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Simultaneous Distributed Generation and Electric Vehicles Hosting Capacity Assessment in Electric Distribution Systems

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ABSTRACT This work presents a strategy, from the perspective of the distribution system operator (DSO), that aims at simultaneously estimating the maximum penetration levels of renewable-based distributed generation (DG) and electric vehicles (EVs) that can be accommodated into an electric distribution system (EDS). To estimate such capacity, operational resources such as generation curtailment and controllable features of EVs can be managed to ensure the safe operation of the EDS and avoid infeasible operational conditions. Through a multi-period representation, the proposed strategy models the variability in demand consumption and DG power production. In addition, driving patterns of EV owners and energy requirements of EVs, obtained through probability density functions, are incorporated in this representation. Inherently, the problem is represented as an optimization model, and to determine its solution, an algorithm based on the metaheuristics greedy randomized adaptive search and tabu search (GRASP-TS) is developed. The applicability of the planning strategy is assessed on a 33-bus EDS under different test conditions and the numerical results show that higher penetrations of EVs and renewable-based DG can be accommodated without impacting the safe operation of the EDS. The results also demonstrate that by controlling the power draw by EV aggregators, an increase of 9% can be obtained in the DG installed capacity compared to the case of uncontrolled charging of EVs. In addition, the scalability of the proposed approach is studied using two distribution systems, the 83-bus system and the 135-bus system, where the results show that the convergence of the algorithm is achieved in a few iterations.

INDEX TERMS Electric vehicle aggregator, GRASP-TS, hosting capacity, distributed generation.

I. INTRODUCTION

The restructuring of the energy market and the popularization of modern technologies such as renewable-based distributed generation (DG) and electric vehicles (EVs) have changed the traditional approaches to deal with the operation and expansion planning problems of electric distribution systems (EDSs) [1]–[3]. This transition has been encouraged by different factors such as diversification of the energy matrix, an economy based on low environmental impact, and mitigation of dependence on fossil fuels. However, the ceaseless integration of these technologies could impact the EDS operation and the quality of the energy supplied to consumers.

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In this context, the distribution system operator (DSO) should seek strategies to properly assess the integration of such technologies using the current EDS infrastructure, without incurring new investments. This condition gave rise to the concept of hosting capacity analysis in EDSs, which is aided with the implementation of operational resources to manage voltage levels and power flows to avoid infeasible operational conditions [4].

One of the first works that evaluates and quantifies the impact of high penetrations of DG connected in power systems is presented by the authors in [4]. Over the years, the hosting capacity analysis has been addressed using different strategies; for example, in [5], a cost-benefit analysis model is proposed to determine the maximum wind-based DG capacity to be connected to an EDS, for which a scheme of generation curtailment is implemented to increase such DG capacity. A sensitivity analysis to estimate the installed capacity of photovoltaic (PV)-based DG units is developed in [6]. Taking advantage of the capacity factor of DG units based on wind and PV technologies, a probabilistic method is implemented in [7] to estimate the DG hosting capacity of an EDS. In addition, in the literature, strategies can be found to maximize the DG hosting capacity through the coordinated operation of energy storage systems [8], implementation of demand response programs and DG reactive power support [9], including the operation of medium- and low-voltage transformers [10] and open unified power quality conditioner [11], the use of dynamic reconfiguration, and static VAr compensators [12], and management of devices for voltage and reactive power control considering voltage-dependent loads [13].

On the other hand, large penetrations of EVs combined with uncontrolled charging of these resources can also significantly impact the EDS operation [14]. In this regard, actions to manage EV charging schemes and mitigate infeasible conditions in the EDS operation caused by such penetrations, are crucial in DSO's planning and operation studies. Different strategies have been proposed to analyze the impacts and determine the maximum penetration level of EVs to be incorporated into an EDS. *Alturki and Khodaei*, in [15], propose an approach based on sensitivity indices to determine the marginal values of increasing the EV demand in specific EDS locations, considering operational limits of the system. *Zhao et al.*, in [16], develop a methodology based on the concept of EV charging region to estimate the EDS capacity of accommodating the new EV demand, ensuring the operational limits. To analyze the maximum demand level of an EDS and in order to guarantee its feasible operation, a strategy that assesses different EV penetration levels is presented in [17]. Another similar approach is presented by the authors in [18], where a probabilistic method is implemented to determine the maximum penetration level of EVs that can be incorporated into an EDS.

Nevertheless, the works discussed on the integration of EVs into an EDS have not explored the benefits that can be obtained when coordinating the EV charging. The authors in [19] propose an approach to assess the EV hosting capacity under controlled and uncontrolled charging scenarios, using a strategy based on voltage constraints. Later, the strategy in [19] is improved in [20], where a strategy based on a demand response mechanism is implemented to maximize the EV penetration level. On the other hand, by taking advantage of the EV charging coordination, the integration of other resources could be maximized, such as heat pumps [21], and DG [22]–[25].

In this connection, the charging scheme should be coordinated to take advantage of those time intervals with lower demand and higher DG in order to mitigate infeasible conditions and, to increase the EV penetration into the system. As controllable demand, EVs have characteristics that can be used to avoid voltage drops and overloading of transformers and EDS circuits. In the DG hosting capacity problem, EVs have been scarcely studied; however, an initial approach is presented in [22], which estimates the maximum DG capacity to be installed considering EVs as uncontrollable loads. To overcome this limitation, some studies present different approaches to increase the DG installed capacity, taking advantage of controllable features of the EVs [23]–[25]. Although these works exploit, from the perspective of the DSO, the benefits that controllable features of EVs can provide in the EDS operation, these studies assume that EVs are placed in the system; therefore, the simultaneous hosting capacity assessment of DG and EVs in EDSs is not considered in such approaches. To address this problem, an initial approach is presented by the authors in [26], where the penetration levels of PV-based DG and EVs are simultaneously increased at the residential level by implementing operational resources such as generation curtailment and the coordination of EV charging schemes.

Although there is a vast number of approaches that address the DG hosting capacity problem, only [23]–[25] consider the effects of EVs. As discussed in the literature review, approaches to simultaneously estimate the hosting capacity of DG and EVs in EDSs have been scarcely proposed, where only the work presented in [26] is found. However, the problem is viewed from the residential level and simulations are carried out in order to determine the maximum penetration of EVs and PV-based DG that can be connected. Unlike previous works, the proposed work aims to fill this existing gap in the literature by developing a novel strategy. Formulated from the perspective of the DSO, the strategy seeks to estimate simultaneously and in advance the amount of renewable-based DG that can be connected to the current infrastructure of the EDS and, moreover, to foresee the impact due to the increasing integration of EVs to the system.

In the formulation of the DG hosting capacity problem, the capacity factor and complementarity of DG units based on wind and PV technologies are addressed. On the other hand, in the EV hosting capacity problem, unlike existing approaches and to reduce the complexity of the problem, EVs are grouped in different EV populations that can be connected in different EDS locations. Each EV population can be controlled independently, through an entity denoted as the aggregator. Simultaneously, the problem is represented as an optimization model, which is based on a multi-period formulation that describes the operation and variability of DG units, variability of demand consumption, controllable EV characteristics, driving patterns of EV owners, and energy requirements of EVs. Therefore, to estimate the maximum DG and EV penetration level, the strategy optimizes operational resources such as generation curtailment and controllable features of EVs, avoiding infeasible operational conditions and reducing the energy losses. Based on the above review, the main contributions are summarized as follows:

- A novel strategy to simultaneously assess the hosting capacity of DG and EVs in EDSs. The strategy, formulated from the perspective of the DSO, consists of

determining the maximum penetration level of DG and EVs, ensuring the safe operation of an EDS. In order to estimate this capacity, the strategy manages operational resources such as generation curtailment and controlled EV charging schemes by coordinating the power draw by EV aggregators. Furthermore, variability in demand consumption and DG power production, technical characteristics of EVs, driving patterns, and energy requirements of EVs are modeled using a multi-period formulation, for a planning horizon of one year.
- A solution technique composed of an algorithm based on the greedy randomized adaptive search and tabu search (GRASP-TS) metaheuristics, which are based on the literature review, has not yet been proposed to solve the DG and EV hosting capacity problem. This technique can be used as a planning tool that could assist the DSO in the decision-making process.

II. PROBLEM DESCRIPTION

This work proposes a strategy to simultaneously estimate the maximum penetration level of EVs and DG that can be accommodated into an EDS. Inherently, the problem is addressed as an optimization model, where the objective function maximizes the installed DG capacity and the EV demand for each aggregator, while the energy losses of the system are also minimized A multiperiod formulation is developed to capture the operation of renewable-based DG (wind and PV technologies), the conventional demand consumption, and the behavior of EVs. Moreover, the effects of different EVs are grouped into populations, which are optimally coordinated by aggregators. It should be noted that, in this work, the aggregator is the entity responsible for operating the EV populations; however, the proposed formulation may comprise charging stations and independent groups of EVs.

A. RENEWABLE-BASED DG MODELING

In DG based on wind technology, wind speed is directly related to the amount of power generated, which is the determining factor for power production. With the wind speed information for different time intervals and using the linearized power curve, equation (1), the active power generated by a wind turbine, can be determined [27]:

$$P^{wt} = \begin{cases} 0, & v < v_I \\ \dfrac{P^{nom^{wt}}}{v_R - v_I} \cdot (v - v_I), & v_I \leq v < v_R \\ P^{nom^{wt}}, & v_R \leq v < v_0 \\ 0, & v \geq v_0 \end{cases} \tag{1}$$

Similarly, in PV generation, the amount of power produced by a panel depends on the temperature and solar radiation, as modeled in (2) and (3). With the irradiation information at different time intervals, the cell temperature can be obtained using (2), and finally, with the value of T_{cel} in (3), the active power injection of a panel can be determined [27]:

$$T_{cel} = T_{amb} + \left(\frac{NOCT - 20}{800}\right) G \tag{2}$$

$$P^{pv} = P^{nom^{pv}} \left\{ \frac{G}{1000} [1 + \delta (T_{cel} - 25)] \right\} \tag{3}$$

B. EV DRIVING PATTERNS AND EV AGGREGATORS

Daily driving patterns of EVs are characterized using the probability density functions (PDFs) developed in [28]. These PDFs are obtained through a statistical analysis of the information presented in [29]. The normal segmented probability functions, modeled in (4) and (5), describe the arrival times (plug into the grid) and departure times (plug out) of EVs during a day. From these equations, one can obtain information related to the occurrence of the arrival time (h^{arr}), the departure time (h^{dep}), and the period when the EV is positioned and available to charge ($D_{t,u}$). To represent the number of kilometers that an EV has traveled, the normal logarithmic function (6) is used. Based on this information, it is possible to determine the initial battery state of charge (SOC) of each EV.

$$f_c(h^{arr}) = \begin{cases} \dfrac{1}{2\pi \sigma_c} exp\left[-\dfrac{(h^{arr} + 24 - \mu_c)^2}{2\sigma_c^2}\right] \\ 0 \leq h^{arr} \leq (\mu_c - 12) \\ \dfrac{1}{\sqrt{2\pi_c}} exp\left[-\dfrac{(h^{arr} - \mu_c)}{2\sigma_c^2}\right] \\ (\mu_c - 12) \leq h^{arr} \leq 24 \end{cases} \tag{4}$$

$$f_s(h^{dep}) = \begin{cases} \dfrac{1}{\sqrt{2\pi}\sigma_c} exp\left[-\dfrac{(h^{dep} - \mu_s)^2}{2\sigma_c^2}\right] \\ 0 \leq h^{dep} \leq (\mu_s + 12) \\ \dfrac{1}{\sqrt{2\pi}\sigma_c} exp\left[-\dfrac{(h^{dep} - 24 - \mu_s)^2}{2\sigma_s^2}\right] \\ (\mu_s + 12) \leq h^{dep} \leq 24 \end{cases} \tag{5}$$

$$f_{pev}(x) = \frac{1}{\sqrt{2\pi}\sigma_{pev}} exp\left[\frac{(lnx - \mu_{pev})^2}{2\sigma_{pev}^2}\right] \tag{6}$$

The information provided by these PDFs can be extrapolated to different populations of EVs; thus, with less computational effort, the proposed approach seeks to manage the controllable features of EV populations instead of individually managing each EV. In this regard, to take advantage of the flexibility that can facilitate these EV populations, it becomes necessary to define an entity that appropriately manages the integration of EVs into the EDS. In the literature, some works adopt aggregators as intermediaries between the EV owners and the DSO [30], [31]. This entity can represent operators of charging stations and/or independent groups of EVs; however, for the purposes of the present work, this agent will be denoted as an aggregator.

The aggregator receives information regarding energy requirements and behavior from EV owners. This information is sent to the DSO, and then the DSO determines, for each time interval t, the power drawn by the aggregator in a way that meets the energy requirements of the EVs' and the EDS's operational limits. To model the aggregators and determine the population of EVs that can be connected to them, the expressions (7)-(15), based on [25], are used.

$$E_{t,u}^{max} = \sum_{v=1}^{\overline{EV}_k} E_{v,k}^{cap} D_{v,t} z_{u,k}, \quad \forall(t,u,k), \tag{7}$$
$$P_{t,u}^{max} = \sum_{v=1}^{\overline{EV}_k} P_{v,k}^{ev} D_{v,t} z_{u,k}, \quad \forall(t,u,k), \tag{8}$$
$$E_{t,u}^{arr} = \sum_{v=1}^{\overline{EV}_k} E_{v,k}^{ini} h_{v,t}^{arr} z_{u,k}, \quad \forall(t,u,k), \tag{9}$$
$$E_{t,u}^{dep} = \sum_{v=1}^{\overline{EV}_k} E_{v,k}^{cap} h_{v,t}^{dep} z_{u,k}, \quad \forall(t,u,k), \tag{10}$$
$$E_{t,u}^{ag} = E_{t-1,u}^{ag} + E_{t,u}^{arr} - E_{t,u}^{dep} + \Delta_t P_{t,u}^{ag}, \quad \forall(t,u), \tag{11}$$
$$\sum_{k \in \Gamma_{ev}^{p}} z_{u,k} = 1, \quad \forall u, \tag{12}$$
$$z_{u,k} = 0/1, \quad \forall(u,k), \tag{13}$$
$$0 \leq E_{t,u}^{ag} \leq E_{t,u}^{max} \quad \forall(t,u,k), \tag{14}$$
$$0 \leq P_{t,u}^{ag} \leq P_{t,u}^{max} \quad \forall(t,u,k), \tag{15}$$

where the indices t, u, and k correspond to sets of time intervals (Γ_T), the location of aggregators ($\Gamma_{AG} \in \Gamma_B$), and EV populations (Γ_{ev}^{p}), respectively.

The maximum storage capacity of the aggregator u at time t is determined in (7). Similarly, the maximum capacity of the power drawn by the aggregator u in time t is given by (8). The energy stored by the aggregator depends on the initial and final SOC of the EV batteries that connect and/or disconnect from the grid; this effect is represented by (9) and (10). Note that these expressions depend on the charging availability $D_{v,t}$ of each EV v at time t; the time when an EV is connected and disconnected from the grid (h^{arr} and h^{dep}); independent features, such as E^{cap}, P^{ev}, E^{ini}, and E^{dep} of each EV associated with the population k; the maximum number of vehicles defined in each population ($\overline{EV}_k$); and the z decision variable, which determines the population that can be integrated into the aggregator location u. The dynamic energy balance of an aggregator is determined by (11), where, for each t, the stored energy of a population of EVs is defined in terms of the energy stored in the previous time ($E_{t-1,u}^{ag}$), energy due to the arrival time of EVs ($E_{t,u}^{arr}$), energy due to the departure time of EVs ($E_{t,u}^{dep}$), and energy demanded from the EDS ($\Delta_t P_{t,u}^{ag}$). An EV population with $\overline{EV}_k$ is associated with an aggregator using the variable $z_{u,k}$; thus, (12) states that only a population k, contained in the set Γ_{ev}^{p}, can be accommodated into the aggregator location u. The nature of z is given by (13), where value 1 defines that the population k must be associated to the aggregator location u, and 0 otherwise. Finally, expressions (14) and (15) limit the stored energy and the power drawn by each aggregator, considering the technical constraints of each EV population.

C. OPTIMIZATION MODEL

The problem addressed in this work consists of two stages. The first stage seeks to estimate, in predefined locations, the penetration level of EVs and renewable-based DG that can be accommodated to an EDS. Meanwhile, the second stage simulates the operation of the EDS as a reaction to the capacities estimated in the first stage. Therefore, the second stage minimizes the EDS energy losses in the whole planning horizon, while EDS technical constraints must be satisfied.

In the proposed approach, the problem is mathematically formulated as an optimization model. The objective function, presented in (16), maximizes the installed capacity of PV- and wind-based DG units (first and second terms, respectively) and the EV demand by defining the maximum EV population that can be accommodated into all aggregators (third term); (16) simultaneously minimizes the energy losses of the EDS (fourth term). To define the priority in each term of (16), the weights τ and β are assigned.

$$\max \ \tau\Big(\sum_{n\in\Gamma_{pv}} P_n^{ins^{pv}} + \sum_{m\in\Gamma_{wt}} P_m^{ins^{wt}} + \sum_{u\in\Gamma_{AG}} P_u^{ins^{ag}}\Big) - \beta\Big(\sum_{t\in\Gamma_T}\sum_{ij\in\Gamma_L} I_{ij,t}^2 R_{ij}\Big) \tag{16}$$

Subject to: $(1)-(3), (7)-(15)$,

$$G(V,I,P,Q) = 0, \tag{17}$$
$$V_{min} \leq V_i \leq V_{max}, \quad \forall i, \tag{18}$$
$$I_{ij} \leq I_{max}, \quad \forall ij, \tag{19}$$
$$P^{ss^2} + Q^{ss^2} \leq S^{ss2}, \tag{20}$$
$$P^{ss} \geq 0, \tag{21}$$
$$P_{n,t}^{inj^{pv}} = x_n P_{n,t}^{pv} - P_{n,t}^{pv(cut)}, \quad \forall(n,t), \tag{22}$$
$$P_{m,t}^{inj^{wt}} = y_m P_{m,t}^{wt} - P_{m,t}^{wt(cut)}, \quad \forall(m,t), \tag{23}$$
$$\sum_{t\in\Gamma_T} P_{n,t}^{pv(cut)} \leq coef_{cut}^{pv} \sum_{t\in\Gamma_T} x_n P_{n,t}^{pv}, \quad \forall n, \tag{24}$$
$$\sum_{t\in\Gamma_T} P_{n,t}^{wt(cut)} \leq coef_{cut}^{wt} \sum_{t\in\Gamma_T} y_m P_{m,t}^{wt}, \quad \forall m, \tag{25}$$
$$P_n^{ins^{pv}} = x_n P_n^{nom^{pv}}, \quad \forall n, \tag{26}$$
$$P_m^{ins^{wt}} = y_m P_m^{nom^{wt}}, \quad \forall m, \tag{27}$$
$$x_n \in \{0,1,2,\ldots,x_{max}\}, \quad \forall n, \tag{28}$$
$$y_m \in \{0,1,2,\ldots,y_{max}\}, \quad \forall m, \tag{29}$$
$$P_u^{ins^{ag}} = \sum_{k\in\Gamma_{ev}^{p}} \sum_{v=1}^{\overline{EV}_k} P_{v,k}^{ev} z_{u,k}, \quad \forall u, \tag{30}$$

where i, ij, u, k, m, n, and t correspond to the sets of EDS buses, Γ_B; EDS circuits, Γ_L; locations of EV aggregators, $\Gamma_{AG} \in \Gamma_B$; EV populations, Γ_{ev}^{p}; candidate buses for installing wind-based DG units, $\Gamma_{wt} \in \Gamma_B$; candidate buses for installing PV-based DG units, $\Gamma_{pv} \in \Gamma_B$; and time intervals, Γ_T, respectively.

The objective function (16) is subject to renewable-based DG power production (1)-(3), the operation model of EV aggregators (7)-(15), and constraints (17)-(30). In this set of constraints, the function given by (17) represents power flow equations, where for each bus i, each circuit ij, and each time t, *Kirchhoff's* first and second laws must be satisfied. To guarantee a secure EDS operation, (18) and (19) define the pre-established limits for voltage magnitude and thermal limit at circuits, respectively. Expressions (20) and (21) define the

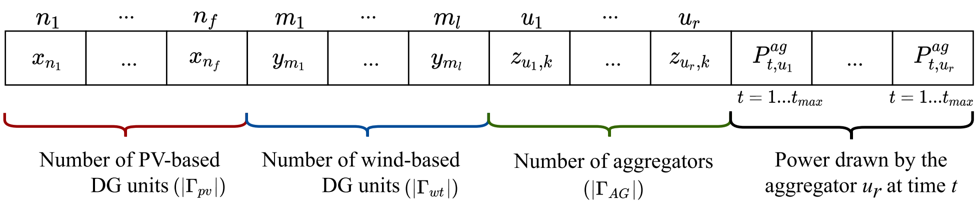

FIGURE 1. Codification of the solution proposal.

transformer capacity of the substation and the requirement that the substation cannot export power to the upstream system, respectively. The set of constraints presented in (22)-(29) determines the operation and maximum capacity of wind- and PV-based DG to be connected in the system. Constraint (22) defines the power injection at time t of a PV-based DG unit ($P^{inj^{pv}}_{m,t}$), located at bus n in terms of the available power $x_n P^{pv}_{n,t}$ and of the generation curtailment $P^{pv^{cut}}_{n,t}$. Similarly, (23) determines the power injection at t of a wind-based DG unit sited at bus m. Note that the power injection of the renewable-based DG is subject to generation curtailments in time intervals where the peak generation could affect the operation of the system; therefore, the DG power injected into the EDS is affected by a percentage generation curtailment for each technology. For each technology, this DG curtailment is limited by (24) and (25), where the sum of generation curtailment for all ts ($P^{pv(cut)}_{n,t}/P^{wt(cut)}_{n,t}$) should be less than or equal to a percentage $coef^{pv}_{cut}/coef^{wt}_{cut}$ of the sum in all time intervals of the available power ($x_n P^{pv}_{n,t}/y_m P^{wt}_{m,t}$). To define the installed DG capacity for wind and PV units, $P^{ins^{pv}}_{n}$ and $P^{ins^{wt}}_{m}$, expressions (26) and (27) are used, respectively. These capacities are defined by the product of the number of PV modules (x_n) with the nominal power of each PV module ($P^{nom^{pv}}_{n}$), and by the product of the number of wind turbines (y_m) with the nominal power of each wind turbine ($P^{nom^{wt}}_{m}$). Variables that define the number of PV modules and wind turbines are established to be integer variables in (28) and (29), respectively. Finally, (30) determines the demand of an EV population k accommodated to an aggregator. This demand is obtained from the product that associates the sum of the capacity of each EV charger ($P^{ev}_{v,k}$) with the binary variable $z_{u,k}$, which establishes that the population k can be accommodated to the aggregator u.

III. SOLUTION FRAMEWORK

The problem formulated in the previous section can be solved using different optimization techniques. However, the performance of classical optimization techniques could be affected due to the non-linearities of EDS power flow equations and, the problem complexity increases due to the number of decision variables. As an alternative, techniques based on heuristics and metaheuristics provide high-quality solutions close to the global optimal solution with less computational effort. Therefore, this work proposes an optimization-based technique composed of two metaheuristics, GRASP and Tabu Search, to solve the EV and DG hosting capacity problem. To illustrate the implementation of this solution technique, this section presents in detail the codification structure, algorithm steps, and general solution scheme.

A. CODIFICATION STRUCTURE OF THE SOLUTION

To solve the problem under analysis, a solution proposal within the search space should be efficiently represented; this is essential to determine the solution to the problem using metaheuristics. Thus, a solution proposal is formulated as a vector, as shown in Fig. 1, where the size of the vector depends on the number of PV- and wind-based DG units ($|\Gamma_{pv}|$, $|\Gamma_{wt}|$); the number of EV aggregators, ($|\Gamma_{AG}|$); and power drawn by the EV aggregator, u_r at time t, determined $\forall r \in 1 \ldots |\Gamma_{AG}|$ and $\forall t \in 1 \ldots |\Gamma_T|$, respectively.

The vector consists of the number of PV modules (x_{n_f}) to be installed at bus n_f ($\forall f \in 1 \ldots |\Gamma_{pv}|$), the number of wind turbines (y_{m_l}) to be installed at bus m_l ($\forall l \in 1 \ldots |\Gamma_{wt}|$), a population of EVs ($k$) to be accommodated to the aggregator u_r using the decision variable $z_{u_r,k}$, and finally, the power drawn (P^{ag}_{t,u_r}) at time t by the aggregator u_r. Therefore, from this information, the total installed DG capacity and the EV demand of an aggregator u ($P^{ins^{ag}}_{u}$) to meet the energy requirements of an EV population k are determined using equations (26), (27), and (30), respectively.

B. CONSTRUCTIVE PHASE

The constructive phase iteratively generates a solution; GRASP provides this solution as the starting point in the local search. Due to the different characteristics of the solution components, this phase is divided into two processes, as shown in Fig. 2. The first one, denoted as Constructive DG, aims at estimating the maximum installed DG capacity. Meanwhile, Constructive AG determines the maximum EV demand that can be accommodated to each aggregator.

The constructive DG consists of determining the maximum PV- and wind-based DG capacity at predefined locations, where different numbers of PV modules and wind turbines are evaluated and while the EDS operational limits should be met. Then, the process starts with an empty solution, for

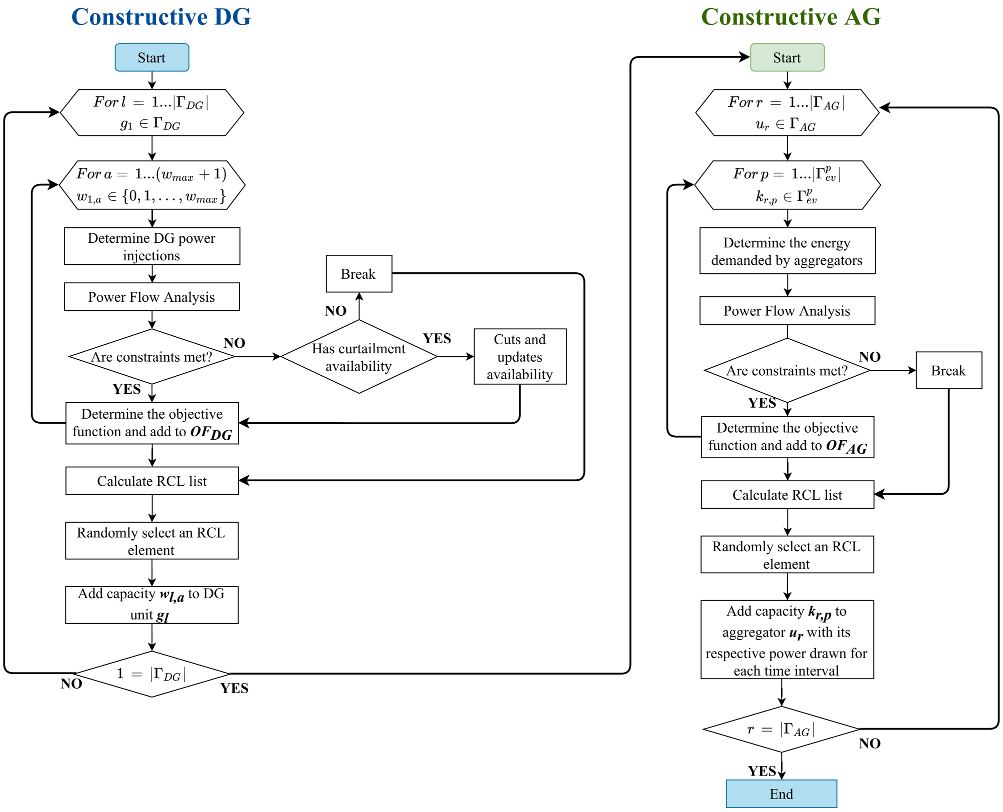

FIGURE 2. Flowchart of the constructive phase.

which the solution components are iteratively added through a *for* loop. For each iteration l, the capacity w_l of the DG unit g_l is added to the solution, where w_l generically represents both the number of PV modules and the number of wind turbines. Simultaneously, for each iteration l, different capacities $w_{l,a}$ for the DG g_l are evaluated using another *for* loop, which starts at zero and can reach the maximum predefined capacity w_{max}. From this loop, each iteration a starts calculating, for each time interval, the DG power production with capacity $w_{l,a}$, using equations (22) and (23). Therefore, the power flow, given by (17), determines the EDS operating condition, considering the integration of the renewable-based DG.

From the solution obtained by the power flow, operational constraints of the EDS, such as voltage magnitude limit, (18); thermal capacity, (19); and substation transformer capacity, (20) and (21) are verified. Note that the feasibility of the EDS operation for each iteration is assessed using the information regarding operational constraints; if these constraints are not met, a generation curtailment can be implemented at those time intervals where there is a surplus of renewable generation. In addition, this operational resource should meet the constraints formulated in (24) and (25), where the curtailment is limited to a percentage that can be defined as a prior agreement between the DSO and DG developers. However, if the maximum generation curtailment availability is reached and the infeasible conditions still remain, then iteration a is ended and the process continues to the next l iteration. Otherwise, when the proposed solution is feasible, the objective function is calculated and its value is stored in the vector OF_{DG}. When the "*for a*" loop is ended, the Restricted Candidate List (RCL) is calculated from the OF_{DG} array, and an element is randomly chosen to be part of the solution. Finally, the DG constructive process ends when $l = |\Gamma_{DG}|$ and, thus, the DG capacity determined is connected into the EDS.

The Constructive AG seeks to determine the maximum EV demand that can be accommodated and managed by each aggregator. This process evaluates different EV populations and determines the power dispatched for each aggregator satisfying the energy requirements of the EVs contained in this population. Then, for each iteration r, the EV demand for an aggregator u_r that belongs to the set Γ_{AG} is determined, considering different populations k_p in the set Γ^p_{ev}. Simultaneously, for each iteration in this "loop *for*", the power drawn by the aggregator u_r is managed for each time interval.

In this process, the charging of EVs contained in the population k_p are managed in order to take advantage of those time intervals in which there is more renewable generation and less conventional demand. Similar to the Constructive DG, the power flow is used to assess the feasible integration of these aggregate loads. In addition, it is essential to guarantee the charging of all EVs contained in each population, while

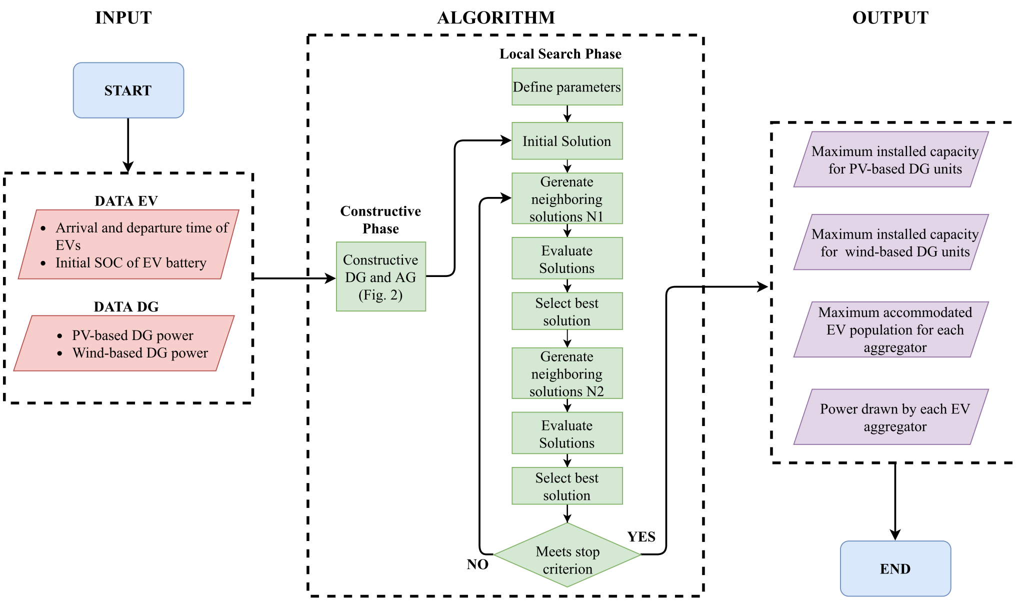

FIGURE 3. General flowchart for the solution framework.

the constraints of EV aggregators ((11), (14) and (15)) should be met. In this regard, when an EV population impacts the EDS operation, the "For, p" loop ends, and thus, only the previous populations (k_{p-1}) are considered as candidates to be added to the initial solution. In other words, for each iteration p, the objective function is calculated and stored in the vector OF_{AG}. When the For, p loop ends, the RCL list is calculated, and from this, a population k_p for the aggregator u_r is randomly chosen. Finally, this process is repeated until the EV demand for all aggregators u_r is determined.

C. LOCAL SEARCH PHASE

The local search phase aims to search for better solutions in the neighborhood of the current solution obtained in the constructive phase. Prior to starting the local search phase, it is necessary to define an appropriate neighborhood structure. In this regard, this work proposes two neighborhood structures: 1) the first neighborhood, denoted as N1, is generated from modifications in the installed capacity of DG (PV and wind) and in the EV demand associated with each aggregator, and 2) the neighborhood N2 is generated from modifications in the power drawn by each EV aggregator at each time interval.

To generate the set of neighboring solutions N1, the following steps are carried out:

- Step 1: Determine the next integer values for the variables x_n (number of PV modules), y_m (number of wind turbines), and $z_{u,k}$ (EV population k into aggregator u).
- Step 2: Generate the set of neighboring solutions from all the possible combinations of the variables determined in Step 1.
- Step 3: Disregard all the infeasible solutions and consider only the set of feasible neighboring N1 solutions.

The process in the neighborhood N2 consists of generating a set of neighboring solutions where, for each iteration c, the power drawn (P^{ag}_{t,u_r}) by the aggregator u_r is modified. Then, when c is equal to the maximum number of aggregators, a neighboring solution is obtained and the process continues until all the neighboring solutions are generated. Therefore, starting from the current solution of the neighborhood N1, the set of neighboring solutions N2 has the following steps:

- Step 1: Make a list of the best time intervals based on those with highest renewable generation and lowest conventional demand.
- Step 2: Generate all the possible combinations between pairs of time intervals, from the obtained list in Step 1.
- Step 3: Determine a list with the worst time intervals, those with high demand and low DG power production. Therefore, two time intervals (t) are chosen from the list obtained in Step 1, and the EV power demand is modified in these ts, considering the predefined limits for energy capacity and power demand.
- Step 4: In this step, for each aggregator u_r, exchanges of power demand (P^{ag}_{t,u_r}) are carried out between the lists obtained in Steps 2 and 3. It is worth mentioning that these modifications must satisfy the limits for energy capacity and power demand, and the energy balance for each EV aggregator given by (14), (15), and (11), respectively.
- Step 5: Recalculate the energy of the EV aggregator (u_r), and if any time interval (t) violates the constraint (14), then the modifications carried out in Step 4 are disregarded. In addition, if infeasible conditions are obtained for all EV aggregators, then this solution is eliminated from the set of neighboring solutions.

- Step 6: Repeat Steps 4 and 5 for all EV aggregators until c is equal to the maximum number of aggregators.
- Step 7: Repeat Steps 4-6 for all solutions in the set of neighboring solution N2.

D. GENERAL SOLUTION SCHEME FOR THE DG AND EV HOSTING CAPACITY PROBLEM

A summary of the proposed methodology to solve the EV and DG hosting capacity problem is presented in Fig. 3. This figure illustrates the three stages identified as input, GRASP-TS metaheuristic, and output. In the first stage, the data information necessary to formulate the problem is given by predicted values for DG power production (PV and wind), EV energy requirements, and driving patterns of EV owners. The second stage is defined by the GRASP-TS metaheuristic used as a solution tool, wherein the constructive phase, an initial solution, is iteratively generated. From this initial solution, the local search phase seeks to improve it, considering two different neighborhood structures (N1 and N2). Finally, when the stopping criterion is reached, the solution determines a) the maximum installed capacity for the wind- and PV-based DG units, b) the accommodated EV population for each aggregator, and c) the power drawn by each EV aggregator.

IV. CASE DESCRIPTION

The proposed strategy is evaluated under different test conditions in a 33-bus distribution system [32]. For this system, the nominal voltage is 12.6 kV; the peak demand is 3.715 MW and 2.30 MVAr; the substation transformer has a capacity of 4 MVA; the maximum and minimum voltage limits are set to 1.05 and 0.95 p.u., respectively; and the thermal limit of the conductors is 220 A.

The planning horizon is considered to be one year, being represented by time intervals contained in the set Γ_T. In this regard, the hourly resolution of one year (8760 h) could be adopted to solve the presented problem. It is known that this high time resolution could provide more accurate results; however, with a high computational effort. To deal with this difficulty, a representative time resolution can be adopted, which describes the planning horizon in a smaller set of time intervals, providing approximate results of good quality and with lower computational effort [33]. Therefore, in this work, a year is represented by 24-time intervals, where these representative ts approximate the operation and variability of renewable-based DG units, the behavior of EVs, and demand consumption variability.

DG units based on wind and PV technologies are considered. The Vestas V47 wind turbine with characteristics of $P_R = 660$ kW, $v_R = 15$ m/s, $v_I = 4$ m/s, and $v_0 = 25$ m/s is assumed. A PV module consists of 80 panels, with characteristics such as $P_{STC} = 200$ kW, $\delta = -0.004$ %/°C, $T_{amb} = 20$°C, and NOCT = 45. The solar radiation and wind speed data are obtained using the online tool "Renawable.ninja", obtained from [34], [35], the expected DG power production profiles are generated. The expected profiles that show the variability of demand consumption and DG power production are shown in Fig. 4.a and 4.b, respectively.

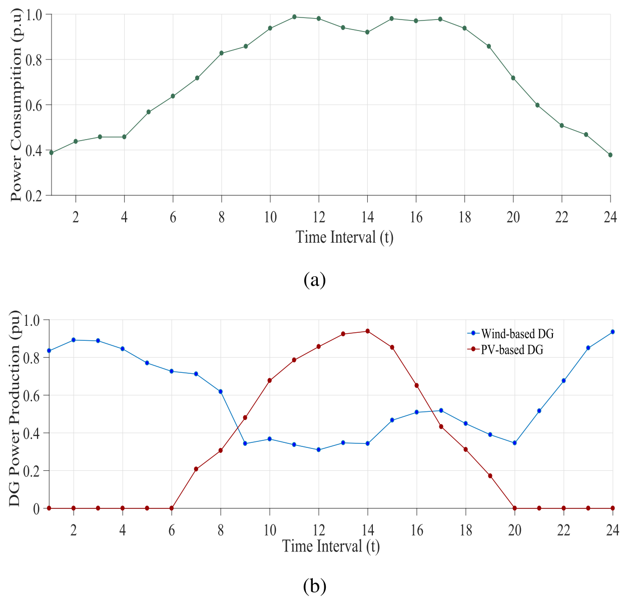

FIGURE 4. Expected value for a) demand consumption, and b) PV and wind-based DG power production.

For illustrative purposes, four predefined locations for renewable-based DG units are assumed; two PV-based DG units can be installed at buses 6 and 14, while two wind-based DG units can be installed at buses 31 and 10. Note that these locations can be defined through mutual agreements between independent DG developers and the DSO prior to the hosting capacity analysis. Generation curtailment can be implemented as an operational resource to avoid infeasible conditions in the EDS operation and enable more DG connections. For each DG unit (wind and PV), a maximum percentage of generation curtailment of 7% is defined for the whole planning horizon.

Regarding EV information, the NISSAN Leaf model with a 24 kWh battery capacity, charger capacity of 4 kW, and battery efficiency of 100% is taken into account. It is also assumed that all EVs must be charged until complete 100% SOC. To facilitate their integration into the grid, different numbers of EVs were grouped into populations in the set Γ_{ev}^{p}. This set contains, as a grouped effect, the information on the EV state of charge at arrival and departure times, and the maximum limit of the energy and power drawn for each EV population. The EVs are clustered in different populations denoted, from 1 to 16, as shown in Table 1, where each population contains different numbers of EVs. This representation

TABLE 1. Set of populations of EVs Γ_{ev}^{p}.

Population (k)	1	2	3	4	5	6	7	8
EVs ($\overline{VE}$)	100	200	300	400	450	500	550	600
Population (k)	9	10	11	12	13	14	15	16
EVs ($\overline{VE}$)	650	700	750	800	850	900	950	1000

enables the EV integration to aggregators through groups of EVs instead of integrating an EV individually, which also reduces the computational burden. Note that the proposed strategy should select only one population to connect to an aggregator, depending on the technical and operational limitations of the EDS.

In this work, a metaheuristic GRASP-TS is used as the solution technique to solve the aforementioned problem. Some parameters used in this metaheuristic are defined as follows: the exchange is prohibited for 3 iterations; the maximum number of iterations in the local search step is set to 20, and the aspiration criterion eliminates a prohibition when the objective function of the neighboring solution is of better quality than the incumbent. In addition, to define the priority in terms of the objective function in (16), the values of $\tau = 0.7$ and $\beta = 0.3$ are used. These values are adopted to optimize the energy losses without significantly degrading the DG capacity to be installed.

V. TEST CASES AND NUMERICAL RESULTS

In order to verify and show the advantages of the proposed strategy, two different analyses are carried out. In the first analysis, the hosting capacity of DGs and EVs is estimated under different test cases. In the second analysis, the penetration level of EVs is gradually increased to assess its effects on the DG hosting capacity.

A. ANALYSIS CONSIDERING DIFFERENT TEST CONDITIONS

For this analysis, four cases are studied under different test conditions to investigate the DG and EV hosting capacity in the 33-bus EDS. These cases are explained as follows:

- Case I estimates only the wind-based DG hosting capacity, disregarding PV-based DG and EVs.
- Case II seeks to estimate simultaneously the wind-based DG and EV hosting capacity. However, the EVs are charged without any control scheme.
- Case III considers the same conditions as Case II; however, the PV-based DG is added as a decision variable.
- Case IV involves the same technologies as Case III. Nevertheless, the EV aggregators can coordinate the charging of EVs.

The results obtained for each case are shown in Table 2. From the solution of Case I, it can be observed that the current infrastructure of the 33-bus EDS can accommodate wind-based DG with a capacity of 4.6 MW. This DG capacity increases by 30% when 3300 EVs are connected through aggregators into the EDS, as determined in the solution of Case II. The increase in DG capacity is a consequence of taking advantage of the availability of wind generation, as seen in Figs 6.a e 6.b, where the injection of wind power increases to meet the demand for EV aggregators. Note that the DG power injection is located at the top of these figures and the demand of the EV aggregators is located at the bottom. However, in this solution, it can be highlighted that this

TABLE 2. Summary of the results obtained for each case for the 33-bus EDS.

	Case I	Case II	Case III	Case IV
Total installed DG capacity (MW)	4.62	6.60	7.30	9.28
Total EV demand (MW)	-	13.20	16.00	16.00
Total number of EVs	-	3300	4000	4000
Energy losses (GWh)	5.50	8.67	1.94	1.17
DG curtailment (GWh)	13.57	19.39	16.07	21.89

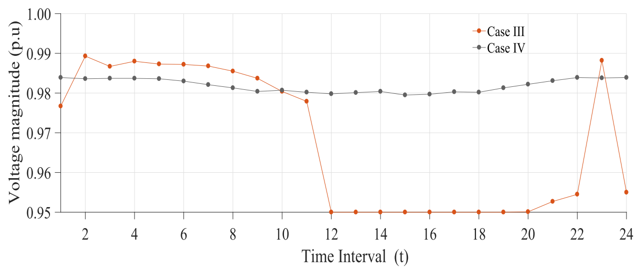

FIGURE 5. Minimum Voltage profile for Cases III and IV.

increase in DG capacity leads to a 36.56 % increase in energy losses compared with Case I.

When the PV-based DG is considered in Case III and its solution is compared with that of Case II, increments of 9.59% and 17.5% in the total installed DG capacity and in the EV penetration are achieved, respectively. Additionally, due to the complementarity in the capacity factor of these DG technologies (wind and PV), energy losses are reduced by 77.62 %. For Case IV, the flexibility of a charging coordination scheme for EVs is explored; the solution shows that, compared with Case III, the installed DG capacity is increased by 21.34%. The charging coordination scheme for the EV populations proves to be efficient to take advantage of those time intervals with higher availability of DG power production and lower conventional demand (Fig. 4.a and 4.b).

Comparing power dispatches between DG units and aggregators, shown in Figs 6.c and 6.d, the coordination of the power drawn by the aggregators implies increasing the installed DG capacity and taking advantage of time intervals in which there is an availability of wind power production. In addition, this EV demand coordination reduces energy losses by 39.69% and improves the voltage magnitude profile, as shown in Fig. 5. This figure shows the minimum voltage profiles for Cases III and IV, where it is observed that, when the EVs are charged without any control scheme, the voltage profile tends to the minimum limit.

The developed methodology determines simultaneously the DG and EV hosting capacity of the 33-bus system. The solution of each case presented different combinations of the installed DG capacity and the number of EVs that are connected in each aggregator. This information is presented in Fig. 7 where, comparing the solution obtained for Cases I and II, it is observed that, with the integration of EVs, the wind-based DG wind unit located at bus 10 presents a significant increase compared with the capacity determined in the solution of Case I. On the other hand, when the

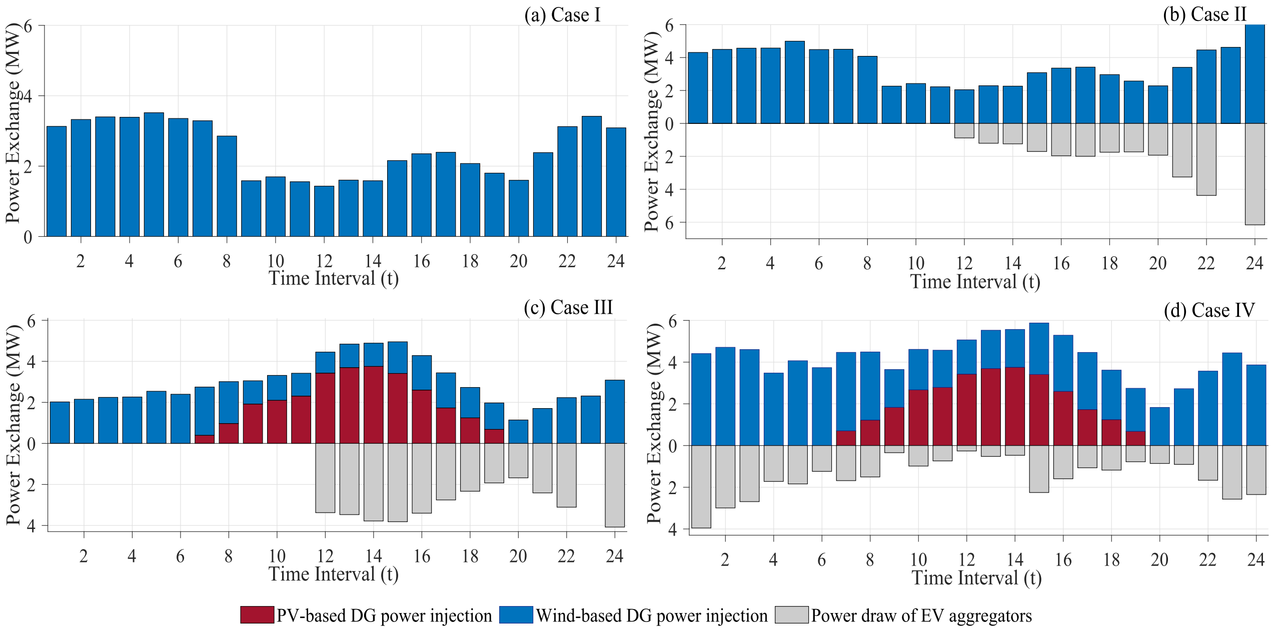

FIGURE 6. Power exchanges of DG units and EV aggregators for a) Case I, b) Case II, c) Case III, and d) Case IV.

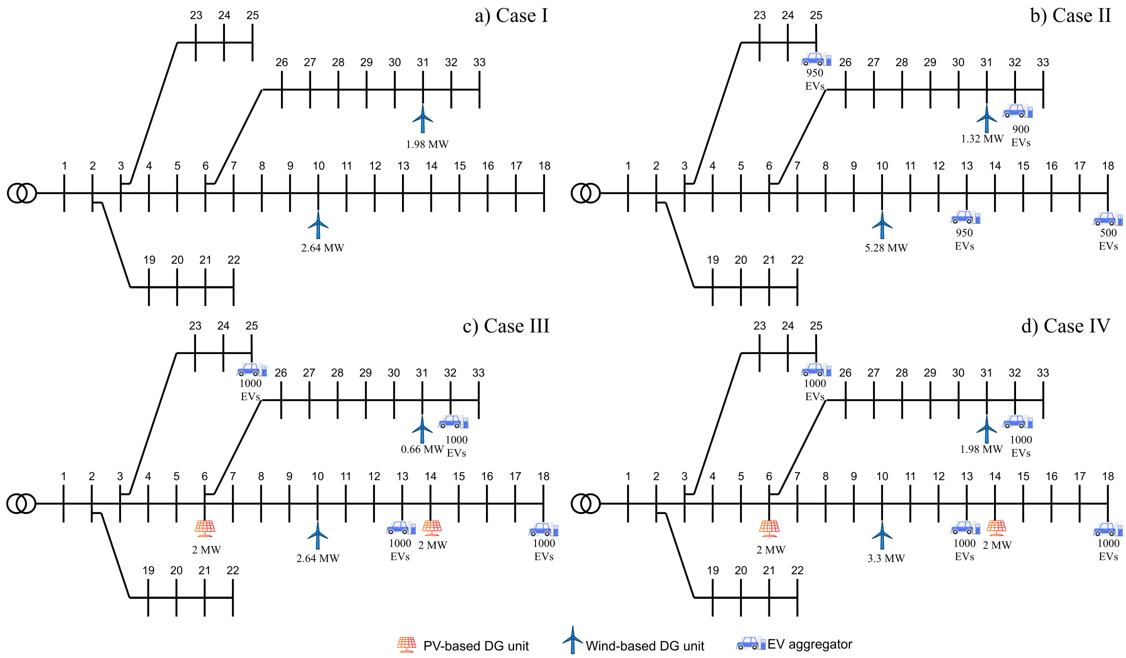

FIGURE 7. Installed DG capacity and accommodated EVs for each aggregator for a) Case I, b) Case II, c) Case III, and d) Case IV studied in the 33-bus EDS.

capacities of the PV-based DG units are dimensioned in the solution of Case III, the aggregator located at bus 18 can accommodate twice the number of EVs that were determined in the solution of Case II. Finally, when comparing the solutions for Cases III and IV, the controlled charging of EVs via aggregators determines a configuration that increases the installed capacity for the wind-based DG.

B. COMPARATIVE ANALYSIS INCREASING THE PENETRATION LEVEL OF EVs

The solutions obtained for Cases III and IV determine that a total demand of EVs of 16 MW is accommodated to the 33-bus EDS. For this analysis, this value is adopted as 100% of the penetration level of EVs. In order to assess the effects of increasing penetration levels of EVs on the DG hosting

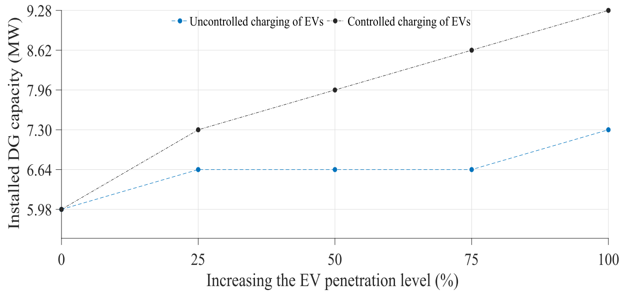

FIGURE 8. Installed DG capacity vs different percentages of EV penetration a) without any charging coordination scheme, and b) via charging coordination scheme by aggregators.

capacity (wind and PV), this penetration level is gradually increased by 25% until reaching 100%. For comparative purposes, the effects of controlled and uncontrolled charging of each EV penetration are analyzed. When the controlled charging option is not available, the range of EV penetration from 25 to 75 % does not maximize the installed DG capacity as shown in blue in Fig. 8. However, coordinating the charging of EVs through aggregators, behavior that is depicted in black in Fig. 8, enables increasing the installed DG capacity for all EV penetrations under study.

C. SCALABILITY OF THE PROPOSED STRATEGY

In order to evaluate and validate the scalability of the proposed algorithm, tests are carried out using two distribution systems: the 83-bus [36] system and the 135-bus [37] system. The 83-bus system contains 11 feeders with a nominal voltage of 11.40 kV, and a peak demand of 28.35 MW and 20.7 MVAr. The upper and lower limits for the voltage magnitude are set to 1.05 and 0.93 p.u., respectively, and the thermal limit for the conductors is set to 350 A. Candidate DG locations are defined at buses 24, 37, and 70 for PV-based DG units and at buses 10, 42, and 80 for wind-based DG. In addition, six aggregators are located at buses 8, 21, 40, 53, 72, and 82.

The 135-bus EDS contains a substation with a nominal voltage of 13.8 kV, tthe peak demand for this system is 6.499 MW and 2.769 MVAr. The upper and lower voltage limits of 1.05 and 0.95 p.u. are adopted, respectively, and the EDS circuits have a thermal limit of 250 A. DG locations are defined as candidate buses to connect new renewable-based DG units. PV-based DG units can be connected at buses 111,

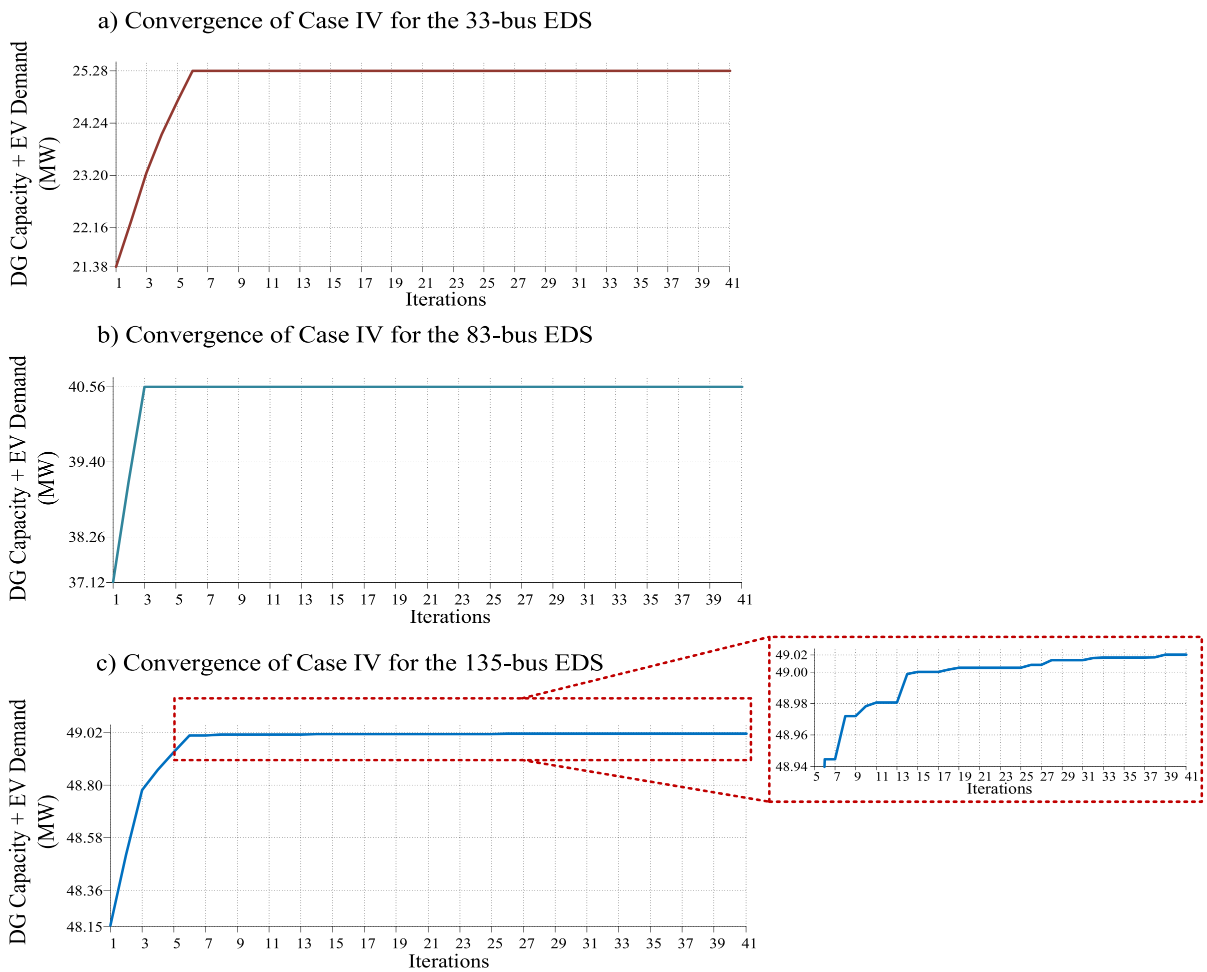

FIGURE 9. Convergence of the proposed strategy for Case IV for the a) 33-bus EDS, b) 83-bus EDS, and c) 135-bus EDS.

90, and 129, while wind-based DG units at buses 125, 116, 95, and 133. EV populations can be connected in eight different aggregators that are located at buses 88, 121, 130, 94, 70, 87, 114, and 100. It is worth mentioning that for test purposes here, the same percentage of 7% of generation curtailment and the same set of EV populations presented for the 33-bus EDS are adopted for these systems. In addition, the same expected profiles for demand and DG are used.

The solutions obtained for the 83-bus EDS are summarized in Table 3. The results show that in Case III, a total DG capacity of 13.26 MW is installed, where 6 MW corresponds to the PV-based DG and 7.26 MW to wind-based DG. However, when aggregators can coordinate the charging of EV populations, such capacity is increased by 19.93%, while energy losses decrease by 11.40%. On the other hand, when simulations are carried out on the 135-bus system, the solution of Case III installs a PV-based DG capacity of 6 MW and 9.24 MW of wind-based DG capacity, totaling 15.24 MW of DG capacity. In addition, the solution of this case determines that 30 MW of demand can be accommodated. Nevertheless, the charging coordination of EV populations via aggregators leads to an increase in the installed DG capacity by 10.46% and EV demand by 6.25%. Consequently, by coordinating the EV demand, energy losses can be reduced up to 92.49%.

TABLE 3. Summary of obtained results for Cases III and IV for the 83-bus and 135-bus EDSs.

EDS	Case	Total inst. DG capacity (MW)	Total EV demand (MW)	Number of EVs	Energy losses (GWh)	DG curtail. (GWh)
83-bus	III	13.26	24.00	6000	2.28	9.24
	IV	16.56	24.00	6000	2.02	12.46
135-bus	III	15.24	30.00	7500	10.65	13.39
	IV	17.02	32.00	8000	0.80	15.40

D. CONVERGENCE OF THE PROPOSED STRATEGY

In summary, the proposed strategy has been assessed under different test conditions using the 33-bus system, for which the hosting capacity of DG and EVs was estimated. In addition, the scalability of the proposed algorithm was evaluated using two EDSs: the 83-bus system and the 135-bus system. Therefore, given that the proposed strategy consists of an iterative algorithm, a convergence analysis is presented in Fig. 9 for Case IV. In Fig. 9.a and 9.b, it is observed that, for the 33- and 83-bus systems, the algorithm converges in few iterations, being needed only 6 and 3 iterations (computational times of 80.95 and 288.67 seconds), respectively. When the algorithm is implemented in the 135-bus system, a computational effort of 602.81 seconds is required, given that the convergence is achieved in 39 iterations as shown in Fig 9.c.

VI. CONCLUSION

A strategy, formulated from the point of view of the distribution system operator (DSO), to estimate the hosting capacity of renewable-based distributed generation (DG) and electric vehicles (EV) in electric distribution systems (EDSs) was presented in this work. To represent the effects of EVs, variability of demand consumption, and DG power production, a multiperiod formulation was developed. The EVs were grouped into different populations that can be accommodated to different EDS locations, and their charging coordination was managed by an aggregator. To maximize the hosting capacity of DG and EVs, operational resources such as generation curtailment and charging coordination schemes of EVs were optimized to guarantee the EDS operation, avoiding technical limit violations and minimizing energy losses.

The proposed strategy was tested on a 33-bus EDS under different test conditions, and the obtained results show that large penetrations of DG and EVs can be connected to the existing EDS infrastructure. The results also show that by applying a coordinated charging scheme for EV populations, the installed capacity of DG was increased by up to 20%, compared with an uncontrolled charging approach of EVs. A comparative analysis showed that, without a coordinated charging scheme for electric vehicles, increases in the percentages of EV penetration do not necessarily lead to an increase in the installed DG capacity. For validation purposes, the scalability of the proposed strategy was studied using the 83-bus and 135-bus EDSs. Results show that, with a low computational effort and requiring few iterations, the developed algorithm determined the solution of the problem.

Directions for future work should include other operational resources, such as the operation of devices for voltage and reactive control and energy storage systems. The GRASP-TS metaheuristic should be recast to address the uncertainties associated with renewable-based DG power production and demand consumption. In addition, for validation and comparative purposes, other solution techniques (i.e., metaheuristics or classical optimization tools) could be implemented to solve the DG and EV hosting capacity problem.

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