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Intelligent state space pruning for Monte Carlo simulation with applications in composite power system reliability

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ABSTRACT

The probabilistic reliability evaluation of composite power systems is a complicated, computation intensive, and combinatorial task. As such evaluation may suffer from issues regarding high dimensionality that lead to an increased need for computational resources, MCS is often used to evaluate the reliability of power systems. In order to alleviate this burden, an analytical method known as state space decomposition has previously been used to prune the state space that is sampled using MCS.

This paper extends the state-of-the-art by proposing a novel algorithm known as intelligent state space pruning (ISSP). This algorithm leverages the intelligence of highly modified population based metaheuristic (PBM) algorithms including genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and artificial immune systems (AIS) to quickly, efficiently, and intelligently prune the state space that is used during MCS. The presented PBMs are modified using domain-specific knowledge to improve their performance and fine tune their intelligence. This new algorithm leads to reductions of up to 90% in total computation time and iterations required for convergence when compared to non-sequential MCS. Results are reported using the IEEE Reliability Test Systems (RTS79/MRTS).

1. Introduction

The reliability assessment of modern power systems is often modeled as a large and complex combinatorial problem. This makes the calculation of reliability indices a challenging task as it drastically increases the dimensionality of the problem with the size of the system. Two examples of this are the IEEE Reliability Test Systems (IEEE-RTS) known as IEEE-RTS79 (IEEE Committee Report, 1979) and MRTS (EPRI, 1987; Pereira and Balu, 1992). These test systems each have 32 generators leading to a minimum state space size of 2^{32}. To address the issues of high dimensionality and computational complexity, works have previously been proposed in order to develop new, improved, and computationally more efficient methods for dealing with the analysis of power system reliability. Examples include Monte Carlo Simulation (MCS) (Billinton and Allan, 1996; Billinton and Li, 1994), analytical state space decomposition (Mitra and Singh, 1996, 1999; Singh and Mitra, 1997), and population based metaheuristics (PBMs) (Patra et al., 2006; Samaan and Singh, 2002; Samaan, 2004; Wang and Singh, 2008; Singh and Wang, 2008).

MCS, a stochastic simulation method, is often used for evaluating reliability indices of power systems at various levels and comes in two flavors: sequential and non-sequential. Sequential MCS samples system states in time order over different periods while non-sequential MCS samples system states proportional to their probability of occurrence. Sequential MCS requires greater computational power but handles sequentially correlated events well, but non-sequential MCS substantially improves computational efficiency. As such, non-sequential MCS is often favored over sequential MCS for many applications where sequential correlations are not important. The major advantage of non-sequential MCS is its inherent ability to handle large and complex power system models and the major disadvantage is that in systems with high levels of reliability the time for convergence can become excessively long. Although the sample size for convergence is independent of the size of the system, the computational effort does increase as calculations like the power flow take a longer time for larger systems. The need to reduce the computational effort for convergence in complex systems has been the driver behind much of the work that has previously been reported in this area. For instance, an analytical, decomposition based method has been proposed in Mitra and Singh (1996, 1999) and Singh and Mitra (1997). The major limitation of decomposition techniques is the ability to handle coherency well, as the use of AC or DC power flow methods causes the system to become non-coherent (Singh and Mitra, 1997).

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This work demonstrates a new algorithmic method named intelligent state space pruning (ISSP) that reduces the computational resources required of MCS by intelligently and efficiently pruning a given state space through the use of PBM algorithms that are modified in a domain-specific manner. Though the ISSP algorithm may be applied to any use of non-sequential MCS, this study focuses on its role in the probabilistic evaluation of composite power system reliability. While PBMs that address adequacy in such situations are typically designed to quickly and intelligently sample states where there is a loss-of-load (states with power loss), we take a new approach and design these algorithms to sample those states where there is no loss-of-load (states without power loss). Through the efficient sampling and removal of non-loss-of-load states, we are able to present the MCS algorithm with a conditional state space that has a higher density of loss-of-load states. It is expected that the use of this conditional state space will allow the MCS algorithm to converge more quickly and consume less computational resources.

Because a major goal of this algorithm is achieving an optimal level of pruning, this paper focuses on four specific PBM algorithms (genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and artificial immune system optimization (AIS)) and their role in the novel ISSP algorithm. The inherent intelligence in each of these algorithms is fine-tuned through multiple modifications that are based on the forced outage rates of system components. While these four algorithms are used in this study due to their general popularity, there is no reason other search algorithms that have been used for practical applications like the Harmony Search (Geem et al., 2001) or Bee Colony Optimization (Teodorovic and Dell'orco, 2005) algorithms could not be used.

The remainder of this paper is structured as follows: Section 2 reviews the foundational concepts used to develop the ISSP algorithm including state space decomposition, PBMs, and the role of PBMs in composite power system reliability assessment; Section 3 proposes and discusses the newly developed ISSP algorithm; Section 4 details the application of the ISSP algorithm to composite power system reliability assessment; and Section 5 presents results, analysis, and other discussions.

2. Background and literature review

Before discussing the ISSP algorithm and its application to the evaluation of composite power system reliability, this section reviews the fundamental and state-of-the-art techniques for improving the convergence of non-sequential MCS as applied to composite power system reliability. This includes a brief review of PBM algorithms, the use of PBMs to improve the state sampling phase of MCS, and state space decomposition. While many of the reviewed works focus on improving the performance of the sampling phase of the direct MCS algorithm (as ISSP does), there are also many works that have focused on improving the computational efficiency of the classification phase of the MCS algorithm. These include the use of differing types of neural networks (Amjady, 2004; Amjady and Ehsan, 1999; Chaturvedi et al., 2009; Reddy and Singh, 1988; Singh et al., 2006; Song et al., 2005), hybrid neural networks (Luo et al., 2003; Leite da Silva et al., 2007; da Silva et al., 2008; Singh et al., 2006), support vector machines (Green et al., 2011), and other methods of pattern classification (Bordeerath and Jirutitijaroen, 2012).

2.1. Population based metaheuristic algorithms

PBMs are intelligent, guided, stochastic searching techniques that each have a nuanced flavor of search that may or may not benefit different types and formulations of problems. Each of these algorithms uses a population of possible solutions that are iteratively and stochastically changed rather than focusing on improving a single solution. More recent examples of such algorithms and their applications include:

- Artificial Bee Colony Optimization (Ajayan and Balaji, 2013; Dhinesh Babu and Venkata Krishna, 2013; Cuevas et al., 2013; Karaboga and Cetinkaya, 2011; Tsai et al., 2012);
- Bat-Inspired Optimization (Bora, 2012; Ramesh et al., 2013; Yang, 2010; Yang and Gandomi, 2012);
- Central Force Optimization (Ding et al., 2011, 2012; Formato, 2007; Green et al., 2012; Mahmoud, 2011; Mohammad and Dib, 2009; Qubati, 2009);
- Cuckoo Search (Gupta et al., 2013; Moravej and Akhlaghi, 2013; Yang, 2009; Zhou et al., 2013);
- Differential Evolution (Storn and Price, 1997);
- Firefly algorithm (Miguel et al., 2013; Mohammadi et al., 2013; Tilahun and Ong, 2013; Silva et al., 2013; Sanaei et al., 2013; Yang, 2009);
- GlowWorm Optimization (Krishnanand and Ghose; Krishnanand and Ghose, 2006, 2008, 2009);
- Harmony Search (Geem et al., 2001; Mahdavi et al., 2007);
- Monkey Search (Wang et al., 2010; Yi et al., 2012); and
- Scatter Search (Glover, 1998; Ribeiro and Resende, 2012).

This study focuses on four of the more common examples of these algorithms including the GA (de Castro, 2006; Goldberg, 1989), PSO (de Castro, 2006; Eberhart and Kennedy, 1995a,b; Poli et al., 2007), ACO (Dorigo, 1992), and AIS (Castro, 2002; Castro and Zuben, 2002; de Castro and Von Zuben, 2000) algorithms.

2.2. PBMs in composite power system reliability

PBM algorithms have been applied to the probabilistic reliability analysis of composite power systems in many instances. These applications have mainly been focused on the use and modification of GA and PSO, but some works have also included AIS and ACO. All those works concerned with the evaluation of reliability will be examined here.

The work in this area begins in Samaan and Singh (2002, 2007) and Samaan (2004), where a foundation is laid for the use of GAs. Methods are developed to evaluate the reliability of both generation and composite systems using chronological and non-chronological loads. Multiple reliability indices are calculated for each scenario and the Roy Billinton Test System (RBTS) is used for evaluation. Results show that the methods presented maintain the accuracy of MCS and reduce the computational effort by 80–90%.

Contributions regarding PSO are made by Patra et al. (2006) where a multi-objective PSO implementation of composite power system reliability is developed and analyzed. The two objectives used are the maximization of the probability of state occurrence and the maximization of load curtailment. These conflicting objectives allow the MOPSO to sample the state space in a more optimal fashion. Accurate results are obtained for the MRTS along with an analysis of the convergence behavior of the MOPSO.

Investigations regarding the combination of population based intelligent search (PIS) methods (GA, PSO, ACO, and AIS) and composite system reliability evaluation are examined by Wang and Singh (2008). This work presents a method for incorporating PIS and time dependent wind turbine generators (WTG) to evaluate the composite reliability using the IEEE-RTS79. Discussions are developed regarding all aspects of these algorithms along with a comparison of PIS and the MCS algorithm used and a discussion of the state sampling methodology. The method is shown to be more effective in terms of computational time.

Further contributions regarding MOPSO are made in Mitra and Xu (2010). Here, the main contribution is the identification of three measures that aid in improving the convergence of reliability