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Methodology for integrating flexibility into realistic large-scale distribution network planning using Tabu search

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ABSTRACT

A successful energy transition will be firmly based on the effective integration of distributed energy resources and on the integration of new flexibility providers into the energy system. To make this possible, a deep transformation in the design, operation and planning of power distribution systems is required. Currently, a lack of comprehensive planning tools capable of supporting operators in their investment plan options exists. As a result, reinforcements of conventional grid assets are common solutions put in place. This paper proposes a methodology to obtain cost-optimal distribution network expansion plans, by modelling a single-stage distribution network planning tool, using conventional assets as well as flexibility contracting from demand response. A Tabu Search metaheuristic has been implemented in order to solve the optimization problem. A case study based on a realistic large-scale city network model is presented, for a planning horizon of ten years with significant load growth due to electromobility penetration. Results show that, in the case study analysed, the use of load flexibility in combination with conventional reinforcements can reduce the total expansion network cost by about 7.5 %. Furthermore, a sensitivity analysis on the cost of flexibility contracting is undertaken. Remarkably, the methodology presented generalises to further alternative solutions by providing a straightforward financial benchmark between the latter and conventional grid expansion.

1. Introduction

The proceeding energy transition requires a transformation of the design, operation and planning of power systems internationally in order to accommodate high shares of distributed energy resources (DER). As DER are connected to power distribution networks, these could require expansions that should be optimized to efficiently integrate DER, ensuring the minimum cost for society. These expansion measures can comprise: i) conventional expansion of primary equipment capacity (transformers, cables, etc.) or ii) non-conventional expansion with active technologies such as advanced control and automation of grid infrastructure equipment and coordination of DER behaviour. The non-conventional approach turns formerly passive distribution networks, dominated by the fit-and-forget approach, into active distribution networks (ADN).

In power system analysis, energy system scenarios are used to model future situations (e.g. in one or more decades) in terms of projected demand and generation. For distribution networks, the types and amount of distributed generation (photovoltaic (PV), wind, combined heat and power, etc.) together with the new loads (electric vehicle (EV) chargers, heat-pumps, etc.) provide the expected load curves over the years. Taking a scenario as given, the peak load can be derived as a reference for the planning analysis [1]. Here it is important to consider that new active loads which respond to some internal or external signal, e.g. demand response (DR), can alter the expected peak-load considered for planning. Therefore, as the peak-load of an ADN becomes more flexible with the increasing amount of active elements and controllability of ADN, the operational conditions of ADN need to be considered already in the planning stage [2]. The next step is then to identify the changes/expansions to be implemented in the network under study to match generation and demand at peak time while achieving technical feasibility. Generally, an increase in the demand with the same infrastructure can cause two types of violations of the operational constraints: in terms of voltage and thermal limits. Exceeding them in non-transient steady-state conditions for a certain time can cause unacceptable system states, posing a menace to assets, people and the environment. Given the aforementioned, the goal of the grid planner is to make optimal investment decisions that alleviate all operational constraint violations for the network under study at future load. The

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Nomenclature

Ω_{br}	set of branches
Ω_{l}	set of conductor branches
Ω_{s}	set of transformer branches
Ω_{dr}	set of buses with contractable flexibility
Ω_{con}	set of available conductor types for investment
Ω_{tra}	set of transformer types for investment
Ω_{fl}	set of contractable flexibility types
i,j	index of buses
br_{ij}	index of branches
con	index of conductor types
tra	index of transformer types
fl	index of contractable flexibility
n	planning horizon [a]
r	discounting rate [%]
l_{l}	length of conductor l [km]
$\propto_{n,r}$	annuity factor for planning horizon n and discounting rate r [%/a]
C_{con}^{op}	annual operational cost of all available conductor types [€/km/a]
C_{tra}^{op}	annual operational cost of all available transformer types [€/a]
C_{fl}^{op}	annual cost for contracting of all available flexibility types [€/kw/a]
C_{con}^{inv}	investment cost of all available conductor types [€/km]
C_{tra}^{inv}	investment cost of all available transformer types [€]
V_{i}^{min}	minimum allowed voltage at bus i [kV]
V_{i}^{max}	maximum allowed voltage at bus i [kV]
I_{br}^{max}	maximum allowed current in branch br [A]
A^{op}	$\sum$of all annuities based on operational cost [€/a]
A^{inv}	$\sum$of all annuities based on investment cost [€/a]
$C_{con,tot}^{op}$	$\sum$of all operational cost for conductors [€/a]
$C_{tra,tot}^{op}$	$\sum$of all operational cost for transformers [€/a]
$C_{fl,tot}^{op}$	$\sum$of all operational cost for flexibility contracts [€/a]
$C_{con,tot}^{inv}$	$\sum$of all investment cost for conductors [€/a]
$C_{tra,tot}^{inv}$	$\sum$of all investment cost for transformers [€/a]
$b_{br_{ij},con}$	binary variable indicating conductor investment decision at branch br_{ij}
$b_{br_{ij},tra}$	binary variable indicating transformer investment decision at branch br_{ij}
$b_{i,fl}$	binary variable indicating decision to contract flexibility at bus i

optimization of investment decision-making mostly considers economic objectives based on investment and operational cost, while potentially other objectives such as reliability, environmental impact and DER hosting capacity can be considered as well. The decision-making for distribution grid expansion comprises decisions on grid capacity, technology choice as well as investment and installation time. The decision on grid capacity is largely dependent on the projected load flows at a certain time, based on the modelled network at future peak-load.

The technology chosen to solve the projected grid violations should ideally depend on the overall benefits of the individual technology as well as their lifetime costs, including initial investment, operation and maintenance cost. The investment related benefits contain not only the benefits of mitigating grid congestions but can also provide further benefits such as increased grid observability, higher resilience, or improved voltage control. To address violations at specific network components or in specific network areas, various technology solutions can be applied in distribution network planning (DNP) and operation. Besides the conventional technology options, such as capacity expansion of transformer or power line rating, non-conventional grid expansion technology options such as the use of flexibility, such as from DR, or actively controlled network elements are gaining increasing attention in research as well as application.

2. State-of-the-art

2.1. Conventional versus active distribution planning

As mentioned, several options can be considered, whose adequate value and long-term effectiveness is understudied under different energy system scenarios [3]. Consequently, today's, existing technology options such as DR are not fully considered in investment decision making, leading to non-optimal investment decisions with respect to technology option, capacity, and time of the investment.

Historically, conventional distribution planning is undertaken for two basic conditions, normal operational conditions as well as emergency conditions. Depending on the expected load growth, the existing network and related preconditions, the planning decisions are based on the optimal location of substations, location and number of feeders and their design, optimal allocation of load and substation capacity, as well as the optimal mix of transformers by substation.

ADN are distribution networks with a higher degree of automation and control. Therefore, ADN planning extends the complexity of conventional planning with additional operational considerations. Some of the operational schemas involve loads, distributed generation (DG) and storage, such as active and passive feed-in management, like the automatic or on-demand curtailment of DG as well as the use of the load flexibility provided by DR. Other operational schemas in ADN are more focused on active grid elements such as the switching of regulation taps of distribution transformers (i.e. on-load tap changer (OLTC)), network reconfiguration and generally advanced control schemas for voltage control (e.g. involving voltage regulators, DER control, OLTC, etc.) [4,5]. Each of these active technologies can defer network investment or even replace a conventional network investment. However, these non-conventional technologies usually entail higher operational costs, which deserve further investigation.

Large-scale integration into distribution networks of electrically chargeable vehicles (ECV) and DER in general, creates the need to plan the distribution grid expansion along the expansion of distributed generation and new loads [6].

2.2. Meta-review of conventional and ADN planning review papers

A significant number of review papers on conventional and ADN planning have recently been published. Henceforth, in this paper we carry out a *meta*-review. Table 1 shows a brief description of the characteristics considered in the review papers. To solve conventional planning problems, various exact (mathematical programming) as well as approximate optimization approaches have been taken [7–11]. While some of the authors classify the overall optimization approach as optimization method [8–10], others divide the later into mathematical formulation and solution method [7,11].

Embedded in these optimization methods are solution methods with common problem simplification techniques to handle the computational complexity of distribution grid expansion planning models, such as constraint relaxation, problem decomposition or stopping the search process early when a feasible solution is found. When computational time with exact mathematical models reach limits, clustering techniques as well as (meta-) heuristic algorithms can be applied [12,13].

Table 1
Characteristics used for various classifications by review papers.

	Resener et al. 2018 [10]	Xiang et al. 2016 [11]	Georgil. et al. 2015 [8]	Jordehi 2015 [9]	Ganguly et al. 2013 [7]
Optimization method	X		X	X	
Mathematical formulation		X			X
Solution method		X			X
Decision variables	X	X	X	X	
Objectives	X	X	X	X	
Objective type	X				X
Planning type	X	X	X	X	
Planning duration				X	
Greenfield vs. Brownfield		X	X		
Uncertainty modelling		X			X
Environment of the model	X				
Network model			X	X	
Load model				X	
Reliability feature					X

Metaheuristics are generalized heuristic optimization methods, often inspired in nature, that do not guarantee optimality but can generate good results. Therefore, these are mostly classified as part of the family of approximate optimization algorithms [13]. Such algorithms, as mathematical programming based approximate optimization in [14] and knowledge-based expert systems in [15], have a long history in operations research and specifically in conventional DNP often included alongside Artificial Intelligence approaches [16,17]. Within metaheuristics, one can distinguish between population-based and single-solution based algorithms [13,16,18]. Common examples of population-based metaheuristics are genetic algorithms (GA) [16,19] and particle swarm optimization (PSO) [20]. While Tabu Search (TS), Simulated Annealing and Iterative Local Search are popular single-solution based metaheuristic search algorithms [18,21].

Generally, the various approaches found in literature share some commonalities, such as the mathematical formulation which describes how the objective function of the optimization approach is formulated; The decision variables, such as the location and/or size of substation, feeder, reclosers, storage systems, ECV charging stations and DG [8–11]; the objective function, such as minimization of system losses, enhancement of reliability, and minimization of environmental impact or cost-effective DER integration; The objective type, which describes whether an objective function is formulated as single-objective or multi-objective; and the planning type, which differentiates between single-period or static models and multi-period or multistage models [8–11].

None of the authors of the review papers use flexibility modelling as a characteristic for benchmarking ADNP publications. Also, more generically, loads are distinguished as elastic or non-elastic in ADN load model formulation. Demand side management has not been taken into consideration in the reviewed DNP problems [9]. Flexibility is not discussed in general in [20], though DR (as load dependent electricity price) is mentioned once in reference to a reviewed paper.

2.3. Review of papers on DNP including load, generation and storage flexibility

A large number of papers treating DNP and some type of flexibility, such as from loads, generation or storage, have been reviewed. The twelve most relevant of those are analysed in this paper in greater detail, and classified in Table 2. Publications that present general planning frameworks, DG or DER hosting studies or papers that are focused on energy system scenario studies, have not been included in this review. Of the reviewed papers, there are only few publications with DNP models that incorporate load flexibility, and none of them presents a validation of the model by a case study on a realistic large-scale network. Of those reviewed papers, seven apply some type of load flexibility as non-conventional expansion measure (e.g. DR, EV smart charging, etc.); six apply flexibility from DGs (e.g. DG dispatch, DG curtailment); three apply flexibility from storage (e.g. EV including vehicle-2-grid, distributed energy storage systems, etc.). Regarding the solution method for the DNP problem, six of the reviewed papers use mathematical programming, one in combination with a heuristic method (i.e. combining OPF with a heuristic). The other five papers use metaheuristics, one in combination with a numerical method to solve the Distribution Optimal Power Flow (DOPF) [22], and one paper uses a heuristic method [23]. Most of the papers use a feeder-type network model, while two use a real network model, obtained from DSOs. The number of buses in the network models of the reviewed publications ranges from 18 to 355. While all papers model the medium voltage (MV) level, some include network elements of the low voltage (LV) or high voltage (HV) levels. Only one paper includes all three voltage levels, though only 118 buses are included, based on a real network, and the solution method used is a simple heuristic [23].

While relatively small feeder-type network models are convenient for many DNP studies, they have various limitations. Their representativeness in large areas with diverse socio-economic and technical characteristics can be limited, especially when large-scale grid modernization is expected. Also, their value and accuracy with respect to benchmarking of advanced optimization algorithms such as network reconfiguration, Volt/Var optimization, etc. is limited [24]. Finally, feeder-type models usually lack geographical information, which limits their meaningfulness in topological studies on reconfiguration as well as for resilience studies in the wake of natural disasters. Self-explanatory, real network models do not incorporate these constraints, though they can mostly not be used in public research, due to their confidentiality as they are considered critical infrastructure [25]. Therefore, realistic network models can be a effective alternative to confidential real network models, while also overcoming the limitations of the feeder-type models [26,27].

The International Smart Grid Action Network (ISGAN) defines flexibility in the context of power systems as *"… the ability of power system operation, power system assets, loads, energy storage assets and generators, to change or modify their routine operation for a limited duration, and responding to external service request signals, without inducing unplanned disruptions."* [28]. Among all the existing types of flexibility that could be applied in power systems, we focus on DR. In this paper we consider flexibility contracting as the ability of the distribution system operator (DSO) to contract load flexibility from DR through a third party. We assume that these contracts are concluded such that the DR service is provided reliably. Therefore, considerations regarding the uncertainty of successful DR provision from loads participating in DR schemas as well as operational and financial considerations of DR service provision are beyond the scope of this paper. From the DSO perspective, the flexibility is contracted as a result of the long-term planning exercise, with possible adoptions in the operational time frames of the DSO.

In this paper, we contribute to the state of the art by proposing a decision-making tool for the use of load flexibility from DR as an alternative to conventional network reinforcements for future peak-load in a realistic large-scale distribution network. This tool for DNP leveraging DR is based on the TS metaheuristic and implemented in Python 3. Using this model, we study the conventional grid expansion necessary to accommodate the future peak-load caused mostly by the growth of loads in the form of chargers for ECV in a Spanish city with approximately 160,000 inhabitants. Naturally, the DNP model can be applied to other case studies internationally, underlying different

Table 2
Reviewed DNP papers treating flexibility, their methods and network modelling.

Reference	Mathematical programming	Meta-heuristic	Optimization method	Load flexibility	Generation flexibility	Storage flexibility	Network model	No. of buses	LV modelled	MV modelled	HV modelled
[29]	✓		MILP*	✓			feeder-type	24		✓	
[30]		✓	MO-PSO†	✓			feeder-type	33		✓	
[31]	✓		MINLP‡	✓			feeder-type	69		✓	
[23]			heuristic	✓	✓		real network	118	✓	✓	✓
[22]		✓	SPEA2§ & DOPF**		✓		feeder-type	355		✓	
[33]	✓		heuristic & OPF††		✓		feeder-type	27	✓	✓	
[34]		✓	GA		✓		real network	267		✓	
[35]		✓	PSO			✓	feeder-type	30		✓	
[36]	✓		MILP			✓	feeder-type	18		✓	
[37]	✓		SOCP‡‡	✓			feeder-type	122		✓	
[38]	✓		SOCP	✓	✓	✓	feeder-type	50		✓	✓
[39]		✓	GA	✓	✓		feeder-type	33		✓	✓
This paper		✓	TS	✓			realistic large-scale network	2762	✓	✓	✓

* MILP – Mixed Integer Linear Programming.
† MO-PSO – Multiobjective PSO.
‡ MINLP – Mixed Integer Non-Linear Programming.
§ SPEA2 – (improved) strength pareto evolutionary algorithm[32].
** DOPF – solved here using backward-forward sweep as numerical method to solve the OPF problem for radial distribution systems with sufficient precision.
†† OPF – Optimal Power Flow, here solved using mathematical programming (within MATPOWER).
‡‡ SOCP – Second Order Cone Programming.

technical standards and power system regulations. We then compare the economic cost, in terms of annuities, of conventional expansion with that of conventional expansion combined with the use of flexibility. We assume that flexibility contracts can be activated at a given set of nodes in the network, while it is up to the optimization algorithm to decide which of those flexibility contracts will finally be activated.

The rest of the paper is organized as follows. Section 3 describes the problem formulation for ADN planning. Section 4 explores the TS algorithm as a solution method. Section 5 presents the case study for ADN planning. Next, section 6 shows the results obtained with a detailed discussion of our findings and section 7 concludes the study.

3. Problem formulation

The single-stage ADN planning problem in this paper aims at identifying optimal investment decision-making by considering conventional (power lines and transformers) and non-conventional (contracted flexibility) distribution network expansion technologies and solutions.

The objective function minimizes the sum of annuities for investment and operational cost resulting from the overall network expansion in the year of the planning horizon. The annuity for investment entails the investment cost for lines and transformers discounted with the discounting factor over the expected lifetime of the asset. The calculation of the total annual cost is based on the annuity for investment plus the annual maintenance cost for transformers and lines and the annual contracting cost for flexibility. The annuities are used to make costs relative to assets with different expected lifetime comparable (e.g. flexibility). This ensures a better comparability of conventional network expansion investments, e.g. on power lines and transformers, with very long lifetimes of up to 40 years with non-conventional alternatives, such as flexibility products which have a much shorter life cycle and generally a different cost structure.

Voltage limits for each voltage level are defined by an upper and a lower admissible operational voltage. Thermal limits are defined by a maximum admissible current in steady-state conditions for transformers and power lines or cables. Full connectivity and radiality of the network are ensured, when lines or transformers are removed or added.

The simultaneity of consumption and generation throughout the network and over the duration of a year, can create various network loading situations. Due to the increasing penetration of DG in many distribution networks, reverse power flows can occur locally, which must be accounted for in planning. The loading situation with the projected maximum loading of the system is the relevant one for planning and defined as network-peak. The future network at the peak-load situation is defined by loads, generators, upper-level system supply and their consumption and generation profiles. It is based on a deterministic input, describing the distribution and sizing of loads and generators throughout the network at peak-load. The detailed future network under peak-load considered in the case study is reported in section 5.

The future network at the planning horizon year results in constraint violations, which are removed by determining the optimal set of binary expansion decision variable states for all branches (transformers and lines) as well as binary contracting decision variables for flexibility contracts present at some network nodes. While the former decision variables represent the installation of additional or capacity expansion of existing transformers and lines, the latter represent the load reduction of contracted flexibility at the time of the network peak relevant for planning. The optimal set of decision variables, produces a network candidate with the lowest total annual cost at the planning horizon, while all operational constraints are met and all loads are supplied. Power distribution losses are not included in the optimization objective but are relevant and they are considered in the calculation of voltage drops and therefore are taken into account to ensure no constraint violations occur.

3.1. Mathematical problem formulation

Below, the objective function and the respective constraints are described mathematically.

3.1.1. Objective function

$$min f = A^{inv} + A^{op} \text{s.t. investment constraints} \quad \text{network security constraints} \tag{1}$$

$$A^{inv} = C^{inv} * \propto_{n,r} \tag{2}$$

$$A^{op} = C^{op}_{con,tot} + C^{op}_{tra,tot} + C^{op}_{fl,tot} \tag{3}$$

$$\propto_{n,r} = \frac{r}{1-\frac{1}{(1+r)^n}} \tag{4}$$

$$C^{inv} = C^{inv}_{con,tot} + C^{inv}_{tra,tot} \tag{5}$$

$$C^{op}_{con,tot} = \sum_{br_{ij}\in\Omega_l}\sum_{con\in\Omega_{con}} b_{br_{ij},con} * C^{op}_{con} * l_l \tag{6}$$

$$C^{op}_{tra,tot} = \sum_{br_{ij}\in\Omega_s}\sum_{tra\in\Omega_{tra}} b_{br_{ij},tra} * C^{op}_{con} \tag{7}$$

$$C^{op}_{fl,tot} = \sum_{i\in\Omega_{dr}}\sum_{fl\in\Omega_{fl}} b_{i,fl} * C^{op}_{fl} \tag{8}$$

$$C^{inv}_{con,tot} = \sum_{br_{ij}\in\Omega_l}\sum_{con\in\Omega_{con}} b_{br_{ij},con} * C^{inv}_{con} * l_l \tag{9}$$

$$C^{inv}_{tra,tot} = \sum_{br_{ij}\in\Omega_s}\sum_{tra\in\Omega_{tra}} b_{br_{ij},tra} * C^{inv}_{tra} \tag{10}$$

3.1.2. Network security constraints

The network security constraints describe the operational limits for network equipment. A maximum and minimum permissible voltage as well as a maximum permissible current are given in section 5.1.

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{11}$$

$$I_{br}\vee \leq I_{br}^{max} \tag{12}$$

Furthermore, a network connectivity constraint ensures full network connectivity at all times. This means that all nodes and consequently all loads are connected and none remains isolated. A network radiality constraint ensures that the network remains radial after new transformers and lines are added.

To validate the feasibility of network candidates and identify constraint violations, AC power flows based on the Newton Raphson method are executed. Further details on the implementation of the power flow solver in pandapower networks can be found in [40].

4. Solution Method: Tabu search

Developing a model for long-term planning of large-scale ADN is a challenging undertaking. Remarkably, the large number of decision variables and the large non-convex search space characterized by many local optima make the optimization problem very hard to solve. To overcome these limitations, we rely on a metaheuristic optimization algorithm. Among the metaheuristic search algorithms, population-based algorithms seem easier to initially implement as there are many generic template programs available, but they require often complex mechanisms to manage the solutions of the population. Generally, their performance for large-scale DNP has yet to be proven. The selected solution method to find the optimal expansion decisions for the year of the planning horizon is based on the TS *meta*-heuristic. Using TS, one can leverage the broad expert knowledge of the system behaviour, combining technically and economically appropriate simple heuristics with the guiding intelligence of the TS algorithm. This feature allowing expert knowledge to be encoded to produce technologically likely feasible candidate solutions combined with the guided search of the TS algorithm implementation was promising as regards tackling realistic large-scale networks [41,42]. In TS, simple heuristic rules, that are in-line with power system engineering principles and network design standards, can be defined as elementary moves. This approach helps to navigate and reduce the search space by constraining the neighborhood solutions (or network candidates) created during the search process.

4.1. Algorithm overview

An overview of the TS algorithm developed is depicted below and displayed in Fig. 1. A random candidate as an initial solution for TS would not be promising in the combinatorial optimization problem at hand. This is because the theoretical or unconstrained search space contains only scarcely feasible solutions, which would most likely result in a high computational burden to find the first feasible solution from which the TS algorithm could work efficiently. Thus, the TS procedure starts from an initial feasible solution that might be far from the optimum.

Starting from the initial solution, a set of neighborhood solution candidates is generated. Thereafter, the objective function value of each solution candidate is calculated. The list of candidate solutions is sorted by the OF value and starting from the candidate with the best value, the feasibility is checked by power flow analysis and connectivity checks. In metaheuristic approaches for DNP, this is a common approach to check for constraint violations [22,30,35,39]. In our implementation, using pandapower, running the power flow takes only 50 ms for the case of the

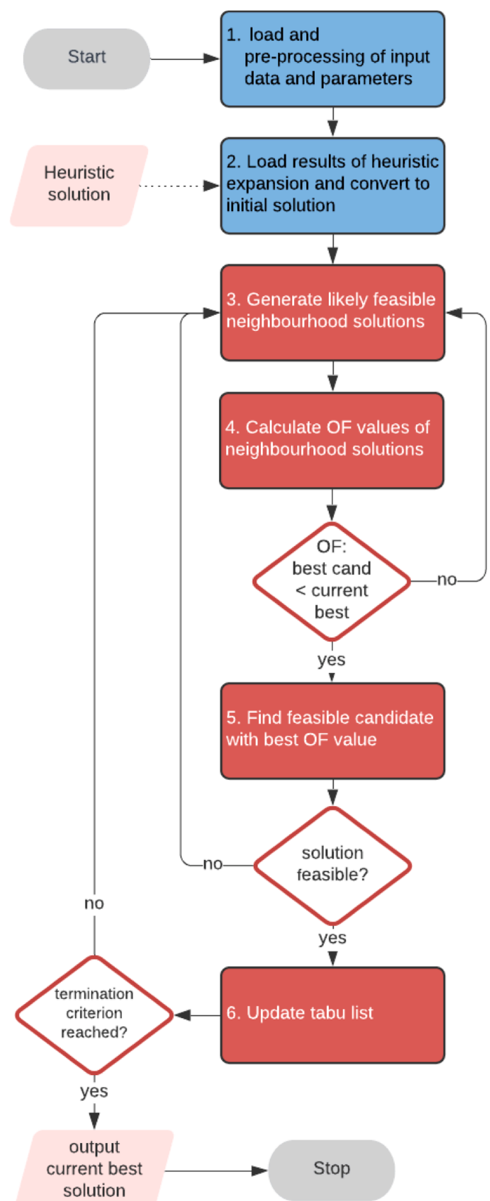

Fig. 1. TS flowchart.

realistic large-scale network presented in section 6.2 (on an intel core i7, dual core @ 1.8 GHz, 4 GB RAM). This procedure is repeated until a first feasible candidate is found. Consecutively, the current best solution as well as the tabu list are updated. The update of the tabu list comprises the tabu-activation for moves that lead to the newly accepted, current best solution as well as the deactivation of tabu-active moves, based on the tabu-tenure criteria. Finally, if the termination criterion is not reached, a new set of solution candidates are created from the neighborhood of the newly assigned current best solution.

Below, the production of the initial solution with a simple heuristic and the metaheuristic TS implementation are described in more detail.

4.2. Heuristic solution

The simple heuristic solution (HS) algorithm produces the initial solution (network) to be used as the starting point in the TS algorithm. As mentioned, this represents the network expanded to cover the load situation resulting from the future scenario. The algorithm as well as the necessary input data and parameters are described below.

4.2.1. General HS procedure

The HS method provides a feasible network that is not optimized for cost or any other objective.

Initially, the pre-processing based on the scenario analyzed is undertaken, as shown in Fig. 2. The RNM files are parsed into a georeferenced pandapower network. Operational and planning parameters are defined. The resulting network is populated with loads and generators, according to the input scenario. Such a network, here called “network 2030”, is not feasible, as it suffers constraint violations due to the new loads and generators. This network is then passed to the HS algorithm (Fig. 3), which expands it until no constraint violations are present. Finally, the feasible network, called “expanded network HS solution”, is obtained.

Note that the heuristic solution produced with this HS algorithm is not optimal, and very likely over-dimensioned. However, it is a feasible solution and the initial point from which the TS algorithm starts its optimization search.

5. Case studies

In this section, a set of case studies analyse the impact of projected equipment/investment cost, combining conventional network expansion and non-conventional flexibility solutions.

5.1. General modelling assumptions

The network security constraints are parametrised as follows. The voltage constraint for the MV network and for the LV network levels are set to +/-10% of the nominal voltage. The power capacity limit for lines is set to 100% and for transformers is set to 90% of their respective

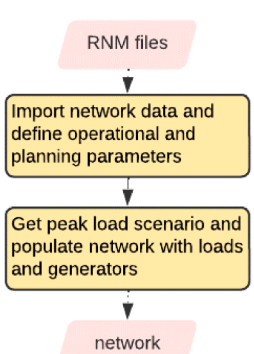

Fig. 2. Pre-processing for HS.

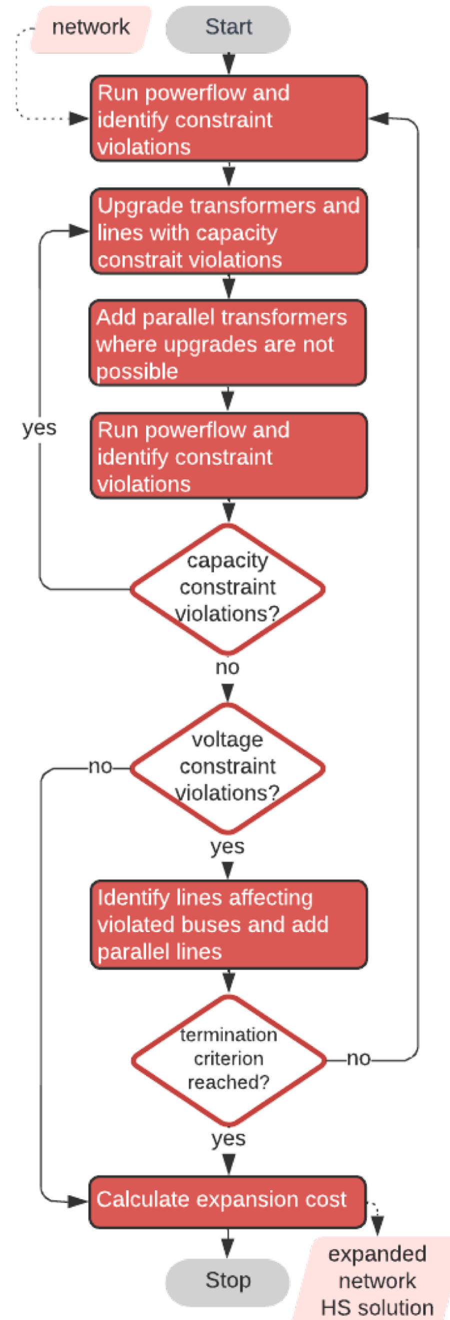

Fig. 3. HS algorithm flowchart.

nameplate capacity values.

Economic assumptions regarding asset investment are parametrized as follows. The discounting rate for the remuneration of assets is based on the Weighted Average Cost of Capital (WACC). This discounting rate is set at 6 %. The regulatory expected lifetime of 40 years for transformers, power lines and cables is based on Spanish regulation [43]. The planning horizon is set to ten years. The investment and maintenance cost for conventional network expansion assets is based on the official state gazette no. 297 [44]. The economic assumptions regarding the provision of flexibility are formulated as an estimated annual capacity price for the contracted flexibility that indirectly entails the cost of the energy used when providing the flexibility service. The cost for flexibility contracting used for the large-scale case in section 6.2, is based on the result of the sensitivity analysis undertaken in section 6.1.3. A possible price range for the flexibility contracts found in the literature is

50 to 140,000 €/MW per year, which is derived from various cost information sources on the electric power system in Spain [45], the Spanish electricity market operator [46,47] as well as the relevant sources from the flexibility market operation in the UK [48,49]. Inspired by this literature research and tested with the planning model, a range of annual flexibility cost ranging from 0 to 5,000 €/MW is used in this sensitivity analysis.

For the heuristic search procedure, the minimum additional capacity margin of new transformers is set to 40 %; the limit on maximum parallel power lines to be added is set to 4; the maximum number of parallel transformers after expansion is set to two and four for the MV and LV level, respectively.

The peak load hour relevant for expansion planning is based on the dataset on load curves by the Spanish transmission system operator REE [50]. The peak load is then scaled with respect to the total installed load of the case study in the Albacete network.

5.2. Load scenarios and initial solution

The initial solution is based on the simple heuristic described in 4.3, and used as a starting point for the TS algorithm. The two load scenarios considered (2020 and 2030) and results are described below.

5.2.1. Albacete district in 2020

The network model, shown in Fig. 4, comprises roughly one third of the urban area of the city of Albacete in the autonomous region of Castilla-La Mancha, Spain with its roughly 165,000 inhabitants residing in an area of approximately four by four km. This open-source network model (CC BY-SA 4.0) is publicly available to download [51].

The displayed network is a subset of the full Albacete network that is built applying the Greenfield RNM [52,53]. At the beginning of the planning period, in the year 2020, the network contained two voltage levels, namely 20 kV (with 134 buses and 32 km of power lines), and 1 kV (with 2628 buses and 66.55 km length). There are 121 MV/LV distribution transformers installed with a total nameplate capacity of 61.5 MVA. There are 2507 LV loads totaling 40.24 MW and 12.07 Mvar as well as 12 MV loads totaling 35.59 MW and 10.68 Mvar. The power consumption at peak hour is the relevant time slice for expansion planning and is estimated using simultaneity factors applied to individual consumer peaks, as described in [53].

5.2.2. Albacete district in 2030

Based on load growth assumptions considered in this case study, the Albacete district system introduced in the previous section undergoes a significant load growth due to substantial installation of ECV chargers until the year 2030. Based on the Eurelectric scenario with a high ECV penetration, four million ECV are expected to be operational in Spain by 2030 [54]. This translates to 11,335 ECV chargers with a total installed capacity of 47.77 MW for Albacete and 3575 ECV chargers with 14.9 MW for the district modelled in this case study. Following the ECV charger classification contained in IEC 61851 [55], the charging power is allocated to 93.5% of the chargers (39.19 MW) assumed to be slow chargers with a power rating of 3.7 kW each, 6.2% (7.77 MW) to be quick chargers with 11 kW each and 0.3% (0.8 MW) to be fast chargers with 22 kW rated power each. These are normally distributed over the city and installed on LV buses only. The total ECV load active in the network represents 25 % of the total expected charging capacity, which is the peak-load contribution expected in the Eurelectric scenario.

For this network model, we assume that all ECV quick, rated at 11 kW, and fast chargers, rated at 22 kW, are capable to participate in DR by reducing their load to 50 % of their contracted power at peak hour [55]. Furthermore, 392 pre-existing loads with sum of 12.53 MW provide flexibility similar to the ECV chargers, reducing their load to 50 % and providing a total load reduction potential of 6.26 MW. This results

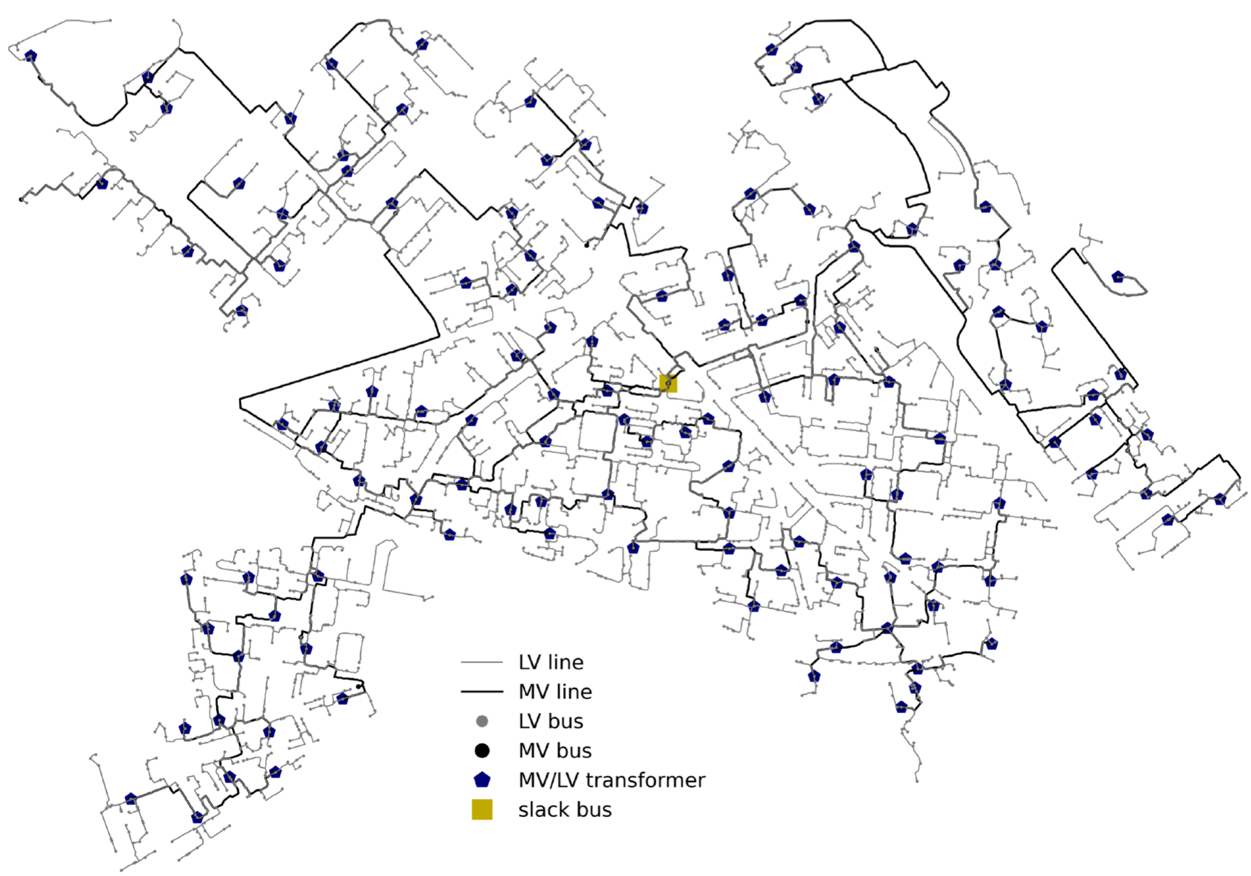

Fig. 4. Network model of district of Albacete.

in a total DR potential of 7.67 MW.

5.3. MV/LV-Feeder: Optimization of conventional expansion

To illustrate the conventional and non-conventional expansion optimized by the TS algorithm developed, a small MV/LV-Feeder from the northeastern corner of the Albacete district, described in section 5.2.1, is presented below. The MV feeder with five MV/LV distribution transformers and their respective LV feeders are isolated from the original network (section 5.2). This feeder contains two voltage levels, namely 20 kV with five buses and 1,196 m of power lines and 1 kV with 91 buses and 2,718 m in length. The five MV/LV transformers have a total nameplate capacity of 2.45 MVA. The loads consist of 222 LV loads totaling 2.53 MW and 0.57 Mvar.

In this case study, multiple analyses are carried out to understand the functioning and the consistency of the solutions obtained by the TS algorithm based on the MV/LV feeder presented.

6. Results and discussion

Firstly, the initial solution produced by the HS algorithm is presented. Secondly, solutions optimized by the TS algorithm are shown, both with and without non-conventional expansion using flexibility contracting. Next, under a reduced load-growth scenario, a comparison is made between two levels of flexible load activation potential. Where in one case, and the base scenario in this paper, the load reduction of activated flexibility contracts is reduced to 70% of the installed load capacity, in the other case the load reduction of activated flexibility contracts is reduced to 0 %, practically switching off the entire flexible load. Finally, the results of a sensitivity analysis are presented, showing

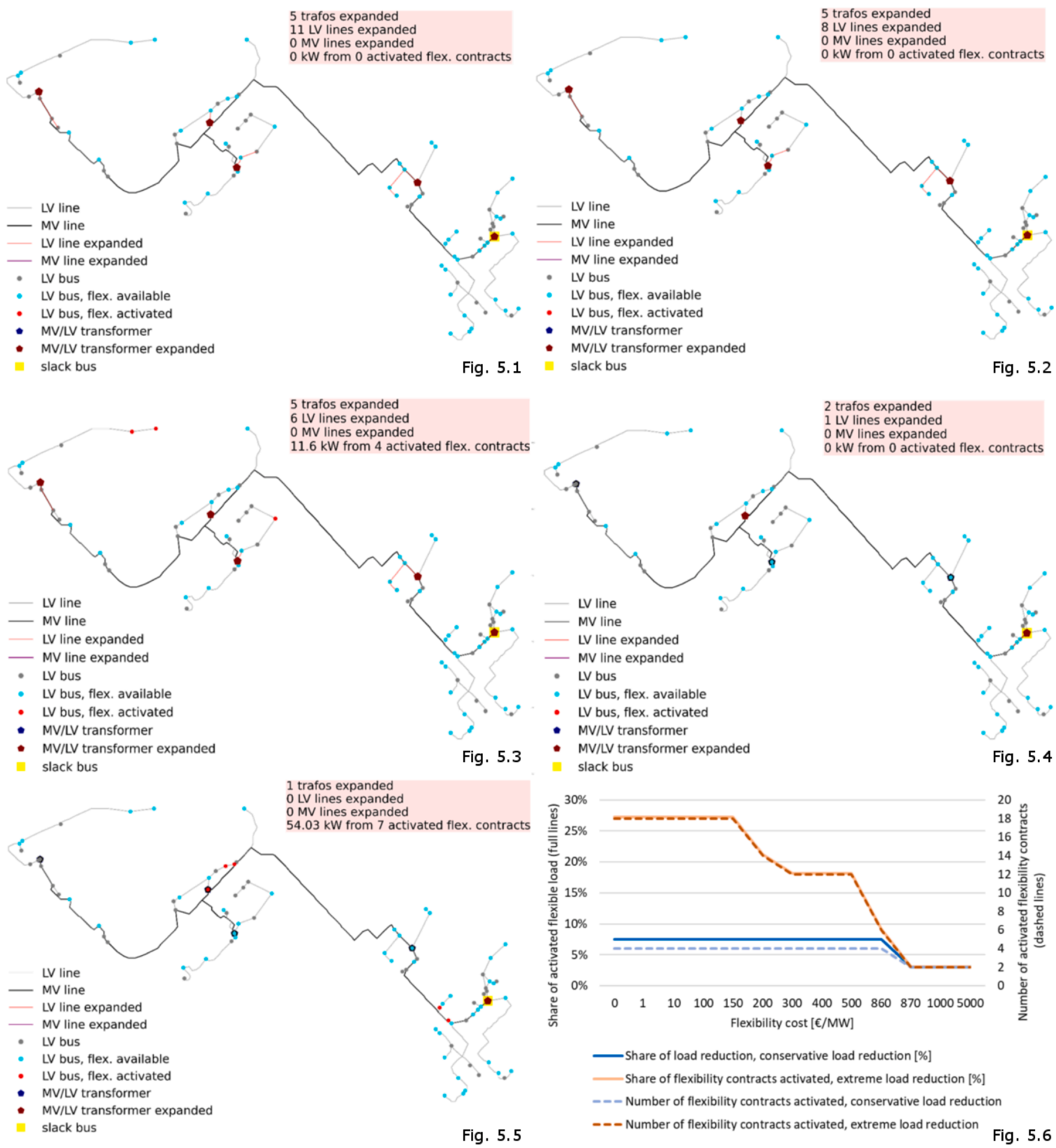

Fig. 5. Feeder case studies, network plot results and results of flexibility cost sensitivity analysis.

how sensitive the application of flexibility as an expansion measure is to the price of flexibility. This sensitivity analysis is conducted on a large number of values for flexibility cost, though only a small selection of the corresponding results is presented and discussed below. In addition, to further test the results found, the sensitivity analysis is undertaken for two scenarios, varying the load reduction of activated flexibility contracts, with a reduction to 0 % as well as to 70% of the installed load capacity.

6.1. Feeder-type network

6.1.1. Standard scenario with and without flexibility

The initial solution based on the simple HS algorithm described in section 4.3 contains five transformer expansions with a total of 1.47 MVA additional nameplate capacity and eleven parallel line expansions with additional 250 m of length. As can be observed in Fig. 5.1, all transformers are expanded, from the transformer situated directly at the slack bus (indicated as a yellow square) to the one situated at the end of the MV-feeder. The expanded LV line segments appear in all LV networks below the expanded transformers. This results in a total annuity of 16,664.37 € for the MV/LV feeder for the initial solution produced with the simple heuristic.

Running the TS algorithm on the initial solution presented in the previous paragraph produces an optimized solution as shown in Fig. 5.2. This solution contains five transformer expansions with a total of 1.24 MVA additional nameplate capacity and eight parallel line expansions with additional 210 m of length. Compared to the initial solution, three parallel line expansions totaling 40 m have been removed and one transformer expansion has been downgraded from 630 kVA to 400 kVA. With 16,534.89 € the total annuity for the MV/LV feeder expansion is 2.16 % lower compared to the initial solution presented in the previous case. This is achieved by avoiding the expansion of three LV power lines.

In this case the use of flexibility contracting as an alternative to conventional expansion is introduced, assuming the 2030 scenario, as described in section 5.2.2. The price considered for flexibility is 5,000 €/MW and year. Compared to the initial solution, this results in a network expansion with five transformers and additional nameplate capacity of 1.24 MVA, as in the previous case. The expansion of power lines results in six LV power lines with a total of 180 m, instead of eight power lines with 210 m compared to the previous case. Additionally, four flexibility contracts are activated, with a total load reduction of 11.6 kW, as shown in Fig. 5.3. The resulting expansion annuity is 16,420.62 €, which is 0.7 % less than the solution only with conventional expansion measures presented in the previous case. It can be observed that in this scenario, a significant reduction of total annuity is not achieved, as the available flexibility does not provide sufficient load reduction to allow for less transformer expansion, compared to the previous case.

6.1.2. Scenario with reduced load including flexibility

In the case of reduced load-growth, the loads are scaled to lower levels than in the 2030 base scenario described in section 5.2.2. The reduced peak-load consequently results in the removal of all but two transformers and one power line expansion from the initial solution. A stronger reduction of the expansion measures is obtained as expected, as the initial solution is based on the peak-load of the 2030 scenario and the oversized expansion, as shown in the first two cases. No flexibility contracts are activated, as seen in Fig. 5.4. The resulting expansion annuity is 6,322.11 €, which is unsurprisingly, significantly lower than in the scenarios at 2030 load-growth. This confirms the sensitivity of the planning algorithms to the future load in the year where the expansion is projected.

The prior case reduces the contracted flexible loads to 70% of their installed power. The following case assumes the same as the previous scenario but allows the flexible loads to be reduced to 0 %, in case of flexibility contract activation. As may be observed in Fig. 5.5, this results in the removal of all but one transformer and the removal of all power line expansions from the initial solution. Additionally, seven flexibility contracts are activated, resulting in a 54.03 kW load reduction. It can be clearly observed that the second to last transformer in the MV-feeder is not expanded, as compared to the previous case; instead, some of the flexibility downstream of the transformer is activated. Likewise, it can be observed that in this case the power line expansion, that was present in the previous case is removed, while some flexibility downstream of this power line is activated.

This illustrated well how flexibility, if sufficiently available, can work as an alternative to conventional power line expansion, selected by the TS algorithm due to the use of ejection chains, as described in section 4.4. The overall annuity, with 3,221.12 €, is therefore unsurprisingly low. Despite representing this extreme case, these results highlight the importance of the amount of flexibility that can be made available for each load, being a critical factor for flexibility to serve as an alternative to conventional reinforcements.

6.1.3. Scenarios with sensitivity to flexibility cost

In order to identify the sensitivity of the ADN planning methodology to the cost of flexibility, a brief sensitivity analysis is undertaken. As in the previous section, two levels of load reduction in case of flexibility contract activation are analyzed. In the more conservative case, the flexible loads active power consumption is reduced to 70 % of its peak-load contribution. In other words, 30% of the nominal active power of the load is available as flexibility. In the more extreme case, this reduction reaches 0 %, practically corresponding to a deactivation of the respective loads. In other words, 100 % of the nominal active power of the load is available as flexibility.

The sensitivity analysis has been undertaken by running the TS optimization for a wide range of flexibility cost, from 0 to 5,000 €/MW. It is to be noticed that the values on the horizontal axis are not on a linear scale, but skewed around some of the threshold values for the cost of flexibility. The results of this analysis, for both levels of load reduction, are shown in Fig. 5.6. It can be observed how the more extreme load reduction level leads to a significantly higher share of flexibility contract activation, here up to 27%, as long as the cost of flexibility remains below roughly 860 €/MW. This is due to the fact that the higher total load reduction in the respective network segments allows the flexibility contracting to serve as an effective alternative to non-conventional expansion measures such as power line or transformer expansion.

For the case with the more extreme load reduction, it shows that below an annual cost of 150 €/MW the cost did not limit the application of flexibility as an alternative to conventional expansion. For more conservative load reduction, on the other hand, it shows that this threshold value is at 860 €/MW.

The results of all the case studies presented in sections 6.1.1, 6.1.2 and 6.1.3 serve to illustrate the basic behavior of the planning method, reducing the network expansion cost from the initial solution to the minimum while serving the peak-load and satisfying the technical constraints. Both for the case with conventional and non-conventional (flexibility) expansion measures. In addition, the different load reduction potentials for activated flexibility contracts in section 6.1.2, demonstrates that flexibility can work well as an alternative to conventional grid expansion, if it is available in sufficient capacity at the relevant locations of the network. The last case study in section 6.1.3 exemplifies the impact of different cost for flexibility contracting on the application of flexibility as an alternative to conventional expansion. Furthermore, the more complex injection of moves in the form of ejection chains, with flexibility contracting as an alternative to transformer expansion, is observable.

6.2. Realistic large-scale network

In the first case, flexibility is not available to be contracted, but the

TS algorithm searches for network candidates with a better objective function value that fulfils all constraints. The resulting network is shown in Fig. 6. The expansion needs for conventional expansion is shown in Table 4, with a total annual cost of 282,609.18 € for a load growth of 19.78 % between 2020 and 2030. The evolution of the objective function value during the search procedure of the TS optimization is shown in Fig. 7.

The load and asset data between this case and the one in the next paragraph is compared in Table 3.

In the second case, flexibility contracting is available as an alternative expansion measure. Based on some values from real-world applications of flexibility in distribution systems [48,49], a value of 5,000 €/MW has been selected for this case study on the realistic large-scale network.

This results in the activation of 87 flexibility contracts at 78 buses, reducing the peak load contribution of those loads by 50%, which translates to a total of 618.27 kW load reduction. At 5,000 €/MW for the contracting of flexibility, this results in savings of 21,189.56 € or 7.5 % compared to the annual cost for conventional expansion only. The expansion needed for conventional expansion with the peak-hour relief by contracting load flexibility is shown in Table 4, with a total annual cost of 261,419.62 €. As shown in Table 3, these savings are mostly realized due to a reduction of 2.61 MVA in transformer capacity and an reduction of 0.92 km in the LV power lines expanded, compared to the case with conventional expansion only.

The network after expansion with conventional and flexibility measures is shown in Fig. 9. The evolution of the objective function value during the search procedure of the TS optimization is shown in Fig. 8.

In Table 3, load and asset data between the cases with and without flexibility contracting are compared, as depicted above.

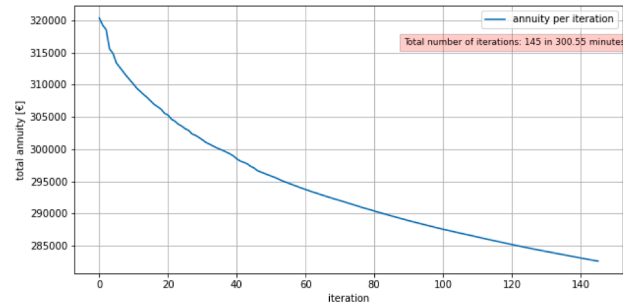

Fig. 7. Total annuity of selected candidate solutions during the search procedure, without flexibility.

Table 3
Load growth and network elements at 2020 and 2030 after expansion.

RNM	2020	2030	2030 + DR
P_load_tot [MW]	75.83	90.83	90.21
Q_load_tot [Mvar]	22.78	22.75	22.62
P_losses [MW]	1.59	2.23	2.21
P_losses [%]	2.1	2.46	2.45
Transformers			
MV/LV count	121	129	129
MV/LV capacity [MVA]	61.5	78.99	76.38
Power lines			
MV power lines [km]	32.01	32.17	32.17
LV power lines [km]	66.55	82.0	81.08

6.3. Future challenges and research

These results, based on the DNP methodology introduced in section 4, show the potential for contracting flexibility to reduce the peak hour

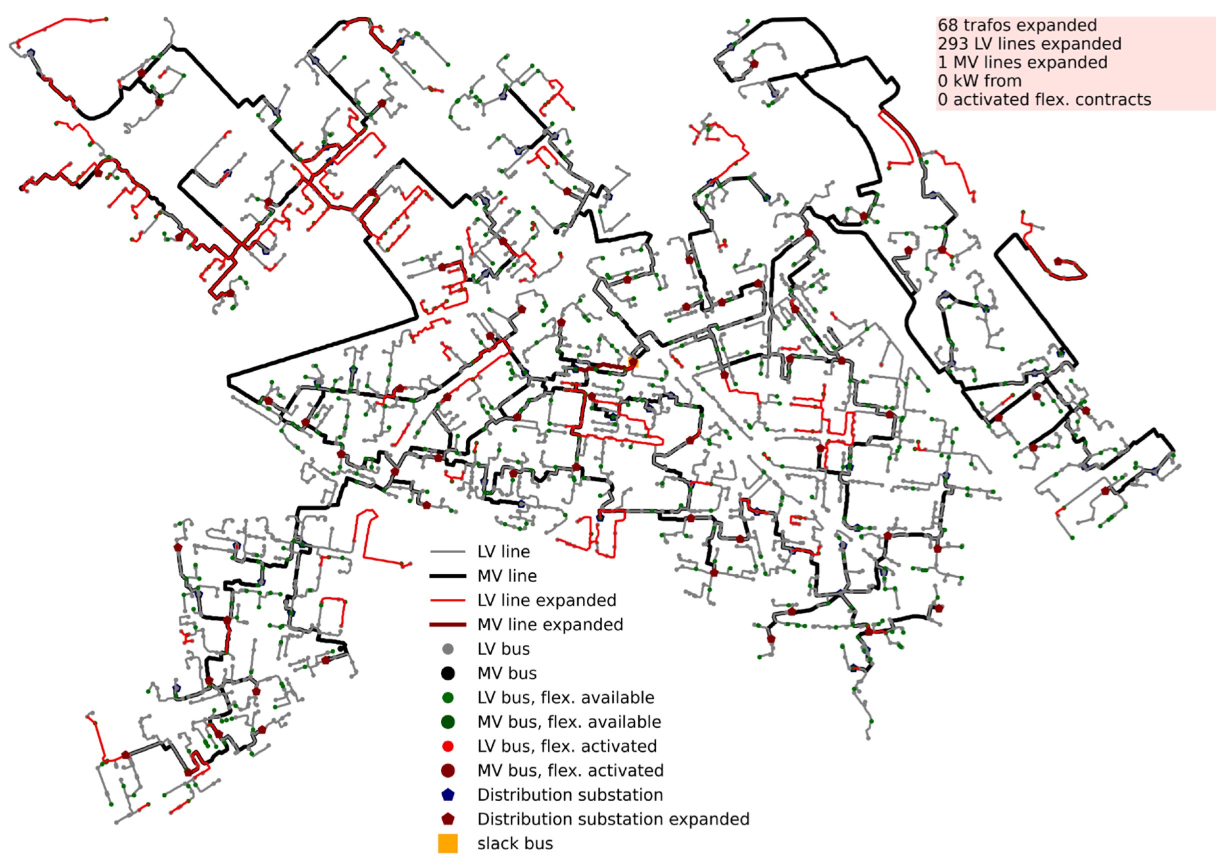

Fig. 6. Network expansion plot without flexibility activation.

Table 4
Total cost for conventional expansion and for conventional plus flexibility contracts.

	2030	2030 + DR*
Total annuity:	282,609.18 €	261,419.62 €
of which:		
Power lines	60,493.59 €	56,910.99 €
Transformers	222,115.60 €	201,417.26 €
Flexibility	0 €	3,091.38 €

* at 5,000 €/MW per year.

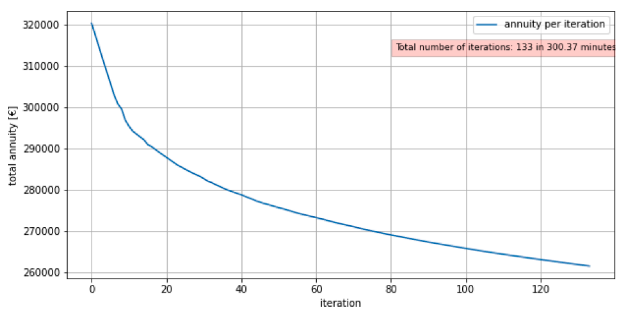

Fig. 8. Total annuity of selected candidate solutions during the search procedure, with flexibility.

load critical to the planning problem. For further research, illustrative challenges are to be presented, for instance on how to use the potential flexibility provided by larger ECV charging stations in car parks or commercial buildings on the MV level or decarbonized heating systems such as heat-pumps.

While we have shown that flexibility contracts can significantly reduce conventional network investments for capacity expansion, it remains to be seen how reliable the flexibility provision at the peak-load can be assumed. Compared to flexibility contracts, conventional network expansion measures are characterized by high investment cost upfront, but once installed, the equipment provides the capacity constantly and reliably. Generally, two approaches are taken to rely on flexibility. Explicit flexibility provision through flexibility contracts, in which the provider has the obligation to fulfil the contract and implicit flexibility, which relies on dynamic network tariffs that are high enough at peak hours and therefore incentivize load reduction. In the case of implicit flexibility, the fulfilment of the load reduction depends on socio-economic preferences of consumers which cannot be ensured deterministically. In the case of explicit flexibility provision, the providers' fulfilment of the obligation to provide contracted flexibility is ensured by financial reward as well as penalties in the event of non-compliance with the reaction to the control-signal sent by the DSO. At the cost of flexibility of 5,000 €/MW or 5 €/kW per year, the economic incentive to provide flexibility seems too low to sufficiently mobilise DR participants. Especially as this cost must not only incentivize the consumer to adopt consumption behaviour but also serve to recuperate the cost for the installation and maintenance of ICT and the operation of the aggregator service.

Further research shall be undertaken to evaluate the impact on expansion cost due to various DER (heat-pumps, PV, storage, etc.) at different scales deployed in the network. Furthermore, the impact on expansion cost due to more smart grid technologies such as distribution transformers with OLTC, dynamic network reconfiguration through switching operations or dynamic line rating shall be evaluated. The TS optimisation method can be improved by introducing more specific and better-targeted move insertions to create a higher rate of feasible and high-quality candidates per iteration. Lastly, upgrading the model towards a multistage planning model is a promising future line of research.

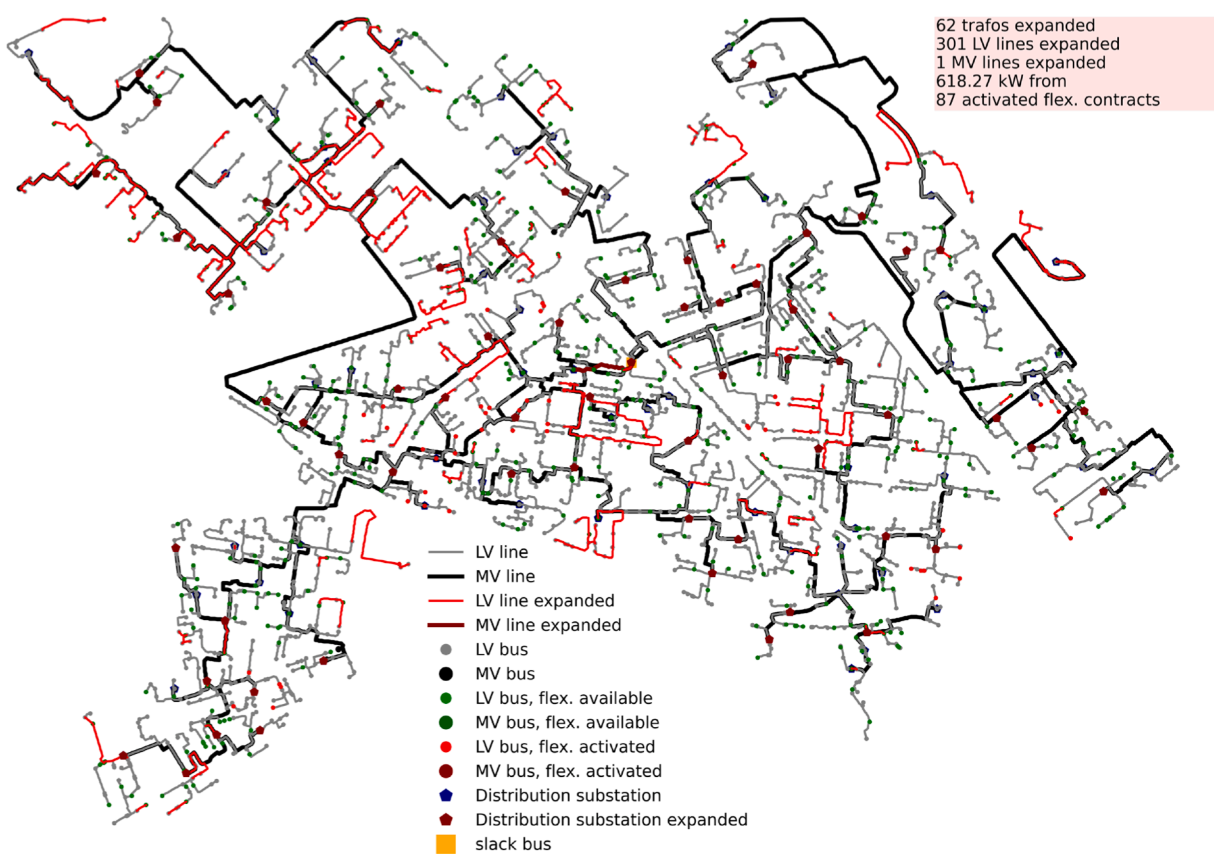

Fig. 9. Network expansion plot with flexibility activation.

7. Conclusions

This paper demonstrates that Tabu Search is effective in solving the distribution network planning problem using load flexibility as an alternative to conventional network reinforcements. The approach to first produce a technically feasible but not cost-optimal solution with a rather simple heuristic method, which is consecutively optimized by the Tabu Search algorithm has proven to be successful. In addition, the usage of ejection chains, as they are known in Tabu Search literature, is shown to be useful to swap non-conventional with conventional expansion measures. The use of Tabu Search as a metaheuristic optimization algorithm, whose implementation allows relatively much freedom to implement the very domain-specific technical and regulatory characteristics and planning requirements, allows us to deal well with even large-scale networks on city scale with 2762 buses.

A sensitivity analysis with respect to the cost of flexibility contracting has shown that different thresholds exist, depending on the particular feeder conditions and the available load flexibility, below which load flexibility provision is preferably used over conventional expansion, in discrete steps.

The paper shows that the use of load flexibility, as an alternative to conventional expansion can reduce the total cost with respect to the conventional expansion solution by 7.5 % for the analysed large-scale case study, at a load flexibility cost of 5,000 €/MW and year. Taking into account the high costs of distribution system expansion for the underlying load growth scenario, this would translate into major savings if applied for the whole distribution systems of a country or region.

Some recommendations for further research entail the analysis of the impact of a range of relevant energy system scenarios, the modelling of smart grid technologies as well as performance improvements on the Tabu Search algorithm.

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 used for the research is publicly available and provided in the references of the paper.

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