve	Variable charging price High return on investment High EVs availability Short-time connectivity of EVs Minor battery degradation effect

comprises demand response, bidirectional charging, and open market. The open market stage represents the ultimate form of modeling in which EVs not only sell energy to grids, but also to all forms of electric networks (e.g., smart grid, microgrid, etc.). Furthermore, service providers shall opt for other revenue sources in order to break even, as the returned investment per user is small. Ancillary service is mainly an additional revenue source, such as peak shaving, frequency regulation, and so on. The services provided by EV users fall generally into two categories: base load energy supply service and ancillary services. The energy supply service is not favoured by many authors [28] due to the fact that it requires gathering a large number of EVs for long time, which would restrict the EVs usability as vehicles. Also, the cyclic charge/discharge of batteries might result in premature battery replacements, which add on the cost of the EVs. The whole scenario might not be feasible after all. Thus, the ancillary services are preferred because of their short ramp-up time feature that averts the downsides of the energy supply service. Table 2 lists the EVs' service types and their associated characteristics.

A thorough study of many business models was done in [100] to come up with proposals of that reflect what consumers want in a business model. A Dutch sample online survey revealed that V2G business model shall be characterized by the following: emphasis on functional attribute rather than financial, aggregator is supplied by utility companies opposed to car companies, functional attributes of customers are more important than financial counterparts, and V2G service is used by EV owners at private stations at homes. Surprisingly, the aggregation service is preferred from utility companies, which adds a new source of revenues for them. Also, EV users are more interested in the functional service than the financial payback to which they are subject. A proposed business model incorporating previous findings shall be devised for best outcomes.

D. OBSTACLES TO V2G

High investment cost is one of the major hurdles encountering EVs adoption, which might impede the progress of integration. Hence, there should be a well-formulated business model that enables the users to recover their investment costs and charge their EVs at rather acceptable prices; this is the topic of [101]. The reference formulated a business model to assess three scenarios along with case studies through which the business model is proved profitable. These scenarios represent different situation that EV users would often face in the daily driving pattern. EV users could need to use charging service at home (private home charging), public places (traffic hot spot charging) such as malls, and in highways (highway charging). Of course, each case needs different charger specifications that suit the associated driving pattern. In each case, the required capacity of charging stations is computed such that the charging service operators cover their costs. Mainly, the private home charging would be profitable if the EV users incur lower costs than the regular combustible engine vehicles. This happens only if the EVs users drive for long distance mileage; charge at rather low prices during night times; and take advantage of subsidies of EV purchases.

As a result, the private home charging is speculated to be one of the early adopted charging stations. In regard with the hot spot charging stations, there has to be enough number of EVs (roughly tens of EVs) in that zone so as to break even, while the number of EVs should be hundreds or even thousands for the highway charging stations to become profitable. Unexpectedly, absence of cyber insurance raises EVs charging costs, as it secures infrastructure information that is increasingly proportional to the charging cost and inversely proportional to the incurred profit [102]. Moreover, the reference proposed a learning algorithm that helps EVs drivers in decision-making process, such as buying cyber insurance, charge or discharge in a timely fashion. The learning algorithm showed that it can reduce the charging cost and increase the discharging profit as the same time. Smart charging strategies are also valuable approaches to reduce the charging cost for V2G [99].

In [103], the authors confirmed the notes highlighted in [101], EV users deter from V2G services because of the high contracted cost they experience caused by the uncertainty of the EVs availability, through a survey composed of two parts: one for EV and another for V2G, and it proposed two approaches to overcome this issue. One is to cancel contract requirements totally and allow EV users to provide the V2G service at will, following a pay-as-you-go-basis to eliminate part of the prohibitive associated cost and make the service more attractive. A different approach, also, is that an aggregator provides upfront payment to EV users in order to alleviate the uncertainty associated with the V2G process. EV batteries, also, could be an obstacle to EVs deployment into grids due to forbidden capital cost and projected cost throughout batteries life cycle. The main reason according to [101] is the high cost per kWh of EV batteries, so incurred revenue does not result in profit making scenario. The authors in [102] investigated the feasibility of reusing batteries after being retired from EV services to reimburse part of capital cost. In fact, the paper presented a business model of several stakeholders that are subject to taking advantage of the re-used batteries (second-life batteries). Having done qualitative case studies, the model came up with deciding factors are to be analyzed in order to re-use implement secondary-life batteries. Batteries ownership, inter-industry partnership, and government support are the deciding factors through which an entity can decide to adopt secondary-life batteries. At early stage of the secondary-life battery market, it is essential to have government supports through incentives for various projects and policies related to battery liability and energy storage. Existing business models do not support the secondary-life battery concept, so end-of-life battery strategy has potentials to create suitable business models for such concept. Battery degradation rates is a dimension of EV batteries in which most literature do not take into consideration [101].

Hence, authors articulated the battery degradation factor into a business model through policies that regulate the battery usage to prolong their functionality, so the battery degradation factor can be assumed incorporated in the business model. The authors in [101] approached the battery problem actively trying not only to include the battery degradation factor into a mode, but also to extend the battery life through certain procedures. The developed algorithm assessed the battery degradation factor and recommended some techniques to prolong battery life, thereby improving business model outcomes. Nevertheless, [102] stated that the battery degradation factor is detrimental to economic feasibility of a business model under certain charging mode. It was found that the business model is economical if the battery degradation rate was ignored, and vice versa. In addition, a distributed wind generation system was simulated to offset such a battery degradation factor, resulting in an economic business model. The authors found that under smart charging mode, the business model was economical, and the battery degradation rate was much lower than that in uncoordinated charging mode. Also, intelligent energy system in the presence of renewable energy sources was recommended in [101] to compensate for the battery deteriorated life cycle.

The rate at which EV batteries capacity is measured can be accelerated with acceptable accuracy for efficiency purpose. This case was investigated experimentally in [104] resulting in a reduction in measurement time by 90 % with proper error rate, so overall efficiency was improved significantly. Battery charging station has external factors that might indirectly impact the battery life cycle, thereby affecting the business mode at hand. For instance, the battery station location, size, and charging techniques would alter the business model in such a way that the whole scenario can be turned upside down. Hence, authors in [101] discussed this matter and proposed a model that approached the battery charging station optimal planning methods. The model opted to maximization of net present value throughout the project life cycle. The model was applied to case studies that showed the optimal model help balancing demand-supply rate, so operators can reap profits from the optimal planning model. EVs batteries, also, experience a cost reduction attributed to imposed policies regarding batter life span and battery swap practice.

E. MARKET STRUCTURE

Traditionally, business models resemble the conventional power generation models whose stakeholders involve transmission system operator (TSO), DSO, energy supplier, and final customer. These different parties are fixed regardless of the electricity market within which they operate. A new market envisioned in [105] introduced a new actor to the model known as charging system provider (CSP) whose role is to supply all required elements except for the energy needed. In other words, CSP's business is governed by so-called business-to-business offers concept that is concerned more about purchasing charging stations; preparing electrical connections of the charging stations to the grid; provision of energy management business; provision of information technology system for billing system; maintaining the charging stations and IT systems. Hence, CSP is an enterprise that is mainly engaged in the electrical infrastructures and system markets, and whose main business is in preparing designs and selling energy management systems, without participating in generation, transmission, or distribution of electricity. The model, also, gave further details about selling energy management system called charging point manager CPM that can function either as a retailer or as an EV owner. The former is about selling energy in public areas like malls, and the latter is more about buying energy for its own EVs. There were many mathematical equations that constituted the cost-revenue model to realize the anticipated profits from the ancillary services that would be provided. This model is applicable under certain assumptions pertaining to energy cost and amount offered for selling. Unlike traditional models, according to the authors this envisioned model facilitates the integration of all parties in the V2G business. A comparison is made in Table 3 that addresses this model and the other models presented earlier in [94].

Presence of EVs according to [105] can alter the way that an electricity market is perceived in such a way that new models can be generated. Essentially, it is vital to settle the mobility case of EVs to finalize the business model. That is, EVs can be either charged at fixed charging points, called retailer-to-charging-point, or can be charged freely in networks, called retailer-to-EV. It all boils down to whether DSO view an EV user as a static load or movable load. The former facilitates DSO interactions with EVs at the expense of difficulty in customer behavior prediction, while the latter is quite the opposite. Furthermore, different charging schemes were simulated to analyze both models noticing that the retailer-to-charging-point is more compatible to public parking spaces and charging stations. On the other hand, the retailer-to-EV model can be used otherwise.

An intermediary party is vastly outlined in the literature, especially parking garage operators mentioned in [1], [6], [8], [106], [107]. Although the parking garage operators scheme seem proper for VGI, the related studies are only technical-operational-related aspects, or only specific related to local solutions. For instance, the authors in [106] used a greedy scheduling procedure to control the charging

TABLE 3. Vehicle-to-grid system architecture.

V2G Architecture	Feature
Direct (aggregator-free)	Deterministic estimate of EVs number Direct communication between ISO and EV users System is practically infeasible at large-scale Limited scalability factor Membership is required for charging Energy and financial supply
Indirect (aggregator-based)	Probablestic estimate of EVs number Communication line between ISO and aggregator Scalable Flexible Self-service charging Energy and financial supply
Charging System Provider	Probablestic estimate of EVs number Direct communication line between ISO and Charging Point Manager Infrastructure-oriented services Excludes energy supply

process in parking garage areas. The algorithm was economically assessed, but the whole business model and opportunity cost were ignored. On the contrary, authors in [6] considered locally generated power from solar sources to charge EVs, forbearing from energy market concept. The business model started grasping attentions in the VGI context literature in which authors in [6], [97], [108] emphasized on this point. They forecasted the EVs scattering pattern over a decade and contrasted that with EVs' mobility behavior to show that extra demand peaks could be averted via smart charging techniques. The behavioral factors could be detrimental to the effectiveness of smart charging techniques, knowing that end users will not contribute to grids stability or renewable energy integrations if there are no motives. The user acceptance of smart charging was outlined in [108], where network stability and renewable energy integration were found to be the most influential factors for user acceptance. Moreover, the financial compensation was investigated to second unselfish motives like network stability. In [109], authors extended the previous papers work to explore the VGI case with the parking garage operators as mediators and assess the case using actual data. Optimal logical control algorithm was introduced in [46] as a smart charging technique to optimize V2G process. This algorithm was tested with other six traditional optimization charging strategies (e.g., un-i/bi-directional smart charging) to find out the approach with the lowest charging cost. In short, optimal logical control algorithm reduced the charging cost by 47.94 % compared to a simple charging strategy, which indicates the gain of adopting such algorithm that would turn business models profitable.

IV. POWER GRID IMPACTS

The grid impacts of EV deployment has been investigated extensively in the literature. The various charging rates and dynamic behaviors of EVs complicate these impacts further. This pushed researchers to put their efforts on studying these effects, including voltage drop, stability, system and equipment overloading, phase unbalance, and so on so forth [110]. These impacts are offset by the potential opportunities of the EVs, but the need for mitigating techniques is vital [21]. In order to develop the mitigating techniques, a profound knowledge in power system analysis, power system components, power electronics, and many other power-related fields is essential. The information presented in Table 4 indicates the diverse and deep know-how needed, and it elaborately addresses the grid impacts issues and challenges.

The charge/discharge scheme directly affects the degree to which these impacts are harmful. For instance, the dumb charging technique has more noticeable effect than that of smart charging. Moreover, there are different techniques, algorithm, and optimization approaches that alleviate these power grid impacts significantly as listed in Table 5. These potential impacts are elaborated further in this section to address the system vulnerability in such cases.

A. LOAD PROFILE IMPACT

Large-scale penetration of EVs to an electric network burdens it further such that the EVs charging might coincide with load profile peak-hours load, worsening the load profile status. The EVs additional load should be anticipated earlier to account for it and set necessary mitigation scenarios. In order to make such anticipatory information, exclusive data of each and every EV usage should be available [111]. Besides, some information is required, like the time at which an EV charger starts functioning and the amount of energy required, and thus the collective evaluation of EVs integration effects on the load profiles are accurately considered [112].

Many case studies were conducted to investigate the EVs deployment impact on electric network load profiles. Many electric networks around the world were considered for this study; for example, the network outlined in [109], where USA grid load profile is put under test of EVs impact with the assumptions that EV users can charge anywhere anytime to account for worst case scenario. National Household Travel

TABLE 4. Grid impacts.

Grid Impact	Key Issue	Challenge
Load Profile	High coincidence factor of EV load and load profile Low load factor	Estimate timely integration rate of EVs Avoid simultaneity in load peaks and EVs peak
Voltage profile and phase unbalance	Large charging rate and degraded voltage profile Single-phased charging and unbalance	Maintaining voltage profile within standardized limits Avoid voltage unbalance
System loss	High power loss	Control transmitted power capacity
Distributed transformer	Overloaded transformer Degraded loss of life factor Winding hot-spot temperature increase	Accounting for outside parameters (e.g., ambient temperature, power quality, etc)
Transmission cable	Overloaded cables Power quality issues causing further degradation (e.g., proximity effect and skin effect)	Maintaining thermal capacity of cables within limits Different behavior related to power sector (transmission, subtransmission, distribution)
Harmonic distortion	Harmonics generated from charging stations	Improving harmonic indices (THD and TDD) in dynamic networks
Stability	Voltage stability Frequency stability	Modeling nonlinear characteristics of EV charging system

TABLE 5. Techniques to mitigate grid impacts.

Charging Scheme	Mitigation Technique
Unidirectional	Quadratic Programming Heuristic Algorithm Dynamic Programming Optimized Selection Linear Programming nonLinear Programming Fuzzy Linear Programming Valley-Filling Technique Demand Side Management Bee Algorithm Rule-based Charging Algorithm Stochastic Dynamic Programming Markov Chain Water-filling algorithm
Bidirectional	Particle Swarm Optimization Mixed-Integer Linear Programming Linear Programming Genetic Algorithm Time of Use Pricing Stochastic Inventory Theory Queuing Theory Lagrangian Relaxation Priority List

Survey (NHTS) had gathered EVs related travel data that shaped the analysis in this work. The data covers travelers' trips, travel distance, start-end-time of trips, start-end-location of trips. The results showed that the EV charging demand overlaps with the load peak hour and late afternoon peak hours, which corresponds to work arrival time and home arrival time, respectively. The solution proposed in [109] was a delayed control scheme to avoid such peak hours increase.

Moreover, German grid was studied to assess its readiness for EVs deployment in 2030 in [113]. Three distinct storage usage scenarios were studied: unmanaged (dumb) charging usage, grid stabilizing storage usage, and for-profit storage usage. Interestingly, the results revealed that a million EVs that are under uncontrolled charging scheme would not impact the grid by more than 1.5 % load peak increase, but the whole conventional cars (42 million cars) would roughly double the load peak in case of replacing them with EVs. Also, a million EVs could reduce the load peaks if they are used as storage units.

The authors in [114] addresses Western Australian electric network resilience for EVs deployment in three different charging scenarios that represent multitariff scheme. The assumption holds for this study is that all new vehicles come to service are EVs to enhance the adoption rate. The grid can tolerate additional loading of 200,000 EVs during peak hours in uncontrolled charging scenario. The study, also, showed that the utilization of multiple tariff scheme or smart charging scheme in which EVs charging times are shifted to valley hours enable the grid to accommodate additional 900,000 EVs. Nevertheless, the multiple tariff scheme comes at a price, the network component would keep overloading at nonpeak hours. Distribution transformers, for example, are utilized fully during peak hours, and they are cooled down at other hours to prolong their lifetime periods. The multiple tariff approach does not allow the transformers to cool down, as they are overloaded at nonpeak hours, so they deteriorate fast. Thus, one should balance the multiple tariff scheme with economic implications for improved outcomes.

Estonia power grid experienced a large scale of EVs integration that reached 30 % of the total number of cars [115]. The impact on the grid were insignificant for both controlled and uncontrolled charging approaches. It was only 5 % increase in load peak for uncontrolled charging, while it is reduced to 4 % for controlled charging. Furthermore, the controlled charging scheme disperses the EVs load overnight hours, thereby flattening load profile. In [116], the authors addressed Flemish urban grid load profile is put under test of EVs impact considering three different scenarios for slow charging: uncoordinated charging, residential off-peak charging, and EV-based off-peak shaving. The paper test both LV and MV systems for slow charging modes and fast charging option, where both systems specifications were addressed for analysis purpose. It turned out that the load profile impact is less sensitive with fast charging option than that of slow charging, as the fast charging option accounts to a small portion of EVs' group, especially if battery size is large. In fact, the number of EVs that can be added to an existing system considering the load profile of the fast charging option is reduced by 10 % or less.

On the contrary, the slow charging modes form the basis for home charging stations, so the majority of EVs charging approach is of a slow charging mode. The EV penetration capacity is influenced strongly by the selected slow charging mode with the considered load profile, which could vary between 40 % to 100 %. On one hand, the EV-based off-peak shaving mode has the least impact against the load profile, thereby allowing the highest EV penetration level. On the other hand, the off-peak residential charging mode impacts the load profile the most among the three slow charging modes. This is attributed to the fact of the matter that simultaneous charging at the start of the off-peak period could be detrimental.

A case study was discussed in [117] of a Greek distribution network was tested for fast charging case to analyze its effect on a load profile. In this paper, the fast charging (static and dynamic) is to be tested for full scale, as opposed to [114] that assumed the fast charging adoption is minimal. Also, the authors presented a methodology to estimate the fast charging demand and compute their impacts on the load profiles. The results showed that the load profile would be affected much; thus distribution networks need to be designed in accordance with such scenario. Smart charging was proposed as a potential solution to the existing grid to avoid reinforcement.

Moreover, uncoordinated/coordinated charging schemes with 30 % and 100 % EV penetration rates were tested on an Egyptian network in [118] to observe daily load profiles. The results had two sides: higher penetration rates result in severer load profile impact, thereby adversely affecting network components, and the coordinated charging mitigates such effects substantially, resulting in a smoother load profile. Generally, one of the impediments of EVs is the charging duration that might render it impractical. The advent of electronic infrastructure brought about development in charger efficiency and effectiveness, but this development is still minor. The authors in [119] tested so-called ultrafast charging mode at DC stations against slow charging mode at private stations and fast charging at public stations, as well. The slow charging mode has three types-namely, unregulated, regulated, and regulated with V2G intervals. The three charging modes were tested on a Bosnia and Herzegovina MV grid to evaluate the way they affect several power-related concepts including load profiles. The results revealed that the degree to which an EV charging process impacts the load profile relies on the charging mod as well as the EV penetration rate. Also, it was found that the unregulated slow charging is the worst charging mode among other types since it raised the load peaking substantially, impacting the load profile badly. The fast charging and ultrafast charging, on the other hand, were much more moderate in such impacts. That being said, the regulated charging (regulated and V2G intervals) would shift the peak loads to night times, thereby minimizing the load profile adverse impact significantly; hence, the EV penetration rate could be increased.

Traditionally, many research papers evaluate the limits to which electric grids are subjected in terms of EV penetration rates to anticipate the effects. Instead, [111] used real transportation statistics to realize actual EV demands and all its ramifications. Additionally, the EVs speed was modeled with four driving courses of road, highway, urban, and traffic jam periods. The three charging standards were considered to account for different load peak timings depending on the different charging rates of these standards and their associated load profile pattern for such scenarios, and the results showed that the EVs escalated load profiles in G2V mode; however, the V2G mode lessened such impact much. In addition, the authors in [111] based its EVs behavior pattern on the 2009 National Household Travel Survey to model EVs mobility parameters. The resultant load profiles from the simulated cases suffer from EVs penetration coincidence with load peaks during a day, around hour 19 in that particular case. However, this increase does not surpass 14.5 % of the load peak without EVs penetration. Also, the general view about load profile increase is that it is not critical since the power factor of domestic charger stations is over 0.95.

Typically, the bad effects accompanying EVs integration to electric grids are resolved through proposed schemes and algorithms to lessen such impact, such as smart charging, valley-filling algorithm, etc. Demand side management can be the answer for settling the EV integration shortcomings. A decentralized control algorithm was proposed in [120] to alleviate EVs integration impacts. The reference addressed the effects of EV integration, and it proposed the algorithm to control house appliances, including EVs, to flatten load profiles at distribution transformers level. There were many cases and their associated strategies through which the authors concluded that the algorithm would lessen the EVs adverse impacts, thereby flattening the load profiles. Also, so-called active distribution network was coupled with V2G and demand management technique in [121] to find optimal dispatching technique of EVs. Alternatively, authors in [122] claimed that an optimal EV charging control integrated with utility demand response would allay the load profile negative effects. The charging control method is constrained with TOU and direct load control (DLC). It was noticed that an uncontrolled charging mode raises load profile peak by more than 50 %, which would introduce several power-related impacts against the network. Hence, TOU+DLC and TOU+DLC+optimal control charging work on shifting the peak loads to off-peak times.

Nevertheless, the optimal control technique is essential to assure load profile flattening, as the TOU+DLC alone would still generate sudden load peaks the EVs charging rates is subject to sudden changes while EVs are plugged in to reach their SOCs. The TOU and the game theory concepts were merged in [123] to take users psychology into consideration, which was superior to the traditional TOU strategy in terms of load profile flattening. Furthermore, the Korean electric network was simulated in [124] to take different EVs integration scenarios that entail EVs specifications, EVs driving patterns, charging rates, and charging locations in 2020. Under several charging scenarios, the reference shows that the load profile would be impacted badly, leading to adverse effects on the grid reliability measures. The TOU tariff system, however, could resolve this issue, where EVs load is shifted from peak hours to nonpeak hours. Similarly, authors in [125] discussed the impact of TOU on users' behavior during peak hours in the presence of EV charging. The study was conducted at two different seasons (winter and summer) whose load profiles are different. Moreover, the study considered different penetration rates and different charging schemes to account for normal and fast charging approaches. Advanced metering infrastructure (AMI) is essential to display real-time electricity prices for TOU deployment. The paper merely focuses on customer behavior in terms of EVs penetration rate in response to TOU pricing. However, the customer behavior investigations based on many factors: seasons, EV penetration rate, and EV charging approach, which makes it challenging to set such pricing tactic. The results showed the importance of TOU to flatten load profiles and avoid new peaks through proper price setting. Renewable distributed generation was suggested as a method to meet the peak-hour requirements in order to shave peak loads in [65], [126].

Optimization techniques were employed in [127] to smoothing the load profile in the simulated case. The proposed strategy is composed of two stages: an aggregator optimizer uses Bee Algorithm (BA) to compute optimal charging of each EV, followed by distributing this calculated charging power among EVs using fuzzy logic controller (FLC); this approach was compared to constant power (CP) charging and constant time (CT) charging techniques. The resultant outcomes indicated that the load profile of this approach is smoother than both the standard methods (CP and CT), proving its superiority.

Alternatively, smart charging is a good candidate to mitigate load profile peaking. Authors in [58] used an aggregator profit maximization technique to optimize EVs charging times, thereby avoiding simultaneous peaks.

Peak loads can be treated (shaved) by many means, one of the most widely adopted solution is utilization of EVs batteries (V2G) [48]. An effective approach was formulated in [90] to utilize EVs batteries for travelling and load peak shaving purposes. A dynamical strategy was outlined to control discharge rate so as to use the batteries capacity for peak shaving service. This strategy measures the influence of EVs battery capacity on peak shaving performance with so-called a peak-shaving index, which is the ratio between the EVs injected power to the customer maximum power demand. Basically, the peak load support varies in accordance with the load profile drift. The peak shaving service is proportional to the magnitude of the load peak at hand. The whole scheme was verified in a practical distribution system in Australia. The results showed that the peak shaving strategy provided the maximum support during the peak load instants. The V2G controlling side is challenging and complex. In [123], authors proposed a special substation topology that enables EVs to act as energy sources during demand peak times. This substation is an integrated AC-DC that enables EV charging and EV utilizing for peak shaving intentions. The power converter topology was analyzed for EVs discharging up to medium voltage level.The authors concluded that the microgrid prototype can sustain peak loading with the aid of V2G for a short time. Other techniques used optimized charging approaches without the EVs batteries [128], [129].

Aside from the complexity associated with the number of variables considered in studies, the results usually are more accurate. Authors in [130] proposed a fuzzy-logic scheme that imitates the EV driver decision-making process for charging. The study aims to improve the EVs load profile estimation by incorporating a huge database of field -recorded driving patterns, parking times, and parking locations. The lack of enough data for EVs urged the authors to assume that the drivers' behavior and their lifestyle remain unchanged by shifting to EVs. It was shown that an EV with a large battery capacity improves confidence in making the next trip without the need for re-charging, and hence its impact on the load profile is more lenient than EVs with small battery capacities.

B. VOLTAGE PROFILE AND PHASE UNBALANCE IMPACT

EV integration to grid draws additional power, which in turn, causes voltage drop that might violate the regulated voltage limits in the system. Also, EVs that are an AC-based and a single-phase charge mode lead to phase unbalance; another quality issue caused by EV adoption. A full power system analysis is to be implemented to test the voltage profile intactness. The Chinse voltage regulations (7 % at 10 kV) were used in the Monte Carlo Simulation implemented in [131] to assess the EV charging on system voltage regulations. Uncontrolled charging scheme, penetration rate of 60 % or more, resulted in violation of the named voltage limit (7 %) in many sectors in the network. However, the V2G model maintains the voltage limits even at 90 % of EVs penetration rate, because of the load levelling being used in V2G approach that exhibits lesser voltage differences between peak and off-peak hours.

Generally, any EVs penetration rate that is 50 % or beyond would violate the voltage deviation limit of 7 % as stated in [132]. Smart charging is the answer to maintain all voltage nodes within limits. Moreover, a Bosnia and Herzegovina MV grid was scrutinized in terms of voltage profile considering different EVs penetration rates at three charging modes: unregulated, regulated, and regulated with V2G. Also, the voltage constraint imposed was within 10 % of the nominal voltage value. The MV network experienced a violation for unregulated charging scheme, but the regulated schemes (with/without V2G) improved the performance significantly [119]. The voltage profile status is an increasing function of the EV penetration rate. The LV network, on the other hand, is subject to similar voltage profile impacts as investigated in [133]. The approach and methodology followed in [119], [133] still hold for [134] except for the network voltage level of testing. In fact, LV network would not experience any voltage profile violation if EVs penetration rate is low for unregulated charging scheme, but it can support higher rates for regulated slow charging scheme. Of the MV and LV networks, the voltage profile impact is more pronounced on the LV network since they are directly connected to the EVs charging stations; this is clear from the [133] and [119]. Also, coordinated charging displayed superior performance over uncoordinated charging as a function of EVs penetration rate for voltage profile factor in [116], [118], [135]–[142].

A case study of Bogota, Colombia network was conducted in [143] to investigate the effects of EVs integration (between 10 % to 100 %) on the voltage profile. The voltage profile gained at 100 % EVs penetration rate was as low as 82 % of the nominal value, leading to unhealthy network. However, the low voltage values were attributed to the distance of the end point from the distribution transformer. In other words, the network is still sound if the distribution system spans short distances.

A distribution model was formulated in [117] to test its voltage profile soundness for motor-based appliances that might be exposed for abnormal voltage values. The study considered many scenarios for different number of EVs to paint a thorough picture of the EVs voltage effects. The simulation results indicated that the feeder voltage gets depressed as the EVs penetration rate escalates, and it is more profound at feeders' end points. The depressed voltage profile impacts the home appliances, especially the motor-based ones.

In the contrary, [10] claimed that EVs charging does not affect the network voltage limits. Actually, the reference stated that EV penetration rate does not violate the voltage deviation tolerance by more than 1 % only, and the only issue accompanies a wide EV integration to grid is system component overloading conditions. Furthermore, [144] drew a conclusion that voltage acceptable ranges are not crossed by EV charging, but system components could experience slight overloading conditions. Interestingly, fast charging might be more severe than normal charging mode as illustrated in [10]. The paper outlines a case study in Ontario, Canada to examine the voltage profile in both cases, and the finding was that current system shall be upgraded. Moreover, load side management can help keeping voltage limits within acceptable measures.

Certain control methods and algorithms have been proposed to deal with voltage issues resulted from EV integration into grids. One of these solutions is the distributed voltage control approach [120] that controls not only the EVs load type, but also the household loading. Through many cases considered, it was clear that at certain EV penetration rate, the voltage constraint limits are violated, but the proposed controller does really help improving the voltage profile, thereby gaining high potentials in alleviating EVs grid-integration bad impacts against voltage profile. Linear programming optimization technique was practiced in [138], which maintained voltage profile within acceptable limitations compared to standard EV penetration procedure. Authors in [140] suggested TOU scheduling, which shifts additional EV loads to off-peak hours, to mitigate the voltage drop caused by large EVs penetration rates. According to the authors, the optimal time to start off-peak shifting resides between 11 pm and 12 am; this time selection is a tradeoff between both utility and customer benefits. Interestingly, the TOU enabled a 30 % of EVs penetration rate to existing network. A controlled charging algorithm was proposed to minimize voltage variations at different nodes in order to reduce the whole voltage variation of the entire network. The algorithm aided minimizing the voltage profile significantly for the whole network. Coordinated charging, delayed charging, off-peak charging, intelligent scheduling, and smart charging were some of the techniques recommended in [135] to tackle the voltage profile deviation issue.

The authors in [140] made several interesting findings about the voltage profile impact that were inferred from many researchers. The residential EV chargers affect the secondary wires more than the primary ones in terms of voltage variations. Also, the size of the chargers play an important role in quantifying the voltage drop. The voltage drop is positively dependent on the charger size. In fact, the charger size is linearly proportional to the voltage drop rate. For example, a 5-kW charger would entail double the voltage drop of a 2.5-kW charger. In regard with the electric distance of residential chargers from distribution transformers, it is directly proportional to the voltage drop.

In [122], the authors showed that TOU+DLC charging and TOU+DLC+optimal control charging reduces the voltage profile degradation significantly, especially the latter approach. This is because the optimality minimizes the maximum power for individual EV user for charging scheduling. The conventional paradigm of an EV in V2G system is to view it as a load in the charging mode and as an energy source in the discharging mode. An algorithm presented in [145] which considered variability of battery performance over time, so a variable objective function governed the power transfer in the V2G process. The connection voltage point and the coordination of charge/discharge process of EVs compose the underlying variable objective whose constraints are SOCs, charge/discharge time, and connection point voltage. A case study proved the advantage of this approach through a tight control of the nodal voltage at the connection points, which in turn aid maintaining the voltage profile within limits.

Uneven distribution of EV chargers in residential network could cause a severe phase unbalance condition owing to a diversity reduction as the EV number rises, leading to many bad consequences, such as harmonics, nuisance tripping, etc. [137], [146]. Voltage imbalance is prominent at the distribution feeders end due to the long distance from the main distribution stations [147]. A particular Phase (a) was selected to be the sole connection point for all EVs in a grid to evaluate the impact of a single-phase charging scheme on phase unbalance issues. The outcome outlined in [148] showed that a severe unbalance condition arose, which needs special consideration upon adopting EV charging. Also, a real 12.47 kV network was studied in [142] to investigate unbalance voltage effects under many EVs penetration rates ranging from 10 % to 80 % along with single and double AC level 1 and AC level 2 charger types. The authors in [119], [133] found that fast charging shall not be used at LV side, as it impacts voltage balance factor badly, and this can be alleviated by dedicating a separate circuit for the fast charger. Also, slow charging shall be evenly distributed at all phases to avoid such impacts. The findings did not go off from expectations in having a direct proportionality between the unbalanced voltage and the EVs penetration rate. The peak and off-peak hours, also, play a major role in affecting the voltage unbalance, leading to a compound effect if combined with high penetration rates.

In contrast, authors in [116] stated that the impact of such a single-phase charging scheme is negligible for both voltage and current unbalance, and the phase unbalance still remains within acceptable ranges. This discrepancy is attributed to the diversity factor assumption in the reference. Few active chargers mean higher diversity, and vice versa. Either way, the phase balance remains within the limits, as the total impact of the diversity and the number of active chargers that are in two opposing directions is acceptable.

Solutions suggested were smart charging, gird reinforcement, and grid optimization to mitigate the unbalance effects. Flemish LV network was selected in [116] to study the effect of a 100 % EVs integration in terms of voltage profile and voltage unbalance as well. There were many charging scenarios for the analysis-namely, uncoordinated, uncoordinated with voltage drooping, peak shaving, and peak shaving with voltage drooping. The behavior of each technique differs for voltage profile and voltage unbalance. The voltage droop was found that it eliminates the voltage that is below 85 % of the nominal value, enhancing the voltage profile thoroughly. Nevertheless, in accordance with EN50160 standards, voltage profile should not fall below 90 % for certain number of times, which is not met in the voltage droop case. On the contrary, the peak shaving technique does meet the EN50160 standard requirements, thereby attaining improved voltage profile. In general, the voltage droop approach does help reducing the voltage profile and voltage unbalance, but it needs a prior coordination in EV charging simultaneity, which is provided by the peak shaving technique. Therefore, the two approaches can assure EVs integration without an advanced charging coordination without any violations. This implies there is no need for the peak shaving approach if the coordination has already been done. Importantly, the charging duration is different for both cases. The voltage droop case slightly impacts the charging duration, but this is not the case for the peak shaving technique, as the standstill time is fully utilized.

Advanced optimization techniques were employed to further investigate this factor, for instance GA was utilized to examine the voltage unbalance caused by PHEV fleets in [149]. The PHEV was modeled as a voltage-controlled node in order to not only allow for active power exchange, but also reactive power exchange for voltage support. The main objective of this study is to optimize the number of EVs being connected at all phases before start violating the voltage phase unbalance limitations. The simulation showed that PEV fleets can degrade the bus voltage unbalance if the fleets act as loads. On the other hand, the voltage unbalance would be improved should the GA is applied. Kyoto protocol seeks to reduce CO2 emission for environmental concerns, and Republic Korea intends to replace 10 % of the total number of vehicles by EVs. This provoked many situational researches to evaluate the integrity of the Korea Electric Power Corporation (KEPC). Voltage sag and voltage unbalance were the core topics in [150] to assess KEPC with these two indices. Additionally, a number of EVs penetration rates was taken into consideration for slow charging scheme only. The resultant measures showed that voltage unbalance is more common than voltage sag, and it is more sensitive to EVs penetration rate. Actually, at 10 % penetration rate, the voltage unbalance limits are exceeded, while limits exceeded at 20 % for the voltage sag case. The referenced standard for both indices is the IEEE standards.

The Malaysian LV network went through an analytical testing in [151], [152] for voltage profile and voltage unbalance impacts as EVs are integrated into the grid. The scenarios considered for the voltage unbalance were unbalanced EVs charging and an evenly distributed charging, while controlled versus uncontrolled charging were the modes for the voltage profile assessment. The evenly distributed charging mode showed improved performance compared to the unbalanced charging scheme, where the given power network saturated for a small EVs integration rate for the unbalanced charging. Moreover, the controlled charging scheme suffers from no issues for both voltage limits and voltage unbalance.

The Dutch network, also, went through an analysis test in [153] for voltage drop and voltage unbalance. It was concluded that a 15 % to 20 % EV penetration would bring the network to its extreme limits. Demand side management was suggested as a proposal to lessen such effects. Tariff-based charging scheme takes advantage of variable prices to shift the peak load to off-peak hours, thereby improving voltage profile. The tariff-based charging was considered in [148] to study its effectiveness for voltage unbalance through different scenarios. Ultimately, the network suffer from voltage unbalance at certain EV penetration level, so the tariff-based technique was proven to allay this impact significantly.

The discrepancy between the researchers for the impact of both voltage profile and unbalance phase condition stem from different factors that govern each proposed study, such as network strength, EV charging characteristics, EV penetration rate, EV connection point, and so on. The control of EV penetration rate can keep the system voltage within limits, and proper load management model can prevent phase unbalance from violating the regulations [21].

C. SYSTEM LOSS IMPACT

EVs integration to grid draws more power from generation plants through transmission line system which contributes more into system losses; power utility entities suffer the most as they bear most of this burden. Coordinated charging is essential to lessen the resultant power losses that might appear significantly at as low as 10 % of EV penetration rate [137]. Extensive literature work has been accomplished to investigate this problem.

Danish distribution grid was tested to evaluate EV penetration effect in [154]. The power system analysis was conducted at the normal case, followed by a gradual increase of EV penetration rate up to 50 % in the uncontrolled charging approach. Significantly, the system losses rose to 40 % more compared to the base case. The controlled charging, on the other hand, would decrease the system losses by 10 %. In addition, a case study in [155] applied the same approach on residential and industrial areas to explore EV charging on power system losses, reaching a conclusion that the worst-case scenario occurs not during the load peak hours as expected. Instead, it happens during off-peak hours because most of the EVs are presumably charging at night times; the worst-case scenario gives a 40 % increase in losses. Likewise, the same findings were stated in [132], [156], which boil down to system losses rise as EV penetration rate increases. Load side management can be used to lessen system losses as done in [156]]. The paper used real-time control technique to reduce losses based on controlling the EVs charging process. Additionally, the paper investigated the transformer losses associated with EV deployment in which winding loss and core losses (hysteresis losses and eddy current losses) were addressed. A detailed case study on an Australian grid was held in which 1200 radial-configured nodes network is tested with an EV integration at 45 V level There was a range of transformer loadings along with many EV penetration levels for this study. A detailed transformer model is finalized, and a regular Australian residential load profile is utilized in the paper along with different EVs penetration rates that could reach 42 %. Transformer losses (mostly contributed from winding copper losses), reached 300 % for a high penetration rate. Core losses, on the other hand, show less variation, but they still add significant losses contribution.

Bosnia and Herzegovina MV grid experienced three charging modes as mentioned before in [119], [133] to analyze the network from energy losses perspective. As expected, losses are driven by the EV penetration rate (i.e., there is a positive proportionality between the penetration rate and the losses). Also, V2G can slightly increase the losses due to the fact that it prolongs the charging time, but regulated charging would improve the energy losses a bit. V2G, coordinated charging, and smart charging would alleviate the losses degradation a bit as pointed out in [135], [138], [157], [158]. Furthermore, the case in Bogota, Colombia network claimed that losses are a function of a number of simultaneous EV connections in a distribution system, battery capacities and charger specifications, conductor parameters and the section length, residential demand behavior, and the distribution system configuration [143]. At 100 % EV penetration level, the power loss is as high as 0.82 pu, leading to a 25 % overload to the Columbian network, which in turn jeopardizes the grid stability.

An interesting relationship was formulated in [117] between feeder power losses and the number of EVs connected. It was found that the total power losses increase exponentially as the number of EVs increase, thereby limiting the allowed number of EVs in grids substantially. Conversely, [159] stated that the network losses behave in a linear manner with an increase EV penetration rate. Moreover, the losses are a function of current flow and line resistance, which means the conductor length is essential in considering the losses. Power losses were mitigated using linear programming-based optimization strategy in [138]. Authors in [159] quantified the power losses increase for a Hungarian network as a consequence specific EV integration rates for uncoordinated charging mode and delayed charging mode. It was shown that the power losses could increase to nearly 50 % and 35 % for uncoordinated charging and delayed charging, respectively, which clearly highlight the superiority of the delayed charging approach. The authors in [134] support the previous findings in a case study in an Egyptian network. Optimization techniques would help alleviating the network power losses as demonstrated in [145] in which the EVs connection voltage and the scheduled charge/discharge rate were the objective function of the proposed model. This technique was proven successful in limiting the power losses in the provided case study.

Typically, EV penetration increases transmitted power, thereby raising system losses. Thus, coordinated EVs charging, distributed generation units, and otherwise are practical solutions to this issue. Fast charging could have more impact than the normal charging mode as revealed in [9]. The proposed solution is to utilize load side management to better control the associated losses.

The control over the system losses due to EV penetration is not easy because of the stochastic nature of residential households as well as the EV penetration rate, so optimization techniques come into play. In [158], the authors proposed an optimization model whose objective function is to minimize system losses caused by adopting EVs charging scheme. The paper uses stochastic programming for optimal coordinated charging load profile along with minimal system losses. The absence of accurate data of housing households urged utilizing such stochastic programming technique. Moreover, the same reference stated that the system losses can be reduced, and grid load factor can be increased at the same time using stochastic programming of controlled EV charging. However, the grid reinforcement is inevitable at some cases. A feasibility study held in Ontario during off-peak hours in [160] to optimize grid parameters of EVs charging in terms of system losses. Under different statistical figures and assumptions, the study revealed that about 6 % of EVs in Ontario region, or 12.5 % of EVs in Toronto, which are equivalent to nearly 500,000 vehicles that can be realized by 2025 without any additional transmission or generation investments.

D. SYSTEM COMPONENT IMPACT

Additional load follows a large fleet integration of EVs requires generating plants to transmit large amount of power to load sides. This might cause an overload condition to the power system and its components (e.g., transformers and cables) since it might not be designed to cater for such additional EVs loading, which could place restrictions on adopting EVs widely. Many researches were carried out to explore this aspect that are mainly summarized as follows.

1) DISTRIBUTION TRANSFORMER

Distribution transformers are essential components of power system which are prone to damages due to overloading conditions. Early studies showed that transformers are impacted adversely in the presence of PHEVs charging. For instance, a case study in Southern California was performed in [161] to assess transformers performance under the stress of uncontrolled charging. In [162], the authors analyzed all transformer losses caused by accommodating additional EV loads, such as core loss, copper loss, and primary/secondary voltage deviation. The study stated a 30 % of EVs integration rate is enough to overload the transformer beyond its rated limits. Also, a thermal model was formulated to compute hot spot of winding temperature and transformer loss of life (LOL). The results indicate that the level-1 charger type has a little effect on the transformer loading, but the level-2 charger might render transformers failure because of excessive temperature rise. The paper suggested smart charging and load management to contain the impacts. The previous findings were supported in another study that indicated the superiority of the AC level 1 charger over the AC level 2 charger [122]. The authors in [163] contradicted this result in Morelia, Mexico network, where a scenario involves a 10 % EV penetration rate with AC level 2 charger. The transmission transformers were not affected, and the scenario was assumed safe for the transformers in the grid. The maximum number of EV deployment level for an existing network was simulated in [164] to set the maximum limitations of that particular network. Likewise, [165] examined the Ottawa distribution grid ability to accommodate specific numbers of EVs. An optimization strategy to maximize the EVs deployed into the grid was adopted, too. Also, the example given in [166] reached to an aggressive result claiming that transformers lifespan can be degraded by 93 % because of PHEV charging. Time-series model was used to represent the aging factor of transformers as PHEVs penetrate grids. The test system model comprised three houses, a transformer, and a distribution substation, which form the specific scenario for the transformer lifespan calculation. A different study stated that a PHEV penetration rate that is as low as 10 % could force transformers to overloading conditions [154].

The distribution transformer life span due to thermal aging factor is statistically modeled in [167] using ambient temperature, initial SOC, and the EVs charging starting time. The model indicated that the transformer LOL is highly dependent on the effective load and the temperature at each instant of time, so varying results are expected throughout the year. Transformer capacity in Toronto network was under investigation in [168], where the worst-case scenario of integrated EVs is employed during minimum, medium, and maximum load hours in order to set boundaries of safe power operation process. Noticeably, ambient temperature is vital in determining the system capability to accommodate EVs integration into the grid, which is directly related to the number of deployed EVs. The charger size is another factor to consider. In fact, the study claimed that chargers that are sized 10 kW or more, necessities a system upgrade to have the ability of taking EVs safely.

Other references compared and contrasted uncoordinated charging and coordinated charging for transformer impact purpose. The authors in [119], [133] addressed three charging modes: slow charging, fast charging, and private charging stations, and the slow charging has three types-namely, unregulated, regulated, and V2G. The regulated charging had the minimal impact, followed by the regulated charging. In regard with fast charging mode, the impact is much lower than that of the slow charging owing to the small share of fast charging stations as compared to the dominant share of the slow charging stations. The fast charging small share point is backed up by [116], [169] and the source proposed peak shaving strategy to fight additional load brought up by EVs integration. The peak shaving approach is implemented with/without fast charging option, and the results conform to the early findings (i.e., fast charging effect is limited).

Furthermore, the smart charging strategy was employed to alleviate the impact on the transformers. The results were more noticeable in [170] for AC level 2 scheme, where the aging factor reduced by 48.9 % and 74.8 % for VT and AZ, respectively. On the other hand, the reduction in AC level 1 case was only 12.8 % and 49.4 % for VT and AZ, respectively. Similarly, authors in [154] concluded the same results with the emphasis on a high EV penetration applies more stress on transformers lifetime. Indeed, a high penetration rate could escalate the aging factor up to 10,000 times the normal situation [171]. Conversely, it was stated in [170] that existing transformers could take additional loading of EVs penetration in most cases. Under uncontrolled charging approach, the AC level 1 charging approach has a slight effect on transformers, whilst level 2 could lead to transformers failure owing to extreme operating temperature in case of a high EV penetration rate. The transformers can be alleviated of these effects through appropriate load management and shifting EVs charging periods to off-peak hours. Furthermore,

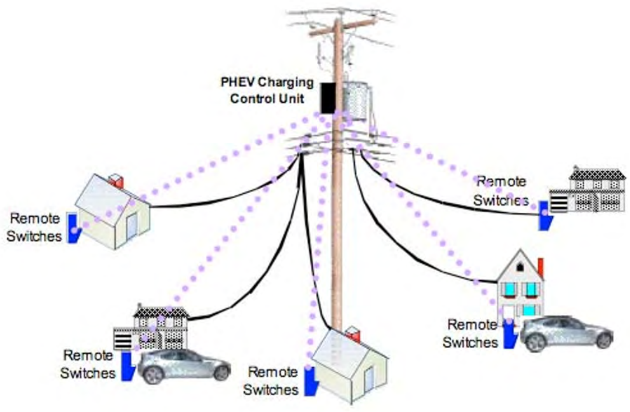

FIGURE 11. Infrastructure of PHEV charge control and demand management [174].

a simple case study was conducted in [172] that includes five homes and two PHEVs and concluded that no transformer overloading conditions experienced except for all PHEVs charging simultaneously at peak times with level 2 charging. In [173], authors conducted similar simulations with an addition of PHEVs and only few cases resulted in overloaded transformers. The undergoing model for transformers aging assessment was a hot spot winding temperature model that included harmonic currents effect for more accurate results.

Demand side management can be employed to control transformers loadability under EV charging scenario. Authors in [174] tested transformers loading under several EV charging scenarios to look closely to peak hours that can be alleviated much simply by applying demand side management technique rather than installing new transformers to take up additional loading caused by EVs. The proposed strategy is a combination of AMI that monitors residential loads, EV controlling unit, and remotely-controlled switches for EV outlets and residential loads as depicted in Fig. 11. In addition, de-centralized demand side management was proposed in [175] that is formulated as a convex optimization problem that is solved by so-called water-filling algorithm. The concept behind this work is that the load profile of low voltage side of the transformer is flattened so as to avoid excessive overloading. Also, load side management in conjunction with off-peak EVs charging were suggested to prolong transformer lifespan and avoid many technical complications that would otherwise be manifested because of uncontrolled EVs charging on transformers. A case study in Southern California was performed in [170] to assess transformers performance under the stress of uncontrolled charging and to propose potential solutions that are smart charging and load side management. In fact, smart charging reduces deteriorated transformer aging factor and decreases uncertainty of PHEVs charging [175].

TOU charging scheme is another form of regulated charging to which [176] based its research in which a time-varying price approach and its impact on distribution transformers aging factor is studied. A transformer thermal aging model represents the transformer aging factor at different EVs integration rates to simulate the rate of change of the transformer aging factors with different EVs deployment levels. It was shown that at high EVs penetration rate, the transformer aging factor accelerated excessively. However, the V2G option with the TOU scheme provides an economic advantage to end-users, but this might be offset by the technical shortcomings on a selected network. The authors introduced two optimization techniques to balance the end-user's economic benefits and the transformer aging degradation factor, which are subject to further researches. A mix of TOU charging derivatives were listed in [177] looking for the minimum transformer LOL. A hierarchical charging with TOU showed the lowest transformer LOL among other options. On the other hand, a centralized scheme with valley-filling strategy was the worst scheme impacting the transformer LOL. A wide spectrum of charging strategies was addressed in [161] for investigation of transformer hot-spot temperature and aging factor under different EVs penetration scenarios. The charging strategy list consists of uncontrolled, TOU, valley filling, valley filling with time slot rejection, valley filling with modified time slot rejection, and forced cool-down period. It was proven that the uncoordinated charging and TOU charging were the most negative strategies, whereas the forced cool-down period strategy was the one with the lowest adverse impact.

Some charging strategies can be combined for enhanced outcomes, such as the one presented in [122] that offered a different combination seeking optimal transformer performance. TOU+DLC method and TOU+DLC+optimal control charging method were scrutinized for transformer LOL index. The optimal control option works to shift EVs loading and reducing the total residential loading, thereby prolonging the transformer life cycle. Smart charging, TOU-midnight, and Photo Voltaic (PV) rooftop option were mixed altogether in different configurations for transformer LOL analysis in [178]. The transformer LOL is at its minimum for either TOU-midnight charging or smart charging were considered. PVs are another generation source that would balance the increasing demand of EVs, and this paper showed that the LOL of the two charging schemes mentioned before could be reduced by 75 % upon adopting PV panels. Strictly speaking, the transformer LOL are only within their annual limits if both TOU-midnight and smart charging were combinative. A different study in [143] claimed that transformers LOL are retained if at least 10 % of capacity margin is imposed. The previous studies approached LOL qualitatively, but [179] developed a risk assessment method to quantify risks associated with transformer LOL. An EV brand effect was investigated in [180], where Tesla S and Toyota RAV were considered for dual charging power level 2 type using TOU pricing approach. The resultant outcomes are in favour of Tesla S brand since it impacts the transformer LOL in a lesser extent compared to Toyota RAV. The paper, also, mentioned that the charging in one cluster during off-peak times is of more damaging effects than charging upon home arrival. The EV generation model is an additional criterion that is used to examine the influential impacts on transformers. The reference used TOU charging scheme in order to target off-peak hours for improved outcomes, and it concluded that an energy consumption factor is the driver behind favoring specific EV brands-generation over other brands so that the transformers LOL is remain intact [138]. Other references recommended regulated charging for its benefits of reducing transformers adverse impacts of EVs deployment [134]–[136], [143], [151], [152], [159]. The effect of adopting PV and battery storage systems on the transformer LOL were investigated in [181], [182] in which they claim that the transformers LOL are prolonged upon these setups.

Alternatively, algorithms could be utilized to resolve the EVs deployment issues against transformers. Rule-based charging algorithm was proposed in [183] to tackle such an issue. Basically, it determines the lowest charging power levels of residential EV stations during peak hours. The consequences of this algorithm were analyzed on the distribution transformers to assess the feasibility of such algorithm. It is important to note that one of the assumptions considered for this study is to limit the arrival/departure trip of an EV to only one a day. Of course, different results would come out if different assumptions were considered. The authors in [127] adopted a two-staged optimization techniques: BA and FLC. The transformer peaks were reduced substantially, and consequently the listed approach outperformed the standard methods (i.e., CP and CT).

Elaborate models can approximate system performance to a great extent of accuracy. One of the transformer models was presented in [184], where a relationship linking the transformer winding temperature to the charging station load profiles through a group of dynamic thermal energy models. This set of models consider a variety of factors for an acceptable performance; these factors include ambient temperature, EVs integration rate, power quality, and base load. Consequently, this set of models were used to evaluate the transformer LOL and to settle the transformer capacity and connection configuration. A pilot study was conducted on a network in Taiwan, where a direct relationship exists between a transformer capacity and connection configuration at one side and the transformer hot-spot temperature. The hot-spot temperature is acceptable if a given transformer is oversized. The proposed model, however, takes the economic side into consideration, so no unnecessary oversizing is exercised.

Additionally, the authors in [185] adopted a model that tests thermal aging factor of transformers on a Portugalian network. This model embraces certain influencing factors like battery SOC, randomness of EVs chargers, charging modes, etc. The model addressed a problem in that network pertaining to oversized transformers and their durability against high EVs deployment rate. The outcomes were not challenging, as these oversized transformers cannot tolerate a certain EVs penetration rate. Hence, other means should be sought to mitigate the transformers LOL factor, such as off-peal tariff charging scheme. This work was extended to power transformers in [186] that reached to the same conclusions except for the slow charging, even if it is utilized fully, preference over fast charging, which contradicts with many claims of some other references. Transformer LOL and its linkage to EVs deployment level was the core of [187] that studied this relationship with a mathematical model describing the statistical pattern of EVs along with the transformer thermal model in order to quantify the transformer LOL well. There were four charging scenarios and several EVs integration rates through which the paper tested the transformer LOL: uncontrolled charging, off-peak charging, smart charging, and uncontrolled public charging. The reference concluded that the transformer LOL mainly relies on two factors-namely, load value and timely temperature.

Furthermore, of all the charging schemes tested, the smart charging showed the most favorable scheme, as the transformer LOL was impacted the lowest. Energy management system can be modeled to prolong the transformer life span and minimize the transformer damage cost as addressed in [188]. The model revolves around shifting EVs charging schedule to valley hours so as to lessen the impact on the supplying transformers, leading to extended life cycle and lower damage cost. Models usually assign optimization techniques for one objective function for simplicity, but [189] developed a co-optimization centralized model in which the transformer LOL and the EV drivers charge/discharge decision are optimized, so overall operational cost is reduced. The model took transformer thermal temperatures, LOL, and accelerated aging factor into consideration for improved model performance. For the sake of comparison, a decentralized model was formulated such that it could be implemented by energy management system, where EV users optimize their own EVs. At V2G mode, both models show a long LOL, as EVs inject so much power into grid that peak hours are lessened. However, the centralized approach causes overloading at high EVs penetration rate, and the decentralized one dictates a transformer upgrading. Hence, the decentralized approach did prolong the transformer LOL, proving its benefits to transformers operation.

Deterministic models do not always reflect the actual system behavior because of the probabilistic nature of many variables involved. EVs integration to grid is no exception, and this matter was tackled in [190] proving that probabilistic models outperform the deterministic ones in presenting the system performance under EVs penetration case. Probabilistic models can be viewed from charging strategy perspectives, such as regulated and unregulated charging for improved performance. TOU charging and dumb charging were considered in [191] for a probabilistic modeling of EV drivers' daily pattern to find safe penetration level that will not harm network transformers. Both scenarios failed to keep loads below transformers ratings at 50 % penetration level. Besides, the dumb charging exceeded the transformer ratings at several penetration levels, but the TOU charging was worse than the dumb charging at the selected time slots. Seemingly, EV drivers chose to charge their vehicles at that particular instant of time because of the economic advantage, resulting in an increase in transformer overloading. Conversely, a study made using the probabilistic load flow analysis within the British Colombia power network stated that only transformers that run near their rated capacity get affected by the uncoordinated charging [192].

2) TRANSMISSION CABLE

What arteries to human body, is what cables to power grids. Hence, the integrity of cables forms a cornerstone of the whole power system reliability, and it can get affected severly by uncontrolled EV integration [193]. A different set of EV penetration rates of coordinated charging, uncoordinated charging, unbalanced charging, and evenly distributed charging in [151], [152] tested a Malaysian network to check the integrity of thermal limits of feeder conductors. The outcomes were conforming to the norms that the coordinated charging is provides the best chance for feeder conductors thermal capacity, followed by the evenly distributed charging. Also, a higher EV penetration rates, entails worse feeder thermal capacity. In addition, [159] had compared the unregulated charging compared to the delayed charging, and the results were challenging. The delayed charging mode offers more than 20 % capacity margin over the unregulated charging, increasing the feeder buffer significantly. The delayed charging was recommended also in [134] over its uncoordinated charging counterpart. These findings were found in [9] in a Canadian distribution system where fast charging and normal charging schemes were employed to evaluate their impacts on line loading condition at different penetration rate stages (zero level up to 30 % level). It turned out that uncontrolled charging impairs the existing cable system, especially for fast charging mode. In fact, the cables can take only 15 % for fast charging and up to 25 % for normal charging, so the reference concluded that existing cable systems shall be upgraded to hold high EV penetration rates. Also, the paper proposed load side management solution to control overloading conditions.

The case study outlined in [136] studied underground cables and overhead lines under the assumption that the fast charging stations can draw power from a 20 kV medium voltage substation. The 400 V cables, stemming from the secondary side of that substation, supplies the fast charging stations, and it goes through remarkable overloading during EVs penetration times. Hence, the cable systems are to be reinforced to adopt EV loading. However, the 20 kV overhead lines are in no danger of cable overloading, and it can support EV charging substation. Moreover, Finnish distribution grid was studied in the context of EV charging load using real load profile data in [144]. The principal conclusion is that the EV penetration rate influence on medium voltage and low voltage cable systems are subtle. In the same manner, fast charging mode would load cables substantially, especially at large scale EV deployment. The fast charging mode against the slow charging mode at several EV deployment rates was the topic of [133] in which the tested cable system was sound for the slow charging mode at both coordinated charging and uncoordinated charging. The reason for the limited effectiveness of the coordinated charging is that the percentage of slow charging stations is small compared to the whole network. That being said, the regulated charging stations without the fast charging option do make a difference in terms of loading the cable system, which emphasized the substantial effect of the fast charging mode on electric networks. Also, the authors in [133], [135] pointed similar notes regarding the fast charging mode. Moreover, [153] proposed DSM to reduce the impact of EVs deployment, thereby increasing cable capacity for set EV integration rates.

TOU is another charging tactic used to regulate the large-scale EV deployment, and it was tested in [136] on residential, commercial and industrial networks at several EV penetration levels. The bottom line is that TOU frees the feeders at different networks substantially (at least 10 % capacity), which proves its superiority over the uncoordinated charging.

Cable system does not only suffer from the EVs deployment, but also from the charging stations that pollute the selected system. Cables in accordance with [194] are prone to skin effect and proximity effect caused by the exposure to high frequency harmonics that deteriorate the life expectancy of the cable system. The bad power quality measures mean unevenly distributed current among the three-phase system, resulting in a high neutral current value. The regulated charging may lessen such effects greatly. Power system comprises transmission lines, subtransmission lines, and distribution lines that function to deliver energy to load centers. The technical specifications and design approaches differ due to differences in loading, voltage drop, length, etc. Transmission lines and subtransmission lines were investigated in [163] to explore the effect of uncoordinated EV charging on a high voltage grid of Morelia, Mexico. Moreover, a 10 % of EVs penetration rate was considered with AC level-2 charger for the study. The transmission lines experienced 35 % loading, while the subtransmission lines had an increment at some lines of nearly 36 %, which is substantial especially if these lines are already overloaded.

EVs are driven by probabilistic measures as mentioned before, which in turn puts an emphasis of probabilistic approaches for analysis to have more realistic and more accurate results. The authors in [190] took this note into consideration when it evaluated the feeder effects of nine UK LV networks. The deterministic approach had no feeder capacity violation at any EV penetration level, which does not conform to the rest of researches in the literature. On the other hand, the probabilistic approach stated that at 70 % of EVs penetration rate, some feeders start exceeding their normal rated capacities. Indeed, the deterministic approach cannot show the technical problems frequency and their associated consequences, and it has the tendency to under/overestimate these impacts. Furthermore, such uncertainties were scrutinized in [195] all together with utility service providers and users' perspectives. A four-quadrant PQ plane two-stage model was employed to allay feeders load peaks during the day. The first step pertains to utility service provider in which feeders' total energy supplied is balanced with the voltage critical values using an optimization technique and a Bootstrap strategy to reduce the feeders load peaks. On the other hand, clients' perspectives were emphasized in the second-stage of the model to allocate a fair share for each EV using active power and reactive power capacity of PQ-plane to meet feeders limits. The feeders overload conditions were improved substantially with this model compared to a simple heuristic approach.

E. HARMONIC IMPACT

Power electronics form the basic infrastructures to EV chargers, which contributes to downgrading system power quality indices upon switching these electronic components; this could result in component de-rating to counter severe harmonic distortion [196]. Voltage total harmonic distortion (THD) was measured in [89] for EV charging, resulting in less than 1 % increment, so system power quality is intact. Moreover, the mentioned paper needs further comprehensive study to confirm these findings, which brings [197] into picture, where dynamic factors of EV charging are taken into consideration, such as charging time uncertainty, charging durations, and charging locations. A Monte Carlo Simulation was conducted to make the assessment, and the results were similar to the previous reference (i.e., negligible EV charging harmonic impact on power grid). The neutral to ground voltage, though, could rise to the point where stray voltage incidents are pronounced.

Nevertheless, authors in [198] showed that EVs fast charging injects rather significant amount of harmonics into the grid. The study revealed that for few EV fast charging units, THD reaches 11.4 % (compared to 8 % maximum value for up to 40th harmonic contents in accordance with EN50160 standard). Active filters solution was proposed to resolve the harmonic issue, where the voltage THD was reduced to be only 5.6 %. Similarly, in both [199], [200] authors showed that unacceptable THD limits precipitated by uncontrolled charging scheme. For example, a case study was held in [127] with different EVs penetration rate scenarios, and it revealed that a charging rate of 18 EVs during peak hours can introduce a voltage THD of about 45 %, which is far away beyond the standard limits. This extreme case represents a 100 % EV penetration rate to account for worst case scenario. Uniform charging could significantly improve the performance, but introducing smart charging is a must to resolve the issue. The reference, also, used so-called decoupled harmonic power flow (DHPF) algorithm that considers system component nonlinearities that are the major source of harmonics. The authors in [201] made a case study of a Jordanian grid to test EV penetration rate on system voltage harmonic profile. The harmonic spectrum under analysis range from third harmonic until 25th harmonic, in which right scenarios were assumed for assessment that include different EV penetration rates, seasons, load peak status, and EV charging status. All of the eight scenarios maintain the voltage THD within standardized limits (5 % for total voltage distortion and 3 % for individual voltage distortion).

Moreover, power-quality (PQ) methodology was employed in [197] to analyze and assess the harmonic impacts due to EVs grid integration to electric networks. Several factors were considered for influencing the charging activities of EVs. EVs were considered as a home appliance, so the PQ method evaluates all home appliances for the harmonic contributions, where harmonic orders were presented for different harmonic levels. Oak Ridge National Laboratory made a statistical estimate of the soled EVs in a specific timeline that formed the basis of this study assessment. Consequently, the final results indicated that the EVs chargers have negligible harmonic contribution impacts up to 2022. A different study in [196] based its results on the 2009 National Household Travel Survey to simulate EVs mobility parameters found that both voltage THD and current THD measurements fall within acceptable ranges according to IEEE519 standard. Usually, the initial odd harmonic levels are dominant if no precautions were made beforehand, which agrees with the outcomes in [202] that held an analytical study on New Zealand network. The study showed that the voltage harmonics did not affect the grid, but the third and ninth harmonic levels are of a concern to make.

The charging level could have a direct relationship to the harmonic quantities injected into grids in which it could be largely detrimental. The level 2 charger and level 3 charger were assessed in [203] to find out their associated impacts. The level 2 charger was found to fall within acceptable range, but the level 3 charger was off the set standardized measures. Seemingly, any large-scale EV integration would impact the selected grid adversely.

Individual harmonic order is one way to evaluate the harmonic impacts. However, it is not feasible to find the integral impacts in reference to the base frequency with the individual harmonic order approach, so total harmonic distortion (THD) comes into play. The THD was utilized in [204] at certain EVs penetration rates to test a different scenario case study on different power system components, such as overhead transmission lines, underground cables, transformers, etc. There were some interesting findings that highlight the harmonic impacts on electric networks. Frequent switching of charger stations worsens the harmonic impacts, so a higher SOC battery would be less damaging in terms of harmonic effects. Furthermore, transformers do not only suffer from harmonics level produced by EVs, but also act as source of harmonics that flow back to the charger stations, so the charger stations should be located at farthest points from transformers. Cables, on the other hand, are the most susceptible component to the harmonic distortion, so they should be well protected. The authors in [146] compared the controlled charging versus uncontrolled charging in which the controlled charging mode shows superiority in terms of lesser harmonic impacts. Also, controlled charging made THD insignificant in [135].

Besides controlled charging, smart charging and V2G according to the same reference could be the answer to mitigate the harmonic impacts on grids that are attributed to rectifiers in the charger substations.

It is noteworthy to consider on-peak hours and off-peak hours for studying the harmonic effects. The difference could be so huge that even 50 % of EV integration rate is THD-acceptable for off-peak hours for a selected network, but it is not for on-peak hours as mentioned in [205]. The THD uses the fundamental frequency current/voltage value as a reference, which makes the THD index variable over a cycle, leading to a probable misleading conclusion. On the contrary, total demand distortion (TDD) index uses the maximum current/voltage value as a reference point, so it is preferred for usage as explained in [196]. It was noticed that THD indices tend to increase at the end of a fast charging cycle owing to a reduction in the current value, resulting in biased conclusions. Nevertheless, the authors noticed that the THD and TDD indices were within the IEEE519 standard values for voltage harmonic measurements, but individual harmonic levels were deviating away from right readings.

The different outcomes of researchers of the influence of such harmonics on the grid attributed to the different EVs specifications and systems under studies. Apart from these differences, many solutions could resolve the problem like filters (passive or active) [196], [204]. Also, it was claimed in [203] that different EV chargers introduce different harmonic levels that are out of phase and have levelized magnitude values, so it is possible to have harmonic cancellation, or even eliminate such harmonics using PWM in these chargers.

F. STABILITY IMPACT

Stability is the resilience of a system when there is a disturbance of any kind. Of course, EVs integration to grid is a disturbance on its own, so its effect is to be examined closely. Although many power system problems have been studied in terms of EV integration, system stability impact study remains almost unattended.

Authors in [206] claimed that grids with EV charging demand is more susceptible to disturbances in terms of both magnitude deviation and time required to reach equilibrium state. This is because of the harmonics injected and reactive power consumed by the electronic components of the EV charger. The simulation ran with different fault conditions for PHEV/no PHEV scenarios for comparison purpose. In the same way, [207] supports these outcomes and represents the EV load behavior as both a constant power and negative exponential components. The paper investigates the grid voltage stability condition accompanying EV charging process, which is downgraded significantly. Generally, the conclusion drawn from literature is that EV charging harms grid stability severely. Nevertheless, authors in [201] examined voltage stability on a Jordanian grid at different situations: without EV, with EVs charging, and with EVs discharging. The conclusion is that the grid voltage stability is barely harmed.

Voltage stability is one aspect of the grid stability indices that is defined as the ability to maintain steady nominal voltage values at all buses after a disturbance. Power electronics form the building block of EVs charger system and that has the vast majority of instability contribution. EV loads according to [201] have nonlinear characteristics, drawing huge amount of power in a short duration, that could drive electric networks out of its stability measures; knowing that electric systems are usually operated near their stability limits. The source emphasizes on the load type of EV loads and its importance to anticipate the impact against voltage stability. If EVs can be assumed as constant impedance load type, there would be no impact regardless of the number of penetrated EVs. However, it is not possible to predict the EV load type prior to EVs integration process, so the authors in [70] suggested a wide area controller technique to dampen instability oscillation resulted from charge/discharge process. Authors in [207] presented a static load model for EVs that comprises a battery energy storage and a charger unit for voltage stability study, which is a major gap in EV-related stability studies. The reference characterized the EV loads as a combination of negative exponential loads and constant power loads. Interestingly, the constant power component is dominant if the voltage is regulated around the nominal value at the point of common coupling (PCC). That being said, the exponential component portion increases as the voltage drop rises. A case study conducted revealed the importance of accurate EV load model for static voltage stability study.

In addition, the EV integration into a grid would reduce the loading margin the most compared to other load models (i.e., P, I, and Z), which in turn would put the whole system security in jeopardy. It is noteworthy to mention that the current practices in modeling EV loads with constant power or constant current models would yield less accurate stability results. An important point to keep in mind regarding stability is the physical location at which a system is tested. That is, the weakest link of the system is analyzed differently from the strongest link to have a broad view of the system stability spectrum. This indicates also the importance of accounting for spatial distribution of loads when studying stability issues, EV load in particular. This concept was incorporated in [208] for voltage stability analysis on two networks: a suburban residential network in Melbourne, Australia, and a semi-rural residential network in Townsville, Australia. Both networks were examined with the same methodology, which involves the worst-case scenario and the best-case scenario. The worst-case scenario is when EVs are added in order from the weakest bus to the strongest, while the best-case is the other way around. Both scenarios could lead to completely different results with the same number of EVs, which was actually proven in both networks. In fact, in the suburban residential network, adding one EV to the weakest bus is equivalent to adding 45 EVs to the strongest bus; even adding more EVs to strongest buses could improve voltage stability measures. Power-voltage curve tool is effective in evaluating the voltage stability of a network. A continuation power flow (CPF) and the power-voltage curve were used to compute the maximum load factor before the voltage collapse in different segments of the selected network in [209]. Consequently, it was shown that at 10 % EVs penetration rate, there is no voltage stability violation; however, if any segment became unavailable for any reason, the voltage stability would suffer. Hence, large EV number integration to a grid would increase the stability risks substantially.

Frequency stability is another aspect of network stability, which is governed by the balance between load and generation, so adding EVs to existing loading would theoretically impact the frequency stability. Frequency response was examined in [201] during a disturbance event for 14 different scenarios on a Jordanian grid. It was shown that in summer season, the frequency stability is more prone to unstable conditions than that in winter season because of the large loading during the summer, which pushes the network to its limits. Similarly, disturbances affect peak hours more than off-peak hours for frequency stability domain. The frequency could increase or decrease depending on the instant at which the EVs penetrate. In other words, peak times have different manifestation than off-peak times in terms of frequency response. However, there was no violation with the frequency response as per National Electric Code (NEC) for this particular application. Regarding voltage stability, there was no effect at all on the examined network on the voltage stability condition.

Other resources put an effort not only to address the stability issues associated with EV charging, but also to propose solutions to eliminate, or at least mitigate the impacts. In [70], authors tried to allay generators of the grid components from operational perspective. That is, a wide-area controller (WAC) provides auxiliary control signals to these power components to improve stability measures. Generator damping factor can be improved through some algorithms that optimize auxiliary control signals, such as particle swamp utilized in this study. Indeed, WAC can dampen oscillations resulted from charge/discharge switching activities more effectively than generators with power system stabilizers. Unlike most of the literature that tested the bad impact of EVs charging on networks stability, the authors in [210] discovered that EV charging could enhance grid transient stability. Transient stability of a proposed system was tested with superconducting magnetic energy storage device (SMES) controller under 3-ϕ LG fault as well as 1-ϕ LG fault states. The results were illustrated through load angle response and voltage response that showed the SMES can enhance the transient stability of the network. Furthermore, fast charging was considered in [211] for transient stability of several EV integration scenarios that all proved the significant effect of such EV integration. Authors in [212] used stochastic Lyapunov function to model the power system stability near equilibrium point.

V. CONCLUSION

This paper comprehensively reviews the application aspects of EVs in the power network field. The charge/discharge modeling is preceded by the capacity evaluation stage in which the EVs mobility effect on available power capacity is addressed. Several sources viewed the matter at hand with different approaches: deterministic, probabilistic, or otherwise with distinct performance measures. The centralized and distributed charging models were compared and contrasted through many papers along with many case studies that shed light on practical considerations for both models. The interaction of EVs with deregulated electricity markets is analyzed throughout algorithms, models, and case studies to propose suitable business models that incorporate the dynamic nature of the deregulated markets. The slow pace of power network upgrading process and the associated costs make it practically impossible to accommodate EVs integration at large-scale without violating some of the grid constraints, especially for weak networks. The paper highlights the potential effects of EV integration on power grids at different rates for different cases. The main electric network components and factors were covered, including, transmission cables, distribution transformers, load factor, stability, and others. Moreover, the reviewed sources suggested some of the techniques to mitigate such detrimental impacts in order to facilitate adopting the EVs into grids.

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