Well-being analysis for composite generation and transmission systems based on pattern recognition techniques

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

Abstract: A new methodology to evaluate well-being indices for a composite generation and transmission system, based on non-sequential Monte Carlo simulation and pattern recognition techniques, is presented. To classify the success operating states into healthy and marginal, an artificial neural network based on group method data handling techniques is used to capture the patterns of these state classes, during the beginning of the simulation process. The idea is to provide the simulation process with an intelligent memory, based on polynomial parameters, to speed up the evaluation of the operating states. The proposed methodology is applied to the IEEE reliability test system (IEEE-RTS), to the IEEE-RTS-96 and to a configuration of the Brazilian South-Southeastern system.

1 Introduction

New methodologies based on probability concepts have been successfully applied to many power system areas including generation capacity planning, operating reserve assessment, distribution systems and so on [1]. The expansion and operation planning of composite generation and transmission systems, however, are predominantly based on deterministic criteria (e.g. $N-1$), and consequently so are the assessment methodologies and tools. Deterministic-based approaches generally have very attractive characteristics such as simple implementation, straightforward understanding and easy assessment and judgement by planners in relation to severe conditions such as network outages and system peak load. Nevertheless, the proper measure of risk can only be achieved by recognising the probabilistic nature of the relevant power system parameters. This recognition was transformed into the well-being analysis framework [2–8] that combines the deterministic perception with probability concepts. This new framework reduces the gap between deterministic and probabilistic approaches by providing the ability to measure the degree of success of any operating system state.

Success states are not carefully examined in the traditional composite reliability analysis [9–11]. In a well-being analysis, however, these states are further split into healthy and marginal states, using a prespecified deterministic criterion. A system operates in the healthy state when it has enough generation and transmission capacity reserves to meet a predefined deterministic criterion. Conversely, if the system is not in any difficulty, but does not have sufficient margin (generation and/or transmission) to meet the specified deterministic criterion (e.g. $N-1$), then it is in the marginal state. The system load is shed because of the generation and/or transmission violations in the at-risk state. This framework recognises the concerns of operation-planning engineers by introducing the idea of marginal states into the conventional composite reliability analysis.

Well-being analysis has been applied in the last decade to areas such as generating systems [5], operating reserve assessment [4], composite generation and transmission systems [2, 3, 6–8]. In composite systems, an enumeration technique for selecting states has been first used [6], with a contingency list (generating and transmission equipment) as the deterministic criterion. Contingency enumeration approaches for selecting states can become unfeasible for large-scale power systems and therefore methods based on Monte Carlo simulation (MCS) are recommended in these cases [8–11]. Chronological or sequential MCS has been used for generating system well-being analysis [5], considering the loss of the largest available unit in the system as the deterministic criterion. The only restriction is that sequential MCS is very time-consuming, particularly for composite systems.

Bearing in mind the computational effort, the best option to calculate composite reliability indices for large, real systems is the non-sequential MCS [9, 10], or the pseudo-chronological MCS [11], when the loss of load cost indices are being evaluated. The application of these algorithms to evaluate composite reliability indices makes it mandatory to know the status of the operating states of the system, which are defined by the availabilities of the generation and transmission equipment, and by the corresponding load conditions. Usually, a power flow analysis is used to define whether this state is adequate or not that is, whether it is success or failure. The computational cost of such analyses depends on several system characteristics, including the network dimension and how rare the failure states are. Thus, the evaluation of a huge number of operating states, especially in the reliability studies of large power

doi:10.1049/iet-gtd:20070109

Paper first received 6th March and in revised form 5th September 2007

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systems, may become extremely expensive or even unfeasible. This analysis becomes even more critical in the case of well-being reliability studies, since the success states must be further evaluated to classify them into healthy and marginal states, based on a contingency list.

Many works have been proposed to reduce the computational cost of composite reliability evaluation. Some of these techniques have successfully used artificial neural network (ANN) [12, 13]. Recently [14], a new methodology was proposed to evaluate the reliability of large composite power systems based on ANNs, specifically the group method data handling (GMDH) [15–18] polynomial network, to reduce the computational effort required during the adequacy analyses of the system-operating states. This approach uses the non-sequential MCS, based on the one-step forward state transition [7] process and a non-aggregate Markov load model [11]. It appropriately captures therefore all equipment and load-level transitions. The proposed GMDH neural network is extremely efficient, from the computational point of view, and it is only used to distinguish success from failure states. Failure states exhibit much more complex patterns and therefore were fully evaluated through power flow and/or optimisation algorithms. This simple idea allowed the assessment of all types of conventional reliability indices [14], including power/energy not supplied and loss of load costs, at all levels, that is, system, areas and buses. These concepts are now extended to cope with well-being indices, which need a more complex pattern analysis framework to further distinguish the success operating states into healthy and marginal. To classify these states, an ANN based on GMDH technique is also used to capture the corresponding patterns, during the beginning of the MCS process. The idea is to provide the simulation process with an intelligent memory, based on polynomial parameters, to speed up the evaluation of these operating states. The proposed methodology is applied to the IEEE reliability test systems (IEEE-RTS) [19], to the IEEE-RTS-96 [20] and to a configuration of the Brazilian South-Southeastern system (BSS).

2 Well-being analysis

2.1 Basic concepts

The distinctive feature of the well-being framework is the classification of the operating states into three groups: healthy, marginal and at risk (or failure). To identify these states, the power system is submitted to a deterministic criterion. For instance, considering only generating capacity, the impact of the largest unit available on the system has to be verified to classify the operating states. Marginal states are those that will not survive without shedding load if the largest available generating unit in the system goes on outage. This degree of danger is measured in terms of probability, frequency and duration. The adequacy analyses of these conditions are quite simple since only the comparisons between generation and load are sufficient.

For composite systems, the criteria are more sophisticated and the performance analyses can be computationally expensive. Usually, a pre-established contingency list is used, involving generating units and transmission elements. The components in the contingency list are based on operation experience and/or on the impact on the system. An optimisation algorithm carries out the adequacy analyses to automatically solve possible load-shedding situations. Healthy (H) states are those that will survive without violating any operating limits as any equipment on the list goes on outage. Marginal (M) states are those that will not survive without shedding load, when at least one component on the list goes on outage. Failure or at-risk (R) states are those in which loads are shed.

2.2 Well-being indices

The probability (P), frequency (F) and duration (D) associated with the H, M and R states are useful measures for composite systems. The $P\{R\}$, $F\{R\}$, and $D\{R\}$ are, respectively, the traditional loss of load probability (LOLP) loss of load frequency (LOLF) and loss of load duration (LOLD) 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 signalled to provide system operators with sufficient time to correct the power-system-operating trajectory to avoid load shedding.

The system state, sampled by a non-sequential MCS process, 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 [7]. These functions utilise a process, designated as the one-step forward state transition, which is able to capture unbiased estimates for frequencies and durations. The same concept can be used to capture well-being indices for buses or for a specific area of the system. As described in [7], a non-sequential MCS is used 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 whether 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). In case, bus or delivery point indices are being evaluated, all elements in the list must be verified and therefore $(n_l + 1)$ adequacy analyses will always be carried out. 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 [14], a pattern analysis to distinguish between success and failure states was proposed based on a polynomial network named GMDH. These concepts are further extended to classify the success states as healthy or marginal. The basic idea is to learn about the distinct characteristics of these success states during the beginning of the non-sequential MCS, and from a certain point of the simulation process, a simple polynomial evaluation substitutes the usual adequacy analysis. This approach will avoid huge numbers of conventional and optimal power flow (OPF) analyses.

3 Proposed methodology

The estimates of the well-being indices for composite systems can be assessed by the following six-step algorithm based on non-sequential MCS and GMDH techniques.

1. Sample a system state 's' based on equipment availability and load level.

2. Analyse 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 curtailment and so on.
3. Classify the analysed state 's' as failure or success: if the state is classified as failure go to step (6); otherwise, go to the next step.
4. If the polynomial network GMDH has already been obtained, evaluate if the sampled success state 's' is H or M, through a simple polynomial calculation and go to step (6); otherwise, go to the next step.
5. Analyse 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 (2); store the result (i.e. H or M) for training and testing the ANN, until these patterns are duly learned; go to the next step.
6. If the accuracies of the estimates for all H, M and R state-type-related indices are acceptable, stop; otherwise, return to step (1).

The major portion of the computational effort required by the algorithm is concentrated on steps (2) and (5), since they involve large-scale optimisation problems. Step (4) minimises the computing time by using the polynomial ANN to be described as follows.

3.1 Polynomial network: GMDH

The GMDH [15–18] 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 second-order polynomial function. During the learning phase, a train and test procedure is used, that is, two different data sets are employed: one for estimating the network weights (polynomial coefficients) and the other for testing which neurons should survive. This procedure 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. 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 the 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.

An illustrative example is shown in Fig. 1 where five input variables were initially presented, but only three of them were found to be relevant, for the output class Y, after the training process has been completed. The exact polynomial is given by: $z = 20 + 8x_1 - 7x_2 + 5x_3 - 0.1x_1x_2 + 0.2x_1x_3$. The input variables are: $x_1 = 0$, if $U < 0.5$, and 1, otherwise; $x_2 = x_3 = x_4 = U$ and $x_5 = 1$. Independent uniform (U) pseudo-random numbers in the interval (0,1) are used to simplify the mapping process. To solve a classification problem, the following pattern is considered: $y = 10$, if $z < 30$; $y = 20$, otherwise.

Five hundred samples are considered for each step of the GMDH algorithm (i.e. training and testing). The following polynomial network is obtained and illustrated in Figs. 1*a* and *b*

$$T = 9.9253 - 4.1111x_2 + 3.6453x_3 + 6.64579x_2^2 + 5.1273x_3^2 - 11.4954x_2x_3$$

$$S = 11.1241 + 4.7679x_1 - 6.5882x_2 + 0.0000x_1^2 + 6.5383x_2^2 - 6.3879x_1x_2$$

$$Y = 0.0000 - 1.0353T + 1.5060S - 0.1537T^2 - 0.26481S^2 + 0.47209TS$$

Considering a threshold '15' (i.e. values of $Y \leq 15$ will be labelled as 'Standard 10' and of $Y > 15$ as 'Standard 20'), error rates of 1.4% and 1.8% are achieved for training and testing, respectively. Moreover, if a range between 13 and 17 is left without classifying theses standards, these error rates become 0.2% and 0.0%. In this case, 72 out of 1000 inputs are not classified. Values within this range will have their associated inputs mapped through the exact polynomial, which corresponds to the assessment of power system state statuses through full adequacy analyses.

3.2 Proposed GMDH network

3.2.1 Input variables: There are many combinations of variables that may be considered as input of the ANN for the success state classification: for example, system load, available generation reserve, bus power injections, circuit flows, equipment unavailabilities and so on. In this paper, the following input variables are adopted, also including some possible extensions (i.e. sum, product and so on): (i) system load and (ii) generation reserve. The major reason for these choices was robustness.

3.2.2 ANN training and testing: To illustrate these concepts, a non-sequential MCS with a well-being framework [7] is initially used for a modified version of the IEEE-RTS-96 (IEEE-MRTS-96) [20]. The complete set of results of the estimated indices is detailed in Section 4.2. For this particular system, considering the adequacy analyses of the first 1000 samples, 963 operating states were classified as success (571 healthy states and 392 marginal states) and 37 states were classified as failure (i.e. at risk). In these data, information on load, generation reserve and equipment availability is duly captured. Such data (i.e. those 963 success states) are used as input for training (481 states) and testing (482 states) of the proposed GMDH neural network. The numerical values 20 and 10 are adopted to represent the desired outputs of healthy and marginal states, respectively. The size of the data sample can be determined by the regularity criterion [15, 16], by the convergence of the coefficient of variation 'β'[10] or by a previously specified number of samples. Moreover, the GMDH polynomial network can be retrained from

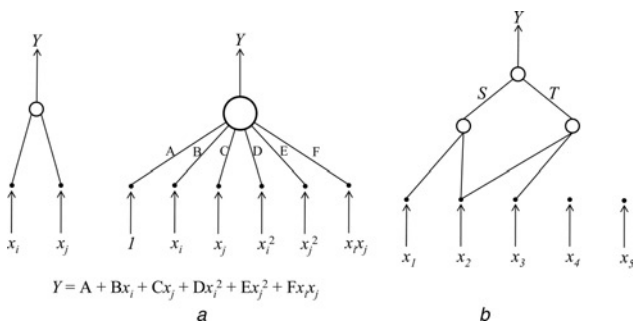

Fig. 1 *Polynomial network*
a Neuron model
b Network architecture

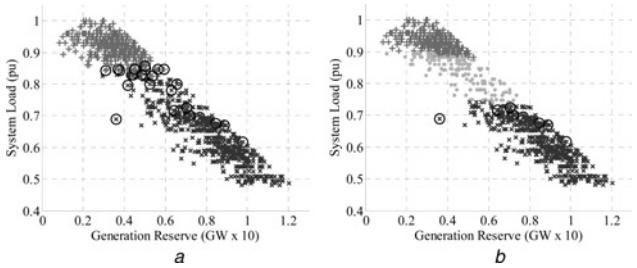

Fig. 2 *Two-dimensional plan 'system load × generating reserve': ANN*

a ANN: GMDH (threshold 15)
b ANN: GMDH (threshold 12–18)

time to time during the MCS process to improve the quality of the estimate outputs.

Considering the IEEE-MRTS-96, the results obtained by the ANN are illustrated in Figs. 2*a* and *b*. In Fig. 2*a*, it is assumed that healthy states (character '×'being attributed the value of 20, during training) are identified when the obtained classifications are greater than a specific threshold value of 15. Similarly, marginal states (character '+' being attributed the value of 10, during training) are identified when the obtained classifications are smaller than 15. Considering the previously mentioned 963 operating states, 933 were correctly classified by the proposed ANN, and there were 30 misclassifications (character '○'), which indicates an error rate of 3.12% (2.70% during training and 3.53% during test). Observe in Fig. 2*a* that there is an area where it is more difficult to distinguish between marginal and healthy states, and therefore the ANN based on the GMDH algorithm does not perform very well. A new procedure is created as follows.

In Fig. 2*b*, healthy and marginal states are identified only when the classification exhibit values above 18 and below 12, respectively. For classifications within this interval (character '•'), it is necessary to run the adequacy analysis to safely define these states. The definition of the range between 12 and 18 was based on simple observations. Clearly, there are more sophisticated ways of establishing the tolerances around states $M(10)$ and $H(20)$, for instance, by using probabilistic and/or fuzzy models. These procedures will automatically set the size of the previous interval, where no decision on the type of state can be made, and therefore a full adequacy analysis will have to be called to correctly assess these states.

In this case, 788 states were correctly classified, 167 states were not classified by the proposed ANN and there were only 8 misclassifications, which means an error rate of 0.83% (0.42% during training and 1.24% during test). Although this procedure is less efficient in terms of speed-ups, it ensures that more operating states are correctly classified. It has to be emphasised that the classifications are carried out by a simple polynomial evaluation instead of adequacy analyses, which are much more time-consuming.

To better cope with the transmission constraints, the previous procedure will be further improved as follows.

3.2.3 State-space subdivision: The application of the well-being framework to composite systems is more complicated because of the inherent complexity of the network constraints. To improve the performance of the proposed ANN based on the GMDH algorithm, the state-space is subdivided into 9 distinct regions, as shown in Table 1. For a given list of contingencies, the idea is to train different ANNs, according to Table 1, to identify the healthy and marginal states. In this paper, only two ANNs will be trained and used in this task as described in Section 3.2.4.

3.2.4 Using two ANNs: The ability of the ANN to discriminate between healthy and marginal states is based on the fact that, for each set of operating states, problem variables must present a well-defined pattern. The ANN must capture such patterns during the training phase to correctly identify them, as one applies the ANN to the new sampled states. In relation to the eight classification errors found by the previous ANN (Fig. 2*b*), it was verified that seven of them belonged to regions 7, 8 and 9 of Table 1 (i.e. operating states with at least one transmission equipment unavailable belonging to the contingency list). This means that the input variables were not able to build a well-defined representative space for those states belonging to these regions. Bearing in mind such considerations, and also to improve the efficiency of the pattern analyses for the well-being framework, two new ANNs are proposed to classify the states in healthy and marginal. The first neural network (ANN1) performs only with success operating states of regions 1–4 (i.e. operating states belonging to sets $G_0 - T_0$, $G - T_0$, $G_0 - T$, and $G - T$), and a second one (ANN2) performs only with success states of regions 5 and 6 (i.e. operating states belonging to sets $G_L - T_0$ and $G_L - T$). Full adequacy evaluations are therefore performed for those success states belonging to regions 7–9.

Figs. 3*a* and *b* present the preliminary results considering the two ANNs using the IEEE-MRTS-96. The neural networks ANN1 and ANN2 are also based on the GMDH algorithm and trained with the same set of variables from the previous example, during the beginning of the non-sequential MCS.

The necessary CPU time to train and test both ANNs was less than 1 s; see Section 4 for more details. The performances of both ANN1 and ANN2 are illustrated in Table 2. As it can be seen, these new results show a significant reduction in the error rates when compared with the corresponding results found as only using one ANN; from 3.12% to 0.11%. The full impact of using GMDH neural network types ANN1 and ANN2 on the CPU time and accuracy of the well-being indices will be shown in detail in the next section.

Table 1: State-space subdivision

Region	$G_0 - T_0$	$G - T_0$	$G_0 - T$	$G - T$	$G_L - T_0$	$G_L - T$	$G_0 - T_L$	$G - T_L$	$G_L - T_L$
Number	1	2	3	4	5	6	7	8	9

G_0, state with all generating equipment available; G, State with at least one generating equipment unavailable but not belonging to the contingency list (i.e. the deterministic criterion); G_L, state with at least one generating equipment unavailable belonging to the contingency list; T_0, state with all transmission equipment available; T state with at least one transmission equipment unavailable but not belonging to the contingency list; T_L, state with at least one transmission equipment unavailable belonging to the contingency list

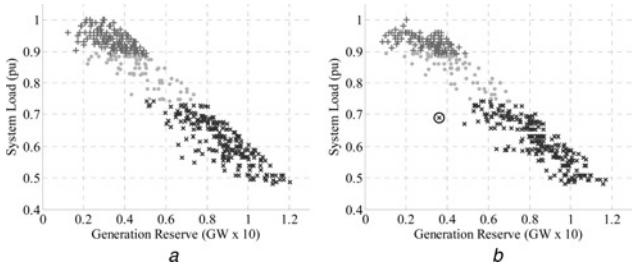

Fig. 3 *Two-dimensional plan 'system load × generating reserve': ANN1 and ANN2*

a ANN1 (threshold 12–18)
b ANN2 (threshold 12–18)

4 Results

For all three systems used in this work to verify the performance of the proposed methodology, the adequacy analysis utilises, for each sampled state, a DC power flow algorithm and, if necessary, an OPF based on a linear programming to solve possible overload problems in the network. The major objective of the OPF is to minimise load shedding (i.e. remedial action) [9–11]. In all cases, the stop criterion used to verify the convergence of the non-sequential Monte Carlo is to have a coefficient of variation $\beta \leq 5\%$ [9–11], for the well-being indices. Moreover, all computations are performed in a Pentium IV personal computer, with 2.8 GHz.

4.1 IEEE-MRTS

The IEEE-MRTS is a modification of the original system IEEE-RTS [19], in which generating capacities and peak loads are multiplied by two, with the aim of stressing the transmission network. This procedure makes the assessment of conventional and well-being reliability indices more complete and complex. The system has 24 buses, 38 circuits and 14 plants (32 generating units). The total installed capacity is 6.8 GW, with an annual peak load of 5.7 GW. A chronological load curve is adopted which consists of 52 repetitions of the peak winter week (week 51 of the original curve). Two case studies are considered with this system: Case 1 – the results are presented without using the ANNs; Case 2 – the results are obtained with the proposed methodology, that is, with the assistance of the ANNs. Keeping in mind the assessment of well-being indices, both cases use the same deterministic criterion based on the following list of events:

- Generation: one generating unit of each plant;
- Transmission: circuit branches 3–24; 9–11; 9–12; 10–11; 10–12; 11–13; 11–14; 12–13; 12–23; 14–16 and 15–24;
- Load: next hour forecast.

An intelligent ordering [7] was used to select the elements (contingencies/events) of this list. Table 3 shows the well-being indices in terms of probability, frequency (occurrences/year) and duration (hours) for the IEEE-MRTS. The indices related with the at-risk states do not change their values with the proposed methodology and therefore are not shown. Taking Case 1 as reference (REF.) results, the percentage errors (shown between brackets) observed in Case 2 are also included in Table 3.

Considering Case 1, the total number of adequacy analyses was 101 334. The CPU time necessary to converge the well-being indices was 3.45 min. Considering Case 2, where ANN1 and ANN2 are being used to assist the evaluation process, 48 592 adequacy analyses were carried out. This means that more than half of the original number of evaluated states is now assessed by a simple polynomial calculation. The total CPU time necessary to converge the indices is 1.62 min, which represents a speed-up of 2.13 in relation to Case 1. The average error is 3.7%, within the uncertainty margins specified by the coefficient of variation $\beta = 5\%$.

In relation to the interpretation of the well-being indices, considering Case 1, the chances of the system to operate in a marginal state are ~36%. In other words, the system will spend, in average, 3144 h/year (i.e. 0.3599 × 8736 h) in a marginal state. One can expect, on average, 392.22 visits or occurrences (occ.) to marginal states, while considering pattern recognition and ANNs (i.e. Case 2), one can expect 378.74 occ./year. For each visit to a marginal state, one can be expected to spend, in average, 8.02 h (Case 1) or 7.73 h (Case 2) in there.

The performance of the networks ANN1 and ANN2 trained for the IEEE-MRTS, with the previously mentioned load conditions, are presented in Table 4. The CPU time spent to train and test both ANNs is less than 1 s. Undoubtedly, the performance of the proposed methodology based on the GMDH techniques is very good in terms of computational efficiency and indices accuracy.

Table 2: ANN1 and ANN2 performances: IEEE-MRTS-96

ANN	Number of input states	Correct classifications	States not classified	Wrong classifications	Error rate Train, %	Test, %	Total, %
ANN1	464	343	121	0	0.00	0.00	0.00
ANN2	427	355	71	1	0.00	0.47	0.23
ANN1 + ANN2	891	698	192	1	0.00	0.22	0.11

Table 3: Well-being indices: IEEE-MRTS

Cases	$P\{H\}$	$P\{M\}$	$F\{H\}$, occ./year	$F\{M\}$, occ./year	$D\{H\}$, h	$D\{M\}$, h
1 (REF.)	0.5881	0.3599	303.08	392.22	16.95	8.02
2	0.6127 (4.18%)	0.3353 (6.83%)	303.12 (0.01%)	378.74 (3.44%)	17.66 (4.16%)	7.73 (3.51%)

Table 4: ANN1 and ANN2 performances: IEEE-MRTS

ANN	Number of input states	Correct classifications	States not classified	Wrong classifications	Error rate, %
ANN1	388	303	85	0	0.00
ANN2	299	240	59	0	0.00
ANN1 + ANN2	687	543	144	0	0.00

Table 5: Well-being indices: IEEE-MRTS-96

Cases	$P\{H\}$	$P\{M\}$	$F\{H\}$, occ./year	$F\{M\}$, occ./year	$D\{H\}$, h	$D\{M\}$, h
3 (REF.)	0.5819	0.3733	262.96	346.46	19.33	9.41
4	0.5831 (0.20%)	0.3730 (0.10%)	256.31 (2.53%)	337.91 (2.47%)	19.87 (2.80%)	9.64 (2.43%)

4.2 IEEE-MRTS-96

The IEEE-MRTS-96 is obtained from modifications carried out on the IEEE-RTS-96 [20], aiming at stressing the transmission network. Thus, the generating capacities and loads are multiplied by two. The new generating installed capacity is 20.4 GW and the new annual load peak becomes 17.1 GW. This system has 96 generating units, distributed among 42 power stations. The hourly load curve used in Cases 1 and 2 is also adopted for the specific load peak of this system. Two case studies are also carried out: Case 3 (without using the ANNs: REF.), Case 4 (with the assistance of the ANNs). Both cases use the same deterministic criterion based on the following list of 37 events.

- Generation – One generating unit of each plant at buses: 126; 226; 326; 125; 225; 325; 113; 213; 313; 128; 228; 328; 118; 218; 318; 121; 221; 321.
- Transmission – Circuit branches between buses: 115–124; 215–224; 315–324; 103–124; 203–224; 303–324; 110–111; 210–211; 310–311; 114–116; 214–216; 314–316; 111–113; 211–213; 311–313; 110–112; 210–212; 310–312.
- Load: next (time instant) level.

Table 5 shows the well-being indices for the IEEE-MRTS-96.

As it can be seen, the differences between both case results are very small, with average error of 1.76%, taking Case 3 as the reference. The total numbers of adequacy analyses for Cases 3 and 4 are 156 900 and 71 921, respectively. The CPU times are 23.85 min (Case 3) and 5.73 min (Case 4), which results in a speed-up of 4.16. It can be concluded that the performance of the proposed methodology based on pattern analysis is again very good. The performance of the networks ANN1 and ANN2 trained for the IEEE-MRTS-96, with the previously mentioned load conditions, is presented in Table 2, previously discussed in Section 3.2.

4.3 Brazilian system

The configuration used for the BSS contains 413 buses, 685 circuits and 255 generating units. The installed capacity and annual peak load are equal to 46 and 41 GW, respectively. This was one among different configurations used in the planning studies during the 1990s. A typical annual curve, with 8736 levels, is used to represent the behaviour of the hourly load in all buses of the system. The estimated reliability indices refer to a sub-area of the Minas Gerais state, which contains 20 buses (15 load buses), where a certain reinforcement is being considered. Two studies are first carried out: Case 5, without using the ANNs (REF.), and Case 6, with the assistance of the proposed ANNs. A list of contingency with five elements (i.e. deterministic criterion) is used for all cases. These elements are considered as critical for the operation of this particular area. The corresponding results (i.e. Cases 5 and 6) for the BSS system are shown in Table 6.

In this particular sub-area of the BSS system, considering only the convergence of the well-being indices (marginal and healthy), the total numbers of adequacy analyses for Cases 5 and 6 are 240 646 and 53 664, respectively. The corresponding CPU times are 89.94 min (Case 5) and 47.06 min (Case 6), which results in a speed-up of 1.91. Two extra

Table 6: Well-being indices: BSS System (sub-area of Minas)

Cases	$P\{H\}$	$P\{M\}$	$F\{H\}$, occ./year	$F\{M\}$, occ./year	$D\{H\}$, h	$D\{M\}$, h
5 (REF.)	0.9787	0.0204	147.70	147.70	57.95	1.21
6	0.9795	0.0197	138.09	138.09	61.96	1.24
7	0.9791	0.0202	151.01	153.32	56.64	1.15
8	0.9791	0.0202	152.08	152.08	56.24	1.16

Table 7: ANNs performances: BSS system (sub-area of Minas)

ANN1 + ANN2	Number of input states	Correct classifications	States not classified	Wrong classifications	Error rate, %
Case 6	750	725	25	0	0.00
Case 8	965	917	48	0	0.00

studies, Cases 7 and 8, are also carried out, and they are similar to Cases 5 and 6. The only difference is that they use an equivalent representation [8] for part of the transmission network. The new network has 79 buses, 137 circuits and 23 power generating stations. The results obtained for these two new cases are also shown in Table 6. The CPU times are 3.70 min (Case 7) and 0.72 min (Case 8), resulting in a speed-up of 5.14. However, if one compares Case 8 (ANNs and network reduction) with the original Case 5, the speed-up is greater than 100.

For this particular sub-area of the BSS, the LOLP and LOLF indices are ~0.1% and 3 interruptions/year, respectively. These values are very small and so will be the differences between the healthy and marginal well-being indices. In some cases, it can be noticed from Table 6 that the frequency of healthy states is equal to that of marginal states. This can be explained because healthy and marginal well-being indices converge first than the conventional reliability failure indices, and the tolerance of 5% allows that the differences between these two frequencies (i.e. $F\{H\}$ and $F\{M\}$) to be smaller than the LOLF index. Keeping in mind the specified tolerance therefore there is no inconsistency.

The performance of the networks ANN1 and ANN2 trained for the BSS system are presented in Table 7. The CPU time spent to train and test both ANNs is again less than 1 s. Undoubtedly, the performance of the proposed methodology is very good in terms of computational efficiency and indices accuracy.

The previously studied sub-area of the BSS system is in fact a reinforced configuration obtained from a well-being study. The original sub-area configuration had a probability and frequency associated with the marginal states equal to 0.4781 and 357 occ./year, respectively. Moreover, the LOLP and LOLF indices were approximately 1% and 11 interruptions/year, respectively. As it can be seen from Table 6, this new reinforced configuration has a probability and frequency associated with marginal states equal to 0.0204 and 147.7 occ./year, respectively. It is interesting to observe that, although the original configuration for this particular sub-area was not too bad in terms of LOLP and LOLF, the conditions considering the predefined deterministic criterion seem to stress the operation of the system, as it can be noticed from the high probability associated with the marginal states. Moreover, observe that the reductions obtained with the conventional reliability indices (i.e. from 1% to 0.1%, in the case of LOLP, and from 11 to 3 interruptions/year, in the case of LOLF) differ from those achieved with the well-being indices (i.e. from 48% to 2%, in the case of the probability of marginal states, and 357 to 148 occ./year). The previous stressing network operating conditions of that particular sub-area were extremely reduced by a simple reinforcement pointed out by the use of the well-being framework, which was made feasible by the proposed methodology.

5 Final remarks

This paper has presented a new methodology based on non-sequential MCS to evaluate the well-being indices for composite generation and transmission systems. The proposed methodology uses pattern recognition techniques based on ANNs, specifically a polynomial network denoted as GMDH, to reduce the computational effort associated with the adequacy analyses, which classify the success states in healthy and marginal. Case studies with standard IEEE systems and one configuration of the Brazilian system have revealed the excellent performance of the proposed approach. Moreover, by combining the proposed methodology with other network reduction techniques, the achieved speed-ups were very high. For instance, considering the Brazilian case, about 240 000 of operating states have to be analysed through standard and/or OPFs, if no assistance from ANN techniques is considered, and about 1.5 h of CPU time is necessary to converge the well-being indices. Conversely, if pattern recognition and network reductions are employed, only 36 000 operating states have to be assessed by adequacy analyses, spending less than 1 min in terms of computational effort. Undoubtedly, the use of additional concepts such as ANNs, network reductions, distributed processing and so on makes power system reliability assessments, including well-being analyses, feasible for real large networks.

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