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Joint optimal operation of photovoltaic units and electric vehicles in residential networks with storage systems: A dynamic scheduling method

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ABSTRACT

The growing penetration of low-carbon technologies in residential networks such as photovoltaic generation (PV) units and electric vehicles (EVs) may cause technical issues on the grid. Thus, operation planning of electrical distribution networks (EDNs) should consider the inclusion of these technologies in order to avoid operational limit breaches. This paper proposes a dynamic scheduling method for the optimal operation of PV units and EVs in unbalanced residential EDNs, considering energy storage systems (ESSs). The proposed method optimizes the joint operation of PV units and EVs, using ESSs to increase the local consumption of the renewable energy. A rolling multi-period strategy based on a mixed integer linear programming model is used to dynamically optimize a centralized decision making, determining control actions for on-load tap changers (OLTCs), ESSs, PV units, and EVs connected to the network. At each time interval, data for PV generation and EV demand is updated using actual information and historical profiles, generating an updated forecast for a one-day-ahead operation in order to properly cope with weather uncertainties and EV owner's behavior without the need of multiple scenarios. The effectiveness and robustness of this approach are verified in different cases via a 107-node test EDN.

1. Introduction

Low carbon technologies such as renewable distributed generation (DG) and electric vehicles (EVs) are rapidly growing in the electrical distribution networks (EDNs) as a response to latter-day challenges related to world's energy consumption growth and CO_2 emissions mitigation [1,2]. In this regards, techno-economic improvements in the solar photovoltaic (PV) industry have surpassed previous expectations leading to considerable cost reductions, making the PV option stand out among other renewable energy alternatives [3]. On the other hand, the use of EVs in the transport sector is expected to increase in the upcoming years, which will reduce greenhouse emissions [3,4]. Hence, the distribution network operator will require smart control methods in order to successfully adopt these technologies.

Many studies have addressed the impacts of DG units on the EDN operation: Voltage profiles, energy losses, restoration actions, and network reinforcements, among others, are directly affected by DG inclusion. Thus, the corresponding economic and technical issues must be assessed to ensure high-quality service for each consumer [5]. PV generation, like any renewable energy source, has specific implications that have to be addressed to guarantee proper network operation. Voltage rise and increase of energy losses are some of the most common problems that appear as a result of high penetration of PV units on the EDNs [6,7]. In order to prevent these issues, different active power control techniques aiming to avoid excessive PV power injection have been studied [8,9].

The penetration of EVs is expected to rise in residential EDNs [4]. EVs recharge their batteries from the grid, i.e., they use electrical energy instead of fossil fuel. The uncontrolled charging of these batteries in a scenario with high EV penetration may cause the EDN to experience overloads, voltage limit violations, and/or excessive increase in energy losses [10,11]. Furthermore, EV charging coordination (EVCC) has been proven to represent significant savings due to energy loss reduction and network reinforcement deferral [12]. Several techniques have been proposed to solve the EVCC problem [13–17]. Mathematical programming formulations for charging cost reduction are presented in [13–15]. In addition, a two-stage optimization process, which uses a prediction unit for the EV demand, is developed in [16] to ensure effective EV charging coordination while aiming overall cost reduction. Finally in [17], a centralized control algorithm, based on corrective and preventive approaches, is proposed to mitigate technical problems related to the connection/disconnection of EV charging points.

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High penetration of both PV units and EVs in the EDN might challenge its operation due to large non-coincident renewable generation and demand. In this context, energy storage systems (ESSs) have emerged to conciliate time-difference between excessive generation and peak demand [18]. Different approaches have been developed to effectively integrate the ESSs into the grid [18–20]. A probabilistic method is proposed in [18] to maximize the benefits related to ESS allocation in residential EDNs; furthermore, it is also established that ESSs must be installed downstream of each distribution transformer to alleviate overloading due to excessive PV generation and EV demand peak. A demand-side management approach using a day-ahead optimization process for the scheduling of both ESSs and DG units is developed in [19]; nevertheless, the economic and operational constraints of the EDN are disregarded. A control scheme based on a mathematical programming model, which considers ESSs and renewable DG units connected in medium voltage networks, is presented in [20]; however, this method is based on a single-phase formulation that does not consider dynamic control.

This paper proposes a dynamic scheduling method for the joint optimal operation of EVs and PV units in unbalanced residential EDNs with ESSs. The adopted optimization strategy allows a dynamic centralized decision-making, which takes into account an updated forecast for both EV demand and PV generation. Thereby, uncertainties related to weather conditions and EV owner's behavior are considered, avoiding the complexity associated with a decision-making based on a large set of scenarios. The proposed method makes it possible to find an optimal scheduling for the on-load tap changer (OLTC), PV units, EV charging, and ESS charging/discharging, not only mitigating technical issues associated with high PV generation and peak demand, but also encouraging the local consumption of the renewable energy produced by the PV units connected to residential EDNs.

Although there is a fair share of researches tackling problems related to the EDN operation, to the best of the authors' knowledge, there is no approach considering an online control for PV units and EVs, using ESSs, that takes into account low voltage (LV), medium voltage (MV), transformers constraints, and the substation OLTC in unbalanced residential EDNs. Supporting this statement, Table 1 shows a summary of works related to this topic. The main characteristics of those approaches were described, while the differences with the proposed method were highlighted.

The main contribution of this work is an online control method for the joint optimal operation of EVs and PV units in unbalanced residential EDNs, which considers ESSs and OLTCs to enforce the grid operational limits (e.g., voltage and thermal limits) through a dynamic scheduling based on an optimal power flow. This can be apportioned into: (1) the adoption of a rolling multi-period optimization strategy (which has been utilized in other applications within the EDN [15,16]) for the joint optimal operation of EVs and PV units, embedded in the concept of high resolution and accuracy in the problem formulation for the near-term modeling; (2) a Mixed Integer Linear Programming (MILP) formulation that considers the EDN complexity of unbalance, multiple voltage levels, the service transformers, and low voltage networks (features typically disregarded in aforementioned approaches for this matter [21–23]); and (3) a novel centralized control method for the operation of the EDN which guarantees the fulfillment of technical limits in MV and LV networks, controlling OLTCs, ESSs, EVs and PV units.

2. Dynamic scheduling method

This section describes the method proposed to dynamically control EDNs with high penetration of PV units and EVs. Considerations and descriptions in regard to the EDN and the aforementioned devices will also be addressed.

The control method is based on an optimization problem that determines the optimal operation of the OLTC, ESSs, PV units, and EV charging schedule. These optimal settings are defined considering a one-day ahead operation (divided into time intervals) and a rolling multi-period optimization strategy, as shown in Fig. 1. The optimization algorithm requires forecast profiles for the available PV generation and EV demand along the one-day ahead period. The creation of these forecast profiles will be further detailed later in this section.

The solution of the optimization problem (MILP model) will define, for the considered time period, the OLTC tap positions, the optimal charging/discharging schedule for the ESSs, the power exchange between the PV units and the grid, and the optimal charging schedule for the EVs. These control actions are mathematically represented through integer variables.

At each time step of the rolling multi-period optimization process (every 15 min, e.g., t_1,t_2,t_3, …), the corresponding optimization problem is solved considering a one-day-ahead period, as shown in Fig. 2. This time horizon makes it possible to define an optimal charging/discharging schedule for the ESSs taking into account forecasted PV generation and EV demand. Therefore, the operation of the devices connected to the grid is optimized, as dynamic schedules for EVs and ESSs are constructed. Although the efficiency of the algorithm does not depends on the time step duration, a 15-min time step was chosen due to the fact that shorter control cycles lead to more control actions, which in turn, has a negative effect on EV batteries [17].

Due to the integer nature of the variables involved in this multi-period process, a high computational effort is required. In order to reduce the processing time, the time period is divided into 25 time intervals with a duration of 15 min for the first one (current time) and one-hour for the remaining 24. In other words, every 15 min a new time period is built (as shown in Fig. 2); hence, the decisions taken for the next 15 min (current time interval) will take into account the day-ahead operation of the EDN. Furthermore, considering that only the settings of the current time interval will be implemented, the integer nature of the control variables is disregarded for all time intervals but the first one, i.e., it is assumed that they are continuous. These approximations reduce the complexity of the optimization model without compromising the quality of the solution.

The proposed method models a residential feeder with MV and LV nodes, including an OLTC at the substation (i.e., at the beginning of the feeder), MV/LV transformers, ESSs installed downstream from the MV/LV transformers, single-phase PV units, and single-phase EV charging points at the households. In addition, the proposed control scheme takes advantage of communication infrastructure offered by future smart residential grids in order to implement the defined control actions [24,25].

High PV generation may cause an energy surplus in the EDN. This energy surplus can be exported to the main grid [26]. In this energy trade-off, the selling price is usually smaller than the buying price in order to encourage the self-consumption of the locally produced PV power [27]. Therefore, the proposed approach assumes that the selling price α^S is always lower than the buying price α^B. If this is not true, additional binary variables must be introduced according to the direction of the power flow at the substation (i.e., importing or exporting).

In order to determine the control actions to be executed by the controlled devices, several considerations must be adopted, which are explained as follows.

2.1. PV power generation

For each PV unit, the algorithm will identify at every time interval the maximum active power that it may inject into the grid without causing operational issues. If in a given time, a PV unit is able to generate more power than the aforementioned limit, that difference will be considered as a power curtailment. It is assumed that all PV units are connected to the low-voltage network, operate with unity power factor, and their power output is controlled by smart power inverters [24]. Furthermore, the PV penetration is defined as the percentage of LV