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Power System Reliability Assessment Considering Impacts of Climate Change

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Abstract

Power system reliability, as one of the most significant issues in power system studies, is affected remarkably by load demand changes. On other hand, climate changes and global warming lead to increasing the electricity demand of a power system. In this paper, the impacts of global change on generation power system reliability indices have been investigated. Loss of Load Probability and Expected Energy Not Supply are considered as power system reliability indices. In addition, a Particle Swarm Optimization method is used to assess these reliability indices. IEEE_79 Reliability test system is selected as a standard test system. The results show that reliability indices are affected noticeably by temperature rising and climate change.

Keywords: Climate Change, Power System Reliability Indices, Loss of Load Probability, Expected Energy Not Supplied, Load demand, Particle Swarm Optimization

1. Introduction

Power system reliability indices are used as the most important constraints by power system planners. As it is shown in figure 1, the assessment of system reliability is applied to three main hierarchical levels, termed HLI, HLII, and, HLIII. At the first level, generation system reliability, the total system generation is investigated to determine its ability to meet the total system demand requirements. At the generation system level, the transmission lines are ignored and considered as completely reliable elements with no failure rate. At the second level, composite power system or bulk system, both generation units and transmission lines are evaluated and the transmission system elements are considered completely reliable. All three parts and elements of a power system (generation units, transmission lines, and transmission system elements) are considered in HLIII studies. The three hierarchical levels are shown in Figure1. In this paper, generation system reliability (HLI) is assessed. The reliability of a system is evaluated using the proper indices. In this paper, LOLE (Loss of Load Probability) and EENS (Expected Energy not Supplied), as the two common reliability indices, are chosen and calculated. Obviously, reliability indices are affected significantly by changes in load demand and the LDC (Load Duration Curve) pattern of a network. Power system reliability can be improved by enhancing the performance and efficiency of generation, transmission, and distribution elements, applying demand-side management methods, and improving load demand patterns. In another word, reducing power consumption leads to a more reliable system without making changes in a power system.

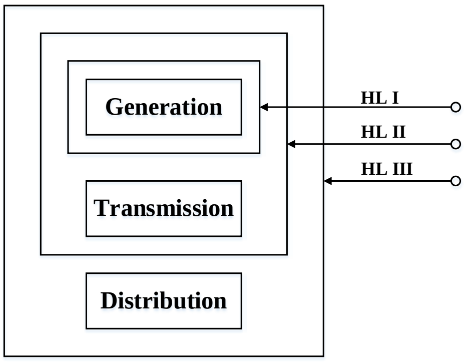

Figure 1. Power System Hierarchical Levels (HL)

On the other hand, climate changes noticeably affect the load demand of a power system [1-4]. However, the impacts of climate change are not limited to rising ambient temperature and can lead to changes in many parameters such as wind speed, humidity, and many other factors. Although all these parameters are important in power system studies, previous studies have shown that temperature has more effects on load demand compared to other variables. In many researchers, the effect of rising temperatures on load demand is investigated using different methods. To determine the relationship between temperature rising and load demand, neural networks have been used widely. Neural networks are powerful techniques and are able to solve complex relations. However, they require a huge amount of information for training and most authors prefer to use simpler methods. For this, a simpler regression approach was proposed by Linder. His method uses regression models to connect demand and temperature based on daily and monthly periods. In this paper, the impact of global warming and increasing the temperature on generation power system reliability indices due to changes in load demand is investigated using the regression method.

The probabilistic adequacy reliability assessment methods can be categorized as analytical and simulation-based methods (Monte Carlo Techniques). Due to their shortcomings, many researchers have used hybrid and meta-heuristic algorithms to calculate the power system reliability indices. In [5-11] generation and composite power system, reliability indices are assessed using the Genetic Algorithm (GA) as a search tool to sample the system states. Also, [12-18] uses other optimization methods to reduce the amount of sampled system states, computational time and achieve better coverage. By using meta-heuristic methods, not only most probable failure states and contribution of each state and system elements at a given load can easily be achieved, but also, computation time is decreased and parallel computation can be done. In this paper, a particle swarm optimization algorithm is used to calculate the generation reliability indices. The algorithm is tested on the standard reliability test system RTS-79 consists of 32 generating units.

The effects and impact of climate change on electricity demand have been analyzed in many papers. The researchers have investigated these impacts on both short-term and long-term periods. Also, the investigations show that temperature has the most effective factor among other parameters such as wind speed and humidity. Authors in [27] have used the neural network as the main method to relate the temperature and load demand. Also, in [28-29], and [2] the regression models are used instead of neural networks. In this paper, we have used the result of the reference [2] regarding the effect of rising 1 centigrade degree on peak and mean load demand on different seasons. The changes in peak load demand due to 1 centigrade degree are shown in Table I, which is applied to the load demand amount of this paper's case study (IEEE-RTS_79 Reliability test system).

Table 1. Changes in peak demand due to 1 degree of temperature rise.

Demand	Winter	Summer	Monsoon
Changes on Peak Demand %	4.2	4.6	2.8

The previous papers have proposed algorithms for assessment of reliability of power system and investigated the changes in load demand due to climate change separately. In this paper, the impact of global warming on generation reliability indices is analyzed.

The rest of the paper is classified as follow: First, the power system reliability assessment methods are described in section II. In section III, the algorithm approach is presented in which the reliability indices are calculated by the PSO (Particle Swarm Optimization) as a commonly used and powerful meta-heuristic optimization algorithm. Also, algorithm approach is presented and is described in this section. Finally, case study and the results and impacts of climate change on reliability indices are shown in section IV.

2. Power System Reliability Adequacy Assessment Methods

Generally analytical (including both discrete and continuous methods) and simulation-based (Monte Carlo Techniques) are the main two basic methods of system adequacy assessment. The main differences between these methods are related to the process of selecting system states and calculating reliability indices.

In analytical techniques, the system is represented using mathematical models and the reliability indices are calculated by solving the equations. The state space, contingency enumeration, and minimal cut set are the most commonly used analytical methods.

Simulation-based techniques, generally termed Monte Carlo Simulation (MCS) methods, solve the problems using random variables. These methods are widely used by researchers for the evaluation of power system reliability. MSC techniques are iteration based and results of all iterations are converted to a distribution function. Then the reliability indices are calculated by the achieved functions.

MCS methods are able to collect information about the both mean value and probability distribution of the reliability indices. In these methods, contingencies with higher probability are more likely to select and maybe simulated several times. Monte Carlo Simulation methods are divided into two main categories: Non-Sequential and Sequential Techniques [19-26].

In analytical methods, the system states are selected in terms of different contingency levels. This selecting process ends while a specific stop criterion is reached. The stop criteria can be a particular element outage numbers or when the probability of a selected state is less than a threshold value. Finally, indices are calculated using mathematical formulation according to the evaluation result of the selected states. Simulation-based techniques select the system states based on the random failure behavior of system elements and the states with a higher probability of occurrence are more likely to select. The stop criterion in these methods can be a specific number of simulations or other stopping rules. Finally, the reliability indices are calculated by averaging the indices obtained from each simulated state.

Both methods have their own advantageous and disadvantageous. The computational time of reliability evaluating is much less independent from the reliability level of the system. One important thing worthwhile to be considered is that in simulation-based methods, the number of selected states increases remarkably by increasing the system reliability level. Also, the outage of a component in a power system may be affected by the outage of other components and simulation methods cannot handle this in simulation process of simulation based methods. Another advantage of analytical methods is that selected states are independent of the system load curve while in simulation methods, the process should be done separately for each selected state.

On other hand, analytical methods have some shortcomings. Many simplifying assumptions are needed in using these methods while the effect of these approximations is not clearly known. Furthermore, they are proper for reliability assessment of small systems, and simulation methods have been proposed to be used in large and complex systems considering the behavior of their random components.

Because of all disadvantages mentioned above, meta-heuristic algorithms have been widely used to assess and calculate the reliability indices. They are able to calculate the reliability indices using evaluating fewer states of the system with acceptable accuracy. Also, more information of the system such as the most failure state and the most probable failure state can be determined easily using these methods. In this paper, a Particle Swarm Optimization algorithm is used to calculate the reliability indices of the test system.

3. Algorithm Approach

In this chapter, the reliability definitions and formulas are given first. Then it is described how to calculate the generation reliability indices by PSO in detail.

3.1 Reliability Definitions

Every generation unit is considered as an element and has its own Failure (μ) and Repair (λ) rate. The Force Outage Rate (FOR) parameter is determined for each generation unit based on equation 1:

$$\mathrm{FOR_i} = \frac{\lambda_i}{\lambda_i + \mu_i} \qquad (1)$$

This parameter is used to calculate the availability of a generation unit (equation 2). Also, each generation unit is considered to have two statuses: (1=on and 0=off). Then a probability value (PS) is calculated for each state of the system depending on the unit's FOR and status (equation 3).

$$\text{Availibility of unit i} = \begin{cases} \text{FOR i} & \text{if related binary is 0} \\ 1 - \text{FORi} & \text{if related binary number is 1} \end{cases} \quad (2)$$

$$\mathrm{PS_j} = \prod_{i=1}^{ng} \text{Availibility j} \quad (3)$$

Where:

Ng= number of generation units

As mentioned above, a system state is shown by generation unit's status. The state of the system in which all units are in upstate is shown in Fig 2.

Figure 2. The sample status of the system

Capacity MW	**115**				**76**				**197**			**100**			**12**					**400**		**50**						**20**			
STATUS	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

The total generated power of a system state is calculated by equation 4. The total generated power is compared to hourly load amount. If the generated amount bigger, it is considered a successful state. Otherwise, it is considered a failure state and will be used to calculate reliability indices.

$$\mathrm{G_i} = \sum_{j=1}^{ng} \mathrm{g_j} * \mathrm{b_j} \quad (4)$$

Where:

G i is the generated power of state i.
ng is the number of generation units.
g j is the capacity of unit j.
b j is a binary number equals to 1 if the unit is on and equals to 0 if the unit is off.

There are 2ng possible states for a system that are evaluated in analytical methods. The most two commonly used indices are Loss of Load Probability (LOLE) and Energy Expected Not Supplied (EENS). These indices are calculated by equations 5 -8 for the system:

$$\mathrm{LOLE_{system}} = \sum_{i=1}^{8760} \mathrm{LOLE_{Loadi}} \quad (5)$$

$$\mathrm{LOLE_{Load\ i}} = \sum_{i=1}^{k} \mathrm{PS_i} \quad (6)$$

$$\mathrm{EENS_{system}} = \sum_{i=1}^{8760} \mathrm{EENS_{Loadi}} \quad (7)$$

$$\mathrm{EENS_{Load\ i}} = \sum_{i=1}^{k} \mathrm{PS_i} * (\mathrm{Load_i} - \mathrm{PG_i}) \quad (8)$$

Where:

8760 is number of hours in a year (for RTS_79, 8736 hours is given in a year).
k is number of failure state at load i.
PSi= probability of sampled failure state i.
Loadi= amount of load at hour i
PGi= power generated at failure state i.

3.2 Reliability Indices Calculation Using PSO

PSO, used frequently by researchers to solve complicated problems, is used to lower the computation burden of the system reliability calculation by searching in the power system possible states and choosing the most probable one. The number of possible states of a system with n generation units is 2n, while PSO is able to search and find the most probable ones, save them and calculate the reliability indices by saved sampled states. In the PSO algorithm, the swarms are updated based on equations 9 and 10:

$$v_i(t) = v_i(t-1) + \rho_1(x_{boss} - x_{i(t)}) \quad (9)$$

$$x_i(t) = x_i(t-1) + v_i(t) \quad (10)$$

Where, xi (t) presents ith swarm, and xboss is the position of the best swarm.

So, the fitness function of the algorithm is defined as PS (probability of a system state). The first collections of states are generated randomly, but the others are selected intelligently according to the PSO operations. Each system state is shown by a swarm in PSO algorithm. The algorithm ends when it reaches the stop criteria which can be a specific number of iterations. The number of proper iterations can be determined based on the size of the problem or the number of the generation units. Finally, reliability indices can be calculated based on the information of saved states' information and the LCD (Load duration Curve). The algorithm steps are given below:

1- Save the power system reliability information (the information includes the number of generation units, each unit power output in MW, and failure and repair rate of each generation unit).
2- Select PSO parameters (including population size, Iterations, C1 and C2 parameters).
3- Save Load Duration Curve information (hourly load demand for a period of one year).
4- Randomly generate the first population consisting of swarms (each swarm represents a system state).
   - While current iteration<maximum iteration do:
5- Calculations of fitness function for each swarm
6- Swarms moving toward their best historical information and the best swarm of the current generation.
7- Evaluating the states (to evaluate states as a failure a success compared to maximum load amount).
8- Saved failure states in an array.
9- Back to item 5.
10- Calculate the LOLE and EENS as generation reliability indices.

4. Case Study and Results

In this paper, The RTS-79 is chosen as a standard reliability test system. The test system includes 32 generation units. The capacities of units are from 12 to 400 MW as smallest and largest respectively. The sum of generated capacities is 3405 MW, while the maximum load is considered 2850MW. Other necessary information such as unit sizes, number of units, forced outage rates, and hourly load demand is given. In the first step, the reliability indices of the system, based on the original load demand information and without considering the temperature rising, are calculated by both an analytical method (unit addition algorithm) and PSO as a meta-heuristic algorithm. The results are given at Table 2.

Table 2. Reliability indices of the test system without considering the temperature rising.

Reliability Index	Unit addition algorithm	PSO algorithm
LOLE	9.355	9.343
EENS	1168	1164.5

In the next step, the increases in load hourly demands are considered based on the 1-degree temperature rise in different seasons. Then the reliability indices are calculated using the PSO algorithm and compared to the original values calculated by the same algorithm. The results are shown in Table 3. Finally, the reliability indices, both LOLE and EENS, are calculated again considering 2 degrees of temperature rise. The results are given in Table 4.

Table 3. Reliability indices of the test system with considering the 1 degree temperature rising.

Reliability Index	Original Value	Considering 1 degree temperature rising
LOLE	9.343	19.9441
EENS	1164.5	2679.3

Table 4. Reliability indices of the test system with considering the 2 degree temperature rising.

Reliability Index	Original Value	Considering 2 degree temperature rising
LOLE	9.343	39.3824
EENS	1164.5	5744.8

The results show that global warming and the temperature rising have remarkably decreased the reliability of the power system. In other words, global warming causes more blackouts and energy loss in a power system. The LOLE index (showing the number of blackout hours in a year), is increased by 10.6 and 30.03 hours in a year by increasing the 1 and 2 degrees of temperature respectively. In addition, the amount of not supplied energy has been increased 1514.8 and 4580.3 MWh in a year due to increasing the 1 and 2 degrees of temperature.

5. Conclusion and Suggested Work

In this paper, the impacts of global warming and temperature rise as one of the most important effects of climate change are investigated on the reliability of a power system. Two LOLE and EENS indices have been chosen to represent the reliability of a system. Also, and Particle Swarm Optimization was used to calculate the power system reliability indices. The standard RBTS-79 reliability test system was considered as the case study. The increase in hourly load demand was considered as the impact of global warming. The reliability indices were calculated considering the 1 and 2 degrees of temperature rise. The results show that global warming has a noticeable negative effect on system reliability by increasing the power blackout hours and not supplying energy amounts. Furthermore, an investigation of the effects of global warming on other power system factors is suggested by the authors. The effect of temperature rise on the failure rate of power system elements such as generation units and transmission lines will be considered in future works.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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