Practice-Oriented Optimization of Distribution Network Planning using Metaheuristic Algorithms

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***Abstract*— Distribution network operators require more advanced planning tools to deal with the challenges of future network planning. An appropriate planning and optimization tool can identify which option for network extension should be selected from available alternatives. However, many optimization approaches described in the literature are quite theoretical and do not yield results that are practically relevant and feasible. In this paper, a distribution network planning approach is proposed which meets requirements originating from network planning practice to guarantee realistic outcomes. This approach uses a state-of-the-art evolutionary algorithm: Gene-pool Optimal Mixing Evolutionary Algorithm. The performance of this algorithm, as well as the proposed model, is demonstrated using a real-world case study.**

Keywords—Power distribution network planning; optimization; distribution network operator; gene-pool optimal mixing evolutionary algorithms

I. INTRODUCTION

The existing planning methods for Distribution Network Operators (DNOs) still involve manual (labor-intensive) generation of alternative expansion plans, based on planning guidelines and experience of engineers. Due to the on-going developments in the electricity sector, the number of possible expansion options increases substantially and they become less straightforward [1]. Network planning optimization tools can help network planners to select among the numerous alternatives for the optimal future distribution network layout [2]. In the international technical literature, e.g. in [3], many different optimization approaches are available to access the Distribution Network Expansion Planning (DNEP) problem. These proposed approaches are mostly built-up from a theoretical perspective, resulting in efficient DNEP models, but lacking practical constraints and realistic expansion rules. Consequently, this often results in (inapplicable) solutions that are not always practically relevant.

Therefore, the goal of this paper is to propose and present a DNEP optimization approach which is based on practically relevant requirements and practices, rather than derived from theory. Preliminary work [4], and network planning principles of Dutch DNOs [1], have been translated into a network planning optimization model to guarantee realistic outcomes (i.e. network expansion options). This approach uses a state-of-the-art evolutionary algorithm: Gene-pool Optimal Mixing Evolutionary Algorithm. In this paper, the performance of this algorithm is compared with a classical genetic algorithm.

This paper is organized as follows. First, Section II describes the DNEP approach, the applied objective (cost) methodology, as well as the optimization problem formulation. Section III describes the two applied algorithms. Section IV demonstrates the DNEP approach using a real-world case and discusses the performance of the algorithms. Finally, some concluding remarks are given in Section V concerning the advantages and limitations of the proposed DNEP approach.

II. DISTRIBUTION NETWORK EXPANSION PLANNING APPROACH

The process of network planning involves decision making about *where*, *how many*, *when*, and *which* type of new asset should be installed in an electric system, such that it meets the forecasted developments (e.g. load growth) within a specified time horizon [1]. The proposed DNEP approach includes carefully designed, realistic expansion options of Medium Voltage Distribution (MV-D) networks. The planning strategies are designed from the point of view of a Dutch DNO. The approach is applicable for ring-shaped MV-D networks which are radially operated (Fig. 2). Nevertheless, the planning strategies and proposed methodologies have broader applications for similar type of networks and topologies.

In this paper, we focus on finding the locations and assets for network expansions regarding long term MV-D network planning. An optimal expansion plan requires minimal costs while satisfying all topological and operational constraints. We consider two levels of the grid: the MV-D network and the MV/LV transformers.

A. Overview of the proposed DNEP approach

The total DNEP approach consists of an expansion routine for MV/LV transformers and of an optimization tool for the optimal expansion of the MV-D network, as shown in Fig. 1. The input of this DNEP environment requires a given future scenario and a case network. The future scenario specifies the load and generation growth during the planning horizon. If a certain scenario leads to bottlenecks in the network (i.e. capacity/voltage problems) within the planning horizon, the DNEP environment will search for proper network

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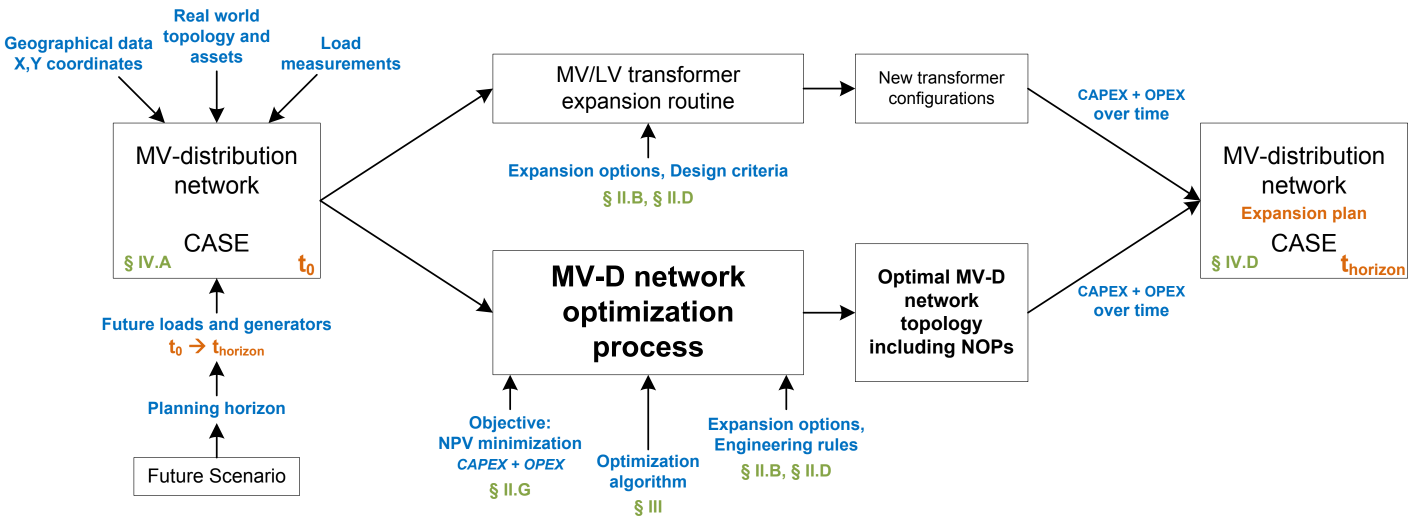

Fig. 1. Overview of the proposed distribution network expansion planning approach, including section references.

expansions.The tool specifies where and which type of new assets should be installed to minimize the total investment (CAPEX) and operational costs (OPEX). The network planning principles of Dutch DNOs [1] have been integrated into this DNEP approach to guarantee realistic outcomes (i.e. network expansions). The core of the DNEP approach is an optimization process for optimizing the locations and the types of new MV cables. A separate routine determines the expansion of MV/LV transformers. It is not necessary to include this in the optimization process, since it is an isolated problem and the expansion solutions per station are limited and straightforward (see Section II.B).

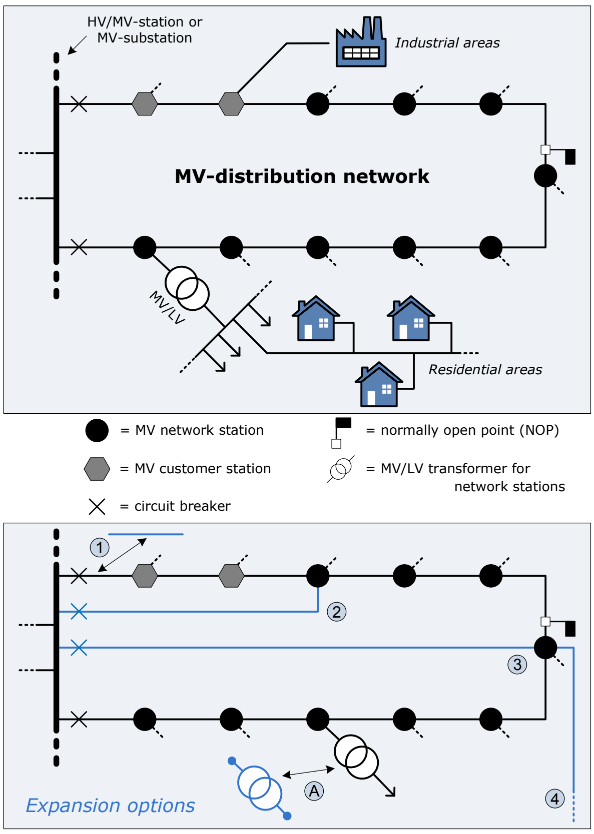

Fig. 2. Typical topology of MV-distribution networks in the Netherlands, including classic expansion options.

B. Practical expansion options

Classic expansion options are used in the DNEP approach to solve bottlenecks in MV-D networks under future (load) conditions. Fig. 2 depicts an example of classic expansion options in a typical MV-D ring (radially operated). Possible solutions to solve bottlenecks in MV-D rings are replacing a cable one-by-one with a cable of higher capacity (option 1 in Fig. 2), adding a total new feeder to the ring, e.g. half-way the upper feeder (2), or half-way the ring (3). This results in a significant increase in capacity. Consequently, new normally-open points (NOP) should be placed to guarantee radial operation and minimizing energy losses during normal operation. Moreover, it is possible to connect the ring with another existing or new MV-D ring / substation (4). The considered types of MV cables are listed in Table I. This list of cable sizes corresponds to the standardized cable packages of Dutch DNOs applicable for MV-D networks. It should be noted that nearly all Dutch MV networks consists of underground cables.

The possible new cables routes and connections are limited by so-called *engineering rules*; which are expansion guidelines applied by DNOs. Engineering rules (e-rules) are implemented to avoid inapplicable solutions and to reduce the search space of the optimization problem. Table II lists two variants of the applied e-rules. Variant A is a more general problem instance and variant B includes engineering rules which are more relevant to MV-D network expansions. The rules 2-4 are based on the principles of Fig. 2 and determine what are the allowed cable connections. Fig. 3 shows a real-world example of a MV-D

TABLE I
LIST OF AVAILABLE MV/LV TRANSFORMERS AND MV CABLES[1]

MV/LV transformer *options*			**MV cable *options***		
ID #	S_{nom}		ID #	Type	I_{nom}
1	100 kVA		1	120 mm^2	215 A
2	160 kVA		2	150 mm^2	295 A
3	250 kVA		3	240 mm^2	370 A
4	400 kVA		4	400 mm^2	475 A
5	630 kVA		5	630 mm^2	605 A

[1] MV/LV transformers of the type oil-filled, MV cables of the type cross-linked polyethylene (XLPE). The identification (ID) numbers are used for the network codification (Section II.F).

network and the remaining candidate cable connections are represented by blue dashed lines). Rules 1,5,6,7 are used to define the allowed cable types for each (candidate) cable connection. Rule 8 is modeled as a constraint in the optimization model. This rule is included to resemble the limited switch-gear space for new feeders in the MV-substation.

The expansion of MV/LV transformers is in practice a standardized and straightforward process: existing MV/LV transformers that become overloaded will be replaced by a new transformer with a higher capacity (option A in Fig. 2). Table I presents the available transformers. An additional transformer is installed when the needed capacity is higher than 630 kVA.

C. Distribution network modeling

Distribution networks are dimensioned for the worst-case (loading) situation. The loads in the MV-D network model are traditionally specified as single maximum values: *peak loads*. This is also due to the fact that detailed measurement data in distribution networks is in general still quite rare (unlike in transmission networks). Load measurements at Dutch MV/LV transformers, for example, only take place once a year and produces a single measurement value: P_{max}. However, load profiles can be properly estimated since the traditional (load) behavior of residential areas can be easily predicted. This will change due to the introduction of new technologies like electrical vehicles, heat pumps and photovoltaic panels [5]. Nevertheless, [5] and [6] show that with an extension of the peak load approach it is possible to include future residential loads and generators in DNEP planning.

In this paper we use the deterministic peak-load approach as this is supported by the available measurement data and geographic information systems. The (peak) load measurements at *network stations* (i.e. LV networks), and *customers stations* (e.g. industries), are modeled as one aggregated load per station. Network stations, including their MV/LV transformers, are owned by DNOs, and therefore, the expansion and resulting costs are taken into account in our DNEP approach. The MV/LV transformer expansion routine determines the necessary capacity for each network station over time.

D. Important design criteria

The generated expansion options are evaluated using planning guidelines of DNOs. First of all, to check for feasible expansion solutions in the MV-network, the maximum allowable loadings of assets should be defined. Table III lists the maximum allowable loading of transformers and cables. Loadings above rated capacity S_{nom} are allowed since the guidelines take into account the thermal dynamics and cyclic load behavior of assets [7].

TABLE III

MAXIMUM ALLOWABLE LOADINGS OF ASSETS AND VOLTAGE LIMITS, CONFORM PRACTICAL PLANNING GUIDELINES.

MV-D cable under *normal operation*	$S_{max} = S_{nom}$
MV-D cable under *emergency situations*	$S_{max} = 1.3 \cdot S_{nom}$
Maximum voltages at stations/nodes	$V_{max} = 1.1 \cdot V_{nom}$
Minimum voltages at stations/nodes	$V_{min} = 0.9 \cdot V_{nom}$
MV/LV transformer	$S_{max} = 1.2 \cdot S_{nom}$

Power-flow calculations are used to check the power flows and voltages of the (expanded) MV-D network for *normal operation* and *emergency situations*. In normal operation, the typical MV-D ring of Fig. 2 is split into two parts by a NOP. The network can be reconfigured (i.e. moving NOPs) in situations of emergency or maintenance to isolate certain cables or network parts. For a ring, this means it should have enough capacity to supply all load when fed only from either end. On the other hand, a higher loading is allowed during emergency situations (for maximal 72 hours). This reconfiguration design arrangement is common in what is often called "European" distribution layouts, in which loops are radially operated [2].

MV-D network cases with *distributed generation* (DG) require an additional check due to the used peak load approach. It requires the evaluation of two worst-case network states:

- Dominance of load (load: 100%, generation 0%)
- Dominance of DG (load: 25%, generation 100%)

Above percentages imply that all present load/generators in a MV-D network are changed accordingly. Moreover, both states should be checked for normal operation and emergency conditions. The DNO's goal of evaluating the abovementioned states is finding the highest (worst-case) possible loadings of MV-D cable connections. Both network states are extremes, however, measurements have shown that they do occur in cases where DG is connected to the MV-D network (e.g. wind turbines or combined heat and power systems at horticulture areas).

E. Time horizon handling and cost methodology

There are different network planning approaches regarding the implication of time [3]. In this paper we use an approach to include energy losses (OPEX) in a net present value (NPV) cost function. Capitalizing energy losses require some information about the factor time to estimate the yearly losses. We assume that the MV-D network is expanded in the year where the first bottleneck is detected in the network: $t_{overload}$. Sufficient capacity is installed at $t_{overload}$ to meet the loading situation at the end of the time horizon. The losses can be estimated for the network topology from t_0 till $t_{overload}$, and for the new network

TABLE II

ENGINEERING RULES FOR MV-D NETWORK PLANNING: EXPANSION CONSTRAINTS FROM A PRACTICAL POINT OF VIEW

	Engineering rules for MV-D network planning	*Variant A*	*Variant B*
1	5 types of available cables: *120mm², 150mm², 240mm², 400mm², 630mm²*	√	-
2	Only new outgoing cables are allowed: from a MV-substation towards a MV station (i.e. no sub-rings)	√	√
3	Not possible to install a new cable between a MV-substation and the 1st MV station of an existing feeder	√	√
4	Not possible to install multiple new cables (i.e. parallel) to a single MV station	√	√
5	Limited types of available cables (planning guideline of DNO Enexis): *150mm², 240mm²*	-	√
6	Existing cables cannot be removed, although replacement with a higher capacity is possible	-	√
7	Not possible to place a NOP on cables going out from a MV-substation (inefficient normal operation state)	-	√
8	Maximum of 3 new outgoing cables from a MV-substation (due to limited switch-gear space in MV-substation)	-	√

topology from $t_{overload}$ till $t_{horizon}$. For the MV/LV transformer expansion routine we assume a multi-step approach where a transformer, that becomes overloaded, will be continuously replaced by a new transformer with a higher capacity, according to the order in Table I.

Energy losses in general depend on the network structure, network loading, and type of assets. Determining the losses is essential for network planning and investment analysis, since they are yearly costs for the DNO. Energy losses are typically divided into load dependent losses (*load losses*) and load independent losses (*no-load losses*). The load losses are usually estimated using the peak loading of assets and an assumed yearly load profile. The peak loading of assets follow from the power-flow calculation, and depending on the asset's property, the accompanying peak loss $P_{peak\ loss}$ can be calculated:

$$P_{peak\ loss} = \alpha^2 \cdot P_{load\ loss} \tag{1}$$

where α is the utilization factor of the asset and $P_{load\ loss}$ the specified losses of the asset at nominal capacity. The loss duration of $P_{peak\ loss}$ for a year, the so-called service time of the load losses T_{loss},is defined by the area of the yearly energy loss profile. This energy loss profile is quadratic related to the assumed yearly load profile of the asset. The service time of the no-load losses T_0 equals the operational hours of the asset which is in general 8760 hours per year. In this study it is assumed that the no-load losses $P_{no\ load\ loss}$ are constant (i.e. independent of voltage variations). In conclusion:

The yearly energy losses for a transformers are

$$E_{loss\ trafo} = P_{peak\ loss} \cdot T_{loss} + P_{no\ load\ loss} \cdot T_0 \tag{2}$$

The yearly energy losses for a cable are

$$E_{loss\ cable} = P_{peak\ loss} \cdot T_{loss} \tag{3}$$

The total costs $€_{OPEX}$ of the total energy losses in year *t* are

$$€_{OPEX}(t) = E_{loss}(t) \cdot €_{elec} \tag{4}$$

where $€_{elec}$ is the electricity price which is based on currently used prices by DNOs for investment analysis.

For the total investment costs $€_{CAPEX}$ of new assets we use the *annuities method* [6],[8]. Basically, the annuities method converts an investment into a series of uniform annual payments - the so-called annuities. The length of this series equals the economic lifetime of the asset $t_{lifetime}$. The annuity (i.e. yearly costs) AN_{asset} of a new asset, for a time horizon with discount rate *i*, can be determined with:

$$AN_{asset} = €_{asset} \cdot \frac{i}{1-(1+i)^{-t_{lifetime}}} \tag{5}$$

The NPV of the series of payments in (5) is exactly equal to the asset's initial cost:

$$€_{asset} = \sum_{t=1}^{t_{lifetime}} \frac{AN_{asset}}{(1+i)^t} \tag{6}$$

The CAPEX for an asset in year *t* becomes:

$$€_{CAPEX\ asset}(t) = \begin{cases} AN_{asset} & if\ \ t_{inst.} \leq t < t_{inst.} + t_{lifetime} \\ 0 & else \end{cases} \tag{7}$$

where $t_{inst.}$ is the year where the asset is installed. In case of the MV/LV transformer expansion, where newly installed transformers can be replaced one-by-one within the time horizon, the AN_{asset} of a newly installed asset starts in year *t* and the remaining payments of the replaced asset stops (can be seen as the residual value). In this study we assume a discount rate of 4.5% and the economic lifetime of all assets to be 30 years. Due to these long lifetimes, a part of the investment costs may fall behind the time horizon. Nevertheless, compared to a classic CAPEX calculation, the annuities method is more reliable for comparing various investment options as well as comparing total costs between different scenarios [8].

F. MV-distribution network encoding

The MV-D network can be seen as a graph with a set of nodes (vertices) and a set of branches (edges). In our case the branches are MV cables and nodes can be MV-substations or MV network/customer stations, as depicted in Fig. 2. The MV-substation can be seen as the general power supply.

To solve the DNEP optimization problem, we specify beforehand all the existing branches and the potential candidate branches. These new candidate cable connections are limited by e-rules 2-4. Let *l* denote the total number of branches, and let *m* denote the total numbers of nodes. We represent a MV-D network as a vector of length *l* of integer-value elements:

$$\boldsymbol{x} = (x_1, x_2, \cdots, x_l), \quad x_k \in \Omega(x_k), \quad k \in \{1,2, \cdots l\} \tag{8}$$

where each x_k corresponds with the k-th branch of the network. The set of possible cable types $\Omega(x_k)$ that can be installed at each branch x_k is given in Table I. The ID number indicates which cable type is installed at a branch. The status of x_k is defined as follows:

- $x_k = ID > 0$: A cable with identification number $ID \in \Omega(x_k)$ is installed at the k-th branch.
- $x_k = 0$: There is no cable at the k-th branch installed.
- $x_k = -ID < 0$: A cable with identification number $ID \in \Omega(x_k)$ is installed at the k-th branch but out of operation. This represents a normally-open point (NOP).

Note that in the original network the x_k branches with status 0 represent the potential candidate branches which are determined by the e-rules.

G. Optimization problem formulation and solution evaluation

The DNEP approach minimizes investment and operational costs. Reliability and safety requirements are already discounted in the applied planning guidelines. The DNEP optimization problem is formulated as a constrained optimization problem. The objective is to minimize the NPV:

$$\mathbf{min}\ NPV(t) = \sum_{t=t_0}^{t_{horizon}} \frac{€_{OPEX}(t) + €_{CAPEX}(t)}{(1+i)^{t-t_0}} \tag{9}$$

Where $€_{OPEX}(t)$ and $€_{CAPEX}(t)$ are respectively the total capitalized losses and cumulative annuities for year *t*.

Subjected to the following constraints:

i. **Connectivity constraint**: All nodes should be connected.

ii. **Radial operation constraint**: NOPs should be placed in such a way that the meshed network is operated radially.

iii. **Normal operation constraints**: In a normal network configuration, the voltage at each node, and the power flow through each cable, should stay within limits (see Table III).

iv. **Reconfigurability constraint**: The network is checked for voltage and capacity in the possible reconfigurability states (see Section II.D).

A feasible solution is one that satisfies all constraints. MV-D networks with DG are evaluated for the 'dominance-of-load' state and the 'dominance-of-generation' state (see Section II.D) and all the constraints must be satisfied in both states.

The evaluation of a solution involves the NPV calculation and the relatively computational expensive constraint evaluation. For each solution, power-flow calculations (PLCs) are used to check the constraints **iii**, and **vi**. The PLCs are performed by our C-coded procedure which is based on the open-source package MatPower [9]. In this study we use the AC power flow model with the Newton-Raphson method to solve the non-linear power flow equations.

III. OPTIMIZATION ALGORITHM: GOMEA

Classical genetic algorithms (GAs) are widely used in power system expansion planning. In this work, we consider a popular implementation of the classical GA. First, a population of n candidate solutions is initialized randomly. All solutions are then evaluated to obtain their objective values and constraint values. In each iteration, n new solutions are generated by randomly pairing 2 parent solutions from the population and using uniform crossover to create 2 offspring solutions by randomly exchanging pairs of variables. By doing so, each time two offspring solutions are fully constructed and then evaluated. We then combine the n parent solutions with the n newly generated offspring solutions into a set of size $2n$. Next, a subset of n solutions is selected from these $2n$ solutions by using tournament selection with tournament size of 4, ensuring convergence by logistic growth of the best solution over time. This selected subset will become the parent population in the next iteration of GA. When performing tournament selection, we need to randomly divide the candidate solutions into groups of equal size. Comparisons between members in the same group are performed to choose the best solution of each group. The comparison mechanism is based on the concept of *constraint domination*. A feasible solution is always better than a solution violating one or some constraints. Between two feasible solutions, the cheaper one is preferred. If both solutions are infeasible, the one with less constraint violations is the better solution.

Despite the ubiquitous usage of GA, different studies show that optimization problems whose decision variables have multivariate or hierarchical dependencies can challenge the effectiveness and efficiency of traditional GA [4],[10]. The recently proposed Gene-pool Optimal Mixing Evolutionary Algorithm (GOMEA) tackles these weaknesses of GA by making use of the dependency information between problem variables combined with a novel variation operator integrating local search into genetic recombination. To exploit variable dependencies, a linkage model is used to describe explicitly groups of variables that are to some degree interdependent, and that should thus be copied together when performing recombination. In this paper, we specifically consider the linkage model that was used most often in GOMEA: the linkage tree. The variation operator of GOMEA helps to efficiently exploit the linkage relations provided by the linkage tree. GOMEA is therefore a strong candidate for solving the DNEP problem.

Like traditional GA, the population of GOMEA is firstly initialized randomly with n candidate solutions, and is then entirely evaluated. In each generation of GOMEA, a selection set of n solutions is selected out of n candidate solutions in the population by the tournament selection mechanism with tournament size 2. A linkage tree is learned from this selection set by a hierarchical clustering procedure [4]. Every existing solution, now termed as a parent solution, in the population then goes through the Gene-pool Optimal Mixing (GOM) procedure to create a new offspring solution. Whereas the recombination operator of GA generates one (or two) whole offspring solution(s) at a time, GOM constructs a single offspring solution in a step-wise manner by iteratively improving a given solution. First, the parent solution is backed up. Then, we traverse every linkage group in the linkage tree. For each linkage group, a donor solution is chosen randomly from the population. The values of the decision variables whose indices are indicated in the linkage group are copied from the donor solution to the parent solution. We evaluate the objective value and constraint values of this partially-altered solution and compare it with the parent solution by the constraint domination mechanism described above. If such mixing can improve the parent solution, the changes are accepted and recorded as the new backup, otherwise the parent solution is reverted to the last backup state. When all the linkage groups in the linkage tree are traversed, an offspring solution is fully constructed. The GOM procedure is applied on n existing solutions in the population, one at a time, to create new n offspring solutions, which form the population for the next iteration of GOMEA. More details about GOMEA can be found in [4].

IV. PRACTICAL CASE STUDY AND RESULTS

Based on real-world data, we designed a practical MV-D network case study, including the presence of DGs, to demonstrate the DNEP approach and the performance of the optimization algorithm. Furthermore, the results of different scenarios will be compared.

A. Medium voltage distribution network case

The MV-D network case is based on a part of an existing 10kV network of DNO Enexis and is depicted in Fig. 3. The network contains 31 busses with the real-world topology and geographical data (e.g. XY coordinates). For confidential and demonstration reasons we use fictive loads and distributed generators. The candidate cable connections are limited by e-rules 2-4 and the remaining possibilities are shown in blue. The geographical aspects are used to estimate realistic new cable lengths, taking into account local circumstances. The available list of new assets is depicted in Table I. The total MV cable costs per meter are in the order of €65,-, and per MV/LV transformer (station) expansion, in the order of €15000,-.

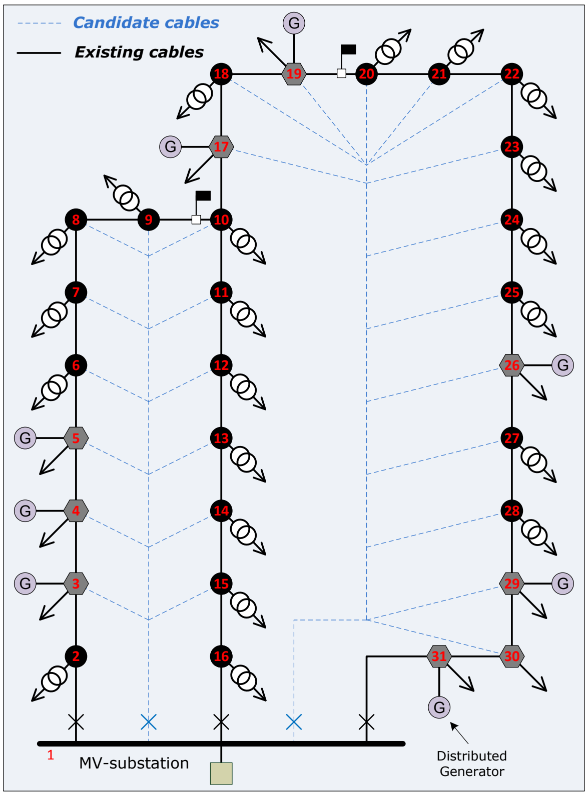

Fig. 3. Topology of 31-bus MV-D network case (detailed data and asset parameters can be found in Table V and Table VI). See Fig.1 for legend.

B. Scenarios

The DNEP approach can be used for scenario-based planning studies. In this paper we define and apply a "classic" and a "smart" scenario to demonstrate. The time horizon of both scenarios is set to 30 years. The *classic scenario* is a traditional 2% exponential load growth per year for all the loads at MV stations. This example load growth is caused by uncontrolled charging of electric vehicles (EV) at households [6] and normal residential load growth. We assume that the installed DGs remain the same over the time horizon. Notice that we included a special constraint in the DNEP approach to evaluate networks with DG (see Section II.G).

In the *smart scenario* we expect a future smart grid that enables control of flexible, less time-critical loads at households and industries [5]. In this scenario we assume that this demand side management (DSM) is employed from a DNO perspective (i.e. peak shaving). Furthermore, [5] and [6] show that it is possible to include future developments, like e.g. EV and photovoltaic panels, in the aggregated load at network stations and customer stations. In our example smart scenario, which is the smart version of the abovementioned (uncontrolled) classic scenario, we assume 10% peak reduction at customer-station loads due to DSM of e.g. industrial processes. In this example, we suppose that the peak load growth at network stations (in the classic scenario) is caused for 50% by charging of EVs and for 50% by normal residential load growth. For the smart scenario, this peak load of EVs is reduced by charging them in a smart way during off-peak hours, like in [6]. Furthermore, the normal residential peak load is reduced by 10% due to DSM of household appliances (e.g. washing machines and tumble dryers) [5]. In general, we can include different type of smart grid scenarios and discount this, in line with [5] and [6], in the input of the model: the aggregated load (growth) at stations.

C. Simulation conditions

We perform experiments with GOMEA and traditional GA on solving the expansion of the MV-D network for the above network. Both optimizers are run with different population sizes. For each population size, each optimizer is run 30 times and the averages are presented as results in the next section. The termination condition for each run is when every solution in the population has the same fitness value.

The MV/LV transformer expansion routine, which performs separate from the optimization process, determines the necessary transformer expansions and associated CAPEX and OPEX costs over the time horizon.

D. Results and discussion

The left and middle graph of Fig. 4 show the comparison over the performance of GOMEA and traditional GA; solving DNEP for the classic scenario and when assuming e-rules variant A (see Table II). The best found solution consists of a new cable connection, a placement of one new NOP, relocation of 2 existing NOPs, and an upgrade on one cable. The associated cash flows (CFs), together with the CFs resulting from the transformer expansion routine, are depicted in the right graph.

It can be seen that GOMEA has a better performance in terms of approaching (near-)optimal solutions quicker than GA by using fewer topology evaluations. In order to come close to the results found by GOMEA, traditional GA requires more fitness evaluations (i.e. longer computation time since fitness evaluations dominate other operations in the runtime) and much larger population sizes, which can be too cumbersome to be handled neatly. It is also interesting to point out that the

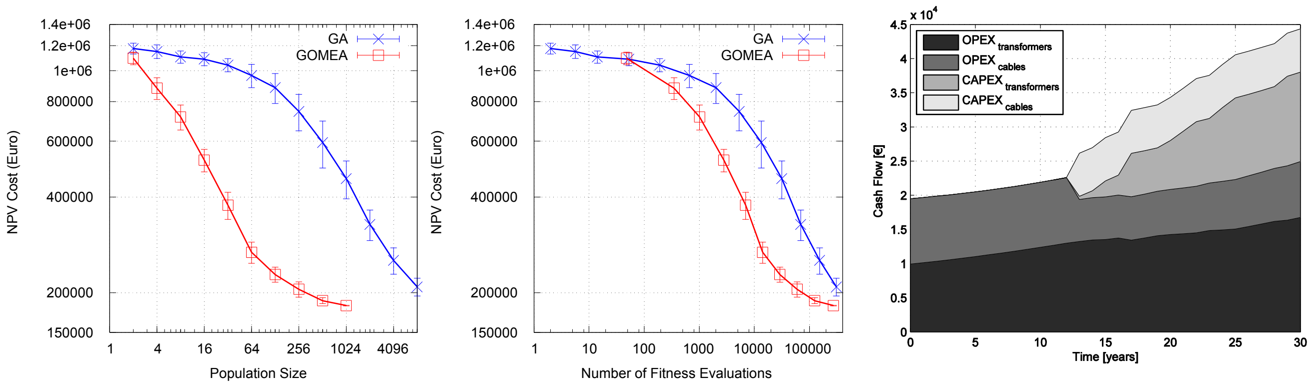

Fig. 4. Classic scenario with e-rules variant A: Performance of algorithm (left, middle) and cash flows over time (right).

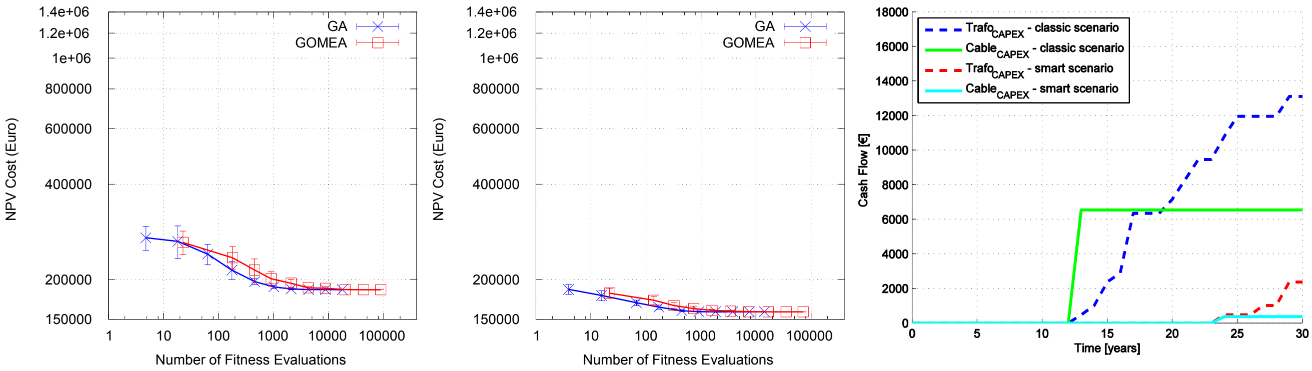

Fig. 5. Classic scenario with e-rules variant B (left), Smart scenario with e-rules variant B (middle), Classic vs. Smart scenario - CAPEX cash flows (right).

performance of GOMEA is more reliable than that of traditional GA when comparing the standard deviations of the results found by both algorithms. With the same population size, the results of GA fluctuate with a larger range, which can be due to premature convergence to local optima in some runs.

In solving real-world problems, it is common to consider available expert knowledge to simplify the problems. Such information can be used to reduce the search space by disregarding unnecessary values of decision variables. The left graph of Fig. 5 shows the performance of GOMEA and GA solving DNEP when considering the e-rules of variant B. Rules 5, 6, and 7 are used in the initialization step of the population. Rule 8 is modeled as an additional constraint. Similar to the previous experiment, the optimal solution consists of a new cable connection (but a different location and type from the result of variant A), a placement of one new NOP, relocation of 2 existing NOPs, and an upgrade on one cable. Clearly, expert knowledge indeed helps to simplify the problem at hand. Both GOMEA and GA require much fewer topology evaluations and smaller population sizes to converge to the optimal solution compared to the previous experiment.

It can also be seen that, in this case, GA outperforms GOMEA. A key reason for this is that with four different constraints already implemented in the optimization model (as described in Section II.G), the e-rule about the maximum number of new connections going out of substations is modeled as an additional constraint. At the time of this work, however, we have not designed an optimally appropriate constraint-handling mechanism for GOMEA yet. In every mixing step in the GOM procedure of GOMEA, we need to compare a partially altered offspring solution with its previous state, and, in this paper, we use the constraint domination mechanism (described in Section III) for this comparison. Constraint domination is not necessarily the best constraint-handling technique for GOMEA, especially when we try to improve a feasible solution: any newly generated solution that violates any constraints will be considered as infeasible and will be rejected. Thus, GOMEA is prevented from traversing infeasible regions of the search space. This can be harmful to the search if it requires to do so in order to approach the optimal solution efficiently. On the other hand, a classic GA generates and evaluates entire solutions at once and tournament selection is only called after all offspring solutions are generated. A GA can therefore accept infeasible solutions into the next generations and thereby traverse infeasible regions of the search space. Important future work is therefore to find a proper constraint-handling mechanism for GOMEA.

Another important observation is that both algorithms can locate the optimal solution by using very few fitness evaluations in the case of solving variant B and that the optimal solution for both variants A and B are quite simple (i.e. only a few changes need to be made to satisfy all constraints). This may indicate that the problem instance at hand is actually easy. DNEP can however be a hard problem in general cases [11], but in this specific case, especially when considering the radiality constraint and setting a maximal number for new connections going out of a substation, it is easy to solve. In general, it is beneficial to be able to solve the problem by reducing the search space and adding constraints to prevent optimization algorithms from considering unnecessary solutions so that we can solve bigger problem instances efficiently. However, the problem instances at hand may belong to a complexity class for which evolutionary algorithms are not normally the best-suited optimizers. Considering the simplicity of the optimal solution, a simpler algorithm, such as hill climbing starting from the existing network topology, is enough to solve the problem and would solve the problem more efficiently.

The middle graph of Fig. 5 shows the experimental result for solving DNEP for the same network when taking into account the effects of DSM on peak loads and load growths. Here, all the original constraints and e-rules variant B are included. In this case, the GA needs few fitness evaluations for finding the optimal solution, which simply consists of an upgrade for one cable. From an electrical engineering point of view, the results demonstrate that, due to DSM, network expansions can be delayed and the amount of required upgrades can be reduced compared to classic scenarios (see Table IV and right graph of Fig. 5). These results further indicate the flexibility of our current model and generality of our solving approach. Considering computational efficiency, however, again, a hill climbing algorithm would be a better optimizer for the particular problem instance at hand.

Nevertheless, the use of evolutionary algorithms, and especially an advanced optimizer like GOMEA, is still justifiable as a preparation for solving more complicated

TABLE IV
NET PRESENT VALUES FOR DIFFERENT SCENARIOS AND E-RULES VARIANTS

	Classic scenario *E-rules A*	**Classic scenario** *E-rules B*	**Smart Scenario** *E-rules B*
NPV	440 k€	442 k€	348 k€
├ **CAPEX**	102 k€ (*23%*)	94 k€ (*21%*)	3 k€ (1%)
└ **OPEX**	338 k€ (*77%*)	348 k€ (*79%*)	345 k€ (*99%*)

problem instances in the future. The demonstration network in this paper consists of a single substation, while a full-scaled grid consists of multiple substations with the possibility of interconnection between different MV-D rings (option 4 in Fig. 2). Furthermore, future cases that includes smart grid planning solutions (e.g. energy storage systems and DSM) as decision variables will propose different challenges.

V. CONCLUSIONS AND FUTURE WORK

This paper has presented a DNEP approach for MV-D networks. The approach meets requirements originating from network planning practice to guarantee realistic outcomes. We investigated two variants of engineering rules and we looked at the performance of the optimizers (GOMEA vs. GA). These approaches are demonstrated by a real-world case.

The results with engineering rules variant A show that GOMEA has a better performance than GA in terms of approaching (near-)optimal solutions quicker by using fewer topology evaluations. It is shown that expert knowledge helps to simplify the problem at hand and reduces the computation time. For variant B, both GOMEA and GA require much fewer topology evaluations and smaller population sizes to converge to the optimal solution compared.

The DNEP approach is suitable for scenario-based planning studies. Different kind of (smart grid) scenarios can be discounted in the input of the model: the aggregated load (growth) at stations. However, we now only consider classic expansion options as decision variables and we include smart grid technologies in the scenarios.

Future work should consider an approach where smart grid planning solutions (e.g. energy storage systems and DSM) becomes decision variables of the optimization model, instead of pre-modeling the flexible controllable load on the input side. This will impose different challenges for the optimization environment. Furthermore, it is encouraged to test a variety of larger real-world networks to identify the scalability of the DNEP approach and the performance of GOMEA. In addition, important future work is to find a proper constraint-handling mechanism for GOMEA. However, already the presented DNEP approach supports network planners by performing functions automatically and to identify which realistic expansion solution, out of all possible alternatives, should be selected. Moreover, the technical and economic impact of various future scenarios can be easily assessed.

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TABLE V

DATA OF MV-D NETWORK CASE

Node information						**Cable distances**			
Node	**Load**		**Transf.**	**DG**		**Existing**		**Estimated**	
[#]	**P** *[kW]*	**Q** *[kVAR]*	S_{nom} *[kVA]*	**P** *[kW]*	**Q** *[kVAR]*	**Branch** *[#]*	**Distance** *[m]*	**Branch** *[#]*	**Distance** *[m]*
1	0	0				**1.2**	481	**1.3**	676
2	35	17	100			**1.16**	246	**1.4**	621
3	1113	539		-1960	-398	**1.31**	761	**1.5**	1199
4	348	216		-980	-199	**2.3**	96	**1.6**	1306
5	871	286		-1960	-398	**3.4**	48	**1.7**	980
6	332	109	400			**4.5**	498	**1.8**	1465
7	132	82	250			**5.6**	86	**1.9**	1551
8	170	82	250			**6.7**	288	**1.10**	2135
9	22	14	100			**7.8**	935	**1.11**	2121
10	202	98	250			**8.9**	200	**1.12**	2121
11	120	0	160			**9.10**	470	**1.13**	1635
12	88	55	160			**10.11**	851	**1.14**	1386
13	284	137	400			**11.12**	220	**1.15**	1144
14	219	136	400			**12.13**	300	**1.17**	2218
15	314	152	400			**13.14**	284	**1.18**	2163
16	185	90	250			**14.15**	479	**1.19**	1988
17	127	79	160	-980	-199	**15.16**	846	**1.20**	2003
18	17	8	100			**10.17**	736	**1.21**	1751
19	896	434		-1960	-398	**17.18**	101	**1.22**	1622
20	314	152	400			**18.19**	154	**1.23**	1720
21	125	77	160			**19.20**	283	**1.24**	1648
22	248	120	400			**20.21**	308	**1.25**	1535
23	85	41	100			**21.22**	133	**1.26**	1451
24	123	76	160			**22.23**	132	**1.27**	1348
25	209	130	400			**23.24**	138	**1.28**	1315
26	566	274		-1960	-398	**24.25**	140	**1.29**	1057
27	266	129	400			**25.26**	103	**1.30**	1124
28	126	61	160			**26.27**	215		
29	360	174		-980	-199	**27.28**	139		
30	273	169				**28.29**	218		
31	263	163		-980	-199	**29.30**	136		
						30.31	160		

TABLE VI

PARAMETERS OF MV/LV TRANSFORMERS AND MV CABLES[1]

MV/LV transformer *parameters*		
ID *[#]*	$P_{load\ loss}$ *[kW]*	$P_{no\ load\ loss}$ *[kW]*
1	1.350	0.190
2	1.905	0.260
3	2.640	0.365
4	3.750	0.515
5	5.200	0.745

MV cable *parameters*			
ID *[#]*	R *[Ω/km]*	X *[Ω/km]*	C *[μF/km]*
1	0.257	0.085	0.38
2	0.20858	0.09592	0.3833
3	0.13517	0.10823	0.43553
4	0.08077	0.09972	0.5344
5	0.0511	0.09272	0.64103

[1] Extension of Table I