DISTRIBUTION PLANNING WITH FUZZY LOADS AND INDEPENDENT GENERATION

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Keywords: Distribution networks, Planning, Fuzzy Sets, Independent generation, Simulated Annealing, Multicriteria Decision Making

ABSTRACT

The classical long range distribution network planning problem consists on deciding network investments to meet future demands at a minimum cost, while attending technical constraints. The decisions whether to construct or reinforce substations and branches lead to a mixed integer programming problem with a great number of decision variables.

Besides, the network injections have a fuzzy nature on account of the non availability of statistical data in what concerns future loads (namely in new areas and due to the presence of independent producers. Moreover several objectives must be taken into account. This leads to a fuzzy multiobjective, mixed integer problem.

This paper presents a case study, adapted from a real network, that illustrates the application of an integrated methodology to deal with the planning problem. This case study aims into illustrating the proposed methodology and to point out its flexibility to adapt to the planner's needs.

1. INTRODUCTION

The cost of a given plan includes not only investment costs in new substations and branches but also operating costs (power losses) and reliability related costs. Thus, the problem has multiple objectives, and it is not generally possible to obtain an optimal solution, due to the conflict among evaluation criteria.

The uncertainty associated to future loads, and to an increasing number of independent generation units connected to the distribution network, introduces additional difficulties to the planning problem. In recent years, uncertainty of loads has being modelled by possibility distributions that represent "typical" situations, as defined by experts' declarations or clustering studies, Miranda and Matos (1). On the other hand, independent generation (IP), depend on natural resources and are not controllable by the distribution utility. In section 2 the basic fuzzy model, to capture load and independent generation uncertainties are presented.

In section 3, the operational model formulated as a multiobjective one is presented. Our approach bases on two main ideas: (1) each solution consists on a plan of investments for the stages of the study period and (2) using the robustness concept, which evaluates the ability of a certain plan to accommodate all uncertainties, the constraints of the basic problem can be relaxed. This is accomplished by introducing a new objective function. This formulation leads to a problem without fuzzy restrictions.

To address the multiobjective problem a two step strategy is presented in section 4. First, using the ε-constraint method, a representative sample of the nondominated solution set is generated. The multiobjective problem turns into an equivalent set of mathematical optimization problems. To solve each of these problems, a meta-heuristic, Simulated Annealing, is used. Second, a decision-aid process takes place, supporting the Planner in making his final decision. Section 5 presents an extension of this second stage allowing the Planner to make *zoom* actions and drive trough the solutions, generated by first stage, backwards and forwards and to make detailed inspections to plans he selects.

Section 6 presents a case study, based on a realistic situation, and all the steps for the problem are presented as well as the description of the generation of efficient alternatives which, in fact, are the efficient expansion plans for the different stages. Simultaneously the simulation of the decision process (where the Planner can choose the preferred plan) is presented.

2. INJECTION MODELS

Load forecasting is difficult to model: most of times there is no frequency of occurrence of events and probabilistic methods are not adequate. Nevertheless uncertainty is often too large to be omitted. Fuzzy numbers seem adequate do model this kind of uncertainty. The present approach uses a fuzzy trapezoidal or triangular model for loads.

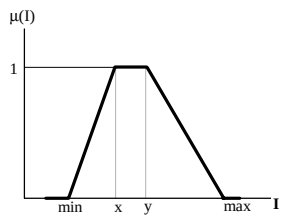

Figure 1: Fuzzy load

A fuzzy possibility distribution for a certain load (modelled as a current) is illustrated in figure 1. According to some expert, this load may assume values in a range between a maximum (*max*) and a minimum

(*min*) and for those extreme cases the membership value is null. The load will assume, almost certainly, a value between x and y (membership value 1).

We also use fuzzy trapezoidal models for IP (Ponce de Leão and Matos, 2). Two types of small hydro and also wind power plants are specifically modelled, along with a complementary model for inclusion of additional information about regularity of flows and winds. The models are based on technical data about independent production and experts' declarations about the rules used in the project. More accurate models can be obtained, if extra information about natural sources is available, composing basic models with linguistic declarations following the methodology proposed by Klir and Folger (3). The models obtained this way are, perhaps, too detailed for planning problems, although they can be useful for operation problems. To be more easily included in planning models, the possibility distributions are approximated to trapezoidal ones. Conventional IP (thermal, diesel, etc...) is modeled as a negative load.

3. PROBLEM FORMULATION

The model addresses a network with n nodes and m potential branches, in a multi-period study with h periods. Substations are represented by artificial branches to an auxiliary node. Decision binary variables γ_{ki} indicate if a branch k is to be constructed, or not, in period i. If branch k exists in period i (δ_{ki}=1) then it has a fuzzy flow $\tilde{x}_{ki}$. Each node j has associated a voltage drop, $\Delta\tilde{U}_{ji}$. In each period i, the fuzzy injection (loads or distributed generation) $\tilde{d}_{ji}$ is known for each node j. Each alternative plan, $\boldsymbol{\gamma}=[\gamma_{11,...,}\gamma_{k1,...,}\ \gamma_{1i,...,}\ \gamma_{ki,...,}\ \gamma_{1h,...,}\ \gamma_{kh}]$, assembles all the decisions about every branch in every plan and period.

A sensitivity matrix $\mathbf{A_i}$ describes the network in each period i, relating the vector of fuzzy flows $\tilde{\mathbf{x}}_\mathbf{i}$ with the fuzzy injections $\tilde{\mathbf{d}}_\mathbf{i}$. The usual branch limit and maximum voltage drop constraints are considered. However the use of fuzzy variables (flows and voltage) soften the constraints allowing some violations within certain limits. A constraint violation degree is evaluated by a robustness index, β that reflects the degree of satisfaction of the fuzzy constraints (i.e. β=1 if the constraint is fully satisfied). Figure 2 illustrates the robustness, β=1-α, concerning the maximum limit, I_{max} of a branch.

A new objective function, maximizing robustness, joins the three original objective functions; minimization of investment costs, minimization of losses and maximization of reliability.

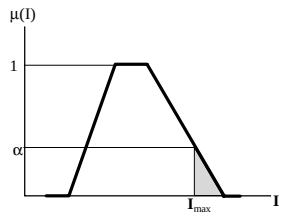

Figure 2: Robustness and severity

Nevertheless, the new operational problem, although non-fuzzy, is a multiobjective combinatorial one. This leads to hard or even impossible resolutions in reasonable time. In the next section we show how to overcome this difficulty.

4. PLAN GENERATION AND DECISION PROCESS

The resolution methodology consists on a two phase strategy. In the first phase, a significant sample of non-dominated solutions is generated. After the generation phase a decision-aid method must take place in order to present to the Planner a set of representative solutions.

Regarding the generation stage, the use of traditional mathematical tools is restricted to limited size problems, because of the combinatorial nature of the problem. Traditional approaches use either enumeration algorithms (branch and bound or dynamic programming algorithms) or heuristic algorithms. Excessive computation time and trapping in local optima, when local search heuristics are used, are the main common problems found when dealing with real size networks.

In this approach we use a modified ε-constraint search method, as presented in Goicoetchea et.al. (4), to generate a sample of the efficient solutions for the multiobjective problem. The basic problem turns into a set of independent optimization problems. However, these partial problems maintain a combinatorial characteristic. We use a meta-heuristic, Simulated Annealing, to deal with the smaller combinatorial problems. The Simulated Annealing method bases on the relaxation of optimality to allow jumps from local optima. Theoretical principles of this meta-heuristic can be seen in Aarts and Korts (5).

The search is made accomplishing the different criteria imposing successively upper and lower limits for the ε-constraint method (a criterion, robustness, is chosen to be optimized and upper and lower limits are successively imposed to the other criteria). This procedure is equivalent to reducing each solution neighborhood considering a new feasible, more restrict, solution space. To each reduced solution space a Simulated Annealing is applied to get the optimal solution. Besides the advantage of generating efficient solutions in feasible time this methodology doesn't imply the use of linear functions. Exact functions to

evaluate non supplied energy and losses can be used without further effort.

The output of this phase is a list of alternative efficient plans, regarding the different attributes' scales, for the whole decision region. This list is generated considering the availability of the independent producers (normal scenery), where the different alternatives are evaluated by the several attributes. Additional calculations are made to get the values of the attributes, for the same plans, but considering that independent generation is not available at all (risk scenery). The Planner is then confronted with a list of plans, characterised by a fixed attribute (investment cost) and conditioned attributes (the others, including robustness).

Phase two consists on a decision-aid process for the multiattribute problem that results from the first phase. The analysis to this final list can be made by the Planner, imposing successively limits to the attributes or using more formal tools adequate to deal with fuzzy multiattribute problems.

If one or more expansion plans, from this first list, seem promising to the Planner, they are retained for further study. It is possible, however, that the robustness of every plan reduces excessively when the independent generation is considered out, this leads the Planner to exclude all of these alternatives and make a new study without considering the IP from the beginning.

5. DETAILED ANALYSIS

To give additional insight in measuring constraints violations, Matos and Ponce de Leão (6) defined an index of severity of violation that measures the level of surpassing maximum flow and (or) maximum voltage drop limits. The equation (1) presents the evaluation of thermal severity.

$$V_I = \frac{1}{I_{\max}} \int_{I_{max}}^{\infty} u(I)dI \qquad (1)$$

These indices allow a more accurate analysis over the plans that derive from the decision-aid stages. The promising alternatives (eventually evaluated by attractive costs, but presenting lower values for robustness), can be analyzed in further detail.

This index is illustrated in figure 2 (equivalent to the grey area divided by the maximum limit) and can be evaluated as a global index (sum of all indices), for a plan, or for each facility. This index allows the Planner to evaluate the extent of violations and identify critical points. The detailed study over a limited number of alternatives (selected after the decision-aid phase), may suggest further investments to increase robustness of attractive solutions. This detailed analysis, can be made at any point of the second decision-aid stage together with forward and backward analysis also available. There is no danger of loosing information as all efficient alternatives, generated in first phase, are actually saved.

6. CASE STUDY

This contribution presents a multistage real sized case study that illustrates the main issues of the approach. The case study data was synthesised from a real network of a zone belonging to the Centre-West region of Portugal kindly made available from a Portuguese Utility. Extra data regarding reliability parameters was based on typical values presented in Lakervi and Holmes (7).

From the original data, some loads were grouped for operational reasons. This task was made according to the method proposed by Willis and Northcote-Green (8), dividing the region in small polygonal areas. After this procedure a synthesised network, with 51 nodes and 75 branches was obtained.

Three possible substations, two of them already operating, feed the system: S_1 connected to node 2 (maximum capacity 2400 A), S_2 to node 20 (maximum capacity 1500 A) and the new S_3 to be constructed if necessary (maximum capacity 500 A). From the existent substations S_2 has a reinforcement capacity of 500 A. The case study also includes three independent generation units connected to the network. Two mini-hydro with regulation capacity are connected to nodes 18 and 15, respectively with 5.25 MW and 4.65 MW rated power and another one having 4.65 MW of rated power without that capacity of regulation is connected to node 41.

Loads are represented by triangular possibility distributions. Three stages are considered and an extrapolation was made in order to consider loads' evolution following a sigmoid curve.

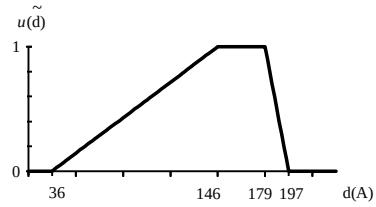

Figure 3: Mini-hydro connected to node 18

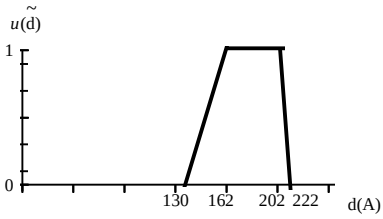

Figure 4: Mini-hidro connected to node 15

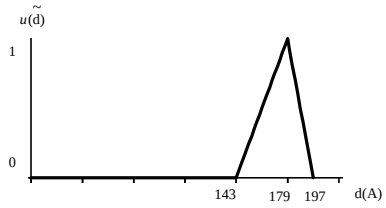

Figure 5: Mini-hidro connected to node 41

In order to accomplish the modified ε-constraint method the robustness was maximized and upper and down limits for the other criteria were fixed. The extreme limits where calculated optimizing each criteria and relaxing the others. As we are considering the solution space area for three objectives it is possible to make a physical analogy and consider that the whole criteria space was divided into elementary cubic spaces which were submitted to successive optimization procedures using the Simulated Annealing (SA).

Several previous decisions had to be made in order to apply the SA procedure: initial "temperature", "temperature" schedule and duration of fixed "temperature". These parameters are derived from previous studies on distribution networks. For the case study, initial temperature was chosen in order to accept in the beginning half of the configurations, temperature schedule was a geometrical one lowering temperature for each interval from 10% and the number of iterations using a fixed temperature was calculated 10 times the average possible neighbors of the initial configuration, for the case in question 600 iterations.

The whole set of efficient alternatives, when considering the normal scenery, amounts to 49 different solutions. Table 1 presents a sample of a group of alternatives from this list, resulting from a previous imposition of limits (preferences) by a simulated Planner on the attribute's values. The solutions presented are evaluated by two crisp attributes, (investment cost and robustness) and fuzzy attributes, (losses and non supplied energy, ENS). The fuzzy attributes are represented by a trapezoidal function and can be interpreted as: the values are more certainly in the interval [x,y], but they may be as lower as min or as great as max.

The second decision process is illustrated by simulating the decisions of an hypothetical Planner, when the alternatives generated in the first phase are presented. We will suppose the Planner decided he could not accept solutions with a robustness lower than 0.6, an investment cost upper than 350, and losses and ENS presenting an x value higher, respectively, than 650 and 3.8. This conducted to Table 1.

At this point the Planner considers that this list has excessive alternatives and, as the values for losses and ENS are within acceptable limits, he decides to make an analysis concentrating only on investment cost and robustness. In a first approach he decides to eliminate solutions which presented, in the risk scenery (table 2), no robustness at all. This lead to eliminating alternatives 80, 75, 46 and 89.

TABLE 1 - Original reduced list

			Normal Scenery							
Nº	**Cost($10^6)**	β	**Losses**				**ENS**			
			min	x	y	max	min	x	y	max
190	303	1.00	298	423	424	617	2.0	2.7	2.8	3.3
80	343	0.79	388	548	555	803	1.3	1.8	1.9	2.2
185	343	0.89	394	550	556	800	1.7	2.3	2.4	2.9
194	298	1.00	305	443	444	652	2.4	3.1	3.2	3.8
172	301	0.84	298	453	459	700	2.0	2.7	2.8	3.4
79	321	1.00	276	438	441	685	2.0	2.7	2.8	3.4
42	248	1.00	424	642	646	972	2.7	3.5	3.6	4.4
75	243	0.57	342	543	551	844	2.6	3.4	3.5	4.3
46	235	0.27	386	587	593	890	2.7	3.5	3.6	4.4
89	210	0.57	398	612	618	959	2.7	3.5	3.6	4.4

TABLE 2 - Risk scenery list

			Risk Scenery					
Nº	**Cost($10^6)**	β'	**Losses**			**ENS**		
			min	x=y	max	min	x=y	max
190	303	1.00	326	490	673	2.3	2.9	3.4
80	343	0.00	378	589	832	1.6	2.0	2.3
185	343	0.89	498	749	1025	2.7	3.4	3.9
194	298	0.91	341	518	717	2.7	3.4	4.0
172	301	0.90	384	587	822	2.9	3.7	3.9
79	321	0.60	344	535	763	2.5	3.1	3.7
42	248	0.23	524	782	1098	3.1	3.9	4.6
75	243	0.00	950	1430	1586	3.0	3.8	4.5
46	235	0.00	1007	1585	2321	3.1	3.9	4.6
89	210	0.00	420	643	892	3.1	3.9	4.6

An observation to the new reduced list made him conclude he might have been excessive strict on eliminating very cheap interesting solutions. He went backwards and included some alternatives with very low costs (42 and 89). At the same time he excluded alternative 172, similar to 190 and less robust, and he got table 3.

TABLE 3 - Simplified list

Nº	**Cost($10^6)**	β	β'
190	303	1.00	1.00
185	343	0.89	0.89
194	298	1.00	0.91
172	301	0.84	0.90
79	321	1.00	0.60
42	248	1.00	0.23
89	210	0.57	0.00

Careful analysis of table 3 lead the Planner to exclude all the alternatives which presented robustness, for normal scenery, less than 1 and he got table 4.

Two expansion plans from this final list, 42 and 194, seem particularly interesting on account of their low values for investment costs. Nevertheless, the solution 42 is very exposed to the risk scenery. The Planner

might think worthwhile and proceed to a detailed severity analysis on both alternatives.

TABLE 4 - Final list

Nº	Cost(10^6)	β	β'
190	303	1.00	1.00
79	321	1.00	0.60
42	248	1.00	0.23
194	298	1.00	0.91

Table 5 presents global severity indices for both alternatives. An analysis of the severity indices of all network components (not described) indicates that the plan 42 presents a 0.02 severity index for only one branch, connecting node 17 to 18, and this situation exists only for the risk scenery. The severity associated with plan 194 is of minor importance, related to a branch as well. This conclusion gives the planner a basis for further economical analysis. He probably will analyze economically both alternatives and ponder the reinforcement for the risk scenery.

TABLE 5 - Severity indices

		Normal Scenery		Risk Scenery	
Nº	Cost	β	V	β'	V
42	248	1.00	0.000	0.23	0.020
194	298	1.00	0.000	0.91	0.005

7. CONCLUSIONS

This contribution shows how to help a Planner to decide about investments on distribution networks in an uncertain environment.

Uncertainty of load and IP, generation using renewable energy, are tackled by the model, allowing the Planner to have a global view of the most promising plans, characterized by cost and reliability objectives.

An example of the final decision-aid process illustrates the flexibility of the procedure.

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