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A VEHICLE-TO-GRID FRAMEWORK FOR POWER SYSTEM UNIT COMMITMENT

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Abstract
The projected growth of plug-in electric vehicles on roads has the potential to produce challenges to the operational stability of power systems, particularly when a significant number of these vehicles charge and discharge concurrently. However, if plug-in electric vehicles in a vehicle-to-grid system are properly managed, they can be transformed from potential problems for the electrical grid to benefits. Some benefits from smart management of plug-in electric vehicles integration into the power grid include cost reduction and load leveling. This study describes a preliminary unit commitment framework for a vehicle-to-grid system. The methodology incorporates controlled charging and discharging as well as battery degradation into the unit commitment problem. The framework described in this study is useful to engineering managers because it enables smart control of plug-in electric vehicle integration into the power grid which can lead to reduction in generation cost and leveling of the load profile.

Keywords
Unit commitment, Vehicle-to-grid, Battery degradation, Plug-in electric vehicles.

Introduction
Due to the alarming rise of global temperatures and the devastating effects of climate change on many communities around the world, the International energy Agency (IEA) has set a goal to reach net-zero emissions by 2050 (IEA, 2021b). According to IEA, the global population of plug-in electric vehicles (PEVs) including battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) is expected to grow from 10 million in 2020 to over 115 million in 2030 (IEA, 2021a). Although increasing the number of electric vehicles is a viable option for reducing carbon emissions, mass adoption of PEVs, which are charged by plugging the vehicles into electrical power sources, would introduce many challenges to existing power systems. The uncontrolled charging and discharging activities of large number of PEVs can significantly stress the power system causing major voltage fluctuations and higher cost of operation (Rahmani, Hossein Hosseinian, & Abedi, 2021). However, through smart management, PEVs can provide ancillary services to support the power system as distributed storage units. PEVs can be integrated into the power systems as load and supply via vehicle-to-grid (V2G). PEVs have the potential to operate as mobile storage units to store the excess generated power or to support the grid through discharging at the given times, resulting in lower cost of generation and higher load-leveling (Y. Wang et al., 2019).

There are many studies on the possible impact of high penetration levels of PEVs on the electricity markets. Shamshirband, Salehi, and Samadi Gazijahani (2019) studied the possible benefits of increasing the profits of PEVs owners to promote consumers to switch to PEVs. The authors proposed a multi-objective model to maximize the owners' profits and minimize the operation cost. The results indicate that mass adoption of PEVs has high potential of reducing greenhouse emissions and voltage instability while achieving significant profitability for owners. In a study by Uko, Egbue, and Naidu (2020), the authors incorporated V2G into the economic dispatch (ED) problem to coordinate charging and discharging activities of 20,000 PEVs. PEVs were found to be effective in addressing demand-side problems and responding to frequency balancing. In addition, controlled V2G has been used to smooth load fluctuations (Kiviluoma & Meibom, 2011), improve voltage stability in urban power grids (Lyu et al., 2020) or offset the power uncertainty in renewable energy resources (M. Wang et al., 2017). Incorporating PEVs in future power system planning is therefore inevitable and can lead to the abovementioned benefits. However, discharging conditions in V2G mode can cause significant degradation to PEV batteries. Therefore, including battery degradation for PEVs involved in V2G is important to analyze the operation of V2G systems from the perspective of consumers (Sufyan et al., 2020). The challenge to this problem is how to evaluate the impact of battery degradation cost on the decision-making process while considering PEVs behavior in a power system with high penetration level PEVs. This research builds on the work by Uko et al. (2020) and proposes a framework to incorporate PEVs' driving patterns and battery degradation into a unit commitment problem through a controlled V2G approach.

Background

A unit commitment (UC) problem refers to a mathematical procedure of scheduling power generation units to meet the forecasted load. UC is often solved along with ED to minimize the total cost of generation (Nemati, Braun, & Tenbohlen, 2018). UC is used to determine the optimal on/off schedule of the generation units, subject to economic and technical constraints. Although, most UC problems are deterministic in nature, many articles on UC are based on stochastic formulations (Håberg, 2019). In addition to the traditional UC problem, studies have considered the uncertainty of incorporating renewable energy (Li, Zhou, Xu, Zhu, & Ye, 2021), and integrating an emission function into the UC problem to minimize the emission cost and the generation cost simultaneously (Nicolosi, Alberizzi, Caligiuri, & Renzi, 2021).

Due to the flexibility of the UC problem, numerous formulations have been proposed in the literature (Abujarad, Mustafa, & Jamian, 2017). An important UC approach is security constrained UC, where transmission constraints are considered. In practice, UC produces a generation schedule in day-ahead market on an hourly basis in real time. In comparison to traditional UC models, security constrained UC problem guarantees feasible power flow by taking in account the network technical characteristics (Hosseini Imani, Jabbari Ghadi, Shamshirband, & Balas, 2018). This is very important for independent system operators to ensure that short-term schedules are economically and technically feasible. However, this introduces more complexity to existing UC problems. Several approaches have been proposed to solve the security constrained UC as a mixed-integer nonlinear problem such as benders decomposition (Yong, Shahidehpour, & Zuyi, 2005), Lagrangian relaxation (Fu, Li, & Wu, 2013) and DC approximation (Isuru, Hotz, Gooi, & Utschick, 2020).

Current research on the impact of a high penetration level of PEVs in power systems is generally focused on regulating power supply and demand balance within the UC problem (Y. Wang et al., 2019) or mitigating the impact of renewable energy variability (Ahmadi, Nezhad, Siano, Hredzak, & Saha, 2019). An accurate model of the charging and discharging activities is critical to the management of the power system. Furthermore, the cost of battery degradation is often neglected in studies (AlHajri, Ahmadian, & Elkamel, 2021; Talebizadeh, Rashidinejad, & Abdollahi, 2014; Vasiyullah & Bharathidasan, 2021). Few studies in the literature have investigated the security constrained UC problem with large numbers of PEVs while considering these factors. Therefore, it is necessary to consider smart charging and discharging of PEVs as well as driving patterns and the impact of battery degradation from V2G activities when studying a high penetration of PEVs in a UC problem (Uko, 2020).

Methodology

This research incorporates V2G into a security constrained UC model with DC approximation to evaluate the impact of PEVs activities on power generation. The DC approximation simplifies the voltage equation which allows the optimization problem to be solved as a mixed integer linear program (MILP). The general model of this problem can be written in the form:

$$\text{Minimize generation cost} = \sum Fuel_{cost} + startup_{cost} + shutdown_{cost} + \ Degradation_{Cost} \quad (1)$$

Subject to

- Generator limit constraints
- Ramping constraints
- Uptime and downtime constraints
- Flow constraints
- Transmission constraints
- V2G constraints

Battery degradation and travel patterns are considered to achieve more realistic integration of V2G into the security constrained UC problem. Driving schedules are utilized as input to determine the distribution of PEVs during the study period. These driving behaviors are then used to generate possible charging schedules of different PEV types. The cost of degradation in equation 2 is a function of charging/discharging cycles, accumulated energy x, battery capacity B_{cap} and battery cost B_{cost}. A linear approximation by Ortega-Vazquez (2014) is used to model the battery life as a function of cycles with slope k.

$$Degradation\ Cost = \left|\frac{k}{100}\right| * \frac{B_{cost}}{B_{cap}} * x \quad (2)$$

Optimization Framework for Vehicle-to-Grid and Unit Commitment

Consider a power system with m dispatchable generators with non-PEV and PEV load demand. Here, the charging stations are randomly assigned to selected buses and it is assumed that all charging stations are managed by one aggregator and that departure times and target SOCs are known in advance. This allows the model to obtain the dynamic SOC of PEVs over the planning horizon. Arrival, dwell and departure times can be simulated or generated using historical travel data sources such as the National Household Travel Survey (NHTS) (McGuckin, 2018). Other information, such as load demand profile, battery's physical properties and types of vehicles are also considered. The goal of the framework described in this paper is to develop a UC model for a smart power grid with V2G services. This UC model incorporates battery degradation and travel behavior of individual vehicles to address the challenges posed by high penetration of PEVs. The flowchart in Exhibit 1 summarizes the steps involved in the optimization model.

Historical travel data of various activities such as work, school and shopping are fit to a non-parametric distribution. This distribution is then used to generate N number of arrival, dwell, and departure times for each vehicle over the planning horizon. In addition to arrival, departure, and dwell times, each PEV is assigned vehicle and battery properties. Random initial, target and minimum required SOC for each vehicle is generated based on battery capacity. Similarly, historical hourly load demand and electricity prices are used to generate hourly non-PEV load profile and charging/discharging costs. Finally, fuel cost, ramp up/down costs and start-up/shutdown costs for each thermal unit are assigned. To start the model, PEVs are assigned randomly to the selected buses at each discrete time step i. This is important to evaluate the feasibility of the solution under security constraints. The objective function of the model is to minimize the total operation cost taking in account the generation cost and the cost of battery degradation. Therefore, total PEV demand (charging) and supply (discharging) during each period is computed while meeting the following constraints:

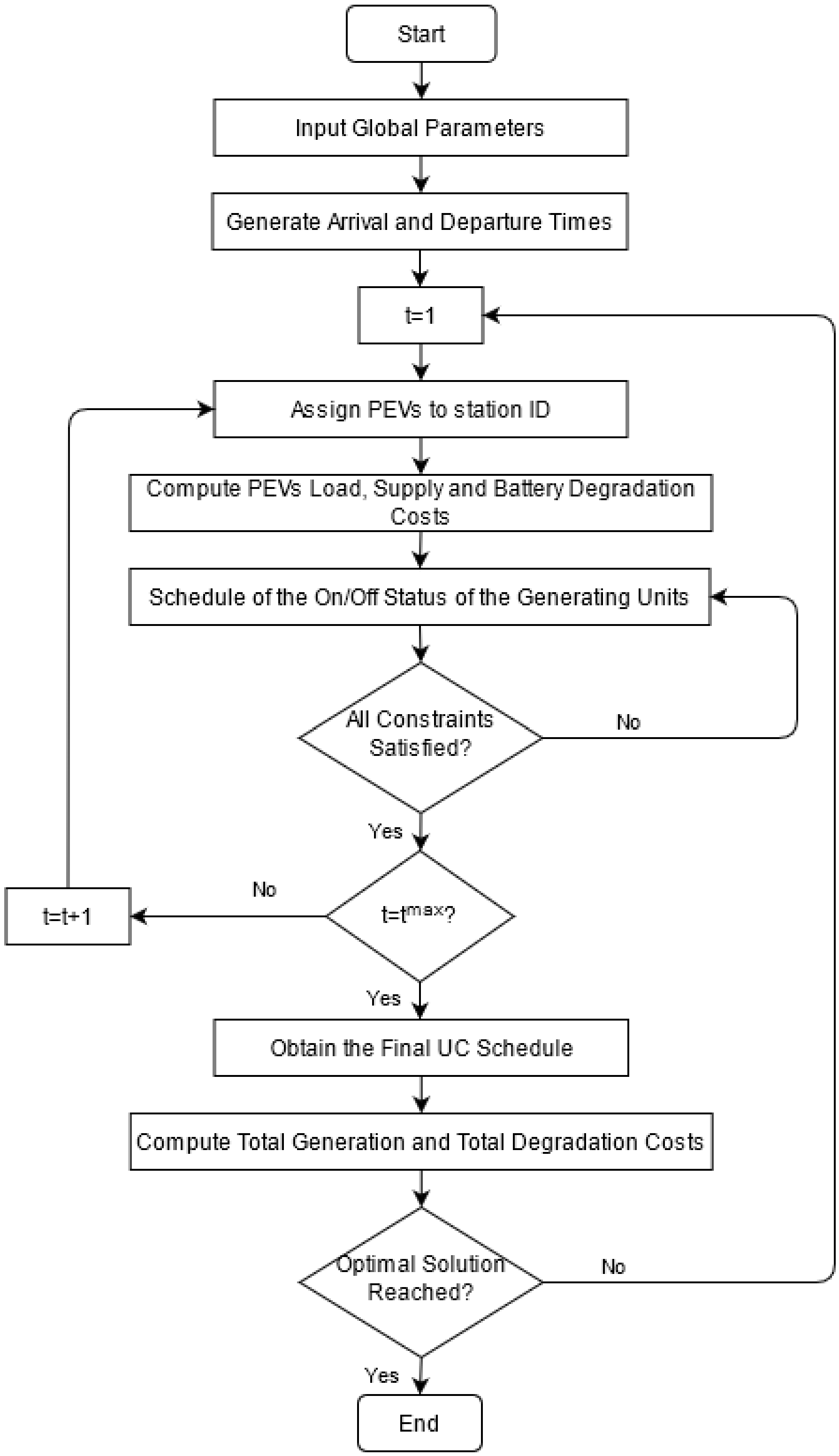
a) Maximum SOC is less than the maximum battery capacity.
b) The battery cannot be discharged beyond the minimum required SOC.

The model checks the start-up and shutdown costs of all units to ensure that the highest priority is given to units with the lowest start-up or shutdown cost. If generating units are operating within the minimum and maximum capacity range, the model will check if ramping up or down is sufficient to meet the load demand without starting-up or shutting down any unit. In addition, generating units are subjected to minimum uptime and downtime. The model then schedules the generation units that meet the above constraints while ensuring that the total power flow P_{nb} between the buses and nodes are balanced according to the following equation:

$$\sum Generated\ Power - \text{nonPEV Demand} - \text{PEV Demand} + \text{PEV Supply} = \sum_{nb} P_{nb} \quad (3)$$

At the end of the planning horizon, the model obtains the optimal unit commitment schedule and computes the total cost of generation and degradation. For high-penetration cases where the PEV demand is higher than the non-PEV demand, the model will ensure higher discharging amount or delay charging activities during the peak load to avoid the higher cost of starting-up more expensive generating units. On the other hand, during low demand periods the model will limit the discharging activities to avoid the shutdown costs as well. This flow balance is essential to load leveling and can explain the behavior of the generating units at different penetration levels. In contrast, if V2G is not implemented PEVs will start charging to their target SOC on arrival and can put the system under higher stress during the peak hours. In addition to higher cost of generation, generating units can be subjected to instability due to high load fluctuations. The flexibility of this model gives it the ability to study different scenarios and evaluate the impact of PEVs on the system.

Exhibit 1. Flowchart of the V2G Unit Commitment Model



Conclusion

Unit commitment is a very important problem in power system management. As electrical power systems evolve, new models are needed to address new changes. In this paper, a framework for a security constrained unit commitment is introduced to address the impact of plug-in electric vehicles on the power system. This work proposes a controlled V2G approach to support the power generation in a system with high penetration level of PEVs. Two main considerations in this work are battery degradation cost and driving patterns.

Future Work

The proposed optimization model is deterministic and uses offline information. In practice, PEV arrival times, load and generation forecast data are stochastic. The work can be extended to be solved as an online model by removing some of the assumptions with respect to arrival times, SOC and load demand. The impact of V2G on the reliability of PEV batteries is not investigated in this research. Reliability analysis is needed to determine any lifetime impact from cycling that could cause unexpected failures. The impact could be translated to a higher degradation cost, which could then be used to improve the proposed model. Furthermore, a future study can incorporate renewable energy sources which represent an increasing share of power generation mix.

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