Prediction of Missing PMU Measurement using Artificial Neural Network

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***Abstract*—This paper presents the concept of the prediction of phasor measurement unit (PMU) data, which are unavailable due to one reason or another at the central control room, using the 3-layered feedforward back-propagation neural network (BPNN). BPNN are used to determine hidden pattern in a process, using the historical data of that process. Work presented in this paper shows that, change in the voltage at PMU buses due to change in the system operating condition can be identified using the artificial neural network, and this information of changing voltage pattern can be used to reconstruct the missing measurement data, by making use of the voltage measurement of remaining PMU buses. The concept is initially tested on an IEEE 39-bus (New England) test system and then finally verified on northern regional Indian power grid, using the PMU measurement of 21st April 2014 between 08:36 AM to 09:36 AM.**

Keywords*— *Artificial Neural Network; Phasor Measurement Units; Wide Area Monitoring System; Smart Grid

I. Introduction

The complexity of power system is increasing rapidly due to factors like demand growth, increasing machine size, long distance power haulage, integration of renewable energy sources, increased competition in the electricity market and large seasonal load variations. In order to utilize the system resources maximum, power grid is often operated close to their limits. Under such scenario, in the present days, Wide Area Monitoring & Control System (WAMCS) has become a very important part of the smart grid. WAMCS provides the power system information in real-time to the system operator, based on which, several near real-time schemes has been developed and implemented like, real-time control of power system, real-time centralized protection etc. Experiences of the different system operator show that the system's real-time data are sometimes unavailable at the control center [1]. Most of the times, it is because of PMU failure, PDC failure or communication link overloading, and sometimes because of incapability of WAMCS to handle big data. Unavailability of the PMU measurements will not only affect the working of the WAMCS but also affect the other real-time schemes linked with WAMCS. In such situations, instead of calculating the missing data using available data and system model, which is time-consuming, it is preferred to predict them using artificial intelligence. Algorithms to predict the missing measurements can be designed using fuzzy logics, decision tree, regression tree or ANN.

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In this paper, authors tried to present the prediction of missing PMU data using the artificial neural network. When the bus voltage magnitude of different buses is plotted with respect to the time, on a 3-D graph, the pattern of change of voltage magnitude on different buses under different system loading conditions can be observed. Fig. 1 shows the pattern of voltage magnitude change for different PMU buses in IEEE 39-Bus system, for 1000 time samples collected through Newton-Raphson load flow under different loading conditions.

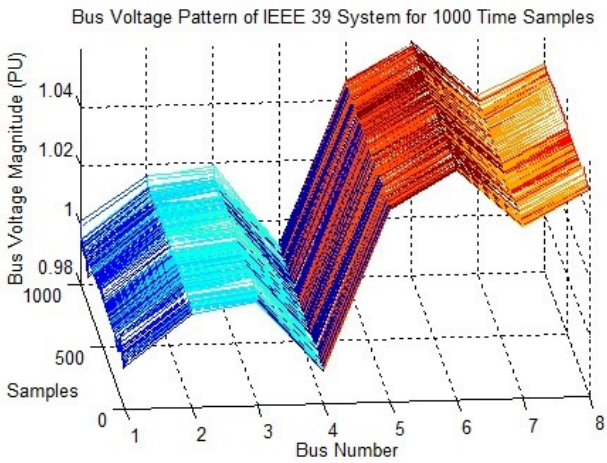

Fig. 1 : Voltage Magnitude Pattern in IEEE 39-bus System

Artificial Neural Network (ANN) is best to determine the hidden pattern of voltage variation, which is the basis for the work presented in this paper. In this work, prediction of the missing PMU measurement is demonstrated for standard IEEE 39-bus test system and a real system of North Indian Power Gird. For IEEE 39-bus system, it is assumed that connectivity of the system network is not changing. However, no such assumptions are made for North Indian Power Grid system because the concept of prediction of missing PMU data is tested with real data obtained from Power System Operation Corporation (POSOCO) of India.

II. Artificial Neural Network

ANN covers a wide spectrum of applications, based on which its architecture, training, and performance algorithms get defined. Feed-forward Backpropagation Neural Network

(BPNN) are a class of neural network, which are used for classification and clustering of the training data, so as to build the knowledge base, later on which will be utilized for prediction purposes. BPNN are designed to find the hidden pattern of non-linear relationship between input arguments and the target arguments [2-3].

To resolve the pattern classification problem, neural network undergoes training; where they repeatedly presented to a set of patterns along with the categories where the pattern belongs. Now when a new pattern is presented to the network, which belongs to the same category of patterns which was presented during training of the network, then the neural network has to classify this new pattern correctly [2-3]. Methodology of the neural network is illustrated in Fig. 2

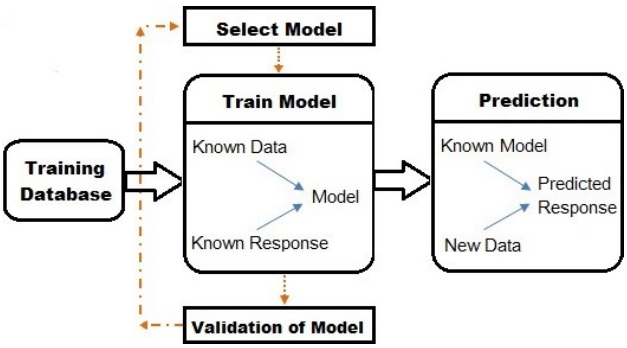

Fig. 2 : Illustration of Artificial Neural Network

The advantage of using the neural network to perform pattern recognition is that ANN can construct non-linear decision boundaries between different classes in a nonparametric fashion and thereby offer a practical method of solving otherwise highly complex pattern classification problems. The pattern recognition can be classified as a supervised learning problem. There is also the unsupervised learning in pattern classification, especially when there is no prior knowledge of the categories into which the activation patterns are to be classified [3]. Here, supervised learning is used to perform the pattern recognition.

From Fig. 2, it can be seen that whole process of missing measurement prediction can be grouped into two parts, first is to select a network and train that network with input and known response, and then validate the trained network for desired response. Repeat the training and validation process until acceptable response with minimal error is produced by the network. Now in second part, accepted network is fed with new inputs, for which response was missing/unknown, and network will produce the predictions based on the pattern knowledge base formed during the training process.

The work presented in the paper mainly aims to predict the missing bus voltage measurement vector of PMU bus. To deal with complex voltage, two separate networks are formed, one for voltage magnitude and another for voltage phase angle [4].

III. Test System & Training Database

In this work, IEEE 39-bus test system [5] and Northern Regional Power Grid (NRPG) of Power Grid Corporation of India (PGCIL) [6] has been used to demonstrate the effectiveness of the proposed method for prediction of missing PMU measurement using ANN.

A. IEEE 39-bus Test System

Single line diagram and system data of IEEE 39-bus standard test system can be found in [5]. MVA base of the system is taken 100 MVA and bus 31 is set to be swing bus with active power generation is limited in the interval of 10 MW to 300 MW.

The training and testing database for IEEE 39-bus system, has been created by 1140 different loading and generation conditions, using the Newton-Raphson load flow simulation in Matlab® R2014a. Considering a random change in loading condition (between 5% to 10%) on various PV and PQ buses, total 1140 patterns were obtained. Out of 1140 patterns, 1000 random pattern has been selected for the training of neural networks, while remaining 140 patterns were used for validation and testing purpose of the networks.

In another published paper [7], authors identified the optimal location and number of PMUs for different test systems. In that work, 8 PMU buses are identified for full system observability of IEEE 39-bus system. So out of 1140patterns, each pattern will contain voltage magnitude and phase angle of 8 PMU buses. It has assumed in this work that PMU measurement of bus number 8 became unavailable, hence out of 16 variables, 14 variable (V_{11}, V_{15}, V_{20}, V_{23}, V_{25}, V_{27}, V_{29}, and δ_{11}, δ_{15}, δ_{20}, δ_{23}, δ_{25}, δ_{27}, δ_{29}) will be used as input, while the other 2 variable (V_8 and δ_8) will be used as output.

B. Northern Regional Power Grid, PGCIL

Northern Regional Power Grid (NRPG) of Power Grid Corporation of India Ltd. (PGCIL), is the largest regional grid in India, which covers around 30% geographical area of India. The reduced NRPG system, considering 220 kV and 400 kV buses only, consist of 246 buses, 376 transmission lines, 42 generating units and 40 shunt reactors. Due to space limitation, details about NRPG system is not provided here but is available with Power System Simulation and Research Laboratory, Indian Institute of Technology Kanpur [6].

Voltage measurement data, of 21st April 2014 from 08:34:14 AM to 09:34:16 AM, for 10 PMU buses of NPRG was provided by POSOCO, PGCIL. The measurement data contains total 105029 time samples at a sampling rate of 25 samples/sec. Each of the time sample will present a system voltage pattern. Out of 105029 time samples, some of the samples was not containing PMU measurement for all buses. So these time samples wasn't considered in this work and hence, total patterns available for training the network get reduced to 88925. Furthermore, to reduce the training time of network, 3557 time samples has been selected with a sampling rate of 1 sample/sec.

In this work, it is assumed that out of 10 PMU buses, PMU measurement data became unavailable for one of the PMU bus with bus ID 'Kanpur-Bus', which is located at Kanpur. So total 18 variable will be used as input and remaining 2 will be used

as response for the training of ANN.

IV. Architecture of Neural Network

The selection of suitable ANN structure for proposed approach includes the selection of a number of layers, number of neurons in each layer, choice of the transfer function for each neuron and connection between various neurons. A three-layered feedforward network can model complex mapping functions reasonably well and therefore two such networks, are used in this work. Each of these networks are trained for voltage magnitude prediction and voltage phase angle prediction separately.

A. Network Structure and Neuron Connections

Out of three layers, first layer is input layer, which consists of the input vectors, second layer is the hidden layer and the third layer is output layer which consists only one neuron. Number of neuron in the hidden layer is equal to the average of neurons in adjacent layers.

First neural network is a basic 3-layers feedforward neural network with connection between different layers are as shown in fig. 3.

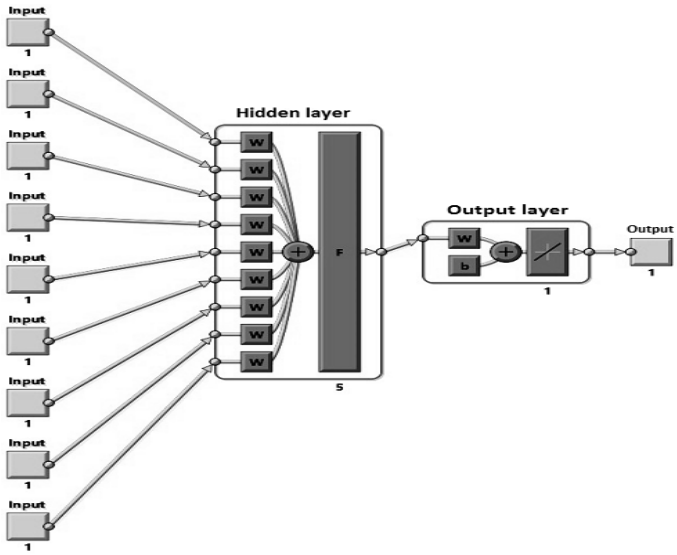

Fig. 3: Basic 3-Layered Network

Second network, shown in Fig. 4, is a modification of basic 3-layered neural network. In modified 3-layered network, inputs are not only fed to the hidden layer but also to the output layer.

For both the network shown in Fig. 3 and Fig.4, hidden layer is activated with tangent sigmoid function, while output layer is activated with linear function.

B. Training Algorithm

Training of both the networks are done using Gradient Descent (GD) algorithm, which is the general purpose first order optimization techniques that updates weights and bias values to minimize the goal functions of several variables [8]. The training is stopped when the mean squared error between the actual output and the desired output is acceptably small.

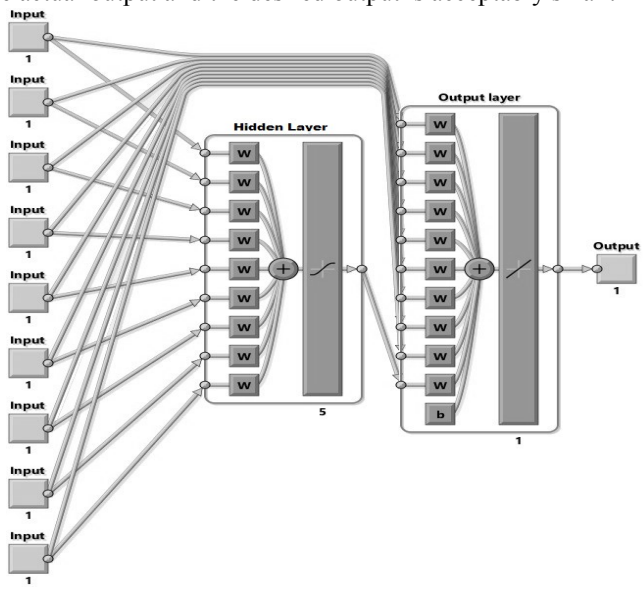

Fig. 4: Modified 3-Layered Network

For layered feedforward networks that are fully connected, back-propagation algorithm can be written in matrix notation. For layered feedforward networks that are fully connected, back-propagation algorithm can be written in matrix notation. In this notation, the biases weights, net inputs, activations, and error signals for all units in a layer are combined into vectors, while all the non-bias weights from one layer to the next form a matrix W. Layers are numbered from 0 (the input layer) to L (the output layer). The back-propagation algorithm then looks as follows [9]:

1. Initialize the input layer:
$$\overrightarrow{y_0} = \vec{x}$$
2. Propagate the activity forward:
For l = 1, 2, …. L;
$$\overrightarrow{y_l} = f_l\left(W_l \vec{y}_{l-1} + \overrightarrow{b_l}\right)$$
Where, b_l is bias vector.
3. Calculate the error in the output layer:
$$\vec{\delta}_L = \vec{t} - \vec{y}_L$$
4. Back-propagate the error:
For l = L-1, L-2, ….1
$$\vec{\delta}_l = \left(W_{l+1}^T \vec{\delta}_{l+1}\right).f_l'\left(\overrightarrow{net_l}\right)$$
Where, T is the matrix transposition operator.
5. Update the weights and biases
$$\Delta W_l = \vec{\delta}_l \vec{y}_{l-1}^T \quad ; \quad \Delta \vec{b}_l = \vec{\delta}_l$$

V. Training and Testing of Networks

To validate the performance of both network, they are first tested with IEEE 39-bus test system. After the satisfactory performance of the feed-forward backpropogation neural networks, they are implemented for reconstruction of PMU measurement of NRPG for real system data.

A. Performance for IEEE 39-bus system

A basic 3-layered feedforward network is trained for voltage

magnitude prediction using the training database developed through load flow, as described in section III-A. After training, network is tested with 138 samples, and Fig. 5 shows the actual error during testing for voltage magnitude prediction using basic network. From Fig. 5, it can be seen that error for voltage magnitude prediction is mostly confined between [-0.00017 PU to 0.000964 PU], with few exceptions.

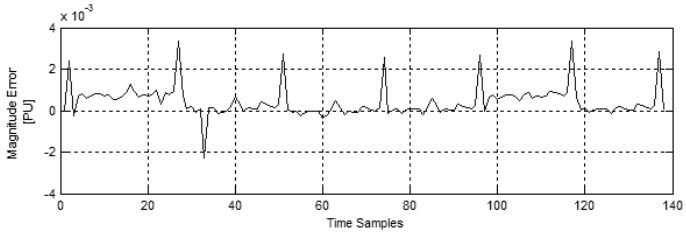

Fig. 5: Voltage Magnitude Error (in pu) for IEEE 39-bus System using Basic 3-Layered Network

Again, basic 3-layred network is trained for voltage phase angle prediction with training database, described in section III-A. After training, network is tested with 138 samples and actual error during testing process is shown in Fig. 6(a). Phase angle error histogram is shown in Fig. 6(b) to depict the accuracy of the network.

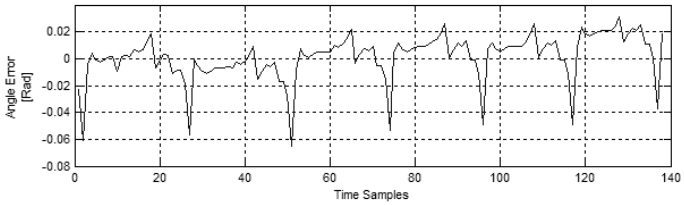

Fig. 6(a): Phase Angle Error (in rad.) for IEEE 39-bus system using Basic 3-Layered Network

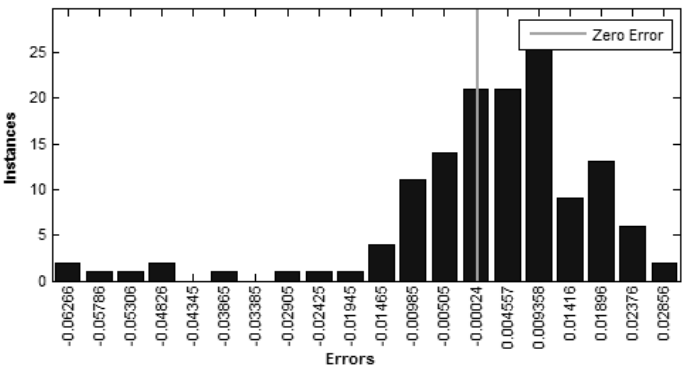

Fig. 6(b): Phase Angle Error Histogram for IEEE 39-bus System using Basic 3-Layered Network

From Fig. 6, it can be seen that prediction error for voltage phase angle is mostly confined between [-0.014 rad. to 0.024 rad] with few exceptions.

Now another 3-layered modified network is simulated and trained for voltage magnitude prediction with same training data, as described in section III-A. After training, network is tested with testing database with 138 samples. Result of testing is shown in Fig. 7(a) in terms of actual error between true voltage magnitude and predicted value, and accuracy of the network is shown in Fig 7(b) with the help of histogram.

From Fig. 7, it can be seen that prediction error for voltage magnitude is mostly confined between [-0.0028 PU to 0.0012 PU], with few exceptions.

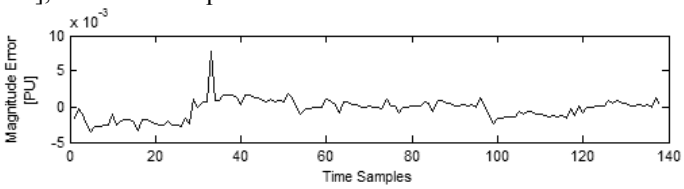

Fig. 7(a): Voltage Magnitude Error (in pu) for IEEE 39-bus System using Modified 3 layered Network

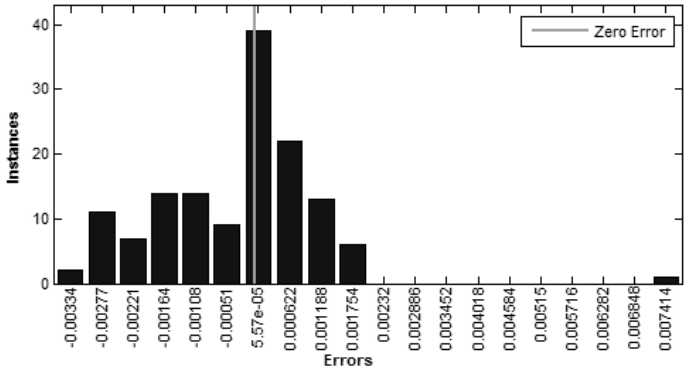

Fig. 7(b): Voltage Magnitude Error Histogram for IEEE 39-bus System using Modified 3 Layered Network

Now, modified 3 layered network is trained for phase angle prediction with the same training data as described in section III-A. After training process, network is tested with 138 testing samples, and the result of testing is shown in Fig. 8(a) in the form of prediction error between true value and predicted values. Accuracy of the network is depicted by error histogram in Fig. 8(b)

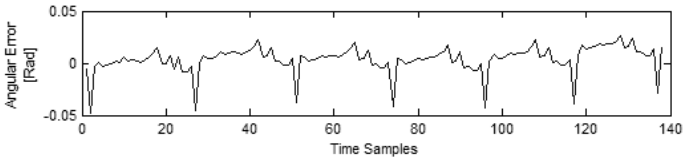

Fig. 8(a): Phase Angle Error (in rad) for IEEE 39-bus System using Modified 3-Layered Network

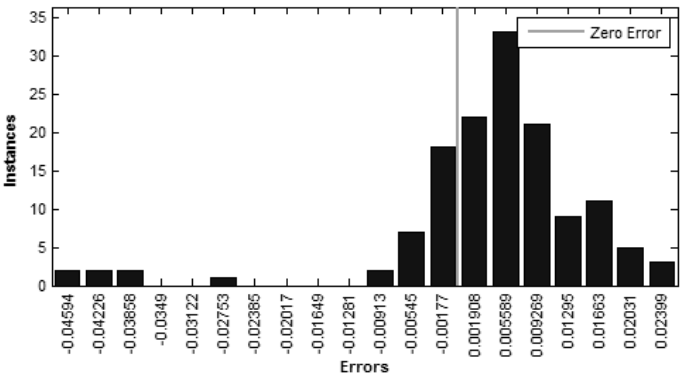

Fig. 8(b): Phase Angle Error Histogram for IEEE 39-bus System using Modified 3-Layered Network

From Fig.8, it can be seen that error in phase angle prediction

using modified 3 layered network is mostly confined between [-0.0055 rad to 0.020 rad], with few exceptions.

B. Performance for NRPG, PGCIL system

For Northern Regional Power Grid PMU measurement data, initially a basic 3-layered feedforward network is simulated and trained with training database as described in section III-B using gradient decant method for voltage magnitude prediction, till mean square error (MSE) is get reduced down to 12.2 x10^{-6} PU.

Then the trained network is tested for 557 testing samples, result of which are shown below. Fig. 9(a) shows the actual error in voltage magnitude prediction by basic 3-layered feedforward neural network for 557 time samples. Fig. 9(b) is the histogram of errors in voltage magnitude prediction, which depicts the occurrence of the error.

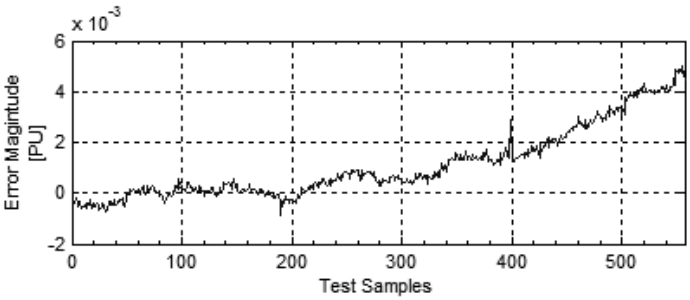

Fig. 9(a): Voltage Magnitude Error for NRPG System using Basic 3 Layered Network

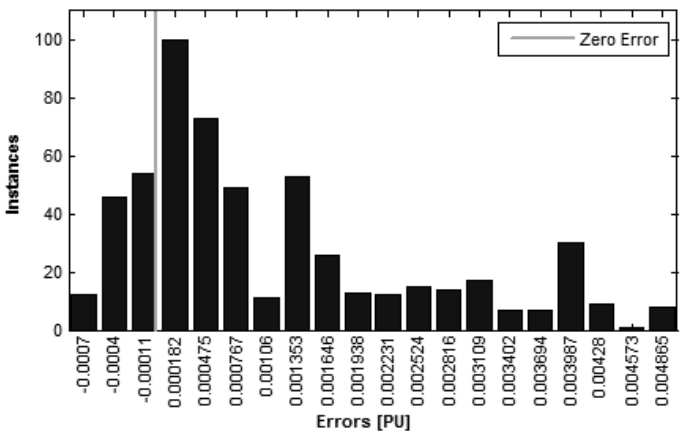

Fig. 9(b): Voltage Magnitude Error Histogram for NRPG System using Basic 3 Layered Network

From Fig. 9, it can be observed that error associated with voltage magnitude prediction using basic 3 layered network is mostly confined between [-0.0007 PU to 0.005 PU]

Another basic 3-layered feedforward network, which is simulated for voltage phase angle prediction, is trained with training data described in section III-B, till mean square error get reduced to 0.6 x10^{-3} radians.

Trained network is then tested with 557 testing samples, result of which are shown in last page. Fig. 10(a) shows the error in phase angle prediction for each of the testing sample, and Histogram of phase angle error in Fig. 10(b) shows the accuracy of the network.

From Fig. 10, it can be observed that phase angle prediction error is mostly confined between [-0.037 rad to 0.0244 rad], with few exceptions.

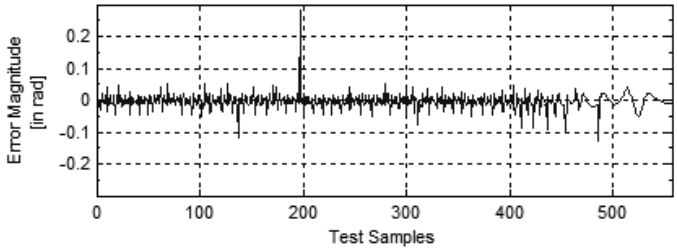

Fig. 10(a): Phase Angle Error for NRPG System using Basic 3-Layered Network

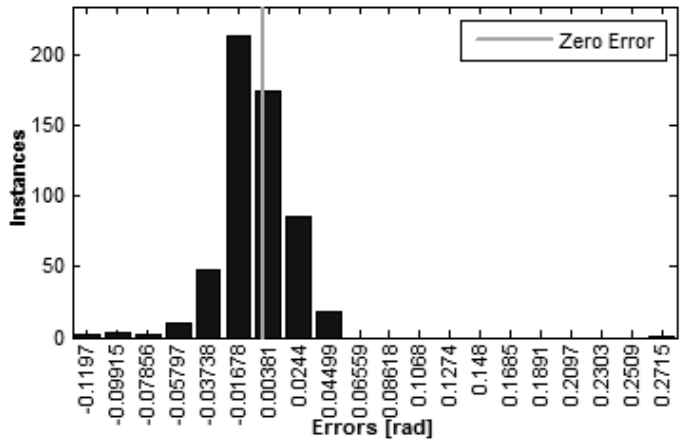

Fig. 10(b): Phase Angle Error Histogram for NRPG System using Basic 3 Layered Network

Lastly modified 3-layered network is simulated and trained for voltage magnitude prediction with same training database, till mean square error is get reduced down to 0.718 x10-6 PU. Than trained network is tested with same old testing database with 557 samples. Performance of the network is shown below in Fig. 11.

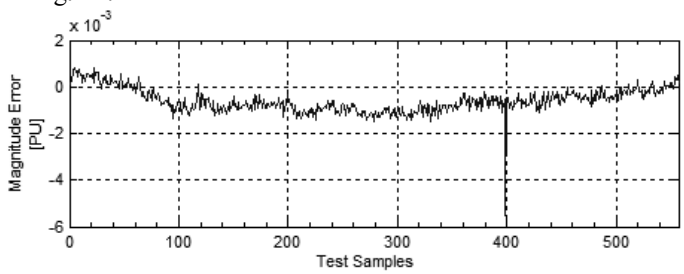

Fig. 11: Voltage magnitude Error for NRPG System using Modified 3 Layered Network

From Fig. 11, it can be seen that prediction error for voltage magnitude using modified 3 layered network is confined between [-0.0012 PU to 0.00068 PU], with few exceptions.

3-layered modified network is also trained for phase angle prediction, till MSE get reduced to 0.95 x10^{-3} radians, and then trained network is tested with old testing database which have 557 samples. Performance of the network can be observed with Fig.12, which shows error between actual and the predicted phase angle for NRPG system.

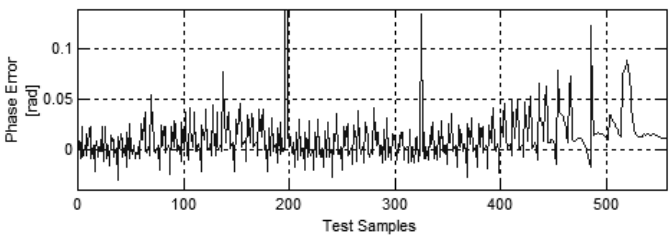

Fig. 12(a): Phase Angle Error for NRPG System using Modified 3 Layered Network

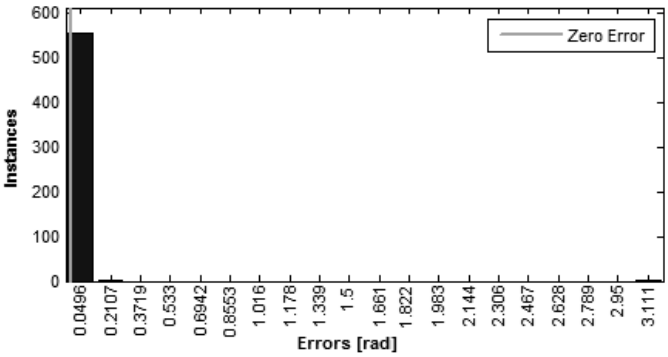

Fig. 12(b): Phase Angle Error Histogram for NRPG System using 3 Layered Network

Form Fig. 12, it can be observed that error associated with phase angle prediction for NRPG system using modified 3 layered neural network is confined between [0 to 0.0496 rad] with few exceptions.

VI. Result Analysis

Performance of various test systems for different network structures are compared in terms of mean error and standard deviation of error from mean value, in table 1.

Table 1 : Performance Comparison

↓ Test System		Basic 3-Layered Network	Modified 3-Layered Network
NRPG System	Magnitude (in pu)	0.0011 ±0.0014	-0.0006 ± 0.0005
	Angle (in rad)	-0.0041 ± 0.0253	0.0168 ± 0.1362
IEEE 39-bus System	Magnitude (in pu)	0.0004 ± 0.0007	-0.0003 ± 0.0014
	Angle (in rad)	0.0016 ± 0.0168	0.0039 ± 0.0125

VII. Conclusion

Prediction of missing PMU data with the help of artificial intelligence is presented in this work. 3-layered feedforward backward propagation neural network is used for the reconstruction purpose. The effectiveness of the proposed approach is tested on IEEE 39-bus standard test system and real Indian power system of Northern Regional Power Grid of PGCIL with two different structure of neural networks.

It is observed in this work, that modified network, in which inputs are also connected to output layer directly along with the output of hidden layer, gives the best results. The work can be extended in several dimensions in future. For instance, it can be used for the reconstruction of other measurement data like power flow through the line. The proposed method of prediction of PMU measurements can also be used in any PMU enabled algorithm for real-time operation and control of large power system.

Work presented in this paper was primarily focused on PMU measurement missing for short time duration, which occurs mostly because of congestion in communication channel or by any other reasons. To achieve better accuracy, it is necessary to retrain the network after each line or heavy load switching.

VIII. Acknowledgement

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