A robust vehicle to grid aggregation framework for electric vehicles charging cost minimization and for smart grid regulation

Ubaid ur Rehman

Department of Electrical Engineering, Polytechnic Institute of Porto, Portugal

A B S T R A C T

In this paper, we propose an optimal hierarchical bi-directional aggregation algorithm for the electric vehicles (EVs) integration in the smart grid (SG) using Vehicle to Grid (V2G) technology through a network of Charging Stations (CSs). The proposed model forecasts the power demand and performs Day-ahead (DA) load scheduling in the SG by optimizing EVs charging/discharging tasks. This method uses EVs and CSs as the voltage and frequency stabilizing tools in the SG. Before penetrating EVs in the V2G mode, this algorithm determines the on arrival EVs State of Charge (SOC) at CS, obtains projected park/departure time information from EV owners, evaluates their battery degradation cost prior to charging. After obtaining all necessary data, it either uses EV in the V2G mode to regulates the SG or charge it according to the owner request but, it ensure desired SOC on departure. The robustness of the proposed algorithm has been tested by using IEEE-32 Bus-Bars based power distribution in which EVs are integrated through five CSs. Two intense case studies have been carried out for the appropriate performance validation of the proposed algorithm. Simulations are performed using electricity pricing data from PJM and to test the EVs behaviour 3 types of EVs having different specifications are penetrated. Simulation results have proved that the proposed model is capable of integrating EVs in the voltage and frequency stabilization and it also simultaneously minimizes approximately $1500 in term of charging cost for EVs contributing in the V2G mode each day. Particularly, during peak hours this algorithm provides effective grid stabilization services.

Keywords:
Electric Vehicles
Aggregation system
Load stabilization
Frequency stabilization
EVs charging stations
Smart grid

1. Introduction

From past decade the numbers of Electric Vehicles (EVs) are rapidly increasing all over the world, and electric cars are now being regarded as an alternative of the conventional Internal Combustion Engine Vehicles (ICEVs) [1]. By scientific studies it has been proved that in near future the growth of EVs with the current pace can help in countering growing fossil fuels shortages and global warming [2]. Several scientific surveys show that by the intelligent penetration of modem EVs in the power distribution system a renewable powered grid could be stabilized even their integration can also increase power generation proportion by the renewable resources [3]. Currently, researchers all over the world are in ager to develop robust techniques to penetrate plugged-in-EVs with both commercial and domestic chargers as the power storage devices. Many recent studies show that in any metropolitan area parked and plugged-in EVs can be used as the quick power storage resource. In past few years the energy storage capacity of the EV batteries has rapidly expanded, till this date, millions of all Electric Sports Utility Vehicles (SUVs) equipped with 80-100kWh batteries are already running on the roads worldwide [4]. It is evident that due to the recent advancements in EV industry, modern electric cars are not only capable of procuring energy from the grid for charging, besides, these cars can also supply energy in return to the grid in peak hours and could contribute in fulfilling the peak energy demands as the peaking plants.

This phenomenon is known as the vehicle to grid (V2G) system [5]. Generally, V2G operation is carried out by using the pre-installed inverters in the EVs when these are parked at the charging booths or through purposely installed mega chargers equipped with high rated inverters [6]. As a decentralization energy resource a fleet consists of few modern EVs can supply power backup in Mega-Watts (MW) to the grid. In literature, several algorithms are proposed with the motivation to practically implement the V2G technology. Some models show that it is possible to use modern EVs to stabilize the grid by the penetration of V2G system, but still the practical implementation of V2G technology is absent. Despite of the huge work still researchers are unable to practically penetrate EVs in the SG as the power storage devices. However, it is an unneglectable fact that EVs could be used to stabilize the sever voltage fluctuations and frequency transients produced by the intermittent energy means [7]. Moreover, modern EVs could also act as the

Nomenclature

List of indices

i	Index of the EVs charging stations (CSs)
j	Index of the Electric Vehicles (EVs)
B_{ij}	Chemical properties of an EV_j battery connected with CS i

List of acronyms

EVs	Electric Vehicles
CSs	Charging stations
DA	Day-ahead
TNO	Transmission network operators
I-Day	Vehicle-to-grid Integration day.
DR	Demand Response
DNO	Distribution network operators
min	Minimal value
$s.t.$,	Subjected to
RP	Reactive power
SOC, s	Battery state-of-charge (SOC)
BDD, d	Battery discharging depth
ADC	Average battery degradation cost
DDF	Function of the degradation density
D	DDF at SOC s.
SolS	"Solution sets" available for the optimization constraint
G2V	Flow of power from grid to EV
V2G	Flow of power from EV to grid.
CAO	Central Aggregation Office

List of Variables

SOC_{ij}^{int}	Primal state of charge of an EV_j arrives at CS i
SOC_{ij}^{fin}	State of charge of EV_j at departure from CS i
$SOC_i(t)$	Maximal energy storage capacity of the EV_j battery
E_{ij}^{int}	Initial amount of power supplied to the EV_j by CS i at the start of charging
E_{ij}^{fin}	Total power supplied by the CS i to EV_j till departure
E_{ij}^{max}	Maximal rate of power which could be supplied by the CS i for charging all connected EVs
$P_{ij}^{up}(t)$	Reserve power supplying (up) signal from CAO to EVs and CSs for grid stabilization
$P_{ij}^{down}(t)$	Receive power (down) signal from CAO to CSs for charging EVs.
$P_{ij-new}^{up}(t)$	Updated reverse power supplying signal (up) signal from CAO to CS i and EV_j
$P_{ij-new}^{down}(t)$	Updated again start obtaining power from the grid signal (down) signal from CAO to CS i and EV_j
$Q_{ij}(t)$	Maximal reactive-power delivering capacity of an EV fleet parked at CS i
$Q_{ij-new}(t)$	Updated value of reactive-power backup available at CS i with the collaboration of EV fleet.
T_{ij}^{arr}	Arriving time of EV_j at CS i
T_{ij}^{dep}	Departing time of EV_j from CS i
N_{CL}	Life-time charging/discharging cycles of an EV battery.
$\$^{BT}, \$_{ij}^{BT}$	Overall battery degradation cost of EV_j connected with CS i
$K_{,1,2}(y)$	Number of objective-functions.
y	Set of optimal solutions.
t	Number of time slots.
$\mathscr{V}_i(t)$	Nominal voltage value at charging hub CS i
$\Delta\mathscr{V}_i(t)$	Values of the uncertain voltage fluctuation at the charging hub of the CS i.
$R^{ref}(t)$	Reference value of the active power signals broadcasted by the TNO
$Q^{ref}(t)$	Reference value of the total reactive power signals broadcasted by the DNO.
$P^{up}(t)$	Maximal power supplied in reverse to the grid by CAO which is only obtained by the EVs fleet.
$P^{down}(t)$	Maximal power obtained by the CAO from the grid then supplied to CSs for charging EVs.
$Q(t)$	Rated reactive power regulating capacity of the CAO considering power storage capacity of all connected EVs.

List of constants and parameters

T_{set}	Set of time slots with similar energy prices.
n	Number of hourly time slots (sets of t).
$\mathscr{S}_{ij}$	Maximal power supplied by the charger i to EV_j.
q_{ij}	Nominal reverse reactive power delivering capacity of EV fleets connected with CSs.
q^{max}, Q_{ij}^{max}	Maximal reactive power delivering capacity of an EV fleet with the collaboration of CS i.
Q_i^{max}	Maximal reactive power delivering capacity of the charging station i to the grid without EV support.
p_{ij}	Value of power consumed by all EVs connected with the CS i from the utility grid in real time (RT).
α, β	EVs and CSs battery coefficients.
PB, PB_{ij}	Price of battery modules connected in the EV_j being charged by the CS i.
η	Overall efficiency of one complete charging/discharging cycle of an EV_j .
$\eta_{ij}^{up}, \eta_{ij}^{down}$	Up/down charging/discharging efficiency of the EV fleet connected with CS i.
$\$_{Rwd}^{up}, \$_{Rwd}^{down}$	Revenue earned by the CSs and EVs for providing up/down power regulation services.
P_{ij}^{max}	Maximal amount of active power supplied by all EVs and CSs back to the grid.
$\$_Q(t)$	Revenue earned by the CSs and EVs by providing reactive power regulation services to the grid.
g_i, y_i	Conductance of the grid side transmission/ distribution lines or value of the reverse reactance of the charging station single connection node.
N_V	Number of vehicles in the EV fleet which collaborates with CAO.
N_{CS}	Number of charging stations associated with the CAO.

spear energy reserve [8], peak load diverting devices [9] and as the frequency stabilization tools [10].

Out of these services, particularly EVs frequency stabilization capability has obtained huge attention of the researchers all over the world [11]. Stable frequency exhibits a very important role in any power network. It is a defined mechanism that the range of frequency in any power system should be within the acceptable limits, even a slight change in frequency level can cause major failure of the whole power network and sometimes ends up as the national level breakouts [12]. Due to the abruptly responding capabilities of EVs chargers (approximately 10 ms), EVs taking part in the up or down power regulation configurations can provide instantaneous response which make V2G system more effective as compare to the other methods, i.e., to start any synchronous machine consume much longer time than the EV power injection into the grid. Moreover, EVs could also be used as a separate power regulation source, i.e., in future due to massive EV numbers on roads, it will be a un-neglect able possibility to use EVs as the supplementary power stabilizers [13]. On the power distribution side of the gird, injection of the real time reactive power by EVs is considered as one of the most valuable contribution in the modern power networks, briefly explained in [14]. Integration of the reactive power (RP) by the V2G system, enables electricity supplying companies to further improve the quality of power with enhanced efficiency on both transmission and distribution sides which eliminates the chances of generator overloading [15]. In addition, controlled EVs charging/discharging does not cause any battery degradation even after thousands of cycles [16].

Moreover, due to the immense and vastly expanding renewable resources penetration in the smart gird, appropriate and efficiently manageable algorithms are now compulsorily required to guarantee the reliable and efficient working of the whole grid [17]. Further, with the assistance of conventional power generation resources, the loads having shift able properties i.e., like EVs charging/discharging could be diverted during both peak and off-peak hours using advance algorithms. Such algorithms can also contribute to the load management by providing services of utilizing backup energy means [18]. Therefore, to practically implement this phenomenon researcher all over the world are trying to find robust techniques to expand the power generation by intermittent resources with the help of EVs and other energy storage appliances [19]. However, modern EVs exhibits higher capability of providing grid levelling services on vast sale, because, a fleet comprised of 10–15 fleets can provide Megawatt Hour (MWH) amount of power backup instantaneously [20].

In past decade, a network of advance metering infrastructure (AMI) has rapidly expanded and has enabled the broader scale integration of intermittent resources in the smart grids all over the world [21]. By using AMI, now any consumer can contribute as energy supplier in the energy market, by selling his domestically produced energy by roof mounted solar plants. Considering this concept, it is likely that with the expansion of EVs numbers, many consumers can use their EVs for this purpose [22]. Since, according to world transportation survey of past decade [23] about 90% EVs are driven for only about 2 h in a day, and stay parked during remaining hours. So during parked hours these could be used for voltage and frequency stabilization services or as an energy trading tool [24]. It is a general practice of power supplies all over the world that they divide a day into multiple time slots, and for each time slot per kWh price of electricity is different, in peak hours it is high as compared to the off peak hours. Therefore, a consumer can utilize his EV in such manner that he can charge his EV in off peak hours and could supply power back to the grid in peak hours, or vice versa [25]. The only threat which in future EVs will face is the threat of battery capacity degradation which is a major drawback of using EV in V2G and G2V mode [26,27]. Therefore, robust and intelligent techniques are required to be developed to reduce this threat and to optimally integrate EV in a smart grid as the grid stabilization tool, which is the basic motivation of this research work. Considering limitations of the upper stated research works, the proposed model is designed to overcome all these constraints effectively. Main contributions of this paper are as follows:

- A deterministic non-linear programming (NLP) based V2G aggregation framework termed as Central Aggregation Office (CAO) is proposed to regulate the uncertain voltage fluctuations and current transients in the smart grid introduced by renewables with the optimal integration of EVs in V2G or G2V modes. This framework consists of two layers and works in the hierarchical prospective 1) Upper Layer, 2) Lower Layer. The upper layer deals with the Day-ahead energy scheduling of the transmission side, while the lower layer deals with the real time load regulation of the distribution side of the gird.
- Transmission Network Operators are referred as "Upper Layer". Its responsibility is to forecast the amount of power which is required for trading in the DA energy market in contrast to the maximal power demand of the DA market. The advantage of this approach is, if the upper layer detects that the amount of power which will be available in the DA market would be insufficient to fulfill DA energy demand or it will be higher than the total power demand then to cope this contingency and to save power loss, it will abruptly define new optimal charging/discharging schedules for all associated EVs and broadcast this information as the updated regulation up/down signals to the lower layer for engaging CSs and EVs. Hence, the difference between power generation and demand is covered by utilizing EVs in the V2G or G2V mode.
- The Distribution Network Operators (DNO) are termed as the "Lower Layer". It deals with the "Real-Time" load regulation by optimally penetrating EVs in the V2G or G2V mode. This layer deals with the voltage and frequency abnormalities i.e., initially it prepares the voltage and frequency transients record in advance considering the past power generation fluctuations record introduced by the renewable resources according to the ecological factors and computes the amount of power required to counter these transients in advance to stabilize the grid. This layer is responsible of simultaneously performing EVs charging/discharging tasks and the grid regulation in real time.
- In the proposed framework we have particularly defined a separate strategy for minimizing the threat of battery degradation which informs all EV owners in advance before they are ready to offer their vehicles for the V2G operation. This method also integrates DC linking capacitor banks of thousands of Farads connected with the commercial EV chargers to provide instant voltage and reactive power support to the grid for shorter durations even if suitable number of EVs are not connected to the CSs network. This is also a major contribution of this paper,

The performance of this model has been verified by intense simulations carried out on the 1EEE 32-Busbar based distribution network [54] as well as we have also performed several case studies to test the robustness of the proposed model. Test results show that our proposed hierarchical aggregation algorithm (CAO) minimizes the overall charging costs of all associated EVs who offer V2G services. It does not cause any energy storage capacity degradation to the used EV batteries. Despite providing instantaneous frequency regulation services to the grid thousands of times, the EV battery SOC capacity do not degrades to the danger level. Note. in rest of this paper the lower level approach is termed as the "V2G Integration day" and denoted by the "I-day".

The rest of the paper is arranged as follows, Section II covers the literature Survey, Section III, presents the basic architecture of the vehicle to grid aggregation system, Section IV, briefly explains the proposed V2G optimization constraint to integrated EVs in the grid. Section V, presents the structure of hierarchical model and high level controlling functions. Section VI, covers the case studies and simulation test results. In last Section VII, concludes this paper and presents the future work statement.

1.1. Literature review

In literature several techniques are proposed with the motivation of controlling sudden voltage/frequency transients and power blackouts. Because, in real world, a power grid faces severe transients due to any unexpected imbalance between demand and supply. For instance, if a higher rated electricity generator fails due to the sudden atmospheric temperature changes [28] and there is no backup power plant of similar rating is available for abrupt operation. In this case, the proportion of the power generation uncertainty extraordinary exceeds. Particularly due to such constraint, in a real-time market the energy procurement tariff could significantly increase, which can affect the energy tariff of the retail market. Sometimes, such transients occur frequently when most of the power grid is being fed by the renewable resources, i.e., by photovoltaic and wind energy, which might cause massive real-time cost fluctuations, and in certain scenarios, such constraints can cause breakdown of the complete power system [29].

Conversely, the mean reversion theory effectively informs retailers about the ratio between current power generation and consumption. Moreover, it also broadcasts updated energy pricing data which is prepared by considering the current weather report, renewable production proportion and after analyzing the power generation proportion of other sources currently being utilized, as well as, chances of occurring transients and voltage imbalances or any other major constraint are also considered. In modern power networks, this data is sent as the average or mean values to the service operators and consumers by the central control office. Generally, before broadcasting this type of data to all stakeholders, first it is compared with the historic records to verify that either the current predictions are correct and will fully ensure consumer satisfaction and either this data will be helpful in maintaining power system stability or not [30]. In a broader prospective it is believed that despite of verification still unexpected transients may keep on occurring for longer periods due to the failure of any part of the power system which can eventually cause consumer dissatisfaction and the higher level power breakdown [31].

A comprehensive overview of the Demand Response (DR) techniques and its numerous classifications in the deregulated energy market is presented in [32]. In [33], authors compare multiple bidding procedures in the wholesale energy market where renewable resources and EVs are connected with the grid. This model only deals with the energy trading and does not propose any V2G aggregation framework. In [34], author presents a common approach for regulating EV charging through aggregator. Although the aggregation algorithm is proposed in this paper, but, this method only schedules EVs charging in off peak hours and does not consider EVs as the voltage or frequency stabilizers. In [35], authors claim of proposing robust EVs aggregation system however they do not utilize full energy stored in EVs nor use V2G mode; they have just defined hours for EVs charging from 22:00 to 7:00am in the offline grid which makes it unfeasible for modern use.

In [36], authors propose a ladder following multilevel programming based algorithm for consumers and retailers. They have deployed current energy cost broadcasting strategy for each consumer and expected that he will manage his own EV charging according to the broadcasted information, which increases the computational difficulties of the proposed algorithm. Although, this technique is decentralized, but despite still the upper level (managerial platform) of this algorithm must be informed about the EVs specifications and owner choice, which does not assure the consumer privacy. The same privacy violation issues are faced in [37]. In [38], authors have used known energy tariff model in the electricity supplying market, which is exactly the same policy used for thermal generators, but in this algorithm they have used this method as a communicator platform between aggregator and retailers which need an efficient communication network to work. Even a slight delay in communication system can cause major difference between demand and supply.

In [39], an automatic load scheduling algorithm is designed particularly this aggregator contribute in the day-ahead (DA) market and tends to enhance the consumer satisfaction level by reducing its own profit which is an un-implementable approach. A stochastic SCUC concept is proposed in [6], which considers reserve bids broadcasted by the retailer who have computed this using (Demand Side Management) DSM strategy, and it also uses arbitrary blackouts data of the wind production plants along with constraints of the transmission side, but the cost analysis of the conventional power plants is absent which does not provide accurate biding data to all stockholders.

In [40,41], hierarchical DSM methods are designed to enhance the contribution of the intermittent resources by re-profiling the power demand. However, the practical feasibility of this work is absent and not studied. Particularly in. [42], a comprehensive study of the DSM based load scheduling is carried out which considers economy of the dispatched power. In the proposed model authors have used multiple techniques to reliably integrate renewable resources in the grid, and used multi-technique method for the renewable integration but, this model needs extreme computation power for execution which makes it completely un-feasible for practical implementation.

In [43] and [44], robust optimization (RO)-based techniques using DSM have been developed, which enables the decentralized structure of the dynamic market pricing. In both models authors have included, a two-stage marketing model as reference in which., consumers directly purchase electricity from the wholesale market, on the contemporary (most recent) tariff. However, after following this model in peak hours all consumers have to purchase the electricity on higher rates which is a common approach. Therefore, the main contribution of this work is absent and hard to grasp.

In [45], a comprehensive study about the use of second hand batteries is carried out, in this research work authors have proposed that the used EV batteries could be employed as backup in the small scale energy storage unit with photovoltaic power generation plant. Authors used second hand batteries from five EVs to enhance the effectiveness of small scale power plant the results proved that second hand batteries could be a feasible option for energy storage in small scaled renewable power plants. In [46], a detailed review on the different charging schemes is discussed, authors have studied several prospects of EVs integration in the grid through V2G and proposed EVs could be used for better load management. In [47], a techno economic analysis of the EVs integration in smart grid by the V2G operation is discussed and in order to level the power demand and tariff as well as EVs integration in peak hours could also minimize the power generation by conventional power plants hence greenhouse gas emission could be reduced. In [48], A look-ahead risk-aversive based EVs load aggregation algorithm is proposed which enables V2G and G2V operation of EVs in the smart grid environment and increases revenue for EV owners and reduces voltage and current transients introduced by the renewables. In [49], a real time controlling strategy for managing EVs in charging stations is proposed which is capable of balancing load on all three phases by the help of EVs. In [50], an EV aggregation planning model to provide ancillary services to the grid is proposed, which also regulates the operation of energy storage systems in smart grid. In [51], a user friendly aggregation model to integration EVs in the smart grid according to the consumer preferences is proposed which helps in regulating frequency transients by the EVs penetration as secondary power resource. In [52]-[53], authors have proposed smart grid regulation models for the ancillary services markets, the proposed strategy penetrates EVs and energy storage systems in the smart grid to enhance the reliability of the grid where renewables are the major power producers. These methods aim to reduces energy cost in peak hours as well as also generate profits for EV owners.

From the above discussion it is proved that still the practically implementable V2G regulation model is not proposed which could have been used for the grid stabilization on the broader scale. Therefore, in this paper we have proposed a robust V2G aggregation algorithm which does not only robustly regulate the EVs charging/discharging tasks, besides it also reduces their charging costs. Moreover, It also contributes in the voltage and frequency stabilization to the grid. This framework also provide assistance to both TNOs and DNOs while integrating the renewable resources in the grid on higher scale further detail of the proposed methodology is stated in next chapter III as follows:

1.2. Basic architecture of the proposed V2G aggregation system

1.2.1. Basic EV aggregation frameowrk

In literature, various strategies for V2G aggregators have been previously defined by the industrial and academic researchers all over the world [55]. The operation of every proposed framework mainly depends on the controlling strategy. In literature, enormous EVs aggregation models have been proposed with the motivation of minimizing the overall energy procurement costs for both EV owners and the energy suppliers. These models work on the bases of costs functions dealing with the already defined sets of power consumption costs of several utilities or govern the EVs charging costs according to the pre-defined values. Such methods commonly work by considering multiple ancillary services provided by or to the energy supplying markets i.e., power stabilization during peak hours, frequency or voltage regulation and overall charging and power procurement cost reduction.

One of the previously developed EVs aggregation model in literature, is capable of both voltages and frequency regulation and presented in Fig. 1 [56]. Note in our model, a similar but much more sophisticated strategy has been proposed. As stated above, basic contribution of our proposed method is, it provides immense operational stability to the SG and the proposed algorithm could be governed with very little computational power, which makes it easy to implement on higher rated power networks. Fig. 1 show all parts of the SG which are compulsory for regulating and maintaining the power flow between SG and EVs. In this figure the central aggregator receives all necessary data of the SG, which then manages the operation of whole power system. Besides the flow of information between DNO, TNO are also managed by the central aggregation office, which is also given in Fig. 1. After receiving all essential data, central aggregation system executes necessary actions to perform the EVs charging or discharging tasks and frequency or voltage regulation services.

The power regulation and EVs charging/discharging operations are executed by considering the current per unit price of electricity in the wholesale energy market i.e., $/kWh and according to the action commands broadcasted by the central energy suppliers. For instance, in response to the voltage stabilization command which was broadcasted by the central transmission network operators (TNOs) or distribution network operators (DNOs) the proposed CAO frequently engages all available resources in real time and successfully provides voltage stabilization support to the grid. As stated above, in our model, only a central aggregation authority termed as "CAO" is responsible of governing charging/discharging tasks of all associated EVs parked at different CSs. Note, the optimization model proposed in [56] also considers all of the above stated conditions to manage the operation of a SG but does not guarantee voltage or frequency regulation services.

Therefore, in our model, the regulation commands are basically divided in two distinct categories, 1) "regulation down signal" whenever the amount of currently available power in the SG is in surplus, then CAO informs all associated EVs to acquire power for charging. Hence, in response of this command, EVs are charged. On the other hand, the "regulation up signal" is broadcasted whenever the amount of power available in the grid is lower than the total demand (demand is high from generation), in this situation, in order to level the difference between demand and supply the energy is acquired by the connected V2G enabled EVs. Whenever EVs are connected to the chargers, these could be used for upper stated operations with the owner consent and in order to respond to the broadcasted commands by the central aggregators as presented in Fig. 2.

As stated in all above references, EV owners can avail the opportunity of energy trading using vehicle to grid system, and aggregation models are responsible of distributing the generated profit between owners which they have earned by contributing to the grid stabilization requested by the TNO and DNO. Moreover, these models also provide several incentives to the owners in return of providing stabilization services to the SG, i.e., they can avail profits in term of lower charging costs. In order to provide power regulation services, each aggregator primarily exchange technical specifications data with all associated EVs by using bi-directional communication methods available on all CSs. Note, in our model, for simplicity, it has been assumed that all EVs are capable of providing grid regulation services but, this service will be only availed when these are connected with the commercial CSs.

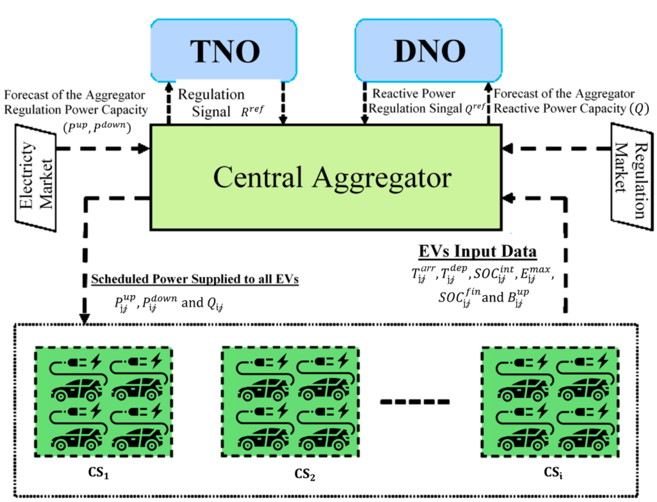

Fig. 1. Proposed EVs aggregation framework which acts as the intermediary platform between electric cars and the central grid operators.

1.2.2. *V2G System Architecture*

The primarily, proposed V2G methods were purposely designed to enable the bi-directional flow of power and these models were only able to charge EVs when owner were willing to follow the defined optimal schedules. In these models no such system was introduced to eliminate the chances of system overloading due to simultaneous charging of several EVs. But in the proposed model, a TNO or DNO can broadcast regulating up or regulation down action signal through modern communication networks. A most commonly used V2G system is shown in Fig. 3. In this system all CSs have been assigned the task of monitoring SOC levels of every EV individually when it arrives and connects with the charger and then stack those EVs in such manners that, whenever their services are required to the aggregator, they must have sufficient power available to contribute to the grid stabilization.

Authors in [57] propose that there should be minimum over five hundred EVs compulsorily available at CSs in a metropolitan area for aggregation purposes i.e., in order to successfully control any voltage or frequency deviation occurs in the grid these EVs can act as backup. Because, a big EV fleet might contain MWhs capacity at any time which could be supplied back to the grid in just milliseconds. Moreover, in literature we have found that in some models even over two thousand EVs are used for this purpose [58]. Therefore, for practical implementation of this approach we have primarily computed the energy storage capacity of currently available EVs in the worldwide market, we found that currently about one MWh energy could be stored in just 11 Tesla P100D electric cars with 90% SOC levels [59], It is evident that currently over 1.4 million Tesla P100 EVs are actually available on roads worldwide [60]. In this scenario, it might be highly effective if government authorities all over the world would install V2G capable chargers on each EV parking lots. According to a survey conducted by IEA in 2020 on Global EV Outlook [61], about 80 % EVs remain parked for over 90% time throughout their life. Besides, it is projected that

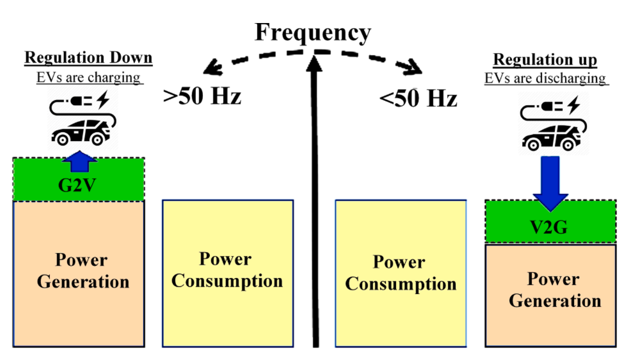

Fig. 2. Layout of the regualtion carried out by the proposed aggregator based on recived up/down commands.

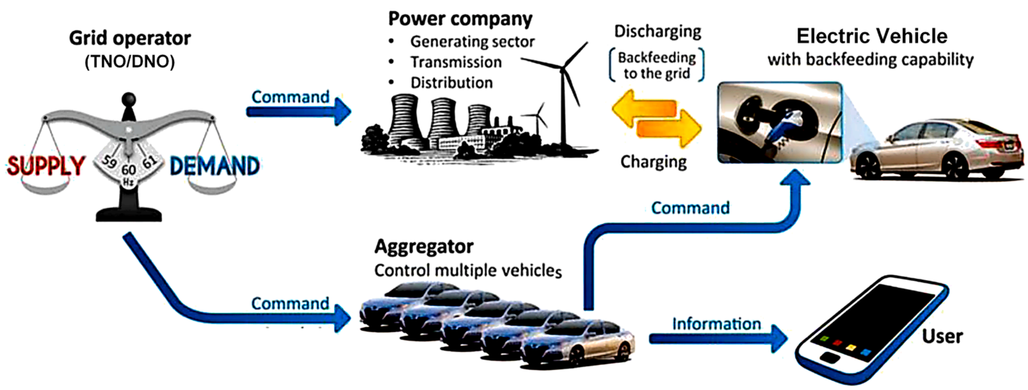

Fig. 3. Proposed V2G network architecture.

worldwide the EV numbers will grow rapidly in next few years. Therefore, it will be a highly regarded initiative of the governments all over the world. Since, parked EVs could contribute to the grid stability and could also be used as the peaking plants in high demand hours [62].

It should be noted that, in contrast to the previous models in the proposed V2G framework CSs are directly governed by the central aggregation office through hierarchical optimization as presented in Fig. 3. In addition, the proposed EV aggregator not only controls the operation of all associated CSs besides, it is also responsible of coordinating and monitoring EVs arrival and departure times. Moreover, this aggregation framework also regulates the charging/ discharging tasks and prepares the transections record of any V2G service provided by an EV using real time pricing strategy on behalf of EV owner. For deep knowledge about this approach a reader can visit [63]. Moreover, this system also performs different tasks (i.e., fast charging, guarantee of the fully charged EV at departure) according to the EV owner request [64]. In addition, in this system, a CS is also able to directly monitor the EVs parking time and it also determines either a connected EV belongs to this particular area and prepares the record of its technical specification i.e., on arrival SOC level, anticipated departure/arrival times, total parked duration and requested eventual SOC at departure by the EV owners, which is than forwarded to the central aggregation authority for additional actions. Commonly, this data is transmitted through batch mode, because, it is considered as the most effective medium of monitoring large number of EVs [65] as presented in Fig. 4.

By deep analysis of Fig. 3, it could be analyzed, initially two types of information flows in any smart power system or smart grid. Primal is the informative data flow, and secondary is the flow of electricity. The informative data flow is commonly comprised of essential technical details, i.e., EV arrival SOC level information, energy cost data, real time pricing information and statistical generation data of the total energy production reserves [66]. In addition, in a smart power system horizon, smart grid operational information mainly depends on the current power demand and generation proportion information which is broadcasted by the TNO or DNO to the aggregation authorities, who further forwards this data to CSs and EVs for fulfilling the desired load regulation i.e., up/down tasks. For instance, these tasks might be a command of EVs discharging to resupply the stored power in EV batteries to the main utility SG. However, the availability time of each EV could be uncertain, therefore, it is very complex to compute. In order to predict, the arrival of hundreds of EVs, the real time transportation data of all associated EVs could be obtained and analyzed by using advance communication networks through central traffic agencies, a reader can visit [67] to obtain further information about this system. As an example we are explaining here, in United States typically an EV is only driven for an hour throughout the day [68]. It has been determined over 90% vehicles remain parked during most of the day. Hence we can conclude in parked hours EVs can provide enough energy storage space to the SG which could be utilized in peak hours as the replacement of peaking plants [69].

1.3. *Proposed V2G scheduling optimization constraint*

By the upper discussion it has been proved that, in a smart grid scenario, EVs integration as the stabilization tool is only possible by introducing a robust EVs aggregation framework Besides aggregators also acts as the data interface between thousands of EVs and smart grid management. Note, the optimization and computational capability of the V2G scheduling constraint particularly depends on two distinct commands, primal is the cost reducing signal while the second is the cost increasing signal to consume/transmit power to/from the grid in $/kWh respectively. In this section, we have presented our main approach which we have implemented in this paper to obtain higher accuracy and robustness during the EVs working mode in V2G. In our proposed algorithm we have also included the battery degradation cost as well as the contemporary state of the SG is also considered. Optimal solution of the proposed optimization constraint is achieved which creates appropriate charging/discharging scheduling strategies for all associated EVs and eventually reduces the overall operational cost i.e. charging cost for all EVs contribute in the V2G service. In addition, our proposed model also ensures the revenues for EV owners who offer their EVs for voltage and frequency regulation services to the SG.

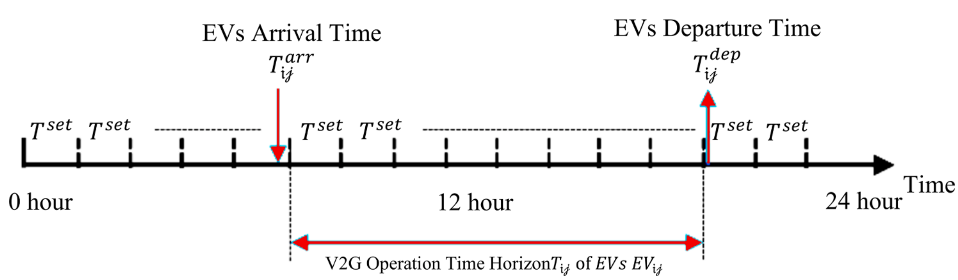

Fig. 4. Operational time horizon of the V2G framework.

1.3.1. *Modelling of the EVs Scheduling Constraint*

In order to model the optimal V2G framework, we have used a full day scenario, which is divided into several hourly time slots i.e., 24 in total. These time slots are represented by variable T_{set}. In this research paper, we have divided a typical day into hourly time slots sets and each time slot set is denoted by n, and stacked in such manners that the duration of a time slot is computed by $24/n$. Here, we infer the required power for charging/discharging an EV during a time slot remains similar throughout the time slot as shown in Fig. 4. In addition, the regulation down and regulation up command signals for a j^{th} EV is broadcasted to i^{th} CS at time instance t and represented by the P^{up}_{ij} and P^{down}_{ij} commands. The arriving interval of a j^{th} EV is represented by T^{arr}_{ij}, and it also denotes that time interval when the j^{th} EV is plugged-in with i^{th} CS. While the time of departure of j^{th} EV is represented by T^{dep}_{ij}. Note that, it also denotes a time interval when the j^{th} EV is departed from the i^{th} CS respectively.

The overall operational time duration of a j^{th} EV in V2G mode when connected with i^{th} CS is represented by T_{ij}, this superscript denotes either EV is charged or discharged during V2G mode in the allocated time horizon. Because, we have divided a day into several hourly time slots, therefore, we can consider the EV parked time T_{ij} as a stack of time slots between EVs arriving time T^{arr}_{ij} and departing time T^{dep}_{ij}, as shown in Fig. 4. The primal SOC of an EV$_{ij}$, is represented by E^{int}_{ij} which shows the EV battery capacity on arrival T^{arr}_{ij}. While, the overall (total) energy storage capacity of an EV battery is represented by E^{max}_{ij}. For the practical implementation point of view, the amount of power which is stored in an EV battery at departure is denoted by E^{fin}_{ij}, and this is the final SOC value of an EV on the departure time T^{dep}_{ij}. Note, the value of E^{fin}_{ij} must be parallel to the owner requested value to fulfil his transportation needs.

Moreover, the eventual amount of energy E^{fin}_{ij} at departure should not be higher than the maximal EV energy storage capacity E^{max}_{ij}. For practical implementation we have inferred that, by analyzing the traffic data acquired by the traffic agencies, a CS can anticipate the most important data for next hourly slots i.e., it can anticipate arriving time of an EV, on arrival SOC level, and required rate of power which must be supplied to EV when it will start charging at CS. While, prior to the start of charging task for an EV at CS, vehicle owner provides information of the expected parked time and required eventual SOC level on departure. This is the responsibility of each CS to calculate the required amount of charging and discharging power for an EV during allocated or requested time horizon T_{ij}. It has to be noted that the cost of regulation down and regulation up services for providing frequency and voltage stabilization during a particular time horizon are similar for all EVs on all CSs which are contributing in the V2G framework. The regulation of charging several EVs simultaneously is only carried out by temporal price variations, but it is not comprised of separate price variations as given in [70].

1.3.2. *Frequency Stabilization Model*

A key feature of the EVs penetration in the SG is, it increases the operation flexibility of the whole power network and helps in maintaining frequency within the acceptable limit through V2G framework. Moreover, due to vast scale deployment of the V2G framework, all associated EVs can provide instant backup against failure of any power plant by providing assistance in frequency regulation. In SG, EVs are integrated by the TNO for frequency regulation services. but, in order to complete this integration, aggregator acts as the intermediary platform and also prepares the financial transection record of any up and down regulation service provided by the vehicle and also prepares record of the forwarded profit in the owner bank account. Whenever, an EV is used for the grid regulation tasks, the rate of exchanged power must be within the desired limits otherwise, there is a possibility of fully depleted EV battery which can cause major storage degradation [71]. Therefore, whenever an EV is used in the V2G mode it is only discharged to certain level to reduce this threat. While, the EV owners must be paid according to the supplied power to the grid for frequency stabilization. Note, the amount of traded energy could be from few kW to several kW depending on the battery maximal SOC of an EV [72]. Table 2, shows the specification of currently available electric vehicles in the market as analyzed, Mustang Mach-E, Tesla model S (p100D), and Nissan Leaf 2020 car models are capable of providing thousands MW of backup to the grid and their integration into the V2G system will be a major achievement in near future.

1.3.3. *Votlage Stabilization Modelling*

In literature, several voltage stabilization models are given but, no one proposes that the DC linking capacitor banks of thousands of Farads connected with the commercial EV chargers could provide voltage and reactive power support to the grid for shorter durations even if suitable number of EVs are not connected to the CSs network. Therefore, as one of the main contributions of this paper, we have proposed the use of commercial EV chargers as the voltage transient's stabilizers. The main motivation of utilizing higher rated capacitor banks connected with the EV chargers for voltage regulation is, it can reduce the use of EVs in the V2G mode. Hence, the threat of EV battery storage capacity degradation is reduced [59].

In order to achieve the desired power for voltage regulation from the EV chargers, we propose that the total value of reactive power which could be obtained from the EV chargers for voltage regulation is proportional to its own power delivery capacity to EV for charging. as well as it is also homologous to its own overall reactive power consumption capacity. Note, EV chargers can only provide voltage regulation support for shorter periods and their power injection depends on the nature of voltage transients. For better understanding it should be noted that, although EV charges could be used for voltage regulations for shorter durations but, if the voltage transients keep on occurring and the capacitor bank is fully depleted then the use of EV connected with this particular charger in the V2G mode could be restricted due to unregulated charging. Since, the grid reliability is the main priority and it remains the top priority in any situation. Therefore, in some cases EVs cannot achieve desired SOC level before departure. Thus, in quest to reduce such possibilities, the value of reactive power which could be supplied by an EV in such cases in contrast to the desired SOC level on departure is computed by following formulation [59].

$$q_{ij} \leq \sqrt{\mathscr{S}^2_{ij} - p^2_{ij}} = q^{max}_{ij} \tag{1}$$

Infer an EV is charging at a CS at maximal rated power and grid sends "provide reverse voltage support signal" to this charger. In this scenario, this charger cannot contribute to the voltage regulation services and cannot supply reactive power back to the grid. Conversely, if the amount of apparent power delivering capacity of this charger exceeds by the real time power p_{ij} which is being consumed by the EV from the main grid, then the amount of useable reactive power which may be supplied by the charger is computed by (1)

Table 1
Parameters of the Simulated Model.

Parameter	Value
Number of aggregators	1
Number of charging stations (CSs)	5
Number of EVs per CS	210
Efficiency of the EV charger	Up (95%) – Down (90%)
Rated charging capacity of a charger	8, 24 and 52 kW
Total number of EVs	1050
Aggregator power delivering capacity	3200 kVA

Table 2
Simulated EVs specifications.

Electric Vehicle Model	Rated battery SOC (kWh)	Cost of Battery/kWh ($)
Nissan Leaf (2020)	40 kWh	246$
Tesla Model S (p100d)	100 kWh	187$
Mustang Mach-E	68 kWh	206$

1.3.4. Formulation of the Battery Degradation Cost Computing Model

From deep literature survey we have determined that all Lithium-ion (Li-ion) batteries exhibit similar Battery Discharging Depth (BDD) and exhibits similar cycle life as presented in Fig. 5. Note, these statistics are computed from the empirical data-sheets of different Li-ion batteries. This analysis perfectly matches with the outcomes of following formulation (2) [73,74].

$$N_{CL}(\mathscr{d}) = \left(\frac{\mathscr{a}}{\mathscr{d}^{\beta}}\right) \tag{2}$$

In this formulation the superscript $\mathscr{d}$ is showing the overall depth of discharging of an EV battery after each charging/discharging cycle N_{CL}. It has to be noted that, in this technique, the effect of ambient temperature on the battery degradation is neglected. The superscript $\mathscr{a}$, β denotes the coefficients of battery specifications, and could be determined by experiments and literature survey. For instance, a similar study has been carried out in ref [67], in this paper authors have proposed a comprehensive solution for computing the Average Degradation Cost (ADC) of a Lithium-ion battery considering its power transferring capability as follows;

$$\mathrm{ADC}(\mathscr{d}) = \frac{\mathrm{RealpriceoftheEVbattery}(\$/\mathrm{kWh})}{\mathrm{TatalamountoftransferablepowerinC/Dcycle(kWh)}}$$

$$= \frac{\mathrm{PB}}{N_{CL}(\mathscr{d}) \times 2 \times \mathscr{d} \times \mathrm{E}^{max} \times \eta^2} \tag{3}$$

where, PB denotes the price of battery, E^{max} denotes the maximal SOC capacity of a battery, and η denotes the battery efficiency of one full charging/discharging cycle. The number of these charging/discharging cycle N_{CL} has been multiplied by 2. Because, a single battery cycle comprised of charging/discharging phases, and in these two phases similar amount of power is supplied to/from the EV battery. It has to be noted that, in upper equation ADC shows the degradation cost of the battery which completes a full cycle with a constant SOC level. Although, for EVs V2G framework in [65] a highly casual index knows as Degradation Density Function (DDF) has been defined which is used to compute even a minor change in battery SOC capacity. This could be computed by following formulation;

$$\mathrm{ADC}(\mathscr{d}) = \frac{1}{\mathscr{d}}\int_{1-\mathscr{d}}^{1} \mathrm{D(s)ds} \tag{4}$$

where, D(s) denotes the ADC at SOC s. Because, ADC shows the average degradation cost which is denoted here by the superscript $\mathscr{d}$, besides it might also be computed by applying Mathematical Integration on the D(s) function considering the upper and lower limits of the

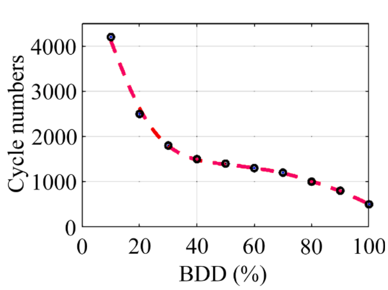

Fig. 5. Anticipated Li-ion Batteries Degradation Depth (BDD) during life time.

battery SOC and by dividing it by the whole span of integration. As stated above, the computed values of ADC could be correct only for particular SOC level, other than this, any other combination of battery charging/discharging can provide different results. Nevertheless, the actual cost of the battery degradation is computed by using the combination of the following formulation [75];

$$\$^{BT} = \mathrm{E}^{max} \times \int_0^T \mathrm{D}(\mathrm{s}(\ell)) \times \left|\frac{\mathrm{ds}(\ell)}{\mathrm{d}\ell}\right| \tag{5}$$

where, $\$^{BT}$ is the overall degradation cost of the EV battery and T is the total size of time horizon.

1.3.5. Formulaiton of the Proposed V2G Load Scheduling Methodology

This section presents basic methodology of the proposed deterministic non-linear programming (NLP) framework which is defined to govern the vehicle to grid (V2G) load scheduling operation. To acquire further knowledge about the NLP a reader can visit [76], here we are not discussing the NLP working in detail. The proposed methodology reduces the threat of higher level battery degradation of EVs take part in the V2G services. Along with, it also enhances the profit for EV owners in such manners that primarily it computes the actual current market cost of electricity generation by conventional resources by using the equation (5) after that it fix a higher rate for V2G service provider EVs for peak demand hours, which is later payed to the owners. Thus, we can formulate the optimization constraint as;

$$\min_{y}\{(y)\}$$

$$s.t., y \in \mathrm{SolS} \tag{6}$$

The above formulation has been defined as the complex constraint comprised of two distinct objective functions, primal is the cost minimization function which deals with the electric vehicle energy storage capacity degradation $K_1(y)$ while second is the revenue enhancement function for the EV owners who have offered their EVs for power regulation services $K_2(y)$. Hence we can write, $K(y) = K_1(y) - K_2(y)$ is a vector comprises of multi-objective functions which is purposely solved to obtain the optimal solution. In this equation, the superscript y shows the set of the optimum solutions (SolS) which has been determined by this constraint. The problem which we have optimized by this function is the random and unregulated EV charging and discharging cycle. Because, this is the biggest contingency cause EV energy storage capacity degradation.

Therefore, in the proposed model we have seriously focused on this constraint. It has to be noted that, in the proposed method, we have allocated equal responsibility to each objective function. Because, equally distributed responsibilities show comparative status of all objective functions during computation to overcome the uncertainty in EVs charging and discharging. The motivation of adopting this approach is to fairly determine the optimum solution using all available functions equally as defined in [33], [36], [37] and [39]. In addition, in quest to compute the globally optimum load scheduling for all associated EVs who contributes in the V2G operation during parked time at any CS, we infer, the primal SOC level $SOC_{\mathscr{V}}^{int}$, the expected departure time $T_{\mathscr{V}}^{dep}$, the arrival time $T_{\mathscr{V}}^{arr}$, and SOC level at departure $SOC_{\mathscr{V}}^{fin}$ details of each vehicle are already known. In several previous models a similar approach has been used to find the optimum solution [3,30,40].

1.3.6. Formulation of the Objective Function (OF)

For obtaining optimal solution, we have used upper defined optimization constraints in such manners that, in OF (Objective Function) $K(y)$ and the variable s could be used to reduce the cost of energy storage capacity degradation in order to increase the revenue for EV owner after performing V2G operation for frequency and voltage regulation of the grid when it is parked. We have defined following OF constraints to achieve the optimum solution.

$$K_1 = \sum_{i=1}^{N_{CS}} \sum_{\ell=1}^{N_V} T_{set}\left(\left| P_{i\nu}^{down}(\ell) \right| \times \eta_{i\nu}^{down} + P_{i\nu}^{up}(\ell)/\eta_{i\nu}^{up} \right) \times \$_{i\nu}^{BT}(\ell) \tag{7}$$

$$K_2 = \sum_{i=1}^{N_{CS}} \sum_{\ell=1}^{N_V} T_{set}\left(\left| P_{i\nu}^{down}(\ell) \right| \times \$_{Rwd}^{down} + P_{i\nu}^{up}(\ell) \times \$_{Rwd}^{up}(\ell) \right) \tag{8}$$

$$\min_{P_{i\nu}^{up}(\ell), P_{i\nu}^{down}(\ell)} K = \min_{P_{i\nu}^{up}(\ell), P_{i\nu}^{down}(\ell)} (K_1 - K_2) \tag{9}$$

$$-P_{i\nu}^{max} \le P_{i\nu}^{down}(\ell) \le 0 \tag{10}$$

Out of upper given constraint, the equation (10) defines the highest and lowest levels of the amount of power which is required for charging an EV and returned to the grid for regulation.

$$0 \le P_{i\nu}^{up}(\ell) \le P_{i\nu}^{max} \tag{11}$$

Note the constraint (11) defines the highest and lowest amount of power supplied to/from EV and grid.

$$0.05 \le SOC_{i\nu}(\ell) + \left(\frac{P_{i\nu}^{down} \times \eta_{i\nu}^{down} \frac{P_{i\nu}^{up}}{\eta_{i\nu}^{up}}}{E_{i\nu}^{max}} \right) \times T_{set} \le 0.95 \tag{12}$$

The constraint (12) has been defined to compute the amount of energy supplied in real time to/from the EV and grid. For computation of this constraint it is necessary that EV_i SOC value after each time horizon $\ell + T_{set}$ must be between 25% and 95% for reducing the threat of battery capacity degradation hence, the life of an EV battery increases. The battery SOC level is computed by following formulation;

$$SOC_{i\nu}^{int} + \sum_{T_{i\nu}^{arr}}^{T_{i\nu}^{dep}} \left(\frac{P_{i\nu}^{down}(\ell) \times \eta^{down} - P_{i\nu}^{up}(\ell)/\eta^{up}}{E_{i\nu}^{max}} \right) \times T_{set} = SOC_{i\nu}^{fin} \tag{13}$$

The constraint (13) is defined to compute the amount of final transferred energy to all EVs. Note, to satisfy this constraint, it is compulsory for each EV to satisfy the eventual power requirements of all EVs. For instance, $SOC_{i\nu}^{fin}$ of all EVs (EV_i) should be equal to set values after supplying power to the grid through V2G mode. The main objective of this condition is to ensure enough SOC in EV batteries to easily fulfil daily transportation tasks.

$$\$_{i\nu}^{BT}(\ell + T_{set}) = \varphi_{i\nu} \times \left[\frac{\beta \times \left\{ \left[1 - SOC_{i\nu}(\ell + T_{set}) \right]^{\beta-1} - \left[1 - SOC_{i\nu}(\ell) \right]^{\beta-1} \right\}}{\alpha} \right] \tag{14}$$

where $\varphi_{i\nu} = \frac{PB_{i\nu}}{2 \times E_{i\nu}^{max} \times \eta_{i\nu}^2}$

We have defined the above constraints using the non-linear multivariate programming constraint. The variables $P_{i\nu}^{up}$ and $P_{i\nu}^{down}$ are considered as the decision rendering variables and show the total amount and delivery rate of power (t/kWh) assigned to each time slot for performing charging/ discharging tasks of all associated EVs.

1.4. Modelling of the reactive power exchanging constraints and its Benefits.

In this research work we have also focused on the reactive power injection into the grid. The key benefit of reactive power injection in the grid is, it provides instant backup against frequency transients by instantly engaging EVs using V2G framework. For global compliance, we have inferred all EVs are equipped with three-phase AC inverters, and having capability of supplying reactive power to the grid in reverse. The main advantage of using EVs for voltage stabilization in the grid could be computed by constraint (15), as follows;

$$\text{benefits} = \sum_{T_{i\nu}^{arr}}^{T_{i\nu}^{dep}} T_{set}\left[Q_{i\nu}(\ell) \times \$_{i\nu}(\ell) \right] \tag{15}$$

It has to be noted, the rate of maximal exchange of active/reactive powers to the grid should be between the power delivering capacity of the EV chargers. It is calculated by $\mathscr{S}_{i\nu}^2$ from formulation (16), as follows;

$$\left(P_{i\nu}^{up}(\ell) + P_{i\nu}^{dwon}(\ell) \right)^2 + \left(Q_{i\nu}(\ell) \right)^2 \le \mathscr{S}_{i\nu}^2 \tag{16}$$

Note we assumed that a charger while charging an EV can simultaneously supply reactive power support for frequency stabilization to the grid. The maximal reactive power delivering capacity of a charger is denoted by $Q_{i\nu}^{max}$, which might be supplied by a charger with the collaboration of an EV and scripted as $i\nu^{th}$. The value of reactive power support is computed by constraint (17), as follows;

$$0 \le Q_{i\nu}(\ell) \le Q_{i\nu}^{max} \tag{17}$$

$$Q_{i\nu}^{max} = \sqrt{\mathscr{S}_{i\nu}^2 - \left(P_{i\nu}^{up}(\ell) + P_{i\nu}^{down}(\ell) \right)^2}$$

The maximal reactive power delivering capacity of a charger in reverse to the grid by using distribution system through CS i and the value of $Q_{i\nu}^{max}$ could be computed by the constraint (18), as follows;

$$Q_{i\nu}^{max} = \sum \sqrt{\mathscr{S}_{i\nu}^2 - \left(P_{i\nu}^{up}(\ell) + P_{i\nu}^{down}(\ell) \right)^2} \tag{18}$$

The maximal voltage value (rated value) which can be supplied by the the grid is computed by formulation (19). Note, in this constraint, the variable $\Delta V_i(\ell)$ denotes the value of voltage transients and fluctuations of that connected point from where the CS i is being feed by the grid. The value of voltage transients in the power grid is calculated by considering the set points of the reactive/active powers for each EV $\left(P_{i\nu}^{up}, P_{i\nu}^{down} and Q_{i\nu} \right)$, as follows;

$$\Delta V_i(\ell) = \frac{1}{3 \times V_i(\ell)} \left[\frac{1}{\mathscr{g}_i} \sum_{\ell=1}^{N_V} \left(P_{i\nu}^{up}(\ell) + P_{i\nu}^{down}(\ell) \right) + \frac{1}{y_i} \sum_{\ell=1}^{N_V} \left(Q_{i\nu}(\ell) \right) \right] \tag{19}$$

where the variables y_i denotes the reactive power supplied back by the CSs, while $\mathscr{g}_i$ shows the conductance of the connection point of a CS with the main power distribution line. The variable V_i shows the value of voltages between phase and neutral at the nodal point of CSs.

2. Propsoed hierarchical V2G optimization model

The section explains the formulation of a high level supervisory method proposed for controlling and optimizing the V2G operation and grid stabilization using real time and Day-ahead (DA) load scheduling techniques. Specifically, the proposed hierarchical model successfully integrates EVs into the grid for voltage and frequency regulations. This hierarchical model is based on two layers; the upper is named as the "DA" (Day-ahead) load scheduling layer, while the lower is named as the "Real time V2G" (I-day) load scheduling layer as presented in the Fig. 6.

2.1. Upper level DA load scheduling layer

In order to effectively control the operation of the power grid, this layer primarily prepares the load schedule for optimizing power procurement in the DA market and implements through central aggregation system. This layer optimally defines the charging/discharging schedules for each associated EV for next full day i.e., for next 24 hourly time slots. Further details of this method could be obtained from ref [77,78]. In the previously developed models, the data of each EV i.e., its arrival and

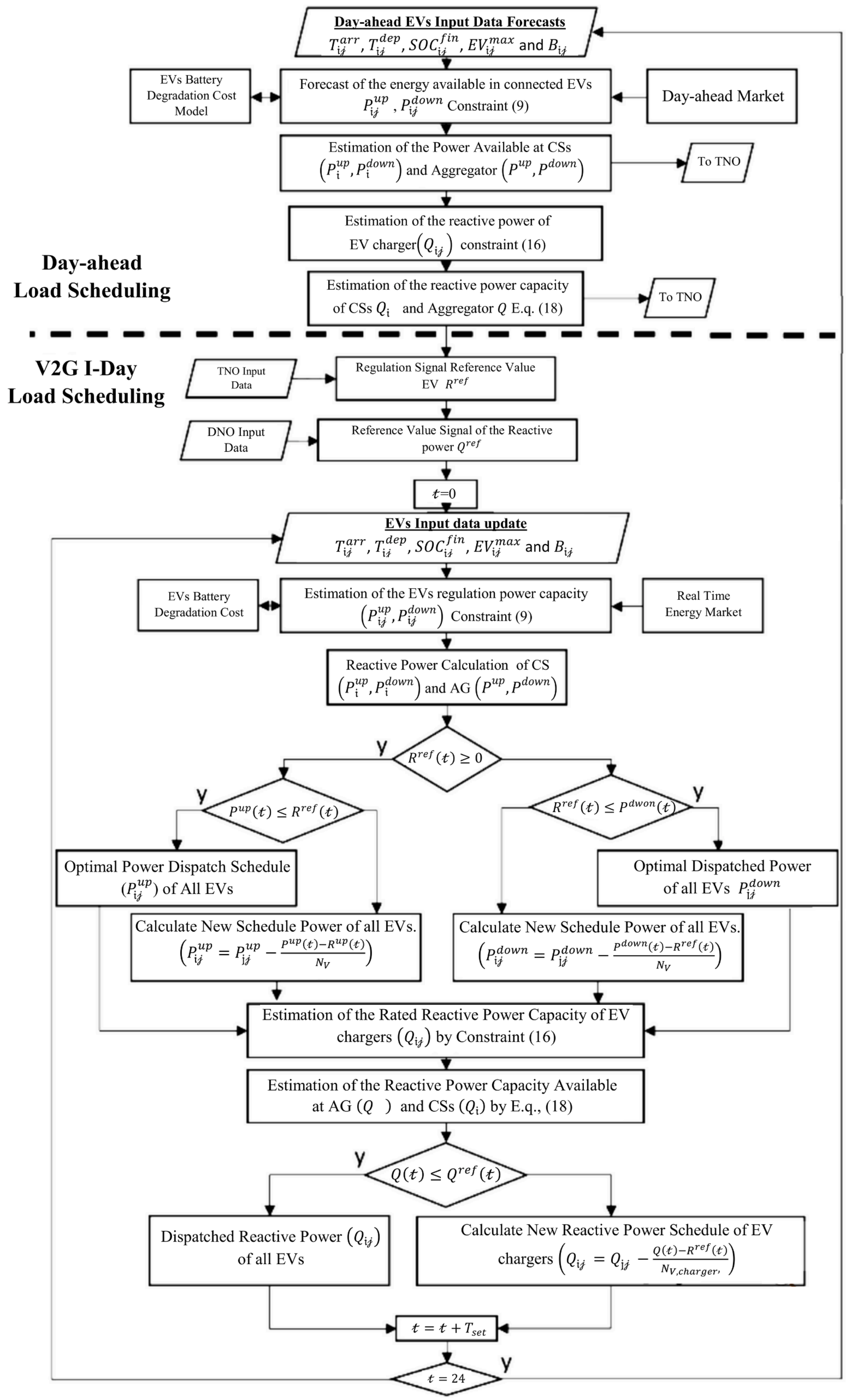

Fig. 6. Complete operation architecutre of the proposed hierarchical model.

departure information T_{ij}^{arr}, T_{ij}^{dep} and its primal SOC capacity SOC_{ij}^{int} in the DA time horizon is hard to predict. Therefore, in the proposed method to minimize the use of computational power and to counter the data unavailability contingency, a separate V2G operation framework is proposed for the integration of EVs into the aggregator which uses EVs historical data to anticipate their next day behavior [78].

In the proposed framework, initially the DA regulation cost data is predicted, and it also obtains EVs arrival time, statistical information of all EVs, while the battery degradation cost computing constraints is employed to define the optimal charging/discharging schedule of all EVs for the next 24 hourly slots. Alongwith, it also predicts the roadmap for regulating the frequency and voltage variations that might occur during next 24 h and broadcast this schedule to both TNOs and DNOs for further implementation. For performance analysis, we have simulated this model in Matlab. By intensive simulations testing we have verified the robustness of the proposed EV aggregator by performing charging/discharging and also checked its capability of providing appropriate amount of power during each time slot by deploying the predicted regulation cost for next 24 hourly slots, EVs statistical data about arriving and departing during different hourly slots. The proposed DA load scheduling method not only minimizes the overall charging cost of an EV besides, it also reduces the threat of EV battery degradation cost using constraint (9) as defined in Fig. 6.

2.1.1. *Vehicle to grid Integration-Day (I-Day) Managing layer*

In order to manage the V2G operation effectively, we have proposed a separate I-Day management layer. Primarily, we have divided a day into 24 hourly slots i.e., and defined different sets of hourly slots T_{set} considering the offered price. The power consumption of each hourly slot is anticipated by analyzing the previous data.

After that, a proper plan for the current day is prepared to successfully govern the V2G operation for frequency and voltage regulation. Moreover, the EV availability information for smooth I-Day operation is also obtained by the DA layer. The I-Day operation is performed in following pattern, initially aggregator receives previous data of the voltage and frequency variations for reference $R^{ref}(t)$ simultaneously it also obtains previous reactive power $Q^{ref}(t)$ data as reference which is then broadcasted by the TNO and DNO to the central aggregator. Fig. 6, presents a conceptual approach of the hour-ahead I-Day operation. Theoretical explanation of this model is given next;

- Initially we have inferred that each associated EV broadcasts its technical data i.e., T^{arr}_{ν}, T^{dep}_{ν}, SOC^{int}_{ν}, SOC^{fin}_{ν} etc. to the central aggregator before plugging-in to the CS. Note, this technical data is updated whenever an hourly slot updates T_{set}.
- The TNOs and DNOs broadcast gird side data of the total active/reaction powers reserves for reference i.e., $R^{ref}(t)$ and $Q^{ref}(t)$ to the central aggregator.
- In the next step, the current pricing data is broadcasted to the aggregator by the wholesale electricity market or by the price regulating market.

After recovering data from each associated EV and electricity market, the central aggregator prepares a schedule to optimize the I-Day operation using constraint (9) which computes the cost of the battery degradation of all EVs. To optimize the charging/discharging operation of each individual EV, it computes the updated optimal schedule for all EVs $P^{up}_{\nu}(t)$, $P^{down}_{\nu}(t)$, respectively. In last, grid deducts/supply required amount of power from/to the aggregator $P^{up}(t)$ and $P^{down}(t)$.

It has to be noted, if the amount of the newly consumed power by the grid is parallel or it is less than the requirement, then aggregator receives updated signal by the TNO. The updated schedules are communicated to all EVs, if power supplied by the EVs is enough or higher than the requested amount of power by the grid, than TNO sends the "regulation done" command to the aggregator. Note, when the gird regulation is successfully done, new schedule for I-Day regulation is computed by using constraint (19–20) and is than broadcasted to all EVs for the next operation.

$$P^{up}_{\nu new} = P^{up}_{\nu} - \left(\frac{R^{ref}(t) - P^{up}(t)}{N_V}\right) \text{if} R^{ref}(t) > 0 \tag{20}$$

$$P^{down}_{\nu new} = P^{dwon}_{\nu} - \left(\frac{R^{ref}(t) - P^{dwon}(t)}{N_V}\right) \text{if} R^{ref}(t) < 0 \tag{21}$$

Upon completion of the voltage or frequency regulation task, using constraint (17) the aggregator again computes the updated value of the total amount of reactive power that could be supplied by the charger $\mathcal{Q}_{\nu}$ back to grid. This acquired data is than forwarded to TNO, which takes further action to deduct spear reactive power $\mathcal{Q}_{\nu}(t)$ from the chargers about which the aggregators had broadcasted the deduction signal. If this amount of energy is insufficient (lower or parallel) for grid regulation, then the DNO broadcasts new $\mathcal{Q}^{ref}(t)$ signal to the aggregator which then further transmits this signal to all CSs. Conversely, if the supplied energy by the chargers though aggregator is sufficient (higher than $\mathcal{Q}^{ref}(t)$) for grid stabilization, then the TNO forwards regulation is done signal to the aggregator and vice versa, after completing this operation aggregator again computes the new regulation schedule by using constraint (22) which is than broadcasted to all CSs.

$$\mathcal{Q}_{\nu new}(t) = \mathcal{Q}_{\nu}(t) - \frac{\mathcal{Q}(t) - \mathcal{Q}^{ref}(t)}{N_{CS}} \tag{22}$$

Upon completion of the regulation task, the upper computation is repeated again for next time slot T_{set}.

SImulations Analysis

To check the performance of the proposed framework, we have carried out two case studies, the detail of these tests is as follows;

- o Case 1: Note, in this analysis, we have used EVs only for the frequency regulation. In addition, to deeply verify the performance of the proposed model during providing frequency regulation services, further two scenarios have been tested: 1) the grid regulation and EVs charging/discharging scheduling is performed without considering the cost of battery degradation, 2) for counter analysis, the cost of the battery degradation is included.
- o Case 2: Note in this test, we have inferred all EVs provide support for both voltage and frequency regulation to the grid. In this case, the simulated data has been acquired by the PJM which is a credible source visit ref [79,80,82]. The simulated test bench is based on 32-busbar power distribution network connected with 4 adjacent radial power delivering networks as shown in Fig. 7, in the single-line diagram.

Basic model of the simulated power distribution system has been acquired by the ref [27]. In quest to analyze the V2G optimization capability of the proposed model, we have purposely selected random locations for the charging stations (CSs) connection in the distribution network. The CSs are connected on following nodes "9, 16, 20, 22 and 32" of the power distribution network. The time of EV arrival and

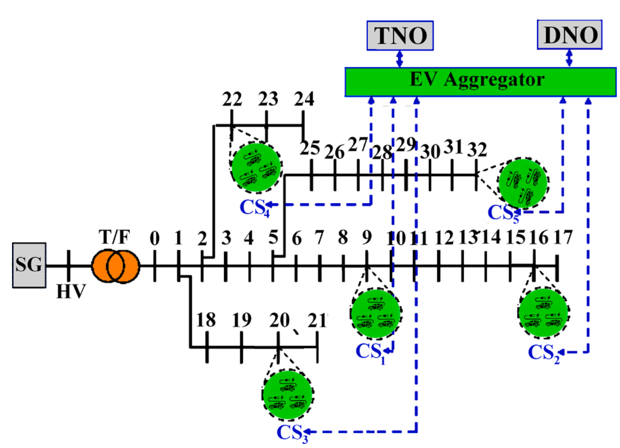

Fig. 7. Diagram of the IEEE 32 bubar power distribution network.

departure and the primal state of charge (SOC) values are determined by employing the Gaussian-Distribution method proposed in ref [37]. In this test, it is assumed that all EV owners want to charge their EVs to 80% before departure. In order to satisfy EV owners it is ensured that upon departure each EV will be 80% charged which will be enough for one-day transportation [80,81]. The simulation test has been carried out for 24 hourly slots (full-day) in which each technical information is updated after 30 min. In this scenario, 1050 electric vehicles are penetrated and stacked in five clusters to ensure their easy access to CSs. Table 1, presents the technical parameters of the simulated model.

Note, in simulated model three distinct types of EVs have been integrated, 1) Tesla Model S P100D, 2) Mustang Mach-E 2020 model and 3) Nissan-Leaf 2020 model. Technical specifications of these cars batteries are given in Table 2; Moreover, the Fig. 8 shows the determined set points of the power dispatch in the DA market, obtained considering the forecasted data of EVs penetration in the DA scenario as shown in Fig. 9. Note, the data acquired form ref [51] has been simulated in real time, because it corresponds to contemporary information of the grid power consumption and variations as shown in Fig. 10, while the offered cost to EV owners for providing the up/down regulation services is shown in Fig. 11. Note, this is the revenue of the owners in term of providing regulation services which will be paid to EV owner as a reward.

To verify the quality of service provided by the proposed aggregation framework, we have compared the amount of power supplied by the EV fleet for the grid stabilization in response the requested up/down regulation signals which were broadcasted by the TNO. Result of this comparison is given in Fig. 12.

By the deep analysis of Fig. 12, we have determined that the proposed model has supplied a significant amount of power to the grid to smoothen the frequency and voltage variations in response to the TNO reverse power supplying signal which was sent to the proposed central aggregation framework for performing the grid regulation task. Fig. 13, presents statistics of the total amount of reactive power which is supplied by the central aggregator to the DNO for controlling the voltage fluctuations in response to the reverse reactive power supplying signal. Fig. 14 show the quality of voltage that has been regulated by the aggregator by providing instant reactive support in reverse.

By the upper discussion, it is proved that our proposed aggregation framework exhibits capability of injecting significant amount of power into the grid for smoothening the voltage and frequency transients, which enhances the reliability and sustainability of the grid as shown in Fig. 15. For deeper analysis we have further enhanced the voltage regulation capability test of our model under extreme voltage fluctuations on the Node 1. In Fig. 16, the comparison of voltage transients at Node 1 with and without our model is given. It is determined that due to the unregulated voltage fluctuations the nominal voltage value of the grid can easily decrease from the set limit and even it can also cause

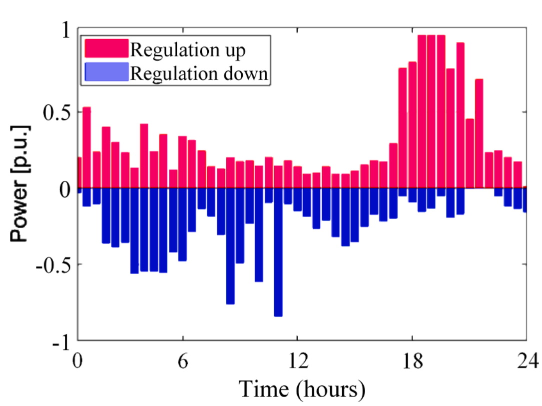

Fig. 8. DA available rated power capaciy estmiation for completing the all EVs charging according to the scheduled load.

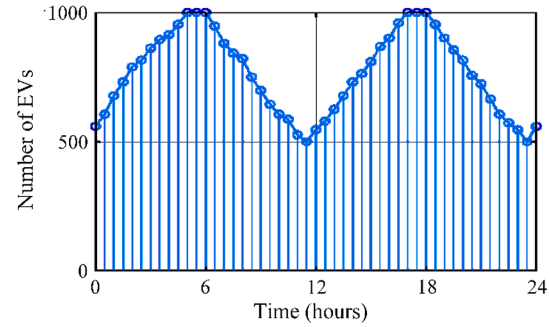

Fig. 9. Forecasted EVs penetration schedule by the proposed hierarchical model for the DA market.

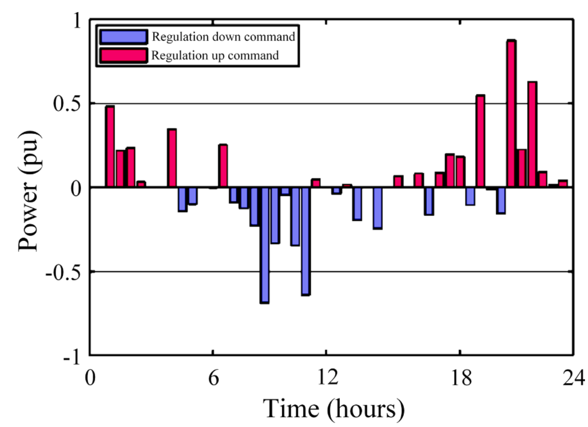

Fig. 10. V2G integration day (I-day) regulation command broadcasted by the TNO $\boldsymbol{R}^{ref}$.

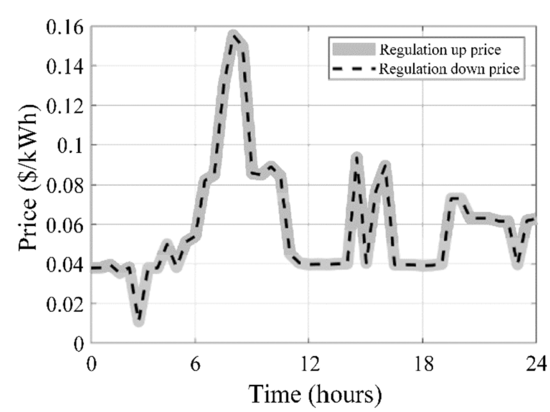

Fig. 11. Anticpated up/down power regualtion cost for 05 December 2020 [51]

higher voltage fluctuations as a chain reaction. On the other hand, our proposed aggregation model regulates the grid and even in case of severe voltage transients it has restricted voltage decrease from the set limit. Note, the voltage transients' statistics given in Fig. 16 are determined by the proposed DA load scheduling model. It is anticipated that, if the reactive power support of the aggregator is absent, then grid can face sever voltage unbalance, mainly this contingency will cause undervoltage on several occasions in a day. Hence this comparison shows that, injection of reactive power provided by the proposed CAO model in reverse to the grid can regulate voltage and frequency transients which increases the quality of service of a grid where most of the power is being generated and supplied by the renewable resources

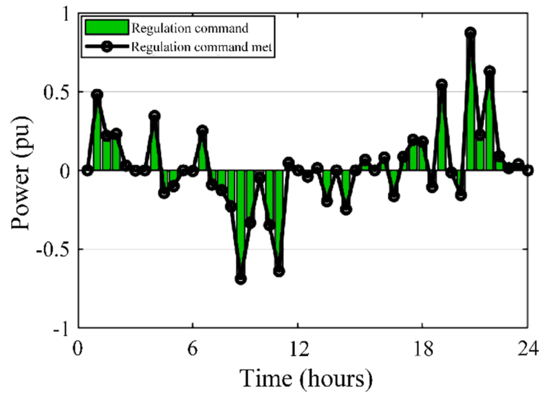

Fig. 12. Provided frequency stabaliztion service to the grid by the V2G aggregation framwork.

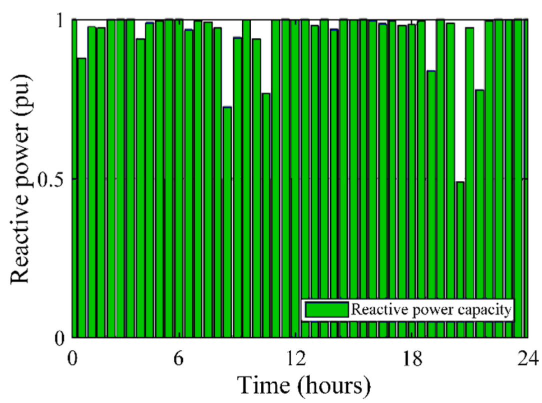

Fig. 13. Total amount of reactive power available at CAO in backup which might be supplied to the grid in reverse for regulation.

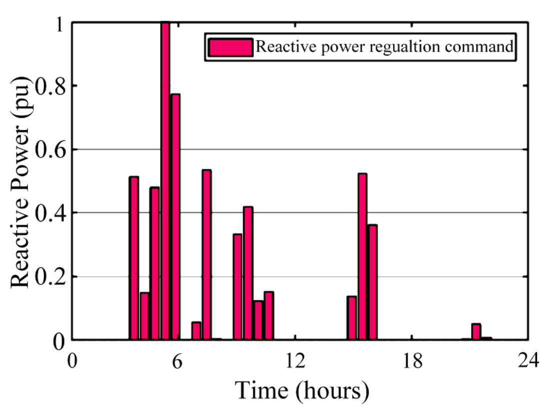

Fig. 14. Amount of reactive power supplied in reverse by EVs to the grid using V2G during I-Day in response to the DNO Q^{ref} regulation signal.

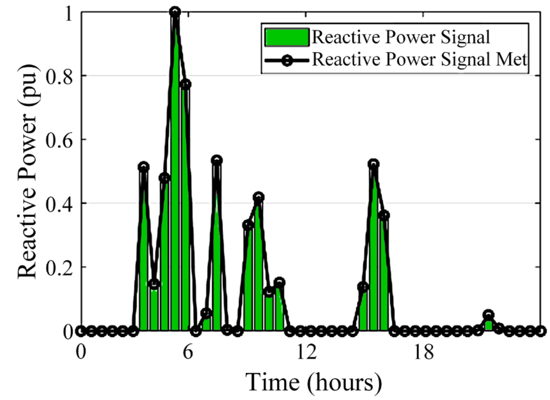

Fig. 15. Rreactive power regualtion service provided by the CAO to the grid.

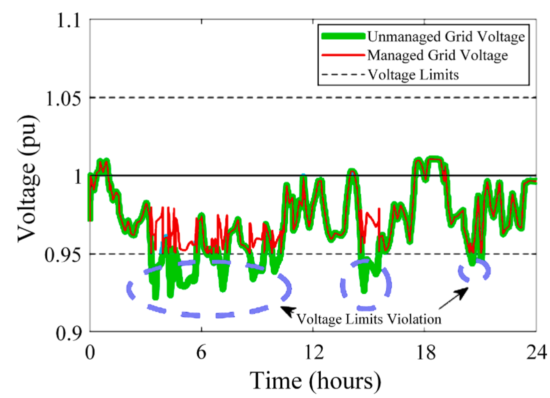

Fig. 16. Votlage regulation service provided by the CAO at Node 1 of the IEEE 32 busbar distribution system given in Fig. 7.

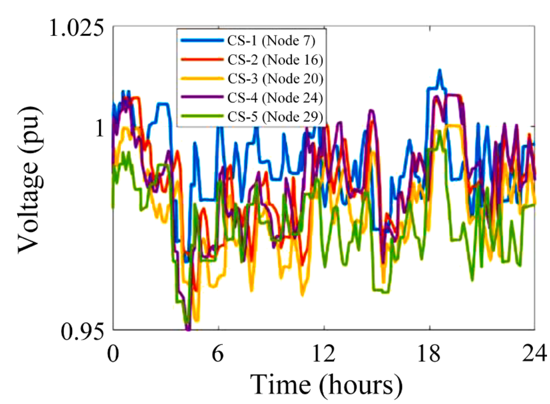

Fig. 17. The regualted votlage transients of the CSs 1, CS 2, CS 3, CS 4 and Cs 5 on the connections nodes 9, 16, 20, 22 and 32, review Fig. 7.

Furthermore, we have also analyzed the aggregator performance for managing the voltage transients at the nodal points of charging stations i.e. at nodes 9, 16, 20, 22 and 32 where the 1–5 CSs are connected, this result is shown in Fig. 17. Similar to previous case, the effectiveness of injecting reactive power into the grid is clearly seen. We have analyzed that the reactive power injected by the aggregator provides stable voltage to all CSs and keep the voltages value within 0.95 per-unit (pu) to 1.045pu at all charging stations connection (Nodal) points. Mathematically this combination is defined as $0.95\text{pu} \le V_i \le 1.045\text{pu}$, where $i = 1:5$.

A determined schedule by the proposed model for 24 h of an electric vehicle (EV) is shown in Fig. 18. As analyzed, this EV owner have strictly followed this schedule and obtained desired 80% charged EV battery on departure. By comparison of two profiles, we came to understand that the results of the V2G revenue computing function which neglects the degradation cost of the EV battery is completely different from our function which considers the degradation cost and generates much more profit for the EV owner in contrast and ensures safe charging/discharging of the EVs and minimizes the SOC capacity degradation threat

In addition, we have also verified the EVs managing capacity of all 5 CSs that how all associated 1050 EVs are managed after implementing our proposed model, Note, for batter performance evaluation in simulation testing we have assigned 210 EVs to each CS. The statistics of EVs

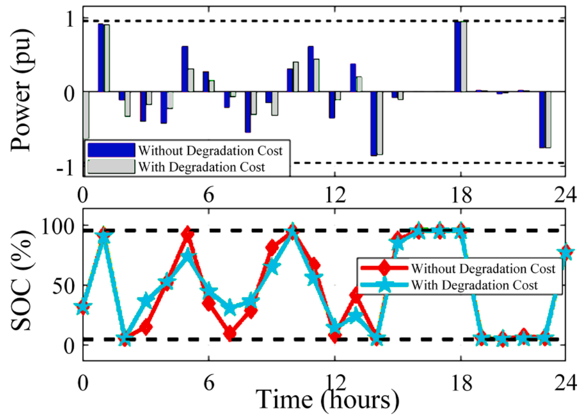

Fig. 18. State of charge (SOC) of an EV which is connected at CS 2 on the busbar 16.

SOC levels associated with all 5 CSs are shown in Fig. 19. It could be analyzed in Fig. 19, from 1 to 210 EVs have been affectively managed by the CS. 1, from 211 to 420 EVs are managed by the CS. 2, from 421 to 630 EVs are managed by the CS. 3, while EVs from 630 to 840 are managed by the CS. 4 and EVs from 841 to 1050 are managed by the CS. 5 respectively. By deep analysis of Fig. 19, we have concluded that, by the implementation of our proposed EVs aggregation model, each CS has fulfilled the requests of all associated EVs and ensures that each EV will depart with the desired SOC level. It is determined that on departure each EV which has participated in the V2G mode is 80% charged which is sufficient for transportation purposes for most of the owners for one day.

Further by the deep analysis of Fig. 19 it has also been analyzed that each CS has managed EVs charging/discharging according to the owners' choice. Each CS has successfully accommodated assigned EVs during different hourly slots of the day and effectively dealt with 210 EVs charging while simultaneously using some of the EVs in the V2G mode. The SOC level of each arriving EV was different, and accommodated according to their owner request. Those EVs who have taken part in the V2G mode were initially charged over 80% with the consent of EV owners, considering their requested departure time. Note that those EVs who have taken part in the V2G mode were charged on priority by the proposed algorithm to ensure proper backup to cope any voltage or frequency contingency on the power grid side if occurs uncertainly. If the additional stored energy in the EVs is not used for regulation services during parked hours, then this surplus energy was supplied to other EVs for charging, but, stopped supply when SOC level dropped to 80%. Whereas, other EVs who were not taking part in the V2G mode were charged according to their arrival queue. i.e., first come first serve policy

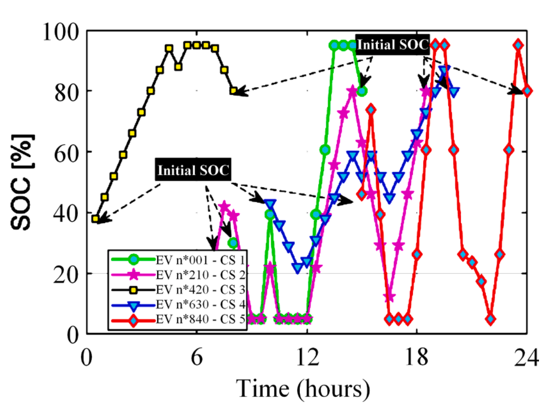

Fig. 19. Different State of Charge (SOC) levels of all modelled EVs managed by 5 CSs. This EVs charging station stack has been acqureid from Fig. 7.

was adopted for such vehicles.

Moreover, we have further extended this test in order to the collect data about the generated revenue for EV owners who have contributed in the V2G service. In addition, we have also tested the vast scale impact of V2G service on the EV battery energy storage degradation and analyzed by the implementation of our proposed model the threat of large scale battery degradation for all EVs is also reduced. Table 3, show the statistics of EV operational cost with our proposed model in contrast to the battery degradation statistics acquired after testing unregulated EVs charging/discharging;

In addition, Table 3 also provides statistics of the daily operational cost of one EV which has been determined by using two different approaches i.e., 1) without considering EV battery degradation cost and 2) with EV battery degradation cost. It has been analyzed that the total operational cost (charging cost) of one EV with the consideration of degradation cost is decreased in contrast to the opposite case, because in this case aggregator has to strictly follow the defined charging/discharging SOC limits for each vehicle. However, with the degradation cost consideration the total cost of using an EV in the V2G cost is increased, since in this mode instead of using a single EV an aggregator has to use multiple EVs. Hence, it is proved that, when the degradation cost is included in the optimization problem the overall operational cost of the EV when it is in the G2V mode is reduced, while the V2G cost is increased. Another reason of increasing the V2G cost is, currently batterers are the most expansive part of an EV. Unregulated use of an EV in the V2G model will rapidly decrease its energy storage capacity [24]. Therefore, V2G mode is expansive. However, when we compare nominal daily V2G cost with fossil fuel based peaking plants, this cost is significantly low [30]. Hence, we can conclude that although, currently as compared to the G2V, the cost of V2G mode is high but in the long term this approach will generate financial benefits to the central grid as well [38].

Table 4, presents the statistics of the battery capacity degradation cost, the cost for charging an EV, and the total operational cost of an EV when V2G mode is not active. It is evaluated that, the battery loses about \$0.062 worth of energy storage capacity each day due to the daily one complete charging/discharging cycle. Which is lower than \$0.44 degradation cost when the V2G mode is active.

To further check the operational cost difference of a single EV using our model in contrast to the commonly used EVs charging strategies, we have performed an operational cost comparison. Results of this comparison are shown in Fig. 20. Note, this comparison has been performed with and without considering the cost of battery degradation for the currently in use charging regulation strategy as well as the results of our proposed mathematical model implementation are also included. It is observed the total cost of charging an EV is significantly reduced by our proposed EV aggregation framework in contrast to the commonly used method (i.e., the charging cost is reduced from \$1.50/day without V2G use to \$0.33/day with V2G use). This price drop is seen because of the EV contribution in the grid stabilization which generates profit for this particular EV and it is compensated in term of charging cost. Results of this comparison are listed in Table 5. By the results of table 5, we can

Table 3
Daily EV operation cost comparison in the V2G mode of our proposed degradation model in contrast to the without degradation method.

EV operation cost (\$)	Without considering battery degradation cost	With considering degradation cost
Cost of battery degradation (\$/day)	−0.4970	−0.4347
Grid to vehicle (G2V) cost (\$/day)	−0.0282	−0.0275
Vehicle to grid (V2G) cost (\$/day)	+0.1650	+0.1430
Total operation cost \$/day	−0.3602	−0.3192

Table 4
Daily cost of charging an EV.

EV operation cost ($)	Total cost ($)
Battery degradation cost ($/day)	−0.062
Cost of charging ($/day)	−1.432
Total cost ($/day)	−1.494

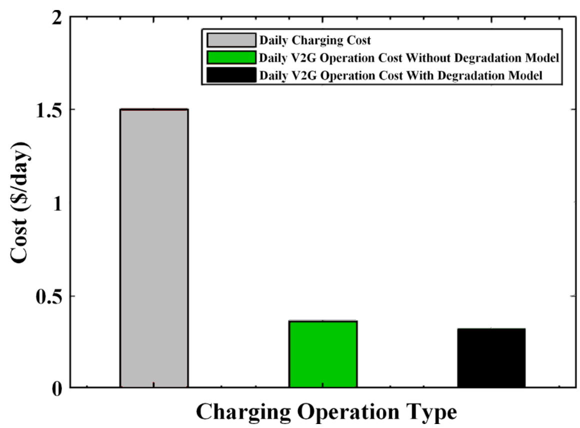

Fig. 20. Daily EVs charging cost comparison of the proposed model (black) without degradation model (green) and unreglated charging (gray).

Table 5
Daily statistics of the voltage regulation support provided by the proposed aggregator (CAO) to the grid.

Daily EV operational cost ($)	Voltage regulation cost ($)	Frequency regulation cost ($)
Daily regulation revenue ($/day)	+1092.24	+169.50
Daily regulation cost ($/day)	−998.37	0
Daily profit ($/day)	+92.42	+169.50
Overall aggregator revenue ($/day)	+262.8	

conclude that, by providing frequency services to the grid through V2G framework an EV can earn revenue and economic benefits in term of the total charging cost. Conversely, by providing voltage regulation service to the grid an aggregator can earn suitable revenue.Fig. 21.

In order to test the capability of limiting the threat of energy storage capacity degradation proportion of the proposed model, we have performed a lifetime degradation depth comparison with [78]. For this test the charging/discharging of an EV who has randomly perfumed V2G and G2V operations for 12 years is tested under both models. Test results show that under our proposed model even after 12 years this EV has only lost about 10% energy storage capacity. In contrast, under the method proposed in [83] similar EV has lost over 38% energy storage capacity which is huge. It means that under real life conditions the method proposed in [83] would perform worse. This comparison also proves that our proposed model is capable of protecting EV from severe battery capacity degradation and could also extend its life span.

3. Conclusion

In this research paper, we have proposed a novel and robust central aggregation hierarchical V2G optimization algorithm to easily integrate thousands of EVs in the smart grid. By optimal integration of thousands of EVs in the V2G framework this model provides voltage and frequency regulation services to the grid. Particularly, this model provides backup support for those grids where most of the power is being generated by the renewables, which ensures reliable operation of the whole power

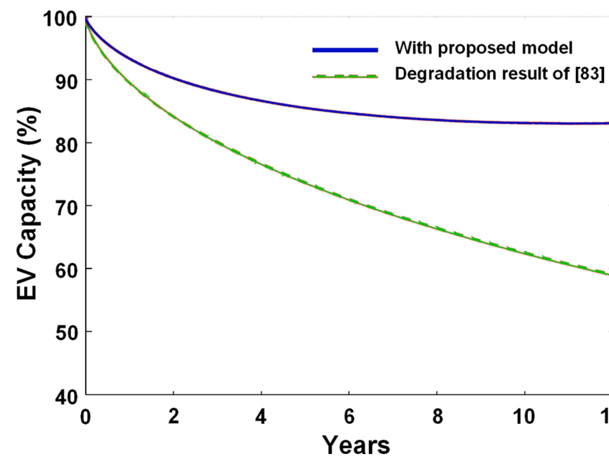

Fig. 21. Battery Degradation depth comparisons with [83].

system and helps in maintaining power quality. This model also generate revenue for central aggregation office (CAO) and for the EV owners who provide their EVs for V2G operation. In addition, the proposed optimization model is capable of performing DA load scheduling of all associated EVs besides it also consistently evaluates the real time performance of all parts of the grid by taking feedback from monitoring and controlling devices. The proposed CAO model also determines any minor contingency that could hinder the implementation of the defined optimal load schedule to regulate EVs charging/discharging. If any contingency i.e., frequency and voltage fluctuations uncertainly occurs in its response the CAO takes all necessary actions to counter such constraints, which enhance the economic outcomes and grid stability which is the main contribution of this paper.

Moreover, to further improve the grid operation, the proposed model increases the optimization capability of the whole power system. It provides authority to both TNO and DNO of controlling and maintaining the voltage and frequency transients introduced due the power generation fluctuations of renewable resources within the acceptable range by the assistance of CAO. In addition, the cost of battery energy storage capacity degradation particularly for V2G contributing EVs is also considered. To reduce the threat of massive battery degradation, this optimization model considers the per cycle (charging/discharging) energy storage capacity degradation cost separately when EVs are being used in the V2G mode. In addition, performance of the proposed model has been validated by intense simulation testing carried out by acquiring the real world renewable power generation and cost data by PJM [82]. Simulation results clearly shows the effectiveness of the proposed model while providing voltage and frequency stabilizing services to the grid under adverse conditions and smoothly performs charging/discharging tasks of all associated EVs. The proposed scheme could be implemented for managing the real-time V2G operation on broader scale in any country of the world.

Future work

In future research, we will further extend this model in such manners that, a separate ageing constraint will be integrated in the proposed hierarchical model to test the long term V2G operation impact on the Li-ion batteries. A more refined model will be developed to anticipate the more accurate EVs behavior in the DA market by using the PJM and European power generation and consumption data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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