Electrical Power and Energy Systems 161 (2024) 110215

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

A hybrid particle swarm optimization approach for explicit flexibility procurement in distribution network planning

Miguel Martínez [a,*], Carlos Mateo [a], Tomás Gómez [a], Beatriz Alonso [b], Pablo Frías [a]

[a] *Institute for Research in Technology (IIT), School of Engineering (ICAI), Universidad Pontificia Comillas, Madrid, Spain*
[b] *i-DE Redes Eléctricas Inteligentes, Spain*

A R T I C L E I N F O

Keywords:
Distribution network planning
Demand response
Flexibility
Network reinforcement
Investment deferral

A B S T R A C T

Flexibility services enable distribution system operators to actively manage the grid for accommodating demand and generation growth while potentially reducing or delaying investments in grid reinforcements. This paper proposes a novel hybrid particle swarm optimization and linear programming methodology that analyzes explicit flexibility procurement as an alternative to conventional network reinforcements in electricity distribution network planning. The distribution system planning problem is decomposed into a master problem and an inner problem. Binary particle swarm optimization (BPSO) is used to determine the optimal investment decisions, binary variables, from a set of candidate grid reinforcements in the master problem. At the inner linear programming optimization problem, a market-based procurement of flexibility services is performed. The inner optimization problem obtains the total cost of flexibility and the volume of flexibility at each network bus required to defer or avoid part of the grid reinforcements. A real 500-bus medium voltage network is used to validate the proposed methodology. Results illustrate cost-effective network plans that combine flexibility procurement with network reinforcements. A sensitivity to the cost and availability of flexibility services is also conducted to calculate the thresholds where flexibility becomes an efficient alternative to reinforcing the network.

1. Introduction

Current annual grid investments in electricity networks are expected to triple by 2030 [1] to meet the United Nations' goal of net zero carbon dioxide emissions by 2050 [2]. Additional network infrastructure will be required to integrate the increasing share of distributed renewable energy generation into the power system as well as to enable the electrification of transportation, buildings, and industry [3]. At the same time, the digitalization of distribution networks (DNs) will allow for better controllability of distributed energy resources (DERs) [4], increasing the flexibility of the whole power system. In the context of power systems, flexibility can be viewed as the ability of market agents to regulate their demand or generation profiles in response to signals provided by system operators.

Distribution system operators (DSOs) can use this flexibility to enhance network planning and operation. The term "non-wire alternative" (NWA) is commonly used to describe any system operator planning practice that is employed to defer or avoid the necessity for the construction or reinforcement of network elements (e.g., power lines, transformers, etc.). In Europe, most DSOs are subject to unbundling regulations that stipulate the separation of generation and distribution activities. Thus, European DSOs cannot own or operate DERs. The preferred NWA practice in Europe is the market-based procurement of flexibility services from DERs or aggregators [5]. Article 32 of the Directive (EU) 2019/944 mandates DSOs in the European Union to incorporate the procurement of flexibility services into their DN development plans to avoid costly network expansions or reinforcements and achieve an efficient and secure operation of DNs [6].

Several authors have developed models to evaluate the techno-economic feasibility of incorporating the flexibility provided by demand response (DR), distributed generation (DG), and energy storage systems (ESSs) into distribution network planning (DNP). A summary of the literature review is provided in TABLE 1, differentiating between implicit and explicit flexibility mechanisms [7]. Implicit flexibility is achieved by incentivizing prosumers and generators to shift load and generation to periods of lower energy or network costs. On the other hand, explicit flexibility mechanisms require a commitment from flexibility providers to temporarily change their consumption or generation when requested by the DSO. In TABLE 1, solution methods for DNP with

* Corresponding author.
E-mail address: Miguel.Martinez@iit.comillas.edu (M. Martínez).

https://doi.org/10.1016/j.ijepes.2024.110215
Received 13 May 2024; Received in revised form 24 July 2024; Accepted 27 August 2024
Available online 8 September 2024
0142-0615/© 2024 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Nomenclature

Indices and sets

i,j	Indices of buses
l	Indices of branches (i.e., lines and transformers)
$n\in\mathcal{N}$	Indices and set of candidate investments in network reinforcements
m	Indices of particles in a population
t	Indices of iterations

Parameters

c_1	Local acceleration constant
c_2	Global acceleration constant
CR_n	Equivalent annual cost of candidate network reinforcement n
CP_j^{CURT}	Distributed generation curtailment cost at bus j
CP_j^{DN}, CP_j^{UP}	Procurement cost of downward and upward flexible active power demand at bus j
CQ_j^{DN}, CQ_j^{UP}	Procurement cost of downward and upward flexible reactive power demand at bus j
$M_{i,j}^{VP}$, $M_{i,j}^{VQ}$	Sensitivity matrices relating active and reactive power injected at j to increments in bus i voltage
$M_{i,l}^{VReinf}$	Sensitivity matrix that relates reinforcing branch l to increments in bus i voltage
$\overline{P}_l$	Maximum active power flow in branch l
P_l^*	Active power flows at the operating point
$PTDF_{l,j}$	Power transfer distribution factors matrix indicating the incremental change of active power in branch l for an injection at bus j
$\overline{V}_i$, $\underline{V}_i$	Upper and lower voltage limits at bus i
V_i^*	Voltage magnitude at the operating point
$Vdev_i$	Vector of bus voltage deviations from limits
v_{max}	Limit to particles' velocities
w_{max}	Maximum inertia weight (first iteration)
w_{min}	Minimum inertia weight (last iteration)
$\overline{\Delta P}_j^{CURT}$	Maximum capacity for distributed generation curtailment at bus j
$\overline{\Delta P}_j^{DN}, \overline{\Delta P}_j^{UP}$	Available capacity of downward and upward flexible active power demand at bus j
$\overline{\Delta Q}_j^{DN}, \overline{\Delta Q}_j^{UP}$	Available capacity of downward and upward flexible reactive power demand at bus j
K^T, K^V	Penalties for deviations from thermal and voltage limits

Variables

c^{reinf}	Equivalent annual cost of investments in network reinforcements
c^{flex}	Equivalent annual cost of procured flexibility
x^{inv}	Investment decision variables on network reinforcements
$x_n\in\{0,1\}$	Investment decision on candidate network reinforcement n
y^{flex}	Flexibility procurement decision variables
p_l	Active power flow in branch l
v_i	Voltage magnitude at bus i
α_i, β_i	Deviations from the upper and lower voltage limits at bus i
γ_l	Deviation from the thermal limit in branch l
δ_l	Deviation of reversed power flow from the thermal limit in branch l
Δp_j^{CURT}	Curtailment of distributed generation at bus j
Δp_j^{DN}, Δp_j^{UP}	Procured volume of downward and upward flexible active power demand at bus j
Δq_j^{DN}, Δq_j^{UP}	Procured volume of downward and upward flexible reactive power demand at bus j
$\varphi^{T,V}$	Penalty term for deviations from grid limits
I_l	Magnitude of the current through branch l
n_l	Number of elements added in parallel when reinforcing branch l
Z_l	Magnitude of the impedance
ΔV_i	Increment in bus i voltage with respect to the operating point
ΔV_l^{drop}	Reduction in voltage drop along a branch l that is reinforced with additional parallel elements
$gbest$	Global-best solution for the population
$pbest$	Own-best solution for the particle
$s_{m,n}^t$	Position of m-th particle in n-th dimension at t
$v_{m,n}^t$	Velocity of m-th particle in n-th dimension at t

Table 1
Literature review of approaches to integrate flexibility in DNP.

References	Methods		DN size	Flexibility	
	MP	Heur.	*No. of buses*	Implicit	Explicit
[9–11,14,15,18–20]	✓		54, 26, 10, 18, 18, 86, 37,123	✓	
[12,16,17]		✓	25, 33, 281	✓	
[13]	✓	✓	134	✓	
[22–25]		✓	21, 133, 2762, 2762		✓
This paper	✓	✓	500		✓

Methods: MP=Mathematical Programming, Heur. = Heuristic algorithms.

flexibility include mathematical programming, heuristics, or a combination of both. TABLE 1 also reports the case study DN with the highest number of nodes analyzed in each reference (DN size).

Implicit demand-side flexibility can be provided in DR programs by customers who change their energy consumption in response to price signals or other incentives [8]. Considering the price elasticity of demand in DNP models influences the optimal network configuration and planning costs [9], as network investments can be reduced or deferred [10]. The potential reduction of investments achieved by lowering peak demand from thermal building loads through DR is analyzed in [11]. In addition, DR can reduce network losses and improve the system's reliability [12]. The response of several DERs (shiftable loads, electric vehicles, ESS, and DG) can be integrated into a single DNP model to postpone or avoid investments in network reinforcements [13].

Other authors, such as [14], combine implicit flexibility provision in DNP with DER expansion planning, which studies the siting, sizing, and flexible operation of DERs. For example, [10] presents a bi-level DNP approach where the minimization of investment costs in the DN and DG (upper-level) is subject to the response of the customers to time-varying tariffs (lower-level). Incorporating investment decisions and operation strategies for ESSs can be used to reduce peak loading, DNP costs, and energy losses, as well as to enhance DN reliability and improve bus voltages [15–17]. However, these models may not be applicable in countries with an unbundled power system.

The unbundling of the power system is addressed in [18] by a tri-level model that differentiates agents involved in DNP, siting and sizing DG, and operating DG and the DN. Besides, [19] proposes a bi-level model in which distribution locational marginal prices (DLMP) incentivize private investments in flexible DERs to reduce network reinforcements. Implicit flexibility as a NWA in a deregulated retail market is further explored by [20], which proposes a closed-loop scheduling mechanism to generate dynamic retail prices associated with the DN's status. These models ([18–20]) have a higher degree of complexity since they model the interaction among several market agents as well as pricing mechanisms.

The main drawback of implicit flexibility is that market participants may not behave rationally and be willing to respond to price signals. In addition, end customers may receive multiple signals (e.g., market prices and network charges) that may be contradictory. These uncertainties do not arise in explicit flexibility mechanisms where DSOs procure flexibility services from aggregators or DER owners. Contracting flexibility services simplifies the interaction between DSOs and flexibility providers. The DSO no longer needs to anticipate the response of other market players to incentives ([18–20]). It receives as input the offers of flexibility services characterized by their location, available capacity, and price [21]. Therefore, explicit flexibility requires a different type of DNP model.

In the literature, few authors have studied explicit flexibility in DNP. For instance, temporary demand disconnections to defer grid reinforcements are analyzed in [22]. The price of the flexible capacity provided by DR customers, modeled as a constant parameter, is key for this flexibility service to result in an attractive alternative. In [23], the cost of explicit flexibility from DR includes customer and DN automation upgrades and an annual availability payment for the flexible capacity. The multi-stage and multi-scenario recursive algorithm proposed in [23] evaluates the cost for the DSO of all combinations of potential interventions, including flexibility. However, populating the recursive function requires substantial initial computations (e.g., power flow calculations, Monte Carlo simulations, etc.) that scale exponentially with the DN's size. Tabu search has been used by some of the authors of this paper to develop single-stage [24] and multi-stage [25] DNP tools for large DNs, such as the 2762 bus grid used in both papers as a case study, that include contracting DR flexibility as a planning alternative. However, DR flexibility is not procured through a market-based model. These models based on metaheuristics do not guarantee to find the global optimum, but they achieve good solutions in a reasonable time and can handle large DNs [24].

This paper proposes a single-stage deterministic approach that evaluates explicit procurement of flexibility as a NWA in DNP. A binary particle swarm optimization (BPSO) algorithm is used to determine the optimal investment decisions, binary variables, from a set of candidate grid reinforcements that minimize the sum of their cost and the procurement cost of flexibility obtained from the inner optimization problem. For a given set of grid reinforcements, the inner linear programming (LP) optimization problem computes the volume of the flexibility services the DSO needs to procure at each bus to achieve a secure DN operation. The main contributions of this paper are:

- To improve existing methodologies based on heuristic algorithms for explicit flexibility services procurement in DNP [22–25], an inner linear programming optimization problem that models a market-based mechanism for procuring flexibility has been added.
- The proposed methodology combines the advantages of metaheuristics, dealing with large-scale DNs, and mathematical programming, ensuring the optimal volume of flexibility is procured for any set of DN reinforcements.
- This paper also assesses the cost and availability thresholds of flexibility services that make them viable as a NWA in DNP. In the case study for a real 500-bus DN, these thresholds are examined with a sensitivity analysis.

The rest of the paper is organized as follows. Section 2 describes the proposed hybrid BPSO and LP algorithm for DNP with flexibility. Section 3 introduces the data inputs and assumptions of the case study. The results of this case study are discussed in Section 4. Finally, Section 5 concludes the paper.

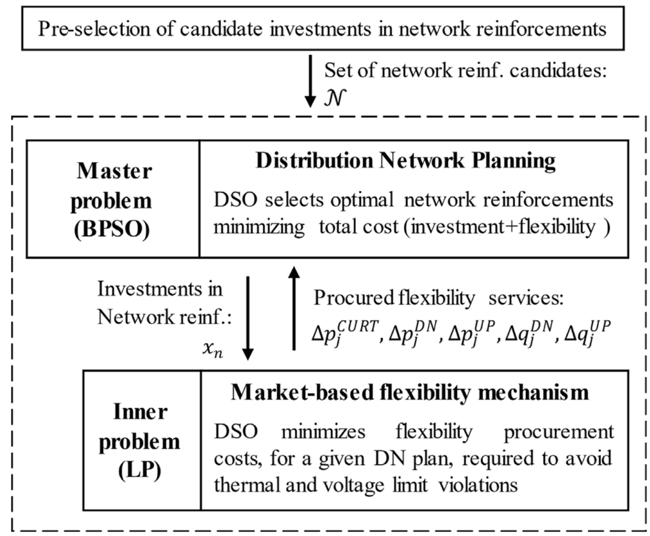

Fig. 1. Decomposition of DNP model in master (BPSO) and inner (LP) optimization problems.

2. Methodology

This paper proposes a single-stage deterministic DNP approach to evaluate the potential savings of deferring or avoiding future grid reinforcements by procuring flexibility services. This hybrid approach, based on BPSO and LP, is selected over mixed integer linear programming (MILP) or second-order cone programming (SOCP) for two reasons. First, for each possible selection of grid reinforcements (i.e., for each particle in the BPSO algorithm), the procurement of flexibility services can be evaluated independently. Thus, in Fig. 1, the DNP problem is decomposed into an investment planning problem and a flexibility services procurement problem, enabling the use of specific algorithms for each problem. Second, the non-linearities in power flows, which introduce a significant degree of complexity into pure mathematical programming methods, can be effectively addressed in metaheuristics through power flow evaluations as in [26]. Then, sensitivity factors are computed to represent the DN physical constraints when clearing the flexibility market. LP flexibility market formulations can provide reliable solutions in comparison to SOCP models [27] and have been preferred by European flexibility market demonstrators for their simplicity and scalability [28].

Although metaheuristics cannot guarantee convergence to the global optimum, they have been shown to be an effective tool for planning large DNs in practice [22–25]. The proposed hybrid approach improves pure heuristic models by introducing a market-based flexibility procurement mechanism. The proposed methodology is validated in Section 4.1 for a test case distribution system.

Active DNP problems can be divided into two levels [29], in our case: investment planning (master problem) and flexibility service procurement (inner problem). The investment decisions (x^{inv}) in the master problem (1)-(4) seek to minimize investments in DN reinforcements (c^{reinf}) and flexibility procurement costs (c^{flex}). The decision variables in the master problem are the investments in grid reinforcements. For any given set of investment decisions on grid reinforcements, the required flexibility services (y^{flex}) to guarantee a secure operation within grid limits are procured in the inner problem (5)-(7). Then, the inner problem feeds back the optimal flexibility procurement results to evaluate the master problem, as illustrated in Fig. 1.

Table 2
Scalability with Number of Variables.

Number of iterations	Computation time*	Maximum number of variables for which convergence to optimum was achieved
150	1.25 h	30
1500	12.5 h	100
15,000	125 h	130

* The computation time in this pre-analysis does not consider the parallelization of the BPSO algorithm. Simulations carried out on a PC with an 11th Gen Intel® Core® i7-1185G7 CPU at 3.00 GHz and 16 GB of RAM.

$$\min_{x^{inv}} F(x^{inv}) + c^{flex} = c^{reinf} + c^{flex} \tag{1}$$

$$\text{s.t. } G(x^{inv}) = 0 \tag{2}$$

$$H(x^{inv}) \leq 0 \tag{3}$$

$$x^{inv} \in \{0,1\} \tag{4}$$

$$c^{flex} = \min_{y^{flex}} f(y^{flex}) \tag{5}$$

$$\text{s.t. } g(x^{inv}, y^{flex}) = 0 \tag{6}$$

$$h(x^{inv}, y^{flex}) \leq 0 \tag{7}$$

A BPSO algorithm is used to solve the master planning problem that selects network reinforcements to minimize DN investment and flexibility procurement costs. The inner LP problem procures flexibility services via a market-based mechanism to minimize flexibility procurement costs for each particle, which represents a combination of DN reinforcements. In BPSO, the particles move over the search space guided by the individual and global best-known solutions (i.e., solutions with the lowest investment and flexibility services procurement cost) until the stopping criteria are met. Finally, this methodology has been developed for planning actual DNs; hence, the size of the search space is automatically reduced using technical criteria to identify and preselect a subset of candidate network reinforcements.

The inputs to the model are DN data, a catalog with technical and economic parameters for DN equipment (e.g., power lines and transformers), and the cost and available capacity of flexibility services at each node. The main outputs are the annualized cost of the required grid reinforcements and the procured flexibility to achieve a future operation that complies with grid limits. The results of this methodology can be compared with the annualized cost of grid reinforcements in a scenario with no flexible capacity available to quantify the savings in avoiding grid reinforcements by employing flexibility. Furthermore, it identifies the optimal location where grid reinforcements and flexibility services are needed.

2.1. Dimensionality reduction

The proposed methodology is designed to plan real large-scale DNs. A scalability analysis of the BPSO algorithm is carried out in TABLE 2. For a simple problem with a known solution, the number of decision variables is progressively increased, checking when the optimal solution is found. This pre-analysis reveals that the number of iterations and computation time required to reach convergence sharply increases with the number of decision variables, having a reasonable computation time until 100 variables.

The number of decision variables has been reduced to a subset of candidate network reinforcements applying technical criteria to achieve a computationally tractable solution. From a technical standpoint, there is no need to reinforce branches (i.e., lines and transformers) located in areas where grid limit violations are not anticipated. Consequently, only

0	1	1	0	1	0
Branch 1	Branch 2	Branch 3	Branch 4	Cluster 1	Cluster 2

Fig. 2. Example of a particle with six binary decision variables.

congested lines and clusters of buses that share similar voltage limit violations, designated as voltage clusters (VCLs), are considered. A depth-first search algorithm determines these VCLs for a planning scenario. This algorithm traverses the radial DN and examines the voltage magnitude for all buses downstream of a given bus. If all of them have undervoltage (or overvoltage) problems, they are clustered into the same VCL. The proposed methodology has the additional benefit of reducing the search space size and decoupling the number of decision variables from the DN size, as only preselected candidate investments are considered.

The particles for BPSO are defined as a vector of binary decision variables with a length equal to the total number of congested branches and voltage clusters previously identified. In this vector, a 1 in the entry of a power line means it must be reinforced, while a 1 in a VCL entry implies that voltage limit violations in its buses are solved using reinforcements. For example, in Fig. 2, branches 2 and 3 are reinforced with parallel elements to increase their capacity, while voltage violations at the buses in cluster 1 are solved with a heuristic algorithm (see Section 2.2) that determines which branches should be reinforced to reduce the voltage drop. The principal rationale for using a *meta*-heuristic, such as BPSO, and the heuristics for identifying potential grid investments is to facilitate the analysis of more complex problems. In Section 4.1, an exhaustive search in a small test case is conducted to verify that the use of BPSO and the simplifications made to reduce the number of decision variables (e.g., clustering of buses) do not significantly affect the quality of the solution.

2.2. Preselection of candidate network reinforcements

Two heuristics are used to determine candidate network reinforcements. If the decision variable (Fig. 2) takes a value of 1, the violation in that branch or voltage cluster is solved using grid reinforcements. When a branch exceeds its capacity limit, it is reinforced by investing in a new element with a higher power rating. On the other hand, solving voltage violations is not straightforward since reinforcing a branch to reduce its voltage drop affects the voltage of several nodes in the DN. Therefore, for each voltage cluster, the candidate branches to be reinforced are ranked by a KPI that measures the reduction in voltage deviations achieved by reinforcing that line [44]:

$$KPI = \sum_{i \in VCL} \left(Vdev_i - M_{i,l}^{VReinf} \bullet \left(1 - \frac{1}{n_l^{MAX}}\right)\right) \tag{8}$$

where $Vdev$ is the vector of voltage deviations over the limits at each bus i that belongs to the cluster (VCL), M^{VReinf} is the sensitivity matrix that measures the impact of reinforcing branch l on the voltage of bus i (see Appendix A), and n_l^{MAX} is the maximum number of equivalent parallel lines of branch l to reinforce. An engineering criterion forcing monotony of decreasing nominal ampacities is applied by providing an upper bound to n_l^{MAX} so that the rated capacity of branch l can only be increased up to the capacity of its upstream branch.

2.3. Master problem

The objective of the master problem (9) is to select, from the pre-identified candidate investments for reinforcing the DN, the combination that minimizes the sum of the annual costs of network reinforcements and flexibility services.

$$\min_{x_n} c^{reinf} + c^{flex} + \varphi^{T,V} \tag{9}$$

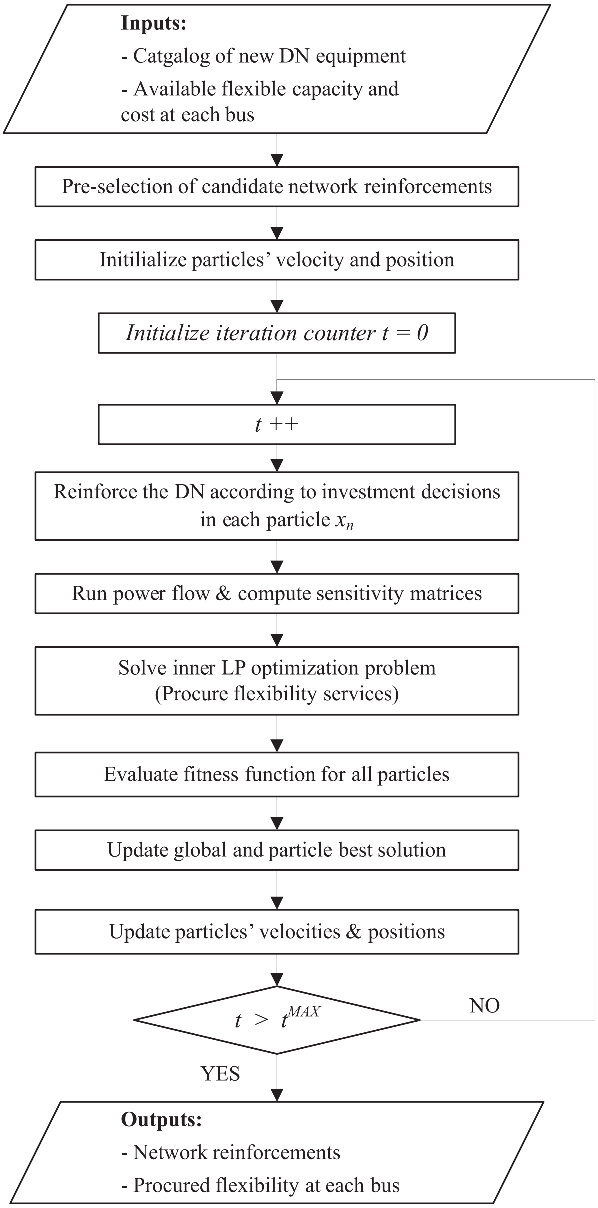

Fig. 3. Flowchart of BPSO algorithm used to solve the master problem.

The first term of (9) is the annual cost of the investments in network reinforcements (x_n), which are the master problem variables. This is modeled in (10), where the equivalent annual cost of the network reinforcements (CR_n) is obtained based on the catalog of new network elements that is provided as input.

$$c^{reinf} = \sum\nolimits_n CR_n \cdot x_n \tag{10}$$

The second term of (9) accounts for the annual procurement cost of flexibility (c^{flex}). In (11), c^{flex} depends on the procured volumes of flexibility services, which are not variables of the master problem, but instead determined by the inner optimization problem. Thus, in the master problem, (11) is evaluated based on the optimum values obtained after solving the inner optimization problem (13)-(26).

$$c^{flex} = \sum\nolimits_j (CP_j^{DN} \Delta p_j^{DN} + CP_j^{UP} \Delta p_j^{UP} + CQ_j^{DN} \Delta q_j^{DN}$$
$$+ CQ_j^{UP} \Delta q_j^{UP} + CP_j^{CURT} \Delta p_j^{CURT}) \tag{11}$$

The BPSO algorithm selects in the master problem the optimal investments in network reinforcements from the pre-identified candidates. Particle swarm optimization (PSO), introduced by Kennedy and Eberhart [30], is a widely used metaheuristic algorithm that performs optimization inspired by the social behavior of the movement of birds in a flock. The flowchart of the BPSO algorithm used to solve the master problem is shown in Fig. 3. More details on the BPSO algorithm implementation and its parameters are provided in Appendix B.

Basic versions of PSO algorithms cannot handle constrained problems, and penalty functions are commonly added to avoid convergence to unfeasible solutions [31]. Given that feasible DN plans should verify thermal and voltage limits, the term $\varphi^{T,V}$ is added in (9) to penalize unfeasible solutions based on the amount that grid limits are exceeded.

$$\varphi^{T,V} = K^V \sum\nolimits_i (\alpha_i + \beta_i) + K^T \sum\nolimits_l (\gamma_l + \delta_l) \tag{12}$$

where α_i and β_i represent the deviations from the upper ($\overline{V_i}$) and lower ($\underline{V_i}$) voltage limits. Similarly, γ_l and δ_l account for the surplus over the thermal limits ($\overline{P_l}$) of the lines for normal and reversed active power flows, respectively. The factors K^V and K^T in (12) are sufficiently large numbers, so any feasible solution is always preferred over an unfeasible one.

2.4. Inner optimization problem

The inner optimization problem optimizes the capacity and location of flexibility services required to solve the congestion and voltage problems, which are not solved at the master problem through network reinforcements. The network configuration, given by the reinforcements selected by the master problem, is assumed to remain fixed in the inner optimization problem. In the inner optimization problem, the DSO can contract several flexibility services, characterized by their location (connected at the j-th bus), maximum flexible capacity available, and price [21]. The contracted volumes for each type of flexibility service at each node are the variables of the inner optimization problem, formulated as a LP problem.

$$\min \sum\nolimits_j (CP_j^{DN} \Delta p_j^{DN} + CP_j^{UP} \Delta p_j^{UP} + CQ_j^{DN} \Delta q_j^{DN}$$
$$+ CQ_j^{UP} \Delta q_j^{UP} + CP_j^{CURT} \Delta p_j^{CURT}) + \varphi^{T,V} \tag{13}$$

s.t.

$$0 \le \Delta p_j^{UP} \le \overline{\Delta P}_j^{UP} \; \forall j \tag{14}$$

$$0 \le \Delta p_j^{DN} \le \overline{\Delta P}_j^{DN} \; \forall j \tag{15}$$

$$0 \le \Delta p_j^{CURT} \le \overline{\Delta P}_j^{CURT} \; \forall j \tag{16}$$

$$0 \le \Delta q_j^{UP} \le \overline{\Delta Q}_j^{UP} \; \forall j \tag{17}$$

$$0 \le \Delta q_j^{DN} \le \overline{\Delta Q}_j^{DN} \; \forall j \tag{18}$$

$$p_l = P_l^* + \sum\nolimits_j PTDF_{l,j} \cdot (-\Delta p_j^{UP} + \Delta p_j^{DN}$$
$$- \Delta p_j^{curt}) \forall l \tag{19}$$

$$v_i = V_i^* + \sum\nolimits_j M_{i,j}^{VP} \left(-\Delta p_j^{UP} + \Delta p_j^{DN} - \Delta p_j^{curt} \right)$$
$$+ \sum\nolimits_j M_{i,j}^{VQ} \left(-\Delta q_j^{UP} + \Delta q_j^{DN} \right) \forall l \tag{20}$$

$$-\overline{P_l} \le p_l + \gamma_l \forall l \tag{21}$$

$$\overline{P_l} \ge p_l - \delta_l \forall l \tag{22}$$

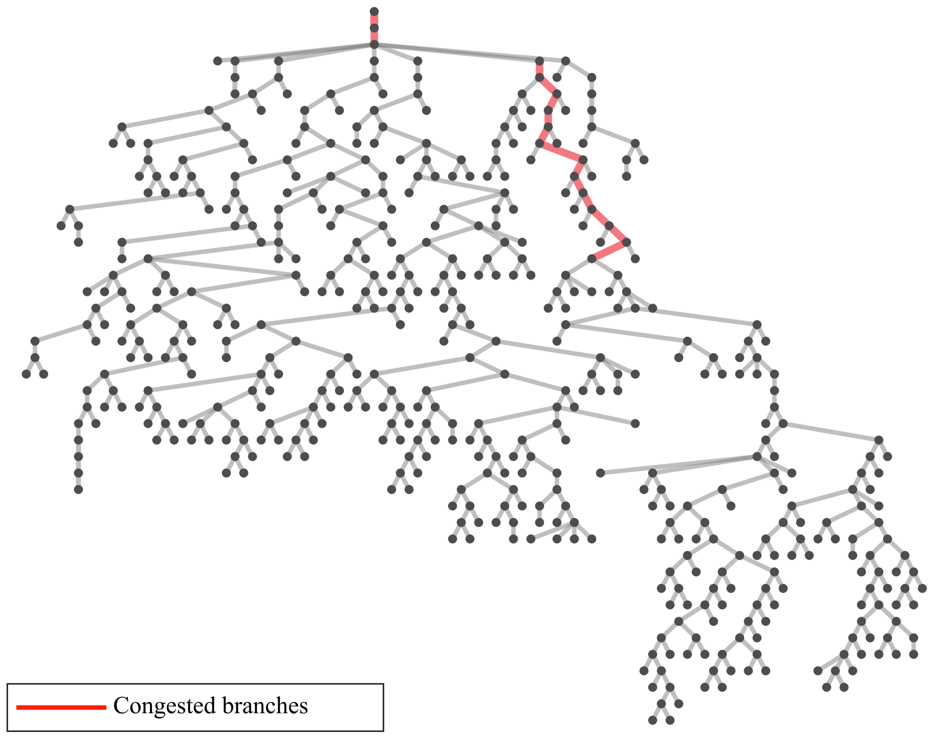

Fig. 4. Location of the identified congested branches.

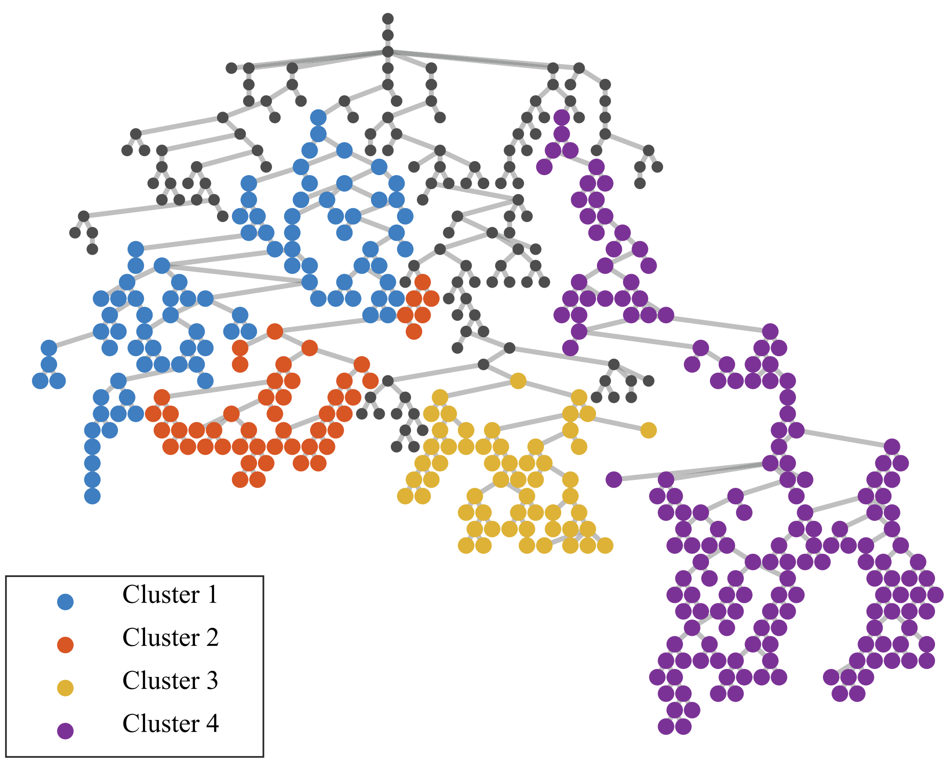

Fig. 5. Clusters of buses experiencing undervoltage conditions.

$$\underline{V_i} \leq v_i + \alpha_i \forall i \quad (23)$$

$$\overline{V_i} \geq v_i - \beta_i \forall i \quad (24)$$

$$\alpha_i \geq 0, \beta_i \geq 0 \forall i \quad (25)$$

$$\gamma_l \geq 0, \delta_l \geq 0 \forall l \quad (26)$$

The objective function of the inner problem (13) minimizes the annual procurement cost of the necessary flexibility services that ensure a safe operation of the DN. The procured volume of the flexibility services at each bus is bounded by the available capacity for flexibility services per bus (14)-(18).

The power flow equations have been linearized as (19)-(20) using two matrices that relate the increments in active and reactive power injections at the j-th bus with: i) the l-th branch flow and ii) the i-th bus voltage. The first, known as the (incremental) power transfer distribution factors (PTDFs), gives the relative change in branch loading due to a change in the active power injection at a bus [32]. For the latter, two sensitivity matrices that are derived from the Jacobian matrix are used to model the effect in bus voltages of changes in active power injections (M^{VP}) and reactive power injections (M^{VQ}) [33]. Note that these sensitivity matrices depend on the operating point and more iterations updating the operating point may be needed to reduce the linearization error.[1] The first iteration takes as the operating point the result of the preliminary power flow. Subsequently, the previous solution is used as the point for the linearization in the next iteration.

Finally, constraints (21)-(24) ensure that thermal and voltage limits are not exceeded. However, when the master problem selects too few network reinforcements, there may not be sufficient flexibility to solve all congestion and voltage problems. Thus, constraints (21)-(24) are implemented using slack and surplus variables to guarantee that the problem is always feasible, even when the available flexible capacity is insufficient to reach a secure DN operation. These deviations over the voltage and thermal limits are penalized in the objective function of the inner problem (13) using the same penalty function ($\varphi^{T,V}$) as in (12). Adding this penalty to inner optimization objective function makes deviations from the thermal and voltage limits less desirable than procuring flexibility, avoiding all violations of grid limits that can be solved with the available flexibility offered to the DSO.

3. Case study

A case study of an actual 20 kV rural DN operated by i-DE in Spain is analyzed. The DN consists of 500 buses and 504 branches and is larger than the ones typically used in the literature. This DN is supplied through a high voltage/medium voltage (HV/MV) 20 MVA substation and contains 243 km of MV power lines. The DN is operated radially with five open branches, and only the MV network is modeled. It is assumed that there are no technical violations in low voltage (LV). Therefore, consumers and DG are represented as aggregated demand and generation connected at terminal MV nodes. The aggregated contracted power at the distribution transformers is 43 MW, and the installed capacity of DG is 7.36 MW.

A worst-case future peak demand planning scenario is built, considering that the demand for each consumer during peak hours is 60 % of their current contracted power. Consequently, the aggregated peak demand is 26 MW. In this scenario, the power flow results in 14 overloaded branches, colored in red in Fig. 4. Besides, the upper and lower voltage limits are defined as 1.05p.u. and 0.95p.u., respectively. Fig. 5 shows the buses with under-voltage conditions, which are grouped into 4 voltage clusters. Thus, each BPSO particle has 18 binary decision variables for candidate investments in network reinforcements.

In addition, an equipment catalog for new network elements (i.e., power lines and transformers) is provided as input to the model. It is created using the reference CAPEX and OPEX values defined by the Spanish regulation [34]. The annualized cost of each asset in the catalog is calculated considering an expected life of 40 years [34] and a 5.58 % discount rate [35].

The procurement cost of flexibility services is more difficult to estimate since limited data from real-world implementations are available. Two factors are considered for estimating the annual procurement cost of flexibility services: i) the number of peak hours throughout the year when the activation of the service is required and ii) the unitary cost of contracting the flexibility for one hour. In the base case, it is assumed an annual procurement cost for active power demand flexibility (CP_j^{DN} and CP_j^{UP}) of 2.34€/kW-yr. based on reports from recent tenders in the UK [36,37].[2] Besides, customers providing these flexibility services can deviate up to 25 % from their peak consumption in the base case. Then, two sensitivities for the procurement cost and availability of flexibility are conducted to illustrate how they affect the total cost of the DN plans and the required investment decisions.

Although the formulation also allows for reactive power flexibility services, they are not considered in this case study for simplicity. The compensation price for DG curtailment is set to 150€/MWh,[3] hence CP_j^{CURT} takes a value of 8.55€/kW-yr. in the base case. Finally, the penalties for deviations from voltage and thermal limits (K^V and K^T) are set to 1 billion €/p.u and 1 billion €/MWh., so any solution that results in a secure operation of the DN is always preferred over unfeasible ones.

4. Results

4.1. 18-bus test distribution system

Two factors have been identified that could result in suboptimal solutions: firstly, the BPSO algorithm may converge to a local optimum, and secondly, errors may be introduced due to the simplifications made to reduce the number of decision variables, which is necessary to deal with large-scale problems. These include the clustering of buses described in Section 2.1 and the heuristics for preselecting candidate DN reinforcements presented in Section 2.2.

This section presents a validation of the proposed hybrid BPSO methodology against a recursive algorithm that evaluates all potential combinations of branch reinforcements and flexibility similar to the one in [23]. In essence, the recursive algorithm is a smart exhaustive search algorithm that does not evaluate infeasible investment options. The recursive algorithm presented in [23] has been adapted to procure flexibility through a market-based mechanism (inner LP optimization problem in Section 2.4.) instead of considering a set of DR interventions. As previously stated, the primary issue with the recursive algorithm is

[1] In the case study, a maximum linearization error of 10^{-3}p.u. is achieved for the bus voltages with two iterations.

[2] Recent tenders in the UK have been reviewed to estimate the cost of flexibility services. Two factors are studied: the number of peak hours and the unitary procurement cost. First, according to UK Power Networks estimations in its 2021 flexibility services tender [36], the utilization hours of flexibility services for reducing peak demand are in the range of 5h – 150h with an average of 57h. Then, the average unitary procurement cost of flexibility services for reducing peak demand is 41€/MWh, with a range from 10€/MWh to 600€/MWh, in Scottish Power Energy Networks' 2021 tender [37]. In the base case, it is considered that the simulated peak demand scenario is occurring 57h per year. Multiplying the number of utilization hours (57h) times the average unitary cost (41€/MWh) yields the annual procurement cost of 2.34€/kW-yr. used in the base case. The full ranges are considered later in the sensitivity to the flexibility cost.

[3] This cost has been estimated assuming that it does not make sense to compensate the DG owner for the curtailment with a higher amount than the revenue they obtain from energy generation in the wholesale market.

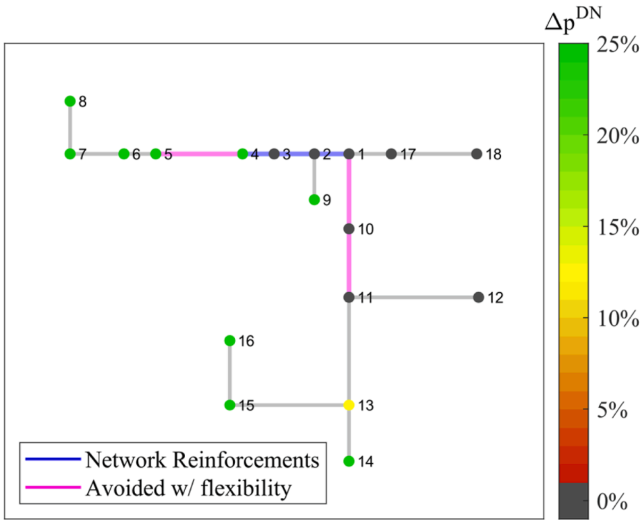

Fig. 6. Peak demand reduction contracted at each bus and avoided network reinforcements for the 18-bus test distribution system.

that its computational complexity increases exponentially with the number of nodes. Therefore, a small grid, the 18-bus test DN from [39], is used to validate the model against the recursive algorithm solution.

The initial configuration of the 18-bus test DN does not exhibit any congestion or under-voltage issues. A future planning scenario is constructed with the assumption of a 20 % increase in demand, resulting in five overloads (on lines 2, 3, 4, 5, and 11) and six voltage limit violations (at buses 5, 6, 7, 8, 15, and 16). The remaining assumptions regarding the procurement cost and availability of flexibility services are consistent with those introduced in Section 3 for the 500-bus real MV grid case study. Fig. 6 illustrates the optimal planning decisions on network reinforcement and flexibility procurement for this scenario on the 18-bus test DN obtained with the proposed hybrid BPSO approach.

TABLE 3 compares the optimal solution achieved with the proposed hybrid BPSO approach and the recursive algorithm. If the monotonicity constraint, imposed in Section 2.2. to determine which lines should be reinforced for reducing the voltage drop along the feeder, is considered, both methodologies converge to the same solution.

Finally, Fig. 7 confirms that the combination of power line reinforcements and procurement of flexibility services can maintain the voltage of all buses above the lower limit. Note that in the initial planning scenario before any grid intervention is considered, there were six nodes with a voltage lower than 0.95, which are within the specified grid limits after applying the optimal solution achieved with the proposed methodology.

4.2. 500-bus actual Spanish distribution system

Following the successful verification of the hybrid BPSO approach within the previous test case, this section presents the results for the 500-bus actual Spanish DN described in Section 3. The proposed methodology is applied to obtain a cost-effective DN plan assuming, for the base case scenario, that a demand reduction of up to 25 % can be achieved in each load network bus. The annual procurement cost of active power demand reduction as a flexibility service is 2.34€/kW-yr. These results are compared to a reference DN plan with only traditional DN reinforcements, which is also obtained by applying the proposed methodology with no flexible capacity. In this reference case, only the investments in transformers and power lines are optimized, selecting among the pre-identified candidates the minimum required reinforcements to achieve a secure DN operation. In Fig. 8, the required DN reinforcements, highlighted in blue, are located at congested branches (see Fig. 4) or upstream branches to nodes with under-voltage problems (see Fig. 5). The total annualized cost of DN reinforcements is 472,923 €/yr.

The proposed approach determines the flexibility that must be contracted at each bus to defer or avoid part of the investments in network reinforcements. The percentage of peak demand reduction required at each bus for the base case is shown based on the color bar of Fig. 9. However, the available flexibility is insufficient to solve all grid violations cost-effectively. Thus, the optimal solution combines flexibility and network reinforcements (highlighted in blue in Fig. 9).

The branches where network reinforcements are avoided with flexibility are highlighted in magenta in Fig. 9. Flexibility is only procured at buses located downstream of these branches. A lower power flow through these lines reduces the voltage drop over the feeder, avoiding the need for network reinforcements to maintain the voltage of the buses in this area above the lower limit. TABLE 4 breaks down the savings in network reinforcements that result from incorporating flexibility into DNP. If peak demand were not reduced through DR, an additional parallel line would have been required for lines 438, 437, and 261 (highlighted in magenta in Fig. 9).

The results are summarized in TABLE 5, comparing the annualized costs achieved for the base case with the proposed methodology and a traditional DNP approach with no flexibility provision. In the base case, 923 kW of active power demand reduction is contracted (3.5% reduction of aggregate peak demand), allowing to reduce by 13.97 % the required

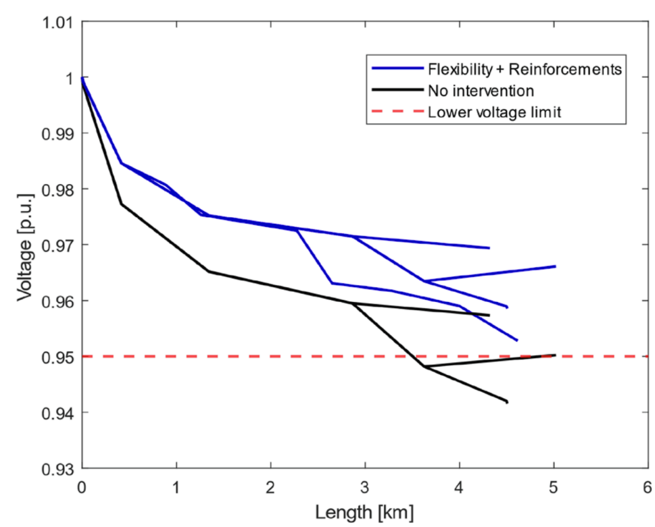

Fig. 7. Voltage drop along the MV feeders in the 18-bus test distribution system. The black lines show the initial condition without grid interventions. The blue lines show the improvement in voltage after grid reinforcement and flexibility procurement. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Validation of proposed approach for the 18-bus test distribution system.

	Flexibility [kW]	Flexibility cost [€/yr.]	Reinforced power lines	Reinforcement cost [€/yr.]	Total cost [€/yr.]	Execution time [s]
Recursive algorithm *(with monotonicity constraint)*	2,724	6,376	2, 3, 4	4,814	11,190	241
Hybrid BPSO	2,724	6,376	2, 3, 4	4,814	11,190	29

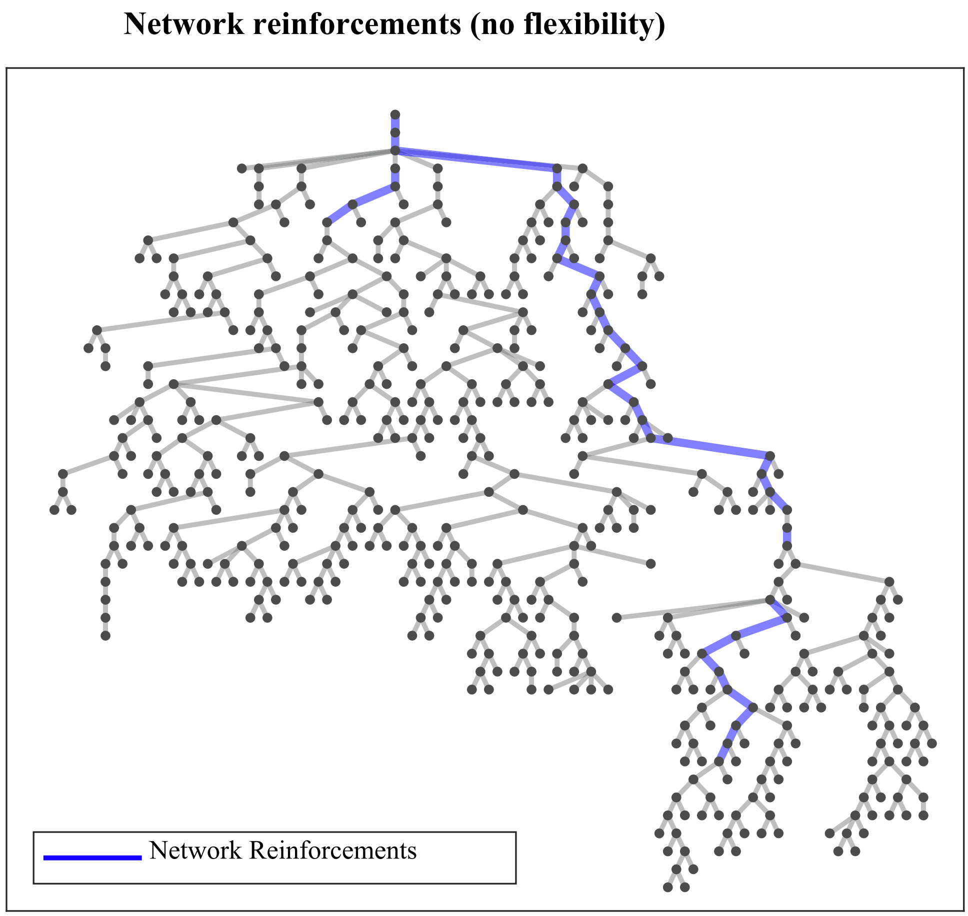

Fig. 8. Required network reinforcements when no flexibility is considered.

annualized investments in network reinforcements.

4.3. Sensitivity to the procurement cost of flexibility

This section presents a sensitivity analysis of the procurement cost of flexibility, which accounts for all the expenses the DSO faces to obtain and activate the required flexibility. This cost includes compensation for flexibility providers. In Fig. 10, a sensitivity analysis is carried out for the annual cost of flexibility in the range of 0.05€/kW-yr. to 100€/kW-yr. For the same amount of required flexible capacity, the total cost of flexibility services increases linearly as their annual fee increases. The DSO continues contracting the same volume of flexibility services until its yearly cost exceeds the annualized CAPEX and OPEX of new network reinforcements.

In Fig. 10, when annual fees exceed 71 €/kW-yr., it is no longer cost-effective to use flexibility as a NWA. Hence, the proposed methodology can effectively be used to find the threshold for the DSO to opt for flexibility or network reinforcements. Although the threshold of 71 €/kW-yr. is specific to this network and planning scenario, this analysis can be replicated for other DNs and planning scenarios. Then, for a particular DNP scenario, the DSO should determine if the cost of flexibility is sufficient to implement DR programs. Note that this threshold has been obtained considering only the benefit of providing flexibility services for congestion and voltage management during hours of peak demand. Customers providing flexibility can also benefit from stacking several flexibility services (e.g., improvement of quality of service) or energy arbitrage, making flexibility provision more attractive.

Thus far, it has been assumed that the procurement cost of flexibility is identical across all buses. However, a major contribution of the proposed methodology is that it allows the DSO to select the most cost-effective offers of flexibility services available in the local market. Fig. 11 illustrates the flexibility procurement for the base case, including varying procurement costs of flexibility for each bus. It is assumed that the utilization of flexibility is 57 h per year, with activation costs randomly assigned to each bus, ranging from 25€/MWh to 100€/MWh. In Fig. 11, the numbers next to each bus represent the cost of flexibility, expressed in €/MWh for that bus. Note that, in Fig. 9, where the cost of flexibility services was identical across all buses, flexibility was procured at the optimal locations to minimize the voltage drop of the feeder, specifically at the buses at the end of the feeder. In contrast, in Fig. 11, the flexibility is contracted in buses situated further upstream on the feeder. Although these flexible units are located at less optimal locations, they have offered their flexibility at a lower price. This results in a higher volume of flexibility contracted, amounting to 993 kW—7.58 % higher than in the base case. This analysis shows that the advantage of hybridizing BPSO with LP as the inner problem is that it ensures the contracting of least-cost offers of flexibility services for any given combination of grid reinforcements.

4.4. Sensitivity to the availability of flexibility

A sensitivity to the available flexible capacity is carried out in this section, considering different values for the maximum flexible peak demand reduction that can be shifted to off-peak hours. This maximum demand reduction potential is expressed relative to each bus' demand and can vary from 0 % to 50 %. The upper plot in Fig. 12 illustrates that increasing the available flexible capacity reduces the cost of network reinforcements.

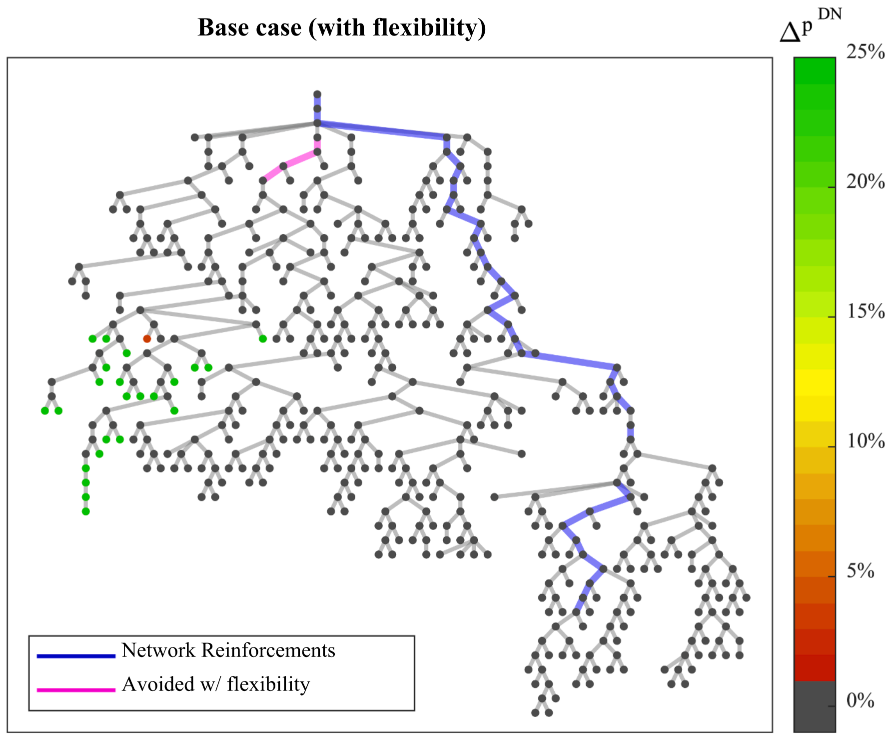

Fig. 9. Peak demand reduction contracted at each bus and avoided network reinforcements for the base case.

Table 4
Deferred/Avoided network reinforcements.

Line	Length [km]	Additional parallel lines	Additional capacity [MVA]	Cost [€/yr.]
438	2.77	1	10.62	19,328
437	1.00	1	10.62	6,978
261	5.70	1	10.62	39,772
Total				66,078

Table 5
Summary of the base case.

	Flexibility [kW]	Flex. cost [€/yr.]	Reinf. cost [€/yr.]	Total cost [€/yr.]
Only traditional DN reinforcements	0	0	472,923	472,923
Base case (with flexibility)	923	2,157	406,845	409,002

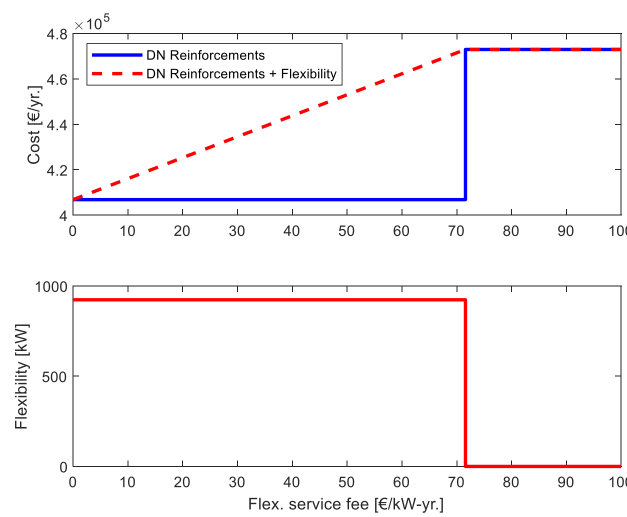

Fig. 10. Sensitivity to the procurement cost of flexibility.

However, enough available flexible capacity is required to avoid network reinforcements. In Fig. 12, when the potential for demand reduction at each node is lower than 14 %, no flexibility is contracted since the available flexible capacity is insufficient to avoid network reinforcements. When the available flexible capacity ranges from 14 % to 15 %, a 6.65 % reduction in network reinforcements' costs is achieved. Furthermore, for available flexible capacities greater than 16 %, the annual savings on DN reinforcements ascent to 13.97 %.

The bottom plot in Fig. 12 shows the total procured flexible capacity required to achieve the reductions in network reinforcements. As the maximum demand reduction for each node increases from 16 % to 50 %, the total procured flexible capacity decreases. When more flexible capacity is available, the required flexibility is less because it is procured at fewer and more optimal nodes with a higher contribution to reducing congestion and voltage problems.

4.5. Implementation of the model

The proposed methodology has been coded in MATLAB®, using MATPOWER [38] for the power flow analysis. The simulations have been carried out on a PC equipped with an 11th Gen Intel® Core® i7-1185G7 CPU at 3.00 GHz and 16 GB of RAM. The BPSO algorithm has been parallelized to take advantage of the CPU's multi-core architecture by evaluating the fitness function for multiple particles in parallel. The computation time on 4 cores averaged 14.31 min for 10 particles in the population and a maximum of 150 iterations. Although BPSO does not guarantee to find the global optimum, it is observed that after 60

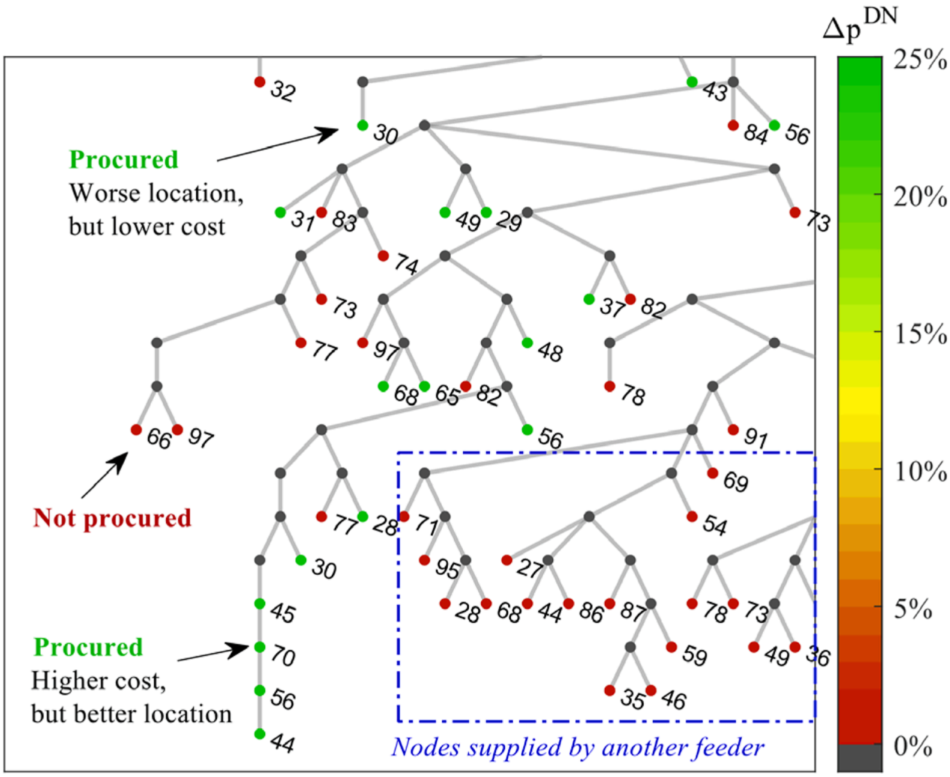

Fig. 11. Flexibility procurement in a modified base case considering varying costs of downward active demand flexibility at each node. The numbers next to each bus represent the cost of flexibility, expressed in €/MWh for that bus.

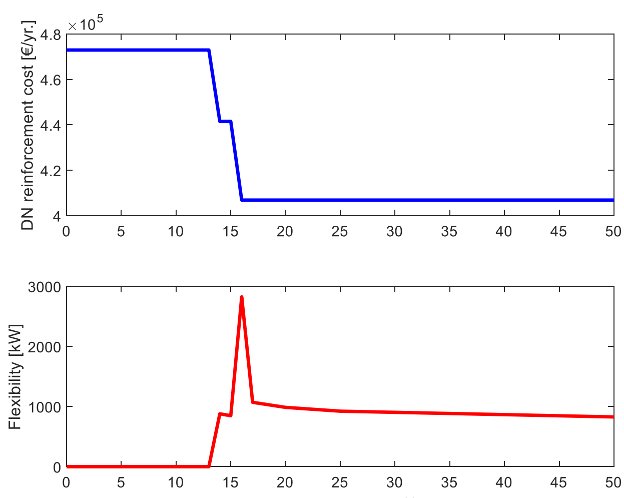

Fig. 12. Sensitivity to the available flexible capacity for demand reduction.

iterations, the solution stabilizes and no further improvement of *gbest* is observed in the base case. The final solution ensures a secure operation of the DN with a 14 % reduction in total DNP costs. In future research, the complexity of the model and case study (e.g., larger DNs) can be increased given the measured computation times.

5. Conclusions

An innovative hybrid BPSO and LP approach for DNP, which considers flexibility services provided by DERs to defer or avoid network reinforcements, is presented in this paper. The master problem determines, from a set of preselected candidates, the investment decisions on DN reinforcements. In addition, the inner LP problem optimizes the volume and location of flexibility services that need to be procured by DSO. The combination of metaheuristics and mathematical programming, as well as the preselection of candidate network reinforcements, is effective in dealing with a large search space. As a result, the proposed approach can be used to plan real DNs, such as the 500-bus MV network analyzed in the case study.

The analyzed case study shows that flexibility could be a cost-effective alternative to defer or avoid part of the required network reinforcements. For instance, in the base case, the total DNP costs decrease by 14 % when flexibility services provided by DR are contracted. The optimal co-planning of flexibility with network reinforcements is required since flexibility could not solve all grid limit violations cost-effectively on its own. Besides, the sensitivities show that explicit flexibility becomes an economical alternative to DN reinforcements when its procurement cost is competitive and sufficient flexible capacity is available. For this case study, procurement costs lower than 71€/kW-yr. and at least 14 % of flexible capacity available at each node make flexibility services attractive. These results are case-dependent, but this approach is valuable to assess the thresholds that make DSOs opt for flexibility in each DN and planning scenario.

The proposed single-stage and single-scenario model is valuable to optimize the necessary combination of flexibility procurement and DN reinforcements in real large-scale grids. Besides, this model could be used in future research as the building block of a new multi-stage and/or multi-scenario DNP tool for large-scale systems. To the authors' knowledge, a multi-stage, multi-scenario DNP problem with flexibility for large-scale DNs has not yet been solved in the literature. Thus, this model could serve, for instance, as the basis for a pseudo-dynamic approach. Moreover, ESSs could also be added as a NWA that provides flexibility to the system.

Table 6
Parameters for the BPSO algorithm.

Parameter	Value	Parameter	Value
Population size	10	w_{max}	0.9
Maximum number of iterations	150	w_{min}	0.4
c_1	2	v_{max}	6
c_2	2		

Table 7
Sensitivity to BPSO Parameters.

Population size	Max. number Iterations	c_1	c_2	Global best solution [€/yr.]	Convergence (number of iterations)	Time per iteration [s]
60	150	2	2	409,002	103	28.05
30	150	2	2	409,002	99	20.54
10	150	2	2	409,002	60	5.93
8	150	2	2	409,002	120	5.62
5	150	2	2	409,221	121	5.24
10	150	1	2	409,002	103	5.85
10	150	2	2	409,002	60	5.93
10	150	2	1	409,002	125	5.91

CRediT authorship contribution statement

Miguel Martínez: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Carlos Mateo:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Tomás Gómez:** Writing – review & editing, Supervision, Conceptualization. **Beatriz Alonso:** Writing – review & editing, Supervision, Data curation. **Pablo Frías:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgments

The authors would like to thank Dr. Fernando Postigo for providing the derivations and the functions to compute the sensitivity matrices. The authors would also like to thank Dr. Jose Pablo Chaves-Ávila and David Martín for their helpful guiding comments. This paper is based on the research carried out in the Flexener project, funded by the "Centro para el Desarrollo Tecnológico Industrial" (CDTI) of the Spanish Ministry of Science and Innovation, financed by the call "Misiones CDTI 2019" (project MIG-20201002).

Appendix A. Sensitivity matrix bus voltage — reinforcements

This section presents the derivation of a sensitivity matrix that relates the changes in bus voltages that result from reinforcing lines of the DN. When a line is reinforced by adding parallel elements, both the impedance (Z_l) and the voltage drop of the line are reduced. The reduction in the voltage drop (ΔV_l^{drop}) along a line l that is reinforced with n_l identical parallel elements is:

$$\Delta V_l^{drop} = Z_l \cdot I_l - \frac{Z_l}{n_l} \cdot I_l = Z_l \cdot I_l \cdot \left(1 - \frac{1}{n_l}\right) \tag{27}$$

This reduction of the voltage drop increases the voltage of the downstream nodes in a radial DN. The radial network's topology is modeled with the transpose of the PTDF matrix, which identifies (with a 1) the downstream nodes of every branch. Then, the increments in voltages (ΔV_i) of downstream nodes, disregarding energy losses, are obtained as follows:

$$\Delta V_i = \sum\nolimits_l - PTDF_{i,l}^T \cdot \Delta V_l^{drop} \tag{28}$$

$$\Delta V_i = \sum\nolimits_l - PTDF_{i,l}^T \cdot Z_l \cdot I_l \cdot \left(1 - \frac{1}{n_l}\right) \tag{29}$$

$$\Delta V_i = \sum\nolimits_l M_{i,l}^{VReinf} \cdot \left(1 - \frac{1}{n_l}\right) \tag{30}$$

where the elements of the sensitivity matrix M^{VReinf} give the increment in the bus voltage at node i when the capacity of line l is increased with n_l identical parallel elements. To compute the matrix, the magnitude of the current I_l in p.u. is approximated to the magnitude of the apparent power in p. u. (i.e., voltages are assumed to remain close to 1p.u.).

Appendix B. BPSO algorithm and parameters

PSO considers a set of randomly initialized particles that move in the search space toward the optimum. The position of each particle m, at iteration t, in the n-th dimension ($s_{m,n}^t$) is defined by the n-th element in the vector of binary decision variables (x_n). The fitness function is evaluated for all particles at each iteration t. All particles track their own-best solution (*pbest*) along with the global-best (*gbest*) solution from the swarm. This information is used to update the velocity of the particles in (31).

$$v_{m,n}^{t+1} = w \cdot v_{m,n}^t + c_1 \cdot \text{rand}() \cdot \left(pbest_{m,n} - s_{m,n}^t\right)$$

$$+ c_2 \cdot \text{rand}() \cdot \left(gbest_n - s_{m,n}^t\right) \tag{31}$$

The first term of (31) represents the inertia based on the weighting parameter w, which is linearly decreased from w_{max} at the first iteration to w_{min}

in the last iteration. The second and third terms indicate individual and swarm intelligence, respectively. The distances from the current position $s_{m,n}^{t}$ to *pbest* and *gbest* are weighted by two acceleration coefficients (c_1 and c_2) and a random number that can take any value between 0 and 1. The velocities are limited to a maximum value (v_{max}) to control the exploration ability of the swarm [40]. The parameters of the BPSO algorithm, summarized in TABLE 6, are set to the standard values recommended in [40].

At each iteration, the velocities from (31) are used to determine the next position of the particles. In BPSO, velocities are seen as the probability of changing its position from 0 to 1 [41]. A transfer function maps the continuous velocity values to a probability of changing position. We use the (best-performing) v-shaped transfer function from [42]. The positions of the particles are updated until the stopping criterion (e.g., maximum number of iterations) is satisfied.

Moreover, a sensitivity analysis to the BPSO control parameters is provided in TABLE 7, which shows that the selected parameters in TABLE 6 achieve the best solution in the shortest time.

First, the effect of the population size is studied. A higher number of particles in the swarm allows to cover larger parts of the search space in each iteration but increases the computation time of every iteration. On the other hand, a small population size has less initial diversity, which can negatively impact the quality of the solution and the number of iterations required to reach convergence. If the population size is lower or equal to 5, the BPSO converges to a worse solution.

Besides, the effect of acceleration coefficients is also considered. Most applications set c_1 equal to c_2 [43]. If c_1 is greater than c_2, particles wander more attracted by their own-best positions. If c_1 is lower than c_2, premature converge to local optima may occur as particles are attracted by the global-best position. Although the optimal solution does not change, setting c_1 equal to c_2 achieves faster convergence.

References

[1] IEA. Smart Grids – Analysis 2021. https://www.iea.org/reports/smart-grids (accessed July 14, 2022).
[2] UN. Report of the Secretary-General on the 2019 Climate Action Summit and the Way Forward in 2020. 2019.
[3] IEA. World Energy Investment 2022. 2022.
[4] Strezoski L, Padullaparti H, Ding F, Baggu M. Integration of Utility Distributed Energy Resource Management System and Aggregators for Evolving Distribution System Operators. J Mod Power Syst Clean Energy 2022;10(277–85). https://doi.org/10.35833/MPCE.2021.000667.
[5] Peppanen J, O'Connell A, Taylor J. Screening Criteria and Methods to Aid the Integration of Non-Wires Alternatives in Distribution Planning. CIRED 2021 - The 26th International Conference and Exhibition on Electricity Distribution, Institution of Engineering and Technology; 2021, p. 2669–73. 10.1049/icp.2021.1497.
[6] Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU. 2019.
[7] Freire-Barceló T, Martín-Martínez F, Sánchez-Miralles Á. A literature review of Explicit Demand Flexibility providing energy services. Electr Pow Syst Res 2022; 209:107953. https://doi.org/10.1016/j.epsr.2022.107953.
[8] Siano P. Demand response and smart grids—A survey. Renew Sustain Energy Rev 2014;30:461–78. https://doi.org/10.1016/J.RSER.2013.10.022.
[9] Gholizadeh-Roshanagh R, Zare K. Electric power distribution system expansion planning considering cost elasticity of demand. IET Gener Transm Distrib 2019;13: 5229–36. https://doi.org/10.1049/IET-GTD.2018.6740.
[10] Asensio M, Muñoz-Delgado G, Contreras J. Bi-level approach to distribution network and renewable energy expansion planning considering demand response. IEEE Trans Power Syst 2017;32:4298–309. https://doi.org/10.1109/TPWRS.2017.2672798.
[11] Troitzsch S, Sreepathi BK, Huynh TP, Moine A, Hanif S, Fonseca J, et al. Optimal electric-distribution-grid planning considering the demand-side flexibility of thermal building systems for a test case in Singapore. Appl Energy 2020;273: 114917. https://doi.org/10.1016/J.APENERGY.2020.114917.
[12] Li Q, Song Q, Wang L, Ni X, Shao S, Tan Y, et al. Asia Energy and Electrical Engineering Symposium. AEEES 2020;2020(2020):538–42. https://doi.org/10.1109/AEEES48850.2020.9121523.
[13] Tavares B, Soares FJ. An innovative approach for distribution network reinforcement planning: Using DER flexibility to minimize investment under uncertainty. Electr Pow Syst Res 2020;183:106272. https://doi.org/10.1016/j.epsr.2020.106272.
[14] Karimi-Arpanahi S, Jooshaki M, Moeini-Aghtaie M, Abbaspour A, Fotuhi-Firuzabad M. Incorporating flexibility requirements into distribution system expansion planning studies based on regulatory policies. Int J Electr Power Energy Syst 2020;118:105769. https://doi.org/10.1016/J.IJEPES.2019.105769.
[15] Shen X, Shahidehpour M, Han Y, Zhu S, Zheng J. Expansion Planning of Active Distribution Networks With Centralized and Distributed Energy Storage Systems. IEEE Trans Sustain Energy 2017;8:126–34. https://doi.org/10.1109/TSTE.2016.2586027.
[16] Li R, Wang W, Chen Z, Wu X. Optimal planning of energy storage system in active distribution system based on fuzzy multi-objective bi-level optimization. J Mod Power Syst Clean Energy 2018;6:342–55. https://doi.org/10.1007/s40565-017-0332-x.
[17] Crossland A, Jones D, Wade N. Energy storage/demand side response in LV networks: Design of cost based planning tools for network operators. IET Conference Publications 2013;2013. 10.1049/CP.2013.0774.
[18] Muñoz-Delgado G, Contreras J, Arroyo JM. Distribution System Expansion Planning Considering Non-Utility-Owned DG and an Independent Distribution System Operator. IEEE Trans Power Syst 2019;34:2588–97. https://doi.org/10.1109/TPWRS.2019.2897869.
[19] Kabirifar M, Fotuhi-Firuzabad M, Moeini-Aghtaie M, Pourghaderi N, Dehghanian P. A Bi-Level Framework for Expansion Planning in Active Power Distribution Networks. IEEE Trans Power Syst 2022;37:2639–54. https://doi.org/10.1109/TPWRS.2021.3130339.
[20] Huang C, Wang C, Xie N, Wang Y. Robust Coordination Expansion Planning for Active Distribution Network in Deregulated Retail Power Market. IEEE Trans Smart Grid 2020;11:1476–88. https://doi.org/10.1109/TSG.2019.2938723.
[21] Shen F, Huang S, Wu Q, Repo S, Xu Y, Østergaard J. Comprehensive Congestion Management for Distribution Networks Based on Dynamic Tariff, Reconfiguration, and Re-Profiling Product. IEEE Trans Smart Grid 2018;10:4795–805. https://doi.org/10.1109/TSG.2018.2868755.
[22] Martinez Cesena EA, Mancarella P. Distribution network reinforcement planning considering demand response support. 2014 Power Systems Computation Conference, IEEE; 2014, p. 1–7. 10.1109/PSCC.2014.7038347.
[23] Martínez Ceseña EA, Mancarella P. Practical recursive algorithms and flexible open-source applications for planning of smart distribution networks with Demand Response. Sustainable Energy Grids Networks 2016;7:104–16. https://doi.org/10.1016/J.SEGAN.2016.06.004.
[24] Ziegler DU, Prettico G, Mateo C, Gómez San Román T. Methodology for integrating flexibility into realistic large-scale distribution network planning using Tabu search. International Journal of Electrical Power & Energy Systems 2023;152: 109201. https://doi.org/10.1016/j.ijepes.2023.109201.
[25] Ziegler DU, Mateo C, Gómez San Román T, Prettico G. Multi-stage distribution expansion planning leveraging load flexibility. Electric Power Systems Research 2024;228:110094. https://doi.org/10.1016/j.epsr.2023.110094.
[26] Miranda V, Ranito JV, Proenca LM. Genetic algorithms in optimal multi-stage distribution network planning. IEEE Trans Power Syst 1994;9:1927–33. https://doi.org/10.1109/59.331452.
[27] Sanjab A, Mou Y, Virag A, Kessels K. A Linear Model for Distributed Flexibility Markets and DLMPs: A Comparison with the SOCP Formulation. CIRED 2021 - The 26th International Conference and Exhibition on Electricity Distribution, Institution of Engineering and Technology; 2021, p. 3181–5. 10.1049/icp.2021.1635.
[28] Valarezo O, Cossent R, Troncia M, Ormeño E, Rodríguez N, Ramos A, et al. MARKET ENABLING INTERFACE TO UNLOCK FLEXIBILITY SOLUTIONS FOR COST-EFFECTIVE MANAGEMENT OF SMARTER DISTRIBUTION GRIDS Deliverable: D10.4 Scalability and Replicability analysis of the EUniversal solutions. 2023.
[29] Liu J, Gao H, Ma Z, Li Y. Review and prospect of active distribution system planning. J Mod Power Syst Clean Energy 2015;3:457–67. https://doi.org/10.1007/s40565-015-0170-7.
[30] Kennedy J, Eberhart R. Particle swarm optimization. Proceedings of ICNN'95 - International Conference on Neural Networks n.d.;4:1942–8. 10.1109/ICNN.1995.488968.
[31] Jordehi AR. A review on constraint handling strategies in particle swarm optimisation. Neural Comput Appl 2015;26:1265–75. https://doi.org/10.1007/s00521-014-1808-5.
[32] Baldick R. Variation of Distribution Factors with Loading. IEEE Trans Power Syst 2003;18:1316–23. https://doi.org/10.1109/TPWRS.2003.818723.
[33] Hashemi S, Ostergaard J, Yang G. A Scenario-Based Approach for Energy Storage Capacity Determination in LV Grids With High PV Penetration. IEEE Trans Smart Grid 2014;5:1514–22. https://doi.org/10.1109/TSG.2014.2303580.
[34] Orden IET/2660/2015. Ministerio de Industria, Energía y Turismo; 2015.
[35] CNMC. Acuerdo por el que se aprueba la propuesta de metodología de cálculo de la tasa de retribución financiera de las actividades de transporte y distribución de energía eléctrica para el segundo periodo regulatorio 2020-2025. 2018.
[36] UKPN. Flexibility Services - Procurement February 2021: Appendix 6 - revenue ranges. 2021.

[37] SP Energy Networks. C31E Procurement and Use of Distribution Flexibility Services Annual Report -. Supporting Data 2022.
[38] Zimmerman RD, Murillo-Sánchez CE, Thomas RJ. MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education. IEEE Trans Power Syst 2011;26:12–9. https://doi.org/10.1109/TPWRS.2010.2051168.
[39] Grady WM, Samotyj MJ, Noyola AH. The application of network objective functions for actively minimizing the impact of voltage harmonics in power systems. IEEE Trans Power Delivery 1992;7:1379–86. https://doi.org/10.1109/61.141855.
[40] Eberhart, Yuhui Shi. Particle swarm optimization: developments, applications and resources. Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No.01TH8546), IEEE; 2001, p. 81–6. 10.1109/CEC.2001.934374.
[41] Kennedy J, Eberhart RC. Discrete binary version of the particle swarm algorithm. Proceedings of the IEEE International Conference on Systems, Man and Cybernetics 1997;5:4104–8. https://doi.org/10.1109/ICSMC.1997.637339.
[42] Mirjalili S, Lewis A. S-shaped versus V-shaped transfer functions for binary Particle Swarm Optimization. Swarm Evol Comput 2013;9:1–14. https://doi.org/10.1016/J.SWEVO.2012.09.002.
[43] Engelbrecht AP. Computational Intelligence. Wiley 2007. https://doi.org/10.1002/9780470512517.
[44] Martínez M, Mateo C, Gómez T, Alonso B, Frías P. Distributed battery energy storage systems for deferring distribution network reinforcements under sustained load growth scenarios. J Energy Storage 2024;100. https://doi.org/10.1016/j.est.2024.113404.