Scalable and Practical Multi-Objective Distribution Network Expansion Planning

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***Abstract*—We formulate the distribution network expansion planning (DNEP) problem as a multi-objective optimization (MOO) problem with different objectives that distribution network operators (DNOs) would typically like to consider during decision making processes for expanding their networks. Objectives are investment cost, energy loss, total cost, and reliability in terms of the number of customer minutes lost per year. We consider two solvers: the widely-used Non-dominated Sorting Genetic Algorithm NSGA-II and the recently-developed Multi-objective Gene-pool Optimal Mixing Evolutionary Algorithm (MO-GOMEA). We also develop a scheme to get rid of the notoriously difficult-to-set population size parameter so that these solvers can more easily be used by non-specialists. Experiments are conducted on medium-voltage distribution networks constructed from real data. The results confirm that the MO-GOMEA, with the scheme that removes the population size parameter, is a robust and user-friendly MOO solver that can be used by DNOs when solving DNEP.**

Index Terms: Capacity planning, Evolutionary computation, Optimization, Power distribution, Power system planning.

I. Introduction

Distribution Network Expansion Planning (DNEP) is a fundamental task that Distribution Network Operators (DNOs) have to perform to work out what the optimal expansion plan is for their networks to satisfy future power demands [1], [2]. More often than not, DNEP involves decision making with respect to multiple conflicting criteria, such as investment cost, energy loss, and reliability, for which a utopian solution that optimizes all these objectives at the same time does not exist. Instead, a set of optimal trade-off solutions exists, in which an improvement in any objective leads to deteriorations in other objectives. For example, a reduction in the investment cost by using cables/lines of smaller diameters increases energy losses.

Despite its multi-objective (MO) nature, DNEP is often solved by aggregation approaches, in which all different objectives are combined into a single objective, so that available single-objective (SO) optimization algorithms can be used [3],[4]. A common aggregation approach is to capitalize non-financial objectives, such as energy loss or reliability, and then aggregate them with other financial objectives [3]. The optimum of such a problem is a single expansion plan whose total cost is minimized. Decision makers are therefore limited to only the integral financial point of view and cannot consider other alternatives if they would like to do (see Section IV for more details). Furthermore, capitalization requires several assumptions, e.g. about the energy price to capitalize energy losses, or the penalty amount that DNOs must pay to the customers when network failures happen to capitalize reliability. It is possible that these terms will change over the planning horizon due to future economic and social situation uncertainties and are thus difficult to be appropriately determined at the beginning. Here, instead of using aggregation approaches, we therefore argue that it is more beneficial to preserve the true MO nature when solving DNEP by employing Pareto-based optimization methods. Being the result of MOO algorithms, the set of optimal trade-off solutions, called the Pareto-optimal set, provides decision makers with diverse alternatives and valuable information in the decision-making process [5].

Multi-objective evolutionary algorithms (MOEAs) have been shown to be a suitable methodology for solving MOO problems. A widely-used MOEA, Non-dominated Sorting Genetic Algorithm II (NSGA-II [6]), has found a wide range of applications in power system expansion planning [5],[7]. Although it is a well-known MO solver, there is still room for further improvement, especially in terms of: (1) the scalability of the approach and (2) the complexity task of setting parameters. Scalability requires that the solvers maintain their effectiveness and efficiency when the size of the problem increases, allowing large networks to be solved within reasonable computational time. In this paper, we compare the performance of NSGA-II with an MOEA, which was recently developed by us, called Multi-objective Gene-pool Optimal Mixing Evolutionary Algorithm (MO-GOMEA [8]), in solving DNEP. MO-GOMEA has been shown to be able to solve academic benchmarks of complicated problem structures in a scalable manner [8]. Here, we show that MO-GOMEA can efficiently solve DNEP, a real-world industrial problem.

Evolutionary algorithms (EAs) are population-based optimization algorithms, which maintain and evolve a population of candidate solutions during the search process. A key question that all users of EAs have to think about before running an EA is how large the population size should be for the problem instance at hand. It is almost impossible to determine the optimal population size beforehand when solving real-world problems. Too small population sizes prevent EAs from solving the problem while too large population sizes waste computing time and resources. This crucial question applies to MOEAs as well. There exist several efforts in getting rid of the population size parameter for SO EAs, but similar works in the MOO realm are barely available. Here, we adapt a population sizing-free scheme for SO genetic algorithms (GAs) [9] to the context of multi-objective optimization. We show that this scheme effectively lifts a significant burden in using MOEAs in a properly configured way to solve real-world problems.

The remainder of the paper is organized as follows. Section II formulates the DNEP problem. Section III introduces MO-GOMEA, NSGA-II, and our population sizing-free scheme. Section IV shows the experimental results of MO-GOMEA and NSGA-II solving DNEP. Section V concludes the paper.

II. DNEP Formulation

This paper focuses on finding expansion alternatives for medium voltage distribution (MV-D) networks according to the point of view of a Dutch DNO. A typical MV-D network in the Netherlands contains underground cables branching out of HV/MV substations connecting MV nodes (MV/LV substations and MV customer substations) in ring-shaped and/or meshed structures. For each distribution ring, a cable is opened on one side, called normally open point (NOP), so that the whole network can operate radially in a normal situation [2]. Our approach here can be easily applied to MV-D networks with overhead lines. Extensions to LV networks require insignificant adaptations, while extensions to HV/MV sub-transmission networks require additional routines to handle multiple cables connecting HV/MV substations in parallel.

A. Expansion options and network encoding

Here, we focus on decision making on reinforcement options for MV-D network cables as our main asset category. Extensions to include MV/LV transformers can be done without significant changes. Each network cable has a nominal capacity that defines the maximum magnitude of the power that can flow through it. Increasing power demands in the future create bottlenecks in the network and overloads on the cables. A feasible solution plan should therefore contain expansion options to solve these bottlenecks. Practical expansion options are: replacing existing cables with cables of higher capacities, adding new feeders (creating new cable connections) within a MV-D ring, or connecting the ring with another MV-D ring/substation [2]. Note that expansion options of adding new cable connections require additional decision making on placements of NOPs to guarantee radial operation of the network.

Before solving DNEP, we need to specify all the existing and potential cable connections (branches) that we want to consider for the expansion plan. By considering expert knowledge, we can disregard impractical expansion options, such as connecting two nodes that are located far apart [2]. Let l denote the total number of (both existing and potential) branches. We represent a MV-D network as a vector of l integer elements.

$$\vec{x} = (x_1, x_2, \ldots, x_l), \quad |x_k| \in \Omega(x_k), \quad k \in \{1, 2, \ldots, l\}$$

where x_k corresponds with the k^{th} branch of the network, and $\Omega(x_k)$ is the set of possible cable types that can be installed at x_k. The status of the branch k can then be indicated as:

- $x_k = ID > 0$: A cable of type $ID \in \Omega(x_k)$ is installed at the k^{th} branch (an active cable).
- $x_k = 0$: There is no cable installed at the k^{th} branch.
- $x_k = -ID < 0$: A cable of type $ID \in \Omega(x_k)$ is installed at the k^{th} branch but out of operation in normal situations. This represents an NOP.

B. Constraints

Given the forecast peak load profile at the end of a planning horizon, the following constraints must be satisfied:

1) Connectivity constraint: All nodes should be connected.

2) Normal operation constraints: In normal operation condition, the voltage V at each node should stay within allowable limits ($0.9 \cdot V_{nom} < V < 1.1 \cdot V_{nom}$), and the power flow through each cable should stay within nominal capacity.

3) Radial operation constraint: NOPs are placed in the network to make the network operate radially.

4) Reconfigurability constraint: When a failure occurs on an active cable, a part of the network will be out of service. The DNO then reconfigures the network by closing NOPs to bring the network back to operation. The network cables can tolerate a mild overload, 130% of nominal capacity, while maintenance activities take place. This constraint requires that the network must have enough redundancy capacity for reconfiguration in such emergency situations.

The evaluation of a solution plan involves multiple computationally expensive power flow calculations (PLCs) to check constraints 2 and 4. In this paper, for PLC, we use the Newton-Raphson method to solve the AC power flow model [1]. We note that the constraint evaluations dominate the computing time of optimization algorithms.

C. Objectives

DNEP itself is actually a dynamic planning problem, addressing the question *when* each expansion option should be carried out. In this paper, we solve a pseudo-dynamic version of DNEP where the dynamic part is simplified as follows. Based on the forecast (annual) load growth rate R, we calculate the peak load for each year over the planning horizon from t_0 until $t_{horizon}$, and determine the year t_{ol} when the first bottleneck (overload) occurs in the network. We then assume that all expansion options satisfying the load situation at $t_{horizon}$ are installed at the same time in the year t_{ol}. In short, to evaluate the objective values, from the beginning t_0 until t_{ol} we use the current network topology, and from t_{ol} until $t_{horizon}$ we use the new network topology.

1) Investment Cost: The investment cost $CAPEX$ for new assets is calculated by the annuities method [1], [10]. This method converts the expenditure on a new asset of $Price_{asset}$ into a series of uniform annual payments, called annuities. If the length of this series equals the economic lifetime of the new asset t_{life}, the annuity AN_{asset} of the asset, for a time horizon with discount rate i, can be calculated as:

$$AN_{asset} = Price_{asset} \cdot \frac{i}{1 - (1+i)^{-t_{life}}} \tag{1}$$

In this paper, we assume a discount rate i of 4.5% and all assets have the same economic lifetime of 30 years. $CAPEX$ for an asset in a year t can be defined as:

$$CAPEX_{asset}(t) = \begin{cases} AN_{asset} & \text{if } t_{ol} \leq t < t_{ol} + t_{life} \\ 0 & \text{else} \end{cases} \quad (2)$$

Then, total $CAPEX$ in a year t can be defined as: $CAPEX(t) = \sum_{\textbf{new asset}} CAPEX_{asset}(t)$.

We minimize the net present value (NPV) of the total $CAPEX$, over a planning horizon with a discount rate i:

$$CAPEX_{NPV} = \sum_{t=t_0}^{t_{horizon}} \frac{CAPEX(t)}{(1+i)^{t-t_0}} \quad (3)$$

If $t_{ol} + t_{life} > t_{horizon}$, a part of the investment cost would not be included in this objective value. However, this annuity method is considered more favorable for comparing costs between multiple scenarios [1], [10]. We will consider DNEP involving multiple scenarios in future research.

2) Energy Loss: Since in this paper we focus on network cables as our main asset category, the energy loss of the network in a year t can be calculated as:

$$E_{loss}(t) = P_{\textit{peak loss}}(t) \cdot T_{loss}(t) \quad (4)$$

where $P_{\textit{peak loss}}(t)$ is the peak loss which can be obtained from the PLC regarding the peak loads in year t. $T_{loss}(t)$ is the service time of peak loss for year t, defined by the area of the yearly loss profile. Since PLC is a computationally expensive operation, performing PLCs for each year from t_0 until $t_{horizon}$ for each solution plan would take a great amount of running time. Here, we assume that the peak loss also has a growth rate related to the load growth R as follows:

$$P_{\textit{peak loss}}(t) = P_{\textit{peak loss}}(t-1) * (1+R)^2 \quad (5)$$

For each solution plan, we first calculate the peak loss at the end of the planning horizon $P_{\textit{peak loss}}(t_{horizon})$ by performing a PLC regarding the network topology of that plan. We then use Equation 5 to calculate backward $P_{\textit{peak loss}}(t)$ for each year t that $t_{ol} \leq t < t_{horizon}$. Note that, for $t_0 \leq t < t_{ol}$, the yearly peak loss for every year t can be computed beforehand by performing PLCs, for only one time, because during this period, all solution plans share the same original network topology due to our pseudo-dynamic scheme as mentioned above.

We want to minimize the total energy loss, which can be evaluated as follows for each solution plan.

$$E_{loss} = \sum_{t=t_0}^{t_{horizon}} E_{loss}(t) \quad (6)$$

3) Total Cost: From a financial point of view, energy losses can be seen as the yearly costs for the DNO. If we have good assumptions about the electricity price, we can capitalize the energy loss and consider it as the operational cost ($OPEX$) of the network. $OPEX$ in year t can then be defined as:

$$OPEX(t) = E_{loss}(t) * Price_{electricity}(t) \quad (7)$$

We want to minimize the NPV of the total cost of both investment cost and operational cost ($CAPEX$ and $OPEX$)

$$COST_{NPV} = \sum_{t=t_0}^{t_{horizon}} \frac{CAPEX(t) + OPEX(t)}{(1+i)^{t-t_0}} \quad (8)$$

4) Customer Minutes Lost Per Year: In this paper, we choose to evaluate the total number of customer minutes lost (CML) per year to quantify the reliability of an MV-D network. Note that if we divide the total CML per year by the number of customers in the network, we can obtain the CML per year per customer or System Average Interruption Duration Index (SAIDI). When a failure occurs on a cable, the circuit breaker of the feeder containing the failed cable would be triggered and the feeder (from MV-substation with circuit breaker to NOP) is then out of operation. Customers associated with nodes connected by this feeder are temporarily out of service. The DNO needs to dispatch their engineers to find out where the failure occurred. How long this procedure takes depends on the number of nodes connected to the feeder. After localizing and isolating the failed cable, the corresponding NOP and the circuit breaker of the feeder can be closed to bring the network back to operation. The amount of time between fault occurrence and service restoration is regarded as the restoration time T_{res}. The number of failures in a cable k per year can be estimated as:

$$NF_k = F_k \cdot L_k \quad (9)$$

where F_k is the annual failure rate of cable k per kilometer, and L_k is the length of cable k. CML for cable k per year is:

$$CML_k = NF_k \cdot NC(Feeder(k)) \cdot T_{res}(Feeder(k)) \quad (10)$$

where $Feeder(k)$ denotes the feeder containing the cable k, $NC(Feeder(k))$ is the number of customers connected to feeder $Feeder(k)$, and $T_{res}(Feeder(k))$ is the average restoration time (in minutes) when cable k fails in feeder $Feeder(k)$ [11], which can be taken to be:

$$T_{res}(Feeder(k)) = 75 + \frac{NS(Feeder(k))}{2} \cdot 10 \quad (11)$$

where $NS(Feeder(k))$ is the number of MV/LV substations and MV customer substations connected to the feeder $Feeder(k)$. We minimize the CML per year of the network.

$$CML = \sum_{\substack{k=0 \\ x_k>0}}^{l} CML_k \quad (12)$$

where l is the total number of cable connections, and we only calculate CMLs for active branches ($x_k > 0$).

III. Multi-objective Evolutionary Algorithms

This section gives short introductions about two MOEAs (solvers) for our MO DNEP problem: the widely-used NSGA-II and the recently-developed MO-GOMEA. We then outline a scheme to get rid of the population size parameter. Both solvers are equipped with an elitist archive, an essential component for state-of-the-art MOEAs, to keep track of the best obtained trade-off solutions [12].

A. Non-dominated sorting genetic algorithm NSGA-II

NSGA-II [6] has been widely applied in power system optimization, from classic expansion planning problems, e.g. transmission [7], and distribution expansion planning [5], to modern renewable and sustainable energy allocation and operation problems, e.g. distributed generations, storage systems [13], and electric vehicles[14]. Typically, NSGA-II explores the search space by performing recombination (i.e. randomly exchanging problem variable values between candidate solutions) and mutation (i.e. randomly altering problem variable values with a small probability) on existing solutions to generate new solutions. Such variation operators are blind to important dependencies among problem variables, called linkage groups, and are thus unable to efficiently create new solutions of higher qualities as the problem size increases if such dependencies exist in the problem.

B. MO Gene-pool optimal mixing evolutionary algorithm

MO-GOMEA [8] was recently developed by considering well-established researches [15], [16], [17] to construct a scalable MOEA, which effectively detects relations among problem variables in existing solutions and then efficiently exploits the learned structure to generate new solutions. Details about MO-GOMEA can be found in the literature [8]. Two key features of MO-GOMEA to this end are outlined as follows.

1) Population clustering [15]: The set of Pareto-optimal solutions can form a very large Pareto-optimal front of many regions, and the solutions in one region may have specific characteristics different from solutions in other regions. To have a good approximation of the whole Pareto front, it is beneficial if we divide the working population into evenly-spread equal-sized clusters, ensuring that different regions of the Pareto-front are searched with a different, relevant search bias, and are allocated the same amount of resources.

2) Linkage learning and new solution generation: MO-GOMEA performs linkage learning procedures to detect linkage groups of problem variables among candidate solutions in each cluster separately. Compared to other advanced MOEAs sharing the same features, such as [16], the linkage model used in MO-GOMEA is simpler, but adequate, and thus takes less computational time to learn. A variation operator, called Optimal Mixing (OM), then exploits the linkage knowledge when generating new solutions by treating problem variables belonging to the same linkage groups together when exchanging variable values among existing solutions.

C. Population sizing-free scheme

Setting the population size parameter is crucial for EAs (and MOEAs). The optimal population size, which is difficult to be determined, depends on the structure and the size of the problem instance at hand and also on the specific EA solver. Here, we adapt a scheme developed for SO GAs to get rid of the population size setting [9]. The idea is that we operate the MOEA with multiple populations of different sizes in parallel but populations of a larger size have a slower generational cycle. We start with a population P_1 of some small size n_1, and then keep doubling the population size to create new populations with size $n_i = 2n_{i-1}$ for $i > 1$. For every 2 generations of population P_i, we run 1 generation of population P_{i+1}. Thus, population P_i executes a generational step every 2^{i-1}-th generation of population P_1. Although each population is run separately, they share the same elitist archive. Note that we do not set a maximum population size. The algorithms keep operating and expanding the population size, and stop when the total allowable computing time is used up.

IV. Experimental results

In this paper, we present experimental results of NSGA-II and MO-GOMEA solving DNEP for a network of 4 MV-substations, 51 nodes and 190 branches, constructed from real data of a Dutch DNO, over a planning horizon of 30 years. All the currently existing cables can be upgraded (replaced with a new cable type) while the total number of new cable connections all over the network is limited to 3, corresponding to the switchgear and cabinet space restrictions of existing MV-substations in this benchmark. More details about the network can be obtained from the authors. Each solver is run 30 times, and is allowed to perform 500000 solution evaluations in each run.

A. CAPEX vs. Energy Loss

Minimizing the the investment cost often results in selecting cables of smaller diameters, which in turn increases energy loss. In contrast, minimizing energy losses encourages investments in more efficient assets, e.g. replacements of legacy cables. Solving DNEP with these two conflicting objectives in the MO fashion provides the DNOs with a full picture of compromises between capital expenditure and operational aspect. Capitalizing energy loss and then solving DNEP by aggregation approaches only return a single solution plan with a minimized total lump sum cost and provide no other alternative if the DNOs are willing to invest more to reduce the energy loss, or vice versa. Energy loss can also be considered as an environmental factor with increasing importance in decision making process of DNOs in transition toward sustainable energy. Therefore, it is beneficial to keep these two objective separate and to solve DNEP in the true MO manner so that the DNOs can make well-informed decisions.

Fig. 1 shows the experimental results of NSGA-II and MO-GOMEA solving DNEP minimizing these two objectives. MO-GOMEA finds more solutions of better qualities than those of NSGA-II. Given the same amount of solution evaluations (i.e. approximately the computing time), MO-GOMEA also outperforms NSGA-II in obtaining a closer and more well-spread solution set along the reference Pareto-front.

B. Total Cost vs. Customer Minutes Lost Per Year

We consider the trade-off between CML per year and the total cost, which comprises the investment cost and the capitalized energy loss. Minimizing the CML will result, when expansions are necessary, in short cables (complementary with minimizing losses) and rearranging the NOPs. Rearranging

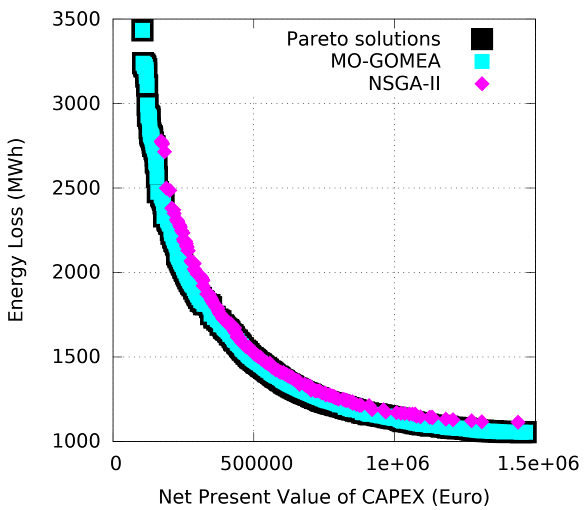

Fig. 1: NPV of CAPEX (Euro) vs. Energy Loss (MWh)

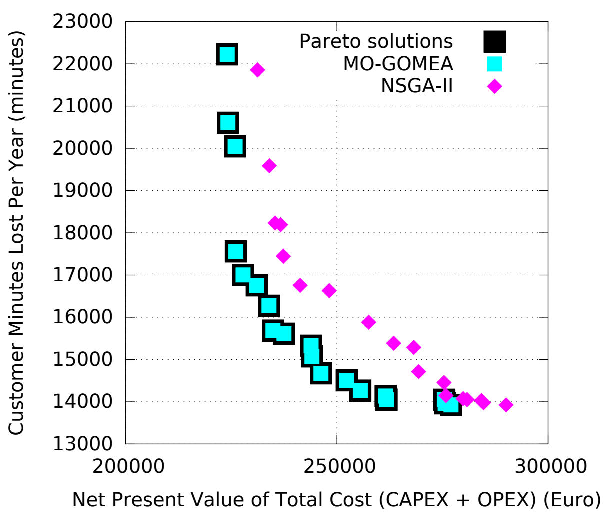

Fig. 2: NPV of Total Cost vs. Customer Minutes Lost Per Year

the NOPs from a reliability point of view will result in short feeders/sections and evenly distributed customers over the feeders. This is conflicting with minimizing energy losses since the NOPs should then be placed at cables with small power flows. This trade-off between the reliability and losses is interesting to take into account.

Fig. 2 shows the experimental results of solving DNEP minimizing NPV of the total cost and the CML per year. MO-GOMEA clearly outperforms NSGA-II in terms of finding many more solutions of better qualities. This confirms the superior scalability of MO-GOMEA. Furthermore, given the same amount of solution evaluations, the linkage learning and optimal mixing procedures of MO-GOMEA help to find better solutions than NSGA-II.

V. Conclusion

In this paper, we formulated DNEP as an MOO problem. We identified 4 objectives that DNOs would like to consider for decision making in practice: investment cost, energy loss, total cost, and customer minutes lost per year (as the reliability). We then employed two MOEAs, the widely-used NSGA-II and our MO-GOMEA, to solve the MO DNEP problem for 2 combinations of 2 objectives. We showed that the robust performance of MO-GOMEA for solving academic benchmarks also extends to real-world problems. The population sizing-free scheme that we developed here furthermore helps MOEAs become more user-friendly, making the population size-less MO-GOMEA an excellent candidate to develop optimization tools for DNOs when solving complicated and large planning problems in the transition toward future energy scenarios.

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