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# ANN assisted network reconfiguration for enhancement of voltage stability in power networks

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**ABSTRACT**

Due to economic reasons arising out of deregulation and open market of electricity, modern day power systems are being operated closer to their stability limits. Maintaining voltage stability and specified voltage levels at all nodes in a large & heavily loaded Power network is a critical & challenging task for power engineers. A number of different approaches have been reported in papers for improvement of voltage stability. In this paper a method for improving voltage stability in a power network has been suggested based on Network Reconfiguration approach. Network Reconfiguration is intended to enhance the voltage stability by determination of switching options that maximizes voltage stability for a particular set of loads and is performed by altering the topological structure of the system. In this paper, reconfiguration of a power network is achieved by addition of new power lines to the existing network. The paper reports an application of ANNs in voltage stability enhancement. A generalized ANN model has been proposed for enhancement of voltage stability under varying load conditions. Training data sets for ANN training is generated by varying both real and reactive loads at the buses. An IEEE-14 Bus system considered to demonstrate the performance of the developed ANN model. The proposed ANN model is trained using conjugate Gradient Descent Back-propagation Algorithm and tested by applying arbitrary input data. The test results of the ANN model are found to be closely matching of the results obtained by off-line simulation.



## Introduction

Voltage control and stability problems are now receiving special attention in highly developed networks as a result of heavier loading. Due to fast growth in power demand, incidence of sudden voltage collapse has been experienced. When such incidents happen, some loads are switched off through automatic cut-off switches, resulting in severe interruptions. The phenomenon of voltage collapse has been observed in many countries and has been analyzed extensively in recent years.

Most of the incidents of voltage collapse are related to heavily stressed power systems where large amounts of real and reactive power are transported over long extra high voltage (EHV) transmission lines, while appropriate reactive power sources are not available to maintain normal voltage profiles at receiving end buses.

Most EHV transmission lines being very sensitive to real and reactive power changes, frequently suffer from voltage instability [1-2]. “Voltage stability is concerned with the ability of power system to maintain the acceptable voltages at all system buses under normal conditions as well as when the system is being subjected to a disturbance”. Voltage stability is classified into large-disturbance voltage stability and small disturbance voltage stability [3]. The former is concerned with a system’s ability to control voltages following large disturbances such as system faults, loss of generation, or circuit contingencies. The latter concerned with a system’s ability to control voltages following small perturbations such as incremental changes in system load. The basic processes contributing to small-disturbance voltage instability are essentially of a steady-state nature. Therefore, static analysis can be effectively used to determine stability margins which show how close current operating point of a power system is to the voltage collapse point. Recently, a large number of papers have addressed the issue of quantifying the distance of a specific operating state to voltage collapse point. In [4-6], the degeneracy of the load flow jacobian matrix, its minimum singular value, and its condition number were used as indices of power system small-disturbance voltage stability. The concept of multiple load flow solutions was proposed to deal with voltage stability problems in [7, 8] and different voltage instability indicators were used to quantify the proximity of a particular operating state to the point of voltage collapse. Because of the nature of the problem, voltage stability analysis has been computationally challenging. With some modifications this paper uses the voltage stability index for stressed power system has been derived by Sunita Dey, C.K Chanda and A. Chakrabarti [9] from a reduced system model, and this index could identify how far a system is from its point of collapse.

The present paper aims to address the problem of voltage stability enhancement using an ANN assisted network reconfiguration approach. ANN’s have been successfully applied to other power system problems like load forecasting [10], and security assessment [11] among others. Kashem et al. [12] have proposed an approach for online network reconfiguration for enhancement of voltage stability in distribution systems using ANN. In this paper, a generalized

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neural network model is proposed to solve the network reconfiguration problem for maximizing voltage stability in power networks. Network reconfiguration for time-varying loads is a complex and extremely nonlinear optimization problem which can be effectively solved by Artificial Neural Networks (ANNs), as ANNs are capable of learning a tremendous variety of pattern mapping relationships without having a priori knowledge of a mathematical function. In the proposed model, a single neural network has been used to determine the optimum switching combinations, which maximizes the voltage stability for a given set of loading conditions.

Network reconfiguration can be used as a real-time control tool in power system operation and planning for enhancement of voltage stability. Network reconfiguration alters the topological structure of a power network either by restructuring of power lines, or by adding new power lines to the original network. In this paper the power network has been reconfigured by addition of new power lines between the buses. From time to time the network cab be reconfigured by changing the ON/OFF status of the newly added power lines, so that, the voltage stability is maximized for a given loading condition. In case of distribution networks, sectionalizing-switches and tie-switches are used for connecting or disconnecting the lines. These switches are used for both protection and network reconfiguration. Modifying the structure of the feeders by changing the ON/OFF status of sectionalizing and tie-switches and there by transferring loads from one feeder to another may significantly improve the operating conditions of the overall system.

For two bus system, the sending and receiving end real and reactive powers being represented as $P_S$, $Q_S$ and $P_R$, $Q_R$, respectively, the power flow equation can be represented as

$P_S = P_L + P_R$ , and $Q_S = Q_L + Q_R$ [ $P_L$ and $Q_L$ are being power losses in lines]

The real and reactive power losses are given by

$$P_L = \frac{r(P_S^{\,2} + Q_S^{\,2})}{V^2} \text{ and } \qquad Q_L = \frac{x(P_S^{\,2} + Q_S^{\,2})}{V^2}$$

$V$ being the voltage at sending end, $r$ and $x$ being resistance and reactance of the line. The power flow equations can then be modified as:

$$P_S = \frac{r(P_S^{\,2} + Q_S^{\,2})}{V^2} + P_R \qquad (1)$$

$$Q_S = \frac{x(P_S^{\,2} + Q_S^{\,2})}{V^2} + Q_R \qquad (2)$$

Comparison of equations (1) and (2) yields:

$$\frac{P_S - P_R}{r} = \frac{Q_S - Q_R}{x} \left(= \frac{P^2{}_S + Q^2{}_S}{V^2}\right) \quad \text{Or}$$

$$Q_S = \frac{(P_S - P_R)x + rQ_R}{r} \qquad (3)$$

Using equation (3) in equation (1), the real power equation becomes:

$$P_S = \frac{r(P_S^{\,2} + \{(P_S - P_R)x + rQ_R\}^2)}{V^2} + P_R$$

$$P_S = P_R + \frac{r\left\{P^2{}_S + \dfrac{x^2P^2{}_S + x^2P^2{}_R - 2x^2P_SP_R + r^2Q^2{}_R + 2(P_S - P_R)xrQ_R}{r^2}\right\}}{V^2}$$

The voltage at sending is the reference voltage, and its magnitude is kept constant. Hence, the sending end voltage is assumed as 1 per unit. Eliminating $Q_S$ from equation (1), a quadratic equation in $P_S$ is obtained as

$$\therefore (r^2 + x^2)P_S^{\,2} - (2x^2P_R - 2rxQ_R)P_S + (x^2P_R^{\,2} + r^2Q_R^{\,2} - 2rxP_RQ_R + rP_R) = 0 \qquad (4)$$

$$\therefore P_{S1,2} = \frac{(2x^2P_R - 2rxQ_R + r)}{2(r^2 + x^2)} \pm \frac{\sqrt{(2x^2P_R - 2rxQ_R + r)^2 - 4(r^2 + x^2)(x^2P^2{}_R + r^2Q^2{}_R - 2rxp_RQ_R + rP_R)}}{2(r^2 + x^2)} \qquad (5)$$

similarly, eliminating $P_S$ from equation (1), a quadratic equation in $Q_S$ is obtained as

$$(r^2 + x^2)Q_S^{\,2} - (2x^2Q_R - 2rxP_R)Q_S + (x^2P_R^{\,2} + r^2Q_R^{\,2} - 2rxP_RQ_R + rQ_R) = 0 \qquad (6)$$

Similarly, for the reactive power $Q_{S1,2}$, because of symmetry of equations,

$$\therefore Q_{S1,2} = \frac{(2r^2Q_R - 2rxP_R + x)}{2(r^2 + x^2)} \pm \frac{\sqrt{(2r^2Q_R - 2rxP_R + x)^2 - 4(r^2 + x^2)(r^2Q^2{}_R + x^2P^2{}_R - 2rxp_RQ_R + xQ_R)}}{2(r^2 + x^2)} \qquad (7)$$

As equations (4) and (6) are in quadratic in nature and to have real roots, the discriminate part of equations (5) and (7) must be greater than or equal to zero. Thus,

$$(2x^2P_R - 2rxQ_R + r)^2 - 4(r^2 + x^2)(x^2P_R^{\,2} + r^2Q_R^{\,2} - 2rxP_RQ_R + rP_R) \geq 0 \qquad (8)$$

$$(2x^2Q_R - 2rxP_R + x)^2 - 4(r^2 + x^2)(x^2P_R^{\,2} + r^2Q_R^{\,2} - 2rxP_RQ_R + xQ_R) \geq 0 \qquad (9)$$

$$1 - 4xQ_R - 4x^2P^2{}_R - 4r^2Q^2{}_R + 8rxP_RQ_R - 4rP_R \geq 0 \qquad (10)$$

$$\therefore 4[(P_R - rQ_R)^2 + xQ_R + rP_R] \leq 1 \qquad (11)$$

For a given net work, the total real and reactive power can be computed as:

$$P_S = \sum P_{loss} + \sum P_{Ri} \quad (12)$$

$$Q_S = \sum Q_{loss} + \sum Q_{Ri} \qquad (13)$$

Where $\sum P_{loss}$ and $\sum Q_{loss}$ are the total real and reactive power losses in the system and $\sum P_{Ri}$ & $\sum Q_{Ri}$ are the total real and reactive loads, respectively. The real network consisting of many lines can be reduced to a system with only one line. By using the single-line method, the total real and reactive powers can be found as

$$P_S = r_{eq}(P_S^{\,2} + Q_S^{\,2}) + \sum P_{Ri} \qquad (14)$$

$$Q_S = x_{eq}(P_S^{\,2} + Q_S^{\,2}) + \sum Q_{Ri} \qquad (15)$$

Where $r_{eq}$ and $x_{eq}$ are the equivalent resistance and reactance, respectively, in the single line. Recalling equation (11), the stability index L can be defined as

$$L = 4[(xP_R - rQ_R)^2 + xQ_R + rP_R] \qquad (16)$$

Hence, for a reduced single-line network, equation (16) can be rewritten as:

$$L = 4[(x_{eq}P_{R\,eq} - r_{eq}Q_{R\,eq})^2 + x_{eq}Q_{R\,eq} + r_{eq}P_{R\,eq}] \qquad (17)$$

Where $P_{Req}$ and $Q_{Req}$ are the total real and reactive loads, respectively, in the distribution network. From equations (12) to (15), the equivalent resistance and reactance of a reduced single line network can be defined as:

$$r_{eq} = \frac{\sum P_{loss}}{\{(P_{R\,eq} + \sum P_{loss})^2 + (Q_{R\,eq} + \sum Q_{loss})^2\}} \qquad (18)$$

$$x_{eq} = \frac{\sum Q_{loss}}{\{(P_{R\,eq} + \sum P_{loss})^2 + (Q_{R\,eq} + \sum Q_{loss})^2\}} \qquad (19)$$

For a stable system, the value of stability index, L is very much less than 1; however, if the value of L approaches 1, this would indicate that the system is close to voltage collapse. If the network is loaded beyond this critical limit, the power becomes imaginary, and at this point the voltage collapse occurs.

**Development of ANN model for enhancement of voltage stability**

The ANN based techniques can map the nonlinear relationship between the load variations and the corresponding optimal system topologies and determine the most appropriate system topology according to the current load pattern on the basis of the trained knowledge. In this paper a multi-layer feed-forward artificial neural network trained with error back-propagation learning (EBPL) algorithm was used for enhancement of voltage stability. Basic topology of the ANN model used in the present work is shown in Fig.1.

**Topology of the ANN**

Input layer, hidden layer, and an output layer.

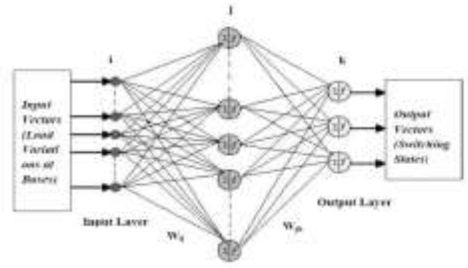


**Fig.1. Architecture of ANN model**

**The Input Layer**

Appropriate selection of input variables is the key to the success of ANN applications. Usually heuristic knowledge is required in choosing input variables. Voltage stability problems are mainly affected by the system's loading conditions. Using network reconfiguration, loading conditions are utilized to find the corresponding switching states for optimum system configuration. The procedure can be expressed as a mapping

$$\{P, Q\} \rightarrow \{\text{Switching states}\} \rightarrow \{\text{Optimal configuration}\} \quad (1)$$

Where P and Q are specified bus net real and reactive power injections. From the individual load variations, there will be several switching states out of those one will be the best switching state which gives better voltage stability. The above mapping shows that variables P and Q, govern the voltage stability of a power system. They are chosen as inputs to the ANN.

**The Hidden Layer**

Computational power of the ANN can be enhanced many fold by addition of hidden layers. But there are no general guidelines to determine the number of hidden layers and neurons. Many applications have proved that ANN's with one single-hidden layer possess sufficient capability of capturing complicated relations between input and output variables. It was observed that one hidden layer with fifteen hidden neurons gives satisfactory performance in enhancement of voltage stability. The weighted input value is limited between two limits using an activation function f (x), where 'x' is the summation of weighted inputs. In general tansigmoidal function of the type: (ex + e-x)/ (ex - e-x) or logsigmoidal functions of the type: 1/ (1-e-x) has been used as activation functions. Sigmoidal activation functions are most suitable for any nonlinear mapping of the input-output combinations, as they have noise immunity for low inputs, normal outputs for range inputs, and saturation for large inputs, ensuring stability of the systems.

**The Output Layer**

For the enhancement of voltage stability problem the number of neurons in the output layer depends on the number of switching states. In the present work three additional power lines are connected to the network. Each line is operated by ON/OFF switch placed on them. For any change in load status of these switches may change. Since there are three switches to be controlled, the number of output layer neurons is three. The Sigmoidal activation function is preferred for output layer. Appropriate scaling (normalization) of the input and output variables are carried out because the output of the chosen activation function lies in [0, 1]. Fig.1 shows the ANN architecture used for designing the ANN model for the prediction of switching states.

**Test System**

The standard IEEE 14-bus system is used to test the ability of the proposed ANN model for enhancement of voltage stability. It has a slack bus (bus 1), 4 voltage controlled buses (buses 2, 3, 6, 8), 9 load buses without attached generation (buses 4, 5, 7 and 9-14) and 2 additional loads are connected to voltage controlled buses 2 and 3. The base load of the test system is 100 MVA. Reactive power limits are imposed at all PV buses except bus 1 which is assumed to be an infinite bus.

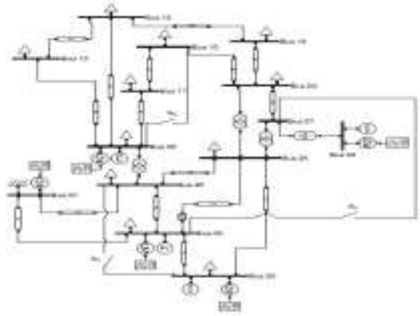

**Fig.2.The Modified IEEE-14 Bus Test system**

The IEEE-14 bus system is modified by addition of three power lines between buses 7-2, 10-6 and 5-3.These lines are added to the network through ON/OFF switches. Depending on the loading conditions, these lines are added or disconnected from the network. The modified IEEE-14 bus test system under study is shown in Fig.2.

**Network reconfiguration technique and proposed reconfiguration schemes**

As discussed earlier, network reconfiguration means restructuring the power lines which connect various buses in a power system. Restructuring of specific lines lead to alternative system configurations. System reconfiguration can be accomplished by placing line interconnection switches into network. Opening and closing a switch connects or disconnect a line to the existing network. If there are N switches in a network, there are 2N possible switching combinations. In this paper an IEEE-14 bus system is reconfigured by addition of three power lines. Based on off-line load flow analysis results three power lines are added between buses 7-2, 10-6 and 5-3. These added power lines are found to affect the voltage stability the most. So, there are all together 8 switching combinations. Improving voltage stability by network reconfiguration, thus involve study of these 8 switching options which leads optimum system configuration that will enhances voltage stability the most under a given loading and generation condition. The challenge in the proposed method thus lies with the task of finding the optimum switching pattern that would maximize the overall voltage stability of the system. The number of additional lines has been restricted to three from the point of view of economic considerations as increasing the number of lines increases cost. The data for the additional lines are given in the following Table. 1.

**Generation of training data for ANN**

Load on the system buses vary from time to time and hence the system becomes heavily loaded at certain times of the day and lightly loaded at other times. Voltage stability can be enhanced by rescheduling the power flow in the lines by transferring loads from the heavily loaded line to lightly loaded ones so that networks can be operated optimally for voltage stability. Training data sets for the ANN is generated by varying both real and reactive power loads on buses. The load is varied randomly in the range of 30% −120% of their base case values at constant power factor. All generators in the system share the additional generation needed to meet the increased load demand. Power flow calculation is conducted at all stages and corresponding voltage stability values are noted for each switching combination and the best switching combination. Hence, the ANN model is designed to accept the load variation at buses as inputs and switching status of switches as output. The switching states of optimal configuration for voltage stability are determined beforehand by off-line simulation. The switching status for each input vector of the training set is found by simulation. The developed ANN model is trained with 60 samples.

**Training and Testing of Ann Model**

The designed ANN model is trained by the back-propagation algorithm. Each input vector comprises of the load variations at various buses and the corresponding switching status of the switches form the target output. These combinations are used to train the ANN. The error is periodically monitored during the training process, which usually decreases as the iteration grows, so does the validation error. When the overtraining starts to occur, the validation error typically tends to increase. Therefore, it would be useful and time saving to stop the training after the validation has increased for a few successive numbers of iterations. The whole training of the ANN is depicted in Fig.3. The trained network is tested with new input vectors which were not used for training the ANN model, and results are compared with the actual simulation results obtained for these new test input vectors.

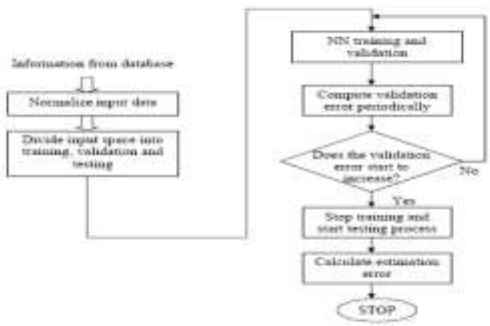


**Fig.3. Flow chart for ANN-based voltage stability Enhancement system.**

**Results and discussions**

The procedure used for obtaining optimal system configuration for improving the voltage stability by ANN Model is obtained below:

a) Specify system's base and maximum loading levels.

b) Vary the load (both P and Q) at buses randomly.

c) The randomly generated load is distributed among all load buses using specified distribution factors.

d) Calculate line flows by using Newton-Raphson load flow solution.

e) Calculate L-index for every switching combination under different loading conditions and find the least value of L-index out of 8 possible switching combinations.

f) Select the set of parameters to train the network. The main parameters selected are number of epochs, learning increment and rate, performance goal with Mean Squared Error (MSE) and minimum and maximum gradient.

g) Real and reactive powers at the buses and the corresponding best switching combinations are used as input-target training pair to train the ANN.

h) Once the training of ANN is complete, the ANN is exploited to predict the optimum network configuration and the corresponding best switching combination, which will lead to best voltage stability of the overall system under any unknown loading condition of the system. A properly trained ANN should theoretically be able to predict correctly the optimum system configuration and switch combination under each and every unseen operating condition of the system. The objective of the present work will be to achieve this goal in practice.

From the experience in training the ANN, it is observed that some of the input and output vector pairs can be eliminated. For example, if all the loads remain fairly constant over a period of time, few samples may sufficiently represent that period, resulting in the reduction of the total number of training vectors. The developed ANN model was tested under random loading conditions which were not used for training the ANN and results were compared with original simulation results, the results are presented in Table.2. The test results shows that the ANN model has been trained properly and it is found that results obtained from the ANN model matched with actual results (Fig.4) with small value of Mean Square Error. Mean square Error is computed for each best switching combination and it tabulated in Table 2. Fig.5 shows the variation of Mean Square Error for different test pattern. In most cases the error is within acceptable limit.

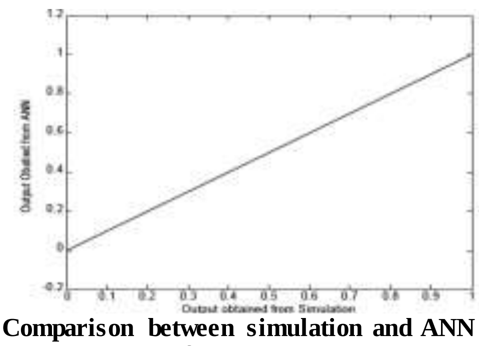


**Fig.4. Comparison between simulation and ANN outputs after training.**

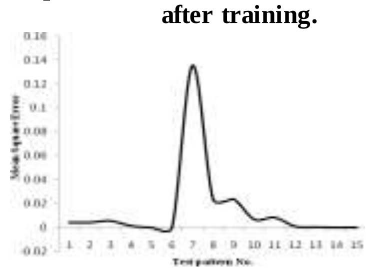


**Fig.5. Variation of MSE with testing pattern no**

**Conclusion**

Voltage stability problems, once associated primarily with weak systems and long lines, are currently a source of concern in highly developed systems as a result of heavy loading. Operators must be able to recognize voltage stability-related symptoms so that appropriate remedial actions can be taken for improving voltage stability. In this paper, the authors have proposed the application of ANNs for voltage stability enhancement. Emphasis has been on investigating whether the complex relationship between switching states and the corresponding loading conditions can be captured, for enhancement of voltage stability by the ANN technique. The proposed ANN-based system was successfully implemented to predict the switching states under any unknown loading condition in an IEEE 14-bus system. Extensive testing of the proposed approach under various loading conditions has demonstrated that the proposed ANN-based approach may be very promising in power system voltage stability enhancement.

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**Biographies**

Sambasiva Rao Pasam was born in Andhra Pradesh, India on 15th June 1985. He graduated in Electrical and Electronics Engineering from J.N.T. University, Hyderabad, India in 2006. He has done post graduation from Bengal Engineering and Science University, Howrah, India in 2009, in power systems as his area of specialization. He was involved in project work under Dr. A. De and Dr. A. Chakrabarti Department of Electrical Engineering, Bengal Engineering and Science University, Howrah, India. Currently he is working for L&T.

Abhinandan De was born in West Bengal, India, on December 21, 1973. He graduated in Electrical Engineering from Jadavpur University, India in 1996 and obtained the Master Degree in Electrical Engineering with specialization in High Voltage Engineering from the same University in 1999. He was awarded the Ph.D. (Engg.) degree by Jadavpur University in 2003. His areas of interests include study of power system transients, diagnostics and applications of Artificial Intelligence. He was awarded Gold Medal and Certificate of Merit a number of times by The Institution of Engineers (India) for outstanding research publications.

Abhijit Chakrabarti was born in West Bengal, India, on November 24, 1956. He received the B.E. (Hons.) degree in electrical engineering from the National Institute of Technology, Durgapur, India, in 1978, the M.Tech. degree in power apparatus and systems from IIT, Delhi, India, in 1987, and the Ph. D. (Tech.) degree from Calcutta University, Calcutta, India, in 1991. He is a Professor in the Department of Electrical Engineering, Bengal Engineering and Science University, Shibpur, West Bengal. He has nearly seven years of industrial experience and around 17 years of experience in research and teaching. He has 74 research papers published in national and international journals and conferences and is the author of several books on power systems, circuit theory, and power electronics, which are his areas of interest. During 1988–1989, he visited Japan through financial assistance from the Council of Scientific and Industrial Research (CSIR), Government of India. Dr. Abhijit Chakrabarti is a recipient of several Awards, including the Pandit Madan Mohan Malviya Award, the Best Research Paper Award (twice), the Merit Paper Award, and the Power Medal Award. He is Fellow of the Institution of Engineers (India).

**Table-1: Line-data for the new lines added to the original IEEE-14 bus system**

| Lines | Starting Bus | End Bus | R (p.u) | X ( p.u) | B/2 (p.u) | Tap setting Value |
|---|---|---|---|---|---|---|
| $L_1$ | 7 | 2 | 0.00000 | 0.17615 | 0.00000 | 1 |
| $L_2$ | 10 | 6 | 0.08205 | 0.19207 | 0.00000 | 1 |

**Table 2: Test results obtained from ANN model and Simulation**

| Input-Sets for Testing % change of Load | | | Actual Output obtained from Simulation | | | Output obtained from ANN model | | | Mean Square Error |
|---|---|---|---|---|---|---|---|---|---|
| S.No | P | Q | $S_1$ | $S_2$ | $S_3$ | $S_1$ | $S_2$ | $S_3$ | MSE |
| 1 | 86 | 81 | 1 | 1 | 1 | 0.9998 | 0.8981 | 0.9490 | 0.0043 |
| 2 | 30 | 58 | 1 | 1 | 1 | 0.9999 | 0.8868 | 1.0126 | 0.0043 |
| 3 | 101 | 82 | 1 | 1 | 1 | 0.9999 | 0.8709 | 1.0112 | 0.0056 |
| 4 | 63 | 70 | 1 | 0 | 1 | 1.0001 | -0.0662 | 1.0095 | 0.0015 |
| 5 | 47 | 76 | 1 | 0 | 1 | 1.0000 | -0.0083 | 1.0039 | 2.8033e-005 |
| 6 | 86 | 44 | 1 | 0 | 1 | 1.0000 | -0.0083 | 1.0039 | 2.8033e-005 |
| 7 | 113 | 73 | 1 | 0 | 1 | 0.9989 | -0.3463 | 1.2453 | 0.1355 |
| 8 | 65 | 41 | 1 | 1 | 1 | 1.0001 | 0.7331 | 0.9903 | 0.0238 |
| 9 | 65 | 119 | 1 | 1 | 1 | 1.0001 | 0.7331 | 0.9903 | 0.0238 |
| 10 | 105 | 79 | 1 | 0 | 1 | 1.0016 | -0.1238 | 1.0735 | 0.0069 |
| 11 | 83 | 65 | 1 | 1 | 0 | 0.9995 | 0.9711 | -0.1565 | 0.0084 |
| 12 | 76 | 72 | 1 | 1 | 0 | 1.0000 | 0.9456 | 0.0045 | 9.9320e-004 |
| 13 | 46 | 75 | 1 | 1 | 1 | 0.9993 | 0.9692 | 0.9946 | 3.2610e-004 |
| 14 | 102 | 57 | 1 | 1 | 0 | 0.9994 | 0.9907 | 0.0001 | 2.8953e-005 |
| 15 | 40 | 50 | 1 | 0 | 1 | 1.0000 | 0.0000 | 0.9978 | 1.6133e-006 |