IDENTIFICATION OF HEDGING POLICIES IN GENERATION / TRANSMISSION SYSTEMS

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Abstract

In this paper we present an algorithm to classify and rank reinforcement strategies of generation/transmission power systems according to their ability to reduce the risk regarding the future. This algorithm integrates a Fuzzy Optimal Power Flow model used to analyse a sample of system states identified in a Monte Carlo simulation given the outage rate of components. The algorithm produces a list of components ranked according to the expected exposure index reduction obtained from the reinforcements. Finally, this information is used together with reinforcement costs to perform a trade off analysis in a decision aid environment.

1. INTRODUCTION

Power system planning has been classically addressed using probabilistic concepts to model uncertainties in data. This approach seems appropriate to represent the system behavior, in terms of component reliability but it is questionable that it is adequate to model load uncertainty specially if long term planning problems are to be dealt with. Uncertainty in load forecasts is of great importance and derives from several factors, many of which are of qualitative nature and depend on impredictable, though determinant, events, such as economic growth, environmental constraints, political developments, etc. Therefore, neither a deterministic nor a probabilistic modeling of loads are adjusted to this kind of uncertainty. In fact, a fuzzy set [1,2] approach would certainly be a more adequate representation in these cases.

If loads are uncertain, then generations, branch flows and voltages will also be uncertain. In [3] we presented a fuzzy power flow model to include fuzzy data in the power flow problem. When loads are defined based on linguistic declarations, such as "more or less 20 MW" or "possibly between 15 and 25 MW, but not more than 30 nor less than 10 MW", one has membership functions for branch power flows and other variables, instead of deterministic descriptions. In [4, 5] we presented a DC Fuzzy Optimal Power Flow - FOPF - model that allows the planner to study one system configuration at time in order to obtain an optimal generation strategy and eventually obtain the power not supplied membership function.

In [5] we also proposed new indices - the robustness and exposure indices - to give the planner useful information on the risk of planning decisions. The exposure index gives an idea of how much uncertainty the system can manage without having load disconnections. This concept plays a central role in this paper, as we will describe how it can be used to identify robust reinforcement strategies to increase the uncertainty the system can accommodate.

Load uncertainties are not the only ones the planner will have to cope. In fact, system components are subjected to a failure-repair cycle usually described using probabilistic concepts [6]. In [7] we presented a Monte Carlo algorithm considering that loads are modeled as fuzzy numbers. This model is important namely because it is a way to integrate two types of uncertainties showing that each one should be used when it is more adequate: load uncertainties are represented by fuzzy sets and the failure-repair cycle of components is modeled by probabilistic concepts. As results, this algorithm estimates the expected robustness and exposure indices and also the membership function of the expected Power Not Supplied.

However, in some systems and for the specified uncertainties, the expected value of the exposure index may be too high indicating that the system is too exposed to uncertainties related to future load scenarios. In those cases, it is important to identify the components that if reinforced will reduce that expected value and that will also reduce the range of the fuzzy number representing the expected Power Not Supplied.

In this paper we will describe how the fuzzy Monte Carlo simulation described in [7] with fuzzy loads can be used to provide the planner information about the most suitable components to be reinforced in order to reduce the risk of the investment decisions.

This can be done by analysing for each sampled state the effectiveness of the specified reinforcement strategies in terms of reducing the exposure index. For each of the strategies being tested variables representing the branch and generator reinforcements will be included in the FOPF problem. If this analysis is conducted for all those strategies along the Fuzzy Monte Carlo simulation it will be possible to keep track of the maximum expansion values required for each component as well as the number of system states for which each reinforcement succeeded in reducing the exposure index to a value below a target. The number of these states will be used to build an indicator function to validate from a statistical point of view the goodness of each expansion strategy.

The paper includes a section briefly dealing with fuzzy load representation after which some concepts concerning the Fuzzy Monte Carlo simulation will be addressed. In section 4 we will describe how the DC - Fuzzy Optimal Power Flow algorithm integrated in the Monte Carlo procedure is modified in order to calculate how a branch or generator should be reinforced to get an exposure index. The methodology will be illustrated with results from a case study based on the IEEE Reliability Test System. Finally, in section 6 some relevant conclusions of this research are drawn.

2. FUZZY LOAD REPRESENTATION

A fuzzy set can be seen as an extension of a classical crisp set. In crisp sets only two logic values representing full and complete lack of membership of an element are allowed. In fuzzy sets a smooth transition between these extreme situations is considered so that, in normalized fuzzy sets, the membership function takes values in [0;1].

A class of fuzzy sets - trapezoidal fuzzy numbers - is specially adequate to model the uncertainty around an interval. In figure 1 a number of this type is sketched representing the uncertainty affecting the interval $[L_2, L_3]$ of active loads. Values less than L_1 and greater than L_4 have a zero value of membership function meaning that they are not adequate to translate the definition of the load. Values in $[L_1, L_2]$ and $[L_3, L_4]$ can represent the concept of the load with degrees of membership lower than 1.0.

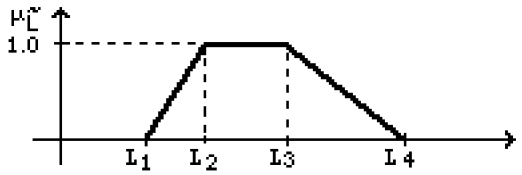


Fig. 1 - Trapezoidal fuzzy load.

A trapezoidal number as the one sketched in figure 1 can be represented by (1) using the extreme points of the intervals having 0.0 and 1.0 membership value. An α-cut of such a number is defined as the crisp set of values having a membership not less than α (2). The central value of a fuzzy number is the average of the 1.0-cut.

$$L = (L_1; L_2; L_3; L_4) \quad (1)$$

$$L_\alpha = \{x: \mu_L(x) \geq \alpha\} \quad (2)$$

3. FUZZY MONTE CARLO ALGORITHM

3.1. General Considerations

The Fuzzy Monte Carlo algorithm presented in [7] allows the planner to evaluate reliability and risk indices of generation / transmission power systems assuming loads represented by fuzzy numbers and the non-ideal nature of components modeled by probabilistic concepts. This algorithm will be summarized in the next points.

3.2. Sampling States

In the first place, system states are sampled according to the forced outage rates of components. This can be done adopting a non-chronological sampling strategy by obtaining sequences of pseudo-random numbers.

3.3. Analysing Sampled States

For each sampled state one runs a Fuzzy Optimal Power Flow. This problem can be considered an extension of a classical OPF with loads represented by crisp values. If, at least, one load is represented by a fuzzy number the OPF will turn into a Fuzzy Optimal Power Flow - FOPF.

In the next paragraphs we will briefly describe the key points of this algorithm. The interested reader is referred to [5] where more detailed information about the DC-FOPF model can be obtained.

The DC-FOPF algorithm assumes that loads are represented by trapezoidal fuzzy numbers and adopts the DC power flow model to represent the operational behavior of the network. The algorithm starts by running a DC deterministic OPF study using for loads the central value of their membership function. This study gives an optimal and feasible solution according to the generation and branch power limits.

We then integrate information about load uncertainties in this optimal and feasible solution by associating a parameter to each load distribution. This leads to an OPF problem organized in a multiparametric formulation that is used to identify vertices of the hypervolume containing all possible load combinations according to certain rules.

Afterwards, one performs as many parametric DC-OPF studies as the number of identified vertices. This process leads to the calculation of partial membership functions of generations, branch flows and Power Not Supplied - PNS. As a final step, the partial membership functions built for each sampled state are aggregated using the fuzzy union operator modeled according to Zadeh [1].

3.4. Risk Indices

The DC-FOPF model also gives, as a result, the lowest level of uncertainty, Iexp, for which the network still can accommodate load uncertainty without disconnecting load. This means that:

- for α-cuts higher than Iexp the system can supply loads without violating branch and generator limits. Therefore for these levels, and no matter the load combination considered, one can conclude that the PNS value will be zero;
- for α-cuts lower than Iexp the system looses its ability to accommodate all the uncertainty. This means that, for these levels there are load combinations leading to non zero PNS values.

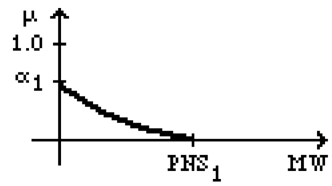


Fig. 2 - Example of a PNS membership function.

This kind of information can be translated into two risk indices: the exposure - Iexp - and the robustness - Irob. The first gives information about the degree of exposure felt by the system regarding the specified uncertainties. Considering the PNS membership function depicted in figure 2 the exposure index is α_1. The robustness index is just the complement to 1.0 of the exposure index. It gives information about how the planner can increase load uncertainty without risking load supply.

3.5. Aggregating Results

For each sampled state analysed, the FOPF algorithm gives the membership function of the PNS and the values of the exposure and robustness indices. For N system states, one can obtain estimates of their expected values using (3) to (5). In these expressions, PNS_i, $Irob_i$ and $Iexp_i$ represent the PNS membership function and the robustness and exposure indices of state i.

$$E(PNS) = \frac{1}{N} \cdot \sum_{i=1}^{N} PNS_i \tag{3}$$

$$E(Irob) = \frac{1}{N} \cdot \sum_{i=1}^{N} Irob_i \tag{4}$$

$$E(I\exp) = \frac{1}{N} \cdot \sum_{i=1}^{N} I\exp_i \tag{5}$$

3.6. Convergence

Following [8], the uncertainty coefficient defined by (6) is used to monitor the convergence of the Fuzzy Monte Carlo simulation.

$$\beta^2 = \frac{V(PNS)}{N.(E(PNS))^2} \tag{6}$$

In this expression E(PNS) represents the current estimate of the expected PNS. This value is calculated considering the sample of crisp PNS values obtained for each state after running the initial deterministic DC-OPF study. V(PNS) represents the corresponding variance. The simulation ends as soon as the calculated β gets not superior than a target pre-specified value.

In [7] the use of convergence acceleration techniques in the Fuzzy Monte Carlo algorithm is also detailed. The conclusion was that the use of a Control Variable Technique approximating the system PNS by the PNS only due to the generation subsystem deficiencies is very efficient in reducing the computational burden. As an example, in some situations the number of states to be analysed to get convergence was reduced to about 22% of the number required without using this technique.

4. BUILDING A LIST OF REINFORCEMENTS TO REDUCE RISK

4.1. General Aspects

As suggested in section 3.4. a non zero exposure index for a given state can be related with, at least, one system component that originates a bottleneck in the system ability to accommodate more uncertainty. Therefore, the planner may want to reduce the risk of the system regarding the specified uncertainties.

It should be noticed that we are dealing with two different sources of uncertainty. The first one is inherent to loads while the second is due to component reliability. That is why it is meaningless to analyse the effect of a reinforcement for one only or even a few states. In fact, the reinforcement of a branch, for instance, may prove to have good results in reducing the exposure of the system only in a small number of states being quite ineffective in many others. In general terms, such reinforcements will not be the most adequate regarding the two kinds of uncertainties we are dealing with.

This explains why the classification of reinforcement plans in terms of their goodness should be conducted in the scope of the Monte Carlo simulation.

4.2. From Candidate to Credible Reinforcements

Some insight about the effectiveness of reinforcement strategies can be obtained by running an initial Monte Carlo simulation as described in section 3. A dual analysis of the OPF problems related to each state gives information about the binding constraints that prevent the accommodation of more uncertainty. This can be used to build a list of candidate components to be reinforced.

Afterwards, a second Monte Carlo simulation should be run integrating, for each state, variables representing the candidate reinforcements as it will be detailed in 4.3. This way, one would get, for each sampled state, information:

- about whether an expansion strategy is able to reduce the exposure index;
- about the reinforcement value that should in fact be used to reduce the exposure index to a target value.

The information obtained from each sampled state is integrated so that a meaningful result is derived considering that the behavior of components is modeled by probabilistic concepts. Therefore, in section 4.4, we propose a new statistical index in order to evaluate the statistical credibility of each reinforcement. The algorithm produces a list of components ranked according to the reduction of the expected exposure index the user can obtain if that component is reinforced.

As a final step, one can perform a trade-off analysis in order to identify the non-dominated border of the set of plans. To this purpose, plans are characterized by the expected exposure index and by the cost of the respective reinforcement. This way, fuzzy concepts and probabilistic models are integrated in a decision aid environment to help the planner in selecting robust plans.

4.3. Variables Representing Reinforcements

In this section we will describe how the FOPF algorithm can be used to obtain the reinforcement of a component - branch or generator - to reduce the exposure index to a target. This can be done by introducing in the formulation

variables ΔP_{gi} and ΔP_{bj} representing generator i and branch j expansions.
The initial DC-OPF study referred as the first step of the FOPF formulation will now be given by (7) to (11). In this formulation P_{gi} represents the generation of generator i and c_i is its incremental cost. L_{ci} represents the central value of load membership function connected to bus i and a_{ji} is the DC model sensitivity relating the branch j active flow to the bus i active injected power.

$$\min z = \sum c_i.P_{gi} \quad (7)$$
$$\text{subj.} \quad \sum P_{gi} = \sum L_{ci} \quad (8)$$
$$P_{gi} \leq P_{gimax} + \Delta P_{gi} \quad (9)$$
$$\sum a_{ji}.(P_{gi} - L_{ci}) \leq P_{jmax} + \Delta P_{bj} \quad (10)$$
$$\sum a_{ji}.(P_{gi} - L_{ci}) \geq P_{jmin} - \Delta P_{bj} \quad (11)$$

If this problem is unfeasible the exposure index is 1.0 meaning that there is at least one set of loads belonging to the 1.0-cut of their membership functions for which the expansion strategy is not effective.

Let us now consider that problem (7-11) is feasible. The next steps of the FOPF algorithm consist of integrating information about load uncertainty in the solution of this problem and identifying a set of vertices of the hypervolume enclosing all possible load combinations. Details leading to the multiparametric formulation and the rules to identify those vertices can be found in [5].

For each of the vertices in the selected set a parametric analysis starting with the solution of problem (7-11) should be conducted. For sake of clarity this process will be explained using a system supplying two loads represented by the trapezoidal fuzzy numbers (12) and (13). Figure 3 shows the rectangles corresponding to the 0.0 and 1.0 cut of their membership functions. These rectangles are built expressing (12) and (13) in terms of their central values (L_{c1} and L_{c2}) leading to (14) and (15).

$$L_1 = (L_{11}, L_{12}, L_{13}, L_{14}) \quad (12)$$
$$L_2 = (L_{21}, L_{22}, L_{23}, L_{24}) \quad (13)$$
$$L_1 = L_{c1} + (\Delta_{11}, \Delta_{12}, \Delta_{13}, \Delta_{14}) \quad (14)$$
$$L_2 = L_{c2} + (\Delta_{21}, \Delta 22, \Delta_{23}, \Delta_{24}) \quad (15)$$

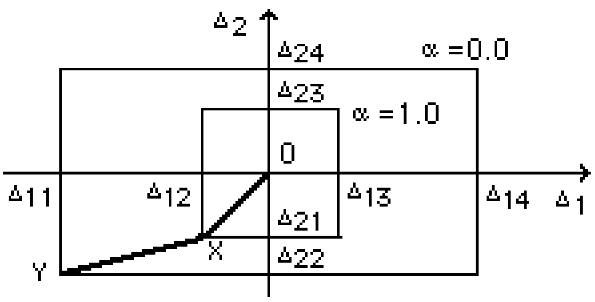


Fig. 3 - Rectangles corresponding to 0.0 and 1.0 cuts of the domain of possible load values for two loads.

If vertex Y was selected in the previous step one will have to solve two parametric problems. The first one to obtain dispatches for load sets in OX and the second one, departing from X, for the sets in XY till the target Iexp is reached. If a parameter ∂ varying in [0.0,1.0] is associated to this process one can solve the parametric problems:

- starting with the solution obtained for O from the initial deterministic DC-OPF study and setting ∂=1.0. Varying ∂ from 1.0 to 0.0 load sets in OX are analysed;
- after resetting ∂ to 1.0, the second study starts at the solution obtained for X. In these processes one may have to perform some iterations of the Dual Simplex method to regain feasibility of the optimal solution.

As an example to highlight the introduction of variables ΔP_{gi} and ΔP_{bj} let us consider the parametric problem related to XY. The power balance equation (8) and constraints (10) and (11) related to branch limits will have to be modified according to the following formulation:

$$\min z = \sum c_i.P_{gi} \quad (16)$$
$$\text{subj.} \quad \sum P_{gi} = \sum (L_{ci}+\Delta X_i+(1.0-\partial_i).(\Delta Y_i-\Delta X_i)) \quad (17)$$
$$P_{gi} \leq P_{gimax} + \Delta P_{gi} \quad (18)$$
$$\sum a_{ji}.(P_{gi} - L_{ci} - \Delta X_i) \leq P_{jmax} + \Delta P_{bj} + \sum a_{ji}.(1.0 - \partial_i).(\Delta Y_i - \Delta X_i) \quad (19)$$
$$\sum a_{ji}.(P_{gi} - L_{ci} - \Delta X_i) \geq P_{jmin} - \Delta P_{bj} + \sum a_{ji}.(1.0 - \partial_i).(\Delta Y_i - \Delta X_i) \quad (20)$$

The reinforcement values will be obtained after solving the initial DC-OPF followed, for each vertex, by the two parametric studies. The second parametric study has to be solved until ∂ gets inferior than the target exposure index. If all these parametric studies are feasible the reinforcements correspond to the maximum values assumed by ΔP_{gi} and ΔP_{bj} during this process.

As a final remark, it should be noticed that in this formulation there are no variables representing Power Not Supplied. In fact, we are checking if a reinforcement strategy is adequate to reduce the exposure index to a given target. This means that if that strategy is adequate, the PNS should be zero for all levels of uncertainty above the referred target. In terms of the parametric problems this means that for all vertices and without having to disconnect load:

- the first parametric problem should be feasible for ∂ in [0.0,1.0];
- the second problem should be feasible for ∂ in $[Iexp^{target},1.0]$.

If this is not satisfied for, at least, one vertex one concludes that at a level of uncertainty above the target the system still has bottlenecks that cannot be solved by the reinforcement of the components being tested.

4.4. Evaluation of the Goodness of an Expansion: Statistical Index

In order to check if the strategy k corresponding to the reinforcement of a branch or generation is effective from a statistical point of view, one can monitor the uncertainty $\beta_I{}^k$ coefficient related to an indicator function I(x). This function:

- takes the value 1.0 the exposure index of state x is

reduced to, at least, the target value;
- is 0.0 if the previous condition does not hold.

Let us consider that, after sampling N states, in N_c of them there are bottlenecks causing the exposure index to be higher than the target. Among these N_c states, let N_1 and N_0 be the total number of states for which I(x) takes values 1.0 and 0.0. The expected value of I(x) and its variance are given by (21) and (22).

$$E(I) = \frac{N_1}{Nc} \qquad (21)$$

$$V(I) = \frac{1}{N_c - 1} \cdot \sum_{i=1}^{N_c} (N_1.(1 - E(I))^2 + N_0.(E(I))^2) \qquad (22)$$

The $\beta_I{}^k$ coefficient can now be calculated by (23). Using this coefficient a reinforcement strategy is validated from a statistical point of view as soon as the calculated $\beta_I{}^k$ gets inferior than a specified threshold.

$$(\beta_I{}^k)^2 = \frac{V(I)}{N_c.(E(I))^2} \qquad (23)$$

5. CASE STUDY

5.1. System data

The described algorithm will be exemplified using the 24 bus, 38 branch, 32 generator network sketched on figure 4 based on the IEEE Reliability Test System - RTS (500 MVA was adopted as power base). The RTS original system is a generation dominated one meaning that deficiencies of the generation subsystem contribute in a decisive way to reliability indices. Therefore, G. C. Oliveira et al proposed in [9] some changes in the RTS data leading to the Modified RTS - MRTS - in order to balance the relative contributions of the generation and transmission subsystems deficiencies.

According to [9] the original generator limits were doubled and bus central load values were multiplied by 1.8 as presented in tables I and II. Using these central values trapezoidal fuzzy numbers were adopted to describe load uncertainties. The extreme values of the 0.0 and 1.0 cuts correspond to (0.9, 0.95, 1.05, 1.1) of the central value. In tables I and III one also presents the FOR values used for generators and branches.

Table I - Generator characteristics.

bus	Gen no.	Pg^{max} MW	Inc cost $/MWh	FOR	bus	Gen no.	Pg^{max} MW	Inc cost $/MWh	FOR
1	1	40.0	3.0	0.1	15	3	24.0	2.0	0.02
1	2	40.0	3.0	0.1	15	4	24.0	2.0	0.02
1	3	152.0	4.0	0.02	15	5	24.0	2.0	0.02
1	4	152.0	4.0	0.02	15		6310.0	6.0	0.04
2	1	40.0	3.0	0.1	16		1310.0	5.5	0.04
2	2	40.0	3.0	0.1	18		1800.0	9.0	0.12
2	3	152.0	4.0	0.02	21		1800.0	8.0	0.12
2	4	152.0	4.0	0.02	22		1100.0	2.0	0.01
7	1	200.0	5.0	0.04	22		2100.0	2.0	0.01
7	2	200.0	5.0	0.04	22		3100.0	2.0	0.01
7	2	200.0	5.0	0.04	22		4100.0	2.0	0.01
13	1	394.0	6.0	0.05	22		5100.0	2.0	0.01
13	2	394.0	6.0	0.05	22		6100.0	2.0	0.01
13	3	394.0	6.0	0.05	23		1310.0	5.0	0.04
15	1	24.0	2.0	0.02	23		2310.0	5.0	0.04
15	2	24.0	2.0	0.02	23		3700.0	7.0	0.08

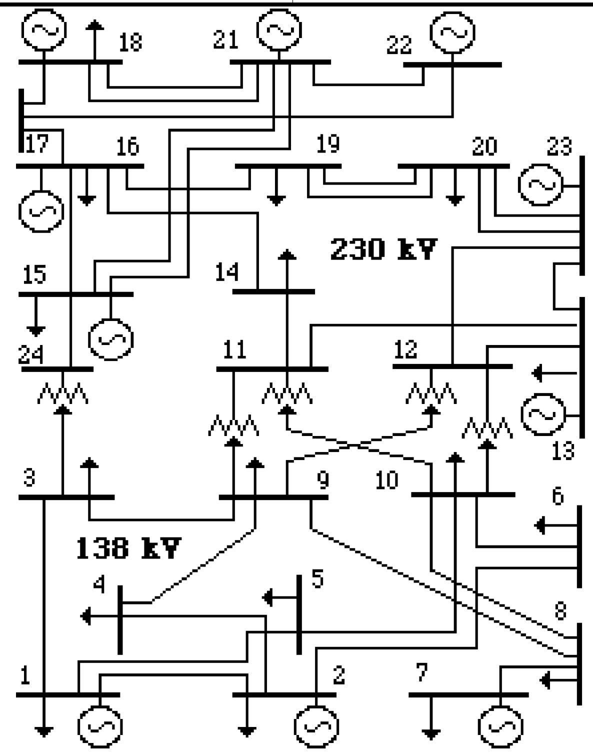


Fig. 4 - IEEE MRTS network.

Table II - Bus central load values.

bus	load (MW)	bus	load (MW)
1	194.4	13	477.0
2	174.6	14	349.2
3	324.0	15	570.6
4	133.8	16	180.0
5	127.8	17	0.0
6	244.8	18	599.4
7	225.0	19	325.8
8	307.8	20	230.4
9	315.0	21	0.0
10	351.0	22	0.0
11	0.0	23	0.0
12	0.0	24	0.0

Table III - Branch characteristics.

extreme buses	x (pu)	p^{max} MW	FOR	extreme buses	x (pu)	p^{max} MW	FOR
1	2.0139	175.00044		12	13.0476	500.00050	
1	3.2112	175.00059		12	23.0966	500.00065	
1	5.0845	175.00038		13	23.0865	500.00062	
2	4.1267	175.00045		14	16.0389	500.00048	
2	6.1920	175.00055		15	16.0073	500.00041	
3	9.1190	175.00043		15	21.0490	500.00052	
3	24.0839	400.00175		15	21.0490	500.00052	
4	9.1037	175.00041		15	24.0519	500.00052	
5	10.0883	175.00039		16	17.0259	500.00044	
6	10.0605	175.00132		16	19.0231	500.00043	
7	8.0614	175.00034		17	18.0144	500.00040	
8	9.1651	175.00050		17	22.1053	500.00068	
8	10.1651	175.00050		18	21.0259	500.00044	
9	11.0839	400.00175		18	21.0259	500.00044	

9	12.0839	400.00175	19	20.0396	500.00048
10	11.0839	400.00175	19	20.0396	500.00048
10	12.0839	400.00175	20	23.0216	500.00043
11	13.0476	500.00050	20	23.0216	500.00043
11	14.0418	500.00049	21	22.0678	500.00057

5.2. Basic Reliability Evaluation

In the first place we ran a Fuzzy Monte Carlo simulation using the data just presented in order to get insight about the overall behavior of the system. This simulation was performed specifying 10% for the β coefficient and using the control variable technique briefly described in 3.6.

This simulation is very efficient from a computational point of view. This is due to two key factors. In the first place, convergence is reached after analysing only 721 system states. Secondly, our experience indicates that each FOPF run just takes, in average, a surplus of 40% computational time when compared with the initial DC-OPF study inherent to each FOPF run. This seems quite a low price considering the amount of information obtained if compared to one modeling loads by crisp numbers.

In figure 5 one presents the E(PNS) membership function. This simulation also indicates that the expected exposure and robustness indices are 0.303 and 0.697.

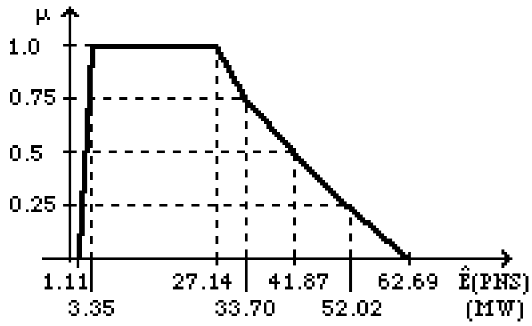


Fig. 5 - Membership function of the expected PNS.

5.3. Building a List of Credible Reinforcements

After performing the Monte Carlo simulation referred in 5.2, a list of candidate components was specified in order to evaluate their ability to reduce risk. This list includes:

- branches 2-6, 3-24, 6-10, 7-8, 9-11, 9-12, 10-11, 10-12, 12-13 and 14-16;
- generators 1/4 (generator 4 in bus 1), 2/4, 7/3, 13/3, 15/6, 16/1, 18/1, 21/1, 22/6 and 23/3. This corresponds to evaluate the effectiveness of expanding the generation capacity of all buses already having generators.

For each component of this list the simulation gives:

- the number N_1 of states for which a reinforcement of a suitable value is able to reduce the exposure index to a target value;
- the number N_0 of states for which, no matter the reinforcement, the target value will not be reached;
- the maximum value of the reinforcement among all the N_1 previously referred states;
- the expected exposure index if that component is reinforced by this maximum value;
- the uncertainty $\beta_I{}^k$ coefficient of the indicator function evaluated as described in 4.4.

The simulation was performed using an exposure target index of 0.0. In table IV are listed the results obtained after analysing 1000 states for the 20 expansion plans.

Table IV - Results for the 20 specified expansion plans.

strategy number	branch or line	N_1	N_0	Max. reinf. (MW)	Iexp	$\beta_I{}^k$
1	2/4	220	133	725.0	0.102	0.041
2	1/4	211	141	725.0	0.106	0.044
3	23/3	168	195	1190.0	0.154	0.057
4	13/3	111	204	725.0	0.159	0.076
5	14-16	124	246	225.0	0.208	0.073
6	7-8	105	271	190.0	0.217	0.083
7	6-10	88	293	45.0	0.231	0.094
8	21/1	14	299	1165.0	0.229	0.261
9	18/1	11	296	655.0	0.237	0.296
10	15/6	26	333	945.0	0.241	0.189
11	16/1	28	334	720.0	0.249	0.182
12	7/3	5	360	720.0	0.276	0.444
13	22/6	8	368	125.0	0.293	0.372
14	10-12	3	378	105.0	0.302	0.575
15	12-13	3	376	25.0	0.302	0.575
16	2-6	0	381	------	0.303	------
17	3-24	0	378	------	0.303	------
18	9-11	0	380	------	0.303	------
19	9-12	0	380	------	0.303	------
20	10-11	0	380	------	0.303	------

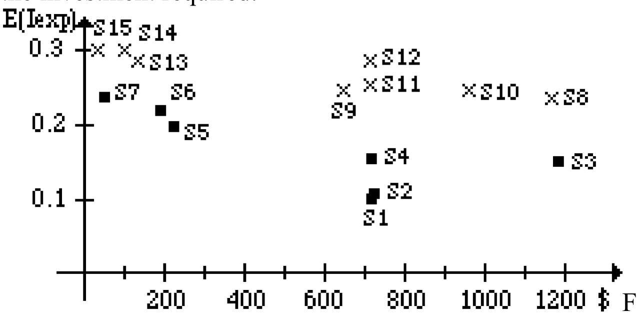
These results indicate that the first seven plans have a $\beta_I{}^k$ coefficient less than 10%. Among these, the expansion of the generation capacity of buses 1 and 2 are clearly the most adequate to reduce the expected exposure index. It should also be noticed that among the listed strategies the last five ones are of no interest to reduce that index. In fact, they are not able to reduce the exposure index in a single system state. Strategies 12 to 15 also show little ability to reduce the referred index.

As a final remark one should notice that the number of states given by N_1+N_0 varies when the results obtained for these twenty plans are analysed. This is explained considering that one is modeling components reliability by using different FOR values. According to tables I and III, one can see that the FOR for generators is quite larger than for lines. This leads to a more significative number of generator outages. Therefore, the number of states given by N_1+N_0 is, in general, smaller for generators than for lines. In fact, in a large number of states a generator whose reinforcement in under test is itself out of service. Therefore, those states are not computed neither in N_1 nor in N_0.

5.4. Trade-off Analysis

The results presented in table IV can finally be used together with information about costs of reinforcing the capacity of generators and branches to perform a trade-off analysis. Each reinforcement strategy can then be characterized by two values: the expected exposure index and the investment associated to that reinforcement.

The reinforcement strategies can be represented in the plan (Iexp, Investments) so that one can identify and eliminate the dominated ones. Among the strategies in the non-dominated set, the planner can finally select one according to the risk he is prepared to accept and taking into account the investment required.



ig. 6 - Trade off analysis of the reinforcement strategies:

• - strategies with β_I^k lower than 10%.

x - strategies with β_I^k higher than 10%.

In figure 6 one represents the first 15 reinforcement strategies listed in table IV. For didactic purposes, the investment required for a strategy was estimated assuming $1.0/MW both for branches and for generators. As a result one can clearly conclude that, among the strategies having β_I^k lower than 10%, S2, S3 and S4 are dominated ones.Therefore, the planner should choose a reinforcement strategy among the set integrating S1, S5, S6 and S7.

5.5. Reliability results for two reinforcement strategies

As a final step the Fuzzy Monte Carlo was run assuming that the capacity of branch 14-16 and generator 2/4 were reinforced to 725.0 and 875.0 MW. In figures 7 and 8 the E(PNS) functions are presented. As expected, the range of uncertainty of these functions is reduced if compared to the one of figure 5. As an example, the maximum value of the 0.0 cut is reduced by 16.6% and by 59.1% for branch 14-16 and for generator 2/4 expansion.

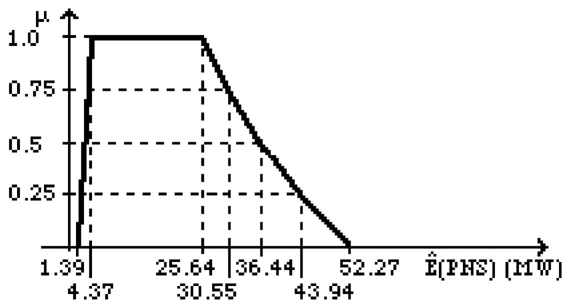


Fig. 7 - E(PNS) for branch 14-16 expansion.

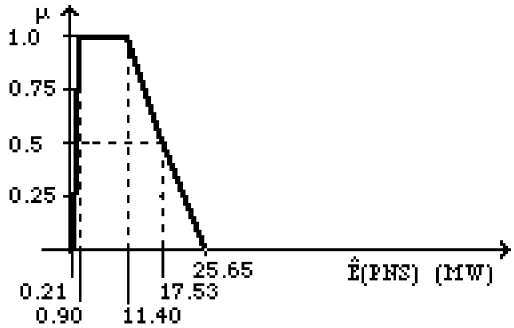


Fig. 8 - E(PNS) for generator 2/4 expansion.

6. CONCLUSIONS

This paper presents a model to evaluate the goodness of composite power systems expansion plans in terms of reducing the risk regarding the uncertainties in loads and in the behavior of components. Therefore, the planner has a tool to define a hedging policy indicating which investments are more effective and which ones have virtually no or little impact in accommodating more load uncertainty. This information will certainly be important in terms of a planning process where the user wants to adequately represent the uncertainties affecting the future.

It is important to notice that uncertainties are modeled using two different frameworks. Regarding long term planning, loads are more adequately modeled using fuzzy set theory while the component reliability is represented using probabilistic concepts. This seems more adequate not only from a conceptual point of view but also regarding the available data for loads and components.

The final result is a set of non-dominated reinforcement plans, describing a trade-off compromise between investments and the exposure of system design to data uncertainties. In this respect, this work shows how fuzzy sets help in establishing a bridge between system analysis and decision making.

7. REFERENCES

1) L. A. Zadeh, "Fuzzy Sets", Information and Control, pp. 338- 353, August 1965.
2) A. Kaufmann, M.M. Gupta, Fuzzy Mathematical Models in Engineering and Management Science, North Holland, Amersterdam, 1988.
3) V. Miranda, M. A. Matos, J. T. Saraiva, "Fuzzy Load Flow - New Algorithms Incorporating Uncertain Generation and Load Representation", 10th PSCC, Graz, August 1990; in Proceedings of the 10th PSCC, Butterworths, pp. 621-627, London, 1990.
4) V. Miranda, J. T. Saraiva, "Fuzzy Modelling of Power System Optimal Load Flow", IEEE Trans. on Power Systems vol. 7, no. 2, pp. 843-849, May 1992; also in Proceedings PICA'91, Baltimore, USA, May 1991.
5) J. T. Saraiva, V. Miranda, L.M.V.G. Pinto,"Impact on Some Planning Decisions From a Fuzzy Modeling of Power Systems", IEEE Trans. on Power Systems, vol. 9, no. 2, pp. 819-825, May 1994; also in Proceedings of PICA'93, Phoenix, USA, May 1993.
6) N. Balu, M.V.F. Pereira, "Composite Generation/

Transmission Reliability Evaluation Methods", IEEE Proceedings, vol. 80, no. 4, pp. 470-491, April 1992.
7) J. T. Saraiva, V. Miranda, L. M. V. G. Pinto, "Generation/Transmission Power System Reliability Evaluation by Monte Carlo Simulation Assuming a Fuzzy Load Description", presented in PICA´95, Salt Lake City, USA, May 1995, pp. 554-559; to be published in IEEE Trans. on Power Systems.
8) M.V.F. Pereira, L.M.V.G. Pinto, "A New Computational Tool for Composite Reliability Evaluation", IEEE Trans. on Power Systems, Vol. 7, no. 1, pp. 258-264, February 92.
9) G.C. Oliveira, M.V.F. Pereira, S.H. Cunha, "A Technique for Reducing Computational Effort in Monte Carlo Based Composite Reliability Evaluation", IEEE Trans. on Power Systems, Vol. 4, no. 4, pp. 1309-1315, October 1989.