Using Artificial Neural Networks to Estimate Rotor Angles and Speeds from Phasor Measurements

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***Abstract*—This paper deals with an improved use of phasor measurements. In particular, the paper focuses on the development of a technique for estimation of generator rotor angle and speed, based on phasor measurement units, for transient stability assessment and control in real-time. Two multi-layered feed-forward artificial neural networks are used for this purpose. One for the estimation of rotor angle and another for the estimation of rotor speed. The validation has been made by simulation in a power system because techniques for the direct measurement were not available. Results obtained with the help of a simple one machine to infinite bus system are presented and compared against those obtained using analytical formulas derived from the generator classical model.**

***Index Terms*—Artificial Neural Networks, Phasor Measurement Units, Security Assessment, Transient stability, Estimation.**

I. Introduction

Power system security assessment consists of evaluating the ability of the system to face various disturbances and of proposing appropriate remedial actions able to counter its main weaknesses, whenever deemed necessary [1]. Power system security covers a wide range of aspects, usually subdivided into static and dynamic phenomena. Power system stability currently refers to the "dynamic" part of security. The rotor angle and speed of the synchronous generator are the most important reference quantities in power system dynamic security assessment and control. As economic considerations continue to demand the operation of power systems closer to their stability limits, there is an increasing need for reliable and accurate means to determine limiting operating conditions. There are obvious differences between the real-time stability prediction problem and offline stability assessment. In conventional offline transient stability assessments, the critical clearing time (CCT) is to be found; in the prediction problem, the CCT is not of interest. Instead, one can monitor the progress of the transient in real-time thanks to the technique of phasor measurements [2].

The current and potential applications of Phasor Measurement Units (PMUs) have been well documented in [2,3,4]. An emerging application of this technology is to track the state of the system immediately following a transient event to select an appropriate remedial control action. One such real-time control strategy is already being implemented at Florida-Georgia interface [5] and others are currently under development [6,7]. A possible use of PMU measurements can be made to predict a developing transient and initiating important relays, or other control actions such as generation tripping [8], load shedding [9], and FACTS devices [7,10].

A fuzzy hyper-rectangular composite neural network, which utilizes real-time phasor angle measurements to provide fast transient stability prediction, is presented in [3,11]. In [12] two methods for solving the real-time prediction problem are presented, solving the model forward in time in order to predict future behavior and solving the model faster than real-time if computational resources permit.

Both methodologies [11,12] rely on so called classical generator model to infer rotor angles from phasor measurements and numerical computation of the rotor speeds. The discussion attached to [12] raised very important issue of accurate synthesis of rotor angles from phasor measurements obtained by a PMU placed at extra high voltage (EHV) side of step-up transformer.

In this paper, the use of artificial neural networks (ANN) to estimate rotor angles and speeds based on real-time phasor measurements, is presented. First the technology of phasor measurements and reasons to estimate rotor angles and speeds, are introduced. Then we present the development of the neural networks for angle and speed estimation. Simulation results, obtained using simple one machine to infinite bus system, are shown to illustrate the validity of the proposed methodology.

II. Why to Estimate Rotor Angles and Speeds from Phasor Measurements

PMUs are power system devices that provide measurements of real-time phasors of bus voltage and line currents. A number of PMUs are already installed in several utilities around the world for various applications such as monitoring, control, protection, and state estimation. The capabilities of a PMU are illustrated in Fig. 1. The measurement set is composed of the bus voltage magnitude V_B and angle θ_B, as well as the line and injection currents magnitude and angles

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$I_1, I_2, I_3, I_L, \theta_1, \theta_2, \theta_3$ and θ_L.

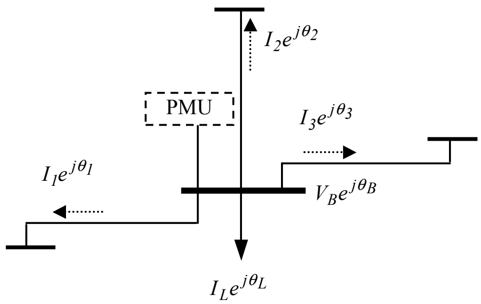

Fig. 1 Phasor measurements from a PMU

The important engineering observations are:

- The rotor angles and speeds of the synchronous generators are the most important quantities in power system transient stability assessment and control.
- PMU measured quantities are electrical variables that may experience fast changes unlike rotor angle which is a mechanical variable. PMU measured quantities can experience discontinuity under switching in the electrical network.
- Wrong or noisy rotor angles and speeds may result in wrong transient stability prediction and wrong determination of control actions.

The simplest way to compute rotor angles from phasor measurements is to rely on the classical generator model and relate phasors to reactances (step-up transformer, generator) to get rotor angles [11,12],

$$E' \angle \delta = V_t \angle \theta_{tV} - jX' I_t \angle \theta_{tI}\,, \tag{1}$$

where E' is the constant voltage, V_t is generator terminal voltage, X' transient reactance, and I_t generator terminal current. Having calculated rotor angles at different time instants the rotor speed can be approximated as,

$$\omega(t) = \frac{\delta(t+1) - \delta(t)}{\Delta t}\,. \tag{2}$$

All these provided that MV (medium voltage) generator voltage and current phasors are available. In more general situations phasor measurements are not taken directly from generator buses. In this case, for algebraic relation of measured voltages V_m and the generator (internal) voltages and currents, the reduced admittance matrix Y_{bus} can be solved for the generator internal voltages,

$$\begin{bmatrix} I_g \\ 0 \end{bmatrix} = \begin{bmatrix} Y_{11} & Y_{12} \\ Y_{21} & Y_{22} \end{bmatrix} \begin{bmatrix} V_g \\ V_m \end{bmatrix}, \tag{3}$$

where V_m are the measured voltages, V_g are the generator internal voltages and I_g are the generator internal currents.

A simple manipulation gives,

$$Y_{21} V_g + Y_{22} V_m = 0 \quad \Rightarrow \quad V_m = -Y_{22}^{-1} Y_{21} V_g + \varepsilon \tag{4}$$

This can be solved for the generator voltages by least squares. An important observation is that the simple relations (1,2,3,4) require a priori knowledge of system parameters or reduced admittance matrix whose entries may experience changes due to factors influencing it and reliable system parameter identification may be required. In addition, extremely rapid acquisition of breakers status, that is topology changes, is required (incidence matrices are necessary for building admittance matrix).

Of course, one can rely on more detailed generator model aiming to improved accuracy but this would require a proper machine parameter identification.

One more problem may arise and obstacle phasor measurements from providing a real picture of rotor angles; the lack of direct measurements of the plant auxiliaries.

To make better use of PMUs it is necessary to cope with the aspects identified above.

PMUs are mainly placed at EHV network buses. For the purpose of the methodology considered in this paper we suppose that a PMU is located at EHV side of step-up transformer. One reason is the facts mentioned above, and the second one is that the direct measurements of selected states are faster than extracting the same states from the system state estimator.

The rotor angle is a nonlinear function of the machine terminal variables and the main idea is to employ a pattern recognition scheme to map the patterns of inputs (terminal variables measured by a PMU) to the required rotor angle. This mapping can be represented by

$$f : \{u_k\} \in R^n \rightarrow \{\delta_k\} \in R^1 \tag{5}$$

where $\{u_k\} = [V_k(t), I_k(t), V_k(t-1), I_k(t-1), \theta_{vk}(t) \ldots]^T$ at any instant k, and n depends on the number of input variables as well as number of previous measurements used.

To realize the mapping of the machine terminal variables measured by a PMU to the rotor angle we use the multi-layer feed-forward ANN. Multi-layer feed-forward ANNs with back propagation supervised learning have several advantages over conventional computing methods. Those advantages are robustness to input and system noise, learning from examples, ability to memorize, handling situations of incomplete information and corrupted data, and performing in real-time.

III. Artificial Neural Networks

An ANN is characterized by its architecture, training or learning algorithms and activation functions. The architecture describes the connections between the neurons. It consists of an input layer, an output layer and generally, one or more hidden layers in-between. Fig. 2 illustrates one of the commonly used networks, namely, the layered feed-forward ANN with one hidden layer. The layers in these networks are interconnected by communication links that are associated with weights that dictate the effect on the information passing through them. These weights are determined by the learning algorithm.

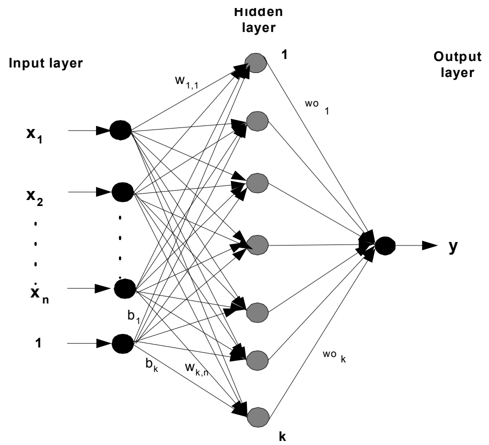

Fig. 2 A typical layered feed-forward neural network with one hidden layer.

The output of node j in the hidden layer is given by

$$h_j = g\left(\sum_{i=1}^{n} w_{ji} \cdot x_i + b_j\right) \quad (6)$$

and the output of the network by

$$y = \sum_{i=1}^{k} (wo_i \cdot h_i), \quad (7)$$

where w_{ji} are the weights connecting the inputs to node j in the hidden layer, b_j is the bias to the node, and wo_i are the weights from the hidden to the output layer.

Depending on the learning algorithm the ANNs can be categorized as:

- Fixed Weight ANNs: these do not need any kind of learning.
- Unsupervised ANNs: These networks are trained (weights are adjusted) based on input data only. The networks learn to adapt using experience gained from previous input.
- Supervised ANNs: These are the most commonly used ANNs. In these networks, the system makes use of both input and output data. The weights and biases are updated for every set of input/output data. The Multi-Layer Perceptron (MLP) falls into this category.

The activation function relates the output of a neuron to its input based on the neuron's input activity level. Some of the commonly used functions include: the threshold, piece-wise linear, sigmoid, tangent hyperbolic, and the Gaussian function [13]. The learning process of the MLP network involves using the input-output data to determine the weights and biases. One of the techniques used to obtain these parameters is the back-propagation algorithm [13,14]. In this method, the weights and biases are adjusted iteratively to achieve a minimum mean square error between the network output and target value.

MLPs are the most widely used ANNs in applications. They have been used mainly for pattern recognition, control, classification, etc. The steps for engineering applications are:

- Step 1: *Input selection – Feature extraction*: this is the first step in any pattern recognition problem. It has a direct effect on the performance and size of the ANN.
- Step 2: *Training data:* The training data are obviously crucial.
- Step 3: *Selection of ANN*: Size – How many inputs, hidden neurons, hidden layers, etc?
- Step 4: *Training of ANN*
- Step 5: *Tests*

There are two different ways in which this algorithm can be implemented: incremental mode and batch mode. In the incremental mode the weights and biases are updated after each input is applied to the network. In the batch mode the weights and biases of the network are updated only after the entire training set has been applied to the network. The batch mode is used in this paper.

IV. Development of the Neural Networks for Rotor Angle and Speed Estimation

The purpose of the ANNs is to estimate the rotor angle and speed of a synchronous machine using voltage and current measurements, which are obtained by PMUs. We have trained two different neural networks: one to estimate the rotor angle (ANN1) and another to estimate the rotor speed (ANN2).

A. Input selection

The inputs to the neural network ANN1 are the voltage, current, angle of voltage and angle of current at the EHV bus, at time instants t, $t-1$ and $t-2$, totaling 12 inputs. The output of the neural network model consists of one neuron representing the rotor angle for a specific operating condition,

$$\delta(t) = f\begin{Bmatrix} v(t), v(t-1), v(t-2), i(t), i(t-1), i(t-2), \theta_v(t), \\ \theta_v(t-1), \theta_v(t-2), \theta_i(t), \theta_i(t-1), \theta_i(t-2) \end{Bmatrix} \quad (8)$$

where $v(t)$ and $i(t)$ are the positive sequence terminal voltage and current at the time t, $v(t-1)$, $v(t-2)$, $i(t-1)$ and $i(t-2)$ are the voltage and current at the time $t-1$ and $t-2$, θ_v and θ_i are the voltage and current angles at the same time instants.

On the other hand, for ANN2 we use the same inputs as with ANN1, with three inputs added, the rotor angle obtained from the output of ANN1 at time instants t, $t-1$ and $t-2$. For this reason the number of inputs for ANN2 is 15. The output of the ANN2 consists of one neuron representing the rotor speed as illustrated in Fig. 3.

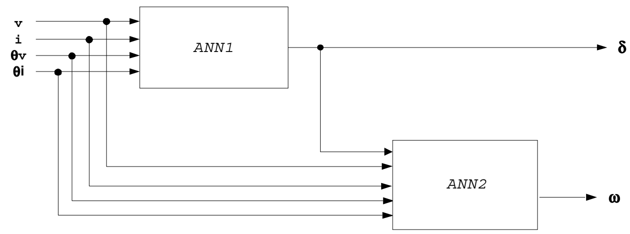

Fig. 3 Arrangement of the ANNs for angle and speed estimation

B. Selection of ANN

The ANNs used are of the multi-layer feed-forward type, with one hidden layer. Fig. 4 represents the multi-layer feed-forward network used for the purpose of this paper.

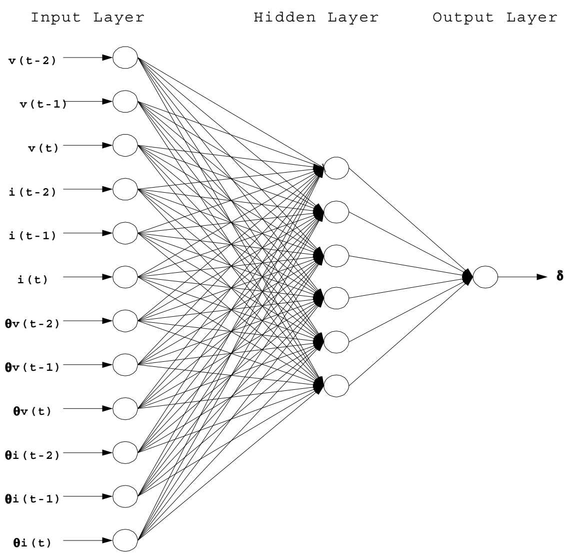

Fig. 4 Proposed layered feed-forward ANN model for rotor angle estimation

The number of units in the hidden layer is determined experimentally, from studying the network behavior during the training process taking into consideration some factors like convergence rate, error criteria, etc. In this regard, different configurations were tested and the best suitable configuration was selected based on the accuracy level required. The number of hidden units for the ANN1 is 40 and the number of hidden units for ANN2 is 35. Tangent hyperbolic activation function is used for these units, while linear activation function is used for output neurons for borh of ANNs . The neural networks were trained off-line.

V. Simulation results

Configuration of a single machine to infinite bus power system is given in Fig. 5 where a synchronous machine is connected to the infinite bus through two parallel transmission lines. This system is very helpful in understanding transient stability basic effects and concepts [15,16].

A. Simulations, training, and testing

The *Neural Network Toolbox* from MATLAB™ [14] software tool was used to create, train and test the neural networks. The training algorithm used is the Levenberg-Marquard algorithm because it provides fast convergence [14].

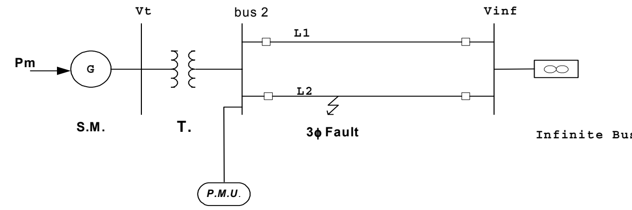

Fig. 5 One Machine to Infinite Bus system

The initial weights as well as the initial biases employed random values between 0-1. The inputs and targets are normalized so that they have values between –1 and 1. A power system may be subjected to different kind of disturbances. It is impossible to use all the responses of the teaching system under different disturbances as the training set. The contingencies represented are three-phase short circuit at beginning of the line L2 or at the end of the same line near to infinite bus.

All the three-phase faults were applied at 0.1 sec. The faults were released either by self-clearance or tripping the faulted line. This is common practice in stability studies. All the disturbances were applied to different generation levels [1100, 850, 600, 500, and 300 MW]. The training data uses 180 patterns, each containing 80 input-output pairs (in average). Total number of input-output pairs is equal to 14400. To test the neural networks 60 unseen patterns are used. Generation of the data for training and testing is summarized in Table I. For each short-circuit and generation level, 3 out of 9 patterns are with fault duration randomly chosen from interval [0.05,CCT-0.01] *ms*, 3 from interval [CCT-0.01,CCT+0.01] *ms*, and 3 from interval [CCT+0.01,0.35] *ms*.

TABLE I
Generation of Training and Testing Data

	Training				Testing			
Gen.	Self-clearing fault		Tripping the line		Self-clearing fault		Tripping the line	
Level (MW)	Beg. Of L2	End of L2	Beg. Of L2	End of L2	Beg. Of L2	End of L2	Beg. Of L2	End of L2
1100	9	9	9	9	3	3	3	3
850	9	9	9	9	3	3	3	3
600	9	9	9	9	3	3	3	3
500	9	9	9	9	3	3	3	3
300	9	9	9	9	3	3	3	3

Testing patterns consist of one pattern from all three, above mentioned, intervals that are not used in training. All real-time environments exhibit some level of noise from instrumentation. The effects of noise on the response of the system are assessed by randomly perturbing the inputs (additive noise uniformly distributed in the range [-0.02,0.02]) to the neural networks. The noise is added to voltage and current magnitude, only. First the ANN1 is trained and tested, according to the procedure descried above, then the same training and testing patterns are used with the ANN2.

To generate the ANNs training and validation data sets, the MATLAB™/ *SIMULINK* software tool [14,17] is used. Also, using this simulation tool the values of voltage and current phasors to compute the rotor angle and speed using the generator classical model, were obtained. The sampling interval in the simulations is taken equal to 20 ms (every cycle of fundamental frequency, this is reasonable value in view of the fact that modern PMUs are capable to provide the measurements every 1-5 cycles [10]). In our simulations a detailed (seventh-order) model of the generator, is used.

B. Results

As a measure of performance, the root mean square error defined as

$$RMSE = \sqrt{\frac{1}{p}\sum_{p}(t_p - o_p)^2}\ , \qquad (9)$$

is determined for each of two ANNs after 1000 iterations of the training rule. In (9), p represents the number of input-output training pairs, t_p is the target output for the $p-th$ training, o_p is the output of the ANN. The RMSEs for training and testing are given in Table II. For the comparison, the RMSEs obtained using the classical generator model for all three presented cases are given in Table III (in equation (9) target output is replaced by exact angle and speed values and the output of the ANN with the values obtained using the classical generator model).

TABLE II
ROOT MEAN SQUARE ERROR AFTER 1000 ITERATIONS

ANN	Training error	Testing error
ANN1	0.0020 (rad.)	0.0092 (rad.)
ANN2	0.0004 (rad./s)	0.0024 (rad./s)

TABLE III
ROOT MEAN SQUARE ERROR FOR THE CLASSICAL GENERATOR MODEL

	Stable	Unstable	Critically stable
Angle (rad)	0.1307	0.1607	0.1803
Speed (rad/s)	0.6004	0.9576	0.6988

Results obtained for three cases (stable, critically stable, and unstable) are presented and compared against the computation of the variables based on the classical generator model. Only the results obtained in the simulations that include the noise in the input variables are included in this paper. All three presented cases correspond to the faults at the beginning of the line L2 released by opening the faulted line. CCT is equal to 0.292 seconds for this particular fault. If the fault duration is less than the CCT, the system response is stable. The evolution of rotor angles and speeds (exact, estimated, and obtained based on classical generator model) are illustrated in Fig. 6 and 7. As the exact values of the rotor angles and speeds are considered those extracted directly from the simulation model.

An unstable system response (fault duration greater than the CCT) is illustrated in Fig. 8 and 9. When the fault duration is equal to the CCT system becomes critically stable. Fig. 10 and 11 represent the variables evolution for this case.

Observe from Fig. 6, 8 and 10 that much better tracking of the rotor angle was obtained by its estimation using the proposed methodology than if we rely on the classical generator model and simple algebraic relations (1,2). Presence of the noise in measured variables results in slightly harsh aspect of rotor angle calculated by (1). Rather harsh aspect in rotor speed is observable in all presented system responses if analytical formulas (1,2) derived from the classical generator model are used. The harsh aspects in rotor angle and speed are much less observable in the estimation using the ANNs. If the level of accuracy, in transient stability

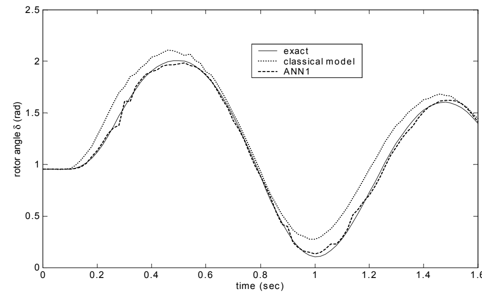

Fig. 6 Rotor angle (stable case)

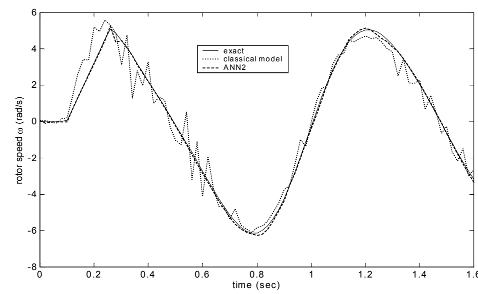

Fig. 7 Rotor speed (stable case)

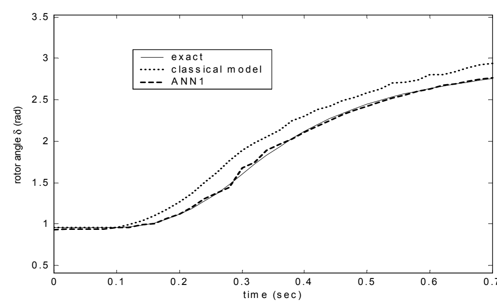

Fig. 8 Rotor angle (unstable case)

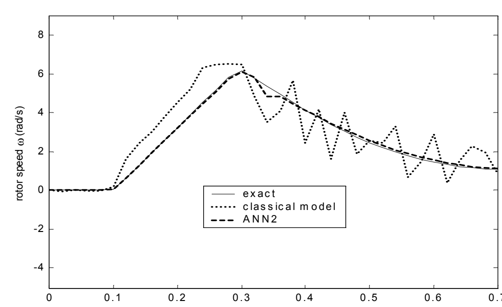

Fig. 9 Rotor speed (unstable case)

assessment and control, is high then observed errors in the computation of the variables using (1,2) can result in wrong prediction and control actions determination. The results clearly indicate that the ANN-based approach to estimate rotor angles and speeds from phasor measurements, has potential to be useful in tracking transient behavior of a power system following a disturbance.

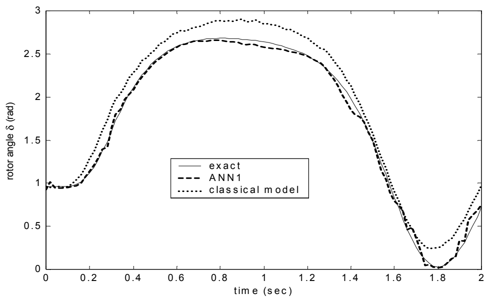

Fig. 10. Rotor angle (critically stable case)

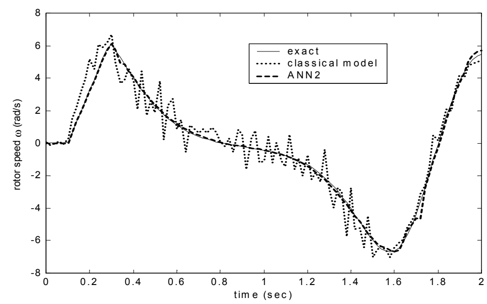

Fig. 11 Rotor speed (critically stable case)

C. Remarks

In this paper, an important question of improved use of the measurements available form PMUs for accurate and reliable dynamic security assessment and control is examined. The primary objective of the paper is to highlight potential of using ANNs for this purpose.

Presented results are preliminary in view of the fact that some practical aspects are not considered. Although identified as a source of uncertainties the lack of direct measurements of plant auxiliaries is not considered. In addition, different measurement rates from PMUs should be examined (more than every cycle of fundamental frequency as used in this paper). Selection of input variables is not justified in this paper. Further work will be carried out on the selection of input variables, modeling of PMUs, and all the mentioned aspects not included in this paper. Despite of the high accuracy of available PMUs there is other equipment "in the loop", such as voltage and current transformers, that may introduce errors and added noise in the simulations mimics these errors.

VI. Conclusions

The use of the ANNs to estimate synchronous machine rotor angles and speeds from phasor measurements, is presented in this paper. The proposed approach includes two ANNs, one to estimate rotor angle and another, that include estimated angle as the input signal, to estimate rotor speed. Results obtained with help of a simple one machine to infinite bus system are presented and compared to those obtained using the classical generator model and simple algebraic relation of phasor measurements to rotor angles and speeds. Presented system responses (stable, critically stable, and unstable) indicate that the proposed approach outperforms the approach based on classical generator model. Ongoing process of restructuring electric power industry will increase need for reliable and accurate transient stability assessment and control. The use of ANNs for this purpose offers attractive way to cope with these new requirements. Further work will be carried out by using real PMUs coupled with a power system simulator, on investigating influence of plant auxiliaries, and estimating center of angles and speeds of a individual power plant comprising more generating units. Further work will be directed by aims defined within the EXaMINE project [7].

VII. Acknowledgment

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