A GENERAL METHODOLOGY FOR DISTRIBUTION PLANNING UNDER UNCERTAINTY, INCLUDING GENETIC ALGORITHMS AND FUZZY MODELS IN A MULTI-CRITERIA ENVIRONMENT

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Abstract - This paper presents a new comprehensive methodology based on genetic algorithms and fuzzy sets concepts for multistage electric distribution network planning. The model presented is an extension of previous deterministic developed models, taking in account several aspects usually neglected in other approaches like, for example, multiple criteria and a thorough representation of uncertainties. New concepts are developed, such as the tree of fuzzy futures, fuzzy inadequacy and solution robustness. Decisions are taken from a multicriteria approach and under risk analysis policies, namely by minimizing possible future regrets. The merits of the approach are discussed by analyzing its application to a study based on a real case, in a Portuguese utility EN, SA.

INTRODUCTION

Many mathematical models have been proposed in the past for electrical distribution network planning, but most of these neglect that one is dealing with a dynamic multi-temporal problem under uncertainty. These models have been aimed at a so called "optimal solution" and are based on an approach usually considered unacceptable by system planners: single criterion optimization. Only recently have we come across some consistent attempts to build models for system expansion which include "service after failure" considerations [1,2].

Furthermore, targeting at optimization has obscured the real aims of a planning procedure - in general, costs (investment + losses) were minimized and everything else was treated as constraints. Therefore, the sense of multiple criteria to judge the solutions was absent from the models. Besides, the representation of uncertainties has been so far relatively naïf: one would try and find the "optimal" solution for one or two future scenarios, each studied as if it were deterministic.

This paper describes a new methodology for distribution planning, applied to a practical case worked together with EN - Electricidade do Norte, S.A., a Portuguese power distribution utility in the north of Portugal belonging to the EDP - Electricidade de Portugal, S.A. group.

Instead of an optimal expansion plan, one aims at defining a flexible strategy that may lead to acceptable decisions in face of the uncertainties of the future. The concepts involved are more related to risk analysis than to optimization and, in fact, the procedures followed are more close to the reasoning of engineers and the practice in utilities than previous theoretical models have displayed

To define such strategy, one works in a full multi-criteria environment (taking in account several objectives when assessing the merits of possible plans) and uses as tools genetic algorithms (to generate dynamic solutions) and fuzzy set concepts (to model uncertainties and decision making).

For the representation of uncertainties we use three different techniques:

- Reliability is modeled by probabilistic models.

- Fuzzy numbers model other continuously perceived uncertainties: cost of equipment, reliability indices, load growth forecasts, cost of energy not delivered, etc.

- Possible futures, perceived as discrete alternatives, are represented in the form of a tree of futures, representing the possibilities of evolution within the planning horizon. These futures correspond to different global background scenarios (economic, legislative, etc.) that lead to different levels of demand or other variations. This approach has, been adopted in [3,4], for instance.

This paper will be devoted to explaining how risk adverse strategies may be built, for system expansion planning. The central idea is not to plan for the average future, but to take planning decisions such that, whatever plausible future occurs, the regret felt for having taken them is kept as low as possible.

This is *not* a conservative risk-adverse policy. On the contrary, plans developed under such principles usually display a diversity of solution resources (which assure their flexibility) while the more classical "optimization for the average future" tends to propose less flexible solutions (as if putting all bets in one horse). Examples of this discussion may be found in [3,5].

The work reported comes as a convergence of several years of research effort. The first author (VM) has originated the development of fuzzy models for power system analysis,; such as Fuzzy Power Flow [6], Fuzzy Optimal Power Flow [7] and Fuzzy Reliability Analysis [8]. The two authors have together worked on the development of Genetic Algorithms applied to distribution network expansion planning [9].

THE CASE STUDY

We now present the real case studied jointly with EN, S.A.. Illustrative as they are, its results should not be taken as a description of the final decisions taken by the utility.

The area studied is in the center of Vila Nova de Gaia, a major city in the neighborhood of Porto, and the central problem is the location and scheduling of a possible new substation (Santa Marinha, see Fig. 1) and the reorganization of the 15 kV network (composed of several open loops). The loads were concentrated in 16 major nodes, besides the substation nodes (the load not directly related to the area under study has been allocated to the existent 4 substations).

FUZZY MODELS

A. Criteria

The criteria used to evaluate the merits of a proposed strategy for network expansion were:

- **IC** - Fuzzy investment cost;
- **PL** - Fuzzy power losses;
- **VQ** - Fuzzy voltage drop quality;
- **RB** - Fuzzy Reliability (energy not supplied).
- **IN** - Fuzzy inadequacy;
- **EX** - Exposure (crisp);

B. Tree of fuzzy futures

Uncertainties related to future developments are organized in a "tree of fuzzy futures". This concept is illustrated in Fig. 2, applied to load growth. A central idea in a tree of fuzzy futures is the concept of *path*. Fig. 2 defines the following paths for load growth: P_1 - $ABCD_1E_1$; P_2 - $ABCD_1E_2$; P_3 - $ABCD_2E_2$; P_4 - $ABCD_2E_3$.

Associated with a path, a *plan* may be developed for the expansion of a distribution system. A *strategy* consists of a set of coordinated plans that cover all possibilities of network development in a tree of futures.

The tree of fuzzy futures is a way of introducing granularity in the information we have about the possible futures - the paths form a discrete set, but each path is in fact represented as "blurred", also contaminated with continuous uncertainty modeled by fuzzy sets.

The tree of futures in Fig. 1 was used in the case study, with a planning horizon of 15 years (5 fuzzy stages, in years 0-1-3-5-15); the initial load is 52.9 MW in year 0 (1994), and the final uncertain load range is 104-180 MW.

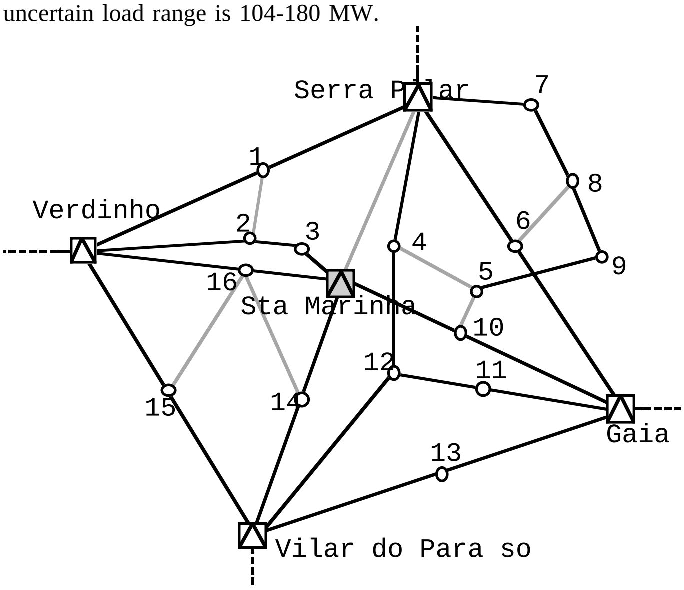

Fig. 1 - General scheme of the 15 kV system studied. Dotted elements represent possible expansion alternatives. Sta Marinha substation does not exist in 1994. Existing cables and substations may be reinforced or replaced.

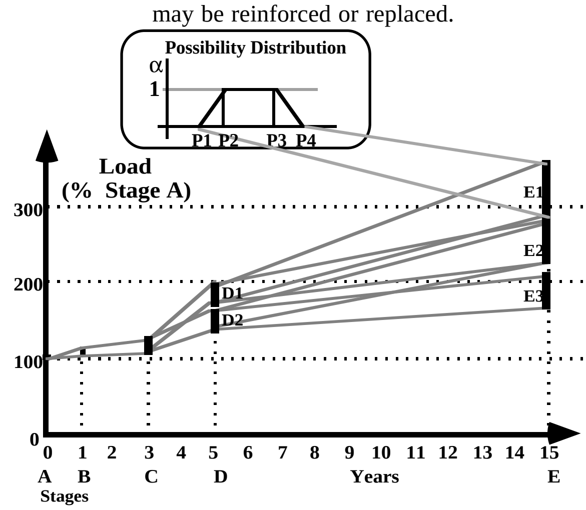

Fig. 2 - Tree of fuzzy future loads and possibility distribution for future C_1.

C. Fuzzy costs

Fuzzy models are the base of the representation of continuous uncertainties (except those related to the failure-repair cycle of components). First of all, we represented the uncertainty in the costs of equipment and building factors through fuzzy values - therefore, adding all these fuzzy costs gives a fuzzy estimate of the cost of a solution IC.

D. Fuzzy Power Flow

We recall that whenever the load scenarios are defined by fuzzy loads, we must use for system analysis a DC or a AC Fuzzy Load Flow (FPF) model [6]. As a result, we will get a fuzzy description of line power flows - and power losses and their cost PL will become uncertain (fuzzy) and so will voltage values.

E. Fuzzy Voltage quality

A solution has been considered unfeasible if the voltage drop exceeds a certain voltage threshold (8%). As we are dealing with fuzzy voltage drops resulting from the Fuzzy Power Flow, the fuzziness of node voltage values may be translated into a fuzzy index as follows (see Fig. 3):

if $V_j(\alpha)$ is a fuzzy node voltage, expressed through a membership function associated to membership or possibility level α,

if $I(v)$ is a non decreasing function describing a voltage quality index, as a function of voltage level v at a node

then VQ_j is a fuzzy voltage quality index given by the functional composition

$$VQ_j(\alpha) = \mathrm{Max}\ \{ I \circ V_j \},\ \text{at every } \alpha \text{ level}$$

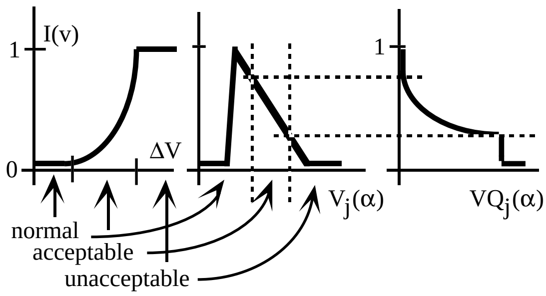

Fig. 3 - Building a fuzzy voltage quality index $VQ_j(\alpha)$ from a fuzzy

nodal voltage $V_j(\alpha)$ and a quality index $I(v) \in [0, 1]$.

F. Fuzzy reliability

A fuzzy description of loads means that we will also have a fuzzy reliability criterion to deal with. The Power Not Supplied PNS value is fuzzy just as a result of the uncertainty in load values. Furthermore, nothing prevents us from considering that the failure rates λ and repair times r are also affected by uncertainty. Under this light, λ and r could have a fuzzy definition, and the unavailability U and the average annual energy not supplied ENS will also be fuzzy, from the fuzzy multiplication of fuzzy numbers:

$$ENS = \lambda \, r \, PNS \quad \text{or} \quad ENS = U \, PNS$$

where λ - fuzzy failure rate
r - fuzzy mean repair time
U - fuzzy unavailability
PNS - fuzzy average Power Not Supplied

Therefore, a reliability criterion RB, translated by PNS or ENS values, is also fuzzy. The fuzzy reliability assessment of a distribution network has followed the techniques presented in [8]. Reliability evaluation in the study included branch failures, switching device location and load transfer through open loops.

Finally, because the possible values of branch flows could exceed branch limits, we have defined two new criteria: the *robustness* of a solution (based on the α-cuts above which the fuzzy flows are within branch limits) and the *inadequacy* of a network (based on the sum of the fuzzy flow subsets that exceed branch limits).

F. Robustness and Exposure

Robustness RO is the only non-fuzzy criterion. We define technical robustness of a solution as an index deriving from a FPF study. As it is clear in Fig.4a, for some scenarios of loads the power demand will have the possibility of exceeding the limit P_{max} in branch capacity. This happens below membership level α; so, $(1-\alpha)$ is an index of how much uncertainty the system is able to cope with - it is a robustness index (and $EX = \alpha$ is an Exposure index). Therefore, minimizing α, in terms of planning, means that the planner wishes to accept solutions that cover or are technically sound in a wider range of possible future scenarios.

Two solutions with robustness associated with α_1 and α_2 are only comparable for the levels above which they are both robust, which means that they would both operate normally and fail from time to time. Below Max $\{\alpha_1, \alpha_2\}$, one of them would still be able to meet the loads, but the other one would fall into a situation of possible repressed demand. Comparisons between more than two solutions must be made by successive destilations guided by the $(1-\alpha)$ index.

G. Inadequacy

The right tail of the branch power flow distribution will be used to define the fuzzy concept of *branch inadequacy* IN_{br} (Fig. 2 b). It may be interpreted as the consequence of some adverse demand scenarios, for which the distribution system will not be able to cope with. Facing this structural constraint, the utility will not authorize more loads to connect to that particular line. Therefore, the actual load allowed will be less than the forecasted load - it is an event of a nature different from disconnecting load that was previously being supplied.

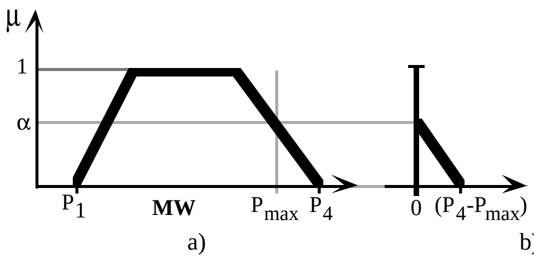

Fig 4. a) Possibility distribution for a line power flow; below level α, load *may* exceed the thermal limit P_{max} - b) fuzzy description of the branch inadequacy; system inadequacy will be obtained by adding branch inadequacies

One is facing here a situation of possible repressed demand, which incurs in social costs of a nature different from those related to power not supplied as a consequence of failures. Therefore, we decided to keep this analysis independent of reliability evaluations, by making explicit a new criterion.

We have thus defined a measure of *system inadequacy* IN_{sys} of a distribution system as the (fuzzy) sum of the possibility distributions of branch inadequacies:

min **IN**$_{sys}$ = \i\su(br=1;n. branches; **IN**$_{br}$)

H. Fuzzy operations

The basis of fuzzy set theory will not be described in this paper. The reader is invited to consult paper [10], for a quick reference and an overview of fuzzy sets on Power Systems.

The comparison between two fuzzy numbers is based on the concepts of Removal, Median and Amplitude presented in [11]. This comparison is mostly needed during the selection procedure of the Genetic Algorithm, namely because in general we will be minimizing in all the objectives evaluated under a fuzzy criterion. The application of these criteria proved adequate to the problems he have dealt with.

THE NEED FOR A STRATEGY

Solving for a path in the tree of futures means that one has anticipated that this particular path would be followed. But decisions to be taken today are influenced by decisions at a later time. Therefore, even if two paths share some nodes, it is just natural that optimal decisions at the very same node would be different, according to the path studied.

In many aspects of the planning activity, engineers face decisions that are not only irreversible, but also that have consequences that escape the law of large numbers (which roughly states that the frequency of occurrence of an event will only approximate its probability for a large number of trials).

Therefore, assessing the merits of long term investment policies on the basis of average returns is meaningless in many cases: the future will happen only once, and it is unlikely that there will be any repetition of events or circumstances, such that a bad decision could be later compensated by a lucky one. This explains the success of risk analysis approaches to system planning, in many fields of activity; in power systems, several authors have also stressed its importance [5].

An acceptable strategy, for a decision maker, will be one in which decisions are not largely regrettable, no matter which plausible (or feared) future occurs. Certainly, decisions will not be optimal, for the actual path followed along but they will not (if possible) have catastrophic consequences. In fact, the best strategy would be the one that would minimize the regret felt for any decision, no matter what future becomes actual.

The concept of regret is central in this risk analysis approach. It is deeply related with other two concepts: robustness and exposure. A solution would be 100% robust if it would be considered good in no matter which future. Exposure is associated with futures for which regret would be felt, related to some decision taken.

THE NEW METHODOLOGY

The main steps of the new methodology are:

1. Previous step: defining all the data required, including the tree of fuzzy futures;

2. For each path in the tree of fuzzy futures:
   -> determine the (conditional) ideal plan in terms of the attribute values, as if one would know that precisely this path would occur;

3. Considering all the paths and all the conditional ideals:
   -> determine the strategy that minimizes the regret (felt for the decisions taken), in all futures.

GENETIC ALGORITHMS

Genetic Algorithms (GA) are search and optimization methods based on natural evolution [12] and have been extensively described in the scientific literature. We will not describe the basis of GA because they have been often enough addressed in many published papers in Power Systems (see for instance [9]). However, it is important to emphasize the most important reasons that lead us to the use of GA in this model:

- GA do not require "well behaved" objective functions, easily tolerating discontinuities and non-linearities which are hard to include in pure mathematical programming methods.
- The results of a GA are not only one "optimal" solution but a large group of solutions.
- GA are well adapted to distributed implementations, allowing computation time to be drastically reduced.

Two crucial issues deserve attention when building a GA: chromosome coding and fitness evaluation. A chromosome is just a string of bits representing the variables in a problem; the coding strategy, however, is determinant in the efficiency of the algorithm - it may represent, under implicit form, many constraints, which is very advantageous. Fitness evaluation tries to measure the "desirability" of the solutions - therefore, building a fitness function may include not only the positive criteria under which solutions are measured, but also penalties for violating constraints that could not be represented directly in the coded chromosomes.

A. Chromosome coding and Fitness functions

The chromosome coding in this study has followed the general strategy described in [9].

A solution is a dynamic sequence of network topologies through time. The fitness of a solution must reflect both its desired and the unwanted properties. Unwanted features are, for example, unfeasible topologies or non-radial configurations (open loops are accepted, but not closed loops). These features are firstly investigated and if detected, determine immediately a low fitness value for the solution. If a solution x passes this topological test, its fitness is then evaluated under the following scheme.

In <u>Step 2</u> of the methodology, the fitness fuzzy value f of a solution x, within a trajectory in the tree of futures, is obtained from the fuzzy equation

$$fitness(x) = M - c_1(IC+PL) - c_2VQ - c_3RB - c_4EX - c_5IN$$

where

M - Large (enough) constant value

c_i - constants externally fixed

and the other indices have been already defined.

When dealing with the tree of futures as a whole, in <u>Step 3</u>, fitness is now evaluated as follows: if, in each criterion

$f_{opt;ik}$ - Value of attribute i in future k, for the ideal

$f_{x;ik}$ - Value of attribute i in future k, for alternative x

then $Regret_{ik} = Max\ \{0, (f_{x;ik} - f_{opt;ik})\ \}$

and the general objective will be to minimizing the overall regret in the decisions to be taken, translated by maximizing

fitness(x) = M - \i\su(i=1;6; (c_i . min{Max [($Regret_{ik}$), k=1...n]}))

where...

M - Large (enough) constant value

c_i - parameters

n - number of paths in the tree of futures

i - number of criteria

which means minimizing the overall regret in the decisions to be taken.

In order to obtain a picture of the non dominated border of the solution set obtained at the end of the genetic process, we have adopted an approach that gave very good results: rewarding "geographical isolation". Whenever a solution is detected at any generation with enough different (and good) objective value for some criterion, it gets a reward added to its fitness value and is kept surviving to the next generation. This allowed a nice covering of a (thick) non dominated border of the solution domain.

THE IMPORTANCE OF MULTI-CRITERIA

The application of this methodology and the GA model allowed us to recognize a very important result, with direct implications in future model developments: we were able to identify projections of domains of feasible solutions, in the attribute space, that were clearly <u>not convex</u>.

In Fig. 5 and 6 we depict one of such cases: the projection of the GA solutions for a 15 kV planning problem(different from the case study) over 4 time stages, at the end of a *circa* 300 generation process, on two planes, formed by couples of criteria, such as: in Fig.5, investment vs. reliability, seems quite classical; in Fig. 6, investment vs. losses displays clearly a non convexity.

The fact that the set of solutions is not convex (with special incidence on the non dominated border) makes it evident that some classical approaches of "pseudo-multicriteria", that would just perform an optimization using as single criterion a linear function of all criteria in the problem (adding them up multiplied by some weights) are misused: they can never detect "hidden" solutions in the concave parts of the solution set which, in fact, might become the most attractive to the decision makers (who knows?).

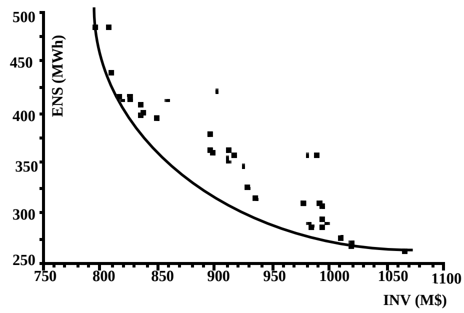

Fig. 5 - Investment versus ENS: solutions after a Genetic Algorithm exercise for a distribution problem

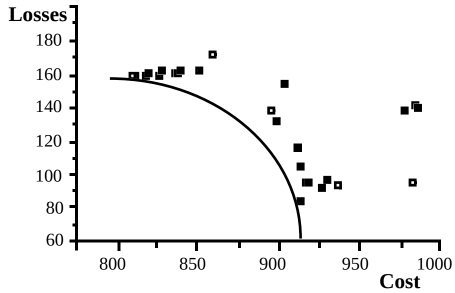

Fig. 6 - Investment versus Power Losses: the same solutions as in Fig. 5 display now a non convexity in this domain projection

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This discovery gives even more importance to the use of GA, because we have demonstrated that they deal adequately with this feature of the planning problems.

RESULTS

The results from Step 1 are:

- A large set of (fuzzy) non-dominated solutions obtained by the genetic process described above.

- A conditional decision set for each trajectory in the tree of fuzzy futures. From this set we are able to determine the ideals for each criterion, in each possible trajectory. These values will be used in phase 2 to calculate possible regrets from the decisions taken.

Applying the Genetic Algorithm platform, followed by engineering judgement, we were able to define the ideals for each path in the tree of futures of Fig. 1. These ideals are plotted in Fig. 6 as circles in the plane [Cost x Reliability]. The average run time in a NeXT machine was of 400 seconds for each path.

A second Genetic Algorithm was then run to find strategies that would in all cases minimize the regret felt for not having implemented an ideal solution in every path. The average run time in a NeXT machine, for the whole tree of futures, was around 30 minutes. However, a parallel solution as described in the next Chapter, using 5 workstations, reduced almost 5 times this run time, to around 6 minutes, which is absolutely acceptable for a planning model and so complex.

The final solution consists of the following robust strategy, described in terms of substations (R/A stands for "reinforce or alleviate", meaning the need of either a transformer capacity reinforcement or load transfer to other substations:

Stage A (0-1 year) : Do nothing.
Stage B (1-3 years) : Build Sta Marinha (31.5 MVA)
Stage C (3-5 years) : R/A Verdinho (+31.5 MVA)
R/A Serra do Pilar (+31.5 MVA)
Sta. Marinha Substation alleviates the load in the neighboring substations; however, load growth still forces load transfers from Verdinho and Serra do Pilar to the new substation.
Stage D (5-15 years) :
If D1 happens: Reinforce Sta Marinha (+31.5 MVA)
R/A Gaia (+31.5 MVA)
R/A VPR (+31.5 MVA)
If D2 Happens: Reinforce Sta. Marinha (+31.5 MVA)

Results gave also important indications about which main feeders should be reinforced or newly built, and when. All these results took in consideration also uncertainties in costs, reliability indices and other. Namely, reliability has been assessed taking also in account the influence of switching device location policies.

The maximum regrets for implementing the robust strategy are displayed in Fig. 6. One may see that the robust strategy does not coincide with any of the "optimal" solutions for each path in the tree of futures. It is interesting to notice that in some cases the robust strategy leads to improving reliability (as in futures P2 and P4). The regrets in the Cost criterion represent the value of the "lack of perfect information".

Figure 7 shows, in a bi-dimensional space, global deviations that are obtained with the best risk aversion strategy, relatively to the ideal solutions that would be possible to adopt, if one could perfectly know beforehand what future would occur.

These deviations can be interpreted as potential regrets, from the "risk analysis" point of view. Both investment cost and ENS are fuzzy and therefore they are represented here by their *removal* values of the possibility distributions.

These regret values may be seen as the opportunity cost for a crystal ball - utility management has the option of paying for hedging or buying such ancient technological device and guessing the future. It is the cost of information.

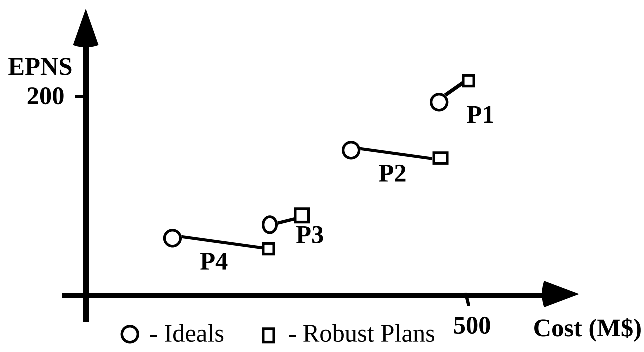

Fig. 7 - Ideals for each path and actual regrets felt, in each of the possible futures.

PARALLEL PROCESSING

The platform developed at INESC allowed us to take advantage of parallel processing, in order to speed up run times. This is achieved by building a cluster of workstations, linked by a LAN such as Ethernet. One of the workstations acts as a Master and all the machines may process, in parallel, the analysis of different alternatives, in order to determine their fitness values. This is the most time consuming operation (remember that fitness evaluation includes fuzzy power flow, fuzzy reliability, fuzzy investment calculations...).

The operations that require centralized control by the Master station are very simple indeed - selection, crossover and mutation are mainly comparisons and bit operations. Therefore, the execution time of a Genetic Algorithm is reduced (divided) almost by the number of stations in parallel, and increased by the communication time through the LAN. When fitness evaluation is a heavy operation (as it is the case here), communication times become negligible and the parallel processing in a cluster of machines becomes very advantageous.

CONCLUSIONS

This paper presents a new methodology for electric distribution network planning. This methodology leads to the substitution of the *single criterion* /*optimal solution* concept by a new integrated notion of *expansion strategies* in order to obtain solutions that are more flexible and adaptable to changing futures.

It was developed based on two points: a technique grounded on genetic algorithms and fuzzy set concepts for the generation of solutions and expansion strategies; and a planning philosophy based on the robustness evaluation of these strategies, guided by a paradigm of multicriteria risk analysis.

The main purpose of this model is to respond to the system planning fundamental requirements:

- It is able to deal with real sized networks.
- Allows a multitemporal representation
- Generates sets of solutions.
- Permits multicriteria analysis, keeping the criteria and their respective tradeoffs explicit.
- Allows the planner to obtain indices that measure the distance between the strategies to implement and the ideal solutions he would choose if he could have a perfect knowledge about the future.
- Is well suited to distributed implementations, leading to reduced acceptable computation times.

The planning philosophy adopted is the one that minimizes the *regret* in the decisions taken - and this implies that the consequences of these decisions are evaluated within the large set of uncertainties and futures defined.

So, the combination of GA and Fuzzy Sets concepts proved to be both suitable and resourceful, enhancing the representation ability of the models and the flexible interpretation of concepts such as fitness.

The real case study worked out jointly by a team of researchers and engineers from an utility fully demonstrated the usefulness of the new methodology and its adherence to reality, being mature to be considered as a potential addition to the tools currently adopted in practice. It further showed the need to provide the possibility of including other criteria or constraints, such as limits on short-circuit levels, which is trivial to do within the Genetic Algorithm framework.

The success of the approach and the models presented open the way for developing planning aid tools for distribution design that represent reality and its constraints in a way closer to the reasoning of planners and decision makers.

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