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Artificial Neural Networks Applied to Reliability and Well-being Assessment of Composite Power Systems

by

A.M. Leite de Silva, L.C. Resende, L.A.F. Manso and V. Miranda

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Artificial Neural Networks Applied to Reliability and Well-Being Assessment of Composite Power Systems

Armando M. Leite da Silva, *Fellow*, *IEEE*, Leonidas C. de Resende, Luiz A. da Fonseca Manso, and V. Miranda, *Fellow*, *IEEE*

***Abstract*—This paper presents a new methodology for assessing both reliability and well-being indices for composite generation and transmission systems. Firstly, a transmission network reduction is applied to find an equivalent for assessing composite reliability for practical large power systems. After that, in order to classify the operating states, Artificial Neural Networks (ANNs) based on Group Method Data Handling (GMDH) techniques are used to capture the patterns of the operating states, during the beginning of the non-sequential Monte Carlo simulation (MCS). The idea is to provide the simulation process with an intelligent memory, based only on polynomial parameters, to speed up the evaluation of the operating states. For the conventional reliability assessment, the ANNs are used to classify the operating states into success and failure. However, for the well-being analysis, only success states are classified into healthy and marginal by the ANNs. The proposed methodology is applied to the IEEE Reliability Test System 1996 and to a configuration of the Brazilian South-Southeastern System.**

***Index Terms*—Artificial neural networks, composite reliability, group method data handling, Monte Carlo simulation, pattern analysis, well-being analysis.**

I. Introduction

THE reliability assessment of composite power systems may be divided into two frameworks: conventional and well-being analysis. The so called conventional reliability restricts its analysis to failure states, presenting results in terms of loss of load indices. These indices associate probability, energy, frequency, duration and cost with system failures [1]-[5]. In limiting its analysis to failure states, the conventional reliability is not able to estimate how far from the "success/failure" border the system operates, endangering the perception of possible weaknesses.

An analysis dedicated to success states is possible through the preventive reliability or well-being analysis [6]-[9]. The conceptual basis for the evaluation of the well-being indices consists in splitting the operative states of the system into three groups: healthy, marginal and at risk (or failure). For the identification of these states, the system is submitted to a deterministic criterion, usually, based on a pre-specified list of contingencies [8], [9]. The division of the states used for the preventive reliability (well-being analysis) allows the previous identification of the regions under critical operation, supplying important data for the definition of safer operative procedures.

For large power systems, the reliability evaluation methods, both conventional and well-being, based on MCS, are more attractive than state enumeration methods [4], [5], [7], [9]. Among the simulation methods, three options have been considered: non-sequential, sequential, and pseudo-chronological. A detailed description of these methods may be found in [1]-[5], [7], [9]. The use of *non-aggregate Markov load models* [5] and of techniques such as the *one-step forward state transition* [9] provided the non-sequential MCS a greater capacity to represent chronological aspects, increasing the precision of the estimated indices. With these new characteristics, joined with its greater computational efficiency, the non-sequential simulation emerges as the most indicated choice, when one wishes to evaluate large composite generation and transmission systems. However, with the continuous interconnection of power networks, the evaluation tools, including those related with composite reliability assessment will have to deal with ever larger power systems.

This paper presents an integrated approach for assessing the conventional and preventive reliability indices of large power networks. Firstly, the system network is divided into areas. These areas are defined bearing in mind: the reductions that will be applied to the representation of the network; the equipment that will have stochastic representation; and the load points in which the reliability indices will be evaluated. Then, based on the load model and in the one-step forward transition process, described in [9], the non-sequential MCS is used along with ANNs, based on the GMDH algorithm [10]. For such, a pre-classification of the operating states is performed through this ANN type, where the states analyzed during the beginning of the simulation process are selected as input data for training and test sets. With this procedure, a great number of states are classified by a simple polynomial evaluation, providing significant reductions in the computational time and cost required. The main reason for choosing the GMDH is that, whenever the classes associated with the training samples are available, models based on supervised learning provide better performance when faced with new cases than others that use unsupervised learning. Also, the ANNs based on GMDH algorithm usually leads to simpler architectures and faster training processes than it would be obtained with others approaches [11], [12]. The proposed methodology is applied to the IEEE Reliability Test System 1996 (IEEE-RTS 96) [13] and to a configuration of the Brazilian South-Southeastern System.

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A.M. Leite da Silva and L.C Resende are with the Institute of Electric System and Energy, Federal University of Itajubá – UNIFEI, Brazil.

L.A.F. Manso is with the Electrical Eng. Department, Federal University of São João del-Rei – UFSJ, Brazil.

V. Miranda is with the Institute for Systems and Computer Engineering of Porto – INESC Porto, and with the Faculty of Engineering of the University of Porto – FEUP, Portugal.

II. Composite Reliability

A. Conventional Analysis

The estimates of conventional composite reliability indices are obtained through non-sequential MCS following three major steps [2]:

a) Select a system state (i.e. load level, equipment availability, etc.);
b) Analyze the performance of the selected states (i.e. check if available generating units and circuits are able to satisfy the associated load without violating any operating limits; if necessary, activate corrective measures such as generation redispatch, load curtailment, etc.);
c) Estimate reliability indices (i.e. loss of load indices, etc.); if the accuracy of the estimates is acceptable, stop; otherwise go back to step (a).

Loss of load indices can be estimated by non-sequential simulation techniques, as the mean over N sampled system state values x^k of the test function $F(x^k)$, i.e. [4], [5]:

$$\widetilde{E}[F] = 1/N \sum_{k=1}^{N} F(x^k) \tag{1}$$

All the basic reliability indices can be estimated by the previous equation, depending on the definition of the test function F. The estimate uncertainty is given by the variance of the estimator, and this uncertainty is usually represented as the *coefficient of variation* β [2], [4], [5].

The major portion of the computational effort required by the composite reliability algorithm is concentrated on step (b). The objective is to identify if the system, in the sampled state, is capable of meeting the demand without violating its operating limits, from the static point of view. This requires the solution of a power flow algorithm followed by the monitoring of some system variables. If this analysis identifies operating violations or a potential load curtailment, a large-scale optimization problem must be solved in order to avoid or, at least, minimize the necessary load shedding.

Observe that patterns for success states are more easily achieved, due to general system characteristics related with adequate generation and transmission reserve capacities. Conversely, failure states are related with rare events emerging from specific system operation conditions due to, for instance, local transmission constraints. Therefore, it would be necessary to build specific ANNs in order to measure, in terms of reliability indices, all consequences of these failures. Unfortunately, the computational benefits of avoiding several optimization evaluations would be vanished by the computational effort of building several ANNs.

B. Well-Being Analysis

The probability (P), frequency (F), and duration (D) associated with the healthy (H), marginal (M), and (at risk) R states are useful measures for composite systems. The P{R}, F{R}, and D{R} are, respectively, the traditional LOLP (Loss of Load Probability), LOLF (Loss of Load Frequency), and LOLD (Loss of Load Duration) indices. Well-being analysis for composite systems is, therefore, a natural extension of composite reliability analysis that allows the qualification of the deterministic criterion on a probabilistic basis. The marginal states must be appropriately signaled to provide system operators with sufficient time to correct the power system operating trajectory in order to avoid load shedding.

The system state, sampled by a non-sequential MCS process, i.e. step (a) of the conventional analysis, is defined from the equipment availabilities and system load level. The well-being composite system indices are evaluated based on specific test functions described in [9]. These functions utilize a process, designated as the one-step forward state transition, which is able to capture unbiased estimates for frequencies and durations. As described in [9], a non-sequential MCS is used in order to make the well-being framework accessible for real (i.e. large) composite power systems. Observe that after running an adequacy analysis for the sampled state, and checking that no operation constraints are violated, to distinguish if this state is healthy or marginal, there will be up to n_l (size of the contingency list) additional analyses. If at least one element in the list moves the system into failure, then the sampled state is marginal.

In a traditional composite reliability evaluation, for each sampled state, only one adequacy analysis is necessary to classify the states (i.e. success and failure). In a well-being framework, up to (n_l + 1) adequacy analyses can be required to classify the success states (i.e. healthy and marginal). Moreover, if frequency and duration indices are assessed, more evaluations will be necessary to capture these values. In conclusion, the evaluation of the well-being framework for real composite systems is very time consuming and may not be achievable, unless some intelligent state adequacy network assessment is considered.

In the next section, it will be shown a methodology which uses a polynomial network (i.e. GMDH) for a faster evaluation of system operating states. Such methodology will be applied to the composite reliability algorithm to reduce the computational effort spent in step (b) (conventional reliability) and in the deterministic criterion application (well-being analysis). In conventional reliability, the aim is to obtain a pattern only for the success states, since the failure or at risk states will be fully analyzed to determine all consequences of load curtailments. This procedure will ensure the assessment of all reliability indices at all levels, i.e. system/area/buses. However, in the well-being analysis, the objective is to classify the success states as healthy or marginal. Therefore, after the identification of a success state, it is submitted to the deterministic criterion through ANNs evaluations.

III. Proposed Methodology

A. Network Reduction

In order to solve large composite systems, the original network is divided into areas based on a Ward equivalent [14], and suitable optimization processes are applied. These areas are:

- *Equipment Outage or Contingency Area* – involves a full representation of random behavior of transmission and generation elements;
- *Optimization Area* – involves representation of all its elements for load flow and remedial action analysis. The elements in this network that do not belong to the Contingency Area are not allowed to fail, but generators may be redispatched and loads can be curtailed, if necessary;
- *External Area* – includes an equivalent representation of the remaining components outside the Optimization Area. The network reduction is carried out through the Ward equivalent [14].

The representation of the sub-networks/areas is schematically illustrated in Fig. 1. In principle, reliability and well-being indices can be calculated for the *Optimization Area* and for its corresponding sub-areas and buses. However, in order to increase the accuracy of the algorithm, it is advisable to define an *Interest Area* located within *the Equipment Outage Area*. This new area corresponds to the part of the system, whose performance indices will have more relevance in the decision-making processes. Bearing in mind both computational effort and the accuracy associated with the reliability and well-being indices, a complete description of the way these areas are defined and the effects of the size and characteristics of the system were investigated in [15].

To obtain the External Area, the remaining network outside the Optimization Area is reduced through the Ward equations. The equivalent generation and loads, located at the boundary buses, are obtained from the application of the corresponding Ward equations to the Base Case load flow, supplied by the user. However, to reproduce the External Area reactions due to forced and planned contingencies from the Contingency Area, it is necessary to obtain the maximum quantity of active power that can be generated at each boundary bus. For such, a *Maximum Case* for the power flow, considering the whole system, should be obtained through an optimization process, which maximizes the active power exported from the External Area to the Optimization Area. Following that, the equivalent generation limits, at the boundary buses, are obtained through the application of the Ward equations in the operation point defined by the *Maximum Case*.

B. Polynomial Network

The GMDH can be interpreted as a feed forward neural network with supervised learning that performs a polynomial mapping between input data and the desired output, where each neuron output can be expressed by a 2nd order polynomial function. During the learning phase, a train and test procedure are used, i.e. two different data sets are employed: one for estimating the network weights (polynomial coefficients), and the other for testing which neurons should survive. This approach allows network architecture to be determined automatically in the training process. ANN layers are constructed one by one, and each new generated neuron is, in fact, an estimate of the desired output.

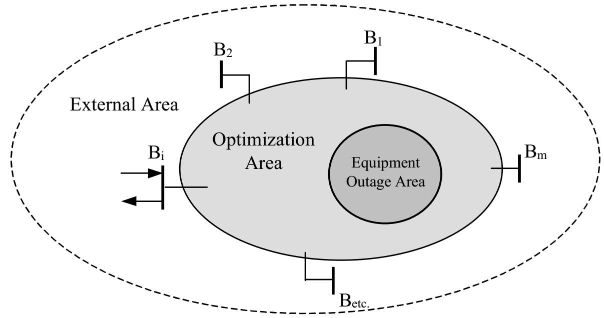

Fig. 1. Network representation.

The training process continues until no better estimates are obtained with the generation of new layers. In this case, only one neuron is saved in the last layer (the one that provides best estimates), and only those neurons that are necessary to generate the output neuron are preserved in the previous layers. An important feature of the GMDH is that only the relevant input variables are preserved in the remaining reduced network [10]-[12].

The capacity of the neural network to distinguish between success and failure states is based on the fact that, for each group of sampled states, the corresponding variables must present a well defined characteristic pattern. The network should, during the training phase, capture these patterns as to perform correct classifications, when applied to the system or to the new sampled states.

There are many combinations of variables that may be considered as input of the ANN for state classification: e.g. system load; available generation reserve; bus power injections; circuit flows; equipment unavailability; etc. In [16], the following input variables are adopted: capacity reserve per area, unavailable generation per area, and unavailable transmission capacity (in MW). However, in [17], the system load and generation reserve were adopted as input variables. The major reason for these choices was robustness. The input data for network training and testing are obtained from initial states sampled by the Monte Carlo simulation. The size of the data sample is determined by the convergence of the coefficient of variation "β" [16], [17]. In these references, it was used a coefficient $\beta = 20\%$ to define the data sets that will classify the success states, in the conventional analysis, and to further distinguish these success states into healthy and marginal, in the well-being analysis.

The concepts and performance of these methodologies were illustrated through the application in several systems. Undoubtedly, the ANNs networks proposed to analyze the operating states adequacy have presented very good results for all systems.

C. Algorithm

The estimates of the reliability and well-being indices for composite systems can be assessed by the following eight-step algorithm based on network reduction, non-sequential MCS and GMDH techniques. This algorithm is also illustrated by flowchart presented in Fig. 2:

1) Define the contingency, optimization and external areas and reduce the transmission network according to Ward equivalent;
2) Sample a system state "s" based on equipment availability and load level;
3) If the conventional reliability polynomial network GMDH has already been obtained, evaluate the sampled state "s" through a simple polynomial calculation; if "s" is success go to step (5); otherwise, go to the next step;
4) Analyze the performance of the sampled state by verifying whether that specific configuration of generators and transmission equipment is able to supply that specific load without violating system limits; if necessary, use remedial actions such as generation rescheduling, bus load shedding etc.; store the result (i.e. success or failure/at risk) for train and testing the conventional reliability ANN, until these patterns are duly learned; go to the next step;
5) Classify the analyzed state "s" as failure or success: if the state is classified as failure go to step (8); otherwise, go to the next step;
6) If the well-being polynomial network GMDH has already been obtained, evaluate if the sampled success state "s" is healthy or marginal, through a simple polynomial calculation and go to step (8); otherwise, go to the next step;
7) Analyze the impact of the deterministic criterion (i.e., the contingency list) on the success state "s", by using the same type of assessment described in step (4); store the result (i.e. H or M) for training and testing the well-being ANN, until these patterns are duly learned; go to the next step;
8) Estimates all H, M and R state-type related indices; if the estimate accuracies are acceptable, stop; otherwise, return to step (2).

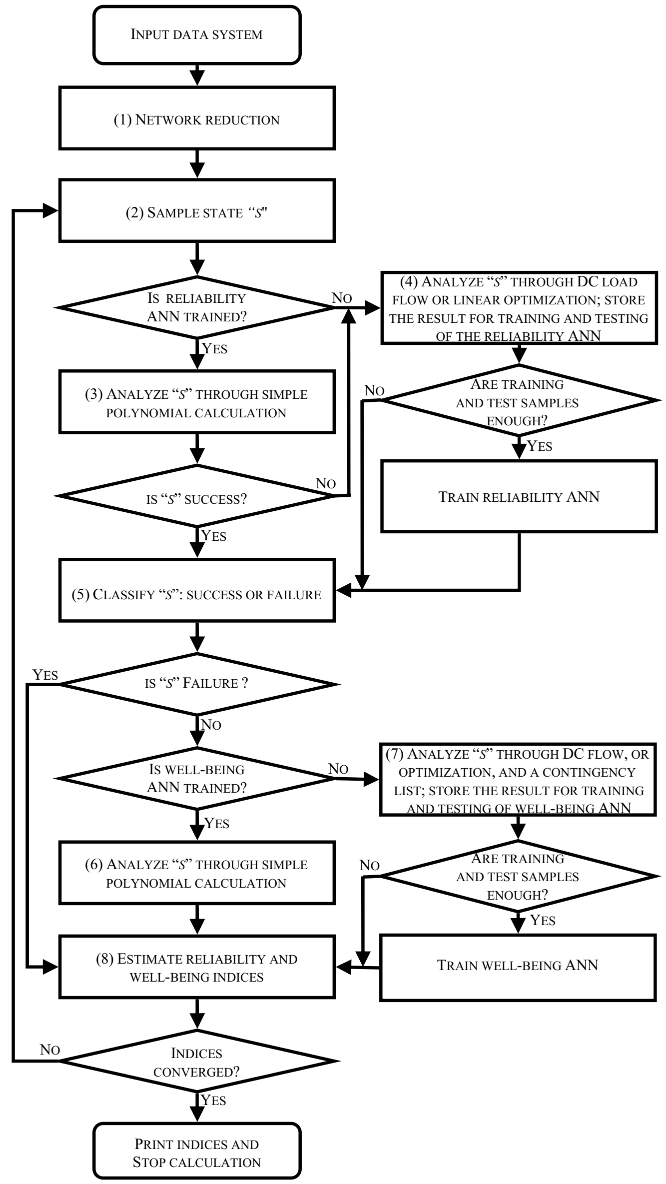

Fig. 2. Flowchart for proposed methodology.

IV. RESULTS

The systems used to test the proposed methodology are: the IEEE-RTS-96 and a configuration of the Brazilian South-Southeastern System (BSS). The adequacy analysis of each sampled state is performed by DC power flow and by an interior point linear optimization algorithm, whose main objective is to minimize load curtailments. In all tests, a convergence criterion of $\beta \leq 5\%$ (for all system reliability and well-being indices) is adopted for the non-sequential MCS. All cases were performed in a Pentium IV processor with 2.80 GHz.

A. IEEE-RTS-96 System

The IEEE-RTS-96 system (IEEE Reliability Test System 1996) [13] results from modifications performed in the IEEE-RTS [18]. This system has 73 buses, 120 branches and 96 generating units, distributed in 42 power plants, with a total generating capacity of 10.21 GW for a system peak load of 8.55 GW. The load curve of the original IEEE-RTS is adopted. This load curve is converted into a non-aggregate Markov model to be used in the non-sequential Monte Carlo simulation. Fig. 3 shows the reduced system, according to the concepts presented in Section III.A.

Two case studies are performed for the IEEE-RTS-96 system: in the first one (Case 1), the results are presented without using network reduction and neural networks (reference); in the second one (Case 2), the proposed methodology is used. The Optimization and Contingency Areas include 13, 21, 22 and 23; see Fig. 3. The characteristics of the resulting network reduction and the corresponding ANNs, for both the IEEE-RTS-96 and BSS systems are presented in [15]-[17]. It these works, the modeling and performance analyses were separately carried out for the conventional reliability and well-being framework.

Table I shows for both cases the results achieved for the conventional reliability indices (i.e. EENS, LOLP, LOLF and LOLD), and for the well-being indices: P{H} and P{M} are the probabilities associated with the healthy and marginal states; F{H} and F{M} are the frequencies of H and M states; and D{H} and D{M} are the durations of H and M states.

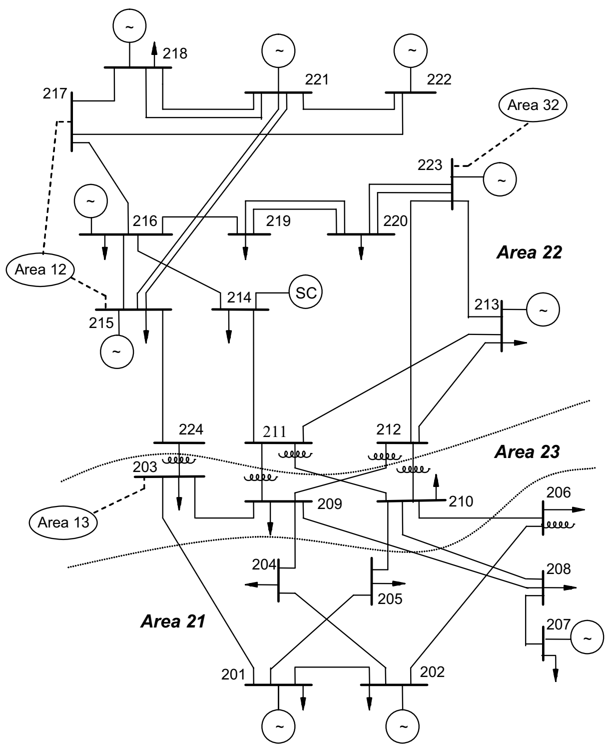

Fig. 3. IEEE MRTS 96: (Optimization and Contingency Areas ⇒ 13, 21, 22 and 23).

TABLE I: COMPOSITE SYSTEM INDICES – IEEE-RTS-96 SYSTEM

Indices:	Case 1	Case 2	Error (%)
EENS (MWh)	280.8	276.0	1.73
LOLP	0.0011	0.0011	4.14
LOLF (occ./y)	2.02	1.90	6.09
LOLD (h)	4.73	4.83	2.09
P{H}	0.9688	0.9695	0.08
P{M}	0.0301	0.0293	2.37
F{H} (occ./y)	50.17	52.58	4.81
F{M} (occ./y)	50.68	51.63	1.87
D{H} (h)	168.7	161.1	4.50
D{M} (h)	5.19	4.97	4.14

For Case 1, the total amount of sampled states was of about 3×10^6, being necessary 231.87 minutes of CPU time for to achieve the convergence of the indices. Through Case 2, is studied the impact of using network reduction and ANNs. The number of states was 1.6×10^6, a number much lower as compared to Case 1. The reduction in sampled states resulted in the lessening of the CPU time down to 62 minutes, which represents a speedup of 3.74 in relation to Case 1. As it can be seen in Table I, the differences presented between the two cases are very small, with an average error about 3%, within the uncertainty margin of coefficient β. These "errors" have to be interpreted as "deviations" that can be statistically within acceptable confidence levels, bearing in mind the Monte Carlo simulation process. These aspects will not be deeply discussed in this study.

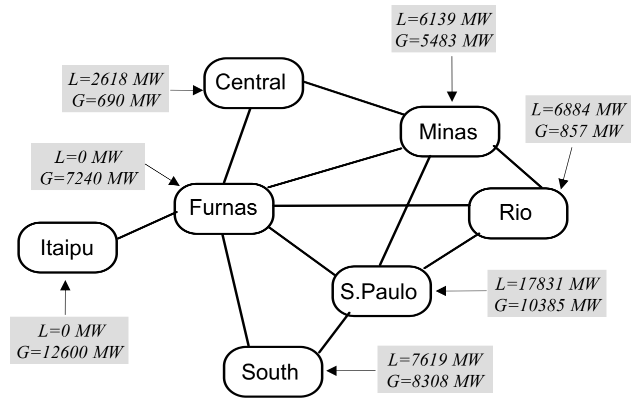

Fig. 4. Simplified diagram of the BSS system.

TABLE II: COMPOSITE AREA INDICES – BSS SYSTEM

Indices:	Case 3	Case 4	Error (%)
EENS (MWh)	1319	1275	3.31
LOLP	0.0105	0.0103	2.00
LOLF (occ./y)	11.36	12.01	5.66
LOLD (h)	8.07	7.47	7.32
P{H}	0.5110	0.5084	0.51
P{M}	0.4786	0.4813	0.58
F{H} (occ./y)	387.68	395.06	1.90
F{M} (occ./y)	387.39	403.25	4.09
D{H} (h)	11.53	11.25	2.44
D{M} (h)	10.81	10.43	3.45

B. BSS System

The configuration used for the Brazilian South-Southeastern System (BSS) contains 413 buses and 685 circuits. The installed capacity and annual peak load are equal to 46 GW and 41 GW, respectively. This was the configuration used in planning studies during the 90's. A typical annual curve, with 8736 levels, is used to represent the behavior of the hourly load in all buses of the system. The estimated reliability and well-being indices refer to the area of the *Minas Gerais* state which contains 20 buses (15 load buses).

Two case studies were performed. The first one (Case 3) presents the results without using ANNs and network reduction. The second one (Case 4) uses the proposed methodology. The results obtained for the BSS system are presented in Table II. Considering Cases 3 and 4, the total of sampled stated in the Monte Carlo simulation was 484,926 for Case 3 and 338,399 for Case 4. The CPU times were 490.05 minutes for Case 3, and 10.88 minutes for Case 4, resulting in a speedup of 45.03. The performance of the proposed methodology is very good in terms of accuracy, with overall average errors around 3.13%.

V. FINAL REMARKS

The assessment of composite generation and transmission reliability and well-being indices for large power systems is a difficulty task, involving lots of computational calculations.

The major portion of these evaluations comes from adequacy analyses, based on power flows and optimizations related with actions taken to correct the system operation conditions.

This paper has presented a new integrated framework for the assessment of reliability and well-being indices of large composite power systems. Based on transmission network reduction and on artificial neural networks (ANNs), specifically the *Group Method Data Handling* (GMDH) polynomial network, the aim was to reduce the computational effort and the CPU time required during the simulation. The proposed approach also uses the non-sequential Monte Carlo simulation (MCS), based on the *one-step forward state transition* process and a *non-aggregate Markov load model*. It appropriately captures, therefore, all equipment and load level transitions.

The proposed methodology allows the assessment of all types of composite reliability indices, including power/energy not supplied and loss of load costs, at all levels, i.e. for system, areas and buses.

Case studies with the IEEE-RTS-96 and BSS (Brazilian South-Southeastern System) systems, demonstrated the good performance of the proposed methodology, not only in terms of CPU time savings but also in relation to the accuracy of the reliability indices. This proves the effectiveness of all recent ideas, including ANNs, network reductions, distributed processing, etc. to make the assessment of composite reliability feasible for large power systems.

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Armando M. Leite da Silva (S'77, M'78, SM'91, F'00) was born in Rio de Janeiro, Brazil, in 1954. He received the B.Sc. degree from the Catholic Univ. of Rio de Janeiro (PUC-Rio) in 1975, the M.Sc. from the Federal Univ. of Rio de Janeiro (COPPE-UFRJ) in 1977, and the Ph.D. degree from Univ. of Manchester (UMIST), U.K., in 1980. He worked at the Electrical Engineering Department, PUC-Rio, as a Professor until 1994. From 1990 to 1991, he was a Visiting Researcher at the Research Division of Ontario Hydro, Canada. From 2003 to 2004, he was a Visiting Researcher at the Power System Unit, INESC Porto, Portugal. Since 1994, he has been a Professor at the Institute of Electrical Systems and Energy, Federal University of Itajubá (UNIFEI), Brazil. Prof. Leite da Silva received the Sebastian Z. de Ferranti Premium Award from the Power Division of the IEE, U.K., in 1992. He has published over 250 research papers in international journals and conferences on electric power systems reliability, planning, operation, optimization and market.

Leonidas Chaves de Resende was born in São João Del Rei, Brazil, in 1974. He received the B.Sc. from the Federal University of São João del-Rei (UFSJ), in 2000, and M.Sc. and Ph.D. degrees from UNIFEI, in 2002 and 2006, respectively. He is now a post-doctoral researcher, at the Institute of Electrical Systems and Energy, UNIFEI, Brazil.

Luiz Antônio da Fonseca Manso was born in Bias Fortes, Brazil, in 1961. He received the B.Sc. degree from the Federal Univ. of Juiz de Fora - UFJF, in 1985, the M.Sc. from PUC-Rio, in 1989 and Ph.D. from UNIFEI, in 1999. Since 1988, he has been an Associate Professor at the Electrical Eng. Department, UFSJ, Brazil.

Vladimiro Miranda (M’90, SM’04, F’05) received the graduation, Ph.D., and Agregado degrees in electrical engineering from the University of Porto, Porto, Portugal in 1977, 1982, and 1991, respectively. In 1981, he joined the Faculty of Engineering, University of Porto and currently holds the position of Professor Catedrático. He is currently Director of the Institute for Systems and Computer Engineering of Porto, INESC-Porto, Portugal. He has authored many papers and has been responsible for many projects in areas related with the application of computational intelligence to power systems.

Artificial Neural Networks Applied to Reliability and Well-Being Assessment of Composite Power Systems

Armando M. Leite da Silva, *Fellow*, *IEEE*, Leonidas C. de Resende, Luiz A. da Fonseca Manso, and V. Miranda, *Fellow*, *IEEE*

***Abstract*—This paper presents a new methodology for assessing both reliability and well-being indices for composite generation and transmission systems. Firstly, a transmission network reduction is applied to find an equivalent for assessing composite reliability for practical large power systems. After that, in order to classify the operating states, Artificial Neural Networks (ANNs) based on Group Method Data Handling (GMDH) techniques are used to capture the patterns of the operating states, during the beginning of the non-sequential Monte Carlo simulation (MCS). The idea is to provide the simulation process with an intelligent memory, based only on polynomial parameters, to speed up the evaluation of the operating states. For the conventional reliability assessment, the ANNs are used to classify the operating states into success and failure. However, for the well-being analysis, only success states are classified into healthy and marginal by the ANNs. The proposed methodology is applied to the IEEE Reliability Test System 1996 and to a configuration of the Brazilian South-Southeastern System.**

***Index Terms*—Artificial neural networks, composite reliability, group method data handling, Monte Carlo simulation, pattern analysis, well-being analysis.**

I. Introduction

The reliability assessment of composite power systems may be divided into two frameworks: conventional and well-being analysis. The so called conventional reliability restricts its analysis to failure states, presenting results in terms of loss of load indices. These indices associate probability, energy, frequency, duration and cost with system failures [1]-[5]. In limiting its analysis to failure states, the conventional reliability is not able to estimate how far from the "success/failure" border the system operates, endangering the perception of possible weaknesses.

An analysis dedicated to success states is possible through the preventive reliability or well-being analysis [6]-[9]. The conceptual basis for the evaluation of the well-being indices consists in splitting the operative states of the system into three groups: healthy, marginal and at risk (or failure). For the identification of these states, the system is submitted to a deterministic criterion, usually, based on a pre-specified list of contingencies [8], [9]. The division of the states used for the preventive reliability (well-being analysis) allows the previous identification of the regions under critical operation, supplying important data for the definition of safer operative procedures.

For large power systems, the reliability evaluation methods, both conventional and well-being, based on MCS, are more attractive than state enumeration methods [4], [5], [7], [9]. Among the simulation methods, three options have been considered: non-sequential, sequential, and pseudo-chronological. A detailed description of these methods may be found in [1]-[5], [7], [9]. The use of *non-aggregate Markov load models* [5] and of techniques such as the *one-step forward state transition* [9] provided the non-sequential MCS a greater capacity to represent chronological aspects, increasing the precision of the estimated indices. With these new characteristics, joined with its greater computational efficiency, the non-sequential simulation emerges as the most indicated choice, when one wishes to evaluate large composite generation and transmission systems. However, with the continuous interconnection of power networks, the evaluation tools, including those related with composite reliability assessment will have to deal with ever larger power systems.

This paper presents an integrated approach for assessing the conventional and preventive reliability indices of large power networks. Firstly, the system network is divided into areas. These areas are defined bearing in mind: the reductions that will be applied to the representation of the network; the equipment that will have stochastic representation; and the load points in which the reliability indices will be evaluated. Then, based on the load model and in the one-step forward transition process, described in [9], the non-sequential MCS is used along with ANNs, based on the GMDH algorithm [10]. For such, a pre-classification of the operating states is performed through this ANN type, where the states analyzed during the beginning of the simulation process are selected as input data for training and test sets. With this procedure, a great number of states are classified by a simple polynomial evaluation, providing significant reductions in the computational time and cost required. The main reason for choosing the GMDH is that, whenever the classes associated with the training samples are available, models based on supervised learning provide better performance when faced with new cases than others that use unsupervised learning. Also, the ANNs based on GMDH algorithm usually leads to simpler architectures and faster training processes than it would be obtained with others approaches [11], [12]. The proposed methodology is applied to the IEEE Reliability Test System 1996 (IEEE-RTS 96) [13] and to a configuration of the Brazilian South-Southeastern System.

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A.M. Leite da Silva and L.C Resende are with the Institute of Electric System and Energy, Federal University of Itajubá – UNIFEI, Brazil.

L.A.F. Manso is with the Electrical Eng. Department, Federal University of São João del-Rei – UFSJ, Brazil.

V. Miranda is with the Institute for Systems and Computer Engineering of Porto – INESC Porto, and with the Faculty of Engineering of the University of Porto – FEUP, Portugal.

II. Composite Reliability

A. Conventional Analysis

The estimates of conventional composite reliability indices are obtained through non-sequential MCS following three major steps [2]:

a) Select a system state (i.e. load level, equipment availability, etc.);
b) Analyze the performance of the selected states (i.e. check if available generating units and circuits are able to satisfy the associated load without violating any operating limits; if necessary, activate corrective measures such as generation redispatch, load curtailment, etc.);
c) Estimate reliability indices (i.e. loss of load indices, etc.); if the accuracy of the estimates is acceptable, stop; otherwise go back to step (a).

Loss of load indices can be estimated by non-sequential simulation techniques, as the mean over N sampled system state values x^k of the test function $F(x^k)$, i.e. [4], [5]:

$$\widetilde{E}[F] = 1/N \sum_{k=1}^{N} F(x^k) \qquad (1)$$

All the basic reliability indices can be estimated by the previous equation, depending on the definition of the test function F. The estimate uncertainty is given by the variance of the estimator, and this uncertainty is usually represented as the *coefficient of variation* β [2], [4], [5].

The major portion of the computational effort required by the composite reliability algorithm is concentrated on step (b). The objective is to identify if the system, in the sampled state, is capable of meeting the demand without violating its operating limits, from the static point of view. This requires the solution of a power flow algorithm followed by the monitoring of some system variables. If this analysis identifies operating violations or a potential load curtailment, a large-scale optimization problem must be solved in order to avoid or, at least, minimize the necessary load shedding.

Observe that patterns for success states are more easily achieved, due to general system characteristics related with adequate generation and transmission reserve capacities. Conversely, failure states are related with rare events emerging from specific system operation conditions due to, for instance, local transmission constraints. Therefore, it would be necessary to build specific ANNs in order to measure, in terms of reliability indices, all consequences of these failures. Unfortunately, the computational benefits of avoiding several optimization evaluations would be vanished by the computational effort of building several ANNs.

B. Well-Being Analysis

The probability (P), frequency (F), and duration (D) associated with the healthy (H), marginal (M), and (at risk) R states are useful measures for composite systems. The P{R}, F{R}, and D{R} are, respectively, the traditional LOLP (Loss of Load Probability), LOLF (Loss of Load Frequency), and LOLD (Loss of Load Duration) indices. Well-being analysis for composite systems is, therefore, a natural extension of composite reliability analysis that allows the qualification of the deterministic criterion on a probabilistic basis. The marginal states must be appropriately signaled to provide system operators with sufficient time to correct the power system operating trajectory in order to avoid load shedding.

The system state, sampled by a non-sequential MCS process, i.e. step (a) of the conventional analysis, is defined from the equipment availabilities and system load level. The well-being composite system indices are evaluated based on specific test functions described in [9]. These functions utilize a process, designated as the one-step forward state transition, which is able to capture unbiased estimates for frequencies and durations. As described in [9], a non-sequential MCS is used in order to make the well-being framework accessible for real (i.e. large) composite power systems. Observe that after running an adequacy analysis for the sampled state, and checking that no operation constraints are violated, to distinguish if this state is healthy or marginal, there will be up to n_l (size of the contingency list) additional analyses. If at least one element in the list moves the system into failure, then the sampled state is marginal.

In a traditional composite reliability evaluation, for each sampled state, only one adequacy analysis is necessary to classify the states (i.e. success and failure). In a well-being framework, up to $(n_l + 1)$ adequacy analyses can be required to classify the success states (i.e. healthy and marginal). Moreover, if frequency and duration indices are assessed, more evaluations will be necessary to capture these values. In conclusion, the evaluation of the well-being framework for real composite systems is very time consuming and may not be achievable, unless some intelligent state adequacy network assessment is considered.

In the next section, it will be shown a methodology which uses a polynomial network (i.e. GMDH) for a faster evaluation of system operating states. Such methodology will be applied to the composite reliability algorithm to reduce the computational effort spent in step (b) (conventional reliability) and in the deterministic criterion application (well-being analysis). In conventional reliability, the aim is to obtain a pattern only for the success states, since the failure or at risk states will be fully analyzed to determine all consequences of load curtailments. This procedure will ensure the assessment of all reliability indices at all levels, i.e. system/area/buses. However, in the well-being analysis, the objective is to classify the success states as healthy or marginal. Therefore, after the identification of a success state, it is submitted to the deterministic criterion through ANNs evaluations.

III. Proposed Methodology

A. Network Reduction

In order to solve large composite systems, the original network is divided into areas based on a Ward equivalent [14], and suitable optimization processes are applied. These areas are:

• *Equipment Outage or Contingency Area* – involves a full representation of random behavior of transmission and generation elements;

• *Optimization Area* – involves representation of all its elements for load flow and remedial action analysis. The elements in this network that do not belong to the Contingency Area are not allowed to fail, but generators may be redispatched and loads can be curtailed, if necessary;

• *External Area* – includes an equivalent representation of the remaining components outside the Optimization Area. The network reduction is carried out through the Ward equivalent [14].

The representation of the sub-networks/areas is schematically illustrated in Fig. 1. In principle, reliability and well-being indices can be calculated for the *Optimization Area* and for its corresponding sub-areas and buses. However, in order to increase the accuracy of the algorithm, it is advisable to define an *Interest Area* located within *the Equipment Outage Area*. This new area corresponds to the part of the system, whose performance indices will have more relevance in the decision-making processes. Bearing in mind both computational effort and the accuracy associated with the reliability and well-being indices, a complete description of the way these areas are defined and the effects of the size and characteristics of the system were investigated in [15].

To obtain the External Area, the remaining network outside the Optimization Area is reduced through the Ward equations. The equivalent generation and loads, located at the boundary buses, are obtained from the application of the corresponding Ward equations to the Base Case load flow, supplied by the user. However, to reproduce the External Area reactions due to forced and planned contingencies from the Contingency Area, it is necessary to obtain the maximum quantity of active power that can be generated at each boundary bus. For such, a *Maximum Case* for the power flow, considering the whole system, should be obtained through an optimization process, which maximizes the active power exported from the External Area to the Optimization Area. Following that, the equivalent generation limits, at the boundary buses, are obtained through the application of the Ward equations in the operation point defined by the *Maximum Case*.

B. Polynomial Network

The GMDH can be interpreted as a feed forward neural network with supervised learning that performs a polynomial mapping between input data and the desired output, where each neuron output can be expressed by a 2nd order polynomial function. During the learning phase, a train and test procedure are used, i.e. two different data sets are employed: one for estimating the network weights (polynomial coefficients), and the other for testing which neurons should survive. This approach allows network architecture to be determined automatically in the training process. ANN layers are constructed one by one, and each new generated neuron is, in fact, an estimate of the desired output.

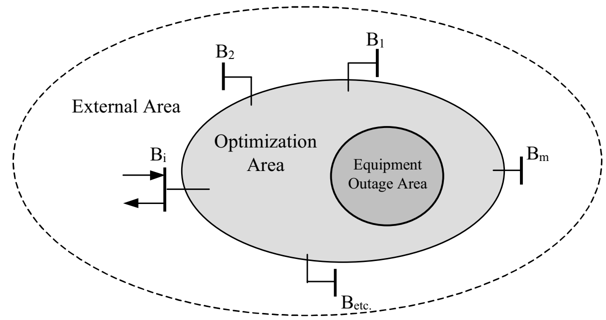

Fig. 1. Network representation.

The training process continues until no better estimates are obtained with the generation of new layers. In this case, only one neuron is saved in the last layer (the one that provides best estimates), and only those neurons that are necessary to generate the output neuron are preserved in the previous layers. An important feature of the GMDH is that only the relevant input variables are preserved in the remaining reduced network [10]-[12].

The capacity of the neural network to distinguish between success and failure states is based on the fact that, for each group of sampled states, the corresponding variables must present a well defined characteristic pattern. The network should, during the training phase, capture these patterns as to perform correct classifications, when applied to the system or to the new sampled states.

There are many combinations of variables that may be considered as input of the ANN for state classification: e.g. system load; available generation reserve; bus power injections; circuit flows; equipment unavailability; etc. In [16], the following input variables are adopted: capacity reserve per area, unavailable generation per area, and unavailable transmission capacity (in MW). However, in [17], the system load and generation reserve were adopted as input variables. The major reason for these choices was robustness. The input data for network training and testing are obtained from initial states sampled by the Monte Carlo simulation. The size of the data sample is determined by the convergence of the coefficient of variation "β" [16], [17]. In these references, it was used a coefficient $\beta = 20\%$ to define the data sets that will classify the success states, in the conventional analysis, and to further distinguish these success states into healthy and marginal, in the well-being analysis.

The concepts and performance of these methodologies were illustrated through the application in several systems. Undoubtedly, the ANNs networks proposed to analyze the operating states adequacy have presented very good results for all systems.

C. Algorithm

The estimates of the reliability and well-being indices for composite systems can be assessed by the following eight-step algorithm based on network reduction, non-sequential MCS and GMDH techniques. This algorithm is also illustrated by flowchart presented in Fig. 2:

1) Define the contingency, optimization and external areas and reduce the transmission network according to Ward equivalent;
2) Sample a system state "s" based on equipment availability and load level;
3) If the conventional reliability polynomial network GMDH has already been obtained, evaluate the sampled state "s" through a simple polynomial calculation; if "s" is success go to step (5); otherwise, go to the next step;
4) Analyze the performance of the sampled state by verifying whether that specific configuration of generators and transmission equipment is able to supply that specific load without violating system limits; if necessary, use remedial actions such as generation rescheduling, bus load shedding etc.; store the result (i.e. success or failure/at risk) for train and testing the conventional reliability ANN, until these patterns are duly learned; go to the next step;
5) Classify the analyzed state "s" as failure or success: if the state is classified as failure go to step (8); otherwise, go to the next step;
6) If the well-being polynomial network GMDH has already been obtained, evaluate if the sampled success state "s" is healthy or marginal, through a simple polynomial calculation and go to step (8); otherwise, go to the next step;
7) Analyze the impact of the deterministic criterion (i.e., the contingency list) on the success state "s", by using the same type of assessment described in step (4); store the result (i.e. H or M) for training and testing the well-being ANN, until these patterns are duly learned; go to the next step;
8) Estimates all H, M and R state-type related indices; if the estimate accuracies are acceptable, stop; otherwise, return to step (2).

IV. Results

The systems used to test the proposed methodology are: the IEEE-RTS-96 and a configuration of the Brazilian South-Southeastern System (BSS). The adequacy analysis of each sampled state is performed by DC power flow and by an interior point linear optimization algorithm, whose main objective is to minimize load curtailments. In all tests, a convergence criterion of $\beta \leq 5\%$ (for all system reliability and well-being indices) is adopted for the non-sequential MCS. All cases were performed in a Pentium IV processor with 2.80 GHz.

A. IEEE-RTS-96 System

The IEEE-RTS-96 system (IEEE Reliability Test System 1996) [13] results from modifications performed in the IEEE-RTS [18]. This system has 73 buses, 120 branches and 96 generating units, distributed in 42 power plants, with a total generating capacity of 10.21 GW for a system peak load of 8.55 GW. The load curve of the original IEEE-RTS is adopted. This load curve is converted into a non-aggregate Markov model to be used in the non-sequential Monte Carlo simulation. Fig. 3 shows the reduced system, according to the concepts presented in Section III.A.

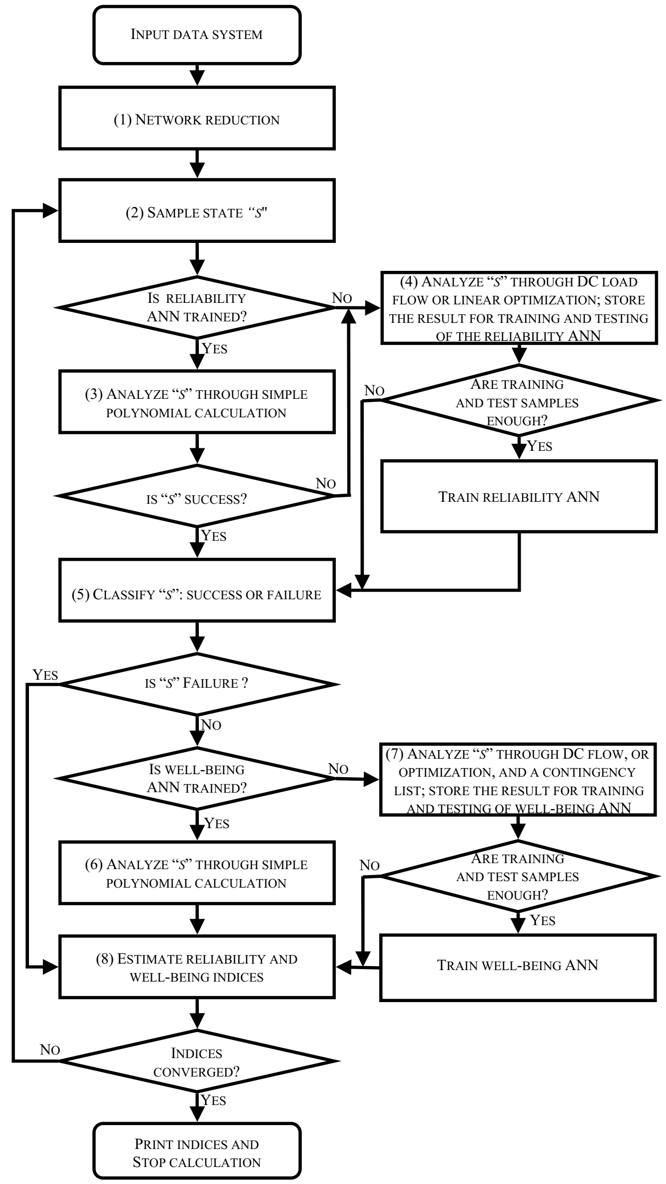

Fig. 2. Flowchart for proposed methodology.

Two case studies are performed for the IEEE-RTS-96 system: in the first one (Case 1), the results are presented without using network reduction and neural networks (reference); in the second one (Case 2), the proposed methodology is used. The Optimization and Contingency Areas include 13, 21, 22 and 23; see Fig. 3. The characteristics of the resulting network reduction and the corresponding ANNs, for both the IEEE-RTS-96 and BSS systems are presented in [15]-[17]. It these works, the modeling and performance analyses were separately carried out for the conventional reliability and well-being framework.

Table I shows for both cases the results achieved for the conventional reliability indices (i.e. EENS, LOLP, LOLF and LOLD), and for the well-being indices: P{H} and P{M} are the probabilities associated with the healthy and marginal states; F{H} and F{M} are the frequencies of H and M states; and D{H} and D{M} are the durations of H and M states.

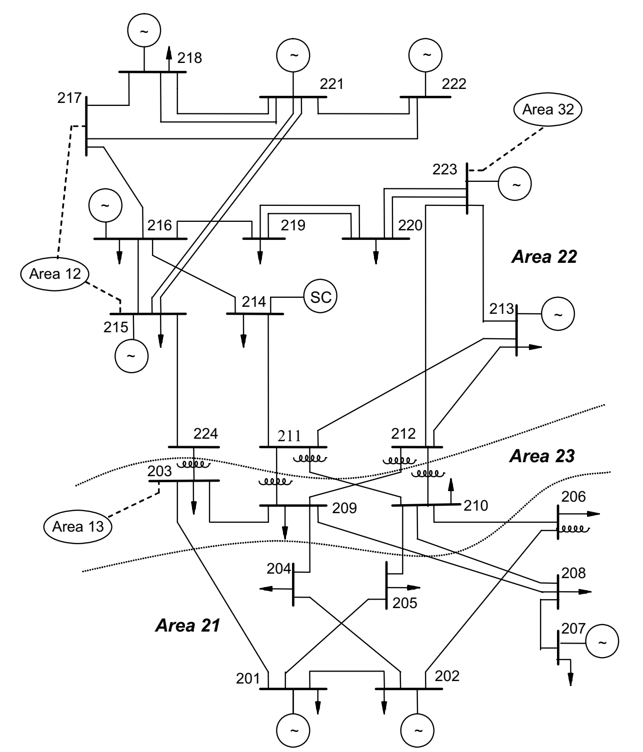

Fig. 3. IEEE MRTS 96: (Optimization and Contingency Areas ⇒ 13, 21, 22 and 23).

TABLE I: COMPOSITE SYSTEM INDICES – IEEE-RTS-96 SYSTEM

Indices:	Case 1	Case 2	Error (%)
EENS (MWh)	280.8	276.0	1.73
LOLP	0.0011	0.0011	4.14
LOLF (occ./y)	2.02	1.90	6.09
LOLD (h)	4.73	4.83	2.09
P{H}	0.9688	0.9695	0.08
P{M}	0.0301	0.0293	2.37
F{H} (occ./y)	50.17	52.58	4.81
F{M} (occ./y)	50.68	51.63	1.87
D{H} (h)	168.7	161.1	4.50
D{M} (h)	5.19	4.97	4.14

For Case 1, the total amount of sampled states was of about 3×10^6, being necessary 231.87 minutes of CPU time for to achieve the convergence of the indices. Through Case 2, is studied the impact of using network reduction and ANNs. The number of states was 1.6×10^6, a number much lower as compared to Case 1. The reduction in sampled states resulted in the lessening of the CPU time down to 62 minutes, which represents a speedup of 3.74 in relation to Case 1. As it can be seen in Table I, the differences presented between the two cases are very small, with an average error about 3%, within the uncertainty margin of coefficient β. These "errors" have to be interpreted as "deviations" that can be statistically within acceptable confidence levels, bearing in mind the Monte Carlo simulation process. These aspects will not be deeply discussed in this study.

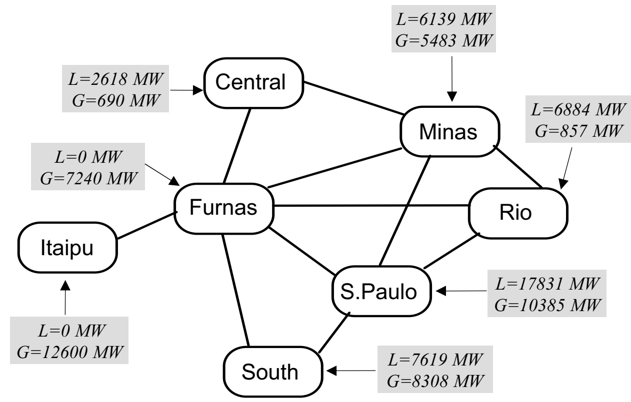

Fig. 4. Simplified diagram of the BSS system.

TABLE II: COMPOSITE AREA INDICES – BSS SYSTEM

Indices:	Case 3	Case 4	Error (%)
EENS (MWh)	1319	1275	3.31
LOLP	0.0105	0.0103	2.00
LOLF (occ./y)	11.36	12.01	5.66
LOLD (h)	8.07	7.47	7.32
P{H}	0.5110	0.5084	0.51
P{M}	0.4786	0.4813	0.58
F{H} (occ./y)	387.68	395.06	1.90
F{M} (occ./y)	387.39	403.25	4.09
D{H} (h)	11.53	11.25	2.44
D{M} (h)	10.81	10.43	3.45

B. BSS System

The configuration used for the Brazilian South-Southeastern System (BSS) contains 413 buses and 685 circuits. The installed capacity and annual peak load are equal to 46 GW and 41 GW, respectively. This was the configuration used in planning studies during the 90's. A typical annual curve, with 8736 levels, is used to represent the behavior of the hourly load in all buses of the system. The estimated reliability and well-being indices refer to the area of the *Minas Gerais* state which contains 20 buses (15 load buses).

Two case studies were performed. The first one (Case 3) presents the results without using ANNs and network reduction. The second one (Case 4) uses the proposed methodology. The results obtained for the BSS system are presented in Table II. Considering Cases 3 and 4, the total of sampled stated in the Monte Carlo simulation was 484,926 for Case 3 and 338,399 for Case 4. The CPU times were 490.05 minutes for Case 3, and 10.88 minutes for Case 4, resulting in a speedup of 45.03. The performance of the proposed methodology is very good in terms of accuracy, with overall average errors around 3.13%.

V. FINAL REMARKS

The assessment of composite generation and transmission reliability and well-being indices for large power systems is a difficulty task, involving lots of computational calculations.

The major portion of these evaluations comes from adequacy analyses, based on power flows and optimizations related with actions taken to correct the system operation conditions.

This paper has presented a new integrated framework for the assessment of reliability and well-being indices of large composite power systems. Based on transmission network reduction and on artificial neural networks (ANNs), specifically the *Group Method Data Handling* (GMDH) polynomial network, the aim was to reduce the computational effort and the CPU time required during the simulation. The proposed approach also uses the non-sequential Monte Carlo simulation (MCS), based on the *one-step forward state transition* process and a *non-aggregate Markov load model*. It appropriately captures, therefore, all equipment and load level transitions.

The proposed methodology allows the assessment of all types of composite reliability indices, including power/energy not supplied and loss of load costs, at all levels, i.e. for system, areas and buses.

Case studies with the IEEE-RTS-96 and BSS (Brazilian South-Southeastern System) systems, demonstrated the good performance of the proposed methodology, not only in terms of CPU time savings but also in relation to the accuracy of the reliability indices. This proves the effectiveness of all recent ideas, including ANNs, network reductions, distributed processing, etc. to make the assessment of composite reliability feasible for large power systems.

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Armando M. Leite da Silva (S'77, M'78, SM'91, F'00) was born in Rio de Janeiro, Brazil, in 1954. He received the B.Sc. degree from the Catholic Univ. of Rio de Janeiro (PUC-Rio) in 1975, the M.Sc. from the Federal Univ. of Rio de Janeiro (COPPE-UFRJ) in 1977, and the Ph.D. degree from Univ. of Manchester (UMIST), U.K., in 1980. He worked at the Electrical Engineering Department, PUC-Rio, as a Professor until 1994. From 1990 to 1991, he was a Visiting Researcher at the Research Division of Ontario Hydro, Canada. From 2003 to 2004, he was a Visiting Researcher at the Power System Unit, INESC Porto, Portugal. Since 1994, he has been a Professor at the Institute of Electrical Systems and Energy, Federal University of Itajubá (UNIFEI), Brazil. Prof. Leite da Silva received the Sebastian Z. de Ferranti Premium Award from the Power Division of the IEE, U.K., in 1992. He has published over 250 research papers in international journals and conferences on electric power systems reliability, planning, operation, optimization and market.

Leonidas Chaves de Resende was born in São João Del Rei, Brazil, in 1974. He received the B.Sc. from the Federal University of São João del-Rei (UFSJ), in 2000, and M.Sc. and Ph.D. degrees from UNIFEI, in 2002 and 2006, respectively. He is now a post-doctoral researcher, at the Institute of Electrical Systems and Energy, UNIFEI, Brazil.

Luiz Antônio da Fonseca Manso was born in Bias Fortes, Brazil, in 1961. He received the B.Sc. degree from the Federal Univ. of Juiz de Fora - UFJF, in 1985, the M.Sc. from PUC-Rio, in 1989 and Ph.D. from UNIFEI, in 1999. Since 1988, he has been an Associate Professor at the Electrical Eng. Department, UFSJ, Brazil.

Vladimiro Miranda (M’90, SM’04, F’05) received the graduation, Ph.D., and Agregado degrees in electrical engineering from the University of Porto, Porto, Portugal in 1977, 1982, and 1991, respectively. In 1981, he joined the Faculty of Engineering, University of Porto and currently holds the position of Professor Catedrático. He is currently Director of the Institute for Systems and Computer Engineering of Porto, INESC-Porto, Portugal. He has authored many papers and has been responsible for many projects in areas related with the application of computational intelligence to power systems.