

Applications of the Particle Swarm Optimization in Composite Power System Reliability Evaluation

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ABSTRACT

This chapter introduces a novel technique to evaluate composite power system reliability indices and their sensitivities with respect to the control parameters using a dynamically directed binary Particle Swarm Optimization (PSO) search method. A key point in using PSO in power system reliability evaluation lies in selecting the weighting factors associated with the objective function. In this context, the work presented here proposes a solution method to adjust such weighting factors in a dynamic fashion so that the swarm would always fly on the entire search space rather than being trapped to one corner of the search space. Further, a heuristic technique based on maximum capacity flow of the transmission lines is used in classifying the state space into failure, success and unclassified subspaces. The failure states in the unclassified subspace can be discovered using binary PSO technique. The effectiveness of the proposed method has been demonstrated on the IEEE RTS.

Keywords: sensitivity analysis, state space reduction, population-based intelligent search methods.

1. INTRODUCTION

Composite system reliability evaluation aims at determining the reliability of the given power system taking into consideration both transmission and generation systems. In recent years, the task of composite system reliability evaluation has become more complicated. This complexity can be attributed, in part, to the rapid increase in electrical demand and the liberalization of the electricity markets. In fact, the time and computational burden that are spent in evaluating system indices and their sensitivities with respect to the control parameters are of great concern to many researchers and companies all over the globe. Since the inception of reliability evaluation methods, a reasonable amount of work has been presented in the literature to handle the task of reliability evaluation efficiently. Numerous techniques have been proposed in the literature to assess composite system reliability. In this context, analytical and Monte Carlo simulation methods have been used for composite system reliability evaluation (Deng & Singh, 1992; He, Sun, Kirschen, Singh, & Cheng, 2010; Oliveira, Pereira, & Cunha, 1989; Wang, Guo, Wu, & Dong, 2014). It is worthy pointing out here that, composite system reliability evaluation based on analytical approaches are extremely fast; however, they tend to be tedious as the system size increases. On the other hand, Monte Carlo simulation has the ability of handling reliability analysis of complicated systems and

has been used for that purpose for a long time. However, the major downside of using Monte Carlo simulation in composite system reliability evaluation is that the time consuming during the course of reliability evaluation increases with system size. These concerns have led to the development of several Population-based Intelligent Search methods, (PIS), such as Genetic Algorithms, Particle Swarm Optimization, Ant colony, and so forth. These population-based techniques along with the some other reliability assessment methods such as importance sampling, state space pruning, and state space decomposition would be helpful in reducing the search space and handling the task of reliability evaluation efficiently.

The use of Binary Particle Swarm Optimization in power system reliability has been found to be an efficient tool in evaluating the reliability indices. However, the task of choosing the weighting factors that are associated with the objective function tends to be tedious and time consuming as trial and error approaches are usually used to prevent the particles from being flying in one direction. In view of these reasons, the development of an automated approach to adjust these weighting factors could save some effort in solving the task of reliability evaluation efficiently.

Composite system reliability indices include, but are not limited to, loss of load probability (LOLP), loss of load frequency (LOLF), loss of load expectation (LOLE), expected energy not supplied (EENS), and expected demand not supplied (EDNS). Even though these indices are of a great importance in both planning and operational power system reliability evaluation, they lack the ability of identifying the influence of each area or equipment on the system reliability. Due to these reasons, significant efforts have been devoted to this area in recent years to evaluate what the system's reliability justifications are and where the best location to invest is which is referred as sensitivity analysis.

Several methodologies for calculating the sensitivity of some reliability indices with respect to the variations in components parameters and system operating limits have been introduced in the literature. One of the advantages of using sensitivity analysis is that it allows planners to enhance the overall system reliability by improving the reliability of each component in a separate manner. The study of the sensitivity of these indices can be viewed as measures of deficiency in both generation and transmission subsystems and, hence, provide sense to the areas that to be reinforced.

In performing sensitivity analysis of the reliability indices as well as the evaluation of the system reliability, the computational time is of concern especially for the online applications. In this chapter, a heuristic technique is used to prune the state space; and thereby reduce the computational effort in evaluating the well-known reliability indices and their sensitivities with respect to component parameters and system operating limits. The heuristic technique differs from the already existed pruning techniques in that it classifies the state space into success, failure and unclassified subspaces instead of pruning the success subspaces. This method is based on calculating the line flow capacity limits of the transmission lines and evaluates the capability of the transmission lines to carry the load. The power carrying capabilities of the transmission lines are calculated at each bus and between buses for every loading scenario. However, some failure states may not be captured by using the line capacity flow model. These states are aggregated in the unclassified subspace. Also, this work proposes a technique to search for failure states in the unclassified subspace, which is developed based on a bounded and directed BPSO. This technique dynamically adjusts the weighting factors associated with the fitness function of the BPSO to force the swarm to fly on the unclassified subspace. Instead of using the dynamically directed BPSO search method to search for failure states in the entire state space, we use this technique to search for failure states in the unclassified subspace. Another intelligence factor is added to the BPSO that reverses the direction of the particles to search in the unclassified subspace if the algorithm discovers that some particles have entered the success and/or failure subspaces. The proposed algorithm tracks the behavior of the particles and then adjusts the objective function coefficients correspondingly. The behavior of the swarm can be evaluated by examining the probabilities of the visited states.

In this chapter, a new technique that is based on the complementary concept is introduced to increase the efficiency and ability of the use of the intelligent search methods in power system reliability evaluation. To show the intelligence property of BPSO technique, a comparison between BPSO and Monte Carlo Simulation methods was presented.

2. BACKGROUND

The BPSO technique has been amply used in power system reliability analysis as a searching tool for success or failure states (Green et al., 2010; Green et al., 2011; Green et al., 2011a; Green, Wang, Alam, & Singh, 2011b; Green et al., 2010; Green et al., 2010a; Zhao & Singh, 2010; Wang & Singh, 2008; Miranda, Carvalho, Rosa, Silva, & Singh, 2009; Yang & Chang, 2009; Suresh & Kumarappan, 2013). PSO has been used in optimal power system reliability planning in (Bakkiyaraj & Kumarappan, 2013). Also, PSO has been used in selecting the control procedures of FACTS (flexible AC transmission system) to improve composite power system reliability in (Padmavathi, Sahu, & Jayalaxmi, 2014). The BPSO have been used in power system reliability evaluation as searching and scanning tool to search for failure states rather than searching for a single optimum point. An improved particle swarm optimization method has been proposed in (Gholami, Hoseini, & Mohamad Taheri, 2008) to evaluation the annualized indices composite power systems. In searching for failure states, several objective functions have been proposed. The objective function of the BPSO can be single objective or multi-objective. In (Green et al., 2010) (Green et al, 2010a; Green R. C., Wang, Wang, Alam, & Singh, 2010b; Green et al., 2011; Green et al., 2011a; Zhao & Singh, 2010) a single objective function has been used, which is minimum load curtailment to search for success states to be pruned from the state space. The use of multi-objective BPSO as a searching tool for failure states in composite system reliability evaluation has been proposed in (Wang & Singh, 2008; Miranda et al., 2009; Yang & Chang, 2009; Suresh & Kumarappan, 2013; Patra et al., 2006; Mitra & Xu, 2010). One objective is used to maximize load curtailments and the other is used to maximize probabilities of the visited states. These two objective functions were intended to prevent the particles from being trapped to one corner of the state space. Every objective function has a weighting factor by which an algorithm can direct the swarm to fly on the desired search space. The weighting factors associated with the fitness functions have been carefully selected in order to keep the particles to search in the entire state space (Mitra & Xu, 2010; Patra et al., 2006; Benidris, Elsaiah, & Mitra, 2013). Even with two objective functions, if the weighting factors are not chosen carefully, the particles might be trapped to one corner of the search space. To circumvent this difficulty, an effective approach that adjusts these weighting factors is presented in this chapter.

The computational time in evaluating power system reliability, whether using analytical, simulation or intelligent methods, is another difficulty that facing the application of these methods on large systems within the operational time horizon. Several research papers in the power system reliability literature have introduced techniques to reduce the search space and the computational efforts in estimating reliability indices and their sensitivities with respect to system control variables. Singh and Mitra (1997) have introduced the concept of the state space pruning. In their work, arbitrary sets of coherent acceptable subspaces were pruned out from the state space using the concept of partitioning vectors. Then, they perform Monte Carlo simulation for the remaining subspaces. The number of pruned subspaces is system dependent and trade – off between the required time to prune the acceptable subspaces and the required time to perform Monte Carlo simulation for the rest of the subspace. Mitra and Singh (1999) have also used the concept of state space pruning to calculate the frequency and duration indices of composite power systems. Another papers developed the concept of state space pruning using Population-based Intelligent Search (PIS) methods (Green, Wang, & Singh, 2010; Green, L. Wang, Z. Wang, Alam, & Singh, 2010; Green, Z. Wang, L. Wang, Alam, & Singh, 2010a; Green, Wang, Alam, & Singh, 2011; Green, Wang, Alam, & Singh, 2011; Green, Wang, Alam, & Singh, 2011a; Zhao & Singh, 2010). The Genetic Algorithm (GA) and the modified GA were used in (Green et al., 2010; Green et al., 2010a; Zhao

& Singh, 2010) to prune the state space and use Monte Carlo simulation for the remaining part of the state space. Binary Particle Swarm Optimization, (BPSO), technique was utilized in (Green et al., 2011; Green et al., 2011a) to prune the state space. Green and et al. (2011) have applied the Artificial Immune Systems (AIS) Optimization technique in pruning the state space. A comparative study of using (PIS) methods specifically Genetic Algorithms (GA), Repulsive Binary Particle Swarm Optimization (RBPSO) and Binary Ant Colony Optimization (BACO) was introduced in (Green et al., 2010). In all of these applications, the PIS methods are utilized as heuristic techniques and therefore selection of the acceleration factors is a crucial part to guarantee the best performance of these methods.

Our approach in pruning the state space works in the other direction of the already existed pruning techniques. In this chapter, instead of pruning the success subspaces, we identify the “definite” failure subspace. We call it definite because all the states inside the boundary of this subspace are definitely failure states. The boundary of this subspace surrounds the origin (all the components are in the down state) of the entire state space.

Different from common applications of BPSO, BPSO is used in this work as a scanning tool to search for a set of system states that significantly contribute to system reliability indices rather than searching for a single optimum or near optimum point in the state space. Also, the applications of the BPSO in power system reliability evaluation have been based on calculating the exact probabilities of the visited states; BPSO is used in chapter to estimate the reliability indices based on a complementary concept.

3. NETWORK MODELLING USING LINEAR PROGRAMMING AND DC LOAD FLOW

In performing reliability and sensitivity analysis of composite power systems, a power flow or optimal power flow with objective of minimum load curtailment is usually required to test whether the state under consideration is a failure or success state. Therefore, the task of performing optimal power flow, OPF, is essential in evaluating the reliability indices of power systems. Toward this end, three power flow models have generally been used for composite system reliability assessment. These models are the full AC power flow model, the transportation model or capacity flow model, and the DC power flow model. The task of reliability evaluation using full AC power flow can be inflexible and extremely time consuming. The transportation model, on the other hand, only uses the capacity constraints of the tie-lines and, therefore, it is not applicable for every reliability study. The DC power flow model has been widely utilized in reliability assessment of power systems due to its simplicity of formulation and implementation. Moreover, the DC power flow model has the advantage of being suitable for studies that require extensive computational burden such as composite system reliability and security assessment. Consequently, this model is adopted during the realization of the presented work.

Linear programming with DC power flow model has been used in calculating the reliability indices of composite power systems. If under any scenario the curtailment is unavoidable, the linear programming tries to minimize the amount of load to be shed. Using DC load flow, there are three main constraints which are power balance equation, generation capacity limits and line capacities. The equality constraints are the power balance at each bus and the inequality constraints are the capacity limits of generating units and power carrying capabilities of transmission lines. The load curtailment minimization problem can be posed as (Mitra & Singh, 1996),

$$Loss\ of\ Load = \min \left(\sum_{i=1}^{N_b} C_i \right) \quad (1)$$

subject to

$$\hat{B}\delta + G + C = D$$

$$\begin{aligned}
G &\leq G^{max} \\
C &\leq D \\
b\hat{A}\delta &\leq F_f^{max} \\
-b\hat{A}\delta &\leq F_r^{max} \\
G, C &\geq 0 \\
\delta &\quad \text{unrestricted}
\end{aligned} \tag{2}$$

where N_b is number of buses in the system, N_t is number of transmission lines, $\hat{B}$ is the augmented node susceptance matrix ($N_b \times N_b$), b is the transmission line susceptance matrix ($N_t \times N_t$), $\hat{A}$ is the element-node incidence matrix ($N_t \times N_b$), δ is the vector of node voltage angles ($N_b \times 1$), C is the vector of bus load curtailments ($N_b \times 1$), D is the vector of bus demand ($N_b \times 1$), G^{max} is the vector of maximum available generation ($N_b \times 1$), F_f^{max} is the vector of forward flow capacities of lines ($N_t \times 1$), F_r^{max} is the vector of reverse flow capacities of lines ($N_t \times 1$), and G is the solution vector of the generation at buses ($N_b \times 1$).

In the standard minimization problem given by (1) and (2), all generation and network constraints have been taken into consideration. Also, it has been assumed that one of the bus angles is zero in the constraints (2) to work as a reference bus.

4. STATE SPACE REDUCTION TECHNIQUE

In evaluating the reliability indices of composite systems, an optimal power flow with an objective of minimum load curtailment is performed. The DC power flow model in conjunction with the linear programming optimization problem is the most commonly model used in power system reliability evaluation. Performing DC optimal power flow for huge number of scenarios of contingency analyses takes a considerable amount of time and computational efforts. A fast method to perform such screening procedure is of necessity. Further, searching for failure states in the entire state space is time consuming and, hence, a reduction technique is required to reduce the computational time. A heuristic technique is presented and described in this section. This heuristic technique is developed based on calculating the line flow capacity limits of the transmission lines. This technique models power system networks based on network configuration, available generation, loading conditions and transmission line availabilities, and power carrying capabilities.

By examining the above linear programming problem, it can be noted that for any sampled state if one of the following two conditions is satisfied, we can conclude that this state is a failure state: (1) total generation is less than the total load and (2) sum of the capacity of the lines connected to a bus is less than the loading of that bus. Given these conditions, we can construct a heuristic technique that reduces the search space significantly. The procedures can be described as follows (Benidris & Mitra, 2013),

1. Subtract the loads connected to the generation buses from the sampled amount of generation at these buses.
2. Construct a line capacity capability flow matrix, (LCM), for the given sampled configuration. This matrix can be constructed in the same manner as constructing a “Ybus” from the branch/node incidence matrix (A) except that instead of using “-1” for the branch that assumed to enter a node, we use “1”. Further, instead of using the diagonal susceptance matrix, we use diagonal capacity matrix (C) that is, the diagonal entries are the line capacities. The LCM matrix can be expressed as follows,

$$LCM = A^T \times C \times A \quad (3)$$

where A^T is the transpose of matrix A .

3. If at any bus the total generation is larger than the corresponding diagonal element of the LCM matrix, adjust the generation at that bus downward to the corresponding diagonal element.
4. For a state (x), if the value of any of the diagonal elements of the matrix LCM is less than the absolute value of the power injection at the corresponding bus or the total generation is less than the total demand, this state is guaranteed to be a failure state.

After reading system data, system states are sampled. For every sampled state, the above search space reduction technique is applied. Failure states are then passed to the linear programming optimization problem and they are solved for the conditions of these states and the reliability indices are updated. These processes are repeated for every sampled system state.

5. REDUCTION IN COMPUTATIONAL TIME

In calculating reliability indices, an optimization problem usually needs to be performed for every system state with different loading scenarios. The process of preparing and modeling power system data to be tested for reliability analysis is performed one time. However, running an optimization problem is required for every system state or any change in system parameters. From a study of wide variety of system sizes and configurations, the optimization problem takes most of the calculation time. For instance, on average, the time required to solve an optimization problem for the systems we have tested took more than 95% of the calculation time for each system state. By performing the reduction technique, not all the states need to be passed to the optimization problem. In other words, if a state is guaranteed to be a success state, no useful results can be shown by solving an optimization problem. On the other hand, failure states should be passed to the analyzer to calculate bus indices. As mentioned above, system indices of the definite failure subspace can be calculated without the need of solving the optimization problem.

The problem of deciding whether we need to perform BPSO for the unclassified subspace can be solved by running the BPSO for a few iterations. If the reliability index under consideration does not change for a few iterations, the algorithm is to be terminated and the indices calculated by the line capacity model are enough to describe the reliability of the system.

5.1 Reduction in Computational Time in Case of Ignoring the Unclassified Subspace

If the transmission lines of the system under consideration are very reliable and have high power limits in comparison with system loading conditions which is the case for most power systems, the proposed line capacity flow model can capture most of the failure states. In this case, performing the search method is not necessary and ignoring this subspace will not cause significant errors.

If we assume the total time required to evaluate system indices by passing every single state to the solver (optimization problem) is T , the total time required to evaluate system indices by passing only the failure states to the solver is T_r , the time required to evaluate every system state is t , the time required by the optimization problem to evaluate every system state is t_r , number of samples is N and the loss of load probability of the system is LOLP, then by ignoring the unclassified subspace the percentage of reduction in the computational time η can be calculated as,

$$\eta = \frac{T - T_r}{T} \times 100\% \quad (4)$$

where

$$T = N \times t$$

$$T_r \approx N \times [LOLP \times t + (1 - LOLP)(t - t_r)]$$

here T_r is approximated because the time of performing the heuristic technique to identify the failure states is very small in comparison with the time of preparing system data for every sampled state and the time required by solving the optimization problem.

After some manipulations, equation (4) can be rewritten as,

$$\eta \approx (1 - LOLP) \frac{t_r}{t} \times 100\% \quad (5)$$

As an example, if we assume 100,000 states were to be sampled and evaluated in order to reach the desired tolerance and every state takes about 0.01 seconds and if we assume the LOLP of the system is 0.01 and the optimization solver takes 95% of the calculation time of each state, then the time required with solving optimization problem for “every state” is 1000 seconds and the time required by passing only the failure states to the solver is 59.5 seconds. Therefore, the percentage of time reduction of using this technique is 94.05%.

5.2 Reduction in Computational Time in Case of Including the Unclassified Subspace

In case of ignoring the unclassified subspace causes considerable error in evaluating system indices, the proposed directed BPSO should be used. In this case, calculation of the percentage of time reduction is not straight forward and system dependent. Therefore, calculation of this time cannot be determined beforehand.

To calculate the time reduction, another time which is the time spent by performing the BPSO algorithm, T_{BPSO} , is to be added to the time spent to perform the line capacity model, T_r . Now, equation (4) can be rewritten as,

$$\eta = \frac{T - (T_r + T_{BPSO})}{T} \times 100\% \quad (6)$$

The computational efforts required by the algorithm proposed in (Mitra & Xu, 2010) for the entire state space is found to be only 19.31% of performing Monte Carlo Simulation with State Space Pruning (Mitra & Singh, 1999) on the modified IEEE RTS. Since we are applying a dynamically directed BPSO on a subspace of the entire state space, T_{BPSO} in our case should be less than 19.31% of T . Also, the number of states to be visited is very small; hence, the required memory will be small too.

6. THE COMPLEMENTARY CONCEPT

The concept of complementary has been applied in several disciplines to calculate/estimate a parameter from its complementary value. The complementary concept in composite power system reliability evaluation can be defined as: every reliability index that can be evaluated from the failure states, has a complementary value that can be evaluated from the success states as long as the boundaries of an index and its complementary value are known such as probability and energy indices or the index can be equally likely determined from the success or failure states such failure frequency indices. For example, the boundary (minimum and maximum values) of the probability of system failure and the probability of system success is between 0 and 1. Also, the boundaries of expected load curtailment and the expected load supplied are between 0 and the peak load. Frequency indices can be evaluated either from the failure states that transit upwards to success states or from success states that transit downwards to failure states. The complementary concept estimates reliability indices from visited states; rather than the entire state space.

6.1 Theoretical Background

The complementary concept starts with the fact that the sum of the probabilities of the state space is one. Therefore, the sum of the probabilities of the success states and the failure states is also one. The number of states in a state space is 2^n where n is the number of the components. Most power system components (generation and transmission) are highly reliable. Therefore, the state that all system components are in the up state has the highest probability. Not only that, the probability of a state with only one component being in the down state usually less than the probability of the state with all the components are in the up states of order of $1/q_i$ where q_i is the unavailability of component i . This probability order can be generalized for the rest of the states, that is the probability of a state that has two components in the down state (i and j) is less than the probability of a state with all the components are in the up state of order of $1/q_i q_j$. Therefore, as the number of the components in the down state increases, the probability of a state decreases with reciprocal of the multiplication of the un-availabilities. Therefore, if an intelligent search method discards the states with very small probabilities and captures the states that have most effect on system reliability, the number of states that need to be evaluated can be decreased significantly.

For example, consider a system with ten identical components with availability of 0.95. The probability of all the components are in the up state is 0.59874 and the probability of one component being in the down state is 0.03151. Therefore, the probability order between the two states is 19. The probability of a state with two components are in the down state is 0.00166. The probability order between this state and the state with all components are up state is 361. The probability of the state with all components are in the down state is 9.76563×10^{-14} . Therefore, even with ignoring the states that have small probabilities, we can accurately evaluate the behavior of the system.

For this system, if we consider at most one component being in the down state, we need to evaluate 11 states out of 1024 states and the sum of the probabilities of these states is 0.91386. If we consider at most two components are in the down state, we need to evaluate 56 states out of 1024 states and the sum of the probabilities of these states is 0.98850. This behavior is trivial for small systems with identical components; however, for large systems with non-identical components, it is difficult to trace the behavior of the system analytically. Therefore, if we allow some error tolerance, an intelligent search method can capture the states that have most effect on system reliability. Therefore, the reliability of the system can be approximately evaluated through these states. The indices evaluated from these states, however, will not be equal to the exact indices. Therefore, a method to estimate these indices from the specified states is of necessity. In this work we introduced the concept of complementary to estimate reliability indices.

As the algorithm searches through the state space, the reliability indices and their complementary values become close to each other. For example, the difference between the probability of system failure calculated from the failure states, q , and the probability of system failure calculated from the success states, $(1 - p)$, goes gradually to zeros as the search progresses. Since, the search method is not intended to visit the entire state space and the reliability indices can approximately evaluated from the relevant states, the reliability indices can be referred to the relevant subspace. Since the sum of probabilities of the entire state space is 1 and the sum of probabilities of the visited states is $q + p$, then a reliability index can estimated over the evaluated subspace as follows,

$$\hat{f}_i(x) = f_i(x) \times \frac{1}{q + p} \quad (7)$$

where $f_i(x)$ is the reliability index under consideration and $\hat{f}_i(x)$ is its estimated value.

6.2 Mathematical Justification

If we evaluate the entire state space and if we denote the loss of load probability as q and the probability of load availability as p , then the following relationship holds,

$$p + q = 1$$

On the other hand, if we evaluate part of the state space, then $p + q < 1$. In this case the estimated value of q , ($\hat{q}$), and estimated value of p , ($\hat{p}$), will be less than or equal to the exact values, that is $\hat{q} < q$ and $\hat{p} < p$.

If the search tool were able to visit all the failure states without the need to visit the entire state space, then $\hat{q} = q$ and $\hat{p} < p$. On the other hand, if the search tool were able to visit all the success states without the need to visit the entire state space, then $\hat{q} < q$ and $\hat{p} = p$.

Searching for all the failure states or all the success states is computationally expensive and equivalent to state space enumeration. If the search tool intelligently searches uniformly for both success and failure states and if the algorithm does not evaluate the entire state space, then $\hat{q} < q$ and $\hat{p} < p$.

If the algorithm searches for the states that have the most effect on system reliability, then a high cumulative probability of the state space can be evaluated through a small fraction of the state space. Therefore, q and p can be approximated as,

$$q + p \approx 1$$

Through the search process, the q index represents the sum of the probabilities of the failed states visited so far and p index represents the sum of the probabilities of the success states visited so far. The sum of the probabilities of the states visited so far is $q + p$. Therefore, the estimated value of the probabilities of failure over the visited subspace can be expressed as follows,

$$\hat{q} = \frac{q}{q + p} \quad (8)$$

and the estimated value of the probabilities of the success over the visited subspace can be expressed as follows,

$$\hat{p} = \frac{p}{q + p} \quad (9)$$

Same relations can be applied for the other indices that can be calculated from the failure states as well as from the success states.

7. DYNAMICALLY DIRECTED DISCRETE PARTICLE SWARM OPTIMISATION SEARCH METHOD

In performing the proposed heuristic technique, some failure events may not be captured. These events can occur in three scenarios. In the first scenario, an area of the system is isolated from the generation areas (area with loads only) and the transmission lines connecting the loads of this area are sufficient to carry the loads. In the second scenario, an area of only load buses is connected to the rest of the system through a tie line that cannot carry the total load of this area but the transmission lines of this area can carry the load. In the third scenario, line impedances force the power to flow through some capacity limited lines and the load flow will not converge without load curtailment. These scenarios cannot be detected by considering the power carrying capabilities of the transmission lines. Therefore, a search tool should be used to capture these events. However, the search space can be bounded by definite failure

subspace and definite success subspace which makes the search method converges to these events with less computational effort.

7.1 State Space Description

Figure 1 shows the state space of a three dimension system. The above reduction technique can detect the definite failure subspace but cannot detect the boundary of the definite success subspace. However, since the reliability indices are evaluated based on the failure states, analysis of the entire success subspace is not important. A large chunk of a success subspace can be truncated by considering all the transmission lines in the up state and determining the vector of minimum generation to satisfy the load. Any state in the state space that has a generation vector larger than or equal to the minimum generation vector is guaranteed to be a success state. Therefore, the boundary of the success subspaces can be used to control the BPSO. Also, most of the unclassified failure states lay around the boundary of the definite failure subspace. Therefore, an intelligent search method, which is bounded between the boundaries of the success and failure subspaces, can efficiently converge to failure states in the unclassified subspace. In this chapter we use “directed” BPSO to search for these states. Nothing sacrosanct about using PSO, any intelligent search algorithm can be used.

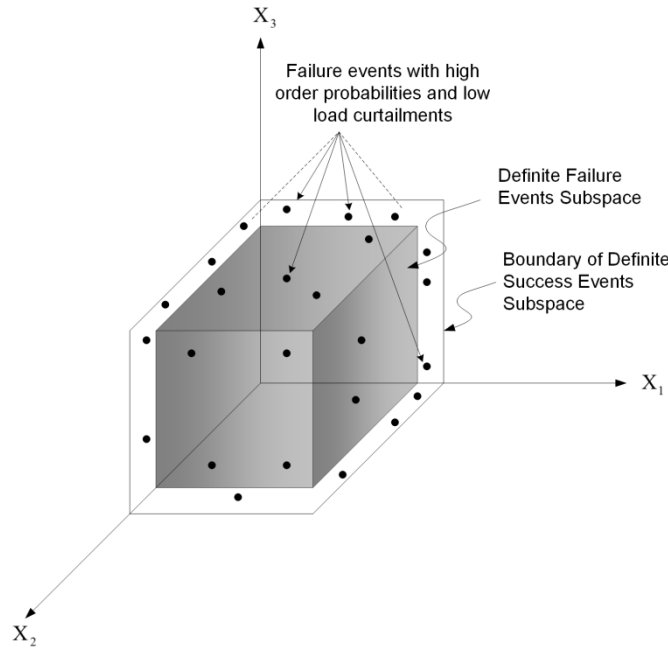


Figure 1. A state space of three dimension system

7.2 Particle Swarm Optimization

The particle swarm optimization technique (PSO) has been proposed by Kennedy and Eberhart (1995). Later, Kennedy and Eberhart proposed a discrete binary particle swarm optimization (BPSO) to solve combinatorial optimization problems (Kennedy & Eberhart, 1997). The PSO has been proven to be an effective optimization technique and has, therefore, been used in the presented work. In this chapter, we use the BPSO to search for success and failure states rather than looking for optimal solution. In other words, different from common applications of BPSO, BPSO is used in this work as a scanning tool to

search for a set of system states that significantly contribute to system reliability indices rather than searching for a single optimum or near optimum point in the state space. Through the scanning and searching process, the algorithm uses probabilities and severities of the visited states to evaluate reliability indices. Further, generation and transmission lines states are represented as up or down states; where up states are represented by 1's and down states are represented by 0's. Moreover, we apply bi-objective function that searches through the entire state space for success and failure states. Such objective function is also capable to prevent particles from being trapped to one area of the search space. It is worth noting here that the size of the state space is 2^n where n is the number of system components. Therefore, even for medium systems, the number of states is very large and it is impractical to test the entire state space. Hence, the concept of the estimated indices is adopted in this study so that searching all over the entire state space is reduced (Mitra & Xu, 2010; Patra, Mitra, & Earla, 2006).

BPSO technique searches through the state space and tests the visited states for a possibility of load curtailment. In performing the search process, for every generation, particle velocity v_i or the direction of movement of particle i from position x_i can be governed by the following objective function (Kennedy & Eberhart, 1997; Mitra & Xu, 2010; Patra et al., 2006):

$$\begin{aligned} v_i = & v_i + rand() \times c_1 \times (Ppbest_i - x_i) \\ & + rand() \times c_2 \times (Pgbest_i - x_i) \\ & + rand() \times c_3 \times (Cpbest_i - x_i) \\ & + rand() \times c_4 \times (Cgbest_i - x_i) \end{aligned} \quad (10)$$

where $rand()$ is a uniformly distributed random number between $[0, 1]$, $Ppbest_i$ is the particle best position from the probability of a state prospective particle i has ever encountered, $Pgbest_i$ is the group of particles best position from the probability of a state prospective the group has ever encountered, $Cpbest_i$ is the particle best position from the load curtailment of a state prospective particle i has ever encountered, $Cgbest_i$ is the group of particles best position from load curtailment of a state prospective the group has ever encountered and c_1, c_2, c_3 and c_4 are acceleration factors.

The change in particles positions can be defined by a sigmoid limiting transformation function and a uniformly distributed random number in $[0, 1]$ as following,

$$x_{id} = \begin{cases} 1, & rand() < S(v_{id}) \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

where x_{id} is the d^{th} component of particle i and $S(v_{id})$ is the sigmoid function of d^{th} component of particle i which can be expressed as,

$$S(v_{id}) = \frac{1}{1 + e^{(-v_{id})}} \quad (12)$$

Changes of probabilities are limited by V^{max} which limits the ultimate probability of a bit in particle i to have zero or one. Choosing very large or very small values for V^{max} can limit the chance of exploring

new vectors. Therefore, a careful selection of V^{max} should be performed. In this work, for a flat start, we have chosen V^{max} to be 2.2 which makes $S(v_{id})$ between 0.9 and 0.1. For next iterations, V^{max} is changed according to particles positions as described in the solution algorithm.

7.3 Use of BPSO in Power System Reliability Evaluation

One of the differences between using BPSO in power system reliability evaluation and Monte Carlo is that the former evaluates the relativity indices by summing up the probabilities of the visited states, while in the latter; the reliability indices are evaluated by dividing the number of encountered failure states to the number of samples. It is well known that Monte Carlo simulation is extremely time consuming in calculating reliability indices for the designated accuracy. However, in performing Monte Carlo simulation, no need to visit all system states since it calculates the weighted values not the exact values. On the other hand, to calculate reliability indices using BPSO, all failure states or success states need to be visited, which is computationally expensive, if not impossible for large systems. Therefore, another technique to overcome this drawback is required. New indices have been introduced in (Mitra & Xu, 2010; Patra et al., 2006) which are normalized LOLP, ($LOLP_{norm}$) and projected LOLP, ($LOLP_{proj}$) to eliminate the necessity of visiting all the failure and success states. The $LOLP_{norm}$ is the ratio between the sum of the probabilities of the failure states (LOLP) to the sum of probabilities of the states encountered so far ($1+LOLP-DLOLP$); where DLOLP is the dual value of the LOLP which is one minus the sum of probabilities of the success states encountered so far ($1-\text{sum of the probabilities of the visited success states}$). The $LOLP_{proj}$ is the crossings between the tangents of the LOLP and DLOLP. The normalized LOLP can be expressed as follows,

$$LOLP_{norm} = \frac{LOLP}{1 + LOLP - DLOLP} \quad (13)$$

Again, $LOLP_{norm}$ and $LOLP_{proj}$ are the same as the weighted LOLP index used in Monte Carlo simulation. However, $LOLP_{proj}$ converges to the approximate value of the LOLP faster than $LOLP_{norm}$ (Mitra & Xu, 2010). It can be noted that even though BPSO and Monte Carlo Simulation both evaluate the weighted index, the number of states to be visited using BPSO is significantly less than the number of states to be visited using MCS (Mitra & Xu, 2010).

7.4 Role of BPSO in Reliability Evaluation

Different from common applications of BPSO, BPSO is used in this work as a scanning tool to search for a set of system states that significantly contribute to system reliability indices rather than searching for a single optimum or near optimum point in the state space. Through the scanning and searching process, the algorithm uses probabilities and severities of the visited states to evaluate reliability indices. However, if the search process is not set properly, BPSO may converge to a single point and no new states would be discovered. If this is the case, reliability indices might be over or under estimated. Several methods have been proposed to spread the search of the PIS methods (Miranda, Keko, & Duque, 2008; Parsopoulos & Vrahatis, 2002; Peram, Veeramachaneni, & Mohan, 2003; Miranda, Carvalho, Rosa, Silva, & Singh, 2009; Wang & Singh, 2008). In (Miranda et al., 2009), it has been found that forgetting the global best

and resetting the memory term improves the spreading of the PIS methods. In this work, this method is adapted.

7.5 Directed BPSO

By examining the state space, all possible outcomes of the combination of generation and transmission, the probabilities of the upper part states are larger than the probabilities of the lower part states. Further, load curtailments of the lower part states are larger than load curtailments of the upper part states. If the swarm was to fly on the upper part, it is unlikely to encounter failure states and the opposite is true for the lower part. As mentioned above, using multi-objective function does not guarantee that the particles will fly on the desired search space unless the weighting factors are chosen carefully. Figure 2 and Figure 3 show two situations for badly chosen weighting factors of the objective function. Figure 2-(a) and Figure 3-(a) show the behavior of the particles. Figure 2-(b) and Figure 3-(b) show the expected profile of the reliability indices. In Figure 2, the swarm is trapped to the upper corner of the state space. In this case the normalized LOLP as well as the projected LOLP will be under estimated. As the particles continue to fly on the upper corner, most of the visited states will be success states and more likely no failure states will be captured. Therefore, no much change in the LOLP and the 1-DLOLP is sharply increasing. On the other hand, if the swarm is trapped into the lower corner as shown in Figure 3, most of the visited states will be failure states and unlikely to encounter success states. In this case, LOLP, $LOLP_{norm}$ as well as the $LOLP_{proj}$ will be overestimated. The LOLP index will continue to increase whereas the 1-DLOLP index remains almost constant.

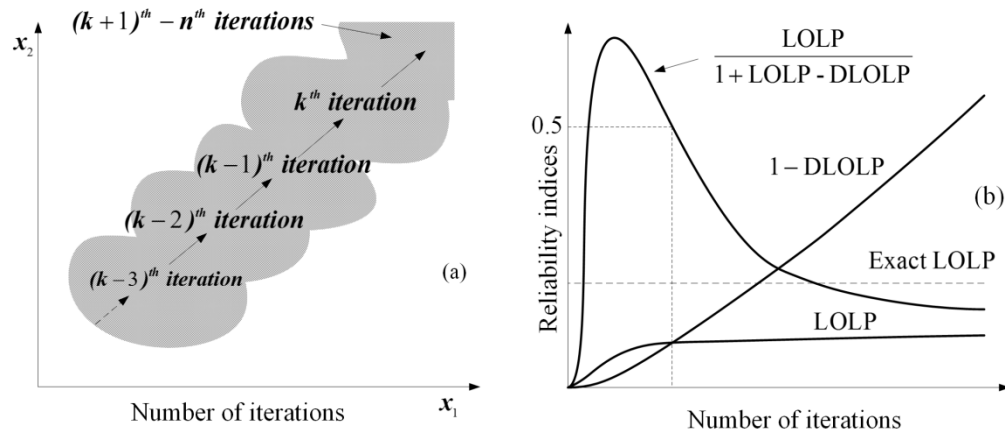


Figure 2. Reliability indices profile in case the particles are trapped to the upper corner of the state space

To direct the BPSO to fly on the unclassified subspace and overcome the difficulty of choosing the weighting factors as well as the change in probability limit, we propose a technique that tracks both the normalized LOLP and the number of the new visited states or the mutation rate. This technique was developed based on the normalized loss of load probability index ($LOLP_{norm}$). The $LOLP_{norm}$ has been introduced in (Mitra & Xu, 2010; Patra et al., 2006) to estimate the LOLP index without the need of searching the entire state space. After performing a few iterations, if $LOLP_{norm}$ continues to increase that means the particles are trapped in the lower corner of the search space. On the other hand, if $LOLP_{norm}$ continues to decrease, that means the particles are trapped in the upper corner of the search space. Also, if

no new states are visited and the designated reliability index does not converge to the specified accuracy, then V^{max} is limiting the probability of bit change. Also, if the algorithm discovers that the swarm is entered the classified success and failure subspaces, the weighting factor are adjusted accordingly as shown in Figure 4. The procedures of preventing the particles from being trapped into one area are described in detail in the solution algorithm.

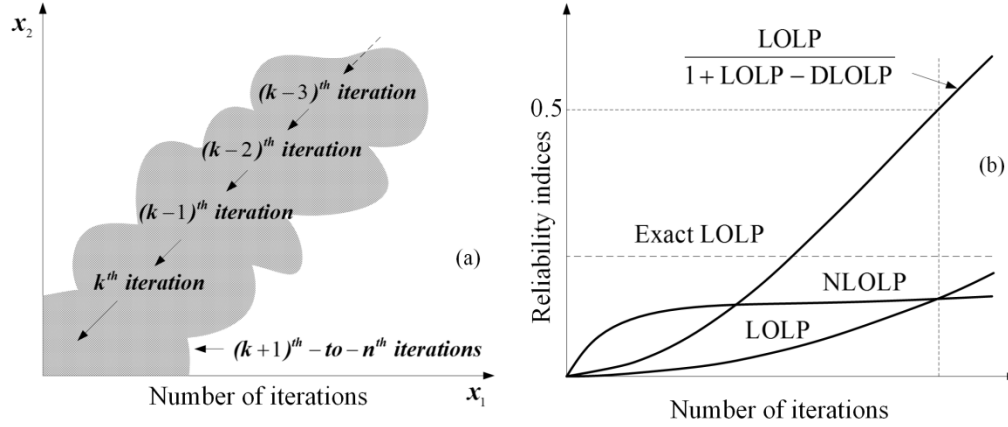


Figure 3. Reliability indices profile in case the particles are trapped to the lower corner of the state space

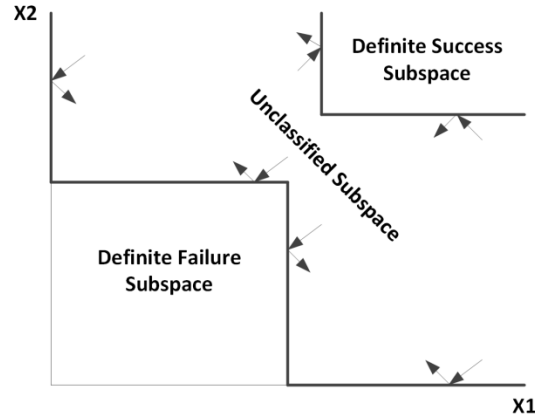


Figure 4. Redirecting the swarm in case it enters the success or failure subspaces

8. COMPARISON BETWEEN THE PROPOSED METHOD AND THE EXISTING METHODS

The existing methods of evaluating power system reliability indices can be divided into three categories: analytical methods, Monte Carlo simulation and the use of the intelligent search methods. Analytical methods are difficult to apply for large and complex systems. On the other hand, Monte Carlo simulation is easy to implement but it takes long time to converge. The intelligent search methods have been utilized in power system reliability evaluation to reduce the computational time. Intelligent search methods have been used in power system reliability to search for failure and success state in the entire state space such as the methods presented in (Mitra & Xu, 2010; Patra et al., 2006). Also, the intelligent search methods

have been used in pruning the success subspace and applying Monte Carlo simulation on the remaining part of the state space such as the methods presented in (Green, Wang, & Singh, 2010; Green et al. 2010; Green et al. 2010a; Green et al. 2011; Green et al. 2011a; Green, Wang, Alam, & Singh, 2011a; Zhao & Singh, 2010).

The proposed method prunes both the success and failure subspaces using heuristic techniques and applies a directed BPSO to search for the failure states in the unclassified subspace. The existing methods apply Monte Carlo simulation to search for failure states in the unclassified subspace which requires a significant number of iterations to converge. Also, applying the intelligent search methods on the entire state space can be computationally expensive due to the fact that for each state an optimal power flow is performed. Further, using intelligent search methods for searching for failure and/or success states without the use of a device that directs the swarm can lead to incorrect results (Mitra & Xu, 2010; Patra et al., 2006).

In this chapter, we use a heuristic technique to classify the state space into success, failure and unclassified subspaces. After classifying the state space, a “directed” BPSO is used to search for failure states in the unclassified subspace. From the behavior of the first generations of the BPSO, we use a device to direct the swarm as is explained section 11.

9. CALCULATION OF THE RELIABILITY INDICES

In this work, we have evaluated the well know composite power system reliability indices, namely loss of load probability (LOLP), expected demand not supplied (EDNS), loss of energy expectation LOEE), and loss of load expectation (LOLE). A stopping criterion has been applied to stop the algorithm from sampling if it converges to the desired accuracy.

9.1 Calculation of probability indices

The estimated value of the LOLP index can be calculated as follows,

$$LOLP = \sum_{i \in F} P_i(x) \quad (14)$$

where F is the set of states that have load curtailments, $P_i(x)$ is probability of state i and x represents the state of the system. The estimated dual value of the DLOLP index can be expressed as,

$$DLOLP = 1 - \sum_{i \in S} P_i(x) \quad (15)$$

where S is the set of states that do not have load curtailments and P_i is probability of state i .

The loss of load probability is approximated by the trajectory of the crossings between the tangents of the LOLP and DLOLP. Both LOLP and DLOLP are monotonically increasing functions and they eventually will reach each other. The loss of load expectation index can be calculated from the loss of load probability index by multiplying by the study period.

9.2 Calculation of energy indices

The estimated value of the EDNS index can be calculated as follows,

$$EDNS = \sum_{i \in F} P_i(x) \times C_i(x) \quad (16)$$

where C_i is the amount of load curtailment of state i . The dual value of the EDNS index is the expected supplied demand. The estimated dual value of the EDNS index (DEDNS) can be expressed as,

$$DEDNS = Peak\ Load - \sum_{i \in S} P_i(x) \times L_i(x) \quad (17)$$

where L_i is the amount of the supplied load of state i .

The expected demand not supplied index is approximated by the trajectory of the crossings between the tangents of the EDNS and DEDNS. Both EDNS and DEDNS are monotonically increasing functions and they eventually will reach each other. The loss of energy expectation index can be calculated from the expected demand not supplied index by multiplying by the study period.

9.3 Calculation of Bus Indices

Calculation of bus indices using linear programming produces multiple solutions and hence bus indices will not be unique (Billinton & Li, 1994). To overcome this difficulty, load curtailment philosophies need to be incorporated in the linear programming problem (Billinton & Li, 1994). Such philosophies can be the priority of each load or part of each load. Also, load can be curtailed according to closeness to the fault location. In this chapter, the loads were divided into three parts with different weighting factors for each part, e.g., w_1 , w_2 and w_3 respectively. The first two parts were assumed to represent 25% of the total load and the third part was assumed to represent 50% of the total load. The weighting factor of the first part is assumed to be less than that of the second part and the weighting factor of the second part is assumed to be less than that of the third part or in other words, $w_1 < w_2 < w_3$.

9.4 Modelling of System Components

9.4.1 Modelling of Available Generation

Most buses have several generators which may be similar or different. The unit addition algorithm (Singh & Chen, 1989) is used to construct a discrete probability distribution function for each bus which is known as capacity outage probability and frequency table, COPAFT. This table is constructed based on the capacity states and forced outage rates of units at each bus.

9.4.2 Modelling of System Load

Loads at the buses are modelled based on the cluster load model technique (Singh & Chen, 1989; Singh & Lago-Gonzalez, 1989; Lago-Gonzalez & Singh, 1990; Singh & Deng, 1991). From the chronological loads, clusters are constructed according to the load level and its probability. These clusters are used for each load bus as a percentage of the peak load of the given bus.

9.4.3 Modelling of Transmission Lines

A discrete probability density function is constructed for every transmission line. If a line is tripped for some system state, the line is removed from the bus admittance matrix and its capacity is set to zero.

9.5 Stopping Criteria

A convergence criterion should be applied to stop the algorithm if there is not much change in the reliability indices. In power system reliability analysis using Monte Carlo simulation it was found to be that energy indices are the slowest indices from convergence view point (Billinton & Li, 1994). In this work, we have applied the stopping criterion on the EDNS index.

The stopping criterion considering the EDNS index can be expressed as,

$$\sigma = \frac{\sqrt{\text{Var}(EDNS)}}{E[EDNS]} \quad (18)$$

where $E[\bullet]$ is the expectation operator and $\text{Var}(\bullet)$ is the variance function.

After few iterations, the amount of the change in σ is calculated, if this amount is less than or equal to the specified tolerance, the algorithm is to be terminated; otherwise, the simulation will continue.

10. SENSITIVITY ANALYSIS

Sensitivity analyses of reliability indices reported in the literature have been based on calculating the amount of change of these indices with respect to component parameters such as availability, unavailability, capacity, failure rate and repair rate. One of the advantages of the sensitivity analysis is that it allows planners to distribute the available resources in a cost-effect paradigm to enhance system reliability. In the research reported in this chapter, a shadow-price based method is proposed for performing the sensitivity analysis. Shadow prices are used here as indicators of the area or component in which the investment will improve system reliability. The analyses are performed by casting the dispatch operation as an optimization problem, through minimizing load curtailment or maximizing load supplying capability. The optimization is constrained by generator and transmission line capacities.

Shadow price approach was initially proposed by the former Soviet Union economist *Conte Petrovic* in the late 1930s when he was applying linear programming technique to maximize the output of some products (Li, Qu, & Cui, 2009). Several definitions have been reported in the literature for the shadow price (Ramanujan, Li, & Higham, 2009). For instance, from a primal-dual perspective, it can be defined as the primal (x) and dual (y) solutions of the linear programming problem. From the optimization point of view; however, shadow price can be interpreted as the rate of change in the objective function for an infinitesimal change in the right-hand side of the linear programming problem. From a geometric perspective, shadow price can be understood as the sub-gradients of the objective function along the dimension of resource provisioning changes. As it is seen in this section, shadow price approach has numerous applications in different areas due to its multi-facet nature. It has been used in (Li, Liu, & Salazar, 2006) to forecast the short-term transmission congestion. It has also been used in the evaluation of some construction projects and management (Hui, Pei, & Jie, 2009). However, as was mentioned earlier, shadow price has been used here as a decision-making tool for minimum load curtailment.

The most commonly used indices in composite power system are: Loss of Load Probability (LOLP), probability of system failure to meet the demand, Loss of Load Frequency (LOLF), the expected frequency of encountering failure states, and Expected Demand Not Supplied (EDNS), expected demand not supplied due to system deficiency. LOLP and LOLF from their definitions are based on reliability parameters and cannot be directly related to the operating limits. On the other hand, EDNS is based on failure rates, repair rates and units capacities.

10.1 Sensitivity Analysis of LOLP and LOLF with Respect to Component Parameters

Sensitivity studies of LOLP and LOLF to component reliability have been amply described in the literature. Sensitivity analysis can be conducted analytically by enumerating all system states or by simulation. The work in (Melo & Pereira, 1995; Y. Zhao, Zhou, Zhou, & X. Zhao, 2006; Zhu, 2006; Benidris & Mitra, 2014) provides relationships that are suitable for use in state space enumeration.

The sensitivity of LOLP with respect to unavailability u_i of component i can be calculated as follows.

$$\frac{\partial LOLP}{\partial u_i} = \sum_{x \in X} I_f(x) P(x) \left[1/u_i - S_i/(a_i u_i) \right] \quad (19)$$

where X is the set of all states, x is the state of the system, $P(x)$ is the probability of occurrence of state x , u_i is the probability of failure of component i and a_i is the probability of success of component i . S_i is the state indicator of component i , i.e., $S_i = 0$ if component i is in the down state (failure state) and $S_i = 1$ if component i is in the up state (success state) and $I_f(x)$ is the system state indicator function which can be expressed as follows.

$$I_f(x) = \begin{cases} 1, & \text{if } x \text{ is a failure state} \\ 0, & \text{if } x \text{ is a success state} \end{cases} \quad (20)$$

Proof:

$$\begin{aligned} \frac{\partial LOLP}{\partial u_i} &= \sum_{x \in X} \{ [\partial I_f(x)/\partial u_i] P(x) + I_f(x) [\partial P(x)/\partial u_i] \} \\ &= \sum_{x \in X} I_f(x) \{ [\partial (P(S_1) P(S_2) \dots P(S_i) \dots P(S_m))/\partial u_i] \} \\ &= \sum_{x \in X} I_f(x) P(x) [1/P(S_i)] [\partial P(S_i)/\partial u_i] \end{aligned}$$

If $S_i = 1$,

$$[1/P(S_i)] [\partial P(S_i)/\partial u_i] = [1/P(S_i = 1)] [\partial P(S_i = 1)/\partial u_i] = 1/a_i \left(\frac{\partial a_i}{\partial u_i} \right) = -1/a_i = -S_i/a_i$$

where $a_i + u_i = 1$ and

$$\frac{\partial a_i}{\partial u_i} = \frac{\partial (1 - u_i)}{\partial u_i} = -1$$

If $S_i = 0$,

$$[1/P(S_i)][\partial P(S_i)/\partial u_i] = [1/P(S_i = 0)][\partial P(S_i = 0)/\partial u_i] = 1/u_i \left(\frac{\partial u_i}{\partial u_i} \right) = 1/u_i = (1 - S_i)/u_i$$

Therefore, in general,

$$[1/P(S_i)][\partial P(S_i)/\partial u_i] = (1 - S_i)/u_i - S_i/a_i = 1/u_i - S_i/(a_i u_i)$$

The sensitivity of LOLP with respect to component failure rate λ_i is given by,

$$\frac{\partial LOLP}{\partial \lambda_i} = \sum_{x \in X} I_f(x) P(x) \left[a_i/\lambda_i - S_i/\lambda_i \right] \quad (21)$$

Proof:

$$\begin{aligned} \frac{\partial LOLP}{\partial \lambda_i} &= \sum_{x \in X} \{ [\partial I_f(x)/\partial \lambda_i] P(x) + I_f(x) [\partial P(x)/\partial \lambda_i] \} \\ &= \sum_{x \in X} I_f(x) \{ [\partial (P(S_1) P(S_2) \dots P(S_i) \dots P(S_m))/\partial \lambda_i] \} \\ &= \sum_{x \in X} I_f(x) P(x) [1/P(S_i)] [\partial P(S_i)/\partial \lambda_i] \end{aligned}$$

If $S_i = 1$,

$$\begin{aligned} [1/P(S_i)][\partial P(S_i)/\partial \lambda_i] &= [1/P(S_i = 1)][\partial P(S_i = 1)/\partial \lambda_i] = 1/a_i \left(\frac{\partial a_i}{\partial \lambda_i} \right) = -1/(\lambda_i + \mu_i) \\ &= -S_i/(\lambda_i + \mu_i) \end{aligned}$$

where

$$a_i = \mu_i/(\lambda_i + \mu_i)$$

$$u_i = \lambda_i/(\lambda_i + \mu_i).$$

Then,

$$\frac{\partial a_i}{\partial \lambda_i} = \frac{\partial (\mu_i/(\lambda_i + \mu_i))}{\partial \lambda_i} = -1/(\lambda_i + \mu_i)$$

If $S_i = 0$,

$$\begin{aligned} [1/P(S_i)][\partial P(S_i)/\partial \lambda_i] &= [1/P(S_i = 0)][\partial P(S_i = 0)/\partial \lambda_i] = 1/u_i \left(\frac{\partial u_i}{\partial \lambda_i} \right) = (1/u_i)(\mu_i/(\lambda_i + \mu_i)^2) \\ &= (1/u_i)a_i(1/(\lambda_i + \mu_i)) = (a_i/u_i)(1/(\lambda_i + \mu_i)) = (a_i/u_i)(1 - S_i)/(\lambda_i + \mu_i) \end{aligned}$$

Therefore, in general,

$$[1/P(S_i)][\partial P(S_i)/\partial \lambda_i] = -S_i/(\lambda_i + \mu_i) + (a_i/u_i)(1 - S_i)/(\lambda_i + \mu_i) = a_i/\lambda_i - S_i/\lambda_i$$

The sensitivity of LOLP with respect to component repair rate μ_i is given by

$$\frac{\partial LOLP}{\partial \mu_i} = \sum_{x \in X} I_f(x) P(x) \left[-a_i/\mu_i + S_i/\mu_i \right] \quad (22)$$

Proof:

$$\begin{aligned} \frac{\partial LOLP}{\partial \mu_i} &= \sum_{x \in X} \{ [\partial I_f(x)/\partial \mu_i] P(x) + I_f(x) [\partial P(x)/\partial \mu_i] \} \\ &= \sum_{x \in X} I_f(x) \{ [\partial (P(S_1) P(S_2) \dots P(S_i) \dots P(S_m))/\partial \mu_i] \} \\ &= \sum_{x \in X} I_f(x) P(x) [1/P(S_i)] [\partial P(S_i)/\partial \mu_i] \end{aligned}$$

If $S_i = 1$,

$$\begin{aligned} [1/P(S_i)][\partial P(S_i)/\partial \mu_i] &= [1/P(S_i = 1)][\partial P(S_i = 1)/\partial \mu_i] = 1/a_i \left(\frac{\partial a_i}{\partial \mu_i} \right) = (u_i/a_i)(1/(\lambda_i + \mu_i)) \\ &= (u_i/a_i)(S_i/(\lambda_i + \mu_i)) \end{aligned}$$

where

$$\frac{\partial a_i}{\partial \mu_i} = \frac{\partial (\mu_i/(\lambda_i + \mu_i))}{\partial \mu_i} = \lambda_i/(\lambda_i + \mu_i)^2$$

If $S_i = 0$,

$$\begin{aligned} [1/P(S_i)][\partial P(S_i)/\partial \mu_i] &= [1/P(S_i = 0)][\partial P(S_i = 0)/\partial \mu_i] = \frac{1}{u_i \left(\frac{\partial u_i}{\partial \mu_i} \right)} = \left(\frac{1}{u_i} \right) \left(-\frac{\lambda_i}{(\lambda_i + \mu_i)^2} \right) \\ &= -\frac{1}{(\lambda_i + \mu_i)} = -(1 - S_i)/(\lambda_i + \mu_i) \end{aligned}$$

Therefore, in general,

$$[1/P(S_i)][\partial P(S_i)/\partial \mu_i] = (u_i/a_i)(S_i/(\lambda_i + \mu_i)) - (1 - S_i)/(\lambda_i + \mu_i) = -a_i/\mu_i + S_i/\mu_i$$

Sensitivity analysis of the LOLF index with respect to the reliability parameters can be derived in the same manner of derivation of the sensitivity analysis of the LOLP index. The sensitivity of LOLF with respect to unavailability u_i of component u_i can be calculated as follows.

$$\frac{\partial LOLF}{\partial u_i} = \sum_{x \in X} \left[-I_f(x)P(x) \left(\frac{S_i \mu_i}{a_i^2} \right) + F(x)P(x) \left(\frac{1}{u_i} - \frac{S_i}{(a_i u_i)} \right) \right] \quad (23)$$

where $F(x)$ is the sum of the repair rates of a failure state x that crosses the boundary and can be expressed as:

$$F(x) = I_f(x) \sum_{i=1}^m \lambda_i^{in}(x) \quad (24)$$

where m is the number of components, and

$$\lambda_i^{in}(x) = (1 - S_i) \mu_i - \frac{S_i \mu_i u_i}{a_i} \quad (25)$$

The sensitivity of LOLF with respect to component failure rate λ_i is given by

$$\frac{\partial LOLF}{\partial \lambda_i} = \sum_{x \in X} \left[-I_f(x)P(x)S_i + F(x)P(x) \left(\frac{a_i}{\lambda_i} - \frac{S_i}{\lambda_i} \right) \right] \quad (26)$$

The sensitivity of LOLF with respect to component repair rate μ_i is given by

$$\frac{\partial LOLF}{\partial \mu_i} = \sum_{x \in X} \left[I_f(x)(1 - S_i)P(x) + F(x)P(x) \left(-\frac{a_i}{\mu_i} + \frac{S_i}{\mu_i} \right) \right] \quad (27)$$

10.2 Sensitivity Analysis of EDNS

The Expected Demand Not Supplied (EDNS) is an important index because it inherently reflects the severity of reliability events. The sensitivities of this index with respect to u_i , λ_i and μ_i are the same as for the LOLP index except that they are multiplied by the amount of load curtailments. The sensitivity analysis of the EDNS with respect component capacities was derived as follows (Y. Zhao, et al., 2006; Zhu, 2006; Benidris & Mitra, 2014).

$$\frac{\partial EDNS}{\partial C_i} = \sum_{x \in X} I_f(x)P(x) \frac{\partial L_c(x)}{\partial C_i} \quad (28)$$

where C_i is the capacity of component i and $L_c(x)$ is the total load curtailment when the system is at state x .

The derivative of the total load curtailment with respect to component capacity can be expressed as

$$\frac{\partial L_c(x)}{\partial C_i} = \begin{cases} \pi_{g,i}, & \text{if component } i \text{ is a generator} \\ \pi_{t,ij}, & \text{if component } i \text{ is a circuit} \end{cases} \quad (29)$$

where $\pi_{g,i}$ and $\pi_{t,ij}$ are the Lagrange multipliers or shadow prices of generation capacity constraints and transmission lines carrying capability constraints respectively. $\pi_{g,i}$ can be calculated directly from the optimization problem of (1). However, $\pi_{t,ij}$ depends on circuit parameters which are circuit capacity and

susceptance. These two parameters are dependent variables and cannot be treated separately. Pereira and Pinto (1985) combined the effect of circuit capacity and susceptance on circuit sensitivity and developed the following expression.

$$\pi_{t,ij} = (\pi_{d,i} - \pi_{d,j}) \times (\theta_j - \theta_i) \quad (30)$$

where $\pi_{d,i}$ and $\pi_{d,j}$ are Lagrange multipliers or shadow prices of load constraints of buses i and j respectively and θ_j and θ_i are voltage angles of buses j and i respectively.

11. SOLUTION ALGORITHM

The solution algorithm explains the flow of the procedures of evaluating the reliability indices as well as the technique used to direct and prevent the particles from being trapped in a search subspace. The steps can be explained as follows:

1. Initialize the positions and velocities of the particles, x_i and v_i respectively. Particles positions are initialized by using the forced outage rates of system components; components that are in the up state are represented by 1's and components in the down state are represented in 0's. The length of a particle string equals the number of components. Velocities are initialized to have V^{max} equals 2.2 (probability limits are between 0.9 and 0.1).
2. Check if there are identical particles. If so, discard the identical ones and save the rest of the particles in a temporary array vector by converting the binary numbers to decimal numbers. Check if there are particles already exist in the database, if so set probabilities and load curtailments of the existing particles to zeros to decrease the chance of visiting these states again. Then, save the rest in the database and go to the next step.
3. Compute the exact probability of each particle which represents the probability of a system state. If the probability of a particle is less than a threshold, ε , discard this particle, otherwise go to the next step. In this work, ε was chosen to be 10^{-15} .
4. Set system parameters and update generation and transmission lines status for every particle. Perform the linear programming optimization problem to check if there are load curtailments. Update the reliability indices.
5. Determine and update personal best states' probabilities and best load curtailments. Also, determine and update best global probability and best global load curtailment. Update particles velocities using (4) and update particles positions using (5) and (6).
6. Check the normalized LOLP ($LOLP_{norm}$) whether it is increasing or decreasing and adjust c_1 , c_2 , c_3 and c_4 accordingly. If it increasing, increase the values of c_1 and c_2 and decrease the values of c_3 and c_4 . Perform the opposite if $LOLP_{norm}$ is decreasing. In this work we adjusted the amount of increasing or decreasing these coefficients according to the amount of change of the $LOLP_{norm}$. Any strategy can be used to adjust these factors. However, the optimum adjustment of these factors is out of the scope of this work. We related the amount of change of these coefficients to the amount of change in $LOLP_{norm}$, ($\Delta LOLP_{norm}$), in an exponential form as follows,

$$\begin{aligned} c_{(1,2)-new} &= c_{(1,2)-old} \times e^{(100 \times \Delta LOLP_{norm})} \\ c_{(3,4)-new} &= c_{(3,4)-old} \times e^{(-100 \times \Delta LOLP_{norm})} \end{aligned}$$

7. Check if any of the particles has entered the success and/or failure subspaces. If a particle has entered the success subspace, redirect the particle by using the objective of maximum load curtailment only (ignoring the objective of maximum probability) by setting c_1 and c_2 to zeros. If a particle has entered the failure subspace, redirect the particle by using the objective of maximum probability only (ignoring the objective of maximum load curtailment) by setting c_3 and c_4 to zeros.
8. Check for convergence. If the stopping criterion is met, stop; otherwise go to the next step.
9. Determine the number of newly visited states since the previous iteration. If the number of the new states is less than a threshold, adjust V^{max} and then go to step 2; otherwise go directly to step 2. The threshold is chosen to be 80% of the total number of particles for the first 10 iterations, 50% for the next 10 iterations and 20% thereafter. V^{max} is adjusted according to the direction of the LOLP_{norm} index. If the particles are searching around the success subspace, adjust V^{max} to a large number. On the other hand, if the particles are searching around the failure subspace, adjust V^{max} to a small number. In this work we have chosen 4.0 to be the large number and 2.0 to the small number. Again, the optimum value of V^{max} to better improve the behavior of the search method is out of the scope of this work.

The flowchart of the solution algorithm is shown in Figure 5.

12. APPLICATION

The proposed formulation was applied on two systems, the IEEE RTS (Reliability Test System Task Force of the Application of Probability Methods Subcommittee, 1979) and the modified version of the IEEE RTS. The configuration of the IEEE RTS is shown in Figure 6. The IEEE RTS System has been extensively tested for power system reliability analysis. IEEE RTS consists of 24 buses, 38 transmission lines/transformers (33 transmission lines and 5 transformers) and 32 generating units on 10 buses. The total generation of this system is 3405 MW and total peak load is 2850 MW.

The modified IEEE RTS System is the same as the original IEEE RTS System except that the generation is doubled and the loads are multiplied by a factor of 1.8. The reason of this modification is because the transmission lines of the original system have high power carry capabilities in comparison with the generation and loading conditions. Therefore, this modification will make the transmission lines more stressed. Also, this modification will allow us to test the robustness of the proposed method.

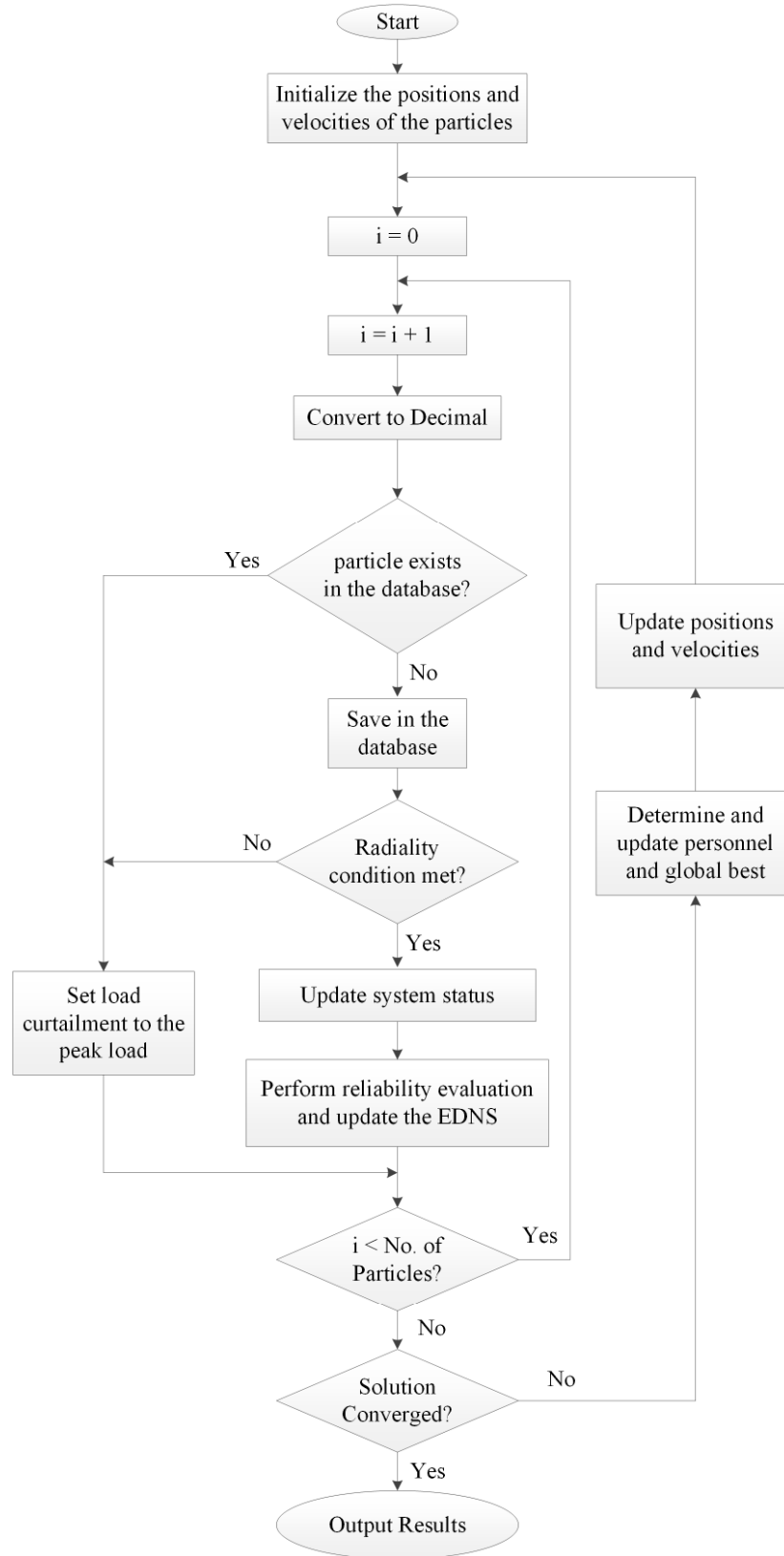


Figure 5. Flowchart of the solution algorithm

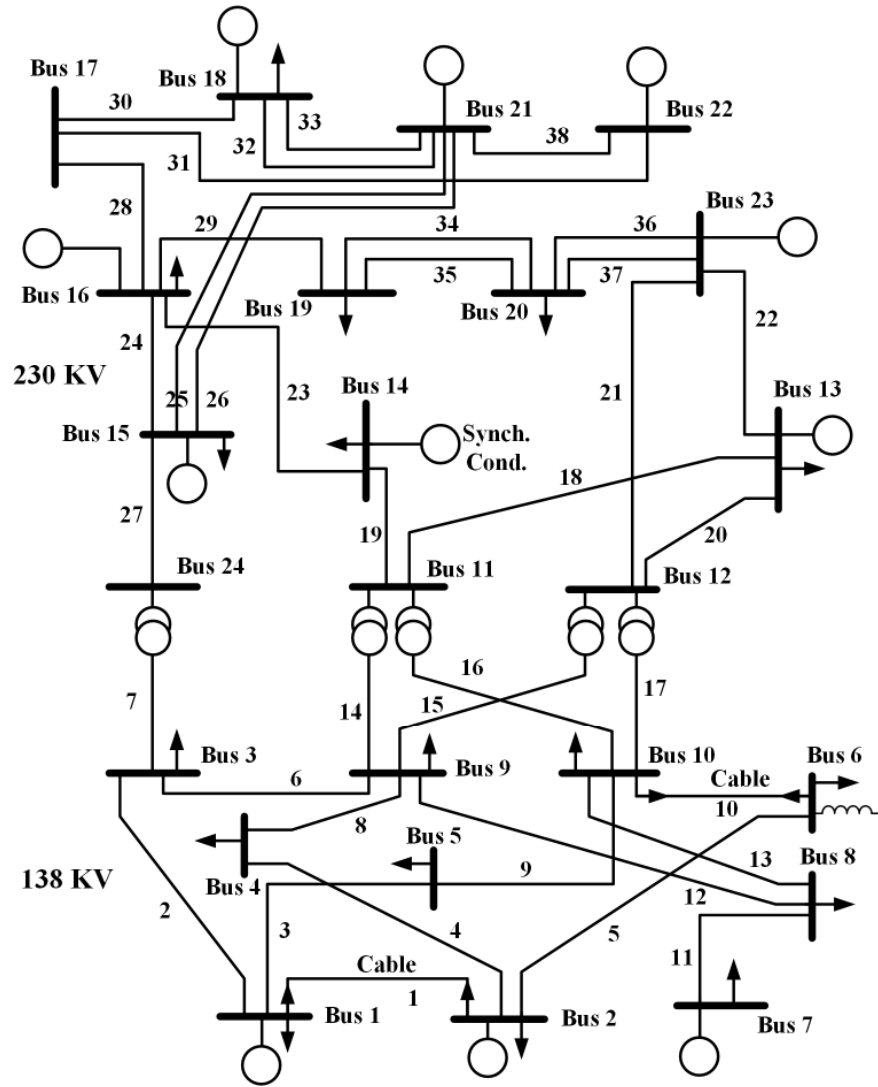


Figure 6. The IEEE Reliability Test System

12.1 Reliability Evaluation

The model was applied on the previously mentioned systems with 50 particles. Analysis of the annual as well as the annualized indices was conducted on the two systems. From Table 1, Table 2, Table 3 and Table 4, it has been found that in calculating the annual indices of both systems and the annualized indices of the original IEEE RTS, the heuristic technique was able to evaluate system indices and no BPSO was performed (terminated after few iterations). On the other hand, in calculating the annualized indices of the modified IEEE RTS, the heuristic technique was not able to evaluate system indices and therefore the proposed BPSO was used to search for the unclassified subspace. Also, from Table 4, the unclassified subspace has a significant effect on the LOLP and LOEE indices and very small effect on the EDNS and LOLE indices. These effects can be interpreted as the unclassified subspace has failure states with relatively high probability but with relatively small load curtailments. This also can be attributed to the fact that failure states that are located far from the origin (all components are in the down state) have

high probability and small load curtailments. Therefore, if we were looking for just the EDNS and LOLE indices, the heuristic technique would be enough for this case.

Table 5 and Table 6 show the reduction in the computational time by using the proposed algorithm as a percentage of the time of evaluating the same indices using Monte Carlo simulation. These times account for calculating the bus indices for all cases. The average base time using Monte Carlo simulation was found to be 1175 seconds for both systems. Table 7 shows the annual bus indices of the original IEEE RTS.

Table 1. Annual Indices of the IEEE RTS

Algorithm		LOLP	EDNS MW/yr	LOEE MWh/yr	LOLE h/yr
Proposed	Heuristic	0.00117	0.16374	1430.465	10.22112
	BPSO	---	---	---	---
	Sum	0.00117	0.16374	1430.465	10.22112
Conventional		0.00119	0.16412	1433.752	10.39584

Table 2. Annualized Indices of the IEEE RTS

Algorithm		LOLP	EDNS MW/yr	LOEE MWh/yr	LOLE h/yr
Proposed	Heuristic	0.08429	14.67784	128225.60	736.360
	BPSO	---	---	---	---
	Sum	0.08429	14.67784	128225.60	736.360
Conventional		0.08451	14.59761	127524.72	738.279

Table 3. Annual Indices of the Modified IEEE RTS

Algorithm		LOLP	EDNS MW/yr	LOEE MWh/yr	LOLE h/yr
Proposed	Heuristic	0.00106	0.07395	645.90125	9.26016
	BPSO	---	---	---	---
	Sum	0.00106	0.07395	645.90125	9.26016
Conventional		0.00105	0.07436	649.61330	9.17280

Table 4. Annualized Indices of the Modified IEEE RTS

Algorithm		LOLP	EDNS MW/yr	LOEE MWh/yr	LOLE h/yr
Proposed	Heuristic	0.06039	10.31755	90134.083	517.259
	BPSO	0.00976	0.12171	1063.256	85.263
	Sum	0.07015	10.43926	91197.375	612.830
Conventional		0.07017	10.44237	91224.549	613.005

Table 5. Reduction in the computational time of the IEEE RTS

Category	Time Spent by		Total Time (seconds)	Time Reduction (%)
	Heuristic technique (seconds)	BPSO (seconds)		
Annual	28.66	0	28.66	97.56
Annualized	144.28	0	144.28	87.72

Table 6. Reduction in the computational time of the Modified IEEE RTS

Category	Time Spent by		Total Time (seconds)	Time Reduction (%)
	Heuristic technique (seconds)	BPSO (seconds)		
Annual	55.60	0	55.60	95.27
Annualized	336.15	409.75	745.90	36.52

Table 7. Bus Annual Indices for the IEEE RTS

Bus No.	LOLP	EDNS MW	LOEE MWh/yr	LOLE hr/yr
1	0.00032	0.00555	48.50943	2.75184
2	0.00002	0.00034	2.929904	0.17472
3	0.00006	0.00188	16.41914	0.52416
4	0.00044	0.00530	46.26799	3.80016
5	0.00124	0.01473	128.67821	10.78896
6	0.00042	0.00423	36.93749	3.66912
7	0.00021	0.00398	34.78341	1.79088
8	0.00013	0.00308	26.94283	1.09200
9	0.00005	0.00125	10.90315	0.43680
10	0.00008	0.00238	20.78260	0.69888
13	0.00028	0.01001	87.42760	2.40240
14	0.00096	0.02881	251.65359	8.34288
15	0.00070	0.03126	273.12752	6.11520
16	0.00110	0.01813	158.37621	9.60960
18	0.00018	0.00862	75.30948	1.52880
19	0.00012	0.00329	28.73840	1.04832
20	0.00037	0.00744	64.97050	3.18864

From Table 1, Table 2, Table 3, Table 4 and Table 5, the proposed heuristic technique in conjunction with the directed BPSO has accurately evaluated the reliability indices with less computational time than Monte Carlo simulations. For IEEE RTS, the reduction in the computational time is around 97.56% for calculating the annual indices whereas for the annualized indices the reduction in the computational time is around 87.72%. For both cases, evaluating annual and annualized indices, the heuristic technique was able to capture the most relevant failure states. However, for the annualized indices, the computational time was longer than the case of the annual indices due to the fact that for annual indices the system is assumed to operate at the peak load.

From Table 3, Table 4, Table 5 and Table 6, the proposed heuristic technique in conjunction with the directed BPSO has accurately evaluated the reliability indices with less computational time than Monte

Carlo simulations. For Modified IEEE RTS, the reduction in the computational time is around 95.27% for calculating the annual indices whereas for the annualized indices the reduction in the computational time is around 36.52%. For the case of evaluating annual indices, the heuristic technique was able to capture the most relevant failure states. However, for the case of evaluating the annualized indices, some significant failure states were not captured by the heuristic technique. In this case, the BPSO was used to search for the failure states in the unclassified subspace.

The comparison between the proposed method and Monte Carlo simulation was used due the fact that Monte Carlo simulation has been used for long time in composite power system reliability evaluation. A comparison between the proposed method and the existing methods can be easily performed. For instance, applying the intelligent search methods such as PSO, GA, BACO, etc., on the entire state space could evaluate the reliability indices of power systems roughly in about the same computational time. However, as it is clear from the presented results, the heuristic technique has reduced the computational time significantly.

Reliability indices at the buses reflect the curtailment or load shedding at each bus according to the philosophy of the applied load shedding procedure. For example, different load shedding philosophies would produce different bus indices. Some loads can be given high priority so that these loads will not be interrupted unless load shedding is not avoidable. In this chapter, the loads were divided into three parts with different weighting factors as discussed previously.

12.2 Sensitivity Analysis

The proposed formulation was applied on the IEEE RTS (Reliability Test System Task Force of the Application of Probability Methods Subcommittee, 1979) and the results are shown in Table 8, Table 9 and Table 10. In these tables, the sign (#) denotes the bus number and (G) denotes the capacity, i.e., #13G197 means bus 13 generating unit capacity 197 MW. From Table 8, Table 9 and Table 10, it is clear that the generating unit (400 MW) at bus 18 has the highest effect on all the studied reliability indices followed by the generating units of buses 21 and 24 for all indices. Consequently, these generating units have the largest impact on system reliability. In other words, these buses are at the highest risk and the most beneficial way to improve the reliability of the system is to increase the availability of these units by adding new units, decreasing repair time and/or using sophisticated methods to decrease units' failure rate.

From Table 8, Table 9 and Table 10, the sensitivity of the LOLP, EDNS and LOLF indices with respect to components' un-availabilities and with respect to the failure rates are positive whereas for the repair rates are negative. This can be attributed to the fact that increasing component failure rate or unavailability would increase the value of the reliability indices (deteriorate system reliability). On the other hand, increasing the repair rate would enhance system reliability. Increasing the repair rate or decreasing the unavailability of a component or decreasing the failure rate can be achieved by different strategies such as hiring more maintenance staff, using more sophisticated methods to reduce the failure rate, installing new equipment, etc.

Table 8. Sensitivity Analysis of the LOLP index for the IEEE RTS

Bus Number Generator Capacity	$\partial \text{LOLP} / \partial u_i$ $\times 10^{-2}$	$\partial \text{LOLP} / \partial \lambda_i$ $\times 10^{-4}$	$\partial \text{LOLP} / \partial \mu_i$ $\times 10^{-4}$
#18G400	33.29905	44.15546	-6.02120
#21G400	33.18920	44.00979	-6.00134
#23G350	26.16603	25.28188	-2.19842
#13G197	20.02105	10.31336	-0.54281
#23G155	11.34010	4.77216	-0.19884
#15G155	11.01719	4.63627	-0.19318
#16G155	10.77760	4.53545	-0.18898
#22G100	4.94948	2.60356	-0.10848
#2G76	4.48367	1.96626	-0.04013
#1G76	4.36122	1.91257	-0.03903

Table 9. Sensitivity Analysis of the LOLF index for the IEEE RTS

Bus Number Generator Capacity	$\partial \text{LOLF} / \partial u_i$	$\partial \text{LOLF} / \partial \lambda_i$ $\times 10^{-2}$	$\partial \text{LOLF} / \partial \mu_i$ $\times 10^{-4}$
#18G400	58.64305	77.76229	-660.80623
#21G400	57.52415	76.27860	-641.89222
#23G350	49.01718	47.36089	-202.50560
#13G197	43.04602	22.17411	-16.60056
#23G155	41.51697	17.47125	-27.43647
#15G155	39.63948	16.68116	-25.43609
#16G155	37.98464	15.98477	-23.49279
#22G100	16.69121	8.78003	-16.78555
#2G76	17.06241	7.48253	-6.30312
#1G76	16.41083	7.19679	-5.96487

Table 10. Sensitivity Analysis of the EDNS index for the IEEE RTS

Bus Number Generator Capacity	$\partial \text{EDNS} / \partial u_i$	$\partial \text{EDNS} / \partial \lambda_i$ $\times 10^{-2}$	$\partial \text{EDNS} / \partial \mu_i$ $\times 10^{-4}$
#18G400	73.95452	98.06572	-1337.25977
#21G400	73.78475	97.84059	-1334.18991
#23G350	68.91659	66.58790	-579.02520
#13G197	29.80471	15.35317	-80.80615
#23G155	20.02147	8.42547	-35.10614
#15G155	18.68813	7.86438	-32.76824
#16G155	18.83241	7.92509	-33.02120
#22G100	11.23545	5.91016	-24.62565
#2G76	9.13458	4.00587	-8.17524
#1G76	8.76626	3.84434	-7.84560

13. CONCLUSION

A heuristic technique based on line power carrying capabilities and minimum generation vector was applied to reduce the search space. The heuristic technique is conservative in that not all the failure states can be captured and no success state can be classified as failure state. The heuristic technique produces three subspaces, definite failure subspace, definite success subspace and unclassified subspace. This technique is based on evaluating the adequacy of the available power generation and transmission lines capacities to meet the load. Some failure states cannot be captured with considering only generation and line capacities. Most of these states are around the definite failure subspace where the latter is detected by the state space reduction approach. In this chapter, a directed Binary Particle Swarm Optimization technique was utilized to search for the failure states in the unclassified subspace which are closely scattered around the definite failure subspace. Also, this work has introduced a complementary concept that is compatible with intelligent search methods to estimate power system reliability indices.

The proposed algorithm is an extension to the use of the intelligent search methods in composite power system reliability analysis and it is intended to overcome many difficulties that are associated with the use of these techniques. An imperative key in using BPSO in composite system reliability evaluation is the selection of weighting factors of the objective function. Such weighting factors are system dependent and, therefore, their appropriate values should be carefully selected in order to prevent the swarm from being trapped to one corner of the state space. In this work, an effective Particle Swarm Optimization technique has been proposed for reliability assessment of composite systems. The proposed method adjusts the weighting factors associated with the objective function in a dynamic fashion so that the swarm would always fly on the entire search space rather than being trapped to one corner of the search space. The method presented in this chapter is not only easy to implement, but it does not use trial and error process, which have been traditionally adapted in PSO based reliability evaluation studies. The effectiveness of the proposed method has been demonstrated on the IEEE RTS and the modified IEEE RTS. In these test cases, it has been shown that the results obtained by the proposed method correspond closely to those obtained using Monte-Carlo simulation, while requiring lower computational burden. The proposed method accurately estimates these indices with less computational effort than the conventional Monte Carlo simulation. Also, BPSO showed an intelligence behavior over the Monte Carlo simulation methods.

From the failure states which are captured by the heuristic technique and the binary PSO the sensitivity analyses of power system reliability indices as well as the evaluation of these indices were performed.

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KEY TERMS AND DEFINITIONS

State Space: All possible outcomes of the combinations of system states.

Pruning: Partitioning the state space into subspaces that can be identified as success and failure subspaces.

Adequacy Assessment: Estimating the adequacy of the generation to meet the demand without including the constraints of the transmission lines.

Composite System: Considering both the generation and transmission in evaluating system reliability.

Complementary Concept: Every reliability index that can be evaluated from the failure states, has a complementary value that can be evaluated from the success states as long as the boundaries of an index and its complementary value are known or the index can be equally likely determined from the success or failure states.

Reliability Indices: Indices that are used to assess the reliability of a system.

Weighting Factors: Factors which are used to adjust the direction of the particle swarm.

Sensitivity: Amount of change in the objective function with respect to the constraints.