Scheduling optimization for smart microgrids considering two-levels transactions of electric vehicles and energy markets

J Garcia-Guarin¹, W Infante², D Alvarez¹, and S Rivera¹
¹ Grupo de Investigación en Compatibilidad Electromagnética (EMC-UN), Universidad Nacional de Colombia, Bogotá, Colombia
² Centre for Future Energy Networks, University of Sydney, Sydney, Australia

E-mail: pjgarcia@unal.edu.co

Abstract. Smart microgrid planning poses some challenges, including bi-directional energy flow both inside and outside the smart microgrid. This research studies at the internal flow level energy transactions with the internal resources of the microgrid, and at the external flow level the energy transactions with external stakeholders to the microgrid. Electric vehicles can operate bidirectionally and participate at the internal and external level of smart microgrids. In this context, this study analyzes electric vehicles both levels. (1) At the level of internal participation, electric vehicles operate in a residential area of a microgrid that is also connected to energy storage systems and elements with uncertainty, such as photovoltaic generation systems and residential loads. Prices are set by considering operating costs within the smart microgrid. (2) The level of external participation refers to an electric vehicle station that offers three services: charging, discharging and swapping battery. Prices are stochastic and come from the spot market prices of electric vehicles. Consequently, it is proposed that the aggregator must plan the optimal scheduling for the visit scenarios of two-level stochastic electric vehicles. The system can also trade energy that come from a local and wholesale energy market. Results demonstrate that two-level operation can help to evaluate the economic impact of electric vehicles.

1. Introduction

Smart microgrids (SMGs) can form smart grids, operating in medium and low voltage levels, and interact with prosumers, demand, and generation [1]. Thus, the prosumers can both generate and consume energy. For example, energy storage systems (ESS) and electric vehicles (EVs) can be added to play the role of prosumers. [2,3]. In addition, EVs can promote significant reductions in emissions of CO₂ [1]. An aggregator can operate the aforementioned prosumers as their own resources and seeks to improve profits for the SMG as a single system [2,4].

EVs have proved to be more efficient; however, currently the total cost of ownership may be more expensive than gasoline vehicles. However, government policies or subsidies can help to change this situation, which should motivate EV demand [1]. Vehicles-to-grid (V2G) have long charging periods unlike combustion vehicles that are quickly recharged [5]. An EV connection program is uncertain and depends on the users’ driving habits [6,7]. In addition, SMG scheduling may have additional problems related to expected demand, renewable generation forecasts and variability of electricity prices [2].

EVs can be integrated with other elements such as ESS, which supply and demand energy to the SMG [8]. However, charging-only EVs may be less attractive for demand management than EVs offering other services such as battery discharge and swapping [7,9]. Therefore, specialized infrastructure should be deployed to offer these services [5]. Battery swapping stations can reduce the
recharging time for electric vehicles [5], becoming competitive with the refueling of gasoline or gas vehicles. However, anxious drivers who may want to swap batteries can make wasteful decisions [10].

Models with participation of EVs and SMGs are listed by author and also include uncertain factors associated with EVs and EMs [2,6,7,9,11–15]. This review covers the comparison of SMG, EM, EV prosumer (EVP), EV distributed (EVD) in residential SMGs and BSS. The models are explained in detail below. EV BSS model of Liu considers the day-ahead programming with two uncertainty sources: the demand for swapping batteries and the photovoltaic generation. Model of Liu neglects other features of EVs such as battery discharge and the uncertainty of EMs [9]. EV BSS model of Infante addresses uncertainty for the visit of EVs to the station and the allocation of EMs spot prices. Visits are forecast by using the K-means method. Model of Infante disregards the operation of EVs distributed in a residential SMGs [7].

SMG model of Lezama and EV BSS model of Garcia schedule operation for a SMG, have access to EMs, and EVs operate as prosumers [2,6,8,15]. The profits fluctuate due to inaccurate EV travel patterns, demand forecast, expected solar generation, and variability of EM prices [2,6,8,15]. Model of Lezama limits its study to EVs in residential areas and disregards the installation of the BSS in the SMG [2,15]. In contrast, model of Infante analyzes a BSS in the SMG and disregards the operation of EVs in residential microgrids [6]. In addition, model of Mark studies the uncertainty of renewables and EVs assigned to nodes, and neglects EMs and state of charge (SOC) of EVs [11].

The EV model of Li T. studies a charging station with EVs distributed and includes stochasticity in the EV arrival distribution, capacity, and initial SOC. Model of Li T. recommends varying electrical prices in future studies, and the EV station does offers no services of swapping and discharging batteries [12]. The EV BSS model of Saker optimizes market prices in real time, analyzes the stochastic arrival of EVs and proposes analyzing bi-directional charging in the future, that is, charging and discharging batteries [13]. The EV BSS model of Li J. solves this problem by proposing two-way flows to the grid and between batteries inside the substation. One problem of this model is the centralization of the substation services [14].

The EV BSS model of Garcia is developed in this article and has two levels of participation of EVs. At the first level, EVs are supplied by a residential SMG and operate in two modes: V2G and grid-to-vehicle (G2V). The operation is coordinated through an aggregator and the distribution of the connection points gives greater flexibility to the demand. The SMG hosts EVs, ESS, renewable generation and residential loads. The first level encompasses uncertainty related to traveling with EV distributed in the residential SMG. The aggregator negotiates in EMs with volatile prices for both energy supply and demand. At the second level, services are centralized in a BSS. The aggregator can accept or reject the swapping of EVs batteries and in case of rejection, it receives a penalty. The BSS is an asset belonging to the aggregator that tries to reduce costs using two connection modes from the BSS to the SMG or from the SMG to the BSS. Additionally, the aggregator schedules the SMG operation considering the two levels of EVs uncertain participation.

In summary, model of Garcia is the most complete according to the literature review and overcomes weaknesses of previous models related to operation in the SMG, battery discharge, distribution of EV connection points in a residential SMG, operation of the BSS, implementation of EMs, monitoring of SOCs of EVs and market price variability [2,6,7,9,11–15]. The variable neighborhood search (VNS)-differential evolutionary particle swarm optimization (DEEPSO) algorithm is used to optimize the SMG with two levels of EV participation. The algorithm was tested at the first level of EVs operation and proved to have the best performance in a microgrid [4,15]. This heuristic also showed a good performance in the second level of EVs participation [6].

The VNS-DEEPSO obtained higher performance than DE/rand/1 in 279 % microgrid with uncertainty of EVs [8]. The VNS search strategy is to explore a number of neighborhoods and store the best suboptimal of the search space [16]. The DEEPSO algorithm has better properties for the exploitation of an optimum operation point, based on three heuristics that intensifies the search. (1) Differential evolution generates new particles, (2) evolutionary algorithms promote self-adaptation and (3) particle swarm optimization improve exploration. Finally, the EV BSS model is formulated in the
following section and optimized with the VNS-DEEPSO algorithm [17]. This heuristic reduces operating costs for scheduling a residential SMG [15]. The optimization results show potential benefits of implementing two levels of participation of EVs and make the following contributions.

- An aggregator manages services in two levels for EVs that use: (1) a residential SMG and (2) the battery swapping station (BSS). The driving patterns for the two levels are uncertain.
- At the first level, EVs are distributed with photovoltaic (PV) generation systems and residential loads in the SMG and the aggregator trades its energy requirements with energy markets (EMs).
- The second level, EV BSS services, extends not only the battery swapping service, since an aggregator coordinates the BSS as its own asset. Discharging and charging decisions of the EV battery bank are used to optimize the SMG profits.

This article is structured as follows. Section 2 presents the formulation of the SMG model with EVs. Section 3 describes the SMG case study. Section 4 discusses the results of the case study, and Section 5 concludes this research.

2. Electric vehicle model with two levels of participation

The planning of the SMG day-ahead (Day + 1) is represented by two levels of participation of EVs, as shown in Equation (1) [2]. The first level (1 EVs) the microgrid services are managed by an aggregator that acts as a middleman between the wholesale and local EMs [2]. EVs are randomized through an urban traffic simulator [18]. The second level (2 EVs) takes a BSS to control the battery swapping. The SOC is controlled with a decision matrix for representing the uncertainty in the visit of EVs and the aggregator negotiates with spot prices for EVs [6]. The participation of EVs by levels and restrictions of the SMG are formulated Equation (1).

\[
\text{minimize } Z = 1EVs_{\text{Day+1}} + 2EVs_{\text{Total}} \cdot 
\]

(1)

2.1. Electric vehicles participation at the first level

The SMG day-ahead planning is performed from a time interval (t) to (T). The costs (C) per power (P) and market prices (MP) revenues are shown in 9 terms for a number (N) of microgrid resources and scenarios (s) in Equation (2).

\[
\sum_{t=1}^{T} \sum_{s=1}^{N_s} \left( \sum_{i=1}^{N_{DG}} p_{DGi(t,s)} \cdot C_{DGi(t,s)} + \sum_{j=1}^{N_{PV}} p_{PVj(t,s)} \cdot C_{PVj(t,s)} + \sum_{k=1}^{N_{ESS}} p_{ESSk(t,s)} \cdot C_{ESSk(t,s)} \right) \cdot \pi(s) \cdot \pi(s) 
\]

(2)

All the terms will be explained in detail below. The first term represents distributed generation (DG). The second term symbolizes the external provider (ext). The third term refers to PV generation. The fourth and fifth term considers ESSs and EVs. The fifth term represents load curtailment (curt). The sixth and seventh term penalizes excess generation (imb) and the load not supplied (imb). The eighth term denotes EMs. The scenarios probability \( \pi(s) \) is formulated with real historical data and Monte Carlo simulations represent the stochastic scenarios. A reduction technique excludes scenarios with low probability [19].
2.2. Electric vehicles participation at the second level
EV BSS prices (Pe) per batteries number (N) to swap (sw), demand (D), discharge (d), and charge (c), and EV BSS market prices (MP) per efficiencies of charge (\(\eta^c\)) and discharge (\(\eta^d\)) of batteries are represented by three terms, as shown in Equation (3). The first term symbolizes the battery swapping income, the second term penalizes the non-supply of the demanded battery swapping and the third term represents the income for charging and discharging batteries with spot market prices of EVs. Stochastic scenarios \(\pi(s)\) are simulated by using the K-means clustering technique [7]. Historical data is taken for EV travel and EMs of [6].

\[
2\text{EVs}_{\text{Day+1}}^{\text{DayTotal}} = \sum_{s=1}^{N_s} \sum_{t=1}^{T=24} \left( -N_{\text{sw}(t,s)} \cdot P_{\text{sw}(t)} + P_{\text{m}(t)} \left( N_{\text{D}(t,s)} - N_{\text{sw}(t,s)} \right) \right) \cdot \pi(s). \quad (3)
\]

2.3. Smart microgrid model restrictions
The EV BSS model is subject to two main restrictions, as shown in Equation (4) and Equation (5). The first constraint represents the SOC EVs that are calculated with identifiers of the charge (\(\delta\)) and discharge (\(\zeta\)) intervals. The charging rate is limited by vehicle battery capacity (\(u^B\)), the type of charger (\(u^y\)), and vehicle brand (\(u^v\)). The coding of the state of charge, discharging and swapping of EVs and SMG are detailed in [2,6]. The second represents the energy being conserved in the SMG, that is, the amount of energy transferred (P) in each period by all interested parties plus the penalties is equal to 0 [2].

\[
\sum_{f=0}^{\delta-1} N_{\text{c}(t-f,s)} + \sum_{f=0}^{\zeta-1} N_{\text{d}(t-f,s)} \leq N_i; \quad \delta \text{ or } \zeta = \frac{u^B}{\min(u^a,v^y)}, \quad (4)
\]

\[
\sum_{j=1}^{N_{\text{PV-DG}}} P_{\text{PV}(j,t,s)} + \sum_{e=1}^{N_e} \left( P_{\text{ESS}^-(e,t,s)} - P_{\text{ESS}^+(e,t,s)} \right) + \sum_{l=1}^{N_{\text{DG}}} P_{\text{DG}(l,s)} + \sum_{k=1}^{N_{\text{ext}}} P_{\text{ext}(k,t)} + \ldots
\]

\[
\ldots + \sum_{v=1}^{N_v} \left( P_{\text{EV}^-(v,t,s)} - P_{\text{EV}^+(v,t,s)} \right) + \sum_{l=1}^{N_{\text{curt}}} \left( P_{\text{curt}(l,t,s)} - P_{\text{load}(l,t,s)} \right) + \ldots
\]

\[
\ldots \sum_{m=1}^{N_m} \left( P_{\text{buy}(m,t)} - P_{\text{sell}(m,t,s)} \right) + \sum_{l=1}^{N_{\text{DG}}} P_{\text{imb}^+(l,t,s)} + \sum_{l=1}^{N_{\text{imb}^-}} P_{\text{imb}^-(l,t,s)} = 0 \quad (5)
\]

where: \(N_i, N_{\text{sw}(t,s)}, N_{\text{c}(t,s)}, N_{\text{d}(t,s)} \in \mathbb{Z} \quad \forall t \in T, \forall s \in S.

3. Description of the smart microgrid case study and simulation
The 26-bus microgrid is based on microgrid from Portugal, has EVs assigned and the lines cover approximately 1.65 km, as shown in Figure 1 [20]. The microgrid also covers services for 2 ESS, 90 residential loads, 5 DGs, 1 external provider, 34 EVs distributed, 1 BSS for 34 EVs and 17 aggregated PV generators [6,20]. At the first level, the EV BSS model is described below and can be simulated it on MATLAB R2019b program with the data from the microgrid, wholesale market (see links in Figure 1) and the BSS implementing can be programmed based on [6].

4. Results and discussion
EV BSS model is solved with the VNS-DEEPSO algorithm in two stages until reaching favorable profits close to [4]. BSS and SMG are optimized in the first stage and the EVs in the residential SMG are resolved in the second stage. Figure 2 and Figure 3 show EVs and markets participation with the SMG. The BSS between 1 and 5 and 14 between 14 and 24 hours supplies power to the residential SMG, while
the distributed EVs exhibit stochastic behavior of charging and discharging EVs. Between 6 and 11 am, the distributed EVs and the BSS are in the charging period, as shown Figure 2. The SMG sells energy firmly during the 24 hours, as shown in Figure 3.

Figure 1. Microgrid with two levels of electric vehicles participation [6,20].

Download VNS-DEEPSO microgrid data from: 1. http://www.gecad.isep.ipp.pt/WCCI2018-5G-COMPETITION/

Wholesale market data from: https://www.aemo.com.au/energy-systems/electricity/national-electricity-market-nem/data-nem/data-dashboard-nem

Figure 2. EVs participation in the SMG.

Figure 3. Markets participation with the SMG.

Figure 4 shows the residential load consumption and ESS. Residential charging, the highest consumption occurs at noon and is similar to the reported literature [6], and ESSs download dramatically at 4 a.m. and load abruptly at 9 p.m.; the low partition of ESS is presumed to occur due to the high participation of EVs. Figure 5 presents the power generation. The generation has an active participation of PV generation; DGs and external supplier supply the day-ahead demand with significant fluctuations.
5. Conclusion
SMGs have evolved to host agents that supply and consume energy. EVs are a closer example of these functionalities. The optimization of EVs as users of the SMG and BSS aims to overcome problems of time planning and service competitiveness with other transport technologies. The EV BSS model covers sources of uncertainty of EVs such as market prices, travel planning and the demand for battery swapping. Furthermore, solar generation and demand forecasting are uncertain and requires the optimization problem to be solved by using two stages of VNS-DEEPSO to obtain favorable profits. The ESSs has a low participation that could be influenced by the high participation of EVs in the SMG. The continued generation and participation of EV yield 24-hour power sales with slight fluctuations in wholesale and local markets. Finally, the SMG covers the variety of connection modes of EVs such as V2G, G2V, from the BSS to the SMG and from the SMG to the BSS. These connection modes should be studied further detail in future research with real SMGs.

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