RELIABILITY EVALUATION OF GENERATION / TRANSMISSION POWER SYSTEMS INCLUDING FUZZY DATA

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Abstract - This paper presents an approach to reliability evaluation of generation/transmission power systems using the Monte Carlo simulation method. In this approach uncertainties are represented using two different frameworks. For one side, probability concepts are used to represent the failure-repair cycle of system components. Loads are represented through classified load diagrams in which each time step corresponds to a fuzzy number. This simulation method allows the user to obtain estimates of the expected exposure and robustness indices and of the Power Not Supplied membership function.

1. INTRODUCTION

Power system reliability has long been considered an important issue in planning studies recognizing that the evaluation of service quality if, for instance, several generator or transmission outages occur, plays an important role. This kind of studies is also important in identifying system components to reinforce so that the system ability to meet the demand is increased. When performing this type of studies the planner recognizes that system components have a non ideal behavior and usually represents this knowledge using probabilistic concepts considering that a large amount of data concerning the behavior of components is available, and the rules governing their life cycle are not likely to change in the future.

In this paper the long term power system planning is addressed. When dealing with this kind of horizon the planner may face several challenges. In fact, as the planning horizon moves away, the probabilistic models may no longer be the most well suited to represent data namely if several unexpected and quite often unique events happen. Fuzzy Set Theory [1, 2] has been successfully used to represent information having a vague nature, to model uncertainty related to the subjectivity inherent to human evaluations or due to incomplete or insufficient data.

This framework was already applied to several issues of power systems modeling as described in the review papers [3, 4]. In [5] a fuzzy AC power flow model is presented to provide membership functions for voltages, power flows, losses,...,. In [6], the integration of an economic criterion leading to a DC - Fuzzy Optimal Power Flow - FOPF - model is described. Afterwards, a first version of a Monte Carlo simulation algorithm where loads are defined by fuzzy numbers was developed and some results were already reported in [7]. This algorithm evaluates fuzzy reliability indices by randomly sampling system component outages. As peak load values are represented by fuzzy numbers, load values are not sampled. Instead, a FOPF is run for each sampled state.

However, the availability of the system depends not only on what happens at peak hours but, in fact, along a full load diagram. Therefore, to get more realistic estimates, in this paper loads are modeled by classified load diagrams in which each time step is represented by a fuzzy number.

The proposed algorithm will be exemplified with results obtained from a case study using the IEEE 24 bus Reliability Test System. They will illustrate possible applications of this model and innovative interpretations of some results.

2. BASICS ABOUT FUZZY SET THEORY

A fuzzy set $\tilde{A}$ (1) is characterized by a membership function $\mu_{\tilde{A}}(x)$ relating each element x_1 to its compatibility or membership degree to the set X_1. An α-cut of a fuzzy set $\tilde{A}$ defined in X_1 is the hard set A_α obtained from $\tilde{A}$ for each $\alpha \in [0,1]$ so that (2) holds.

$$\tilde{A} = \{(x_1, \mu_{\tilde{A}}(x_1)),\ x_1 \in X_1\} \quad (1)$$

$$A_\alpha = \{x_1 \in X_1 : \mu_{\tilde{A}}(x_1) \geq \alpha\} \quad (2)$$

The usual set operations can be readily extended to fuzzy sets using the Extension Principle formulated by Zadeh. Given the fuzzy set $\tilde{O}$, the union $\tilde{A} \cup \tilde{O}$ is given by (4) and (5).

$$\tilde{O} = \{(y_1, \mu_{\tilde{O}}(y_1)),\ y_1 \in X_1\} \quad (3)$$

$$\tilde{A} \cup \tilde{O} = \{(x_1, \mu_{\tilde{A}\cup\tilde{O}}(x_1)),\ x_1 \in X_1\} \quad (4)$$

$$\mu_{\tilde{A}\cup\tilde{O}}(x_1) = \max\{\mu_{\tilde{A}}(x_1), \mu_{\tilde{O}}(x_1)\} \quad (5)$$

A fuzzy set $\tilde{A}$ is a fuzzy number if it is a convex fuzzy set of the real line R such that its membership function is normalized and piece wise continuous. A particular fuzzy number, the trapezoidal one, is sketched in figure 1 and may be represented by (6). This fuzzy number can be considered to express the uncertainty around the interval $[a_2, a_3]$. The central value of a fuzzy number is the mean value of the 1.0-cut. Considering (6), its mean value is (a2+a3)/2.

$$\tilde{A} = (a_1; a_2; a_3; a_4) \quad (6)$$

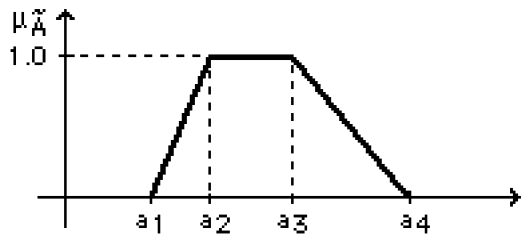

Fig. 1. Trapezoidal fuzzy number.

3. FUZZY LOAD MODELING

A trapezoidal fuzzy load can be specified declaring an interval [a_2, a_3] of values being good representations of the load. Besides, values a_1 and a_4, under and above which the load is assumed not to occur, are also specified. This leads to a trapezoidal fuzzy number as the one sketched in figure 1. Having this in mind, the planner can characterize a load by a set of fuzzy numbers organized in terms of a load diagram. This diagram indicates in the horizontal axis the time period in which each trapezoidal load occurs. It can be rearranged to obtain a fuzzy classified diagram. A classified diagram is obtained from the previous one evaluating the period of time on which the load is larger or equal to a given value.

Let us consider, as an example, the classified load diagram sketched in figure 2 in which each time step is modeled by a trapezoidal fuzzy number. According to this representation in the whole studied period - 100% - the load is not inferior to the fuzzy number L_1. In 20% of the period the load is not inferior to L_3. These percentages can also be interpreted as probabilities for which each particular fuzzy load occurs.

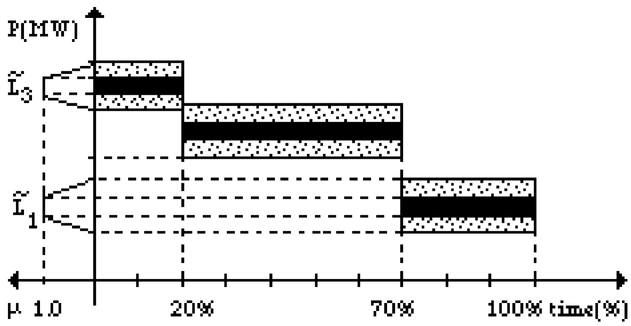

Fig. 2 - Example of fuzzy classified load diagram.

4. FUZZY DC OPTIMAL POWER FLOW MODEL

Briefly, an Optimal Power Flow - OPF - problem is an optimization procedure aiming at identifying the best generation policy for a power system given the loads to supply, the available generators and their generation costs and the model representing the transmission system.

A Fuzzy Optimal Power Flow - FOPF - problem is an extension of a crisp OPF considering that at least one load is represented by a fuzzy set or, in particular, by a fuzzy number. The model described in [6] adopts a DC formulation to represent the operation conditions of the system and includes the active power balance equation and generation and branch power flow limit constraints.

The FOPF algorithm presented in [6] has a number of steps that will now be summarized:

- it starts by a DC crisp OPF to identify an optimal and feasible solution for the central values of the specified load membership functions. The generator cost functions should be adequately linearized namely for those having non linear convex cost functions;
- load uncertainties modeled by fuzzy numbers are integrated by associating a parameter to the 0.0-cut of each load membership function. Therefore, one obtains a multiparametric formulation for which an approximated solution strategy is described in [6];
- this strategy includes the identification of a number of vertices of the hypervolume enclosing all possible load combinations considering a set of rules described in [6];
- for each of these vertices, one performs two successive parametric studies to derive partial membership functions for generators and branch flows. It is also obtained a partial Power Not Supplied - PNS - membership function related to the set of load scenarios for which the generation and transmission subsystems are unable to supply all the specified loads;
- the partial membership functions for each generation, branch flow and PNS are aggregated using the fuzzy union modeled by the maximum operator [1, 2].

5. ROBUSTNESS AND EXPOSURE INDICES

Considering risk analysis concepts, a plan related to a configuration of a power system is fully robust if the planner selects it no matter the values that variables or parameters affected by uncertainty will assume in the future. However, in real life, robust plans are hardly found and so planners have to admit a degree of risk corresponding to an unfavorable future. In attempting to quantify risk, robustness and exposure indices can be used to measure it.

In the power system environment, a non zero PNS membership function corresponds to a risky situation as the system would not have a chance to cope with uncertainty unless some load is disconnected. Considering the PNS function depicted in figure 3, one can say that the system is 1.0-α_1 robust and α_1 exposed. In fact, for uncertainty levels between 1.0 and α_1, PNS is zero and so the system is robust. For levels lower than α_1, a non zero PNS value would be obtained. A fully robust system would then have a robustness index of 1.0, meaning that it is adequate no matter what future implied in the specified uncertainties occurs.

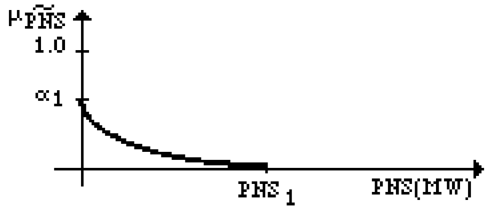

Fig. 3 - PNS membership function.

6. RELIABILITY EVALUATION BY FUZZY MONTE CARLO - FMC - SIMULATION

6.1. General description

Monte Carlo simulation is oftenly used to evaluate reliability indices of large composite generation/transmission systems [8]. In general, this algorithm randomly samples a set of system states by considering the failure-repair cycle of components. In the proposed model, for each sample state a FOPF is run instead of a crisp OPF as loads are represented by fuzzy numbers. The main drawback of this algorithm is the computational time. In

[9] several techniques to improve the convergence of the simulation are described.

6.2. Monte Carlo sampling and analysis of sampled states

System states are sampled by generating pseudo random numbers so that, depending on generator and branch forced outage rates, component outages are identified, under a non chronological strategy. For each state another pseudo random number is obtained to select the time step of the classified load diagram to use. Within a time step, no load values are sampled as uncertainty is taken in account by fuzzy numbers.

Each sampled state is analysed through the FOPF model referred in section 4. Regarding the level of efficiency of the Fuzzy Monte Carlo simulation it should be said that, according our experience, it remains at the same level as the classical one for crisp loads while giving more valuable information. This happens because, in average, each FOPF run is only 1.4 longer than a crisp OPF run.

6.4. Reliability indices evaluation

Let us consider that, for each sampled state x_i, a FOFP is run and that PNS(x_i), Irob(x_i) and Iexp(x_i) are the fuzzy PNS value and the robustness and exposure indices. The expected robustness and exposure indices and the expected membership PNS function are given by (7) to (9).

$$E(\mathrm{Irob}) = \frac{1}{N}.\sum_{i=1}^{N}\mathrm{Irob}(x_i) \quad (7)$$

$$E(\mathrm{I\,exp}) = \frac{1}{N}.\sum_{i=1}^{N}\mathrm{I\,exp}(x_i) \quad (8)$$

$$E(\mathrm{PNS}) = \frac{1}{N}.\sum_{i=1}^{N}\mathrm{PNS}(x_i) \quad (9)$$

The convergence of a Monte Carlo simulation [8, 9] is generally addressed by monitoring an uncertainty coefficient given by (10). E(PNS) represents the current estimate of expected PNS value and V(PNS), approximated by (11), is the corresponding variance. Convergence is reached if the β calculated value becomes not superior to a specified target. In a FMC approach, this criterium can still be applied if one considers, for each sampled state, the PNS crisp value obtained by the initial crisp OPF study referred in section 4.

$$\beta^2 = V(\mathrm{PNS}) / (N.E(\mathrm{PNS})^2) \quad (10)$$

$$V(\mathrm{PNS}) = \frac{1}{N-1}.\sum_{i=1}^{N}(\mathrm{PNS}(x_i) - E(\mathrm{PNS}))^2 \quad (11)$$

The convergence acceleration problem was addressed in [7]. This reference describes the use of the antithetic and the control variable techniques to the FMC. In this scope, several tested cases revealed that the control variable technique is very efficient as the computational time can be reduced up to 25% of the time if no acceleration techniques are used.

7. CASE STUDY

7.1. System data

The FMC approach will be illustrated using the MRTS 24 bus, 38 branch, 32 generator network described in [6]. This network is based on the IEEE Reliability Test System - RTS for which further details can be obtained in [7] and [10].

The classified system total load diagram was discretized in three time steps:

- in the first one, corresponding to 20% of the period, the central value of the load is 110% of the total MRTS load;
- in the second, corresponding to 50% of the period, the central value of load is equal to the total MRTS load;
- in the third, corresponding to 30% of the period, the central value of the load is 85% of the total MRTS load;

Using the load values specified for the MRTS system, trapezoidal fuzzy numbers were adopted to build three sets of load membership functions, one for each time step. The extreme values of 0.0 and 1.0 cuts correspond to (0.9, 0.95, 1.05, 1.1) of the respective central values.

7.2. Fuzzy Monte Carlo results

A Monte Carlo simulation was run to evaluate system reliability considering the classified load diagram defined in 7.1 and using a 10% target for β. Tables 1 and 2 and figure 4 display results obtained using the FOPF algorithm for some sampled system states. These tables include results for a state with all generators and branches in service and using the membership functions corresponding to the intermediate load level. In columns a1 and a4 are the extreme values of the 0.0-cut while a2 and a3 stand for the 1.0-cut of membership functions. Figure 4 shows the PNS membership function if branch 3-24 is out of service.

In these cases the Robustness and Exposure indices assume:

- values 1.0 and 0.0 if all components are in service. In this case the generator/transmission system has capacity to accommodate load uncertainties without load curtailment;
- values 0.0 and 1.0 if branch 3-24 is out of service. In this case, for each $\alpha \in [0,1]$ there is at least one load scenario included in the specified uncertainty for which a crisp OPF run would give a non-zero PNS value;

Table 1 - Generator membership functions (MW).

bus	Gen. no.	a1	a2	a3	a4
7	1	0.0	0.0	11.25	22.50
7	2	177.50	188.75	200.00	200.00
7	3	200.00	200.00	200.00	200.00
13	1	281.92	323.42	394.00	394.00
18	1	0.0	0.0	0.0	0.0
21	1	0.0	149.81	375.88	612.16
23	1	310.00	310.00	310.00	310.00
23	3	330.04	575.32	700.00	700.00

Table 2 - Branch power flow membership function (MW).

buses		a1	a2	a3	a4
1	2	-42.59	-26.09	7.88	25.24
1	5	103.20	116.49	143.06	156.91
2	6	82.19	92.74	113.84	124.77
5	10	-26.86	-12.44	16.40	31.42
8	10	-69.29	-63.33	-51.41	-45.00

12	23	-342.80	-317.04	-247.80	-191.32
13	23	-197.04	-172.22	-97.13	-36.82
20	23	-477.48	-463.16	-415.36	-360.94

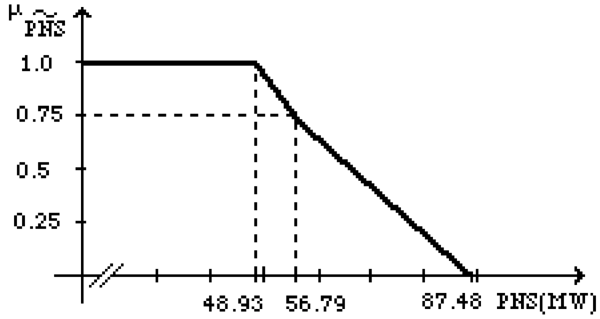

Fig. 4 - PNS if branch 3-24 is out of service.

In figure 5, one presents the calculated E(PNS) membership functions obtained for the trapezoidal fuzzy numbers corresponding to the intermediate load level. The expected values for Exposure and Robustness indices are 0.288 and 0.711, in this case. This E(PNS) membership function can be interpreted as reflecting, for each α-cut, the corresponding load uncertainties. Considering this E(PNS) function, one can see that as load uncertainty grows for lower α-cuts, the amplitude of the related E(PNS) α-cut also grows.

In figure 6, one presents the calculated E(PNS) considering loads defined according to the classified load diagram characterized in 7.1. In this case, the expected values for Exposure and Robustness indices are 0.346 and 0.654. These results indicate that the uncertainty of the expected PNS values is larger if one uses the classified diagram when compared with the one related to figure 5. This happens because the Monte Carlo simulation samples system states for which fuzzy load values corresponding to the higher load level - 110% of central value regarding the MRTS ones - can occur. FOPF runs for this higher load level indicate that PNS values are higher than if the intermediate or the lower load

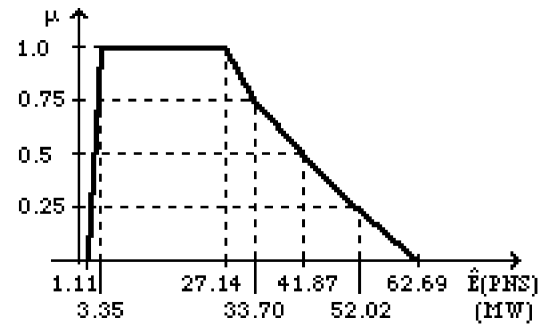

Fig. 5 - E(PNS) function for the intermediate load level.

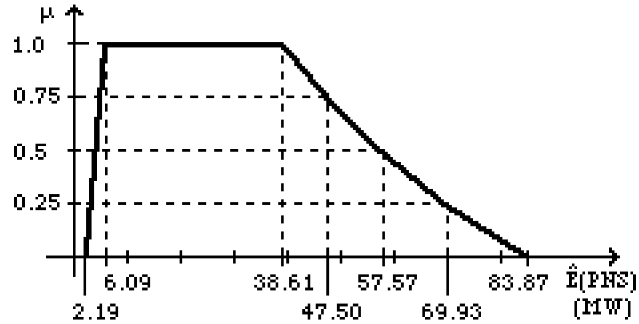

Fig. 6 - E(PNS) function for the classified load diagram.

level are considered. The aggregation of PNS membership functions related to these three levels gives higher PNS values than the ones obtained for the intermediate level. Similarly, E(Iexp) is higher and E(Irob) is lower if the classified load diagram is considered.

8. CONCLUSIONS

In this paper an enhanced fuzzy model to perform reliability evaluations of large power systems was presented. The model integrates two sets of uncertainties modeled by two different theoretical frameworks. Probability models are used to represent the failure/repair cycle of components and the uncertainty associated to load levels along a whole studied period. Within each time step used to discretize that period, fuzzy numbers are used to model load uncertainty. This is an innovative and important feature revealing that fuzzy models are not conceived to replace probabilistic ones. Rather, fuzzy models or probabilistic ones should be used when they are adequate from a conceptual point of view. Finally, this kind of models can be most valuable for planning activities in attempting to identify expansion strategies to minimize the risk the planner will have to handle.

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