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LARGE-SCALE POWER TRANSMISSION SYSTEMS' INTEGRATED ELECTRIC VEHICLE LOAD MODELLING

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A B S T R A C T

A variety of Electric Vehicle (EV) charging algorithms provide various EV charging load profiles, when utilized together, has an impact on the electrical grid functions. Present-day charging an EV Models of demand are either based on level of charging when an EV arrives or smart charging algorithms strengthened with specific charging levels and/or procedures. In this work, a brand-new data-driven technique for calculating EV charging load is suggested. They start by introducing a mathematical model that describes an adaptability of demand for EV charging. The characteristics of several EV load models are then identified, and advanced simulation techniques are suggested to simulate EV charging demand under various power market realizations. The suggested EV load modeling technique may act as a benchmark system by simulating various EV operating schedules, charging levels, and consumer engagement. The suggested framework would also give EV charging infrastructure advice from transmission system operators development in contemporary power networks.

1. INTRODUCTION

Electric cars now account for a minor portion of the transportation industry. Nonetheless, industry experts project that electric vehicle adoption will reach 33% by 2040 and 50% by 2050. The battery is a breakthrough driving the growth in penetration of electric cars, with both an improvement in terms of energy density (kWh/kg) and a decrease in terms of cost per unit of energy (USD/kWh) (Lebrouhi et al., 2021). In 2018, expenses were about 209 USD/kWh. In 2020, every power supply was priced at 137 USD/kWh. A price of $150 USD/kWh is predicted by International Renewable Energy Association (IRENA) during an 2020s, making EVs a practical mode of transportation. A power-source car must have adequate energy for daily commutes as well as spare energy for longer trips (Gallet et al., 2018). Charging tech is evolving particularly important since it is required to provide energy for following day's journey at a fair cost by charging at

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home and going beyond the capability of public charging facilities for batteries. The transport sector will be electrified to reduce primary fuel use while increasing electric sector power generation. This additional electrical energy system necessitates examination from several angles, such as effects on system of low-voltage transmission (Xiang et al., 2019) in addition to the transfer of high-voltage systems. Additionally, it is essential to evaluate an overall performance of electrical system to prevent peak load increases and assure the lowest possible power cost. Electric car charging, when done wisely and in a planned manner, may result in greater use of sources about variable renewable energy (VRE), such as solar and wind power. Tuffner along with Kintner-Meyer's study, for example, proved that adjusting the pace at which charging EVs may compensate for sudden or step variations in power supply from wind farms. Charging EVs in an uncoordinated manner may boost peak energy consumption (Liu et al., 2020). The Idaho National Lab's (INL) EV Project investigates uncoordinated charging of electric cars in several locations, including San Francisco, CA, and Nashville; TN (Sinsel et al., 2020). Electrical energy (where a charger is attached to a vehicle) is comparable in both areas, with availability being low throughout the day and rising in evening. In an latter example, and haphazard reaction to TOU pricing resulted in a fresh surge in demand at non-peak hours. To put it another way, charging electric vehicles presents both possibilities and obstacles (Zheng et al., 2018).

The article's remaining sections are broken down as follows: In Section II, an overview of current research is provided; in Section III, the suggested methodology is explained in greater detail; and in Section IV, experimental data sets and simulation results are presented and discussed. The analysis is finished in Section V, which also makes recommendations for more research.

2. RELATED WORK

The work suggested a unique model investigate impacts of grid-to-EV power exchange on electricity grid demand profile, indication of operational stability, and dependability indices (Mozafar et al., 2018). The present investigation proposes the use of adaptable transmission technology for the PEV and RES incorporation must be coordinated electricity transmission networks (Nikoobakht et al., 2019). The report summarizes the known methodologies for EV charging load modeling. Furthermore, a novel study scale structure model of electric vehicle charging load progression is provided, with a focus on addressing the shortcomings of previous research into dealing with EV scale development (Xiang et al., 2019). The studies and current Efforts are being made to integrate EVs with EPS characterized according to their importance to various energy market stakeholders. This category includes four players: a generating company (GENCO), a distribution system operator (DSO), an EV aggregator, and end user (Patil and Kalkhambkar 2020).

The influence of electric vehicles (EVs) providing main frequency control through vehicle-to-grid (V2G) technology is examined in this research. The project's goal is to provide a series of suggestions to ensure reliable large-scale use of EV vehicles as primary reserve providers (Zecchino et al., 2019). The paper looks at benefits about electric vehicles, both dispersed and centralized intelligent charging in terms of simulating two distinct smart charging algorithms in battery electric cars and assessing their impact on operation and distribution of electric grid resources, and therefore, electric grid CO_2 and Nitrogen Oxides (NOx), possible to reduce CO_2 and NOx emissions, costs, and grid capacity (Cheng et al., 2018).

The paper provides an in-depth examination of the current state of EV industry, norms, infrastructure for charging, and effect of EV charging on grid. Every paper presents the current state of EVs and gives a thorough assessment of key international EV charging and grid connectivity standards (Das et al., 2020). The research looks at present situation and most recent deployment, and difficult problems in implementing electric vehicle (EV) infrastructure and charging systems in conjunction with several international standards and regulations charging codes (Habib et al., 2018). The paper applies application of two-stage stochastic programming in a smart house minimize power costs purchased for the typical family. In this regard, the available electric vehicles (EV) vehicle-to-home (V2H) capacity is employed in conjunction using a Battery Energy Storage System (BESS) under every direction of a system to manage energy for the house (Zeynali et al., 2020). The study gives a comprehensive V2G model with a Hybrid Energy Storage System (HESS). The model's key contribution is the concurrent supply of PFC and DGS at its plug-in connector. Droop reaction (DR) and Inertial Response (IR) are both included in PFC (Hernández et al., 2018).

3. PROPOSED METHODOLOGY

Electric Vehicle (EV) Load Modeling: The electrical grid's load characteristics vary depending on EV charging techniques and levels used. Several assumptions are used in this article to complete an aggregated EV load modeling: 1) There are enough Electric Vehicle (EV) charging stations on a grid, and 2) Every EV user may choose a charging method according to his or her priorities and preferences. The market's dynamics between supply and demand necessitate a requirement for an adequate quantity of EV charging infrastructure. Smart charging algorithms are presumably used by plug-in EVs (PEVs), which include Plug-in Hybrid EVs (PHEV) and Battery EVs (BEVs) and use level 1 and level 2 charging techniques for conductive charging; upon EV departure, and energy requirement of such EVs must be satisfied. In addition, if necessary, PHEV load can be decreased and replaced with gasoline. When EV batteries get dead and plug-in charging mode is unable to fulfill energy consumption requirements for a subsequent journey, BSS regular BEV customers have subscribed to battery swapping services can still switch their batteries. Additionally, BEV owners have access to FC methods. The total EV load at FC stations (FCSs) is presumptively rigid and inelastic. As a result, electric vehicle load characteristics of EVCSs and BSSs play a significant role in flexibility of aggregated EV load.

3.1 Characteristics of Steady-State Electric Load

The EVCS's aggregated EV load model: Customers of EVs frequently utilize charging their EVs in EVCS using level 1 and level 2 procedures. Let K_d stand for a total amount of energy anticipated for PEVs in EVCSs be assigned. Equation (1a) indicates such power restricted from PHEVs but provided by gas stations α_d at present time step l equals a total of actual charging power $K_d(l)$ allotted to PEVs, actual power w_{kt} used to charge a gift to PEVs, and power at following time step$(l+1)$'s $K_d(l+1)$. The PEV demand is constrained by Equation (1b), and A depicts PEV demand's greatest degree of flexibility. In (1c) and (1d), respectively, B and C are restricted to lower and upper bound capacities.

$$K_d(l+1) = K_d(l) + \alpha_d \Delta s\big(w_k(l) + w_{kt}(l)\big)\ \forall l \qquad (1a)$$

$$0 \leq K_d(l) \leq (1+\zeta)F_d\ \forall l \qquad (1b)$$

$$w_k^{min}(l) \leq w_k(l) \leq w_k^{max}(l)\ \forall l \qquad (1c)$$

$$w_{kt}^{min}(l) \leq w_{kt}(l) \leq w_{kt}^{max}(l)\ \forall l \qquad (1d)$$

The charging power limitations are time-dependent and influenced by charging capacity, some connected EVs, and charging algorithms, whereas F_d for aggregated EVCSs can be forecast and is steady over a day. The connection between the utilities and EVCSs is made possible in this paper thanks to use of AMI. Additionally, EVCS is turned on to regulate and coordinate EV charging. The system operator may therefore compute and receive real aggregated limits for EV charging from EVCSs, and direct load control can also be used to implement charging power received from system operator into each EVCS. The day-ahead prediction values serve as a foundation for projected aggregated limitations. Through AMI, gap between estimation and actual implementation may be measured and regularly made up. Given that cost of electricity is often two or three times cheaper than cost of gasoline, it is believed that consumers own PHEVs favor using EVCS to recharge their automobiles. Customers and system administrators are prepared to fill up with gas when price of electricity is greater than price of gas, such as during busiest times of year. The EVCS will reject requests for PHEV charging, and gas stations will supply necessary energy. Therefore, a smart meter is capable of recording in realw_{kt}. The modification of PEV loads' condition in terms of system flexibility is depicted in Figure 1. It is important to note a certain some customers may charge their electric vehicles at secret locations that system operators.

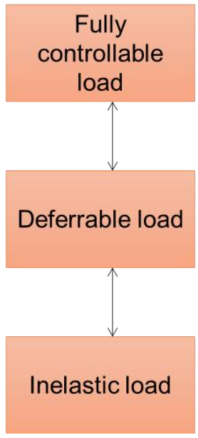


Figure 1. Flexibility in EV load transition

As a result, these EV loads can be thought of as inelastic loads since they were unable to manage. They may be projected using load forecasting algorithms and aggregated to typical loads. Therefore, even if smart charging and private charging networks are not tightly integrated, EVCS load model may still be used efficiently.

BSS EV Load Model: With an emphasis on BSSs, it can be said that they are storage units with constant battery capacities but variable battery switching needs over time. The power used for charging and discharging, and energy stored in BSS (Bs), should fall within respective ranges. The load caused by changing batteries might be viewed as an additional disruption to BSS. A comprises both subscription customer's battery swapping load and additional EV load from BEV customers those charging needs cannot be satisfied by a plug-in charging system but require plug-in charging.

$$A_t(l+1) = A_t(l) + \big(\alpha_d w_d(l) - (\alpha_c)^{-1} w_c(l)\big)\Delta s$$
$$-F_t(l)\ \forall l \qquad (2a)$$

$$A_t^{min} \leq A_t(l) \leq A_t^{max}\ \forall l \qquad (2b)$$

$$0 \leq w_d(l) \leq w_d^{max}\ \forall l \qquad (2c)$$

$$0 \leq w_c(l) \leq w_c^{max}\ \forall l. \qquad (2d)$$

The BSS's vehicle to grid (V2G) feature is presumptively turned. To operate as a storage unit, it can discharge electricity to grid. Power variables A and B are those that show on grid side. To prevent the BSS from charging and discharging concurrently, two variables are multiplied by 0, which equals zero. This restriction, however, is left out of (2). When the cost of battery deterioration and charging efficiency is taken into account, convex issue (2) will have same outcomes just as nonconvex problems with this restriction. Every BSS is classified as an inelastic load since it will charge batteries to meet demand even during peak load periods.

Aggregated FCS EV Load Model: Using high power FCSs as a focal point, aggregated FC load is modeled an inelastic demand and may be predicted easily using load forecasting techniques. The distribution of charging sessions for rapid charging throughout day is such that are mostly concentrated in morning and afternoon. According to statistics from actual FCS operations, total FC demand is predictable and follows a certain curve. Every FC EV load's unpredictability may be handled similarly to that of traditional loads.

3.2 Dynamic EV Load Characteristics

During transient operating states, EV loads can be thought of as constant power; nevertheless, the EVCS controllers primarily govern aggregated EV loads' dynamic behavior. If EVCS design is implemented, both PEVs and BSSs can automatically attempt to transit through during erroneous system operation circumstances in response to system disruptions. It should be noted that a decentralized architecture is used, allowing for EVSE and EVCS in-the-moment communication. When a system is working normally, every inverter-based loads have a frequency response that is typically fixed at EV loads and can provide frequency control services$\pm 0.2\ Hz$.

Following regulation signals, EVCS on operation base point once economic operation base point has been determined by economic dispatch optimization. The high and low regulation limitations, which are total of PEV and BSS regulation bands as shown in equation (3a), must be within EV charging and discharging power constraints. Here, it assumed a certain βe_d^{max} represents ratio of regulation capability to regulatory restrictions. Additionally, assume that system's required capacity for frequency control is B and that capacities for regulation up and regulation down are symmetric. The frequency regulation capacity ratio that system's entire storage capacity can offer isβ. The combined EV load may thus be represented in (3b) as having a real capability for frequency control.

$$e_k(l) = min\left(w_k(l) - w_k^{min}, w_k^{max}, -w_k(l)\right) + min\left(w_d(l) - w_d^{min}, w_d^{max}, -w_d(l)\right) + \left(w_c(l) - w_c^{min}, w_c^{max}, -w_c(l)\right) \quad (3a)$$

$$e_d(l) = min(\alpha e_k(l), \beta e_d^{max}) \quad (3b)$$

That during a grid transient condition, two dynamic properties might be achieved concurrently. The frequency-droop control will be activated by real-time communication with EVSEs supported by EVCSs and BSSs, to grid ride through disturbance frequency event happens also disturbance exceeds a predetermined threshold. The utility's real-time communication tools, EVCSs, and BSSs will track AGC signals and offer frequency regulation services.

3.3 Flexibleness of Combined EV Loads

The combined SOC range of EVs and daily fluctuation in EV load demand has no bearing on charging capabilities as PEVs in EVCSs have *day-ahead flexibility.* Individual PEVs can fulfill their charging needs, and aggregated PEV loads can keep some degree of flexibility if PEVs are set up to prioritize depending on departure time and charging schedule, and power required for charging. Every virtual battery model restriction for PEV charging incorporates individual EV charging schedules, whereas charging and capacity limits for BSSs are set. The cumulative battery switching load curve affects flexibility of BSS. The SOC range of integrated BSSs that hardly affects timing about charging and draining and a necessity for battery swapping is hence a definition of day-ahead flexibility. Economic dispatch simulation may explicitly gain BSSs' day-ahead flexibility, which can use aggregated model and treat it as large battery storage, unlike PEVs, which need to have their day-ahead flexibility determined by simulations that include individual PEVs. The Parameter Identification for Aggregated EV Load Models: Every system operator may quantify and make use of multitimescale flexibility about aggregated EV loads during routine operations. The aggregated EV load will affect market price as analyses instances with considerable EV adoption, It is necessary to use a production cost modeling strategy.

3.4 Model for Economic Dispatch of Parameters

Every combined EV load would be unable to offer system frequency regulation services if communication network latency was excessive and AMI only supported 5-min bidirectional communication. The suggested economic system operator dispatch model taking into account EV load with various charging techniques is provided in (1), (2), and.

$$min\gamma(K_d(L+2) - F_D)^2 + \sum_{l=1}^{L}\left(W_T w_{kt}(l) + W_D O_D(l)\right) + \sum_{l+1}^{L}\left(\sum_{j=1}^{m} D_j\left(O_{H,j}(k)\right) + 2d_c w_c(l)\right) \quad (4)$$

$$\sum_{j=1}^{m}\left(O_{Q,j}(l) + O_{H,j}(k) + w_c(k) - w_d(k) - w_k(l)\right) = K_P(l) + K_E(l) + \Delta O_{H,j}(k)\ \forall l\ \forall j \quad (5)$$

$$O_{H,j}^{min} \le O_{H,j}(k) \le O_{G,j}^{max} \forall l\ \forall j \quad (6)$$

$$O_{H,j}^{min} \le O_{H,j}(l) \le O_{H,j}^{max}\ \forall l\ \forall j \quad (7)$$

$$O_{H,j}^{min} \le O_{H,j}(l) \le O_{H,j}^{max}\ \forall l\ \forall j \quad (8)$$

$$O_{D,j}(l) + O_{Q,j}(l) = \Lambda_{Q,j}(l) \forall l\ \forall j \quad (9)$$

$$0 \le S_{R,i}(p) \le S_{R,i} \forall l \forall j \quad (10)$$

$$O_{D,j}(l) + O_{Q,j}(l) = \Lambda_{Q,j}(l) \forall l\ \forall j \quad (11)$$

Distributing both generating and EV loads, objective function (4) seeks to minimize overall dispatch cost. Every cost of renewable energy curtailment, shedding cost of PHEVs, and cost of penalties for PEVs deviating from daily energy usage make up objective function (4). When V2G operating mode gives EV customers extra battery cycles, degradation cost of EVs is taken into account, combined with quadratic cost of traditional generating units' production and price of charging EVs. Every state and input restriction of EVCS and BSS are represented, respectively, by equations (1) and (2). The limitation on power balance is enforced by equation (5). Equations (6)–(8) are state equations for conventional generating units. The generation of intermittent renewable energy is depicted in equations (9) and (10). Constrictions on transmission lines are described in (11). The transmission line flow limit vector is denoted by$F$. The matrix of distribution factors for power transfer is called$H$. P_{net} is a vector that stores an results of network buses' net generation's preliminary calculations.

3.5 Co-optimization of ancillary services and energy

The frequency control market may allow participation from aggregated EV loads if real-time communication is established between EVCS and EVSEs both EVCS and utility. A more optimum energy dispatch and AS reserve schedule are produced by co-optimization utilizing a single dispatch option every five minutes for energy and AS markets minutes than by sequential optimization, where energy and reserves were cleared sequentially. If objective function introduced in (4) is represented by OFED, a combined optimization model that takes into account energy distribution and AS may be expressed as (1)-(3) and (5)-(14), respectively.

$$O_{D,j}(l) + O_{Q,j}(l) = \Lambda_{Q,j}(l) \forall l \, \forall j \tag{12}$$

$$O_{D,j}(l) + O_{Q,j}(l) = \Lambda_{Q,j}(l) \forall l \, \forall j \tag{13}$$

$$\sum_{j=1}^{m} Q_{H,j}(l) \leq\geq \rho K_P(l) \;\; \forall l \tag{14}$$

Where goal is to reduce overall dispatch costs while still making money from frequency control supplied by EVs. (3) Lists regulation capabilities that EV_s offer. An in is a reserve offered by a conventional generating unit operating online. B in demand percentage, which details a reserve required. Other equations are same as those that were first used in economic dispatch model. You should be aware that PJM market's joint optimization model is described as a single five-minute dispatch for energy, control, synchronized reserves, and non synchronized reserves.

3.6 Procedure for Parameter Identification

In Figure 2, procedures for simulating EV charging load are shown. To mimic EV charging loads, and following process is suggested.

- The regional independent system operator (ISO) imports power grid operating data with assumption that a specific market mechanism would result in a specified degree of BEV, PHEV, and EV charging infrastructure penetration.
- Initial parameters for proposed mathematical model are established based on market data, such as kind of auxiliary service that EV load offers.

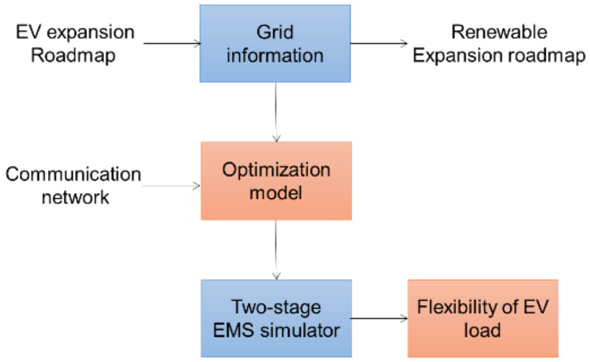


Figure 2: The proposed parameter identification process

- The suggested optimization model is used to simulate demand for EV charging. A two-stage EMS architecture is used to implement every simulation, and AMI is used to establish communication between system and EV consumers.
- Multiple simulations are used to calibrate necessary parameters in a suggested mathematical model. Both goals of power system and those EV consumers are taken into account as simulator facilitates exchanges between EV consumers and system operator.

The linked EVs must provide necessary EV data, such as departure time, SOC, and required minimal charge. The ISO aggregated EV limitations that have been submitted, while also downloading dispatch signals that are necessary. Thus PEV dispatch communication delay is 5 minutes. If real-time communication is allowed, AGC signals can also be delivered to BSSs, and EVCSs are proportionately split.

4. RESULTS AND DISCUSSION

A test system is constructed in this part to replicate a suggested model for EV load. Each parameter identification procedure from Section III-C is used to calculate how flexible about system's aggregated EV loads are.

4.1 Electric Vehicle (EV) Loads Test System for Modified IEEE 118-Bus

To model a combined EV load, an modified IEEE 118-bus test system is used. Every system has 19 online conventional generating units. With following adjustments, test system parameters are used: two wind farms with total capacities of 500 MW and 750 MW are located at buses 24 and 27, respectively. The BSS an SOC could not fall below 5%. Based on the arrival rates of EVs, service users' projected energy usage for battery swapping is calculated. The Poisson probability distribution is also used to produce a real battery switching load from these clients. The real battery switching demand from PEV customers that employ battery swapping services is determined via simulations, with predicted energy consumption of these consumers being set to 0. The test system does not include transmission line restrictions.

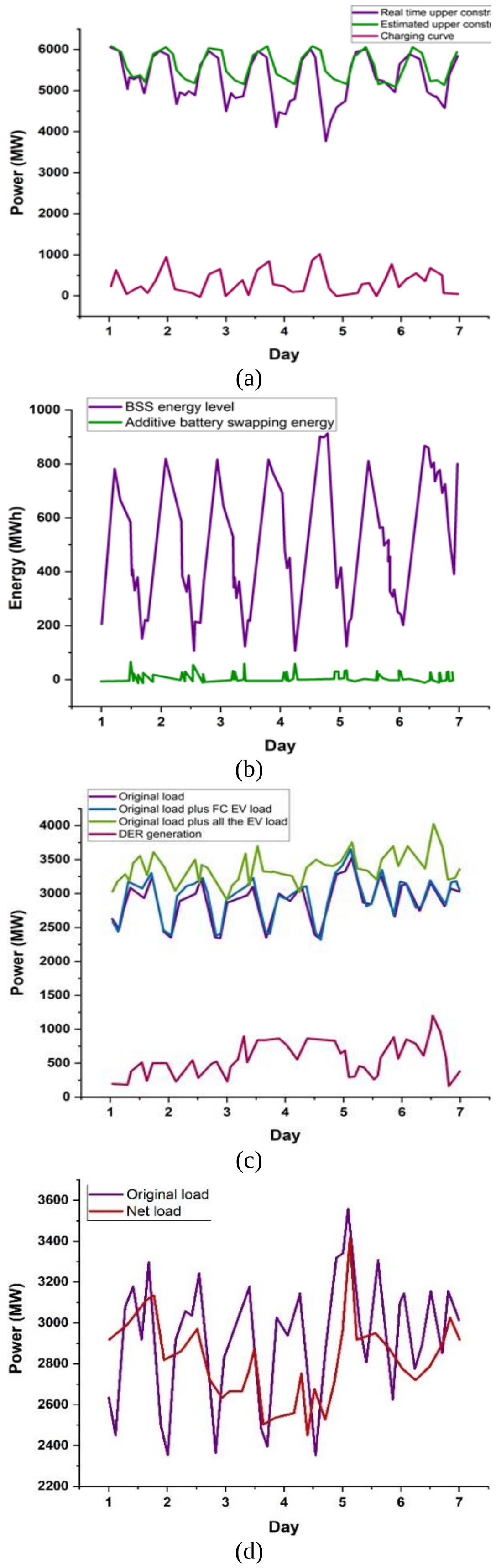


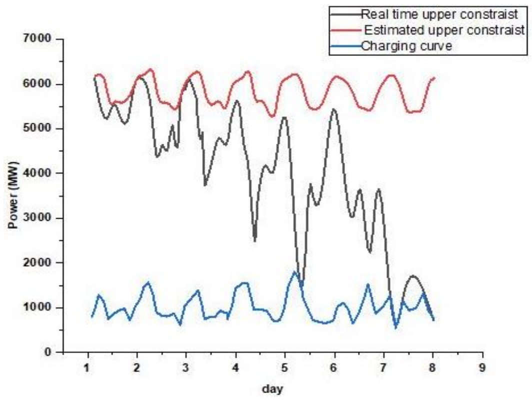
Figure 3. Illustrates the effects of various aggregated EV demands on power grid. (a) The charging curve for EVCS, (b) The energy usage of BSS, (c) Effect of EV load,(d) The net load

4.2 Results of Simulation

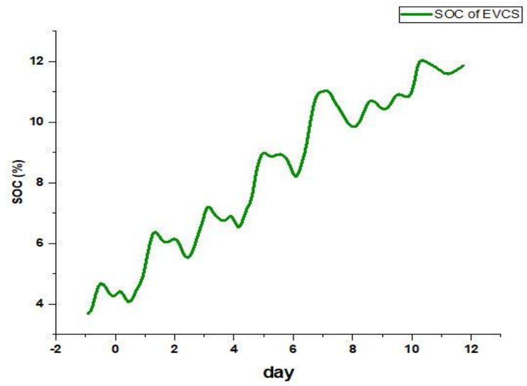
In test system, a suggested framework to execute economic dispatch simulations for a week. To execute all test case scenarios, MATLAB 2017a's CVX optimizer is used. Figure.3(a) shows in upper charging limitation of aggregated EVCS charging in real-time is roughly equal to estimated upper constraint, while lower charging constraint is almost zero and is not shown in to figure. The aggregated EVCS load maintains its flexibility. The economic dispatch outcome is a major factor that determines more than 1200 MW, which is highest charging power. There should be some room for EVCS oversubscription. Because customers typically change their batteries during an day, total BSS energy rises at night and falls during day, as shown in Figure 3(b). The PEV customers' additive battery swapping will reduce aggregated energy from BSS loads to less than 210MWh. Every peak of initial load will rise due to FC load shown in Figure 3(c). Significant EVCS and BSS load give flexibility, while FC load only makes up a minor portion of overall EV load. Therefore, combined EV load is not much changed by FC load; entire EV load incorporating all three charging sources exhibits a renewable follower feature. The net load may be reflected in overall power output as well. of conventional generators, and EMS lowers daily fluctuation about peak and off-peak demand to reduce system demand overall operation cost, as shown in Figure. 3(d).

4.3 Results of Parameter Identification for EV Flexibility

Flexibility of Combined EVCS and BSS Virtual Batteries Day Ahead: According to base case scenario, both maximum and lowest charging demand not considerably alter during week with predicted Energy Consumption (EC) of EVs within 24 hours in plug-in mode. Figures 4(a) and (b) demonstrate a maximum charging capacity would drop significantly once SOC of EVCS virtual battery approaches 70% when daily charging objective is set to $1.5E_C$. When daily charging goal is adjusted minimum charging capacity does not exceed 0.5 EC not significantly improve. However, as shown in Figure 5, battery swapping load from PEVs will significantly rise when Figure 4(d) shows that virtual battery's SOC is under 30%. The flexibility and PEV loads in system, are recommended to maintain EVCS virtual battery's SOC at least between 30% and 70%. Every range about SOC should be maintained between 40% and 60% to guarantee that 0.5 daily PEV requirement has no influence on charging restrictions.



(a)



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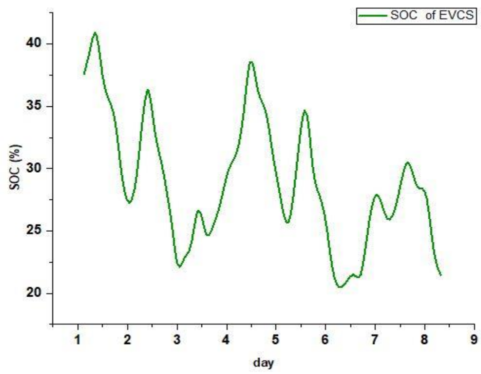
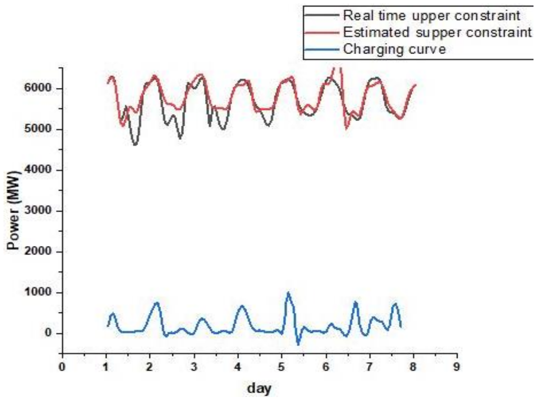


(c)



(d)

Figure 4. Flexibility about aggregated PEV loads throughout an coming day. (a) A 1.5 EC PEV charging curve, (b) 1.5 EC SOC of the EVCS, (c) A 0.5 EC PEV charging curve, (d) EVCS SOC with 0.5 EC

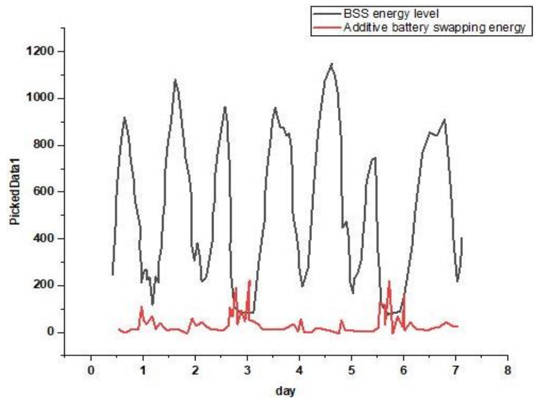
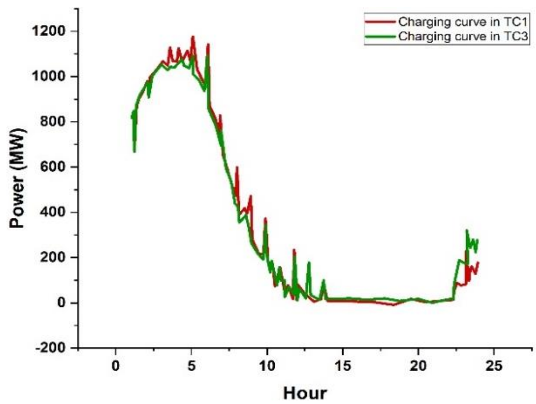
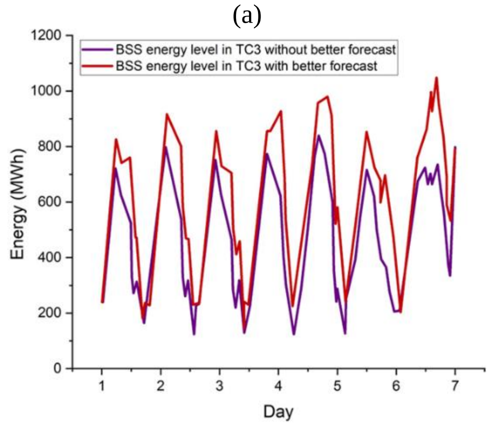


Figure 5. PEVs' added BSS load affects combined 0.5 EC, BSS virtual battery

Flexibility in Real-Time of Combined BSS and EVCS Virtual Batteries: A simulation of whole EV load is possible through a framework utilizing a joint optimization model thanks to EV loads that provide frequency control and real-time system connectivity. With exception of using a joint optimization model rather than an economic dispatch model, they have identical simulation settings as in Section IV-B above. The additional battery switching load from PEVs may be accomplished with initial simulation. When one runs the simulation again after substituting estimated values—which were initially taken to be zero—with simulation results from the first run, results are shown in Figure 6.



(a)



(b)

Figure 6. Comparing a joint dispatch model with an economic dispatch model, (a) The PEV charging curve on day five, (b) BSS use of energy

The EV charging Joint optimization model schedules for EVCSs are equivalent to base case economic dispatch model schedules and scenarios, with exception of a few hours, as shown in Figure 6(a). This is so that the system doesn't have to deploy as many EVs, which would require a considerably larger capacity for frequency regulation. But because of money generated by frequency control given combined EV loads as a consequence of joint optimization, fuel cost falls to 25.79 $/MWh. For these customers' EV demand, Figure 6(b) demonstrates that BSSs will likewise keep their energy level to prevent charging during peak times and use higher than reserved settings.

5. CONCLUSION

This article suggests virtual battery models for aggregated charging levels 1 and 2 for EVCS procedures also aggregated BSSs. To evaluate an effects of aggregated EV loads on system while taking into account two virtual battery models and FC EV loads, a data-driven technique is also implemented. The whole EV load can provide system power demand-side flexibility, according to suggested way. The suggested EV load modeling technique and related test platform may be utilized as a baseline to estimate various EV penetration levels, and market trends, and evaluate an impact of different EV charging infrastructure development strategies on power grid performance.

- The cases when there is insufficient EV charging infrastructure in system and describe how this affects an flexibility of aggregated EV load.
- Every availability of a large number of EV charging stations may be advantageous for EV users, encouraging many users to move from combustion cars to EVs without worrying about EV trip distance. The simulation findings show, that economic dispatch outcome largely determines real maximum charging power. Furthermore, it may be expensive for stakeholders to maintain a high adequate number of EV charging facilities, and it may be challenging to achieve a prompt investment return.

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