LONG TERM MULTI-STAGE PLANNING OF OPEN LOOP DISTRIBUTION NETWORKS UNDER UNCERTAINTY

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Abstract – **This paper presents a new and efficient method based on evolutionary algorithms to address the multi-stage (dynamic) planning of open loop structured distribution networks under uncertainty taking into account distributed generation connected to distribution system. The proposed model can cope with important features implicit in planning studies such as time-phased representation and uncertainty in loads, distributed generation and prices. As European distribution system in urban and suburban areas are operated as open loops, besides using modern reliability indexes as optimization attributes, the traditional approach of contingency coverage perspective in the horizon of study period is introduced as one of the constraints in the model of the problem. Besides optimal radial layout along several stages in time, the algorithm can determine the optimal locations of reserve feeders that achieve the best network reliability with the lowest expansion and operational costs. The uncertainty is modelled using fuzzy numbers. The model and evolutionary algorithms have been applied intensively to real life power distribution systems showing its potential applicability to large scale systems. Results have illustrated the significant influence of the uncertainties in the optimal distribution network planning mainly in terms of topology and supply capacity of the resulting optimal distribution system.**

Keywords: primary distribution network, planning, open loop layout, evolutionary algorithm, dynamic model, uncertainty, robustness, fuzzy sets

1 INTRODUCTION

Electric distribution networks are characterized by a large number of nodes and possible branches. The nodes are the injection points of the network (HV/MV substations), consumer points (loads, MV/LV substations), switching stations and generation from independent producers (distributed generation, DG). Branches in urban areas mostly correspond to electrical cables. The purpose of planning is to connect all the nodes feeding consumers. This is accomplished by deciding which new branches and injection points are to be constructed to achieve minimal cost configurations that obey technical constraints. The problem involves many integer-valued (0,1) variables related to the decisions to build or not to build facilities. In addition, the overall problem is dynamic since the decisions about investments must be scheduled to gather a sequence of network solutions – one solution for each time (load) stage. Network expansion planning becomes even more complex if data for future stages are considered under uncertainty. Then the problem becomes a stochastic-dynamic problem.

Many mathematical models have been proposed in the past for electrical distribution network planning [1,2]. Most of those neglect that one is dealing with a dynamic multi-temporal problem under uncertainty. On the other hand, considering the evolution in power demand through time and consequent topological changes in the networks, dynamic planning have never been a definite success, when applied to real sized networks.

Large network problems have been addressed for linearized objective functions. Branch and bound applications can be found in [3,4,5], mixed-integer programming in [6] together with Bender's decomposition [7] and with branch exchange [8,9]. Dynamic programming approaches have been taken in [9,10,11].

More recently, evolutionary computation techniques have also been proposed [11,12,13,14]. In [14] evolutionary algorithm with integer codification has been proposed giving an optimal solution for a fixed set of data and a single time period only. On the contrary [11,12,13] are string genotype approaches to small-size network problems. For large networks the combinatorial nature of decision making turns such genetic algorithms (GAs) into computationally expensive approaches. Namely, due to the use of standard (binary) solution encoding and genetic operators the following problems have been observed:

- topological unfeasibility (connectivity, radiallity) [11,12],
- dynamic (methods use static models, giving an optimal solution for a fixed set of data and a single time period) [14],
- low heritability (a significant number of offsprings generated by the crossover operator hardly have substructures of their parents),
- suitable building of additional lines (reserve feeder segments used in contingency conditions to improve reliability of supply) is not included, or if it is, then methods are classified as single-stage (static).

In the past, research that attempted to model uncertainty in planning problems was supported by probability theory, while in recent years, uncertainty in loads has been modelled by possibility distributions (fuzzy models) [11,12] and/or by a set of scenarios [12,13].

In this paper, a technique based on two interrelated evolutionary algorithms for long term large scale multi-stage mv distribution network planning under uncertainty has been proposed. EAs are used to generate sets of dynamic distribution network solutions. The master (first) evolutionary algorithm is aimed at optimizing the open loop network layout in the last stage of the study period (e.g. 5-20 years ahead) and the slave (second) EA is used in each iteration of the main optimization procedure to identify schedule (as a set of yearly plans) of additions and reinforcements over study period. This way costs of different horizon year open loop networks are accurately evaluated based on decisions about investments made along several time stages in the study period. To our knowledge, only four researchers have devised methods suitable for the problem of open loop distribution system design, and neither of these is multistage (dynamic) or considers the intrinsic uncertainties of data [15,16,17,18]. The proposed method was tested with real size systems achieving optimal plans in reasonable CPU times compared with the dimensions of such systems. The tested practical problems present significantly larger sizes that the ones frequently found in the technical literature dealing with the optimal multi-stage distribution planning under uncertainty.

2 PROBLEM FORMULATION

2.1 Open loop networks

For reliability reasons, it is common that mv distribution networks (especially in urban areas) present meshed structures, being the system operation performed radialy. This way, system reconfigurations are allowed in case of contingency (for example the loss of a transformer or distribution line). For this reason, any planning model should not strictly enforce structural radiality on the solutions (however, this is what most of the existing methods do). However, very few works have studied the network reliability optimization simultaneously with the minimization of the economic network expansion costs. What generally happens is that the planning process will produce an operational topology (radial) and then the planner will manually place new branches forming open loops, in order to increase network flexibility (e.g. if any, reliability calculations in the planning process are carried out based on radial operational topology only). Generally, this process will most certainly lead to sub-optimal solutions.

Therefore we decided to include reliability in the proposed planning method using two approaches:

- ***explicit*** – in the slave EA fitness is assigned to dynamic solutions based upon economic evaluation of the reliability worth (energy not supplied (ENS), SAIFI and SAIDI),
- ***implicit*** – in master EA open loop layouts is the preferred layout of the distribution network in the horizon year, Fig.1 (the contingency coverage perspective in the horizon of study). With this in mind, the proposed optimal planning method can effectively search for a least-cost solution, while reliability is intrinsic to the layout. On top, specifics of the proposed method allow adequate transformer-level contingency support which other methods usually include though analyses following the optimization.

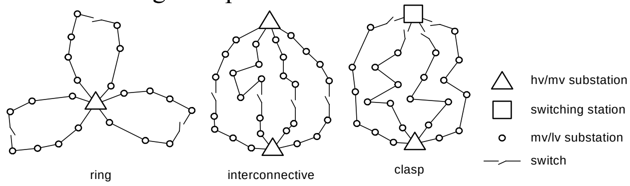

Figure 1: Open loop layouts of mv distribution network

In most of the existing planning methods prior to the planning planner is obliged to define available new ROWs (rights of a way). If using only manually provided reduced set of ROWs planning process usually leads to suboptimal solutions (especially in so called green field supply areas). Therefore, in the proposed approach, connections between all pairs of nodes are available while building open loop layouts in the horizon period (ROWs define complete graph in which every node has a direct connection with the rest of the nodes).

For calculating investment expenditures for connecting two load/supply points GIS (Geographical Information System) tool based on shortest-path algorithm is used. It uses linear elements like road centerlines, cadastral boundaries, ducts, permissible corridors and manually inserted corridors. Costs are calculated based on route length and corrections according to area-specific costs or terrain specifics and corrections for existing feeders that are to be reinforced (i.e. reuse of obsolete cables ducts) [19].

2.2 Planning under uncertainty

2.2.1 Fuzzy data

The nature of the problem that involves predicted data with no statistical support introduces additional difficulties. Following the approach proposed in [20], in our model uncertainty in predicted loads has been modelled by possibility distributions (trapezoidal fuzzy numbers) that represent “typical” situations as defined by experts’ declarations (e.g. demand will be not greater than 630 kVA nor less than 300 kVA, but the most credible range is between 400 and 500 kVA).

The uncertainty of the distributed generation, which is related to a lack of information, is also modelled using fuzzy methods (e.g. intervals represent production in DGs during peak demands, Fig.2). In “fuzzy” power flow analysis demands are modelled as positive trapezoidal fuzzy numbers and DGs productions are modelled as negative “loads” [21].

Besides demands in demand nodes and power production in DGs, fuzzy models are used to represent the following uncertain data:

- reliability data (mean time to locate failure and switch (*MTTS*), mean time to repair failures (*MTTR*) and failure rates (λ) for cables and transformers),
- economic data (costs of developing branches per unit of length, costs per unit of power and energy losses, costs per unit of energy not supplied).

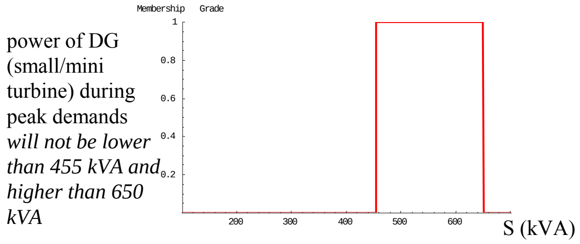

Figure 2: Membership function (fuzzy interval) of DG power generation during peak demands in distribution network

2.2.2 Fuzzy constraints and the concept of robustness

The introduction of fuzzy models to include uncertainty implies that that the related attributes (power flows, voltage drops, reliability indices) and costs are represented by fuzzy numbers.

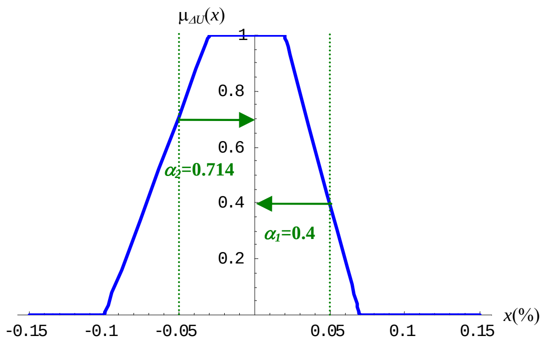

Figure 3: Membership function of voltage drop/increase in some demand node and the corresponding robustness *ro=min{1-0.4, 1-0.714}=0.286.*

These imply technical constraints cannot be evaluated in a strict way. In the deterministic case, possible network configurations are feasible only if they satisfy every constraint and are infeasible if at least one violation occurs. The extension to the fuzzy case introduces a new interpretation of feasibility based on the degree of violation of constraints. Operationally, this is done by introducing the concept of robustness. Following [12], robustness is an index defined as $ro=1-\alpha$, where α is the supreme of the possibility values associated with any violation. A given plan is robust with respect to a specific constraint, if the constraint holds true for every possible value of the uncertain variables. In that case $ro=1$. Otherwise, if some possible values lead to violation of the constraints, *ro* equals the maximum possibility value for which the constraint is not violated.

For example, in Figure 3 membership function (trapezoidal fuzzy number) is given which corresponds to the voltage drop/increase in some demand node. If the limit on voltage increase/drop in normal conditions is set to ±5%, then the robustness of a plan (solution of the problem) in regard of voltage drop/increase in a given node is equal to the *ro=min{1-0.4, 1-0.714}=0.286.*

Let it be N_p the number of time stages in planning period (duration of time stages is usually 1-3 years; it is assumed that an action, if any, is realized during the first year of the time stage), N_{Vi} the number of branches (feeders' segments), N_{SVNi} the number of supply (injection) nodes and N_{SSNi} the number of demand nodes present in time stage *i*. $ro1_{ij}$ represents the robustness of a branch *j* in time stage *i* with respect to a thermal limit constraint in normal operating conditions. $ro2_{ij}$ and $ro3_{ij}$ represent robustness of a particular supply transformer and demand node with respect to thermal limit constraint and voltage increase/drop respectively.

$$ro1 = \min_{i=1,..N_p} \min_{j=1,..N_{V_i}} \{ro1_{ij}\} \quad (1)$$

$$ro2 = \min_{i=1,..N_p} \min_{j=1,..N_{SVNi}} \{ro2_{ij}\} \quad (2)$$

$$ro3 = \min_{i=1,..N_p} \min_{j=1,..N_{SSNi}} \{ro3_{ij}\} \quad (3)$$

Then *ro1*, *ro2* and *ro3* present aggregated robustness indices for some plan with regard to technical constraints in normal operating conditions.

Besides robustness with respect to standard technical constraints adequacy of a given investment plan (solution) is further examined against two additional reliability constraints: maximum allowable SAIDI and SAIFI indices values. This allows planner to disregard plans that face the risk of not being able to met regulation criteria for customer reliability indices.

$$rr4 = \min_{i=1,..N_p} \{rr4_i\} \quad (4)$$

$$rr5 = \min_{i=1,..N_p} \{rr5_i\} \quad (5)$$

$rr4_i$ and $rr5_i$ represent robustness indices for distribution network in time stage *i* with respect to limits on maximal value of SAIDI and SAIFI reliability indices respectively. *rr4* and *rr5* represent aggregated robustness indices with respect to reliability criteria.

By applying the concept of robustness, several fuzzy technical constraints and fuzzy constraints with respect to regulation criteria for reliability of supply have been replaced by only one robustness constraint in the model of the planning:

$$\min\{ro1,ro2,ro3,rr4,rr5\} \geq rob\_gr \quad (6)$$

In other words, a given plan is considered adequate (feasible in EA) only if theirs robustness indices are greater then the robustness limit imposed by planner *rob_gr*.

2.2.3 Ranking fuzzy numbers

The application of optimization method based on evolutionary algorithms requires evaluating and ranking fuzzy numbers related to costs of possible solutions to the problem. In order to include risk aversion in the ranking of fuzzy numbers *Campos Munoz Criterion* (*CMC*) has been used [22]. For a general trapezoidal number $\widetilde{A}=(a,b,c,d)$, the "defuzzified" value given by the *CMC* criterion is:

$$A=(1-\lambda_r)\frac{a+b}{2}+\lambda_r\frac{c+d}{2} \qquad (7)$$

where λ_r is a parameter related with risk aversion. One may give more importance to the smaller (for $\lambda_r<0.5$ planer is a optimist, risk taker) or the larger values (for $\lambda_r>0.5$ planer is a pessimist, no-risk taker) in the uncertainty intervals, by fixing the parameter value in the interval [0,1].

3 OPTIMIZATION TECHNIQUE

3.1 General outline (two evolutionary algorithms)

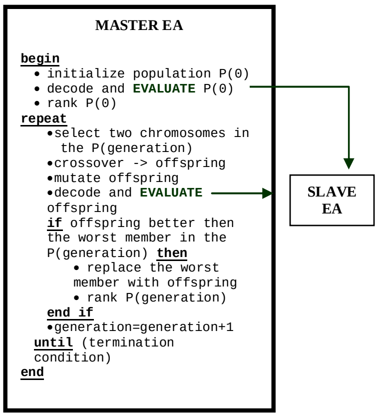

Figure 4: Optimization technique and EA outline

Along several stages in time the proposed optimization technique searches for the set of decisions (associated with ***investment costs*** - new lines, new substations, reinforcement of an existing system, ***operation costs*** – maintenance, demand and energy costs - and ***reliability*** – expected energy not supplied) that "optimize" the global cost of system development. The development of the system is simulated by two interrelated evolutionary algorithms that are used to generate sets of dynamic distribution network solutions. The master (main) evolutionary algorithm is aimed at optimizing the open loop network layout in the last year of the study period (e.g. 5-20 years ahead) and the slave EA is used in each iteration of the master EA to produce an optimized plan for the final year, identifying schedule (as a set of yearly plans) of additions and reinforcements over study period (Fig.4). In other words, the master EA is aimed at static planning of open loop layout (i.e. it determines necessary new additions in the system). Then the slave algorithm further examines the additions optimal realization time and feeds back the master algorithms with the accurate costs of a given open loop layout.

The evolutionary algorithm implementation used in both (master and slave algorithms) is based on the version of EA termed "steady state" EA. The implementation is outlined in Fig. 4 for master EA only (the same applies to the slave EA). The initial population is created randomly and the reproduction process continuous until convergence (i.e. until 95% of population members represent the same solution) or until arbitrarily prefixed number of iterations is reached. When selecting two parents for reproduction (i.e. theirs indexes in the ranked population) the selection function introduced by Whitley is used [23].

The tendency of EA operators to create infeasible solutions was suppressed so as to increase the solution's objective by using the penalty function when evaluating the quality of some infeasible solution. After testing several strategies we decided to use Powell's method [24] as it gave satisfactory results even when applied on highly constrained instances of the problem.

Hereinafter solution encoding and evolutionary operators used in both EA are described in more detail.

3.2 Master evolutionary algorithm

3.2.1 Solution encoding

Driven by difficulties in handling topology (radiality) constraints, inherent to majority of previously published methods especially those using binary representation, we developed both genotype and operators able to process meaningful topological information – demand and supply nodes connectivity is a genetic transmissible property.

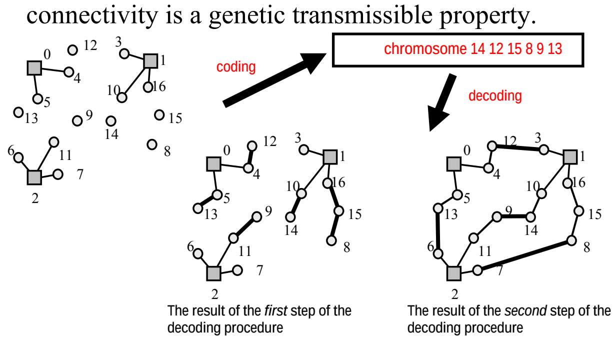

Figure 5: Solution ecoding and decoding in master EA

Different open loop distribution networks are defined by the order of load points (as given in Fig.5 evolutionary algorithm approaches the problem as a sequencing problem). Before evaluating the fitness of some chromosome two-step decoding procedure converts these orders into real interconnective (link) distribution network (Fig.5). In the first step, for each demand node in turn the "closest" (in terms of costs determined in GIS) feeder ending is determined and then in the second step, when all load points are connected to their corresponding feeders, the "closest" feeder endings are found with regard of predefined permissible supply/switching substations pairs. For detailed information on master EA refer to [25].

3.2.2 *Crossover and mutation operator*

Two things that are clearly important in ordering the load points that allow previously mentioned decoding procedure to build good links' routes are the position and relative order of load points in the chromosome. This is the reason why we decided to use FRX and CX operators [24]. Comparing the three different mutation operators on a series of differently structured problems instances resulted in clear winner - the OBM operator [24].

3.3 *Slave evolutionary algorithm*

3.3.1 *Solution encoding*

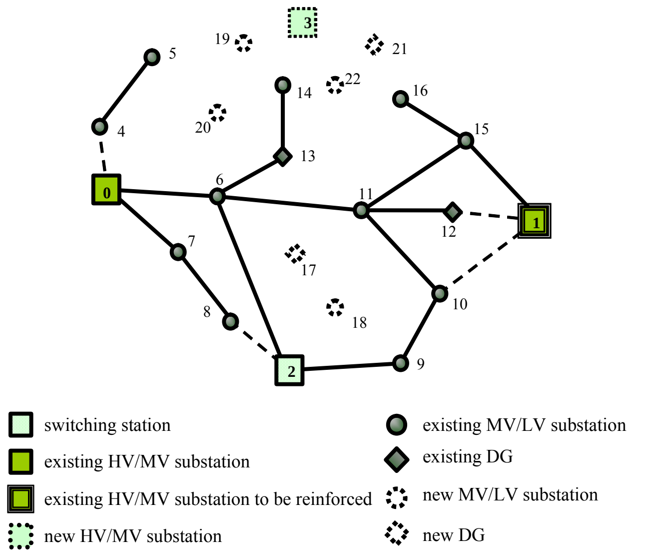

Figure 6: Existing distribution system (illustrative example)

Solution encoding in slave EA has a string structure and contains information about realization times for all newly added or reinforced branches and supply transformers in the distribution system. For example, in Fig. 6 an illustrative example of the distribution system consisting of two existing supply substations (one to be reinforced in the planning period – labelled 1), one switching station – labelled *2*, one new substations to be build – labelled *3*, 11 existing and 4 new demand nodes and 2 existing and 2 new distributed generation nodes is depicted. It is presumed that the dynamics of appearance as well as demand of all new nodes is known from load forecasting procedure. Lines represent existing branches (dashed lines represent existing branches that might be reinforced in the planning period).

In Fig. 7 one possible open loop layout in the horizon period is depicted (red lines correspond to existing branches, green to newly build branches, blue to reinforced existing branches and grey to existing branches not enclosed in the open loop layout).

In the planning period of 10 years henceforward (N_p=5, duration of time stages is 2 years) - 2 new substations, 4 new branches to be laid in obsolete cables ducts and 10 new branches to be laid into new ROWs. One possible dynamic solution (chromosome in slave EA) is given in Fig.8.

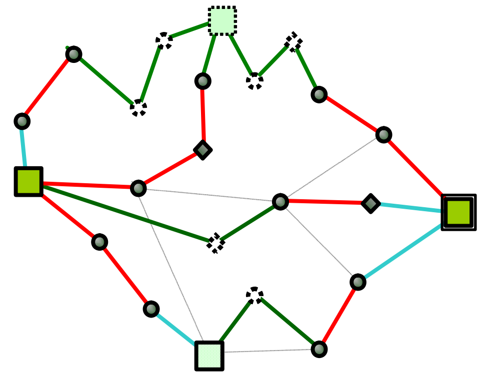

Figure 7: Open loop layout in horizon year for distribution network in Fig.6.

substations		reinforced branches				new branches									
1	3	0-4	2-8	1-10	1-12	5-20	20-19	19-3	3-14	3-22	22-21	0-17	17-11	2-18	18-9
1	4	1	2	2	5	3	4	4	5	3	5	4	4	6	1

$\Downarrow$

chromosome ⇒ 1 4 1 2 2 5 3 4 4 5 3 5 4 4 6 1

Figure 8: Solution encoding in slave EA

Integer numbers correspond to realization times of possible actions (t=1,..5). If t=6 the action will not be realized in the planning period (e.g. for a given example branch 2-18 is not eligible of being constructed in the planning period).

3.3.2 *Crossover and mutation operator*

Crossover operator is well known one point crossover, and the mutations operator is previously mentioned OBM operator [24].

4 THE COMPUTATION EXPERIMENT

In order to demonstrate the features of the proposed methodology, in this section results obtained for an artificial case study generated mostly from the data of distribution system of city of Zagreb (capital of Croatia) have been presented. The area studied consists of 2 existing supply substations, 110 existing demand nodes, 3 existing DGs and 121 existing cables (38 10 kV and 83 20 kV). In Fig.9, besides existing nodes and branches, 7 new demand nodes and 2 new DGs are depicted and encircled (numbers denote time stages in which new nodes shall be in operation).

Planning period is 5 years henceforward. Demands are represented using triangular fuzzy numbers (a_1,a_2=a_3,a_4). Initial load of all demand nodes is 24,399 kVA with coincidence factor f_i=0.6. The final stage uncertain load is the following fuzzy number (24747, 26756, 26756, 29817) kVA. In the planning procedure the planning criteria given in Table 1 were presumed. In Table 2 intervals of reliability data are given.

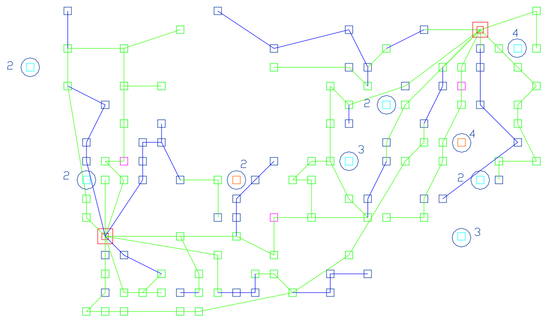

Figure 9: Initial distribution system (case study)

Planning criteria	
Operational voltage (kV)	10
Maximum allowed voltage increase/drop (%)	±5
Maximum allowed *SAIFI* *(yr^{-1})*	0.5
Maximum allowed *SADFI (hours)*	2

Table 1: Planning criteria

Fuzzy reliability data		
	a_1=a_2	a_3=a_4
Mean time to switch (hours)	0.25	1
Cables failure rate (yr^{-1})	0.005	0.024
Mean time to repair cable (h)	1.5	30
MV/LV substation failure rates (yr^{-1})	0.015	0.03
Mean time to repair MV/LV substation (h)	10	35
HV/MV substation failure rates (yr^{-1})	0.01	0.02
Mean time to repair HV/MV substation (h)	15	50

Table 2: Fuzzy reliability data

Out of 38 existing 10 kV cables, 19 must be reinforced by new cables (XHE 49-A 3x185 mm^2, 20 kV).

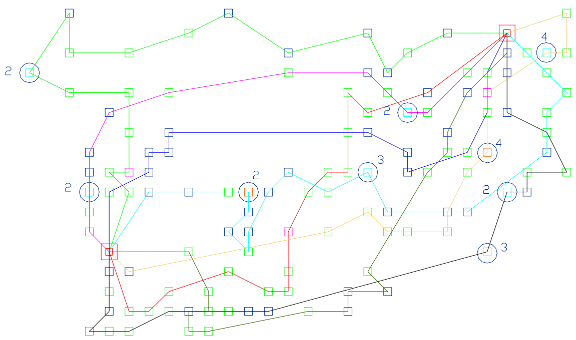

Figure 10: Optimal open loop layout in the horizon year

EA parameters	MASTER EA	SLAVE EA
population size	800	70
prefixed number of iterations	2000000	100
mutation probability	0.7	0.7
bias	1.01	1.07
crossover operator	FRX	single point

Table 3: EAs parameters

In Fig. 10 the optimal open loop distribution system layout in the horizon year is depicted. This is the solution obtained with *rob_gr=0.2*, λ_r*=0.5*, cost of energy not supplied [0.04,0.08] (€/kWh), cost of power losses [6,8] (€/kW), cost of energy losses [0.04,0.08] (€/kWh), interest rate 10%, cost of new cable construction [40,75] (€/m), evolutionary algorithms' parameters given in Table 3 and SAIDI and SAIFI limited by 2 hours and 0.5 yr^{-1} respectively.

The optimal open loop distribution network consists of 130 cables, 117 demand nodes and five DGs. According the open loop layout 48 new cables should be laid in new ROWs and 14 existing cables reinforced in the planning period. 67.77% of cables in open loop network (68 cables) correspond to the existing cables.

In figures, Fig.11, Fig.12, Fig.13, Fig14 and Fig.15 distribution system facilities present in different time stages are depicted.

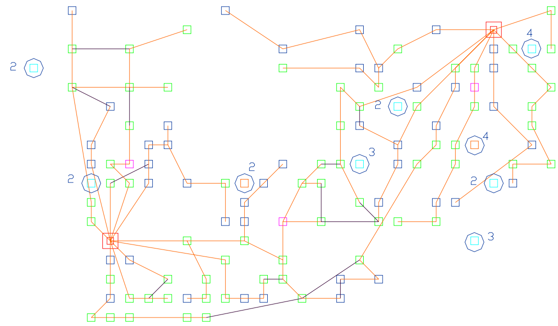

Figure 11: Distribution system in the *first* time stage

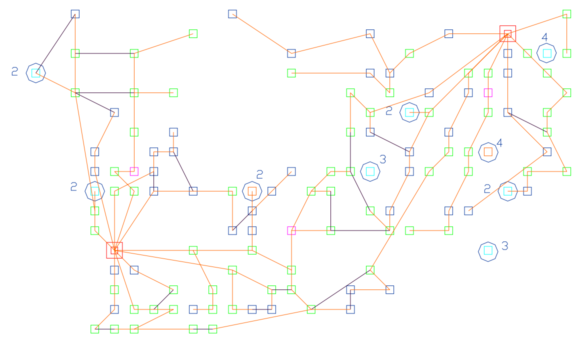

Figure 12: Distribution system in the *second* time stage

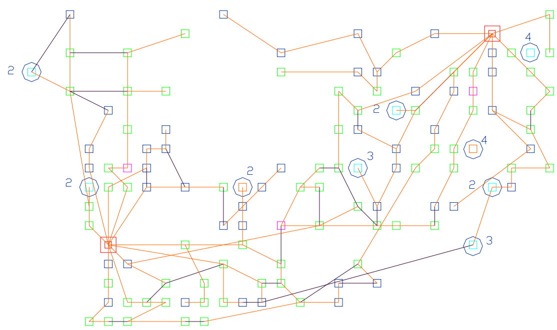

Figure 13: Distribution system in the *third* time stage

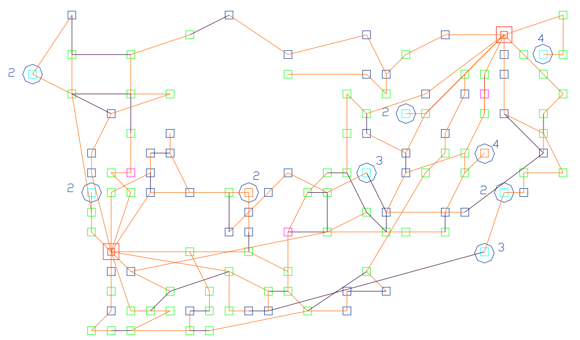

Figure 14: Distribution system in the *fourth* time stage

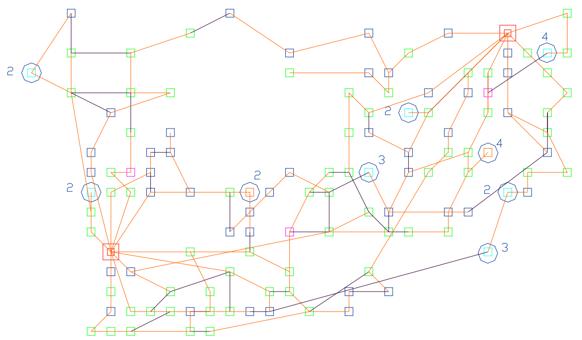

Figure 15: Distribution system in the *fifth* time stage

Orange colour is used to depict the optimal radial operational topology with respect to minimal power and energy losses during peak demands. Dark colour is used to depict reserve cables.

In Table 4 the distribution system data in different time stages are given.

In Table 5 costs of optimal development and reinforcement plan are given. Robustness of a plan is equal to 0.61. The robustness of a plan if distributed generation is not available is equal to 0.38. It could be observed that the optimal plan is adequate even if no DG production is available.

time stage	nodes	no of branches	new branches	operating branches	reserve branches
1	113	127	11	113	14
2	118	138	14	118	20
3	120	145	10	120	25
4	122	158	16	122	36
5	122	161	6	122	39

Table 4: The distribution system data in different time stages

(€)	a_1	a_2	a_3	a_4	crisp value
investments	79214	79214	148528	148528	113871
maintenece	229900	229900	431117	431117	330508
losses	10582	10582	15718	15718	13150
ENS	783	811	8043	8459	4524
Σ(€)	320479	320507	603406	603822	462053
***SAIDI* (h)**	0.155	0.155	1.25	1.25	0.705
***SAIFI* (yr^{-1})**	0.0313	0.0313	0.094	0.094	0.063

Table 5: Costs of the optimal fuzzy development and reinforcement plan

Furthermore, the optimization procedure has been carried out for the deterministic demands and prices corresponding to the most possible values a_2=a_3 (α=1). In Table 6 costs of the optimal deterministic development and reinforcement plan are given.

(€)	a_1	a_2	a_3	a_4	crisp value
investments	87391	87391	87391	87391	87391
maintenece	288921	288921	288921	288921	288921
losses	14719	14719	14719	14719	14719
ENS	5023	5023	5023	5023	5023
Σ(€)	396054	396054	396054	396054	396054
***SAIDI* (h)**	0.87	0.87	0.87	0.87	0.87
***SAIFI* (yr^{-1})**	0.082	0.082	0.082	0.082	0.082

Table 6: Costs of the optimal deterministic development and reinforcement plan

It could be observed that the fuzzy solution presumes larger investment costs. Investment costs of deterministic solution are 23.25% lower than fuzzy investments, and total costs are 14.3 % lower than the total costs of fuzzy solution. However, the deterministic solution robustness to supply the future adverse power demands equals 0.12<rob_gr. In other words, the deterministic solution is inadequate with respect to possibility to satisfy the uncertain future demands.

Planning with fuzzy loads and prices achieves solutions with higher costs (6 new cables more to build/reiforce) but yet with more robustness (the concept is known as hedging policy in planning).

5 CONCLUSIONS

The ability to supply consumers of an urban area without any longer interruption during a feeder or substation transformer outage is assured by the interconnective (link) network configuration. A technique based on two interrelated evolutionary algorithms for long term large scale multi-stage mv distribution network planning under uncertainty has been proposed. EAs are used to generate sets of dynamic distribution network solutions based upon many practical issues not only in an economic sense but also in a sense of technical criteria and physical routing constraints. Fuzzy sets concept to model uncertainties and decision making guided by a paradigm of risk analysis has been adopted. The GIS has been recognised as a source of huge volumes of geo-referenced data useful in decision making. The method is capable to simultaneously plan the distribution system for normal and outage conditions. Reliability has been incorporated using two approaches – reliability indices and open loop as preferred network layout in the horizon year. The tested practical problems present significantly larger sizes that the ones frequently found in the technical literature dealing with the optimal multi-stage distribution planning under uncertainty.

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