Comparison of Unidirectional and Bidirectional charging optimization using a composite EV load model

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SUMMARY

Electric vehicles (EVs) are a promising technology to reduce the carbon footprint, but their significant penetration into the existing power grid infrastructure has increased the overall burden and may affect the power system's stability and reliability. The introduction of Vehicle-to-grid (V2G) technology has shown great promise in frequency regulation, voltage regulation, peak load shifting, and spinning reserve while helping to achieve high integration of Renewable Energy Sources (RESs). This study aims to compare the unidirectional and bidirectional charging optimization techniques proposed to minimize the EV charging cost and the impact of high penetration of EVs on the grid. Through the bidirectional communication infrastructure, the aggregator exchanges real-time data at every given time step between vehicle and the grid to assess and optimize each EVs charging schedule. Once connected to the charging station, EV immediately updates the aggregator with all necessary information. Based on this information, the aggregator sends a command signal to charging stations to charge or discharge connected electric vehicles. Market regulation price and regulation reference announced by the Transmission System Operator (TSO) and Distribution System Operator (DSO) influences the aggregator decision.

In this case study, a Truncated Gaussian distribution function determines EV's time of arrival and departure. This study uses regulation signals provided by the Independent Electricity System Operator (IESO) for ancillary services supply in their regulation market. When grid requests regulation up, the aggregator sends a signal to increase the charging rate of the EVs until they reach their maximum capacity. During regulation down, the aggregator sends a command signal to discharge the EVs connected at the bidirectional charging stations. Whereas at the unidirectional charging stations, the EV changes its charging rate to reduce its energy consumption form the grid. The optimization functions consider charging schedule, initial and final battery SOC, arrival and departure times, regulation prices, battery degradation cost, battery aging cost, and vehicle charging requirements. The study demonstrates the performance of both optimization models using a standardized IEEE 14-bus distribution system. Each charging area consists of a composite load of 700 EVs with representative charging profiles and power ratings. The EV fleet consists of three different electric car models: Nissan Leaf, Nissan e-NV200, and Tesla Model S. The simulation results show the potentiality of using the existing fleet of electric vehicles to support the grid frequency profile while reducing charging costs for EV owners. Additionally, combining V2G technology would shave peak demand and minimize power losses throughout the network, mainly when it requires added active and reactive power during daily peak periods. The IEEE-14 bus optimal power flow is modeled and analyzed in MATPOWER. The test systems are modeled and simulated in MATLAB using YALMIP optimization solvers.

KEYWORDS

Electric vehicle (EV), vehicle-to-grid (V2G), State of charge (SOC), battery performance, charging station, grid regulation, dynamic pricing, smart-grid, unidirectional, bidirectional.

I. INTRODUCTION

In tackling the fossil fuel crises and reducing carbon footprint, electric vehicles are playing a crucial role. EV emerged as the target of growth in the transportation sector. According to China Automotive Engineering Association projections [1], by 2030, the number of electric vehicles in China will exceed 80 million. With a typical EV battery of 60 kWh, an equivalent energy of 4.8 billion kWh could be stored within the vehicles. This represents 22 % of China's daily energy consumption estimated at 21.7 billion kWh in 2019 [2]. Whether an electric vehicle absorbs electricity from the system or transfers it back, the net energy demand is considerable. Therefore, optimal management of EVs users' charging and discharging behavior can provide power to the grid and alleviate energy deficits [3]. Moreover, optimal energy and demand balance using EVs can now play a major role in improving grid stability and reducing peak generation requirements.

V2G technology has shown great promise in improving the stability and reliability of the system through participating in frequency regulation [4], voltage regulation [5], spinning reserve [6], and peak load shifting [7]. Electricity supply frequency is one of the most critical stability indices commonly used in the operation of a power system and should operate within regulatory bounds. Given the real-time response characteristics of EV chargers (usually around ten milliseconds), EVs performing regulation services have a natural advantage over other regulatory entities such as synchronous machines [8].

Through bidirectional communication infrastructure, the aggregator exchanges real-time data at every given time step between vehicle and the grid to assess and optimize each EVs charging schedule. Once connected to the charging station, EV immediately updates the aggregator with all necessary information: Initial/final State of Charge (SOC), arrival time, departure time, and system charging requirements. The aggregator optimization model, based on the information received from the charging stations, sends a command signal to charging stations whether to charge or discharge a group of plugged-in electric vehicles. Figure 1 illustrates the two-way energy and information interaction between EVs and the grid. The nonlinear programming model intends to simultaneously minimize the battery degradation costs and maximize the benefit for EV owners while taking part in grid regulation. This model is applied to both unidirectional and bidirectional vehicles considering constraints and EVs limitations.

Each EV provides grid regulation by injecting/absorbing active power into/from the grid while minimizing battery degradation and charging cost during a 24 hours simulation period. This study considers several scenarios with different EV penetration levels for both unidirectional and bidirectional EV charging optimization models. Section II describes both unidirectional and bidirectional charging techniques and how they can participate in grid regulation. In section III, an objective function models the optimal charging scheduling with constraints and EVs' limitations. Section IV presents possible case studies, while section V analyzes and discusses the simulation results. Finally, section VI draws the primary conclusions and recommendations for future work.
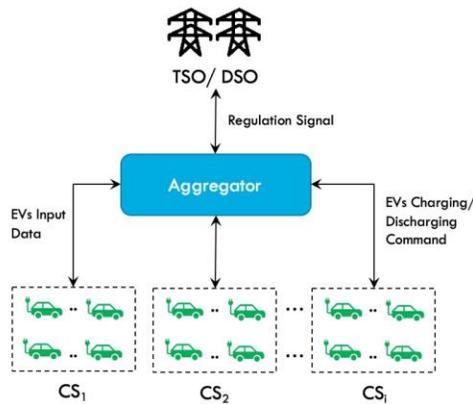

Figure 1. Interaction of EVs fleet with the grid using an aggregator

II. EV CHARGING TECHNIQUES

A. Unidirectional and Bidirectional System Architectures

The main components of the unidirectional and bidirectional systems architecture are the grid, charging station, and the electric vehicle [9]. In unidirectional charging, the energy can flow in only one direction, i.e. from the grid to the electric vehicle. However, in bidirectional charging, the energy can also flow back into the grid. The unidirectional or bidirectional flow of energy can be accomplished through a charging station containing an AC/DC converter and a control unit. The electric vehicle also contains a control unit as well as a high voltage battery. Both control units communicate to decide the amount of energy to exchange, its direction, its duration, and at what time. The flow of energy depends on the state of charge and the battery's rated power, the regulation needs of the grid, and the total load demand. An electric vehicle owner will use a unidirectional charging station to either charge the vehicle or provide regulation services to the grid. Whereas in the bidirectional charging station, the electric vehicle can also inject power into the grid to provide regulation services.

B. Charging Stations Types

Currently, EV charging stations are available in three different charging levels. The higher the level, the faster the charging rate, and the higher the charging power. For a level 1 charging station, an AC to DC converter is located inside the car, and it charges at 120 V with a current ranging from 15 to 20 A. This station typically provides 2 miles of driving distance for an hour of charging. Similarly, for a level 2 charging station, the converter is located inside the car, and it charges at 240 V with a current up to 80 A. An electric vehicle owner can expect to have 9 to 52 miles of driving distance for an hour of charging at a level 2 station. In contrast, DC power is delivered instead of AC power in a level 3 charging station. Its converter is located outside the car because of converter size and cost. Additionally, this level is not compatible with all current electric vehicles and is widely used in commercial locations. It charges electric vehicles at 480 V with a current up to 300 A; thus, an EV owner can expect to have 170 miles of driving distance for half an hour of charging. Existing EVs are compatible with one or two levels of charging stations.

C. Grid Regulation Services

The operation of both unidirectional and bidirectional charging involves an aggregator communicating with each charging station, which is further connected to a DSO. The aggregator organizes and facilitates EVs charging based on the regulation signal received from DSO/TSO and Retailer [11]. The electric vehicle updates all the necessary inputs to the aggregator when plugged at a charging station to predict the regulation capacity available at a bus. An electric vehicle charging schedule is generated based on EV's charging characteristics and regulation signal. The aggregator updates the charging schedule at a defined time step of half an hour based on the regulation signal variation. At defined time step, if the power generation is more than the overall power demand, the aggregator sends a signal to charge the electric vehicle at its rated charging capacity, thus performing regulation down. If the power generation is less than the overall power demand, in unidirectional systems, the aggregator sends a signal to charge the electric vehicle at less than its rated capacity to reduce the overall power demand at a bus. Whereas, in a bidirectional system, the aggregator sends a signal to the electric vehicle so that it injects power into the grid to increase the generation capacity, thus performing regulation up.

III. OBJECTIVE FUNCTION & CONSTRAINTS

A. Objective Function

The objective function J consists of two parts: J_1 the battery degradation cost and J_2, the revenue generated by EV from regulation services [8]. The goal is to minimize J_1 and maximize J_2 simultaneously using the decision variables $P_{ij}^{\downarrow}(t)$ and $P_{ij}^{\uparrow}(t)$ for each EV_{ij}:

$$J_1 = \sum_{i=1}^{N_{CS}} \sum_{j=1}^{N_{EV}} T_{Step} \times \left(|P_{ij}^{\downarrow}(t)| \times \eta_{ij}^{\downarrow} + \frac{P_{ij}^{\uparrow}(t)}{\eta_{ij}^{\uparrow}}\right) \times \epsilon_{ij}^{B}(t) \quad J_2 = \sum_{i=1}^{N_{CS}} \sum_{j=1}^{N_{EV}} T_{Step} \times \left(|P_{ij}^{\downarrow}(t)| \times \epsilon_{\epsilon}^{\downarrow}(t) + P_{ij}^{\uparrow}(t) \times \epsilon_{R}^{\uparrow}(t)\right)$$

So, the objective function becomes:

$$min_{P_{ij}^{\uparrow}(t),\, P_{ij}^{\downarrow}(t)}\, J = min_{P_{ij}^{\uparrow}(t),\, P_{ij}^{\downarrow}(t)}\, (J_1 - J_2)$$

The main parameters used are:

i and j:	Charging station index and Electrical vehicle index
N_{CS}:	Number of charging stations
N_{EV}:	Number of electric vehicles
T_{Step}:	Simulation time step
$\eta_{ij}^{\downarrow}$ and $\eta_{ij}^{\uparrow}$:	Charging efficiencies for regulation down and up
$\epsilon_{\epsilon}^{\downarrow}, \epsilon_{R}^{\uparrow}$:	Energy rewards for regulation down and up
ϵ_{ij}^{B}:	Total wear cost of the battery of EV_{ij}
P_{ij}^{max} :	Rated battery power of EV_{ij}
SOC_{ij}:	State of charge of EV_{ij}
E_{ij}^{max} :	Maximum energy of the battery of EV_{ij}
Pr_{ij}:	Battery price of EV_{ij}
η_{ij}:	Cycle efficiency of the battery of the EV_{ij}
α and β:	Battery related parameters
R^{ref}:	Regulation signal from grid operator

To calculate ϵ_{ij}^{B} , the following equation is used:

$$\epsilon_{ij}^{B}(t + T_{Step}) = \phi_{ij}\left[\frac{\beta \times \left\{[1 - SOC_{ij}(t + T_{Step})]^{\beta-1} - [1 - SOC_{ij}(t)]^{\beta-1}\right\}}{\alpha}\right] \qquad \text{where } \phi_{ij} = \frac{Pr_{ij}}{2 \times E_{ij}^{max} \times \eta_{ij}^2}$$

B. Constraints

In both the unidirectional and bidirectional optimization models, the primary constraint is SOC which is bounded between a range of 4% and 95% as follows:

$$0.04 \leq SOC_{ij}(t) + \left(\frac{|P_{ij}^{\downarrow}(t)| \times \eta_{ij}^{\downarrow} - \dfrac{P_{ij}^{\uparrow}(t)}{\eta_{ij}^{\uparrow}}}{E_{ij}^{max}}\right) \times T_{Step} \leq 0.95$$

1) Bidirectional Model Constraints:

For $R^{ref}(t) \geq 0$: $\quad P_{ij}^{\downarrow}(t) = 0$ & $0 \leq P_{ij}^{\uparrow}(t) \leq P_{ij}^{max} \quad$ and $\quad \sum_{i=1}^{N_{CS}} \sum_{j=1}^{N_{EV}} P_{ij}^{\uparrow}(t) \leq R^{ref}(t)$

For $R^{ref}(t) < 0$: $\quad P_{ij}^{\uparrow}(t) = 0$ & $-P_{ij}^{max} \leq P_{ij}^{\downarrow}(t) \leq 0 \quad$ and $\quad \sum_{i=1}^{N_{CS}} \sum_{j=1}^{N_{EV}} P_{ij}^{\downarrow}(t) \geq R^{ref}(t)$

2) Unidirectional Model Constraints:

For $R^{ref}(t) \geq 0$: $\quad P_{ij}^{\uparrow}(t) = 0$ & $P_{ij}^{\downarrow}(t) = 0$

For $R^{ref}(t) < 0$: $\quad P_{ij}^{\uparrow}(t) = 0$ & $-P_{ij}^{max} \leq P_{ij}^{\downarrow}(t) \leq 0 \quad$ and $\quad \sum_{i=1}^{N_{CS}} \sum_{j=1}^{N_{EV}} P_{ij}^{\downarrow} \geq R^{ref}(t)$

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IV. PERFORMED STUDIES

Four case studies are considered to firstly demonstrate the feasibility of the proposed model, secondly to compare the effectiveness of regulation in bidirectional and unidirectional charging models, thirdly to assess the impact of battery degradation on the overall cost reduction and finally, to assess the impact of EV availability on grid regulation performance. Both cases resolve the same objective function to obtain the charging or discharging rates for every vehicle at defined time steps throughout a day.

A. Case studies

1) *Bidirectional with battery degradation model:* This case includes a battery degradation model in the objective function to optimize the charging and discharging cycles and increase the overall life cycle of the battery. This case represents a more realistic model of the V2G operation, and its results would assess the revenue of an EV owner participating in regulation services while considering the impact on the battery.

2) *Bidirectional without battery degradation model:* This case removes the battery degradation model from the objective function. This allows us to understand the impact of battery degradation in overall cost. Previous studies demonstrated that the battery degradation cost introduced by extra charge/discharge cycles while participating in regulation was negligible compared to regular aging costs [4]. The results from this case serve as a baseline to validate the impact of battery degradation in the objective function and its effect.

3) *Bidirectional with variable EV availability:* EV availability is a challenge in charge scheduling. Case 1 and Case 2 assume that all the EVs continuously participate in grid regulation services. Previous studies suggested that prediction models can be used to assess the number of EVs available at each time of the day for a more realistic approach [12]. This case applies a truncated gaussian normalization model to obtain the number of EVs available throughout the day considering typical daily behaviors of owners.

4) *Unidirectional with battery degradation model:* This model applies to the current EV market, where G2V technology is more prominent than V2G. Previous studies proposed controlling the charging rates to perform regulation services with unidirectional chargers [13]. This study aims to demonstrate that G2V infrastructure can also perform grid regulation services and reduce EV charging costs. This case results allow us to compare with bidirectional models in terms of frequency regulation and charging cost optimization.

B. EV Parameters and the Network Under Study

The EV parameters selected for the case studies belong to vehicles with three types of charging powers, as indicated in Table *1*. Each charging area consists of a mixed fleet of 700 EVs, with each EV having its charging station modeled as a variable load. The distribution network is based on the IEEE 14 bus system comprising conventional generators, transmission lines, synchronous compensators, and step-down transformers with EV loads and Toronto residential load connected on the low voltage nodes.

Table 1. EV parameters

Vehicle type	Charging power (kW)	Battery Capacity (kWh)	Battery Price ($)
Nissan Leaf	7	24	6400
Nissan e-NV200	22	40	9700
Tesla Model S	50	100	24000

Table 2. Data for model simulation

Charger efficiency	90…95 %
Cycle efficiency	99 %
EV fleet	7x700 EVs
SOC range	4 – 95 %
Time step	30 min

C. Optimal Power Flow Analysis

The optimization problem is modeled in MATLAB and computed using YALMIP solver. Ontario regulation market price (Figure 3) is used to calculate the overall benefit for EV owners while providing grid regulation services. The simulation results provide the optimal charging or discharging rates for each vehicle throughout the day using the signal provided by IESO. The simulation output is fed into the MATPOWER Case 14. An optimal power flow analysis allows us to determine EVs impact on grid stability.
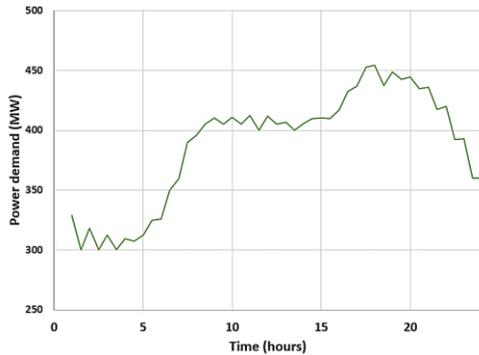
Figure 2. Toronto load profile
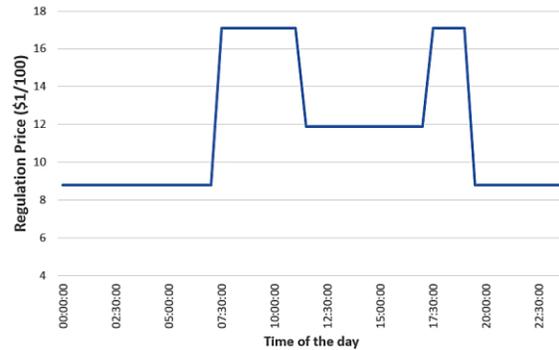
Figure 3. Regulation reward for Ontario market

V. SIMUALTION RESULTS AND DISCUSSION

A. Bidirectional Optimization Model

The real-time power injected/absorbed by the fleet of EVs to provide the grid regulation are compared with the regulation signal sent by the TSO/DSO every 30 minutes (Figure 4). In this case, EVs can meet regulation services as requested by the grid at every time step.
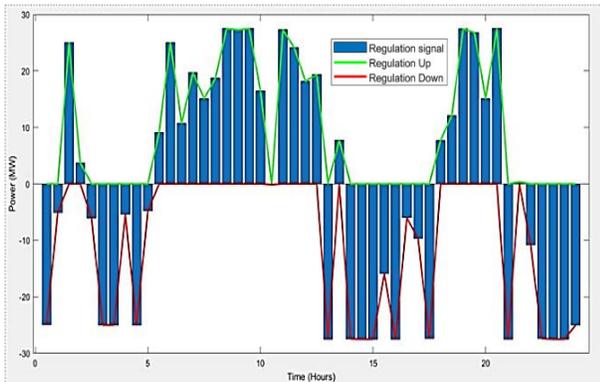

Figure 4. Regulation support by bidirectional EV
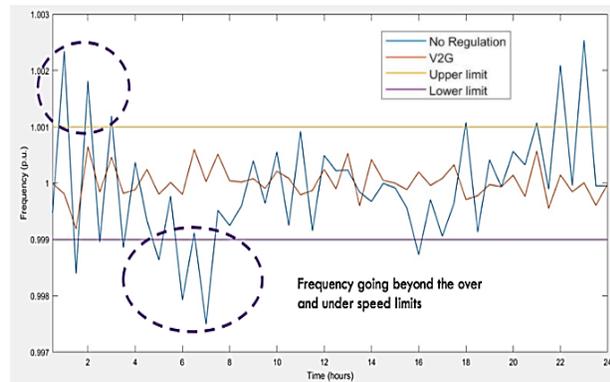

Figure 5. Frequency response by bidirectional EV

In Figure 5, the Toronto frequency profile without regulation is plotted in blue. The frequency, in some instances, goes beyond the permissible limits, which may affect the grid stability and reliability. Whereas, when bidirectional EVs perform regulation up and down as requested by the grid, it improves the grid frequency and maintains it within the tolerance limit, as shown in orange. In case 2, the bidirectional charging station without the battery degradation model has a marginal difference compared to case 1 despite the possibility of V2G having an impact on EVs battery life. In case 3, bidirectional with variable EV availability is also able to regulate the frequency within the permissible limits throughout the simulation as the number of EVs in the case study is enough to meet the requested grid regulation.

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B. Unidirectional Optimization Model

In the unidirectional charging model, EVs cannot take part in grid regulation whenever it is requested by the grid. Hence, regulation up remains zero throughout the simulation. On the other hand, EVs can participate in regulation down if their SOC falls within limits. As shown in Figure 6, they cannot participate in regulation after t =15 hours because they reached their maximum SOC of 95%.
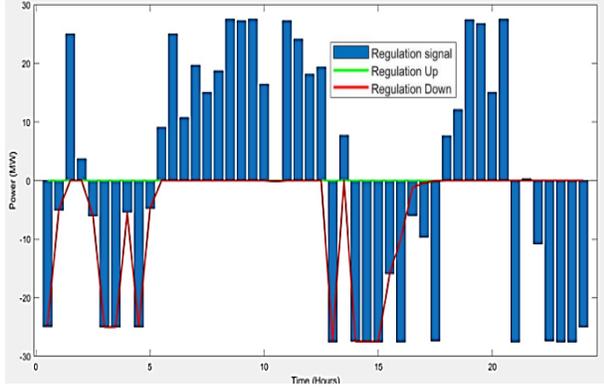

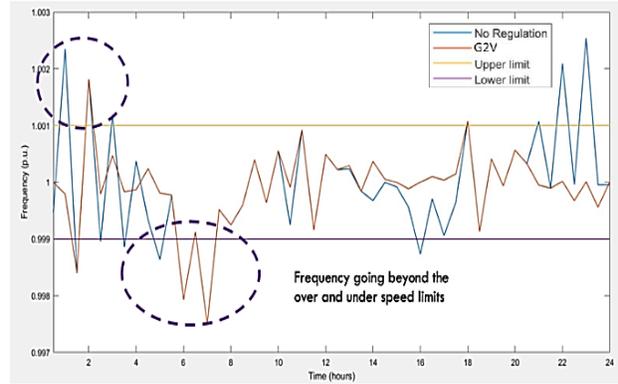*Figure 6. Regulation support by unidirectional EV*   *Figure 7. Frequency response by unidirectional EV*

As unidirectional EVs cannot perform regulation up, they cannot inject active power to bring the frequency back within the permissible limits, as shown in Figure 7. Hence, the frequency profile results replicate the unregulated Toronto frequency profile whenever regulation up is requested from the grid. On the contrary, they can perform regulation down by charging EVs to reduce frequency deviation, as shown in orange, until all the EVs are fully charged.

C. Comparision of Unidirectional and Bidirectional Cost Optimization Models

As shown in Figure 8, the bidirectional charging stations earned profit throughout the day by actively participating in regulation services, whereas the unidirectional charging stations only participated in regulation down until t =15 hours as all EVs get fully charged.

Table 3. Earned profit under given scenarios

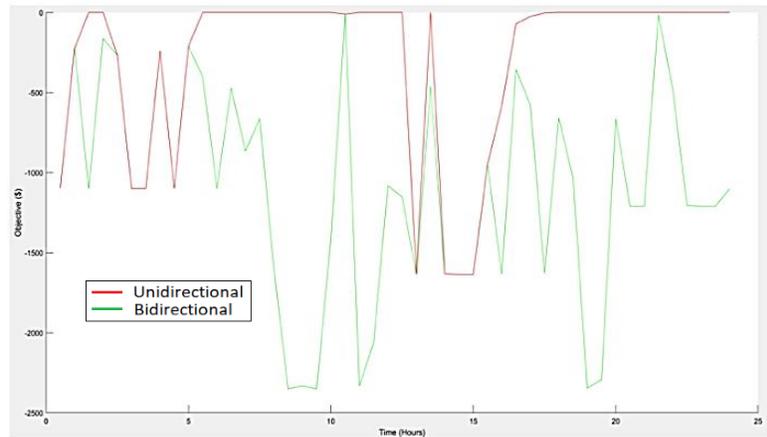| Study	Earned Profit (per day)
Case 1	$ 10.932
Case 2	$ 10.925
Case 3	$ 10.366
Case 4	$ 2.759

Figure 8. EVs' earned profit during grid regulation

The overall profit earned by providing grid regulation services increases significantly b y using the proposed V2G strategy compared to the G2V (i.e., an average of $10.932 per day using V2G versus $2.759 per day without V2G). Table 3 presents the average daily profit earned by an EV from grid support for all the above-mentioned possible cases. The above results show the possibility of earning profit using an EV during idle time.

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VI. CONCLUSION AND FUTURE WORK

This paper demonstrates how V2G and G2V can improve grid stability while minimizing the charging cost of an EV owner. The study conducted using a Nissan Leaf, a Nissan e-NV200, and a Tesla Model S, shows that EV owners can generate around $10 daily by using their electric vehicle for grid regulation services in the Ontario market. The optimization model includes the revenue earned through power exchange with the grid and a battery degradation cost based on the number of charging/discharging cycles. The simulation model uses an IEEE 14 bus system, including the Toronto's residential load profile and EV charging stations modeled as variable loads. The results demonstrate that both unidirectional and bidirectional charging schemes can maintain the frequency profile within grid regulation limits. However, V2G offers higher performance due to its ability to participate in both regulation up and down throughout the day.

This study mainly considers EVs as standard mobile energy storage devices continuously available for regulation services. A further approach would be to integrate a prediction model that predicts the availability of EV at a given daytime and their energy demand. Moreover, this study can be extended to include a voltage regulation scheme, allowing available charging stations to inject or absorb reactive power in order to support the grid voltage profile. Finally, charging stations integrated with remote distributed energy resources, like solar and wind, can be used to charge EVs during off-peak hours and then perform peak shaving.

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