RELIABILITY ANALYSIS OF POWER SYSTEM NETWORKS INTEGRATED WITH POWER CONVERTERS

A PROJECT REPORT

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CERTIFICATE

This is to certify that the Project report entitled '**RELIABILITY ANALYSIS OF POWER SYSTEM NETWORKS INTEGRATED WITH POWER CONVERTERS'** submitted by '**ANUPAMA V N'** to the APJ Abdul Kalam Technological University in partial fulfillment of the requirement for the award of the Degree of Master of Technology in Power Systems, Electrical & Electronics Engineering is a bonafide record of the project work carried out by her under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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ABSTRACT

The increasing electric power demand invites the addition of new and renewable energy sources in the power system. The renewable technologies consist of several power converters to achieve the desired operation. Hence the number of power electronic converters in the power system are also increasing day by day. The reliability of the system gets affected by the increased addition of power electronic converters. So, the role of power converters in determining the reliability of the system is inevitable. The conventional reliability evaluation methods consider the failures caused by power converters as constant. The system addressed here employs a stratified procedure for reliability analysis of a power system network. The reliability model of the system is developed based on the power electronic devices it is composed of and the optimal value of the factors that affect reliability is computed using genetic algorithm. Apart from finding the reliability of the system, a reliability prediction using machine learning regression technique is done. Three test systems including a three-bus system, Roy Billinton Test System and IEEE RTS 24 Bus system are simulated in ETAP software and their reliability analysis is performed to verify the results obtained.

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ABBREVIATIONS

DG	:	Distributed generation
GA	:	Genetic Algorithm
WT	:	Wind Turbine
RES	:	Renewable energy sources
RTS	:	Reliability Test System
SPV	:	Solar Photovoltaic
SVR	:	Support Vector Regression
CAIDI	:	Customer’s Average Interruption Duration Index
EENS	:	Expected Energy Not Served
IGBT	:	Insulated Gate Bipolar Transistor
LOLE	:	Loss of Load Expectation
RBTS	:	Roy Billinton Test System
SAIDI	:	System Average Interruption Duration Index
SAIFI	:	System Average Interruption Frequency Index

CHAPTER 1
INTRODUCTION

1.1 GENERAL BACKGROUND

The growing electric power demand drives the renewable energy sources (RES) to become a dominating element in the power system. At present the tendency of incorporation of distributed generation (DG) power plants in the power system is being widely spread. In recent years, the restructured power system network comprising od RESs such as solar photovoltaics, wind turbines, etc. have dominated the traditional power system structure. Development and integration of DG power plants to the system is considered as a solution for several factors such as the ecological problems, sufficient utilization of the renewable energy resources as well as rational use of energy resources. The use of renewable energy sources is of immense benefits such as reduction of carbon emission to the environment, decrease in the depletion of fossil fuels, etc. This will encourage the use of more and more RESs and hence in the near future, a large portion of conventional generators will be replaced by these renewable technologies.

Even though this development is beneficial to the system, it has notable effects on the reliability of the system. Power electronic devices are the key enabling technology in a wide range of applications including the DG. The RESs comes with several power conversion stages to achieve the desired output and hence it consists of several power converters which are made of semiconductor devices to achieve its desired operation.

The proliferation of power electronic devices in the power system affects the reliability of the system and hence reliability analysis of power electronic converters becomes inevitable. These power converters and power electronic devices are prone to failure since they undergo continuous switching in order to have a desired power level. The chances of outages of these devices are more and hence it affects the reliability of the system. So, the reliability analysis considering the effect of power converters becomes an inevitable procedure. Since RES are incorporated into the system in conjunction with power-electronic converters, the growing proliferation of power electronic converters causes the deterioration of reliability to be more critical.

1.2 MOTIVATION

The main motive of conducting reliability analysis in power system is to have a keen understanding about the operation of the system and to improve the system performance by arranging for maintenance at the critical areas to ensure uninterrupted power supply. Different methods are employed for reliability diagnosis of power system.

The reliability analysis methods of RESs are different from that of conventional distribution system. The conventional methods used for reliability evaluation includes the RES contingencies, but considers the failures caused by power converters connected to RESs as constant or are sometimes ignored. But, the failure rate of the system is immensely affected by these devices. Since the power electronic converters have a prominent role in the reliability of the system, reliability analysis should be done at the converter level and also at the system level.

1.3 OBJECTIVES OF THE THESIS

In this thesis, the reliability analysis of a power system network integrated with power converters is done. The reliability assessment gives equal importance to both the converter level and system level parameters. The optimal value of the factors required for achieving maximum reliability is computed using genetic algorithm. Genetic algorithm gives the best fitted offspring or result by repeated production of generation. Also, a reliability mapping using machine learning is performed and three case studies are conducted to verify the results obtained from genetic algorithm. The case studies are performed in a three-bus system, Roy Billinton Test System and IEEE RTS 24-bus system simulated in ETAP software.

1.4 ORGANIZATION OF THE THESIS

The entire thesis is organized as follows. It consists of seven chapters. Chapter 1 is a brief introduction of the thesis and the motivation and objectives about the same. Chapter 2 deals with the literature review about the several conventional reliability assessment methods and the technical gaps associated with each of them. Chapter 3 gives an outline about the concept of reliability. The basic information regarding the reliability indices and bathtub curve which gives the trend of lifetime of an equipment is discussed in it. Chapter 4 is the methodology followed in the thesis. The methodologies of three stages in the reliability analysis and prediction is discussed. Chapter 5 shows the results that are obtained from the reliability prediction and analysis tools followed by the discussion about the same. Chapter 6 discusses the caste studies and their results. Three case studies are done in three different systems. Finally, chapter 7 gives the conclusion and the future research scopes in this area.

CHAPTER 2
LITERATURE SURVEY

2.1 INTRODUCTION

In recent years, the restructured power system network comprising of RESs such as solar photovoltaics, wind turbines, etc. have dominated the traditional power system structure and the RES has power conversion equipment with it, which is required for its desired operation. [1] looks into the effect of these power conversion equipment on the system reliability. Each of the components are analysed and are ranked according to their contribution towards the system's reliability. This analysis method involving individual ranking of components aids in understanding and identifying the critical components and take necessary measured.

The use of renewable energy sources is of immense benefits such as reduction of carbon emission to the environment, decrease in the depletion of fossil fuels, etc. The renewable energy sources are integrated with power converters, which causes deterioration of the system reliability. [2] incorporates the power electronic converter reliability with the reliability of the system. Both system-level and converter-level reliability analysis is done. A case study is performed in Roy Billinton Test System, which shows the effect of converters on the reliability of the system.

The RESs comes with several power conversion stages to achieve the desired output and hence it consists of several power converters which are made of semiconductor devices to achieve its desired operation. These power converters and power electronic devices are prone to failure since they undergo continuous switching in order to have a desired power level. The chances of outages of these devices are more and hence it affects the reliability of the system. So, the reliability analysis considering the effect of power converters becomes an inevitable procedure. The thermal stress and temperature swing are the two major issues associated with the power converters. [3] analyses the reliability of the converters based on a mission-profile based approach, which is of immense use to find the most influential element.

The main motive of conducting reliability analysis in power system is to have a keen understanding about the operation of the system and to improve the system performance by arranging for maintenance at the critical areas to ensure uninterrupted power supply. The most vulnerable component has to be identified at the earliest to ensure the reliability. [4] identifies the most vulnerable component in the system by using an evaluation method based on minimum path and ranks the lines according to it so as to make it convenient for maintenance.

Different methods are employed for reliability analysis of power system. The reliability analysis of a power electronics-based power system is done in [5] considering individual reliability matrices of each element. This will benefit the end-users and power system operators to reduce the component failures and hence the cost associated with the removal of the failure.

The conventional methods used for reliability analysis include the RES contingencies, but they consider the failures caused by the power converter devices as constant, or negligible and are ignored. But, the failure rate of the system is immensely affected by these devices. In [6], a time-dependent failure rate is considered for reliability analysis of converters, which ensures a more accurate analysis.

[7] proposes a stratified reliability analysis procedure for reliability diagnosis of power system incorporated with distributed generation. The reliability diagnosis of a power system with power converters is done using Monte Carlo simulation and a reliability mapping between the converter-level and system-level is done using machine learning regression. Numerical analysis is performed in IEEE RTS 24-bus system, in three stages, considering an increasing pace of DG integration.

The use of renewable energy sources has several boons including reduction in atmospheric pollution, etc. This will encourage the use of more and more RESs and hence in the near future, a large portion of conventional generators will be replaced by these renewable technologies. Even though this development is beneficial to the system, it has notable effects on the reliability of the system. [8] analyses the power system reliability considering the effect of DG. A variance- based global sensitivity analysis is done in to identify the most influential element and the elements are ranked according to its sensitivity, which helps in identifying the most influential element.

Reliability analysis of a DC microgrid considering device failure rates model is done in [9] and reliability enhancement method is also addressed. The reliability analysis is done based on operation failure rate probability. A failure rate model is computed to perform the reliability analysis. Also, a hybrid energy storage system is proposed to replace the conventional battery energy storage to improve the reliability.

A mission-profile based reliability assessment of a power electronic-based power system is done in [10]. The method considers the mission profile and loading profile, which is highly affected by the thermal stress and temperature cycling of the components. A numerical study is done on a dc power electronic based power system to identify the influence of converters on the system

CHAPTER 3
RELIABILITY

3.1 INTRODUCTION

Reliability of a system can be defined as its ability to deliver its intended performance within its lifetime of operation. This means that, the system's normal or regular performance can be retained during its specific time of operation. But, if failure occur in the system, the continuity of operation cannot be promised. If the failure becomes consistent, the system becomes unreliable and hence proper maintenance of the failure prone areas will have to be arranged to achieve reliability. The reliability of a component, R(t) can be calculated as shown in (3.1), where, λ is the failure rate of the component. Failure rate gives the number of failures that occur at a particular period of time. Fig.3.1 shows the reliability curve [15]. It is inferable from the reliability curve that the value of reliability is at the highest value at the beginning of the lifetime and then decreases with time. The time represents the useful lifetime of the equipment. The decrease in reliability is due to the increase in failure rate due to wear outs that occur with the repeated usage of the equipment.

$$R(t) = e^{-\lambda t} \tag{3.1}$$

Reliability value is quantitatively computed using various reliability indices [16]. The indices include System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), Customer's Average Interruption Duration Index (CAIDI), Expected Energy Not Served (EENS), Loss of Load Expectation (LOLE), etc. [10]. SAIDI is a system index which gives the average duration of interruptions that occurs in the power supply. SAIFI indicates the frequency or, the number of times a sustained interruption is experienced by the customer during a particular period of operation. CAIDI is the ratio of sum of duration of the customer interruption to the total number of customers interrupted. It is the average time needed to restore the services to the interrupted customers. The value of the indices should be as low as possible. Larger value indicates lower reliability. The semiconductor devices that compute the power converters have a large failure rate, because of the continuous switching operations, that is affected by the thermal stress, power loss, etc. of the components. So, the failure rate of those components cannot be considered as a constant. So, the failure rate of power converters has to be obtained based on the critical devices it is made of.

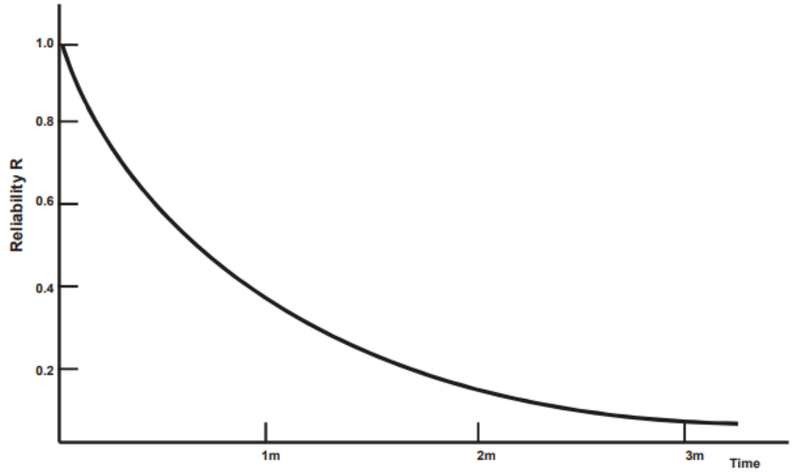

Fig. 3.1. Reliability curve [15]

3.2 BATHTUB CURVE

The Bathtub curve is a standard curve for reliability of any product. Fig. 3.2 shows the graphical representation of the failure rates associated with the operation of any product during its time of service.

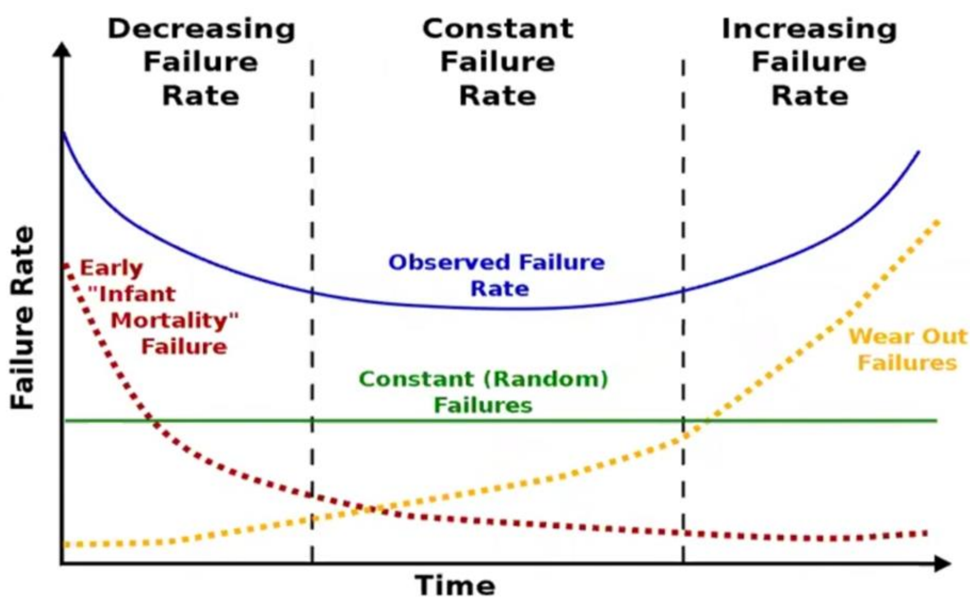

Fig. 3.2. Equipment failure profile – Bathtub curve

The graph consists of a constant failure rate, depicted by the green line, which is associated with any equipment. The red dotted line shows the “early infant mortality” failure of an equipment. In the initial operating period of the equipment, the failure rate will be more due to any kind of design or manufacturing errors. These problems will be identified and solved and hence the failure rate will decease will gradually it settle down as it is used over a period of time. The yellow dotted line in the curve shows the wear out failures. Wear outs occur with the usage of the equipment. So, in the initial operating time, the failures due to wear out is lower and it increases with the time of service. These three failures, i.e., the infant mortality, constant failure and wear out failure are present in all the products. So, considering all the three failures, we obtain the curve called as “Bathtub Curve”, shown by the blue curve, which shows the equipment failure profile.

The curve depicts that, during the initial period of operation of the equipment, the failure rate will decrease and it will more or less flatten out or become constant over a large part of life of the equipment. The constant failure rate part is the useful life or the normal operating region of the equipment. Then, towards the tail end of the lifetime of the equipment, again the failure rate will increase due to the wear outs. This may be reduced by scheduled maintenance or replacement of the components.

CHAPTER 4
METHODOLOGY

4.1 INTRODUCTION

The evaluation strategies for the reliability of RES are different from that of conventional distribution systems. The power that is generated by the RES can be rendered to the system successfully only if the power converters associated with them operates without fail at all times. So, the reliability of the power converters also becomes essential since they can affect the entire system reliability. This chapter discussed the reliability analysis of power system networks incorporated with power converters using different methods. The reliability modelling of converters is discussed, followed by the procedure of reliability analysis using genetic algorithm. The methodology for reliability mapping using machine learning regression is also discussed.

4.2 RELIABILITY ANALYSIS

The reliability of each power converter has to be quantified first. The traditional method of calculating reliability is as shown in (3.1). But it considers the failure rate as constant and independent of time. But the failure rate is affected greatly by many factors, including thermal loading and temperature cycling [17], and hence cannot be considered as constant and time independent. So, we express the equation for failure rate as shown in (4.1) [18].

$$\lambda = \pi_{\mathrm{M}} \pi_{process} \lambda_{\mathrm{Phy}} \tag{4.1}$$

Where, $\boldsymbol{\Pi}_{\mathrm{M}}$ is the contribution to the failure rate from manufacturing of the component, $\boldsymbol{\Pi}_{\mathrm{process}}$ is the overall contribution from the processes and their values are taken as unity, and λ_{Phy} is the failure rate which is of our main concern and its value can be calculated as shown in (4.2).

$$\lambda_{\mathrm{phy}} = \sum_{i}^{states} \left(\lambda_{\mathrm{i}} \pi_i \frac{t}{T} \right) \tag{4.2}$$

Where, t is the duration of the state of the device for a span T. $\boldsymbol{\Pi}_i$ is the overstress factor which is specific to each of the components [19]. The value of λ_i has to be calculated and its calculation procedure is discussed in the coming sections.

4.2.1 Reliability Modelling of Converters

A wind power system, consisting of a permanent magnet synchronous generator, a dc link and an inverter is considered. The output power of the wind turbine varies with the wind speed and angle and hence the device power loss gets affected which ultimately affects the failure rate. Thus, the output power of the wind turbine (WT) P_{wt} at hour t is computed from the hourly wind speed data as shown in (4.3).

$$P_{wt} = \begin{cases} 0, & 0 \leq v_t \leq v_{ci} \\ (A + Bv_t + Cv_t^2)P_{rated}, & v_{ci} \leq v_t \leq v_r \\ P_{rated}, & v_r \leq v_t \leq v_{co} \\ 0, & v_t \geq v_{co} \end{cases} \tag{4.3}$$

Where v_t represents the speed of the wind, P_{rated} stands for the rated power capacity of the WT, v_{ci} stands for the cut-in wind speed, v_r represents the rated wind speed and v_{co} represents the cut-out wind speeds of the wind turbine system [20]. The value of A, B, and C is computed using (4.4), (4.5), and (4.6) respectively [21]. Using the hourly based data, the output power of the wind turbine is computed.

$$A = \frac{1}{(v_{ci}-v_r)^2}\left[v_{ci}(v_{ci} + vr) - 4(v_{ci} * v_r)\frac{(v_{ci}+v_r)^3}{2v_r}\right] \tag{4.4}$$

$$B = \frac{1}{(v_{ci}-vr)^2}\left[4(v_{ci} + vr)\frac{(v_{ci}+v_r)^3}{2v_r} - (3v_{ci} + v_r)\right] \tag{4.5}$$

$$C = \frac{1}{(v_{ci}-v_r)^2}\left[2 - 4\frac{(v_{ci}+v_r)^3}{2v_r}\right] \tag{4.6}$$

The critical devices associated with the converters that are prone to failures are the diodes and IGBTs. So, the total power loss of the converters is mainly contributed by these semiconductor devices. Hence, the total power loss of a diode and IGBT can be expressed as shown in (4.7) and (4.8).

$$P_{loss\_IGBT} = P_{IGBT\_cd} + P_{IGBT\_sw} \tag{4.7}$$

$$P_{loss\_diode} = P_{diode\_cd} + P_{diode\_sw} \tag{4.8}$$

Where, the P_{j_cd} stands for the power loss due to conduction and P_{j_sw} indicates the power loss due to switching of component j. Then, the total power loss that is occurring in the converters can be obtained by the summation of the power loss contributed by each diode and IGBTs as shown in (4.9).

$$P_{conv\_loss} = \sum_{n=1}^{n_G} P_{loss_{IGBT}} + \sum_{n=1}^{n_D} P_{loss_{diode}} \tag{4.9}$$

Where, n_D represents the number of diodes and n_G represents the number of IGBTs respectively. Using the converter power loss value, the junction temperature (T_j) of the IGBT and diode can be calculated as shown in (4.10) and (4.11).

$$T_{j\_IGBT} = T_a + R_{sa_{IGBT}}\, P_{conv_{loss}} + R_{jh\_IGBT}\, P_{loss\_IGBT} \tag{4.10}$$

$$T_{j\_diode} = T_a + R_{sa\_diode}\, P_{conv\_loss} + R_{jh\_diode}\, P_{loss\_diode} \tag{4.11}$$

Where, T_a stands for ambient temperature of the component and R represents the thermal resistances. Then, the thermal stress factor of the IGBT and diode can be obtained as shown in (4.12) and (4.13) respectively.

$$\pi_{Th\_IGBT} = \exp\left[1925\left(\frac{1}{298} - \frac{1}{T_{j_{IGBT}} + 273}\right)\right] \tag{4.12}$$

$$\pi_{Th\_diode} = \exp\left[3091\left(\frac{1}{298} - \frac{1}{T_{j_{diode}} + 273}\right)\right] \tag{4.13}$$

Equation (4.14) represents the temperature cycling factor for the components, i.e., diode and IGBT, where, γ is the temperature coefficient of diode and IGBT, which has a specific value.

$$\pi_{TC} = \gamma\left(\frac{12N_s}{t(i)}\right) f(\Delta T) * \exp\left[1414\left(\frac{1}{313} - \frac{1}{T + 273}\right)\right] \tag{4.14}$$

Where, the value/expression for γ and $f(\Delta Tb)$ a diode or an IGBT can be found in [22]. The failure rate of the system can then be obtained using the above values. as shown in (4.15).

$$\lambda_j = \sum_{i}^{N_s} (\lambda_{0Th}\pi_{Th,j} + \lambda_{0TC}\pi_{TC,j})\pi_M\pi_{process} \tag{4.15}$$

Using similar procedures, the failure rate of components associated with any DG unit connected to the system, like solar PV [11], etc. can be obtained. Using this value of failure rate, the down-state probability P_d of the system can be obtained as shown in (4.16), where $\boldsymbol{\mu}$ is the repair rate of the system.

$$P_D = \frac{\lambda}{\lambda + \mu} \tag{4.16}$$

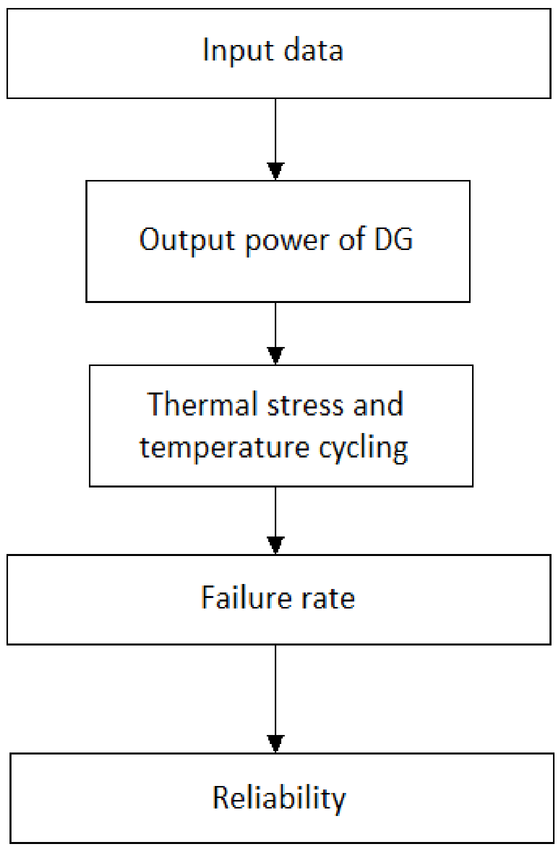

Fig.4.1. Flowchart of the reliability formulation

Fig. 4.1 shows the flowchart of the above discussed method of reliability formulation. As shown in the figure, first the collection of input data is done to compute the output power of the DG. Then, the power loss occurring in each of the devices is calculated, which includes the switching and the conduction losses. After obtaining the total power loss of each semiconductor device, the total power loss of the converter is calculated. Using the converter power values the junction temperature of the semiconductor devices in the converters is obtained, which is then used to find the thermal stress associated with each device. Then, the temperature cycling factor is computed and using these values, the failure rate of the system is obtained. Finally, using the failure rate, the reliability of the system is computed. The reliability is given by the availability or the up-state probability P_U of the system [2], which is expressed as in (4.18).

$$P_U = 1 - P_D \tag{4.17}$$

$$P_U = \frac{\mu}{\lambda + \mu} \tag{4.18}$$

Apart from finding the reliability of the system, the optimal value of the thermal stress factor and temperature cycling factor to achieve maximum reliability is also computed, and for that, Genetic algorithm is used. The procedures to find the optimal value of the thermal stress factor and temperature cycling factor is discussed below.

4.2.2 Reliability Analysis Using Genetic Algorithm

To obtain the optimal value of the thermal stress factor and temperature cycling factor that gives maximum reliability, Genetic algorithm is used. GA employs the fitness function to identify the most appropriate population [23]. Using GA has many advantages such as intelligent and efficient method for identifying the most appropriate individuals, and that the solution gets better over each step, etc. so that, we can clearly identify the critical areas and arrange for maintenance. In [24], an optimal maintenance strategy is adopted using GA. The fitness function for the system to obtain maximum reliability is given by (4.19). The steps to obtain the value of P_D was discussed in the previous section.

$$Max\ Z = 1 - P_D \tag{4.19}$$

Fig.4.2 shows the flowchart of the GA procedure that is being followed. First, the initial population is given, which includes the thermal stress factor, temperature cycling factor and the value of Z. Then initialize the generation counter, i=1. After that, the GA program calculates the fitness function and checks the generations and inspects whether the stopping criterion has been satisfied or not. The stopping criterion that is used here is number of generations=400. If the stopping criterion is satisfied, the results of the iteration will be displayed and the GA procedure will come to an end. If the stopping criterion has not been satisfied, the GA operators such as selection, crossover and mutation of the parents will be done and another generation will be produced. Then, the generation counter will increase by 1 and again the calculation of fitness function and generation evaluation will be done. This repeats until the stopping criterion is satisfied. When the stopping criterion gets satisfied, the results will be printed and the GA procedure terminates and it gives the most optimal value of thermal stress factor and temperature cycling factor which is required to attain maximum reliability.

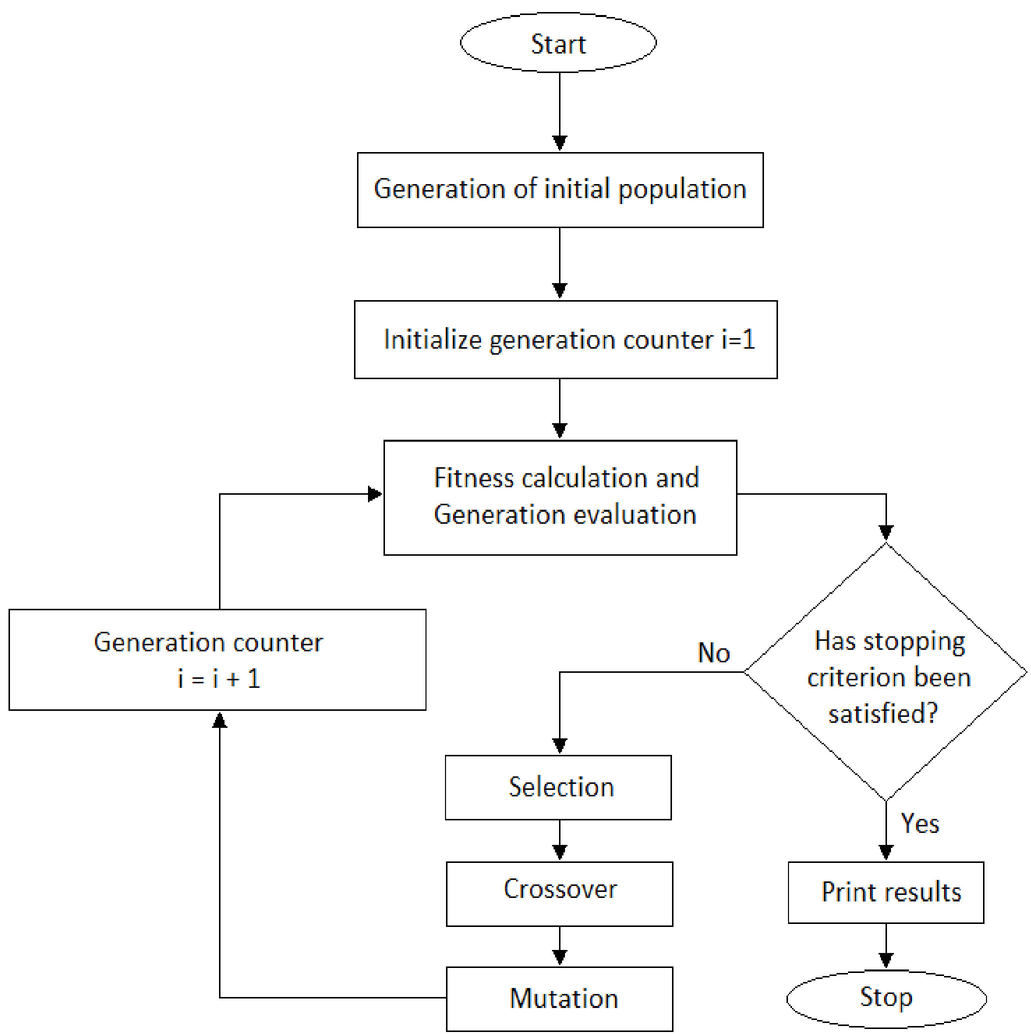

Fig.4.2. Flowchart of power system reliability assessment using genetic algorithm

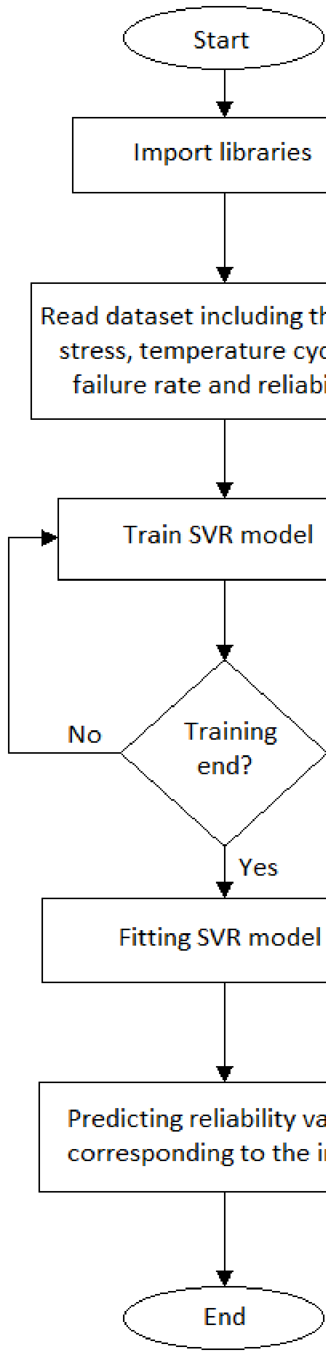

Fig.4.3. Flowchart of reliability prediction using SVR

4.2.3 Reliability Prediction Using Machine Learning Regression

The development of data science has led to a wide range of applications of machine learning in various fields. Support vector regression (SVR), which is a supervised machine learning regression technique is used in this thesis to predict the reliability. SVR will predict the output value corresponding to a certain value of input given, by training the model by an initial set of input and output values. In this thesis, the value of reliability corresponding to values of thermal stress, temperature cycling and failure rate is predicted.

The flowchart for reliability prediction using SVR is shown in fig 4.3. Importing the libraries for the smooth operation of SVR is the first step followed in the procedure of SVR. After importing the libraries, the dataset, including thermal stress, temperature cycling, failure rate and reliability is given. The thermal stress, temperature cycling and failure rate are the input parameters and the reliability corresponding to these factors is the output. After importing the datasets, it is divided into training and testing data and the training of the model will start. After the training, the model will be fitted to the given dataset. At the end of training, testing and fitting, the SVR model is ready to predict the values. Then, we can give the input values and the output reliability value corresponding to the input will be predicted.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 GENETIC ALGORITHM

Fig. 5.1 shows the input values that is given as initial generations to the GA procedure. Twelve inputs each of thermal stress factor, temperature cycling factor and reliability are given as the initial generation. In fig.5.1, the series 1 indicated by the blue curve represents the thermal stress factor, The series 2 shown by the orange curve shows the temperature cycling factor, and series 3 shown by the grey-coloured curve shows the reliability value corresponding to these two factors.

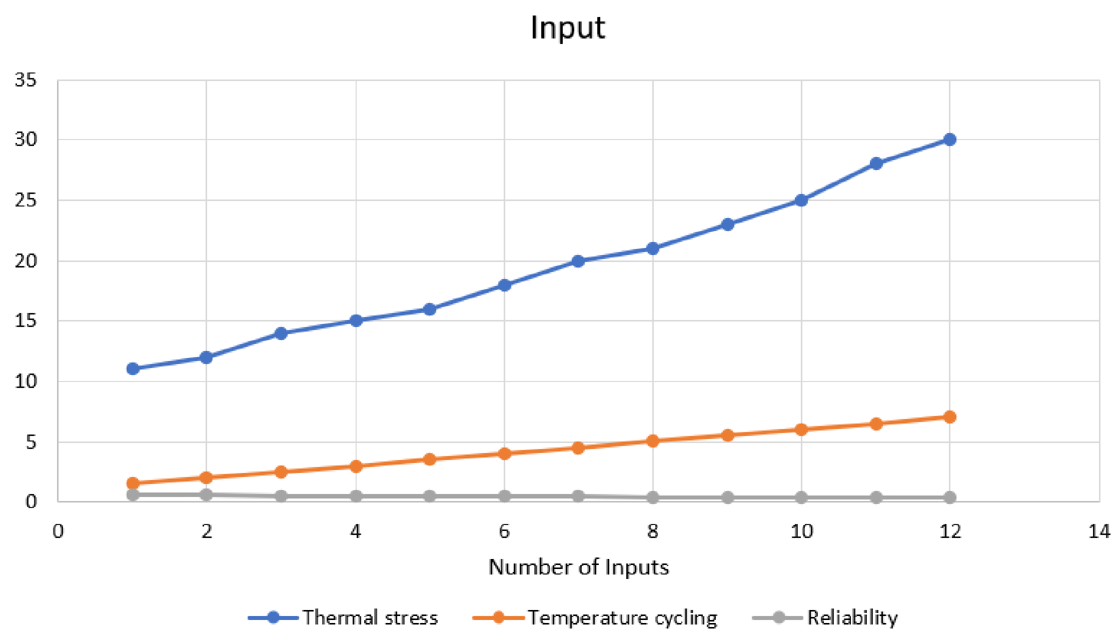

Fig.5.1. Input population

The maximum possible value that reliability can achieve is unity. From the input graph, it can be seen that the value of the up-state probability or the reliability is decreasing and tends towards zero with the increase of thermal stress and temperature cycling factor. The objective is to maximize the reliability of the system i.e., to make reliability value equal to unity, and to find the values of thermal stress and temperature cycling factors at maximum reliability condition. To achieve that aim, genetic algorithm is used and the output at the end of 400 generations is shown in fig.5.2.

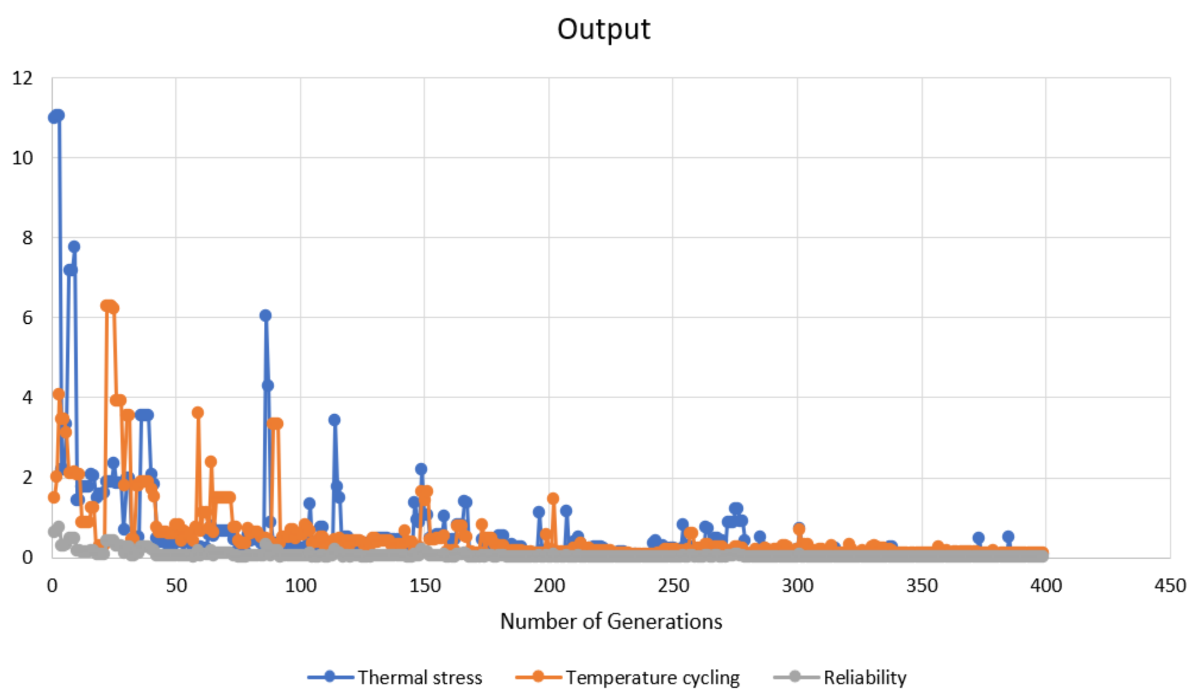

Fig.5.2. Output population

From the output graph, it can be seen that the thermal stress factor, temperature cycling factor, and reliability are getting converged to particular values at the end of 400 generations. The series 1 which shows the thermal stress factor is getting converged to a value 0.0469, the series 2 which shows the temperature cycling factor is getting converged to 0.0917 and the reliability shown by series 3 is converging to 0.9931, which is nearly equal to the maximum value i.e., 1.

Fig.5.3 and fig.5.4 shows the graph of thermal stress factor and temperature cycling factor. From the graph, it can be seen that initially, the inputs given are not agreeing to a particular value, but at the end of the GA procedure, that is, at the end of 400 iterations, all the inputs that we have given are agreeing to a particular value, which means that the iteration has converged. The value obtained is the optimal value of the input factor that gives maximum reliability.

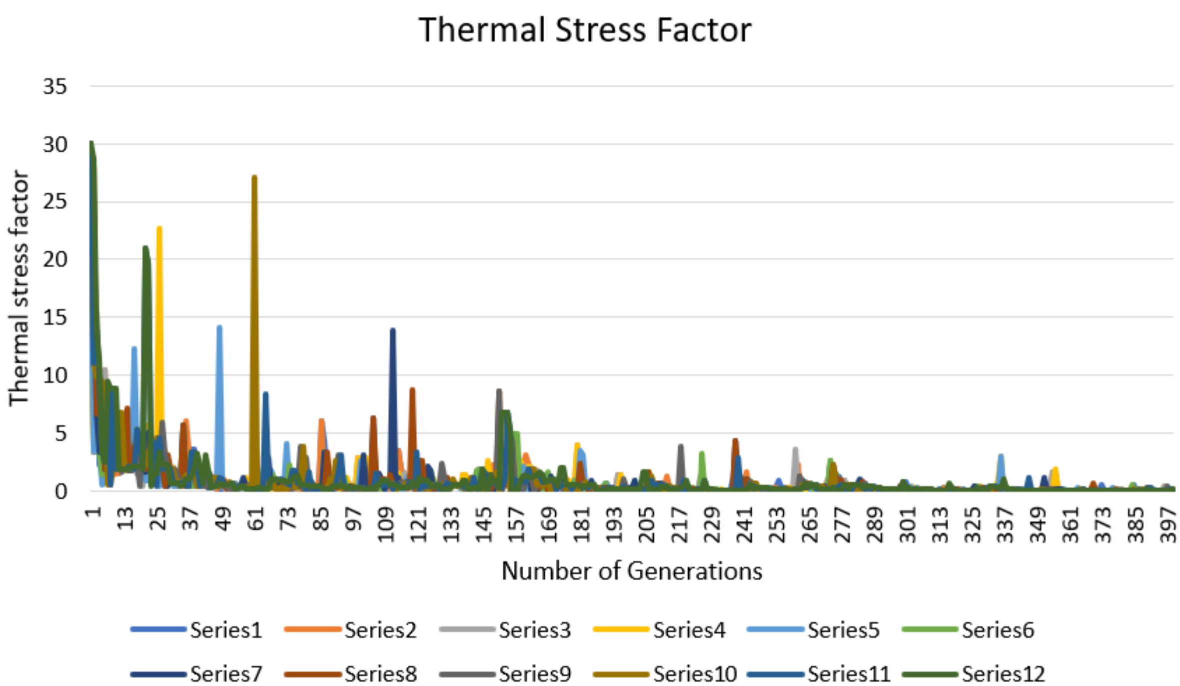

Fig.5.3. Optimized value of thermal stress

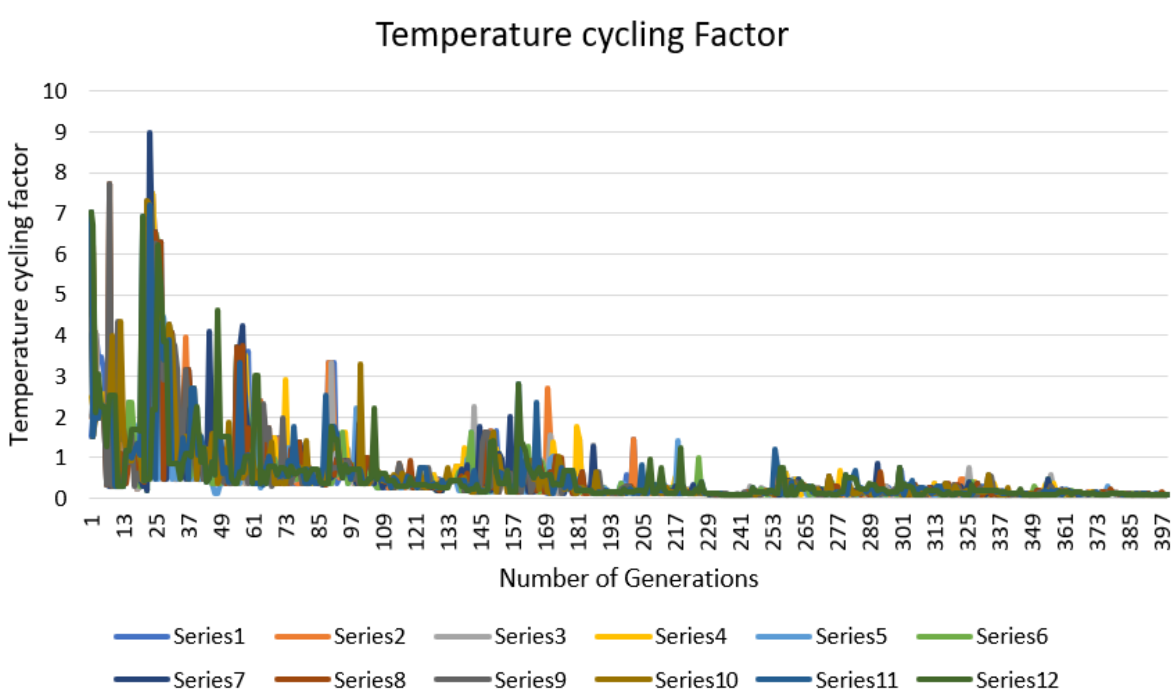

Fig.5.4. Optimized value of temperature cycling

5.2 SUPPORT VECTOR REGRESSION

Fig 5.5 shows the comparison of the reliability values obtained from GA and SVR. The results obtained from genetic algorithm is represented using the blue line and the red line represents the reliability predicted using SVR. From the figure, we can see that the reliability value predicted using SVR matches with the values obtained from GA at almost every point in the graph, which indicates a good accuracy of SVR to predict the system's reliability. So, it can be inferred that SVR can be used to obtain the reliability of the system when there is a need for frequent reliability analysis because it can reduce the complexity in reliability analysis. The computational procedure gets simplified using SVR because only the steps up to the computation of input values such as thermal stress, temperature cycling factor and failure rate has to be done. The procedure of GA does not have to be done since SVR has a high accuracy. This reduces the computational time and complexity.

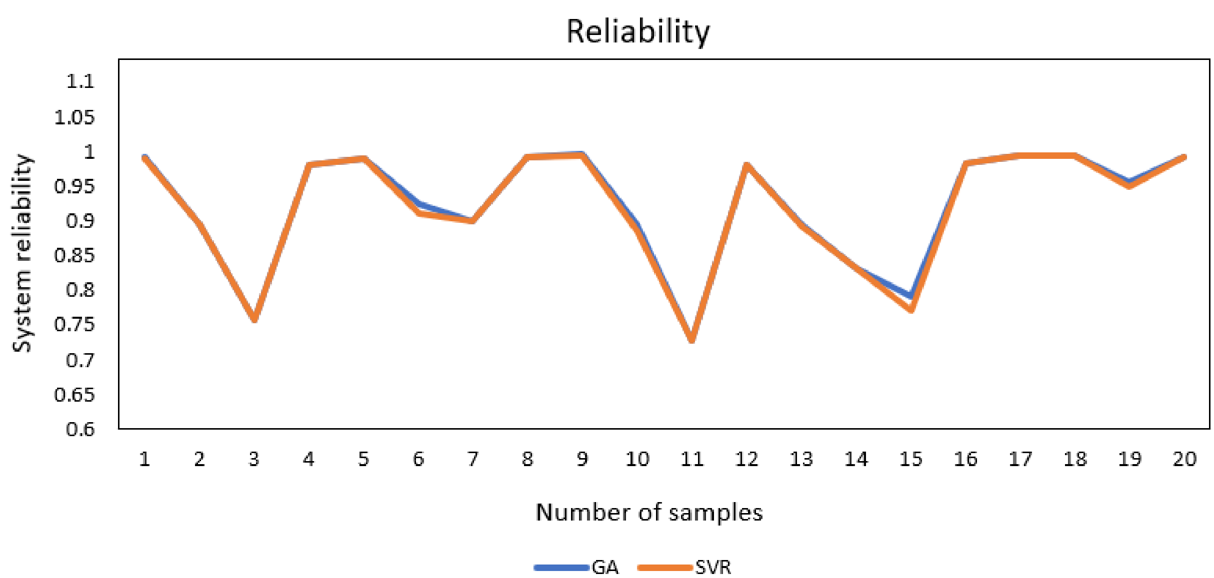

Fig.5.5. Comparison of predicted value of reliability using GA and SVR

CHAPTER 6

CASE STUDY

6.1 INTRODUCTION

The proposed analysis is done in the platforms as mentioned. Genetic algorithm is done in MATLAB version 2021b. Support Vector Regression is done in Google Colab. The results obtained from the above methods is validated by performing three case studies done in ETAP software. The first case study is done on a three-bus system, the second case study is done in Roy Billinton Test System (RBTS) and the third case study is performed in IEEE Reliability Test System (RTS) 24- bus network. Reliability analysis the first two systems is done considering three scenarios. In the first scenario, all the generators used are conventional. The second scenario mimics the penetration of distributed generation into the conventional system. In the second scenario, some of the conventional generators are replaced with distributed generation (here wind turbine). In the third scenario, the optimal values predicted using GA is given to the system in scenario 2 and the reliability analysis is performed. Reliability analysis on IEEE RTS 24-bus network is done considering four scenarios which is discussed in the coming sections.

6.2 CASE STUDY-1

6.2.1 System Description

Case study 1 is performed in a three-bus system as shown in fig 6.1. There are two generator buses and one load bus. The total generating capacity is 2.5 MW and the load is 1 MW. The voltage rating of the system is 2 KV. There are two generators at bus 1 and bus 2 with rating 2 MW and 0.5 MW respectively. The load is connected to bus 3 and the load rating is 1 MVA

6.2.2 Methodology

The reliability analysis is done in three stages. In the first stage, reliability analysis is done in the original system with conventional generators and the corresponding reliability indices are obtained. In the next step, the 0.5 MW generator at bus 2 is replaced with a wind turbine of the same capacity as shown in fig 6.2. There are two inverters connected with the wind turbine and the system's reliability is analysed. In the third stage, the values obtained from GA is given as input to the system integrated with wind turbine and the reliability values and indices is obtained.

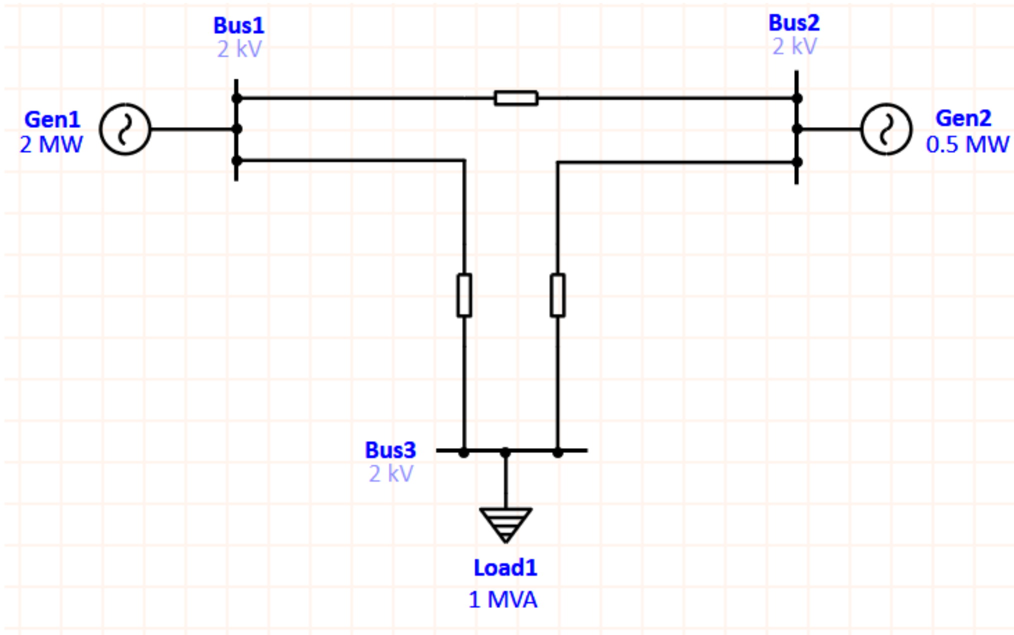

Fig.6.1. Three-bus system with conventional generators

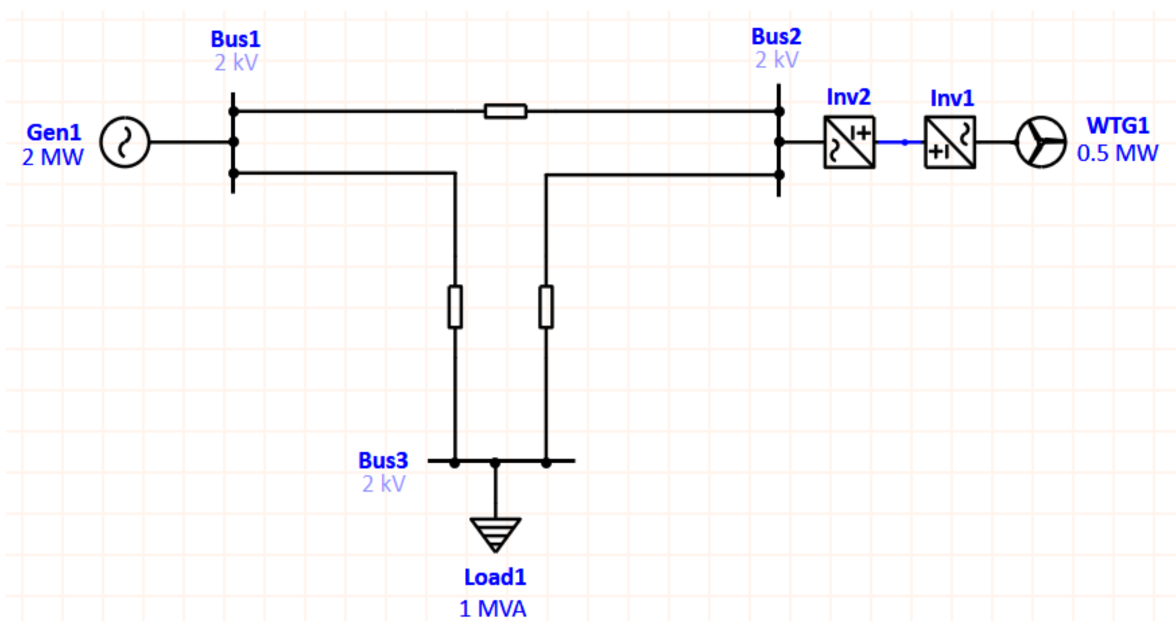

Fig.6.2. Three-bus system with one generator replaced by wind turbine

6.2.3 Results

Fig 6.3 shows the result obtained from reliability analysis of the system with conventional generators. From the figure, it can be seen that the failure rate of the system obtained is 8.204 failures per year and the average outage duration is 427.3 hours. The output of reliability analysis of the second stage i.e., with one generator replaced by a wind turbine is shown in fig 6.4. In the figure, the failure rate and the average outage duration obtained is 9.172 failures per year and 429.3 hours respectively, which clearly indicated a deterioration of reliability since the frequency and duration of outages is increasing.

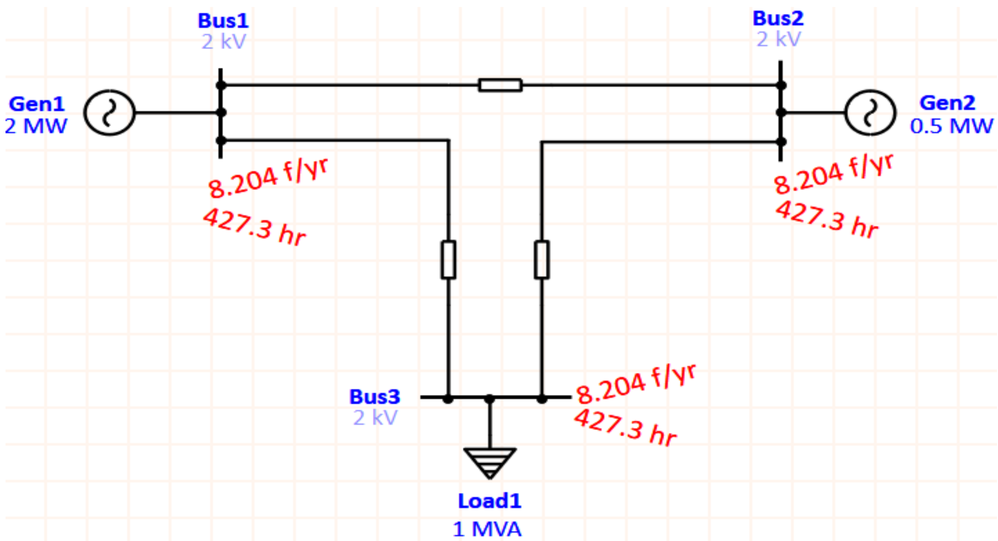

Fig.6.3. Failure rate of three-bus system with conventional generators

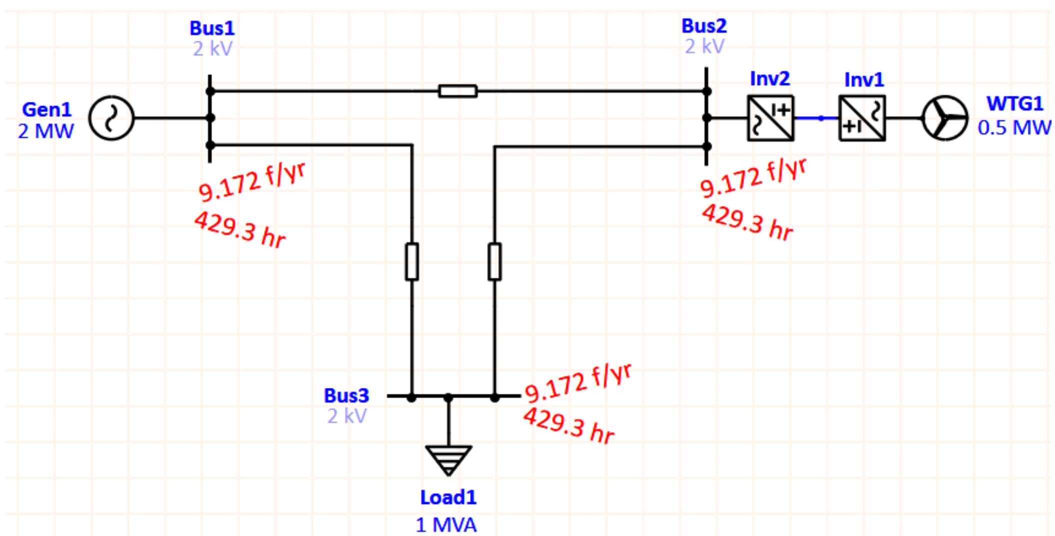

Fig.6.4. Failure rate of three-bus system with one generator replaced by wind turbine

Fig 6.5 shows the output of the third stage where we use the values obtained from GA. We can see that the failure rate and the outage duration has decreased to a value of 0.61717 failures per year and 308.6 hours respectively. So, it can be inferred that there is an observable increase in the reliability of the system by using the values that are obtained using genetic algorithm.

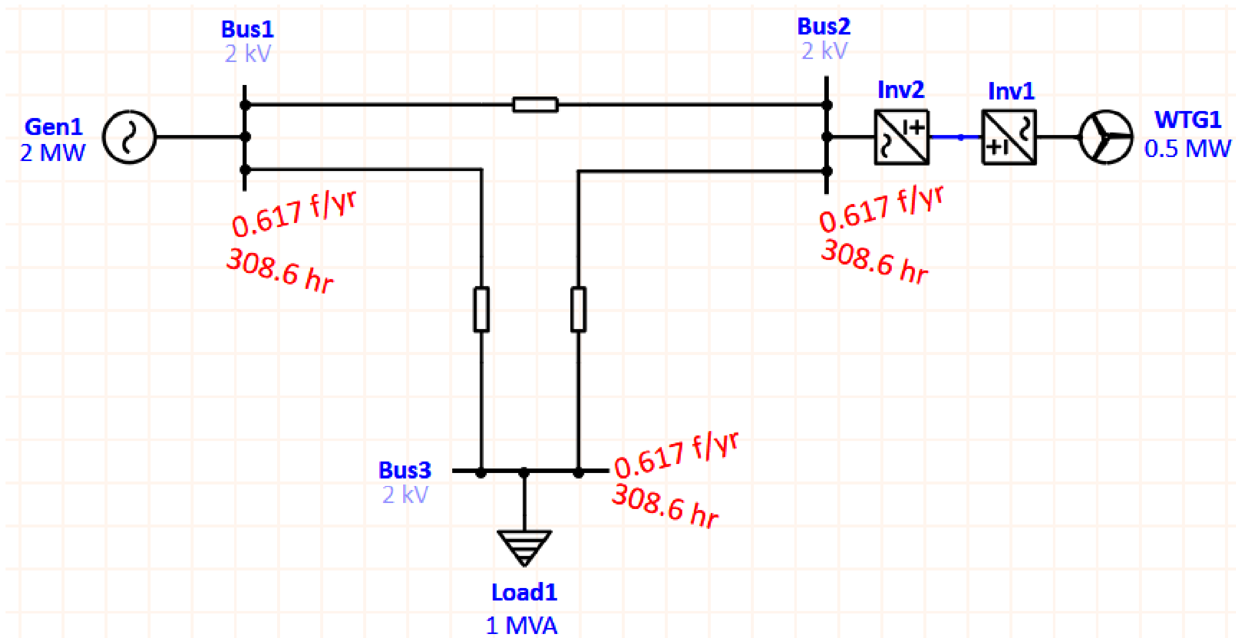

Fig.6.5. Failure rate of three-bus system with one generator replaced by wind turbine using values obtained from GA

The comparison of reliability in scenario 2 and 3 is shown in fig 6.6. In scenario 2, reliability analysis of system integrated with DG without using values from GA is done, and in scenario 3, reliability analysis is done using the values from GA. From the figure, it can be seen that the reliability of the system with DG is obtained as 0.6855 and the same system with input values obtained from GA gives a reliability of 0.97. So, the reliability value has increased by using the optimal values obtained from GA. Similarly, the comparison of reliability indices in the three scenarios is shown in fig 6.7 and fig 6.8. From the figures, it can be seen that the SAIFI and SAIDI of the system has increased with the addition of DG which indicates a deterioration of reliability and the value of SAIFI and SAIDI has decreased to a noticeable value in the third scenario which uses the values obtained from GA. From this, it can be concluded that the reliability of the system deteriorates with the addition of DG and it can be improved to a great extent by using the values obtained from GA.

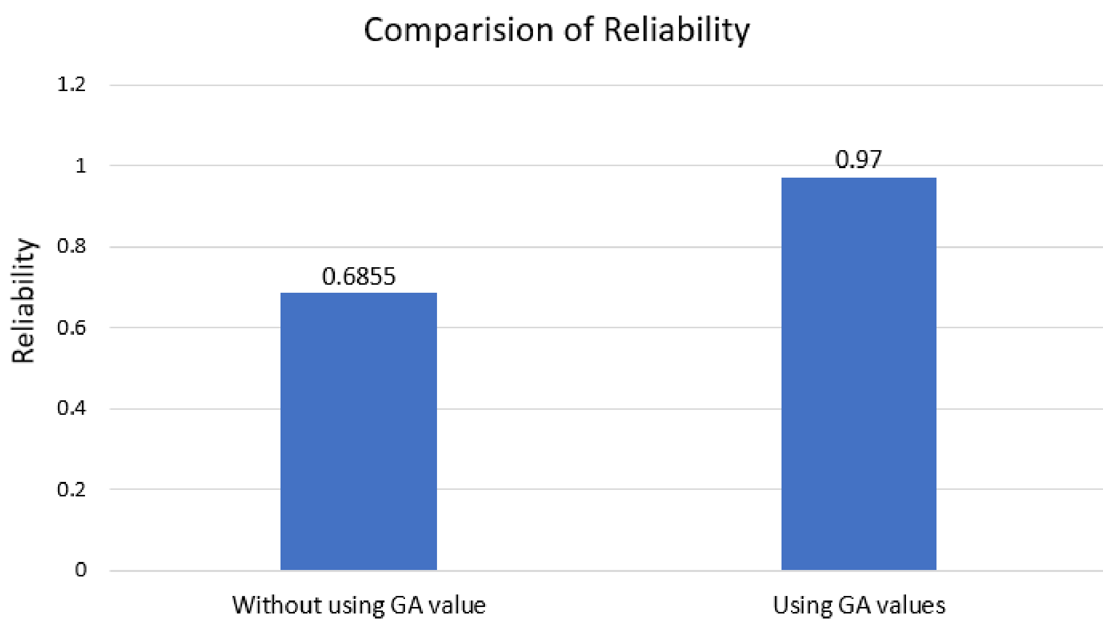

Fig.6.6. Comparison of reliability of 3-bus system without and using values obtained from GA

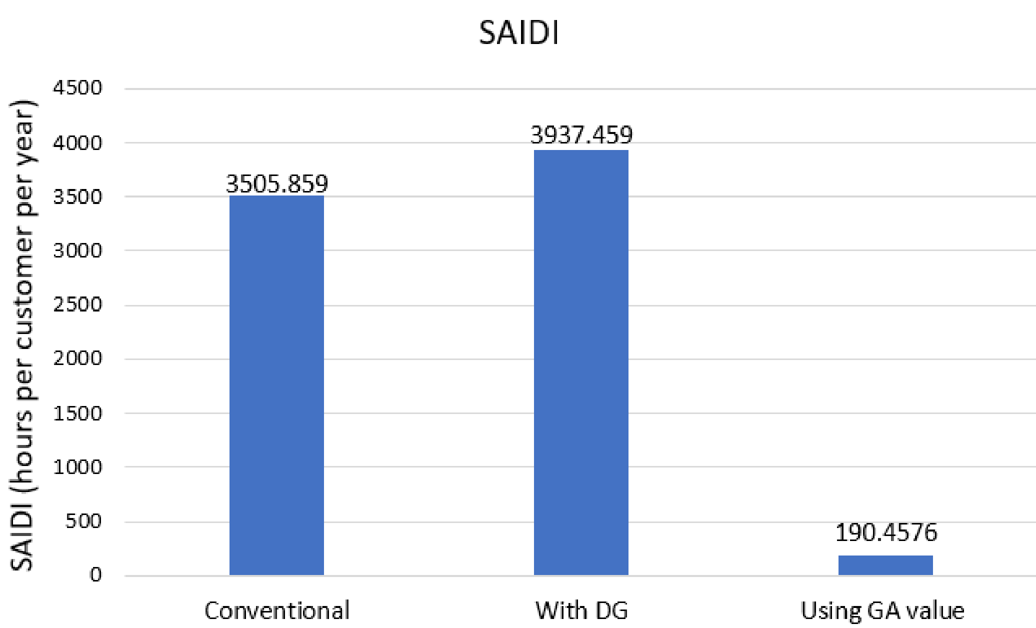

Fig.6.7. Comparison of SAIDI of 3-bus system

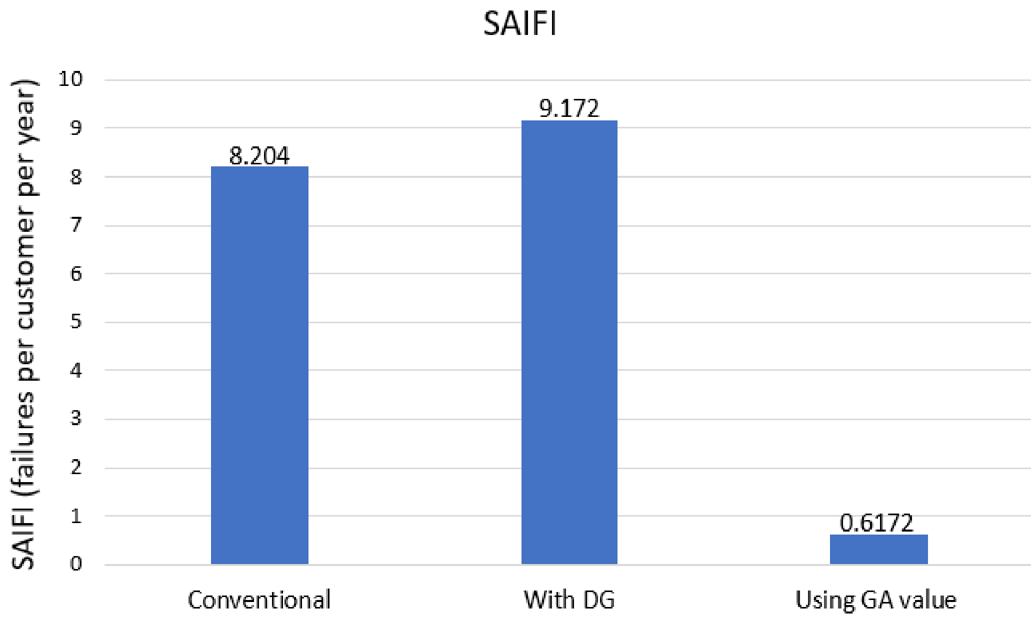

Fig.6.8. Comparison of SAIFI of 3-bus system

6.3 CASE STUDY-2

6.3.1 System Description

Case study 2 is done in Roy Billinton Test System as shown in fig 6.9. RBTS is a six-bus system. There are two generator buses and five load bus. The total generating capacity is 240 MW and the system peak load is 185 MW. The voltage rating of the system is 230 KV [25].

6.3.2 Methodology

The original system with both the generators conventional is considered for scenario 1 and the reliability analysis of the system is done and the corresponding indices for scenario 1 is obtained. In the next scenario, the 130 MW generator at bus 2 is replaced with a wind turbine of the same capacity as shown in fig 6.10 and the system's reliability is analysed. In the third scenario, the values obtained from GA is given as input to the system integrated with wind turbine and the reliability values and indices for scenario 3 is obtained.

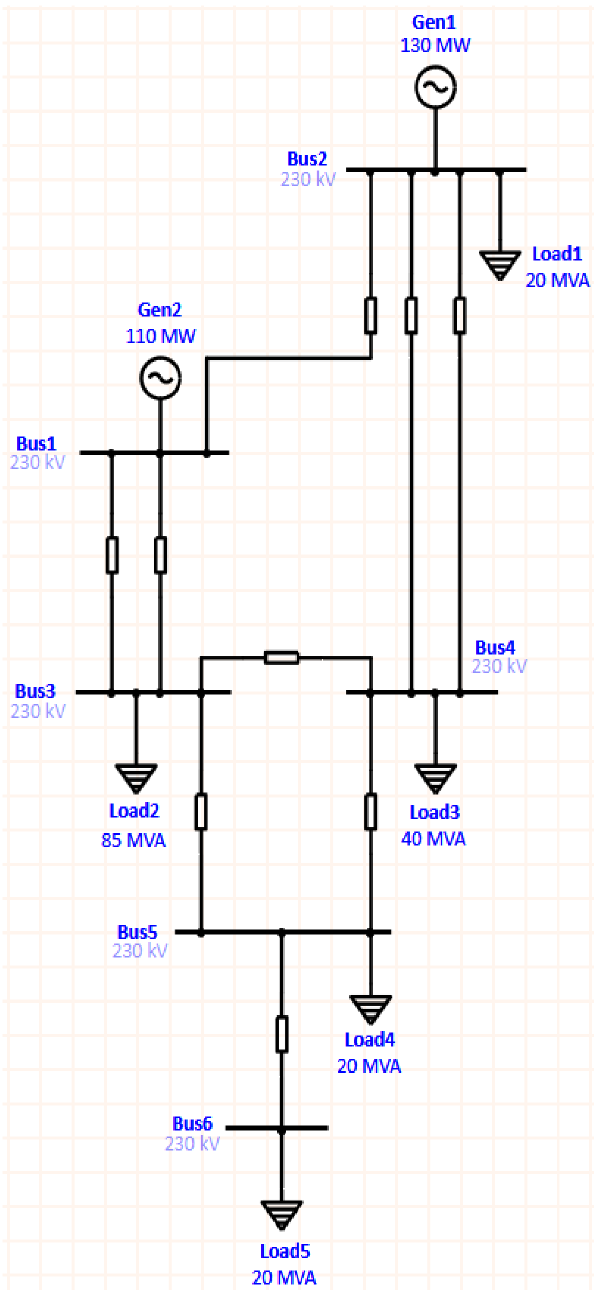

Fig.6.9. Roy Billinton Test System (RBTS)

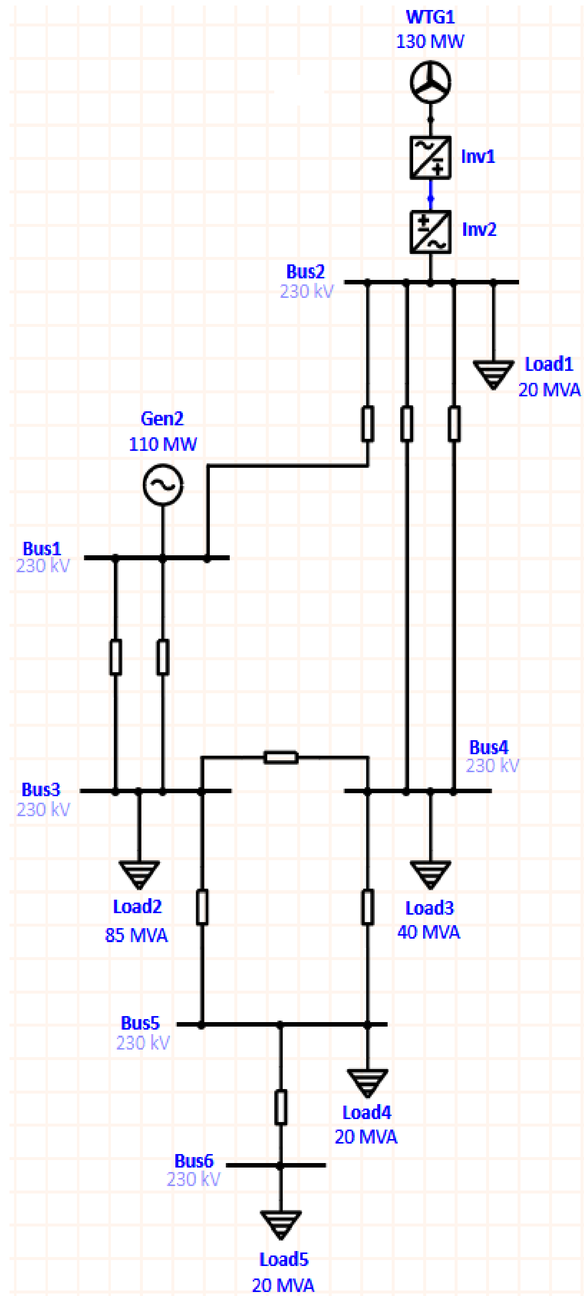

Fig.6.10. RBTS with one generator replaced by wind turbine

6.3.3 Results

Fig 6.11 shows the result obtained from reliability analysis of the system with conventional generators. From the figure, it can be seen that the failure rate of the system obtained is 17.554 failures per year and the average outage duration is 424.3 hours. The output of reliability analysis of the second stage i.e., with one generator replaced by a wind turbine is shown in fig 6.12. In the figure, the failure rate and the average outage duration obtained is 18.522 failures per year and 425 hours respectively, which clearly indicated a deterioration of reliability since the frequency and duration of outages is increasing. Fig 6.13 shows the output of the third stage where we use the values obtained from GA. We can see that the failure rate and the outage duration has decreased to a value of 1.412 failures per year and 268.1 hours respectively. So, it can be inferred that there is an observable increase in the reliability of the system by using the values that are obtained using genetic algorithm.

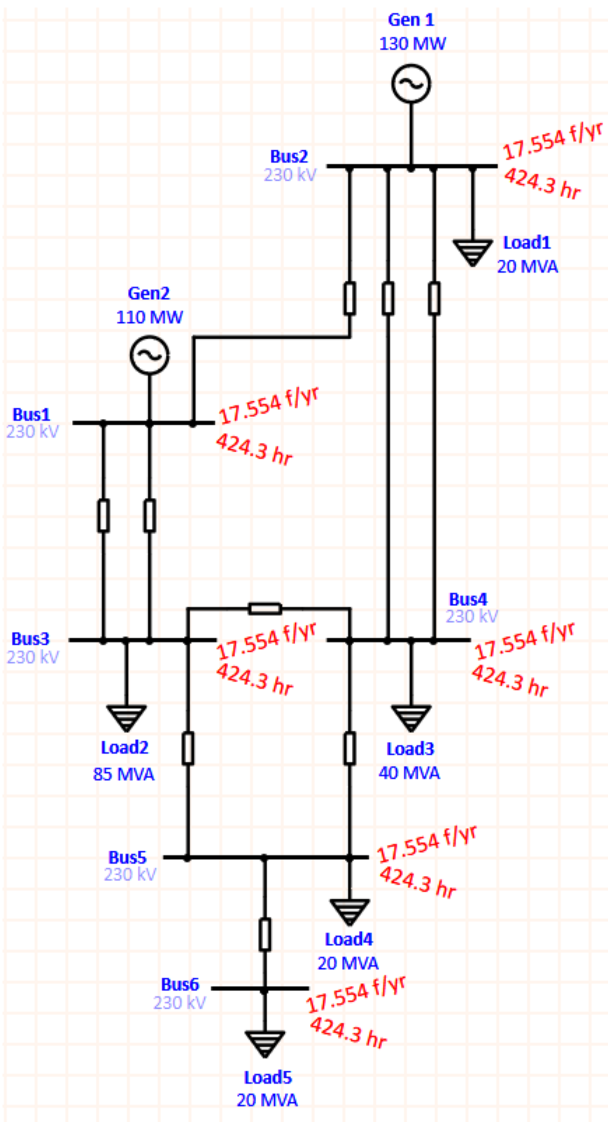

Fig.6.11. Failure rate of Roy Billinton Test System (RBTS)

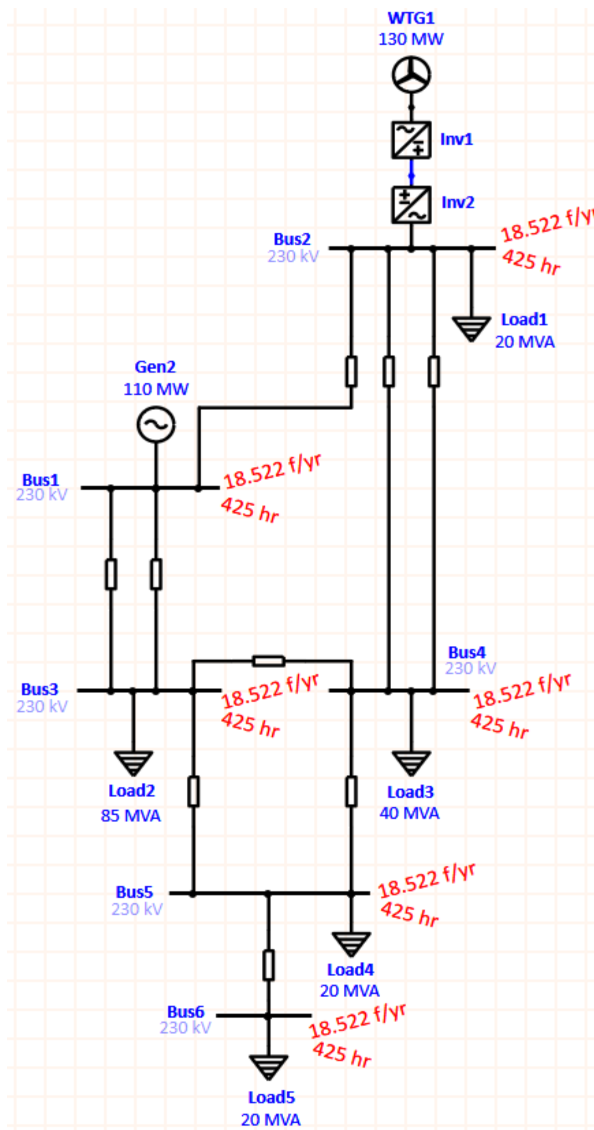

Fig.6.12. Failure rate of RBTS with one generator replaced by wind turbine

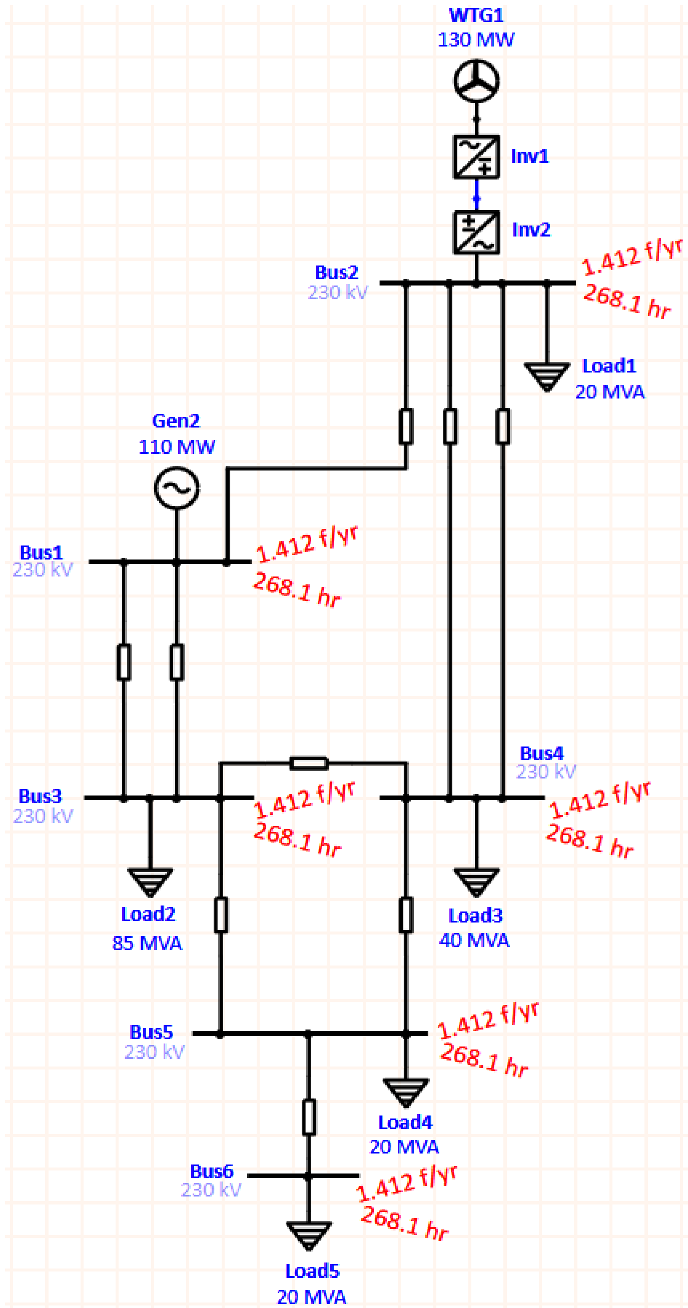

Fig.6.13. Failure rate of RBTS with one generator replaced by wind turbine using values obtained from GA

The comparison of reliability in scenario 2 and 3 is shown in fig 6.14. From the figure, it can be seen that the reliability of the system with DG (scenario 2) is obtained as 0.519 and the same system with values obtained from GA as its input (scenario 3) gives a reliability of 0.934. So, the reliability value has increased by using the optimal values obtained from GA. Similarly, the comparison of reliability indices in the three scenarios is shown in fig 6.15 and fig 6.16. From the figures, it can be seen that the SAIFI and SAIDI of the system in scenario 2 has increased from the initial value in scenario 1 with the addition of DG which indicates a deterioration in reliability and the value of SAIFI and SAIDI has decreased to a noticeable value in the third scenario in which the values obtained from GA is used. From this, it can be concluded that the reliability of the system deteriorates with the proliferation of DG and it has improved by using the optimal values obtained from GA.

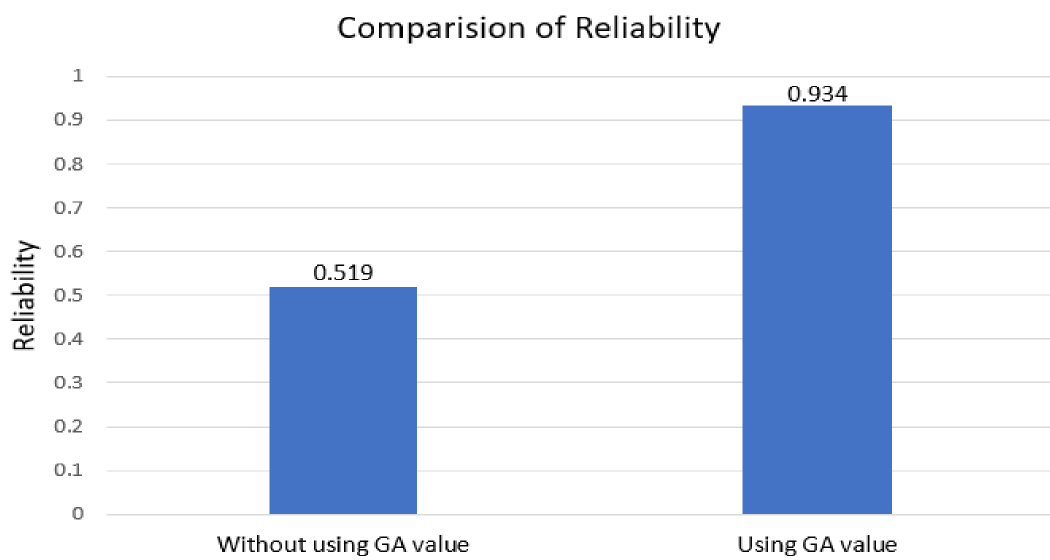

Fig.6.14. Comparison of reliability of RBTS without and using values obtained from GA

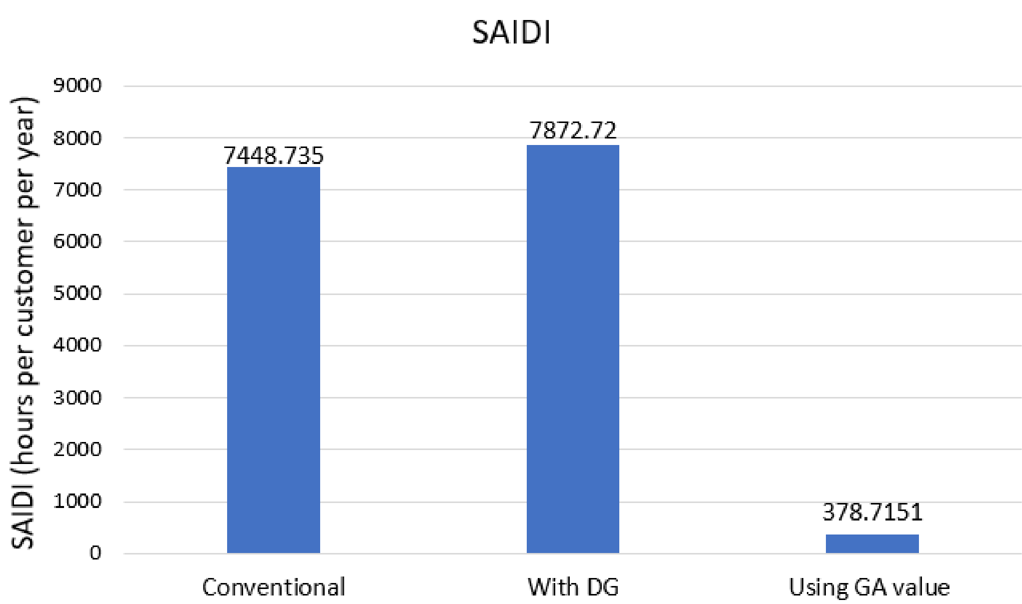

Fig.6.15. Comparison of SAIDI of RBTS

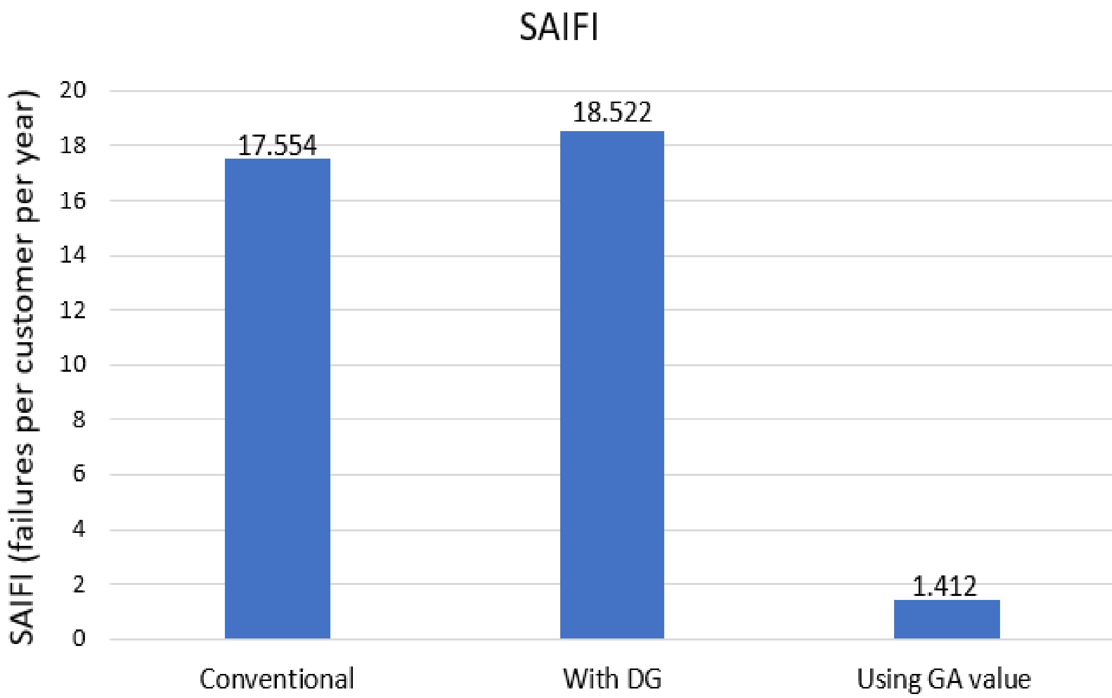

Fig.6.16. Comparison of SAIFI of RBTS

6.4 CASE STUDY-3

6.4.1 System Description

Case study 3 is done in IEEE RTS 24-bus network as shown in fig 6.17. The voltage rating of the system is 230/138KV. The upper buses are at a voltage level of 230 KV and the lower buses are at a potential of 138 KV. The system details are given in [26].

6.4.2 Methodology

For performing this case study, four scenarios are considered. In the first scenario, all the generators are conventional and the original RTS network is applied. In the second scenario, four of the conventional generators are replaced with DG (here WT) as shown in fig 6.18. This scenario shows the initial penetration of DG to the power system. The third scenario assumes that the DG technologies are sufficiently developed and hence three more conventional generators are replaced with WT as shown in fig 6.19. In the fourth scenario, the system in the third scenario itself is used, but the input values to the system is the optimal values that are obtained from GA. Reliability analysis of all the four scenarios is performed and the value of reliability and the reliability indices such as SAIFI and SAIDI are obtained and compared.

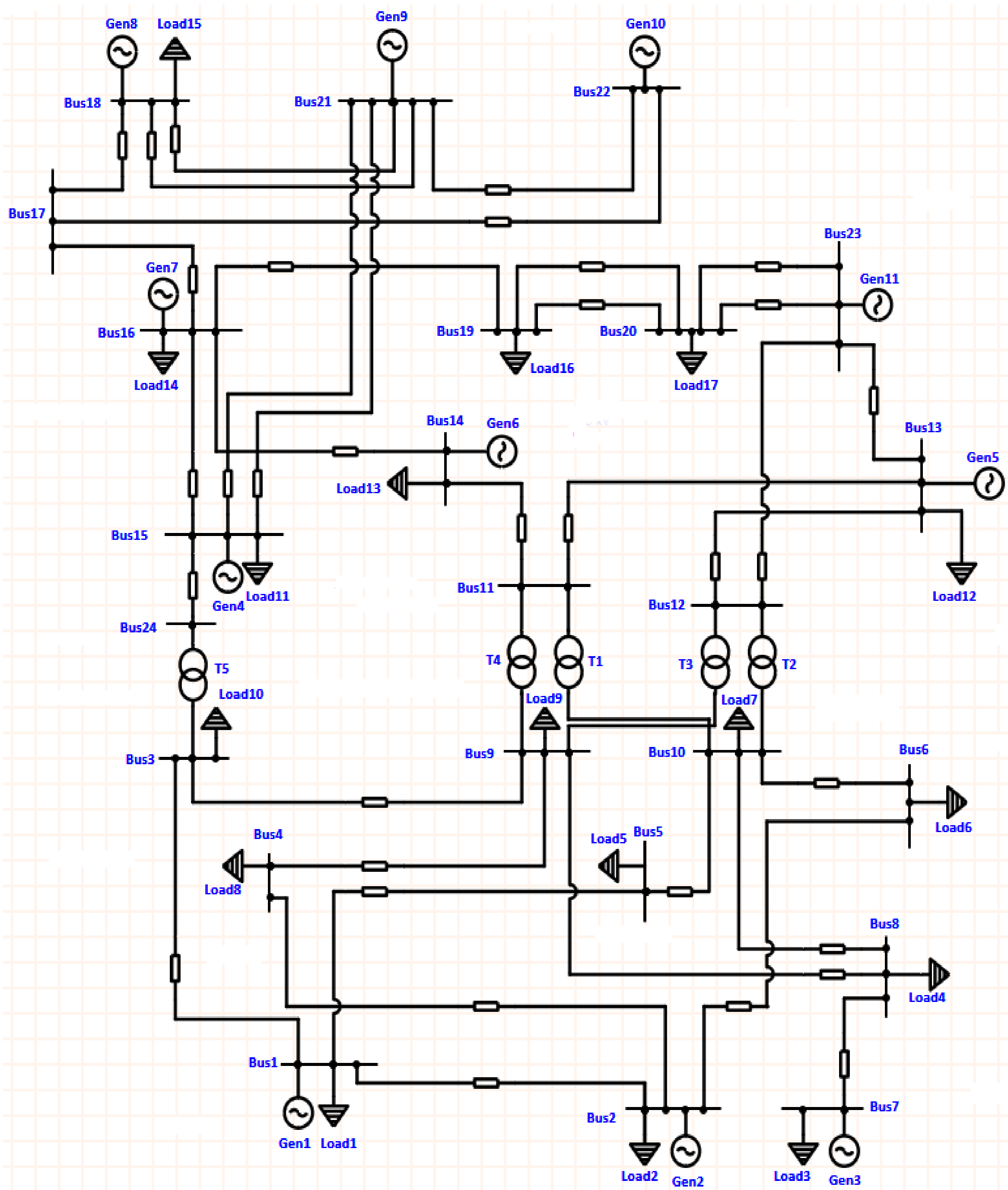

Fig.6.17. IEEE RTS 24-bus network (Scenario 1)

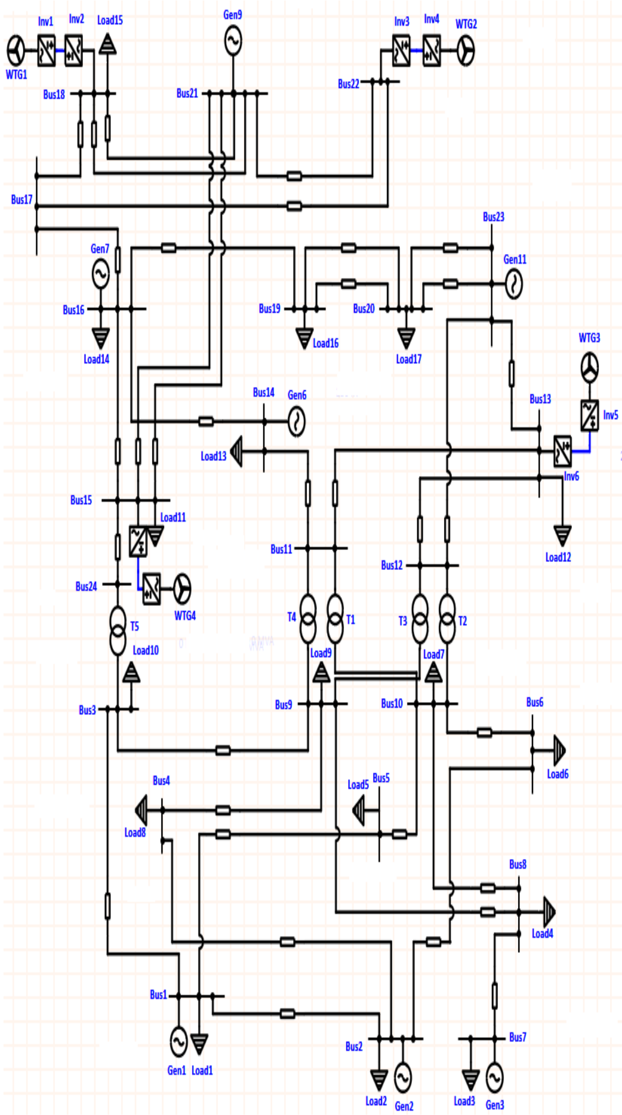

Fig.6.18. Scenario 2 in IEEE RTS 24-bus network

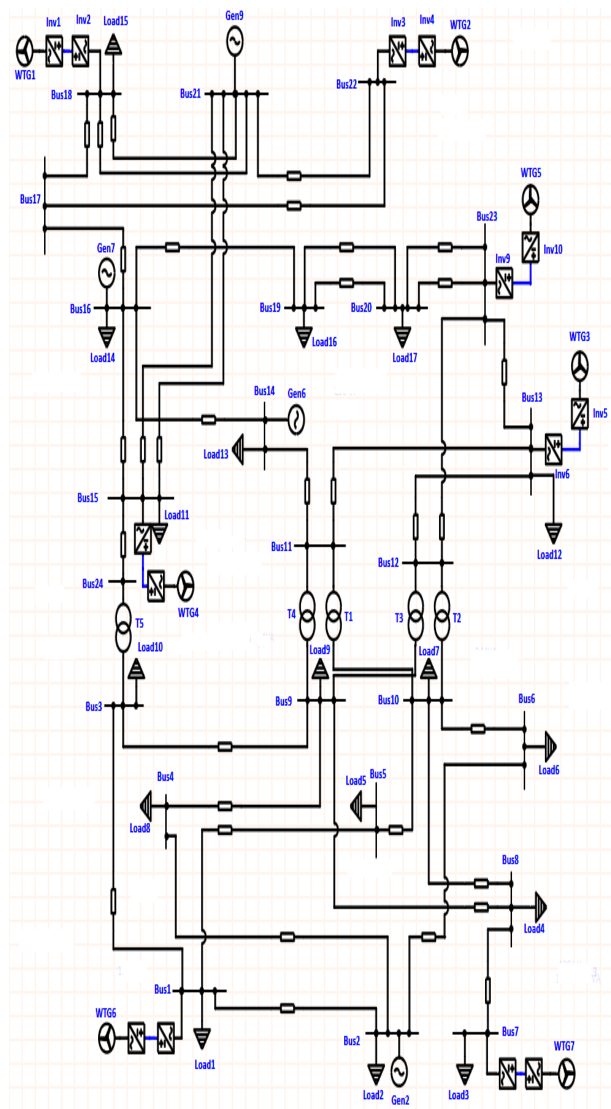

Fig.6.19. Scenario 3 in IEEE RTS 24-bus network

6.4.3 Results

Fig 6.20 shows the result obtained from reliability analysis of the system with conventional generators. From the figure, it can be noted that the failure rate of the system obtained is 66.199 failures per year and the average outage duration is 423.7 hours. The output of reliability analysis of the second scenario is shown in fig 6.21. In the figure, the failure rate and the average outage duration obtained is 68.071 failures per year and 424.6 hours respectively, which clearly indicated a deterioration of reliability since the frequency and duration of outages is increasing.

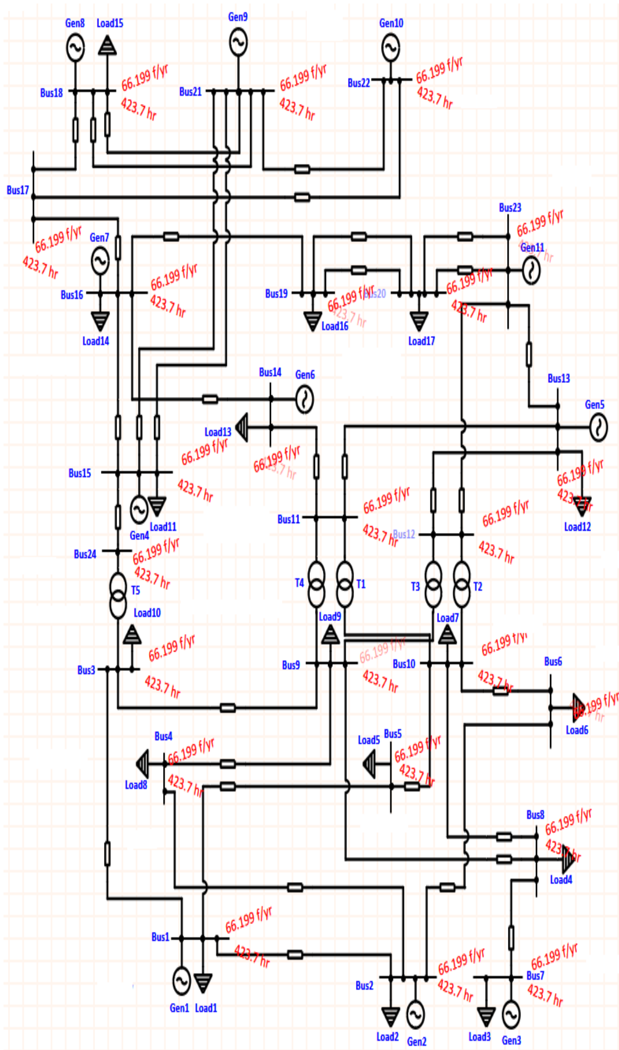

Fig.6.20. Output for Scenario 1

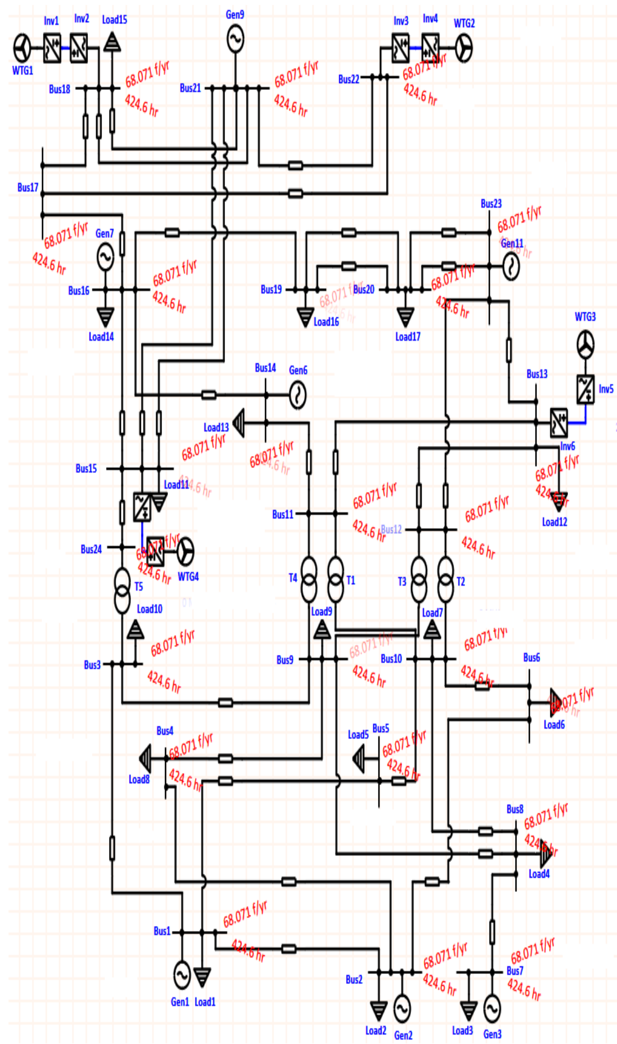

Fig.6.21. Output for Scenario 2

Fig 6.22 shows the output of the third scenario where the DG is assumed to be sufficiently developed. The failure rate and outage duration obtained in this scenario is 70.975 failures per year and 425.5 hours respectively. So, the reliability has decreased with the increasing proliferation of DG to the system. Fig 6.23 shows the output of the fourth scenario where the values obtained from GA is used. We can see that the failure rate and the outage duration has decreased to a value of 5.515 failures per year and 254.8 hours respectively. So, it can be inferred that there is an observable increase in the reliability of the system by using the values that are obtained using genetic algorithm.

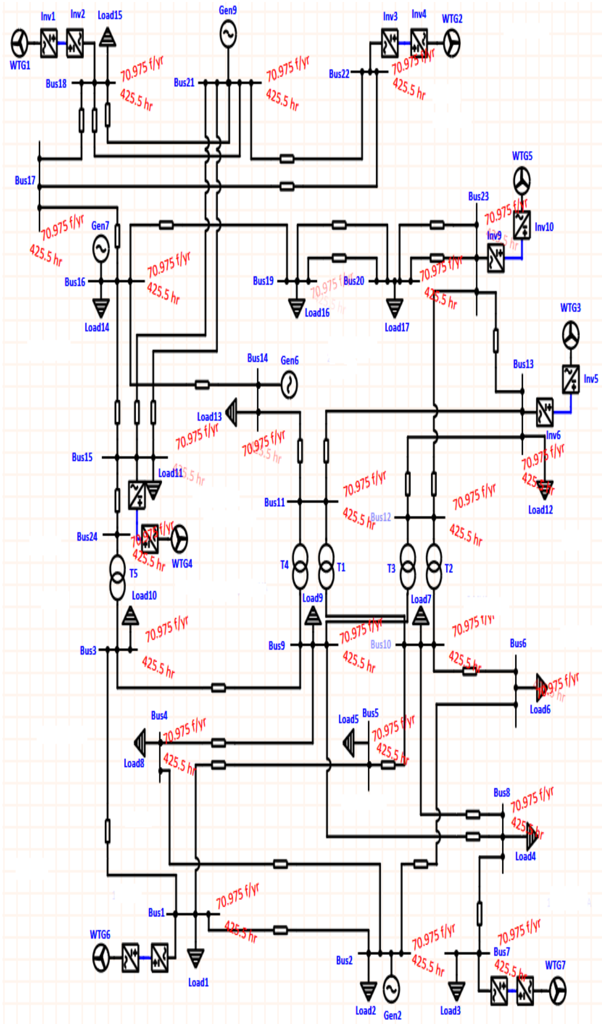

Fig.6.22. Output for Scenario 3

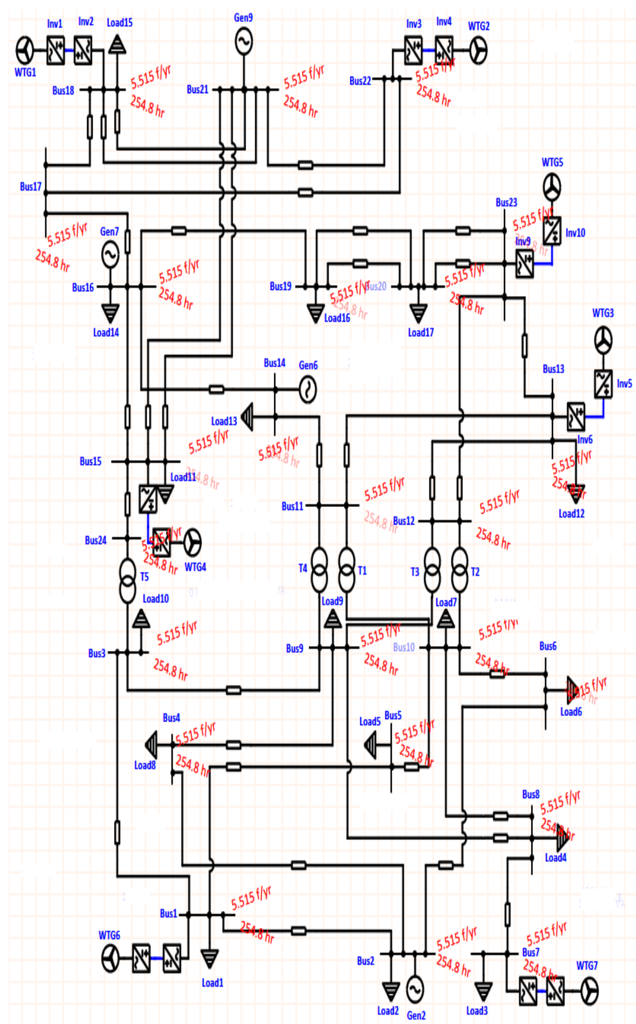

Fig.6.23. Output for Scenario 4

Fig 6.24 shows the comparison of reliability of the 24-bus system without using and using the values from GA. From the figure, it can be seen that the reliability of the system with DG is 0.219 and it has increased to 0.783 by using the optimal values that we have obtained from GA. Fig 6.25 and fig 6.26 shows the comparison of SAIDI and SAIFI of the system for all the four scenarios. The values of SAIFI and SAIDI is increasing with the addition of DG and in the last scenario, using the values obtained from GA, the indices are going down to a remarkably lower value which indicates improvement in reliability.

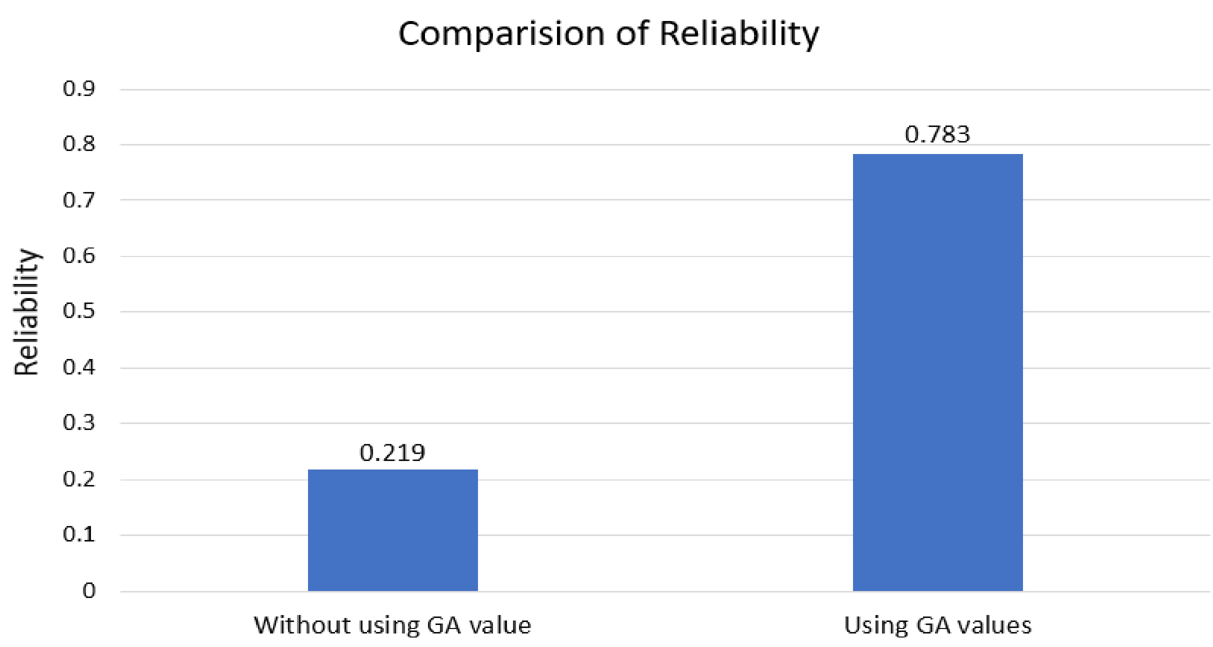

Fig.6.24. Comparison of reliability of IEEE RTS 24-bus network without and using values obtained from GA

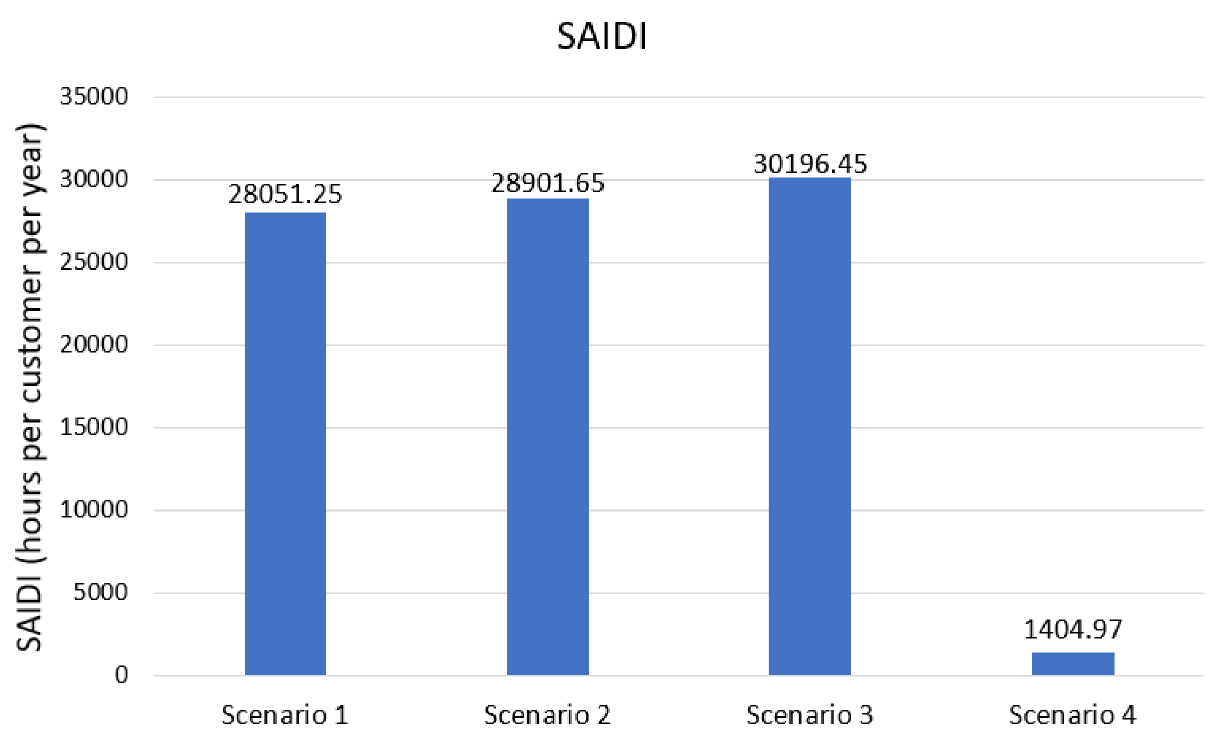

Fig.6.25. Comparison of SAIDI of IEEE RTS 24-bus network

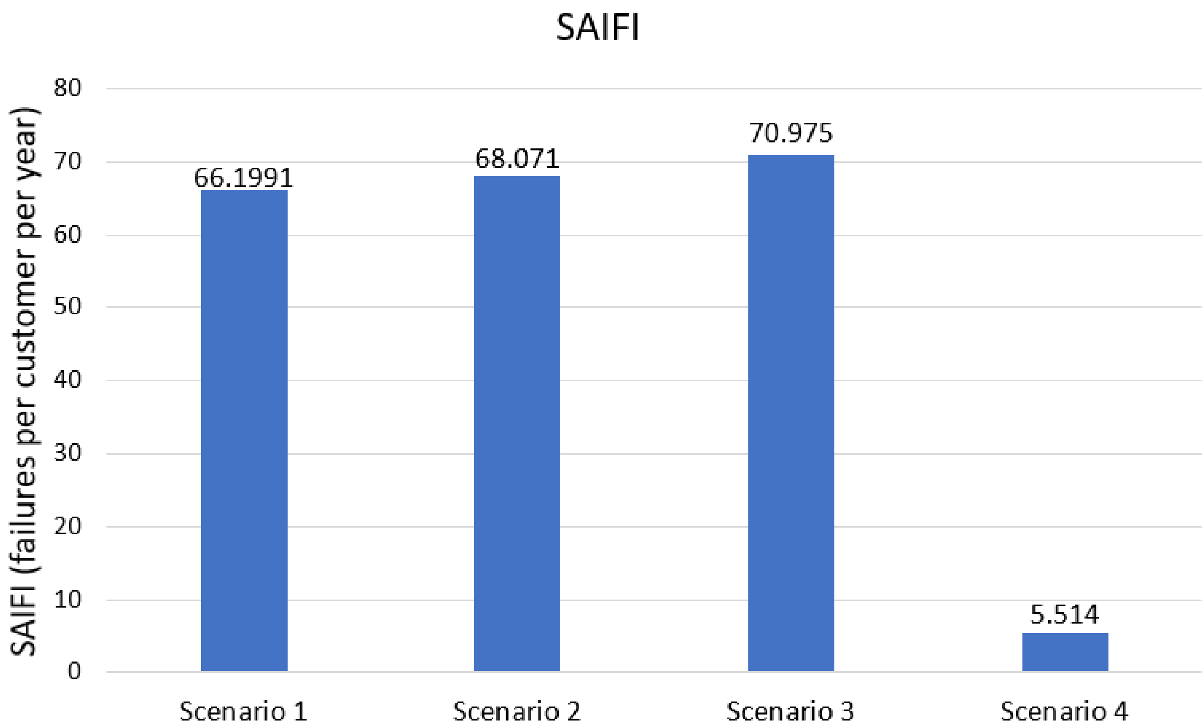

Fig.6.26. Comparison of SAIFI of IEEE RTS 24-bus network

6.5 INFERENCE

From the above three case studies done in a three-bus system, Roy Billinton Test System and IEEE RTS 24 bus system, it can be inferred that the reliability of the systems shows a deterioration with the addition of distributed generation, which is an undesirable performance. From the third case study, it can be seen that, as the proliferation of DG increases, the reliability is going on decreasing. But, in the present situation where the usage of the renewable sources is being promoted in a large extend, the problem of deterioration in reliability becomes barrier. But, using the optimal input values obtained from genetic algorithm, there is a noticeable increase in reliability in all the three cases. So, from this, it can be inferred that, using genetic algorithm, the optimal value of the input parameters which will maximize the reliability of the system can be obtained, so that we can continue using the DG without compromising for the reliability of the system and hence an uninterrupted and highly reliable system will be ensured to the consumers.

CHAPTER 7

CONCLUSION

The reliability of power system is of paramount importance these days since the restructuring of power system is occurring with DG integration. The reliability of the system gets affected with the proliferation of distributed generation. The reliability analysis of power system network integrated with power converters is discussed in this thesis. The reliability model of the converters is done based on the semiconductor devices it is composed of. The method of reliability evaluation using failure rate calculation is discussed. The overall system reliability is computed from the calculated failure rate. The optimization of the parameters that affect reliability is also done using genetic algorithm and the optimal values for attaining maximum reliability is computed. Reliability prediction using SVR is also done and the reliability value of the system corresponding to the input values can be accurately predicted, which simplifies the procedure of reliability analysis of complex systems.

The validation of the results is done by performing three case studies. Case study 1 is done in a three-bus system, case study 2 in RBTS and case study 3 is done in IEEE RTS 24-bus network. In all the three case studies, the reliability value is seen to be deteriorating with the addition of distributed generation networks and the reliability is improved to a noticeable extend by using the input values obtained from genetic algorithm. So, the results from GA are successfully validated in all the three test systems.

The results from the case studies infer that the improved proliferation of distributed generation and the power electronic converters associated with them causes the reliability of the system to deteriorate. But, in the present scenario where the usage of renewables is being promoted in a large extend, the problem of decreasing reliability becomes a barrier to the development and use of DG. If the input values of the DG can be designed as the values obtained from the procedure of genetic algorithm, this problem can be avoided to a far extend. So, by performing an initial optimization analysis by GA can give the optimal values and following that can ensure an uninterrupted and a highly reliable system.

The future research scope in this study can include the reliability analysis by altering the DG sources' locations. The optimal location of the sources to achieve maximum reliability can be found. Also, a sensitivity analysis for the components that compute the system can be done and the components can be ranked according to its sensitivity so that the operators can easily identify the most influential component and can arrange for the maintenance of the same so that we can obtain a highly reliable system.

PUBLICATION

[1] **Naufal N**, **Anupama V N**, **Sheeba R**, “System-Level Reliability Analysis of An Integrated Power System with Increased Proliferation of Power Converters: A Review”, Accepted for publication in the *Third International Conference on Intelligent Computing, Instrumentation and Control Technologies, ICICICT 2022*

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APPENDIX - A

A.1 PROGRAM FOR GA

```
clc
clear all
close all

populatoinSize=20;
popSize=populatoinSize;

bounds=[0 50;0 10];
evalFN='paraiden';
evalOps=[];
options=[1e-4 1];
global gen,popSize

initpop=[11   1.506   0.6153
         12   2.008   0.5881
         14   2.509   0.5478
         15   3.011   0.5262
         16   3.514   0.5062
         18   4.016   0.4761
         20   4.518   0.4493
         21   5.019   0.4346
         23   5.522   0.4122
         25   6.024   0.3920
         28   6.526   0.3668
         30   7.028   0.3507]
```

```
startPop=initpop;
opts=[1e-4 1 0];
termFN='maxGenTerm';
termOps=400;
selectFN='normGeomSelect';
selectOps=0.04;
xOverFNs='arithXover';
xOverOps=7;
mutFNs='multiNonUnifMutation';
mutOps=[6 1000 7];
tic
[x,endPop,bPop,traceinfo] = ga(bounds,evalFN,evalOps,startPop,opts,...
termFN,termOps,selectFN,selectOps,xOverFNs,xOverOps,mutFNs,mutOps)
total=toc
```

Function-

```
function[x,val]=paraiden(x,options)
th=x(1,1);
tc=x(1,2);

lambda= th + tc;
u= 20;
p= lambda/(lambda + u);
F= 1 - p;
val=(F);
```

Generations-

```
function [done] = maxGenTerm(ops,bPop,endPop)
currentGen = ops(1);
```

```
maxGen     = ops(2);
done       = currentGen >= maxGen;
```

Selection-

```
function[newPop] = normGeomSelect(oldPop,options)
q=options(2);
e = size(oldPop,2);
n = size(oldPop,1);
newPop = zeros(n,e);
fit = zeros(n,1);
x=zeros(n,2);
x(:,1) =[n:-1:1]';
[y x(:,2)] = sort(oldPop(:,e));
r = q/(1-(1-q)^n);
fit(x(:,2))=r*(1-q).^(x(:,1)-1);
fit = cumsum(fit);
rNums=sort(rand(n,1));
fitIn=1; newIn=1;
while newIn<=n
  if(rNums(newIn)<fit(fitIn))
    newPop(newIn,:) = oldPop(fitIn,:);
    newIn = newIn+1;
  else
    fitIn = fitIn + 1;
  end
end
```

Crossover-

```
function [c1,c2] = arithXover(p1,p2,bounds,Ops)
```

```
a = rand;
c1 = p1*a     + p2*(1-a);
c2 = p1*(1-a) + p2*a;
```

Mutation-

```
function [parent] = multiNonUnifMutation(parent,bounds,Ops)

cg=Ops(1);
mg=Ops(3);
b=Ops(4);
df = bounds(:,2) - bounds(:,1);
numVar = size(parent,2)-1;
md = round(rand(1,numVar));
for i = 1:numVar
  if md(i)
    parent(i)=parent(i)+delta(cg,mg,bounds(i,2)-parent(i),b);
  else
    parent(i)=parent(i)-delta(cg,mg,parent(i)-bounds(i,1),b);
  end
end
```

A.2 PROGRAM FOR SVR

Import data-

```
import pandas as pd

relblty=pd.read_csv("/content/reliability.csv")

x=relblty[['Thermalstress', 'Tempcycling', 'Failurerate']]

y=relblty['Reliability']
```

Split Dataset-

```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=42)
```

Algorithm-

```
from sklearn.svm import SVR

regressor= SVR(kernel = 'rbf')
```

Fit data into model-

```
regressor= regressor.fit(x_train,y_train)
```

Prediction-

```
Result=regressor.predict([[2.2,1.994,4.194]])

print("Result  is ", Result))
```

APPENDIX B

B.1 REPORT FOR RELIABILITY ANALYSIS OF THREE-BUS SYSTEM

B.1.1 Scenario 1

Project:		ETAP	Page:	1
Location:		19.0.1C	Date:	15-06-2022
Contract:			SN:	
Engineer:		Study Case: RA	Revision:	Base
Filename:	3 Bus System		Config.:	Normal

SUMMARY

System Indexes

ACCI	8204.00 kVA / customer
AENS	3505.8590 MW hr / customer.yr
ALII	8.20 pu (kVA)
ASAI	0.5998 pu
ASUI	0.40021 pu
CAIDI	427.335 hr / customer interruption
CTAIDI	3505.859 hr / customer.yr
ECOST	0.00 $ / yr
EENS	3505.859 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	3505.8590 hr / customer.yr
SAIFI	8.2040 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

B.1.2 Scenario 2

SUMMARY

System Indexes

ACCI	9172.00 kVA / customer
AENS	3937.4590 MW hr / customer.yr
ALII	9.17 pu (kVA)
ASAI	0.5505 pu
ASUI	0.44948 pu
CAIDI	429.291 hr / customer interruption
CTAIDI	3937.459 hr / customer.yr
ECOST	0.00 $ / yr
EENS	3937.459 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	3937.4590 hr / customer.yr
SAIFI	9.1720 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

B.1.3 Scenario 3

SUMMARY

System Indexes

ACCI	617.20 kVA / customer
AENS	190.4576 MW hr / customer.yr
ALII	0.62 pu (kVA)
ASAI	0.9783 pu
ASUI	0.02174 pu
CAIDI	308.583 hr / customer interruption
CTAIDI	190.458 hr / customer.yr
ECOST	0.00 $ / yr
EENS	190.458 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	190.4576 hr / customer.yr
SAIFI	0.6172 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

B.2 REPORT FOR RELIABILITY ANALYSIS OF RBTS

B.2.1 Scenario 1

Project:		**ETAP**	Page:	1
Location:		19.0.1C	Date:	15-06-2022
Contract:			SN:	
Engineer:		Study Case: RA	Revision:	Base
Filename:	Test System		Config.:	Normal

SUMMARY

System Indexes

ACCI	649497.90 kVA / customer
AENS	275603.3000 MW hr / customer.yr
ALII	17.55 pu (kVA)
ASAI	0.1497 pu
ASUI	0.85031 pu
CAIDI	424.333 hr / customer interruption
CTAIDI	7448.735 hr / customer.yr
ECOST	0.00 $ / yr
EENS	1378016.000 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	7448.7350 hr / customer.yr
SAIFI	17.5540 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

B.2.2 Scenario 2

Project:		ETAP	Page:	1
Location:		19.0.1C	Date:	15-06-2022
Contract:			SN:	
Engineer:		Study Case: RA	Revision:	Base
Filename:	Test System		Config.:	Normal

SUMMARY

System Indexes

ACCI	685313.90 kVA / customer
AENS	291290.6000 MW hr / customer.yr
ALII	18.52 pu (kVA)
ASAI	0.1013 pu
ASUI	0.89871 pu
CAIDI	425.047 hr / customer interruption
CTAIDI	7872.720 hr / customer.yr
ECOST	0.00 $ / yr
EENS	1456453.000 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	7872.7200 hr / customer.yr
SAIFI	18.5220 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

B.2.3 Scenario 3

Project:		**ETAP**	Page:	1
Location:		19.0.1C	Date:	15-06-2022
Contract:			SN:	
Engineer:		Study Case: RA	Revision:	Base
Filename:	Test System		Config.:	Normal

SUMMARY

System Indexes

ACCI	52258.78 kVA / customer
AENS	14012.4600 MW hr / customer.yr
ALII	1.41 pu (kVA)
ASAI	0.9568 pu
ASUI	0.04323 pu
CAIDI	268.136 hr / customer interruption
CTAIDI	378.715 hr / customer.yr
ECOST	0.00 $ / yr
EENS	70062.310 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	378.7151 hr / customer.yr
SAIFI	1.4124 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

B.3 REPORT FOR RELIABILITY ANALYSIS OF IEEE RTS 24-BUS SYSTEM

B.3.1 Scenario 1

SUMMARY

System Indexes

ACCI	11325580.00 kVA / customer
AENS	4702738.0000 MW hr / customer.yr
ALII	66.20 pu (kVA)
ASAI	-2.2022 pu
ASUI	3.20220 pu
CAIDI	423.741 hr / customer interruption
CTAIDI	28051.250 hr / customer.yr
ECOST	0.00 $ / yr
EENS	79946540.000 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	28051.2500 hr / customer.yr
SAIFI	66.1991 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

B.3.2 Scenario 2

Project:		**ETAP**	Page:	1
Location:		19.0.1C	Date:	15-06-2022
Contract:			SN:	
Engineer:		Study Case: RA	Revision:	Base
Filename:	24-bus System		Config.:	Normal

SUMMARY

System Indexes

ACCI	11645840.00 kVA / customer
AENS	4845306.0000 MW hr / customer.yr
ALII	68.07 pu (kVA)
ASAI	-2.2993 pu
ASUI	3.29928 pu
CAIDI	424.581 hr / customer interruption
CTAIDI	28901.650 hr / customer.yr
ECOST	0.00 $ / yr
EENS	82370200.000 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	28901.6500 hr / customer.yr
SAIFI	68.0710 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

B.3.3 Scenario 3

Project:		ETAP	Page:	1
Location:		19.0.1C	Date:	15-06-2022
Contract:			SN:	
Engineer:		Study Case: RA	Revision:	Base
Filename:	24-bus System		Config.:	Normal

SUMMARY

System Indexes

ACCI	12142660.00 kVA / customer
AENS	5062377.0000 MW hr / customer.yr
ALII	70.98 pu (kVA)
ASAI	-2.4471 pu
ASUI	3.44708 pu
CAIDI	425.452 hr / customer interruption
CTAIDI	30196.450 hr / customer.yr
ECOST	0.00 $ / yr
EENS	86060410.000 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	30196.4500 hr / customer.yr
SAIFI	70.9750 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

B.3.4 Scenario 4

SUMMARY

System Indexes

ACCI	943458.50 kVA / customer
AENS	235541.5000 MW hr / customer.yr
ALII	5.51 pu (kVA)
ASAI	0.8396 pu
ASUI	0.16039 pu
CAIDI	254.774 hr / customer interruption
CTAIDI	1404.977 hr / customer.yr
ECOST	0.00 $ / yr
EENS	4004206.000 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	1404.9770 hr / customer.yr
SAIFI	5.5146 f / customer.yr

ACCI	System Average Customer Curtailment Index
AENS	Average Energy Not Supplied
ALII	System Average Connected kVA Interrupted per kVA of Connected Load Served
ASAI	Average service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
CTAIDI	System Customer Total Average Interruption Duration Index
ECOST	Expected Interruption Cost
EENS	Expected Energy Not Supplied
IEAR	Interruption Energy Assessment Rate
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index