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Research paper

Optimal open-circuit voltage (OCV) model for improved electric vehicle battery state-of-charge in V2G services

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ABSTRACT

Electric vehicles (EVs) with voltage-to-grid (V2G) capability are useful in augmenting grid capability to handle high energy demand of end users during peak periods. We propose a hybrid state-of-charge (SOC) battery model with aggregator to optimize battery charging and maintain grid stability during peak periods. The proposed SOC model leverages the advantages of three well-known previously proposed battery models namely: Shepherd, Unnewehr and Nernst models. The proposed hybrid model is a combination of the merits of the three specified empirical Lithium-ion battery models to optimize slow charging. This will enhance battery performance by improving its depth-of-discharge profile. This results in enhanced V2G capability and longer driving time for EV owners. Battery parameters used in the simulation are for Nissan Leaf 2019 EV. The proposed SOC model parameters are used to optimize a two-objective function which is used by the aggregator to maximize benefits to both EV owners and DSO. Multi-objective genetic algorithm (MOGA) is used to optimize the objective function because of its ability to obtain non-dominated solutions while still maintaining diversity of the solutions. From simulation results, proposed OCV model improves battery SOC by 10% after V2G operating period (2 p.m.) compared to a case without the model. Also, proposed model earns aggregator $445 and $45 more for voltage and frequency regulation services, respectively. Voltage stability of all 5 considered grid buses of the IEEE 33-node system remains at 0.9–1.0 p.u.

1. Introduction

Electric vehicle (EV) charging systems have the capability of two-way DC–DC conversion, which enables them to transmit energy back to the power grid from which they draw energy. This means that EVs can be used as a means of distributed, on-demand generation to augment the conventional grid. As EVs become more affordable, and as the battery technology becomes more robust, there is an increased uptake of such vehicles in cities and communities all over the world (Anon., 2020a). Fig. 1 shows that there has been an increase in EV purchase since 2018. However, the coronavirus (COVID-19) pandemic has had a negative impact on global EV sales in the first and second quarters of 2020. The quest for greener energy solutions is revolutionizing the way EVs are being used. In addition to lowering greenhouse gas emissions, they can also be used to improve the stability of existing power supply grid (Ding et al., 2020). Intelligent exchange of information between EV users and aggregators can maximize benefits for both grid operators and end users. One key issue in the utilization of EVs to augment the grid is frequency stability and power quality of the energy supplied. Therefore, they are useful in peak shaving and valley filling (Wang and Wang, 2013), energy scheduling (Rigas et al., 2015), reactive power compensation (Choi et al., 2016), voltage regulation (Azzouz et al., 2015), energy storage (Rahmani-Andebili, 2019) and voltage-to-grid (V2G) services (Krein and Fasugba, 2017).

V2G technology refers to a variety of services that EVs provide to the power grid to enhance its stability. During periods of high (peak) and low (valley) energy demand, the grid undergoes voltage and frequency fluctuations which can be harmful if they are not stabilized. EVs can play a vital role in terms of peak-shaving and valley-filling to maintain the grid within safe operating limits. In South Africa in particular, it is becoming apparent that one way of improving the capacity of the current power grid is to encourage municipalities and individuals to become energy producers (Yelland, 2020). The use of electric vehicles as alternative sources of energy to augment the grid during peak or emergency periods, while simultaneously ensuring battery health will be of paramount importance to EV owners. Consequently, this research proposes a hybrid mathematical EV battery model comprising the Nernst, Shepherd and Unnewehr models. We combine the merits of all three equivalent models in a single mathematical equation to provide an accurate representation of the EV battery terminal voltage. Specifically, the Nernst model obtains best accuracy of

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Nomenclature

Indices

a	EV in charging cluster b (CC_b)
b	charging cluster within aggregator
t	time interval (1 h)
t_{end}	instant of disconnecting EV from grid
t_{st}	instant of connecting EV to grid
t_{ab}^{st}	instant of connecting EV a in cluster b to t
t_{ab}^{end}	instant of disconnecting EV a in cluster b from the grid
T_{int}	time interval for which EV is connected to the grid

OCV Model Variables

I_{batt}	EV battery rated current
$I_{batt,act}$	actual current of EV battery at time t
$I_{batt,ref}$	reference current of EV battery at time t
I_{inst}	instantaneous current of EV battery
R	EV battery internal resistance
SOC_{batt}	EV battery state-of-charge
T_{max}	maximum operating temperature of EV battery at time t
T_{min}	minimum operating temperature of EV battery at time t
$T_{opt,t}$	optimal operating temperature of EV battery at time t
$V_{mod,t}$	EV battery module voltage at time t
V_{nom}	EV battery module nominal voltage
V_{OCV}	EV battery open-circuit voltage
V_T	EV battery terminal voltage

Acronyms

DSO	Distribution system operator
EV	Electric vehicle
OCV	Open-circuit voltage
OF	Objective function
PEV	Plug-in electric vehicle
SOC	State-of-charge
V2G	Vehicle-to-grid

Grid/Aggregator Parameters

η_{chg}	EV battery charging efficiency
η_{dchg}	EV battery discharging efficiency
$\eta_d^{ab,t}$	charging efficiency of battery for EV a in cluster b during regulation down period
$\eta_u^{ab,t}$	discharging efficiency of battery for EV a in cluster b during regulation up period
$P_{chg,t}^{ab}$	charging power of battery for EV a in cluster b at time t
$P_{dchg,t}^{ab}$	discharging power of battery for EV a in cluster b at time t
$p_{e,t}$	electricity price at time t ($/KWh)
$p_{freq,t}$	frequency regulation price at time t ($/KWh)
$P_{max,t}$	EV battery maximum power discharge capacity at time t
P_{max}^{ab}	maximum power capacity of EV a in cluster b
$P_{max}^{ab.t}$	maximum power capacity of EV a in cluster b at time t
$P_d^{ab,t}$	charging power of EV a in cluster b during regulation down period
$P_u^{ab,t}$	discharging power of EV a in cluster b during regulation up period
$p_{reg,t}$	price for regulation up services provided by EV ($/KWh)
p_w	EV battery wear price ($/KWh)
$Q_{ab,t}$	reactive power supplied by EV a in cluster b at time t
Q_{max}^{ab}	maximum reactive power supply capacity of EV a in cluster b
$r_{dchg,t}$	approved discharge reward for feed-in-tariff policy ($/KWh)
SOC_{ab}	state-of-charge of battery for EV a in cluster b
SOC_{opt}	EV battery optimal state-of-charge (from OCV battery model)
$s_{reg,t}$	grid regulation signal at time t

the empirical models. Shepherd model provides the best stability for continuously discharging current, and Unnewehr model has good computational efficiency. The advantage of all three models is their simple expression compared to other SOC models such as equivalent circuit model, electrochemical model and data-driven model (Meng et al., 2018). Therefore, research has intensified regarding ensuring optimal charging strategy for EVs that would maximize benefits to both grid operators and EV owners.

An EV aggregator optimizes technical and economic constraints associated with integration of EVs into the grid as a renewable energy source. Therefore, they are involved in providing energy price forecasts for day-ahead scheduling (Bessa and Matos, 2013), managing impact of crowd EV charging on the grid (Clairand et al., 2020) and encouragement of EV owner participation through optimization of battery charging cost (Wei et al., 2016).

Nature-inspired multiobjective optimizers have been used to solve a wide range of engineering problems. For instance, an instantaneous optimization algorithm was proposed to improve the energy control strategy of hybrid electric buses (Shi et al., 2017), an efficient red deer algorithm (RDA) was proposed in Fathollahi-Fard et al. (2020) for tackling engineering problems. Also, in Yu et al. (2021), an efficient approach was applied to EV battery recycling. In this paper, we will adopt a multiobjective approach to optimize EV battery parameters during charging and discharging periods. The objective function model is formulated as a mixed-integer linear programming (MILP) problem which is optimized using a real-coded genetic algorithm. Acquisition and utilization of grid and EV information is facilitated by the EV aggregators, which are responsible for scheduling charging in a manner that is beneficial both for the grid and EV owners. Some of the parameters that will be considered by the EV aggregator include initial battery state-of-charge (SOC), EV plug-in time, desired EV departure time, battery degradation cost and vehicle charging requirements.

Several battery SOC estimation methods have been presented in literature (Meng et al., 2018). These include Coulomb counting method, artificial neural network-based method, impedance spectroscopy-based method, model-based method, and open circuit voltage (OCV) method. The battery model relates the parameters, while the estimation method is what does the SOC estimation. Optimization of SOC for EV batteries for V2G operation is of paramount importance, since the battery is the most

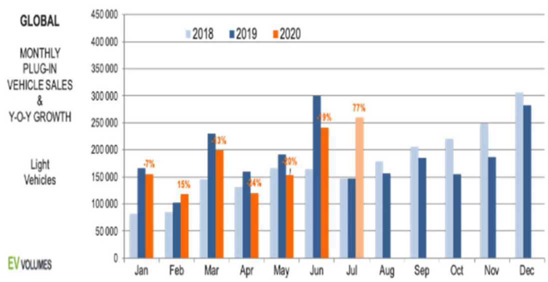


Fig. 1. 3 year trend of EV sales around the world (Anon., 2020a).

expensive single component of the EV, accounting for up to one-third of the total cost of the EV. Therefore, EV owners would be encouraged to participate in V2G services when they are convinced that long-term health of their vehicle battery will not be jeopardized. Furthermore, a lot of research has focused on EV scheduling to improve quality of grid support and benefits to EV owners. However, less research has focused on improvement of EV battery performance by considering its technical parameters. This research will attempt to fill that gap. The SOC model proposed in this paper is based on a hybrid empirical battery model consisting of the Shepherd model (Moore and Eshani, 1996), Unnewehr universal model (Manwell and McGowan, 1994) and Nernst model (Feng et al., 0000). It includes parameters for the battery current, operating temperature and terminal voltage.

The rest of the paper is organized as follows: Section 2 states motivation and contribution of the research, Section 3 reviews related work on EV use for grid support, Section 4 introduces the structure of the EV aggregator used to provide grid support for IEEE 33-bus distribution system. The proposed hybrid empirical OCV model for EV SOC optimization during V2G and G2V operation is also discussed in detail. The objective function (OF) model used for optimization is also discussed. Section 5 presents and discusses the results obtained from the SOC model optimization based on financial benefits to the aggregator as well as distribution grid voltage stability. The results obtained are compared with a case in which V2G services are provided by EVs without using the proposed SOC model. Section 6 concludes the paper.

2. Motivation and contribution

This research is motivated by the fact that a lot of the existing research in EV use for ancillary services is based on what we refer to as logistical approaches. In the context of this paper, logistical approaches refer to methodology that uses scheduling to optimize EV charge/discharge scheduling in V2G mode with the aim of improving benefits to end users and DSO. Therefore, there is need for more research that focuses on improving battery performance in V2G mode. This paper focuses on optimizing the performance of EV battery through simulation by conditioning battery parameters to maximize terminal voltage. This strategy will enhance the charging and discharging cycles of the battery in such a way that the benefits of V2G support services are enjoyed by both DSO and end users. The use of EV aggregator intends to amplify these benefits by using battery model parameters as constraints to optimize the aggregator objective function.

From reviewed related research, there has been no case in which the battery model parameters are considered in the aggregator model objective function. Therefore, we propose this approach which uses optimized battery parameters as constraints for the aggregator objective function. We use an aggregator because the proposed model is scalable, and therefore can be adapted for use with other EV battery models apart from the Nissan Leaf EV.

In terms of the proposed battery model, even though the individual models already exist, this paper proposes a hybrid model which combines three different models into a single model. This is done to utilize the benefits of all three battery models to maximize benefits to all stakeholders.

3. Review of EV use in grid ancillary services

As the technology of EV manufacturing becomes cheaper to implement, there has been a steady increase in purchasing of plug-in electric vehicles (PEVs). Particularly, automotive and battery companies all over the world are discovering ways of making affordable and robust EV battery packs. This consistent reduction in the battery manufacturing cost has also led to a continual fall in the cost of PEVs. BMW plans to have 50% of its total vehicle production manufactured as PEVs by 2030 (Anon., 2020b). Therefore, the V2G capability of PEVs has made them suitable sources of distributed energy generation which can be used to support the existing power grid.

Several researchers have proposed strategies of using PEVs to provide ancillary services for the grid while maintaining grid stability. The research in Mohamed et al. (2020) proposed a stochastic transmission switching integrated interval robust chance-constrained (TSIRC) approach to model uncertainities in a wind park-energy storage system (WPES). The problem formulation involved a max–min–max scenario where the first level maximized hourly profit of the WPES. The second level minimized operation cost of the independent system operator (ISO) and the third level maximized robustness of the WPES. This model was also tested on an IEEE test system and it was observed that lines switching by ISO was reduced by 95% while WPES profit increased by 11.5% by considering effect of stochastic parameters. In Mohamed et al. (2021), the uncertainty of microgrids based on a mix of solar panels, wind and EVs was modelled using three different schemes: smart scheme, coordinated scheme and uncoordinated scheme. A honeybee mating algorithm was used to optimize stochastic variables to implement seamless control of the various renewable energy sources. The effect of crowd charging of EVs on hybrid AC/DC microgrids was investigated in Wang et al. (2020). An IEEE standard test system was used to simulate the AC/DC microgrid. Three different charging patterns were considered: coordinated, uncoordinated and smart charging. Also, additional renewable energy sources such as wind turbine, solar panel and fuel cell were considered in the microgrid scheduling process.

In Ihekwaba and Kim (2017), a dynamic EV load model was developed. It simulated the impact of EV charging on the grid on an hourly basis. The plug-in pattern for EV users was considered to be stochastic, with level 2 charging being adopted. Peak charging periods were assumed to be between 8 a.m. and 2 p.m., and also between 6 p.m. and 10 p.m. on a given day. The IEEE 13-bus system and the Electric Power Research Institute (EPRI) circuit 5 test feeder were considered in the simulation. Results obtained showed that prolonged voltage sag occurred as EVs charged farther away from the service feeder. This underscored the need for intelligent charging strategies for EVs. An intelligent EV charging control strategy was proposed in Zou et al. (2014). The aim was to reduce the cost of the charging process for both grid operation and EV owners, as well as improve grid stability. A discrete-time Markov decision process (MDP) was used to implement the control model.

A coordinated charging scheme considering EVs as distributed energy sources was presented in Wang et al. (2017). The proposed scheme used a constant peak–valley charging price difference strategy to shift the EV charging load to periods when grid energy demand was less. This approach flattened the grid energy profile while simultaneously satisfying EV owners' charging needs. A day-ahead optimal control strategy was proposed to implement a peak-shifting strategy. In Huang (2019), a 75-node residential distribution system was considered with 30 households and 30 PEVs considered in the simulation. Two different PEV models were considered: one had battery capacity of 47.5 KWh and the other had 41.4 KWh capacity. The aim of the proposed control strategy was to minimize charging/discharging cost for the PEVs under V2G operation, and also to maximize peak load shifting while minimizing battery degradation cost. A time resolution of 15 min (96 slots) was used in the simulation. The proposed methodology ensured that increase in the neutral-to-ground voltage of the simulated distribution network was regulated while achieving cost minimization of V2G operation and peak load shifting. In Liu et al. (2019), a decentralized optimization algorithm for solving the Markov decision process (MDP) was used to implement the control model. A novel shrunken-primal–dual subgradient algorithm was used to optimize a nonseparable objective function. The IEEE 13-bus distribution network was used as the test system. Results obtained showed that voltages at nodes where EVs were connected achieved better stability compared to a case in which the algorithm was not considered.

The focus was on optimization of home charging for EVs in Hattam et al. (2017). Two scenarios were considered: where EV users were given incentives to charge their vehicles during the night, and where no incentives were given. The test system was a real-life low-voltage (LV) distribution network in Bracknell, UK. It consisted of 98 feeders and 26 substations which served 4073 households and 121 commercial properties. Simulations were carried out by considering 10%, 30% and 50% EV penetration for the 4073 households. Results obtained showed that incentivized overnight EV charging had a positive effect on the stability of the distribution network. However, it was also highlighted that over-incentivized customers were likely to create clustering situations which could lead to voltage sags and overloading of distribution supply equipment. The research in Kolawole and Al-Anbagi (2019) presented an EV charge/discharge (EVCD) optimization model in the form of mixed integer linear programming (MILP) problem. The objective function (OF) incorporated frequency regulation and electricity pricing from both real and forecasting models. Three charging profiles were considered in the simulation: level one (L1), level two (L2) and fast charging. The frequency regulation forecasting was simulated using the Double Seasonal Holt Winter (DSHW) model, with regulation prices being determined by New York Independent System Operator (NYISO). The results of the proposed simulation model showed that EV owners could successfully participate in frequency regulation services while simultaneously minimizing battery degradation cost.

The cost benefit to EV owners from participating in grid ancillary services was analysed in David and Al-Anbagi (2017). Particularly, a semi-logarithmic model was used to estimate cycle life of the EV battery. This estimate was used to calculate battery degradation cost for providing frequency regulation services. The batteries for three EV models (Tesla Model S, BMW i3 and Nissan Leaf) were compared. From the results obtained, it was concluded that EV batteries with higher capacity and lower cost per KWh provided the greatest financial benefit to EV owners who chose to provide frequency regulation services. In Singh and Tiwari (2019), V2G models were proposed for operating in four scenarios: load stabilization, battery life cycle cost optimization, battery degradation and mixed-objective. The effect of each model scenario was analysed considering peak load, distribution line losses and transformer loading. A 38-node distribution system consisting of industrial, commercial and residential loads was used for the simulation. The impact of the four different charging models for various levels of EV penetration (ranging from 10%–100%) was also considered. The load stabilization model demonstrated improvement for load variance. The battery life cycle cost model reduced battery charging costs, while battery degradation model reduced battery degradation cost. The mixed-objective model improved technical and economic gains for both end users and grid operators.

Research done in Singh et al. (2015) demonstrated how EV charging was coordinated at distribution substation level to provide ancillary services to the grid. Fuzzy logic controllers (FLCs) were used to coordinate charging at various EV charging stations. Particularly, the FLCs were used to determine amount of power to be exchanged between individual charging stations and various subfeeders. FLCs controlled the charge/discharge rate of EVs in each charging station in order to achieve peak shaving and valley filling. The test system consisted of one main feeder and four subfeeders. Six charging stations were considered with 200 EVs in each charging station.

The research reviewed in this section has mainly focused on the optimized scheduling of EV charging and discharging to maximize financial gains to end users and also maintain grid stability for peak shaving and valley-filling. We refer to this as a logistical approach since it involves intelligent scheduling of renewable energy sources to maximize benefits to grid owners and users. On the other hand, we refer to our approach as a technical approach since the focus is on improving battery performance by optimizing battery parameters. This approach aims to demonstrate that considering technical parameters and constraints will improve overall benefits to both end users and DSO compared to a case in which such an approach is not considered. In addition, we focus on the EV as renewable energy source. We assume that improving performance of the battery under charging/discharging conditions would also improve overall benefits to grid players when hybrid systems comprising other forms of renewable energy sources are considered. All reviewed research has demonstrated that EV users are concerned about the long-term effects of participation in V2G support and demand response services on the health of their vehicle battery. The research proposed in this paper aims to include the optimization of the proposed battery SOC model. This is important because the EV battery is the single most expensive component of the vehicle. Also, the battery is the component of the EV that is needed for V2G operation. Therefore, the authors opine that optimizing the SOC parameters for the EV battery while it provides V2G services is a strategy that would significantly improve benefits for both EV users and grid operators.

4. Proposed EV aggregator and OCV model

An EV aggregator coordinates the processes related to the scheduled charging and discharging of a fleet of EVs. These processes include the exchange of information with the distribution grid regarding real-time and forecast regulation pricing from electricity market regulators, and voltage and frequency regulation signals from distribution service operator (DSO) (Amamra and Marco, 2019). The fleet of EVs is distributed among several nodes or buses within a distribution system to avoid overloading any particular bus. Each group of EVs connected to a bus is called a charging station or charging cluster. The aggregator acts as a middleman between EV users and the distribution grid operators. It ensures the optimization of EV scheduling such that financial benefit to end users as well as grid stability is maximized (Essiet and Sun, 2020).

The aggregator considered in this paper consists of a total of 1500 EVs distributed into 5 charging clusters. Each charging cluster consists of 300 EVs connected to various buses within the IEEE

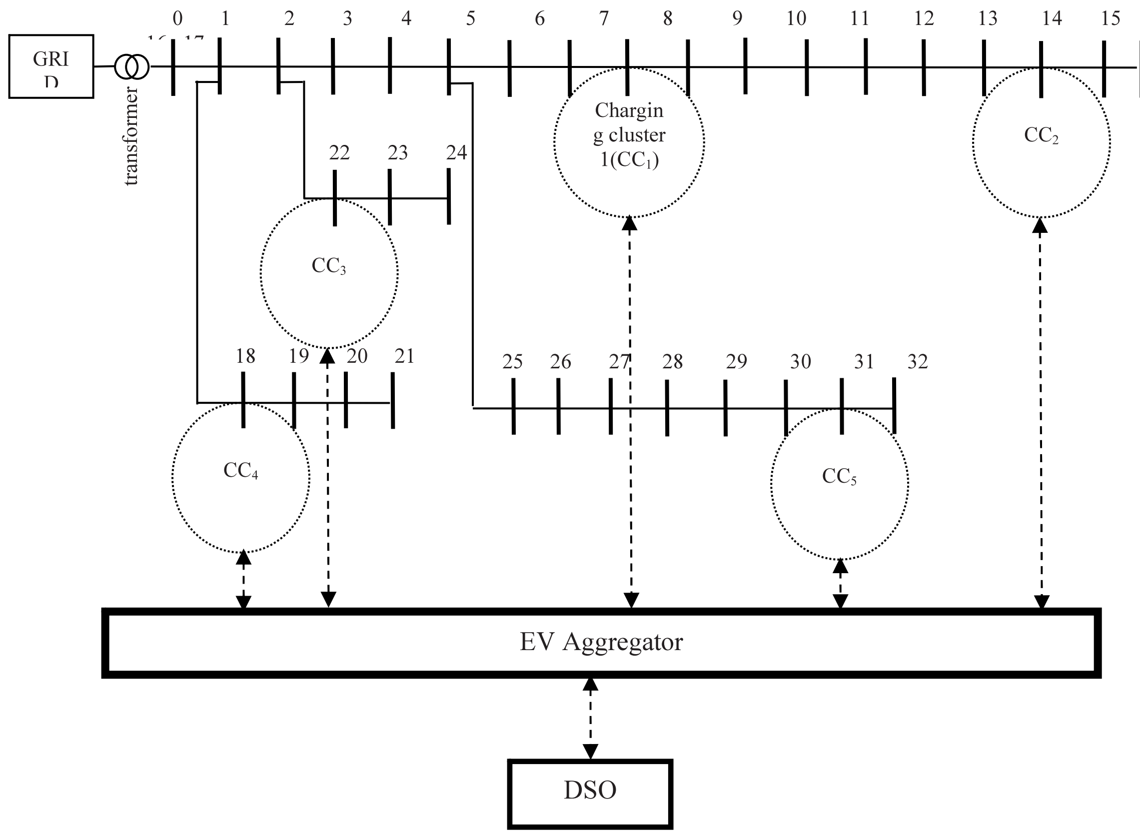


Fig. 2. Line diagram of IEEE 33-node grid bus system.

33-node bus system as shown in Fig. 2. For each of the charging clusters, CC_1, $a = 1, 2, \ldots, 300$; CC_2, $a = 301, 302, \ldots, 600$; CC_3, $a = 601, 602, \ldots, 900$; CC_4, $a = 901, 902, \ldots, 1200$; CC_5, $a = 1201, 1202, \ldots, 1500$. a denotes the number range of EVs in each cluster. The charging clusters are strategically placed at various electrical distances from the distribution grid. This is to account for the effect of voltage sags associated with simultaneous charging of EVs at various charging clusters within the distribution network (Amamra and Marco, 2019). It is assumed that all EVs are of the Nissan Leaf 2019 model, with specifications given in Table 1. It is important to note that there is a bidirectional exchange of statistical and economic data between the DSO and the aggregator. Statistical data refers to information on EV availability based on daily driving habits of owners. Economic data is concerned with daily regulation prices which are made available to DSO from electricity market regulators. There is also a bidirectional exchange of EV user information between the charging clusters and the aggregator. Such information includes EV arrival time, charging duration, and initial EV battery SOC. The aggregation strategy is determined by the control objective of the system, depending on whether regulation or overall grid cost minimization is required. Regulation signal strategy is adopted from Amamra and Marco (2019), in which regulation up signal is activated when grid frequency falls below 50 Hz, while regulation down signal becomes active when grid frequency goes above 50 Hz.

4.1. OCV and equivalent circuit battery modelling

There are several methods that are used for modelling EV battery parameters. These models include equivalent circuit model, electrochemical model, and data-driven model. The equivalent circuit model consists of an internal resistance, and resistor–capacitor networks which relate the EV battery current, SOC, temperature and terminal voltage (Meng et al., 2018). The equivalent circuit model considered in this paper is shown in Fig. 3. From Fig. 3, I is the battery discharge current, R_o is the Ohm resistance, R_1 is the polarization resistance, V_{oc} is open-circuit voltage, R_2 is the concentration polarization resistance, C_1 is polarization capacitance, and C_2 is the concentration polarization capacitance.

Table 1
Electrical characteristics for Nissan Leaf 2019 EV battery module.

Electrical characteristics	Rating
Nominal battery capacity	56.3 Ah
Nominal voltage/cell	3.65 V
Total number of cells	192
Real power rated capacity	39.46 KWh

SOC estimation models are divided into five categories: Coulomb counting method, artificial neural network-based method, impedance spectroscopy-based method, model-based method, and open-circuit voltage (OCV) method. In this paper, we use the OCV method for SOC estimation based on the parameters specified in the equivalent circuit model.

The open-circuit voltage (OCV) battery model is shown in Fig. 4. It is based on a hybrid empirical mathematical battery model consisting of the Shepherd model (Bessa and Matos, 2013), Unnewehr universal model (Clairand et al., 2020) and Nernst model (Wei et al., 2016), as specified in Eq. (1). Eq. (1) is a combination of the merits of the three specified empirical Lithium-ion battery models to optimize slow charging. This will enhance battery performance by improving its depth-of-discharge profile. This results in enhanced V2G capability and longer driving time for EV owners. It includes parameters for the battery current I_{batt}, the battery operating temperature T_{opt} and the battery model estimated SOC based on the hybrid empirical battery model represented by Eq. (1). With respect to the OCV model,

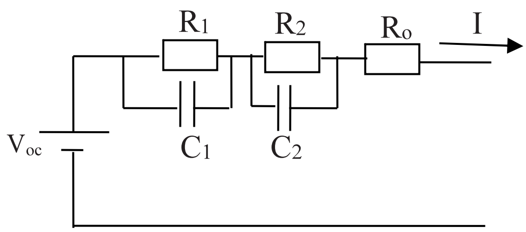


Fig. 3. Equivalent circuit model for SOC estimation.

the battery terminal voltage V_T is used for regulation of reactive power within the distribution grid, while the battery current I_{batt} controls active power. SOC_{ab} of EV a in CC b is modelled and optimized accordingly based on both the model represented by Fig. 4 and the biobjective function specified in Eq. (2).

$$V_T = V_{OCV} - I_{inst}R - R_{pol}\left[\frac{1}{SOC_{batt}} + SOC_{batt} - In\left(SOC_{batt}\right) - In(1 - SOC_{batt})\right] \tag{1}$$

$$\min \sum_{t=t_{st}}^{t_{end}} (F_1 + F_2) \tag{2}$$

where

$$F_1 = \sum_{t=t_{st}}^{t_{end}} \left(\left(P^{ab}_{chg,t}\left(p_{e,t} + p_{freq,t}\right) - P^{ab}_{dchg,t} r_{dchg,t}\right) + (P^{ab}_{chg,t}\eta_{chg} + P^{ab}_{dchg,t}/\eta_{dchg})p_w \right) \tag{3}$$

$$F_2 = -\sum_{t=t_{st}}^{t_{end}} (V_{oc} - V_{R_1\|C_1} - V_{R_2\|C_2} - IR_o) \tag{4}$$

Subject to:

$$-P^{ab}_{max} \le P^{ab,t}_{d} \le 0 \tag{5}$$

$$0 \le P^{ab.t}_{U} \le P_{max,t} \tag{6}$$

$$0.1 \le SOC_{ab} + \frac{\left(P^{ab.t}_{d}\eta^{ab,t}_{d} - P^{ab,t}_{u}\eta^{ab,t}_{u}\right)}{P^{ab.t}_{max}} \times T_{int} \le 0.9 \tag{7}$$

$$0 \le Q_{ab,t} \le Q^{ab}_{max} \tag{8}$$

$$I_{batt,act} \le I_{batt} \le I_{batt,ref} \tag{9}$$

$$T_{min} \le T_{opt,t} \le T_{max} \tag{10}$$

$$V_{mod,t} \le V_{nom} \tag{11}$$

Fig. 4 is a simplified version of the proposed OCV model which enhances SOC of the battery. However, the proposed model is robust because it is capable of estimating SOC for different driving and charging conditions. This research focuses on battery parameters for the Nissan Leaf EV only. While we assume that similar results can be expected from Lithium-ion battery module with similar configuration, further research on performance comparison of battery modules for other types of EV regarding SOC improvement is required.

4.2. Specification of objective function and constraints

In this section, we specify the biobjective function along with constraints including those based on the OCV battery model. The objective function parameters and constraints involve variables that represent the interaction of the aggregator with both EV users via charging clusters and the grid regulator via the DSO.

The objective function specified in Eq. (2) is optimized at the aggregator. It consists of two objectives which must be jointly minimized so the EV owner can get benefit from participation in grid support services. In particular, the first objective (F_1) is based on the feed-in tariff electricity price as specified by grid regulator. The first term is the charging price of the participating EV a from cluster b based on electricity consumption and frequency regulation.

The second term represents the financial reward to the EV owner for participating in voltage and frequency regulation services. Therefore, this term must be maximized to increase benefits to the aggregator, and consequently to the EV owners. The second objective (F_2) represents maximization of EV battery SOC based on minimizing losses due to the open-circuit voltage. The wear cost of the battery is used to estimate the degradation cost of the battery over time. The total financial benefits that accrue to EV a in cluster b via the aggregator are specified according to Eq. (10):

$$ben_{reg,ab}\left(t\right) = \sum_{t^{st}_{ab}}^{t^{end}_{ab}} T_{int}\left(Q_{ab,t}p_{reg,t}\right) \tag{12}$$

For Eq. (10),

$$t = T_{int} = t^{end}_{ab} - t^{st}_{ab} \tag{13}$$

Regarding the constraints, constraint in Eq. (5) applies to a situation in which EV a in cluster b of the aggregator is not in grid regulation mode. In other words, it is charging at the specified time instant t. Therefore, no bounds are set with respect to the battery SOC. Constraint in Eq. (6) represents a regulation up scenario, and therefore the EV battery is discharging back into the grid. Therefore, it prevents the battery from discharging beyond the maximum allowable limit so that battery health is not compromised. For the purpose of model-based SOC estimation (Fig. 3), we need to specify the upper and lower bounds of the SOC that need to be maintained in order to ensure optimization of battery life for both travelling and participation in regulation services. This is done by constraint in Eq. (7). This constraint ensures that fast charging of the battery takes place until 75% SOC. At this point, normal charging continues until 90% SOC. At this point, depending on the demand at the aggregator charging station, the EV can either be disconnected, or allowed to charge further at trickle charge until fully charged.

This charging system is another strategy aimed at enhancing cycle life of the battery. Regarding constraint in Eq. (7), $P^{ab.t}_{max}$ represents the maximum energy capacity of the battery of EV a in cluster b. T_{int} is set to 30 min. Constraint in Eq. (8) represents the maximum limit of reactive power injection by the EV into the distribution grid as specified by the DSO.

The contribution of this research is specified by the constraints in Eqs. (9)–(11). These constraints represent the optimized settings for EV battery operating current I_{batt}, battery operating temperature $T_{opt,t}$ and nominal operating voltage $V_{mod,t}$. These are all obtained from the proposed OCV model representing the EV battery and are applied as additional constraints aimed to improve the battery SOC for a given duration of participation in regulation services. These optimized parameters are obtained from the OCV model by ensuring that the bounds specified for constraint variables in Eqs. (5)–(8) are not violated. Constraint in Eq. (9) ensures that the current required to control active power flow between the grid and the EV battery does not exceed a preset reference value during regulation up period. This helps to maintain the required SOC level of the EV battery so that there

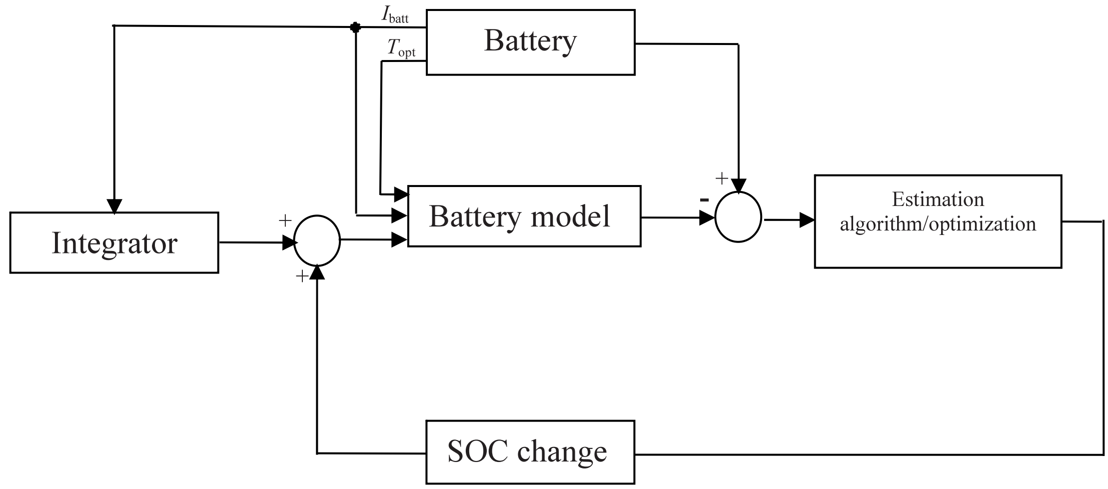


Fig. 4. Model-based SOC estimation.

is enough power left for travelling. Constraint in Eq. (10) ensures that the battery module operates within allowable temperature. For the simulation, T_{optemp} is set at 28 °C, while T_{min} and T_{max} are set at 23 °C and 32 °C respectively. Constraint in Eq. (9) is used to determine the nominal voltage of the battery. It is set to 700 V for the battery module.

4.3. Multi-objective genetic algorithm (MOGA) for implementing grid regulation

The grid regulation algorithm is based on same-day EV scheduling based on general vehicle user information available from Anon. (2014). The aim of this section is to demonstrate how the proposed objective function and model constraints improve the SOC of the EV battery while participating in frequency and voltage regulation services. This proposed approach aims to ensure optimal health of the EV battery while participating in grid regulation services. This is because EV battery cost constitutes up to one-third of initial cost of EV, and subsequent replacement of battery will cost up to 50% of initial battery cost (Borras, 2019).

Algorithm 1.

1. Input $t_{ab}^{st}, t_{ab}^{end}, \eta_{dchg}, SOC_{ab}, I_{batt}, T_{opt,t}, V_{nom}, Q_{ab,t}, p_{reg,t}$

For each CC:

2. Optimize battery model parameters ($SOC_{ab}, I_{batt}, T_{opt,t}, V_{nom}$) based on OCV model
3. Obtain SOC_{opt} based on $SOC_{ab}, I_{batt}, T_{opt,t}, V_{nom}$ and apply to constraint in Eq. (5)
4. Optimize the objective function in Eq. (2) based on received regulation signal at instant t between t_{ab}^{st} and t_{ab}^{end}

If regulation signal $s_{reg,t} = 1$:

5. Return and execute step 2 for instant t
6. Output SOC_{ab} and $P_d^{ab,t}$
7. Check SOC_{ab} at $t + 1$ and compare with SOC_{opt}. Ensure that constraint in Eq. (5) is not violated
8. Repeat steps 5–7 until $s_{reg,t} = 0$

End

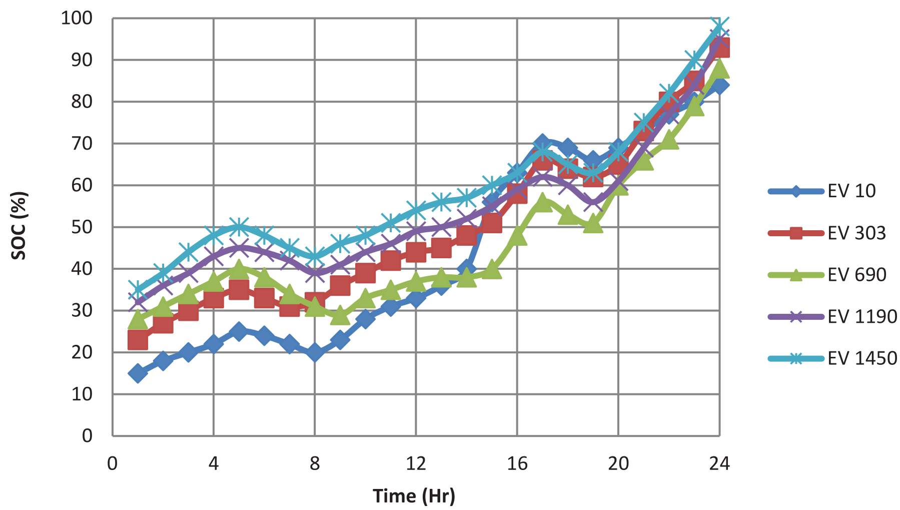
Algorithm 1 is implemented using Scilab's *optim_moga* function. Parameter specifications which are used with the specified function are given in Table 2. Algorithm 1 is implemented on Intel Pentium Core i5 processor with 6 GB of RAM. From Algorithm 1, the priority is to monitor the battery SOC during regulation up period in which the EV battery will be discharging into the grid. From the perspective of the objective function and specified constraints, the aggregator implements grid regulation via EV scheduling at every interval t, where the interval resolution is 30 min. Most of the researches previously carried out with respect to grid regulation using EVs do not incorporate battery modelling as part of the algorithm implemented by the aggregator. We see that the SOC of the EV battery is continually monitored by the aggregator based on SOC_{opt} provided by the battery model parameters at every interval within the regulation up period. The battery SOC SOC_{ab} is evaluated to ensure that constraints in Eqs. (7)–(9) are not violated. Otherwise, the battery is disconnected from the grid regulation service, and continues charging according to constraint in Eq. (5). When SOC_{ab} is no longer in violation of SOC_{opt}, the EV can continue to participate in grid regulation services until t_{ab}^{end}. In this manner, there is a trade-off for the EV owner between profitability from grid regulation services and maintaining battery health.

Table 2
Parameter settings for *optim_moga* function.

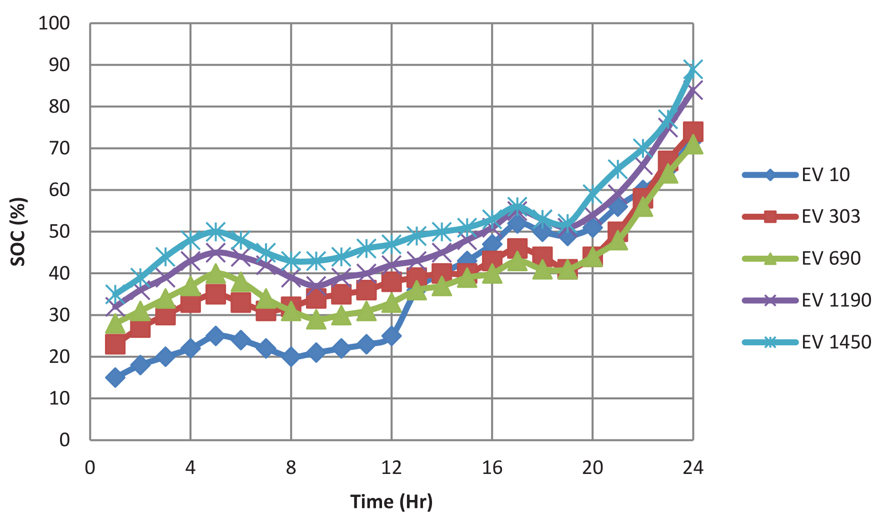
Function parameter	Setting
Population size	100
Crossover probability	0.6
Mutation probability	0.4
Number of generations	20

For the parameter settings in Table 2, the number of generation iterations is set to 20 since we observe that there is no significant improvement in simulation results beyond this number of iterations. Therefore, we use this as the stopping criterion for the algorithm. Crossover probability was initialized at 0.7 but was later adjusted to 0.6 during the simulation to prevent premature convergence. MOGA handles uncertainties by using an explicit averaging approach to eliminate the likelihood of selecting unsuitable candidate solutions for the final Pareto front. We use random search to find good starting points, then grid search to locate the local optima for the selected good starting points.

The dataset used for the optimization is obtained from battery information for the Nissan Leaf EV (Borras, 2019). We consider values for battery rated current (I_{batt}), optimal operating temperature (T_{opt}), and battery nominal voltage (V_{nom}). (See Table 3.)



(a)



(b)

Fig. 5. Simulated EV battery SOC for each cluster (a) With proposed model (b) Without proposed model.

Table 3
Simulation variables.

Variable	Value
Number of CCs	5
Number of EVs/CC	300
Charger efficiency	95%
Charger rating	6.6 KW
Aggregator rating	500 MW (active)
Battery price	$0.013/KWh

5. Results and discussion

For each EV in the clusters, we assume initial SOC (at 5 a.m.) to be 25%, 35%, 40%, 45% and 50% respectively. This is necessary to estimate the ability of the proposed SOC model to ensure healthy battery status during the period when the EVs provide grid support services. It should be noted that for lithium-ion batteries, healthy operation typically occurs between 20% and 80% depth of discharge (DOD). We consider the cost of providing grid support services for a specific day (4th August 2020) based on the system electricity buy price specified in Anon. (2020c). We consider the interval between 8 a.m. and 2 p.m. since that is the period within which system buy price is highest for the specified day under consideration.

We also consider the stochastic nature of driver behaviour for the different clusters in our simulation. Therefore, we assume that between 5 a.m. and 8 a.m., EV users will be commuting. However, it is assumed that every EV in each one of the 5 clusters will be available to provide grid regulation services from 10 a.m. until 2 p.m. EVs will then charge from 2 p.m. until 4 p.m. It is assumed that between 4 p.m. and 7 p.m., EV users will be commuting back home. The period between 8 p.m. and 12 p.m. is used for EV charging only. The average processing time per iteration was 3.2 s, and the processing time for all generations of the algorithm was 8 min and 46 s.

The electrical parameters for the bus system in Fig. 2 are obtained from Baran and Wu (1989). From Fig. 5, we consider the effect of EV participation in voltage and frequency regulation services on battery SOC. We consider a case where the proposed model is used to optimize battery SOC for the specified duration, and vice versa. We also consider SOC for one EV in each of the 5 clusters: EV 10 for CC_1, EV 303 for CC_2, EV 690 for CC_3, EV 1190 for CC_4, and EV 1450 for CC_5. From Fig. 5(a), we observe an increase

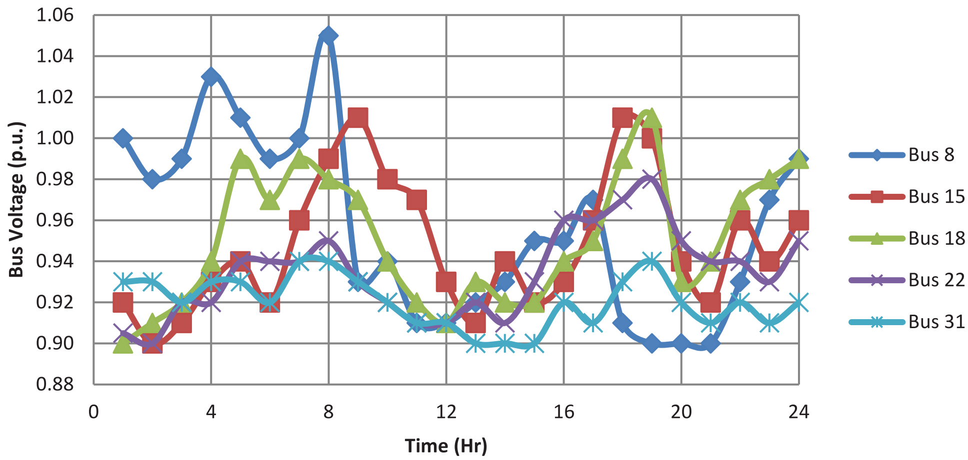


Fig. 6. Bus voltage for 5 EV-connected buses.

Table 4
Aggregator financial benefit for grid support.

	SOC model	Voltage regulation	Frequency regulation
With SOC model	Service reward ($/day)	+1991.76	+953.28
	Service cost ($/day)	−1432.94	−717.39
	Benefit ($/day)	**+558.82**	**+235.89**
Without SOC model	Service reward ($/day)	+1587.39	+694.39
	Service cost ($/day)	−1473.62	−503.25
	Benefit ($/day)	**+113.77**	**+191.14**

in SOC of the EV batteries in each charging cluster even when the EVs participate in grid support services between 8 a.m. and 2 p.m. It can also be seen that by 12 p.m. of the day under consideration, all EVs have achieved more than 80% final SOC. However, this is not the case when the proposed SOC model is not considered during EV participation V2G grid support services (Fig. 5(b)). In this case, we observe that between 8 a.m. and 2 p.m., SOC for EVs in all charging clusters remains almost flat. Also, by 12 p.m. final SOC of EV batteries for charging clusters CC_1, CC_2 and CC_3 is below 80%.

We also consider the effect of grid voltage stability for periods when the EVs in each cluster are in grid-to-vehicle (G2V) mode. The periods in which this occurs are 2 p.m. to 4 p.m., and 8 p.m. to 12 p.m. It is important to consider the effect of additional load of charging EVs on grid voltage stability. From Fig. 6, the per unit (p.u.) voltages of each charging cluster-connected bus was monitored. It was observed that bus voltage for each cluster did not go below 0.90 p.u. between the above specified time periods. This means that the proposed model also ensures that voltage sags which can lead to instability of the distribution grid are avoided.

Fig. 7 shows the EV battery charging cost for EV 1450 for various charging strategies. We consider EV 1450 since it is the farthest from the grid supply transformer. Therefore, we consider the effect of electrical distance on the cost of charging the battery. From the results obtained, the proposed strategy is about 33% cheaper than a case in which grid support is implemented without the proposed model. The reason for this is two-fold. First, the proposed SOC model can maintain SOC of the battery during periods when the EV is in V2G mode (8 a.m. to 2 p.m.). This means that battery health is not sacrificed for the financial gain of participating in grid regulation services. In other words, the proposed model can ensure that a balance between battery performance and profitability is maintained. Second, since EV battery SOC is maintained above 20% during the grid regulation period, the battery will charge up to 80% SOC more quickly, which reduces the amount of time that the battery is kept charging.

Table 5
Daily cost of V2G operation for single EV.

	With SOC model	Without SOC model
EV battery wear cost ($/day)	−0.87	−0.95
G2V cost ($/day)	−0.15	−0.17
V2G cost ($/day)	+1.68	+1.61
Total cost ($/day)	**+0.66**	**+0.49**

This increases the charging cycle lifetime of the battery since the battery undergoes fewer charge/discharge cycles.

In Table 4, we consider the financial benefit to the aggregator for a case in which it adopts the proposed model for providing voltage and frequency regulation services to the grid, and vice versa. For the case of voltage regulation, we see an aggregator gain of $445/day compared to a scenario in which the aggregator does not adopt the proposed model. For the frequency regulation service, there is a daily gain of $45 when the proposed model is adopted. Table 5 summarizes the cost of EV V2G operation for a single EV for the day under consideration. From the results obtained, there is a 26% gain for the case in which the aggregator adopts the proposed model versus a case in which it does not. From all results obtained, it is observed that the proposed SOC model improves the EV battery SOC significantly when it operates in V2G mode. The results have shown that the model improves benefits for the EV owner, aggregator, and grid operators. This provides an incentive for EV owners to participate in grid regulation services without worrying about adverse effects on the EV battery.

To verify robustness of performance of the proposed OCV model, we test performance of the model and optimization algorithm by varying the number of charging clusters and the number of EVs per charging cluster. We simulate the following scenarios:

1. The number of charging clusters remains fixed while the number of EVs per charging cluster is increased.
2. The number of charging clusters remains fixed while the number of EVs per charging cluster is decreased.

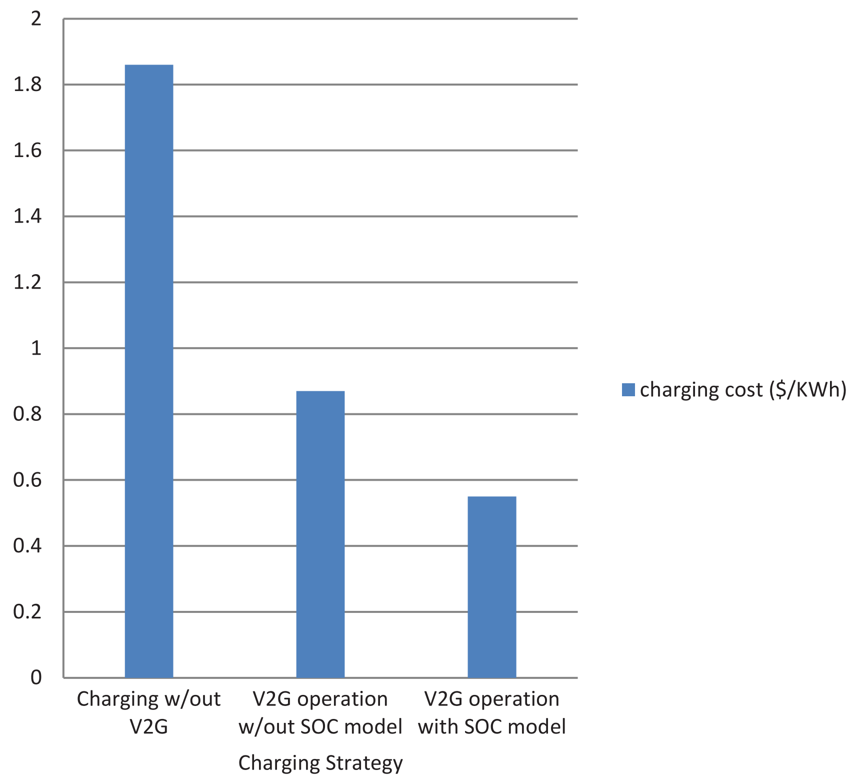


Fig. 7. EV battery charging cost for various charging strategies (considering EV 1450).

Table 6
Robustness test for proposed OCV model and algorithm (best results in boldface).

Performance index	Base case	Case 1	Case 2	Case 3
Average EV battery SOC (EV 10)	**82%**	79%	80%	78%
Average Bus voltage (p.u.) (bus 31)	**0.92**	0.89	0.86	0.88
Aggregator financial reward ($/day) (FR, VR)	+**235.89**, +**558.82**	+201.72, +510.56	+199.42, +497.41	+203.95, +514.88

3. The number of charging clusters is reduced to 3 with 500 EVs per charging cluster (we consider charging clusters at bus 8, 18, and 31)

We use simulated EV battery SOC, bus voltage and aggregator financial reward for frequency and voltage regulation (denoted as FR and VR respectively) as performance indices to evaluate the performance of the proposed model. Results are tabulated and compared to the original case considered in Section 4. For the battery SOC, we consider EV 10 since it has the lowest SOC compared to vehicles in other clusters (Fig. 5(a)). We consider the period between 8 a.m. and 2 p.m. when the EVs are in V2G mode. For the bus voltage comparison, we consider bus 31 which is farthest from the supply transformer. We consider the same period between 8 a.m. and 2 p.m. Results are presented in Table 6. From Table 6, we observe that the proposed model and algorithm perform well for different grid and aggregator configurations. From the results, the configuration used in the base case gives the best performance from simulations. We also observe that reducing the number of charging clusters enhances financial reward to the aggregator. However, more investigation must be carried out to establish proportionality between the number of charging clusters and aggregator financial reward.

Table 7
Mean absolute error (MAE) and root mean square error (RMSE) analysis for successive generations of MOGA.

Generation	MAE	RMSE
1	1.356E−01	4.217E−02
2	1.432E−01	3.125E−02
3	1.386E−01	2.115E−01
4	2.154E−01	2.951E−01
5	2.117E−02	2.473E−02
6	2.216E−02	3.128E−03
7	1.113E−01	2.506E−03
8	3.112E−02	3.953E−03
9	2.115E−02	3.216E−04
10	3.219E−03	2.143E−04
11	2.134E−03	3.143E−05
12	1.136E−03	2.176E−04
13	3.381E−04	1.114E−05
14	3.185E−03	3.219E−05
15	2.116E−03	2.139E−05
16	3.105E−02	1.179E−05
17	2.117E−04	1.964E−05
18	3.738E−04	1.291E−04
19	2.154E−04	2.248E−05
20	3.218E−04	2.956E−05

Table 7 details the results of error analysis of the MOGA approach. We use the mean absolute error (MAE) and root means square error (RMSE) as indices to analyse the deviation from the global optimum values of the selected parameters. From results obtained, it can be observed that successive generations of MOGA yield smaller error values, which is an indication of the stability of the proposed method. Fig. 8 validates optimization results of MOGA using the cost metric. We observe convergence of the cost metric after 150 iterations out of 2500 iterations for each generation of MOGA. The computational complexity of MOGA is

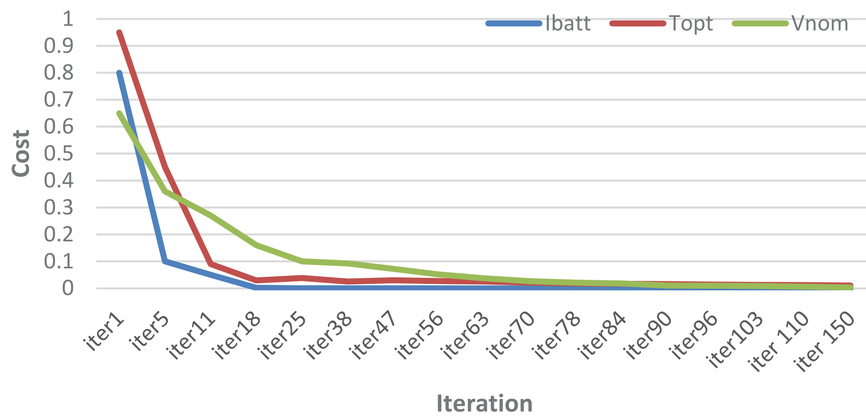


Fig. 8. Cost validation of MOGA for battery electrical parameters considering F_1.

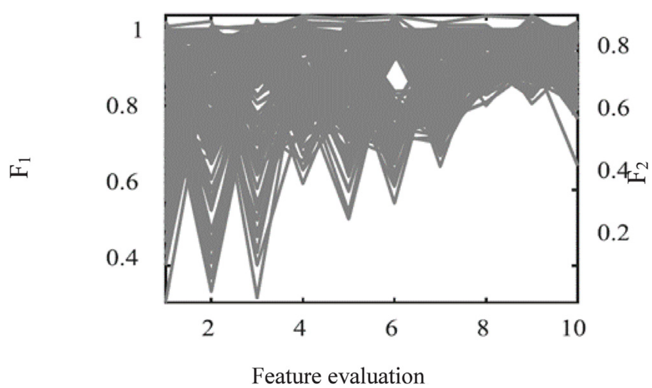


Fig. 9. Cost validation for F_1 and F_2 over successive FEs of MOGA.

$O(2N^2 \log^{M-2} N)$ where N is population size and M is dimensionality of objective function vectors. Fig. 9 shows the cost validation over successive feature evaluations (FEs) of MOGA for both F_1 and F_2. Both objective functions demonstrate steadily reducing cost over successive FEs with F_1 demonstrating faster convergence compared to F_2.

From the results obtained, we believe that the research done in this paper makes it possible to modularize EV aggregators to form clusters of EV charging nodes which contain vehicles with similar battery electrical characteristics. From a managerial standpoint, this would make it easier for aggregators to schedule simultaneous charging and discharging of a fleet of EVs in such a way that EV owners spend less time charging and discharging on the grid.

6. Conclusions

Electric vehicles have the potential to provide substantial support to the existing grid by operating in V2G mode. However, the present high cost of EV batteries and the potential depletion of their cycle life provide little financial incentive for owners to participate in these services. In recent years, there have been many researches that aim to optimize EV battery life cycle while they perform V2G operations. However, in the context of the EV battery, many of these approaches are logistical. The research presented in this paper has proposed a technical approach which focuses on a technical approach which uses an optimized SOC battery model based on a bi-objective approach. The first objective optimizes electricity price based on tariffs provided to an EV aggregator by the distribution system operator through electricity market regulator. The aggregator consists of 5 charging clusters containing 300 EVs each. The second objective optimizes the battery electrical parameters to ensure healthy status of battery for V2G and G2V operation. Nissan Leaf EV battery parameters are used as constraints to analyse the objective function. It is intended that when this approach is used with an aggregator, it can be adapted to optimize SOC for different EV batteries to maximize benefits to both EV owners and grid operators.

From results obtained, the proposed SOC model has the potential to maintain healthy EV battery status. Within limits of the simulation, the following observations were made:

- The proposed model maximizes financial gain to the EV aggregator (and consequently to EV users) when users participate in grid regulation services.
- The proposed SOC model ensures that voltage sags due to extra load resulting from active power being absorbed from the grid during G2V operation are prevented.
- The proposed model ensures that final SOC of all EVs in charging clusters is above 80%.
- The daily charging cost of V2G operation using the proposed model is 26% cheaper than a scenario in which proposed model is not adopted.
  It has also been demonstrated that the proposed model and algorithm are robust when grid and aggregator configurations are modified.

It must be noted that the simulation is limited to battery parameters for the 2019 Nissan Leaf EV only. Further work would concentrate on applying SOC model to parameters representing other EV models. Future work will consider more than three parameters and more constraints. We will also compare the performance of MOGA with other suggested nature-inspired algorithms for such a scenario. Another shortcoming of this research is inadequate data for sensitivity analysis. Also, the effect of increased EV penetration during V2G mode was not considered in this research. We would also compare performance of our proposed algorithm with other well-performing nature-based optimizers. Future research would also consider proportionality between the number of charging clusters and aggregator financial reward. This is important to establish whether aggregators need to configure charging clusters for a given grid system such that financial reward is maximized.

CRediT authorship contribution statement

Ima O. Essiet: Conceptualization, Methodology, Software. **Yanxia Sun:** Conceptualization, Validation, Writing – review & editing.

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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