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Flexibility-Oriented Collaborative Planning Model for Distribution Network and EV Parking Lots Considering Uncertain Behaviour of EVs

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***Abstract*—Increasing grid integration of intermittent renewable energy sources (RESs) and plug-in electric vehicles (PEVs) with uncertain behaviours have necessitated enhancing the flexibility requirements of distribution networks. Thus, in the state-of-the-art distribution network expansion planning (DNEP) models, both flexibility requirements and high penetration of RESs and PEVs should be taken into consideration. In this respect, a novel collaborative planning model for power distribution network (PDN) and plug-in Electric Vehicle Parking Lots (EVPLs) is proposed in this paper, which leverages sizing, siting, and operation of EVPLs to enhance the distribution network flexibility. Also, to model the uncertain traffic flow of PEVs, a new model is proposed and is utilized to obtain a preliminary dispatch of PEV charging and, in turn, an estimated EVPL demand. Afterwards, this estimated demand is fed into the collaborative planning model to obtain the optimal expansion planning solution for PDN, and the size and location of EVPLs. Nonetheless, to provide the network operator with more flexibility sources, it is assumed that the operator can reschedule the charging pattern of some PEVs by compensating the EVPL owners for the difference in retail electricity prices of various hours. Finally, to illustrate the effectiveness of the proposed model, it is implemented on a test network, and the obtained results are discussed.**

Keywords—Plug-in electric vehicle (PEV), distribution network expansion planning (DNEP), flexibility, electric vehicle parking lot (EVPL).

I. Introduction

Increasing penetration of plug-in electric vehicles (PEVs) and renewable energy sources (RESs) with intermittent generation has had a massive impact on distribution networks and has brought about many challenges in power grids, e.g., significant RES generation curtailment, more transformer and feeder congestion, and steeper net-load ramps [1, 2]. This rise in the integration of green technologies accompanied with the development of new types of electricity demand, and, thus changes in the energy consumptions pattern has necessitated enhancing the flexibility of distribution networks [3, 4]. In this respect, many solutions have been proposed to boost the distribution network flexibility, among which one of the most promising is leveraging PEVs. This is because, in the past few years, the number of PEVs, and, therefore, their aggregated demand have risen significantly [5]. Moreover, many countries, such as India, China, Slovenia, Austria, the Netherlands, Ireland, and Norway, have set goals to end the sales of conventional vehicles by the year 2030 [6]; thus, the penetration level of PEVs will continue to rise rapidly in the coming years. Even though the high PEV demand brings about numerous challenges in power grids, leveraging them as a flexibility source not only will make investing in them more beneficial but also can solve some of the challenges happening in highly RES-penetrated networks. To this end, future distribution networks should be planned, while considering this promising flexibility source.

Accordingly, many research studies have been carried out on the distribution network expansion planning (DNEP) with consideration of the PEV integration. In [7], a multi-objective DNEP model has been proposed, where meeting the PEV demand and investing in fast-charging stations has been considered, with the goal of minimizing planning costs and maximizing annual traffic flow captured by fast-charging stations. The authors in [8] have proposed a DNEP model that accounts for future uncertainties in conventional load levels as well as penetration of PEVs. An interdisciplinary study in a coupled traffic-electric network has been conducted in [9], where a mixed-integer linear programming (MILP) planning model is proposed in order to determine the optimal expansion strategies for both traffic network and power distribution network (PDN), through which the size and location of EVCSs are also determined. In [10], a multistage DNEP model is presented, where installing renewable DG units, energy storage systems, and PEV charging stations (EVCSs) together with investing in DN assets are jointly considered as available expansion options. In [11], a bi-level DNEP model is proposed while considering the objectives of DN operator (DNO) and electric vehicle parking lot (EVPL) owners, and the power injection capability of PEVs parked in GPLs is leveraged to supply loads under faulty conditions. Also, authors in [12] suggested a multi-objective expansion planning model for PDN and EVPLs aiming to maximize the profit of EVPL owners and to minimize the distribution network operational costs.

Nonetheless, in none of the mentioned studies, was enhancing the network flexibility taken into consideration. Moreover, owing to complexities in the models proposed in [7–9, 11, 12], considering the network flexibility requirements in those models will lead to the intractability of the resulting problem. On the other hand, a group of studies have used oversimplified traffic flow models so as to achieve a simpler model, which can be efficiently solved. For example, in [10], the PEV demand of the whole distribution network is considered as an input of the planning model, and, therefore, the loading effect of PEVs on specific feeders of the network is masked, which, consequently, will lead into reaching an over-optimistic planning solution. In this respect, to address such issues, we have developed a novel model for multistage expansion planning of integrated PDN and EVPLs, which can be efficiently solved by off-the-shelf software packages and considers the PEV demand relatively accurate. The objective of the proposed collaborative model for expansion planning of the PDN and EVPLs is to minimize the costs of PDN expansion and EVPL installation simultaneously while meeting the growing load and PEV demands as well as enhancing the flexibility at the distribution level.

In this paper, enhancing the flexibility requirements of a distribution network means minimizing the RES generation curtailments together with decreasing the network net-load ramps while meeting the operational constraints of the network. In this framework, the distribution company (DISCO) aims to enhance the flexibility through installing the EVPLs at the places where aggregated effect of PEVs have more potential to help the DISCO in providing sufficient flexibility for high RES integration. With the goal of estimating the PEV charging demand, a new PEV traffic flow model is utilized in this paper. In this regard, the territory area of the DISCO is divided into different zones, in each of which the installed EVPLs should be able to meet the total PEV charging demand of the corresponding zone. Through leveraging this traffic flow model, a preliminary dispatch of PEV charging and, in turn, an estimated EVPL demand in each zone is obtained, which is fed into the collaborative planning model to obtain the best planning solution. Nonetheless, to provide the distribution network with more flexibility sources, it is assumed that the network operator can reschedule the preliminary charging dispatch of a portion of PEVs parked in the EVPLs.

The problem of interest is inherently an instance of mixed-integer non-linear programming (MINLP). Nonetheless, in order to guarantee convergence to the global optimal solution, the proposed planning model is cast as an MILP problem. As we aim to develop an MILP formulation due to its profound benefits over MINLP problems, the non-linear terms in the model formulation, e.g., power flow equations, have been linearized. The proposed MILP collaborative planning model can be solved by off-the-shelf mathematical programming solvers, which provides a great advantage in reaching a high-quality optimal solution.

The remainder of the paper is organized as follows. In Section II, the PEV charging demand is modelled. In Section III, the proposed collaborative planning model is formulated. The proposed model is implemented on a sample distribution network in Section IV. Finally, Section V concludes the paper.

II. EVPL DEMAND MODELLING

A. Modelling the Uncertain Behaviour of PEVs

In this section, a novel model is developed to obtain a preliminary dispatch for PEV charging and estimate the charging demand of PEVs parked at EVPLs. In this respect, the territory area of the distribution network is divided into several zones, each of which includes a number of load nodes. Afterwards, the EVPL load demand for each zone is estimated through the historical data of vehicles travelling into/from the specified area. The estimated demand is fed into the collaborative planning model, formulated in Section III, so as to obtain the optimal solution for expansion of distribution network and installing the EVPLs, which specifies the location and size of EVPLs. The installed EVPLs in each zone should be able to meet the aggregate demand of PEVs in the corresponding zone.

At the first step, the behaviour of the PEVs can be modelled by leveraging historical data to estimate the probability distribution of their arrival and departure time. However, in case of lack of sufficient historical data for PEV trips, the uncertainties associated with PEVs behaviour are modelled using generating scenarios for PEV characteristics, e.g., arrival time, departure time, initial SOC, and desired SOC.

In general, the PEV trips can be divided into two different types: commercial and office [12]. The PEVs with these kinds of trips stop at EVPLs for many hours during which their batteries can be recharged. However, there are differences between the demand for PEVs with each kind of these trips. In an office trip, the PEV owner typically goes to the office in the morning, parks the car for several hours, and returns home in the afternoon. On the other hand, for commercial trips, the arrival and departure times of PEVs to/from EVPLs are not only different, but also the duration between them are much shorter, compared to those for the office trips. As a result, different approaches should be used for modelling the arrival and departure times in these two kinds of trips.

In this respect, based on [13], the scenarios for the arrival and departure times can be generated using Gaussian distribution functions. These scenarios for PEVs with office trips can be estimated using truncated Gaussian distribution functions with the means in the morning and in the afternoon, respectively. However, the arrival and departure times for commercial trips cannot be estimated using a single distribution function since commercial locations usually have more than one rush hour during a day. Thus, at least two truncated Gaussian distribution function should be utilized to estimate arrival or departure times of PEVs with the commercial trips, correctly. The first wave of PEVs usually arrive in the morning and leave around noon, and the second wave arrives in the afternoon and leave in the evening. The scenarios for arrival and departure times of PEVs in each of the waves are generated by utilizing different Gaussian distribution functions.

Similarly, owing to the randomness of initial state-of-charge (SOC) of PEVs, it can be estimated using a truncated Gaussian distribution function in both trip types, according to the approach presented in [14]. Nevertheless, since the duration of a PEV being parked is different for office and commercial trips, the desired PEV SOCs are estimated by using different approaches for each type of trip. For office trips, since the PEV is parked for several hours during a day, the desired SOC of each PEV is estimated by a uniform distribution function from the amount of PEV initial SOC to 100%. However, for the commercial trips, although the interval can be identical to that of the office trips, a truncated exponential distribution function is used to generate the scenarios for the desired PEV SOCs. On these bases, (1)–(6) are utilized to generate the required scenarios for modelling the uncertainties associated with PEVs' behaviour.

$$t_n^{arv} = f(x;\mu_{arv},\sigma_{arv},a_{arv},b_{arv}) \tag{1}$$

$$t_n^{dep} = f(x;\mu_{dep},\sigma_{dep},a_{dep},b_{dep}) \tag{2}$$

$$SOC_n^{ini} = f(x;\mu_{ini},\sigma_{ini},a_{ini},b_{ini}) \tag{3}$$

$$SOC_n^{des,OFF} = U(x; SOC_n^{ini}, 100\%) \tag{4}$$

$$SOC_n^{des,COM} = g(x; \lambda, SOC_n^{ini}, 100\%) \tag{5}$$

$$t_n^{dep} - t_n^{arv} \geq \frac{(SOC_n^{des} - SOC_n^{ini})BC_n}{P^{CH,\max}} \geq 0 \tag{6}$$

where t_n^{arv} and t_n^{dep} are arrival and departure times of PEV n; SOC_n^{ini} and SOC_n^{des} are initial and desired amounts of SOC of PEV n; functions $f(x)$, $g(x)$, and $U(x)$ denote scenario generators based on the truncated Gaussian, truncated exponential, and uniform probability distribution functions, respectively; also, μ and σ represent the mean and standard deviation of Gaussian distribution functions; λ denotes the rate parameter for the exponential distribution, and (a,b) specify the truncated region; BC_n and $P^{CH,\max}$ represent the battery capacity of PEV n and the maximum rate of charge.

Equations (1)–(5) are employed to generate the scenarios for arrival and departure times, initial SOC, and desired SOC for office and commercial trips of each PEV. It goes without saying that to create the scenarios for arrival and departure times, the mean and standard deviation (STD) values considered in (1) and (2) are chosen according to the trip type. Also, expression (6) is a logical constraint to ensure that the PEV battery can be charged to the desired SOC while its stay at the EVPL, the arrival time is before the departure time, and the desired SOC is higher than the initial SOC for each PEV.

B. PEV Charging Control Model

Given the PEVs' behaviour data generated by the before-mentioned approach, the EVPL demand of each zone can be estimated. It is assumed that the EVPL loads in the network would not affect the retail electricity price. Thus, since they are price-takers in the electricity market, the value of retail electricity price is considered constant in the proposed model. In this respect, the following formulation is utilized to obtain preliminary scheduling for charging PEVs and, in turn, to estimate the EVPL demand in each zone:

$$\text{Minimize } C^{CH} = \sum_{n\in\Omega^{EV}} \sum_{h\in\Omega^H} RP_h p_{n,h}^{CH} \tag{7}$$

$$0 \leq p_{n,h}^{CH} \leq \delta_{n,h}^{CH} p^{CH,\max}; \forall n \in \Omega^{EV}, \forall h \in \Omega^H \tag{8}$$

$$\delta_{n,h}^{CH} = 0; \forall n \in \Omega^{EV}, \forall h \notin [t_{arv}, t_{dep}] \tag{9}$$

$$SOC_{n,h+1} = SOC_{n,h} + \frac{\eta^{CH} p_{n,h}^{CH}}{BC_n}; \forall n \in \Omega^{EV}, \forall h \in \Omega^H \tag{10}$$

$$SOC^{\min} \leq SOC_{n,h} \leq SOC^{\max}; \forall n \in \Omega^{EV}, \forall h \in \Omega^H \tag{11}$$

$$SOC_{n,h} = SOC_n^{ini}; \forall n \in \Omega^{EV}, h = \left[t_{arv}\right] \tag{12}$$

$$SOC_{n,h} = SOC_n^{des}; \forall n \in \Omega^{EV}, h = \left[t_{dep}\right] \tag{13}$$

$$d_h^Z = \sum_{n\in\Omega^{EV}} p_{n,h}^{CH}; \forall h \in \Omega^H \tag{14}$$

where n/Ω^{EV} is the index/set of PEVs; h/Ω^H represent index/set of the hours of a day; Z is the index of network zones; $p_{n,h}^{CH}$ is the charging power of PEV n at hour h; $\delta_{n,h}^{CH}$ is the binary variable which indicates if the PEV battery is charging; also, $SOC_{n,h}$ and η^{CH} are the PEV SOC variable and charging efficiency of PEV batteries; RP_h is the retail electricity price in hour h; lastly, d_h^Z denotes the estimated EVPL charging demand in zone Z.

The objective function (7) minimizes the charging cost of all PEVs parked at EVPLs of each zone during a day. Constraint (8) limits the charging power of PEVs. Equation (9) is the non-schedulable time interval constraint. Charging equality constraint is formulated in (10), and (11) is the PEV batteries' security constraint. Constraints (12) and (13) allocate the generated values for initial and desired SOCs to each PEV battery. Finally, the estimated demand for the EVPLs in a specific zone is calculated by (14).

Solving the optimization model (7)–(14) yields the estimated EVPL demand of each zone d_h^Z, which is fed into the collaborative planning model described in Section III.

III. Collaborative Planning Model of PDN and EVPLs

In this section, an innovative collaborative planning model for the PDN and EVPLs is developed, which considers enhancing the flexibility for networks with high RES integration while meeting the growing conventional and EVPL demand. The proposed model is based on the flexibility-oriented DNEP model presented in [15], where dispatchable distributed generation units were utilized to enhance the flexibility. However, in this paper, not only the EVPLs' demand is taken into consideration, but also they are leveraged to provide the flexibility for the distribution network. In this regard, as a result of the problem optimization, the size and location of EVPLs are determined with the goal of meeting the PEV demand, decreasing distribution network cost, and enhancing the network flexibility. The curtailment of PEV generation is also considered as a flexibility source, which the DISCO can leverage only by reimbursing the RES investors for the economic loss due to RES generation curtailment.

To account for the EVPL demand, the obtained preliminary dispatch of PEVs in each zone is considered as the input of the collaborative planning model, as mentioned before. In this regard, it is assumed that the dispatch of a portion of PEVs can be rescheduled in order to provide more flexibility for the distribution network. However, DISCO should compensate for the difference in the electricity prices of different hours if it decides to postpone or bring forward the charging time of a vehicle.

The planning horizon comprises of many planning stages, each of which consists of several representative days. Moreover, to capture the effects of intermittent RES generation and EVPL demand on the network net-load, hourly power flow equations are taken into consideration in the model such that the operating conditions should be satisfied in each hour of the representative days. The proposed planning model is formulated as follows:

$$\text{Minimize } C^T = \sum_{t\in\Omega^T} \frac{1}{(1+r)^{(t-1)D}} \left(C_t^I + \frac{(1+r)^D - 1}{r(1+r)^D} C_t^{OP} \right) \tag{15}$$

$$C_t^I = IC^{FS} + IC^S + \sum_{l\in\Omega^L} \sum_{kp\in\Omega^{KP}} I_{kp}^{PL} x_{l,kp,t}^{PL} \tag{16}$$

$$\begin{aligned} C_t^{OP} &= OMC^S + OMC^{FS} + \sum_{l\in\Omega^{RES}} \sum_{d\in\Omega^D} \sum_{h\in\Omega^H} RP_{d,h} ce_{l,t,d,h}^{RES} \\ &+ \sum_{d\in\Omega^D} \sum_{h\in\Omega^H} RC_{d,h} lc_{t,d,h}^{abs} + \sum_{l\in\Omega^L} \sum_{d\in\Omega^D} \sum_{h\in\Omega^H} RP_{d,h} (\hat{d}_{l,t,d,h}^{PL} - d_{l,t,d,h}^{PL}) \end{aligned} \tag{17}$$

where t/Ω^T and d/Ω^D are indices/sets of planning stages and representative days, respectively; Ω^L and Ω^{RES} represent sets of load nodes and RES-connected nodes, respectively; l is the index of load nodes; kp/Ω^{KP} denote the index/set of investment alternatives for EVPLs; C^T is the total cost during the planning horizon, and C_t^I and C_t^{OP} are the investment and operating costs in each stage; r and D represent the annual interest rate and the number of years in each stage; I_{kp}^{PL} and $RP_{d,h}$ are EVPL investment cost and electrical energy retail price, respectively; $RC_{d,h}$ is the *ramping cost*, i.e., the penalty cost for a unit of network net-load change during an hour; $x^{PL}_{l,kp,t}$ denotes the binary variable which determines if an investment is conducted on an EVPL; $ce^{RES}_{l,t,d,h}$ denotes the amount of RES curtailed energy; $d^{PL}_{l,t,d,h}$ and $\hat{d}_{l,t,d,h}$ are the non-negative variables of the scheduled and rescheduled EVPL demands in load nodes, respectively; $lc^{abs}_{t,d,h}$ is the absolute value of the hourly network net-load variation.

In the proposed planning model, the objective function in (15) minimizes the present value of the total cost, which consists of investment and operating costs over the planning horizon. The investment cost in each stage is formulated in (16), which includes investment costs on feeder sections, IC^{FS}, substations, IC^{S}, and EVPLs. Equation (17) represents the operating cost in each stage, comprising of operation and maintenance cost of substations, OMC^{S}, and feeder sections, OMC^{FS}, the penalty cost due to curtailed RES generation, the *flexibility-oriented cost* (i.e., the penalty cost due to network net-load variations), and the *rescheduling cost*. As mentioned before, to enhance the network flexibility, the network operator is able to reschedule the preliminary dispatch of PEVs charging. Also, for more details about the other cost terms in (16) and (17), interested readers can refer to [15].

$$\left|Z_{i,j} f_{i,t,d,h} + \sum\nolimits_{m\in\Omega^M} c_{m,i} v_{m,t,d,h}\right| \le M(1-y^{FS}_{i,j,t}); \quad \forall i\in\Omega^{FS}, \forall j\in\Omega^j, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{18}$$

$$\sum\nolimits_{i\in\Omega^{FS}} c_{l,i} f_{i,t,d,h} + G^{RES}_{l,t,d,h} = \hat{d}^{PL}_{l,t,d,h} + d_{l,t,d,h} + ce^{RES}_{l,t,d,h}; \quad \forall l\in\Omega^L, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{19}$$

$$\sum\nolimits_{i\in\Omega^{FS}} c_{s,i} f_{i,t,d,h} + g_{s,t,d,h} = 0; \quad \forall s\in\Omega^S, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{20}$$

$$v^{\min} \le v_{m,t,d,h} \le v^{\max}; \forall m\in\Omega^M, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{21}$$

$$\left|f_{i,t,d,h}\right| \le \sum\nolimits_{j\in\Omega^J} y^{FS}_{i,j,t} f^{\max}_j; \forall i\in\Omega^{FS}, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{22}$$

$$0 \le g_{s,t,d,h} \le g^{\max}_s + \sum\nolimits_{e\in\Omega^E} \sum\nolimits_{\tau=1}^{t} x^S_{s,e,\tau} SC_{s,e}; \quad \forall s\in\Omega^S, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{23}$$

$$0 \le ce^{RES}_{l,t,d,h} \le G^{RES}_{l,t,d,h}; \forall l\in\Omega^{RES}, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{24}$$

$$\sum\nolimits_{t\in\Omega^T} \sum\nolimits_{b\in\Omega^B} x_{a,b,t} \le 1; \forall a\in\Omega^A \tag{25}$$

$$y_{a,b,t} \le \sum\nolimits_{\tau=1}^{t} x_{a,b,\tau}; \forall a\in\Omega^A, \forall b\in\Omega^B, \forall t\in\Omega^T \tag{26}$$

$$lc_{t,d,h} = \sum_{s\in\Omega^S} \left(g_{s,t,d,h} - g_{s,t,d,h-1}\right); \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{27}$$

$$lc^{pos}_{t,d,h} - lc^{neg}_{t,d,h} = lc_{t,d,h}; \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{28}$$

$$lc^{abs}_{t,d,h} = lc^{pos}_{t,d,h} + lc^{neg}_{t,d,h}; \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{29}$$

$$\sum\nolimits_{i\in\Omega^{FS}} \left(\left|c_{l,i}\right| \sum\nolimits_{j\in\Omega^J} y^{FS}_{i,j,t}\right) \ge an_{l,t}; \forall l\in\Omega^L, \forall t\in T \tag{30}$$

$$\sum\nolimits_{i\in\Omega^{FS}} \sum\nolimits_{j\in\Omega^J} y^{FS}_{i,j,t} \le \sum\nolimits_{l\in\Omega^L} an_{l,t}; \forall t\in\Omega^T \tag{31}$$

where i/Ω^{FS} and j/Ω^J are the indices/sets of feeder sections and their conductor types, respectively; e/Ω^E denotes index/set of expansion or construction alternatives of substations; m/Ω^M and s/Ω^S denote indices/sets of all network nodes and substation nodes, respectively; also, a/Ω^A and b/Ω^B are the indices/sets of distribution network assets (i.e., substations and feeder sections); $f_{i,t,d,h}$ and $v_{m,t,d,h}$ are continuous variables representing the current flow of feeder sections and nodal voltage magnitudes, respectively; M is a sufficiently large number; v^{max} and v^{min} are the upper and lower limits of nodal voltage magnitudes; f^{max}_j is the current flow capacity of feeder sections; $g_{s,t,d,h}$ is the injected power of substations, and g^{max}_s is the initial capacity of substations; $SC_{s,e}$ is the added capacity to substation s for expansion plan e; $G^{RES}_{l,t,d,h}$ denotes the amount of RES generation; $c_{(.),i}$ is the incidence matrix elements; $d_{l,t,d,h}$ is the conventional demand of load nodes; $lc_{t,d,h}$ is the network net-load variation during an hour; $lc^{pos}_{t,d,h}$ and $lc^{neg}_{t,d,h}$ are positive continuous variables that show the positive and negative amounts of net-load change, respectively; $an_{l,t}$ is the binary variable which indicates if a load node is *in-service*; $x_{a,b,t}$ denotes the binary variable which determines if investments are conducted on distribution network assets; similarly, $x^S_{s,e,t}$ is the investment binary variable for expansion or construction of substations; $y_{a,b,t}$ is the binary variable indicating if a network asset is utilized; similarly, $y^{FS}_{i,j,t}$ is the binary variable for utilization of feeder sections.

The power flow equations are formulated in (18)–(20). In this respect, a linear approximation of Kirchhoff Voltage Law, based on the method applied in [16–18], is considered through (18). Constraints (19) and (20) represent the current flow balance in each of the load nodes. Based on the results presented in [16–18], for planning studies, such DC power flow equations would approximate AC power flow equations accurately enough. Nodal voltage limits, feeder section current constraints, and upper bounds for substation capacities are formulated in (21)–(23), respectively. Constraints (24) limits the amount of curtailed RES generation. As in [15–17], expression (25) ensures that, during the planning horizon, only one investment is conducted on each EVPL and each network asset. As a logical constraint, (26) ensures that each alternative of the distribution equipment is operated only after the corresponding investment has been made. To calculate the flexibility-oriented cost, (27)–(29) determine the network net-load variations in each hour, based on the approach used in [19]. Also, similar to the method applied in [15, 19], the radial operation of the distribution network at each planning stage is ensured through (30) and (31).

$$\sum\nolimits_{l\in\Omega^Z} d^{PL}_{l,t,d,h} = d^Z_{t,d,h}; \forall Z = \{1,\ldots,N\}, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{32}$$

$$\hat{d}^{PL}_{l,t,d,h} \le \sum\nolimits_{\tau=1}^{t} x^{PL}_{l,kp,\tau} PLC_{kp}; \forall l\in\Omega^L, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{33}$$

$$\sum\nolimits_{\forall h\in\Omega^H} \left(\hat{d}^{PL}_{l,t,d,h} - d^{PL}_{l,t,d,h}\right) = 0; \forall l\in\Omega^L, \forall t\in\Omega^T, \forall d\in\Omega^D \tag{34}$$

$$\hat{d}^{PL}_{l,t,d,h} \ge \alpha d^{PL}_{l,t,d,h}; \forall l\in\Omega^L, \forall t\in\Omega^T, \forall d\in\Omega^D, \forall h\in\Omega^H \tag{35}$$

$$\sum_{kp\in\Omega^{KP}} I^{PL}_{kp} x^{PL}_{l,kp,t} \le \sum_{year=1}^{Lifetime} \frac{1}{(1+r)^{year}} \sum_{d\in\Omega^D} \sum_{h\in\Omega^H} RP_{d,b} \hat{d}^{PL}_{l,t,d,h}; \forall t\in\Omega^T \tag{36}$$

where Ω^Z is set of load nodes in zone Z; N is the number of zones in the territory of distribution network; PLC_{kp} is the total charging capacity of an EVPL; α is the percentage of PEVs which require urgent battery charge.

Equation (32) ensures that the EVPL demand at each zone is completely supplied through installed EVPLs in the load nodes of the corresponding zone. Expression (33) sets the maximum power capacity limitation for the EVPL located at node l. Equation (34) guarantees that the daily EVPL demand of each load node is thoroughly met after rescheduling the PEV charging dispatch. Equation (35) ensures that the charging schedules of only the PEVs that do not require an urgent battery charge can be changed. Finally, in (36), it is guaranteed that each installed EVPL is profitable, i.e., the present value of the income gained over its lifetime is more than the corresponding investment cost. It is worth mentioning that defining $d^{PL}_{l,t,d,h}$ and $\hat{d}_{l,t,d,h}$ as positive continuous variables together with (33) and (34) reject the possibility of those variables' having non-zero values in load nodes that no investments on EVPLs have been made.

TABLE I. DATA FOR PEV-OFFICE TRIPS

	Mean	*STD*	*Min*	*Max*
Arrival time (h)	8	2	6	11
Departue time (h)	16	2	12	20

TABLE II. DATA FOR PEV-COMMERICAL TRIPS

		Mean	*STD*	*Min*	*Max*
First Wave	Arrival time (h)	9	2	6	11
	Departure time (h)	13	2	11	15
Second Wave	Arrival time (h)	17	2	15	19
	Departure time (h)	21	2	19	23

TABLE III. SIMULATION RESULTS

Case	*Stage*	*Average ramp rate (MW/h)*	*POP difference (MW)*	*Curtailment cost (k$)*	*Network cost (k$)*
1	1	0.651	5.685	5	258
	2	0.837	5.600	0	
	3	1.134	9.915	0	
2	1	0.634	5.685	11	308
	2	0.802	5.221	11	
	3	1.064	9.147	21	
3	1	0.481	5.710	0	265
	2	0.520	5.097	7	
	3	0.834	7.333	5	

TABLE IV. INSTALLED FEEDER SECTIONS

	Case 2	*Case 3*
Stage 1	4–8(A1), 8–12(A1), 9–13(A1), 9–17(A1), 11–18(A2)	4–8(A1), 8–12(A1), 9–13(A1), 9–17(A2), 11–18(A1)
Stage 2	6–7(A1), 10–11(A1), 13–14(A1), 15–16(A1)	7–8(A1), 9–10(A1), 14–15(A1), 15–16(A1)

IV. NUMERICAL RESULTS

In this section, in order to investigate the model's effectiveness and applicability, the obtained results implementing the proposed collaborative planning model on a test network are presented and compared with traditional approaches. In this regard, using the approach explained in Section II, the uncertain behaviour of PEVs are modelled, and the estimated EVPL demand in each zone is attained. Then, the data is fed into the collaborative planning model to obtain the optimal planning solution.

As the planning model is formulated in MILP form, it can be readily solved by the off-the-shelf software packages. Thus, we implemented the model in GAMS (version 24.7.4), and used CPLEX 12.6 to solve the resulting MILP problem, while the optimality gap was set to 1% as the solver's stopping criteria.

A. *Test System Description*

1) *Distribution Network Detail*

The proposed planning model is implemented on an 18-bus distribution network, depicted in Fig. 1, which is previously used in [15, 20, 21]. In Fig. 1, the rectangles and the circles represent substations and load nodes, respectively. Also, the fixed, reinforceable, and addable feeder sections are shown by single lines, double lines, and dotted lines, respectively. While the fixed and reinforceable branches exist prior to the planning, the addable feeder sections are added to the network only after making corresponding investments. Moreover, five selected zones can be observed in this figure. Three planning stages are considered, while each stage is two

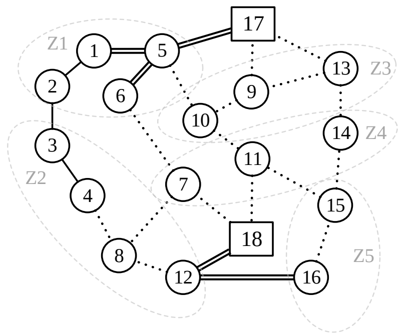

Fig. 1. The sample distribution network and selected zones.

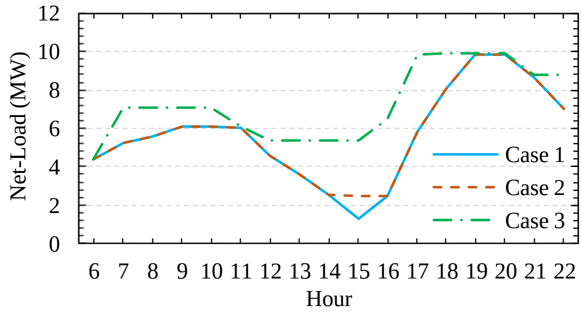

Fig. 2. The distribution network net-load curves of Cases 1–3 during a winter day in stage 3.

years long. Two representative days are taken into account: one to represent summer and the other for winter. Also, as mentioned before, in each day, all twenty-four hours are considered in the model. For each candidate feeder section, two alternatives are considered for installation or reinforcement. The data used for the daily load as well as RES generation profiles, feeder section alternatives, and electricity price are borrowed from [15]. Other data used in the simulations, e.g., EVPL alternatives, maximum load demand, load types at each node, PV and WT generation capacities, and feeder section alternatives are uploaded at [22].

2) *PEV Behaviour Data*

Tables I and II show the data used for the truncated Gaussian distribution functions of arrival and departure times of PEVs to/from the EVPL. The truncated Gaussian functions used for generating the initial SOC scenarios in both commercial and office trips have a mean of 0.5, an STD of 0.3, a minimum of 0.2, and a maximum of 0.8. Also, the lambda coefficient of the exponential distribution function used for generating scenarios for the desired SOC of PEVs with commercial trips is equal to 3. Also, it is assumed that 20% of PEVs need an urgent battery charge. The details regarding the number of PEVs entering each zone are available in [22].

B. *Effectiveness Evaluation of the Proposed Collaborative Planning Model*

To illustrate the effectiveness of the proposed model, the results and planning solutions of three different cases are presented and discussed. In the first two, the DNEP model presented in [15] was used, and in the third case, the proposed collaborative planning model is utilized. These cases are as follows:

Case 1) The PEV demand and the flexibility-cost are not taken into consideration.

Case 2) The flexibility-cost is considered, but the PEV demand is not.

Case 3) Both the PEV demand and the flexibility-cost are taken into account.

To compare the cases, two criteria are defined: peak-off-peak (POP) net-load difference and average net-load ramp rates. The former is the difference between the highest and the lowest values of the network net-load during a specific day. The latter definition is the average of hourly net-load ramp rates during each day.

The obtained results in these three cases are presented in Table III. Also, the network net-load curves for all cases during a winter day in stage three is depicted in Fig. 2. As can be seen in the table, by considering the flexibility in Case 2, the network cost has increased compared to Case 1, while the flexibility criteria have been enhanced. Moreover, since the DISCO aims to decrease the net-load ramp rates when the flexibility is considered, the RES generation curtailment has been leveraged more often in Case 2, which is, in fact, the main cause of higher network cost in this case. However, based on Fig. 2, the net-load curve has not been smoothed considerably in Case 2, which implies that the planned network does not have sufficient flexibility sources.

Nevertheless, by applying the collaborative planning model to the test network in Case 3, not only have the flexibility criteria been enhanced, but also the network cost has decreased compared to Case 2. To be more specific, in Case 3, five EVPLs are installed at load nodes 1, 11, 12, 13, and 16 to meet the PEV demand of the network. The EVPL locations are selected by the optimization problem so that they can help the network the most by providing more flexibility. As a result, while the flexibility criteria have been enhanced, especially in stage 3, the curtailment and network costs have been decreased when the collaborative planning model is employed. The flexibility enhancement is also reflected in the net-load curve, represented in Fig. 2, since the curve is much smoother in Case 3.

Moreover, due to the high penetration of PEVs in future power grids, considering their demand is vital for the sake of obtaining the optimal planning solution. In this regard, the installed feeder sections in Cases 2 and 3 are represented in Table IV, based on the obtained planning solutions. In this table, "A1" indicates that the first alternative is selected for installation. As can be seen from this table, the added feeder sections are different when the effect of the PEV demand is considered in the planning model. It shows that not taking into account the effect of EVPL demand on the distribution network may result in solutions that may not be able to tolerate their high demand. Hence, due to the increasing integration of EVPLs in distribution networks, considering their effects in the planning models are essential.

V. Conclusion

In this paper, we suggested a collaborative planning model for the PDN and EVPLs, aiming at minimizing the network cost and enhancing the network flexibility. To estimate the EVPL demand during each day, an approach was proposed for modelling the uncertain behaviour of PEVs, and a charging control model was represented to obtain a preliminary charging dispatch for PEVs. Afterwards, the estimation of EVPL demand was fed into the planning model to simultaneously find the DNEP solution and optimal size and location of EVPLs. The proposed model was successfully implemented on a test network. The obtained results and solutions showed that by utilizing a collaborative model, not only would the flexibility be enhanced, but also the network cost and the RES generation curtailment would be reduced.

References

[1] A. Kavousi-Fard, A. Abunasri, A. Zare, and R. Hoseinzadeh, "Impact of plug-in hybrid electric vehicles charging demand on the optimal energy management of renewable micro-grids," *Energy*, vol. 78, pp. 904-915, 2014.

[2] S. A. P. Kani, P. Wild, and T. K. Saha, "Improving predictability of renewable generation through optimal battery sizing," *IEEE Trans. Sustain. Energy*, vol. 11, no. 1, pp. 37-47, 2018.

[3] J. Cochran *et al.*, "Flexibility in 21st century power systems," National Renewable Energy Lab. (NREL), Golden, CO (United States), 2014.

[4] "White paper #3 facilitating flexibility." European Energy Regulators (ACER-CEER). [online]. Available: https://www.ceer.eu/documents/104400/5937686/ACER-CEER+White+Paper+3-European+Energy+Regulators+White+Paper+3+Facilitating+Flexibility+2017+05+22/4e03e0b4-0886-606d-b69b-ff48225e83f3 (accessed July, 2018).

[5] "Global EV outlook 2019: Scaling up the transition to electric mobility," International Energy Agency, Paris, France, 2019.

[6] D. Hirst. "Electric vehicles and infrastructure." House of Commons Library. [online]. Available: https://researchbriefings.files.parliament.uk/documents/CBP-7480/CBP-7480.pdf (accessed Februrary, 2020).

[7] W. Yao *et al.*, "A multi-objective collaborative planning strategy for integrated power distribution and electric vehicle charging systems," *IEEE Trans. Power Syst.*, vol. 29, no. 4, pp. 1811-1821, 2014.

[8] W. Yao, C. Chung, F. Wen, M. Qin, and Y. Xue, "Scenario-based comprehensive expansion planning for distribution systems considering integration of plug-in electric vehicles," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 317-328, 2015.

[9] X. Wang, M. Shahidehpour, C. Jiang, and Z. Li, "Coordinated planning strategy for electric vehicle charging stations and coupled traffic-electric networks," *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 268-279, 2018.

[10] P. M. de Quevedo, G. Muñoz-Delgado, and J. Contreras, "Impact of electric vehicles on the expansion planning of distribution systems considering renewable energy, storage, and charging stations," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 794-804, 2017.

[11] M. Moradijoz, M. P. Moghaddam, and M. R. Haghifam, "A flexible distribution system expansion planning model: A dynamic bi-level approach," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 5867-5877, 2017.

[12] M. Mozaffari, H. A. Abyaneh, M. Jooshaki, and M. Moeini-Aghtaie, "Joint expansion planning studies of EV parking lots placement and distribution network," *IEEE Trans. Ind. Inf.*, doi: 10.1109/TII.2020.2964049.

[13] M. Shafie-khah *et al.*, "Optimal behavior of electric vehicle parking lots as demand response aggregation agents," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2654-2665, 2015.

[14] Y. Cao *et al.*, "An optimized EV charging model considering TOU price and SOC curve," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 388-393, 2011.

[15] S. Karimi-Arpanahi, M. Jooshaki, M. Moeini-Aghtaie, A. Abbaspour, and M. Fotuhi-Firuzabad, "Incorporating flexibility requirements into distribution system expansion planning studies based on regulatory policies," *Int. J. Electr. Power Energy Syst.*, vol. 118, pp. 105769, 2020.

[16] S. Haffner, L. F. A. Pereira, L. A. Pereira, and L. S. Barreto, "Multistage model for distribution expansion planning with distributed generation—Part I: Problem formulation," *IEEE Trans. Power Deliv.*, vol. 23, no. 2, pp. 915-923, 2008.

[17] G. Muñoz-Delgado, J. Contreras, and J. M. Arroyo, "Joint expansion planning of distributed generation and distribution networks," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2579-2590, 2015.

[18] M. Jooshaki, A. Abbaspour, M. Fotuhi-Firuzabad, M. Moeini-Aghtaie, and M. Lehtonen, "Milp model of electricity distribution system expansion planning considering incentive reliability regulations," *IEEE Trans. Power Syst.*, vol. 34, no. 6, pp. 4300-4316, 2019.

[19] S. Karimi-Arpanahi, M. Jooshaki, M. Moeini-Aghtaei, A. Abbaspour, and M. Fotuhi-Firuzabad, "A flexibility-oriented model for distribution system expansion planning studies," presented at the 27th Iranian Conference on Electrical Engineering (ICEE), Yazd, Iran, 2019.

[20] M. Jooshaki, H. Farzin, A. Abbaspour, M. Fotuhi-Firuzabad, and M. Lehtonen, "A model for stochastic planning of distribution network and autonomous DG units," *IEEE Trans. Ind. Inf.*, vol. 16, no. 6, pp. 3685-3696, 2019.

[21] S. Haffner, L. F. A. Pereira, L. A. Pereira, and L. S. Barreto, "Multistage model for distribution expansion planning with distributed generation—Part II: Numerical results," *IEEE Trans. Power Deliv.*, vol. 23, no. 2, pp. 924-929, 2008.

[22] "Test distribution network data." [online]. Available: https://1drv.ms/x/s!AuOkAKT1qZvMuSaBZjDyIClka9my