International Journal of Engineering Science Invention (IJESI)
ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726
www.ijesi.org ||Volume 7 Issue 4 Ver. V|| April 2018 || PP 55-60

Reliability Prediction of Composite Power System Using Bayseian Regularization based ANN model

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Abstract : *Power Systems Are Growing With Ever Increasing Demand From Consumers. Network Expansion Is Inevitable To Cope Up With The Exponential Load Growth. Power System Engineer Must Ensure That The Expanded Grid Is Not Breaching The Reliability Limits. Reliability Prediction Of Bulk Power System Remained A Challenging Task For System Planner. Neural Networks Are Good At Handling The Nonlinear Power System Problems. In This Paper Bayseian Regularization Algorithm Based Neural Network Model Is Developed To Predict The Reliability Of The Bulk Power System. Roy Billinton Test System (Rbts) Is Used To Implement The Proposed Methodology. For Judging The Performance Of The Proposed Model Mean Squared Error, Regression Plot And Error Histograms Were Used.*

***Keywords** -Bayseian Regularization, Composite Power System, Neural Network, Reliability*

Date of Submission: 10-04-2018 Date of acceptance: 26-04-2018

I. INTRODUCTION

Bulk electrical power systems cater the needs of exponentially increasing demand for electricity. As global warming becoming a serious concern, worldwide utilities have been endeavoring to integrate environment friendly renewable energy sources with reasonable degree of reliability. Reliability of large electrical system is the ability to meet the aggregate demand with existing generating resources without curtailing any system load [1]. Forecasting the system reliability with large scale integration of distributed generating sources was a rigorous task for power system planner. The uncertainty of power delivered by certain resources like photovoltaic, wind plants cause chaos for accurate prediction of reliability. Certain efforts were reported in the literature to tackle the problem.

A novel method for evaluating reliability considering the cost factor was explored in [2]. The uncertainties of load and accurate forecasting of load was also taken into account. Particle swarm optimization algorithm was exploited for forecasting the reliability of distribution system. Support vector machine technique was used to increase the accuracy of forecast and thereby reducing the forecast error [3]. Forecast error was serious issue while integrating renewables to the modern grid. The challenges were more prominent with presence of wind plants. A production simulation was attempted for reducing the forecast error for renewable sources [4]. Hybrid approaches were promising technologies in the field of neural networks. Back propagation based genetic algorithm was used to accurately predict the wind power output [5]. Forecast error reduction was attempted using a neural network for application of short time periods [6]. Wind power forecast was significantly affected by geographical zones of power system. An adoptable artificial neural network model by considering historical data was created by authors [7]. Power system planner must contemplate the inherent intermittency in solar power output. The impact of forecast error on system planning was observed by authors in [8]. Granular computing technology was adopted by authors in [9], to circumvent the forecast error while integrating the wind plants to the existing grid. Photovoltaic cells cause intermitting power injections to the grid. Authors in [10], developed a probabilistic ensemble framework for accurately forecasting solar output power. Transmission utilities were striving to push the line limits due to limited right-of-way. In [11], authors handle this issue by exercising a probabilistic methodology to place wind plants optimally to relieve the congestion. Accurate prediction of wind power using a probabilistic nonparametric method was developed by authors in [12]. State transition based neural network was deployed for hourly prediction of wind active and reactive power injection to grid was reported [13]. Effect of several factors viz. type of algorithm used for training , data used, number of hidden layers in network and size of hidden layers for reducing the forecast error was effectively examined by deploying various algorithms [14]. Short term photovoltaic prediction problem was addressed using a novel regression technique based on Gaussian process [15].

Former research concentrated on forecasting the generation output of renewable units like wind power plants and photovoltaic sources. Reliability prediction and assessing the forecast was not addressed earlier for composite electrical power systems. This paper, addresses the problem by developing a neural network with an effective training algorithm.

II. Reliability Assessment Methodology

Electrical power systems across the world operate as distinctive zones. Each zone consist dedicated infrastructure for meeting the objective they were intended for. Zone I contains generating resources for meeting the aggregate load of the system. Zone II integrates transmission infrastructure to the existing network. Such system with both generation and transmission components together was popularly designated as composite electrical power system. Zone III includes distribution network along with generation and transmission network. Reliability evaluation of zone III is extremely confronting task to attempt, hence most researchers use the composite system reliability study as the input for distribution system analysis [1].

There are two widely used methodologies for composite system reliability evaluation. Analytical procedures and Monte Carlo simulation techniques are deployed for computing the adequacy of the system. Both the approaches have benefits and drawbacks. Analytical methods utilize mathematical modeling of the existing system. Monte Carlo methods consider the problem as a sequence of trials. For developing the model of the systems, components are to be modeled. Both generators and transmission lines are designed using tow component repairable design.

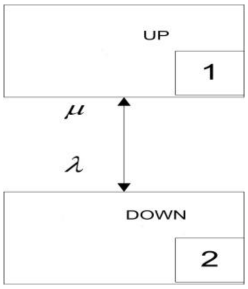

Fig.1 Two state model of components

Component may remain either in operating condition or failed condition as shown in Fig.1. The availability of component in operating state is success probability. Any transition to non-operating condition is termed as failure rate of the component. Similarly, existence of component failure is dictated by failure probability and any transition to operating state is designated as repair rate. The failure rate and repair rate are basic data requirements for reliability assessment.

For implementing the proposed method, a reliability experimental system, called as Roy Billinton Test System (RBTS) was used. The single line diagram of the test network is shown in Fig.2. From the network data and reliability data, the component availability and unavailability was computed. Using these values the basic indices like probability of failure, frequency of failure and annualized indices like expected load curtailed (ELC) and expected energy not supplied (EENS) were calculated using the formulae.

1.1 Reliability Indices

The following reliability indices are expendedin the paper to test and validate the proposed method.

1. Probability of Load Curtailment: $PLC = \sum P_j \; P_{kj}$
2. Frequency of Load Curtailment:$FLC = \sum F_j \; P_{kj}$

Where j is an outage condition in the network

P_j is the probability of existence of outage 'j', $F_j$is the frequency of existence of outage 'j' and $P_{kj}$is the probability of the load at bus 'K' exceeding maximum load that can be supplied at that bus during the outage 'j'

3. Expected Load Curtailed: $ELC = \sum L_{kj} \; F_j$

Where L_{kj} is the load curtailment at bus 'K' to alleviate line overloads arising due to contingency 'j'

2. Expected Energy Not Supplied:$EENS = \sum L_{kj} \; P_j * 8760$

Reliability indices calculated over a period of a year for a single load stage are designated as annual indices. In practice, load keeps changing ever; hence a practical system must have indices imbibing these changes in load. So, fundamental values of annual indices may vary from annual indices computed at peak load condition. Load point index may be helpful in designing the system, comparing with neighboring networks and choosing network alternatives. For power system planner overall composite system index may be quite meaningful.

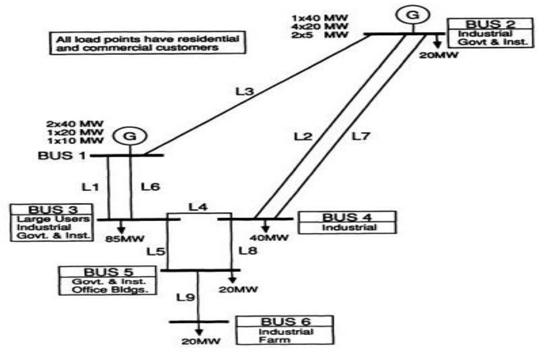

Fig.2 Single line diagram of RBTS system

The test system used is a tinyinformativeevaluation system constructed as section of graduate course in power network reliability judgment at the University of Saskatchewan. The RBTS is a six node scheme [16] it comprises a couple of voltage control nodes, four load nodes, eleven generating elements and nine transmission elements. The minimumand the maximum ratings of the alternators are 5MW and 40MWconsistently. The nominal voltage of the investigationalsystem is 230KV and the voltage bordersfor the network buses are assumedas 1.05 per unit and 0.95 per unit. The systemhas a maximumload of 185 MW and the aggregatefixedgenerating size sumsto 240 MW. The lengths are specifiedas per their real lengths. The topographicaldepiction of the network specifiesthe organizationan additionalphysical appealand can be employedto consider numerous sections of the systemin terms of the real customerslinked to those areas.

III. Bayesian Regularization Algorithm

Training a neural system is foremost task before constructing the network. Several algorithms are available for fulfilling this task. One such algorithm is levenberg-marqart back propagation approach used for solving the nonlinear power system problems. However, it is well suited for small network dimensions. As the size of the network to be implemented increases levenberg-marqart algorithm increases its error and proven to be less effective. Hence, an efficient and adoptable algorithm is required for applying to moderately sized networks.

Bayesian regularization algorithm reduces the squared values of errors and optimizes the combination of weights and errors so as to generalize the process. The validation process termination is disabled so as to enable the training phase. The process continues as long as the blend of weights and values of errors get optimized. However, bias-weight optimization can still be achieved with limitation on validation and training phase settings. The inputs for the neural model are probability of failure, frequency of failure amount and duration of load curtailed. The targeted outputs for the system are expected load curtailed and expected energy not supplied. For achieving this I/O relationship a bi-layer feed forward system was devised with two layers. One such layer is termed as output level and another labeled as hidden level. The number of neurons in the hidden level must be carefully chosen, failing which the performance of the system will be affected.

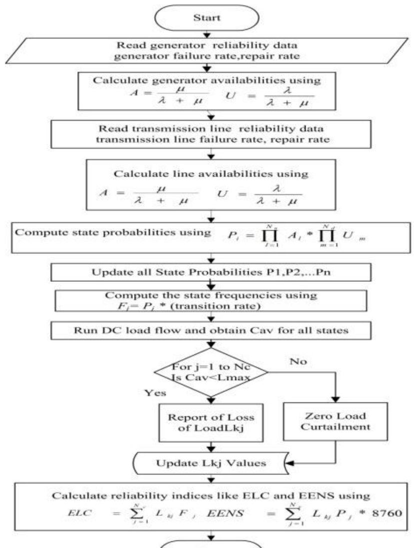

Fig.3. Flowchart for reliability indices computation

In this article, 50 neurons are integrated in the hidden level. The linear blend of weights and squared values of errors are optimized in Bayesian regularization algorithm. This achieves the better generalization characteristic of the network at the last of training stage. The training stage terminates at the scenario which satisfies the following conditions. Highest value of epoch must be attained, during network timeout, optimal performance goal is achieved, and gradient of performance lies below a threshold.

Inputs for the designed network are computed using MATLAB software. The flowchart for computing the reliability indices is shown in Fig.3. The network data and impedance data was used to compute availabilities. Then probability of failure and failure for all the states were computed. DC load flow yield the capacity available for each state. For certain states the load exceeds the capacity available. Such states were labeled as failure states. Amount of load curtailed for all such failure states was updated. From these details the expected load curtailed and expected energy not supplied was calculated.

IV. Simulation Outcomes

For prediction problems, a neural network is essential to align an input data with the targeted output dataset. In this paper an artificial neural system based on Bayesian regularization was designed to forecast the expected load curtailed and expected energy not supplies from four input values.

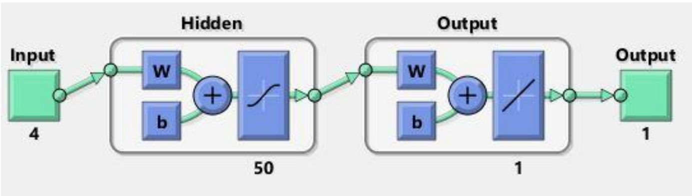

Fig.4. A two layer artificial neural network

For predicting the reliability of the RBTS system a bi-layer neural system with 50 neurons in the hidden layer was devised as shown in Fig.4. Developed network helps for selection of dataset, creating, training and assessing the functioning of the system. Four attributes used as input data set are probability of failure, frequency of failure, amount and duration of load curtailed. If the consistent values of data and sufficient number of neurons are available in hidden level, a bi-layer forward feed neural system may align any dimensional I/O relationship.

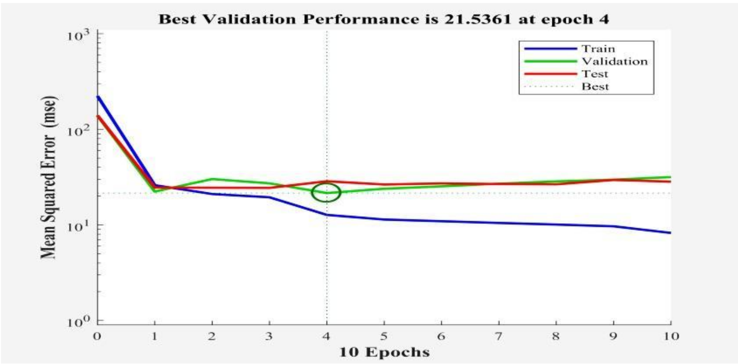

Fig.5. Mean square error plot for the network

The network training will be achieved using Bayesian regularization algorithm for moderately sized system. The total data for the network is broadly distributed into input data values and target data values. The dimension of input matrix is 3000×4 and that of output matrix is 3000×1. Total samples were randomly separated into training sample set, validation sample set and testing sample set. 70% of the total 3000 samples i.e., 2100 elements constitute training set, validation and testing set comprises 15% i.e., 450 for each set. For teaching the network training set is used. As per the error value the network is adjusted. For generalizing the network validation set is used. As generalization progresses the validation terminates. Testing data values have no significant effect on training phase; however they provide a measure of functioning of the system. Bayesian regularization generally takes more time but it will yield best results for generalization of moderately sized network. Training phase terminates as per the adoptive minimization of weights often termed as regularization.

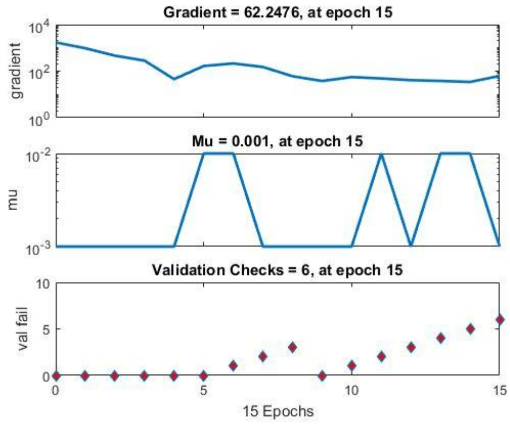

Fig.6. Gradient and validation failure plot

As the initial conditions and sampling will change at every step, training several times may result in different outcomes. The performance of the trained network is assessed using mean square error. The mean of squared values of difference between targets and outputs is called mean squared error (MSE). The plot of mean square error for three sets of data is shown in Fig.5.that shows that best validation performance is attained at epoch 4.

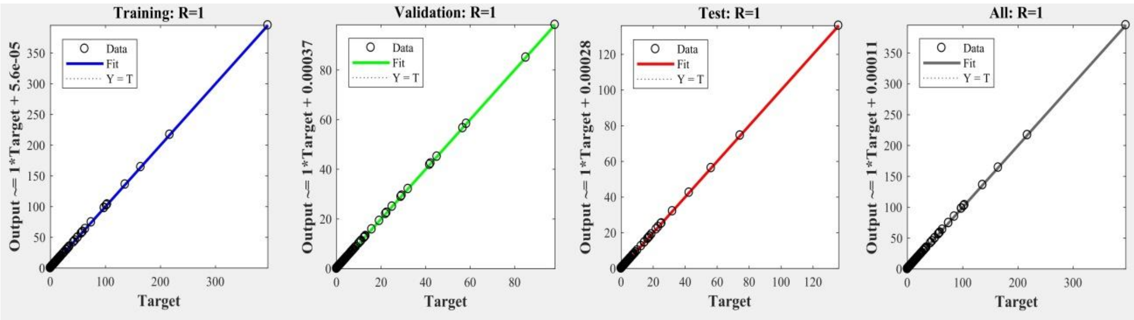

Fig.7. Regression analysis for the given data set

Lower the MSE values better the system design and zero MSE indicates null error. Another set of performance characteristic is specified with gradient, scalar factor and validation failures. These characteristics are shown in Fig.6. The plot depicted satisfactory performance for 15 epochs. Regression for the given data set is shown in Fig.7. Regression analysis shows the association between target values and output values. Unity regression indicates best relationship and null regression signifies weak association.

V. Conclusions

Reliability prediction techniques needed reasonable accuracy in order to exercising for real world problems. This article developed an artificial neural network model utilizing Bayesian regularization algorithm. Four attributes viz., probability of failure, frequency of failure, amount and duration of load curtailed were given as inputs for the trained network. Expected load curtailed and expected energy not supplied was considered as target output. Once the network was trained properly, it would generated targets for any inputs for which it was not trained before. Mean square error (MSE) and regression analysis were used for appraisingthe performance of the network. Mean square error indicates how well a trained network suits for real world problems. The MSE gave best validation performance at epoch 4. Regression plot also proven that the network was well trained. Ideal regression plot must be at 45 degrees intersecting top-right and bottom left points of the plot. The simulation results revealed that most of the data was aligned on 45 degree line. From the results it can be concluded that the trained network will be suitable for any real world prediction applications. As the model was suitable for moderately sized networks, sophisticated algorithms may be explored as future work foroperating on large complex networks.

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Venkatasatheesh Babu.K "Reliability Prediction of Composite Power System Using Bayseian Regularization based ANN model "International Journal of Engineering Science Invention (IJESI), vol. 07, no. 04, 2018, pp 55-60