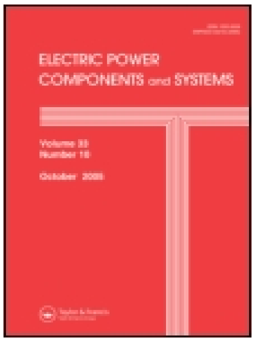

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Power System State Forecasting Using Artificial Neural Networks

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Power System State Forecasting Using Artificial Neural Networks

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This paper presents a new method for power system state forecasting using artificial neural networks (ANN). The state forecasting problem has been solved in two steps: the filtering step and the forecasting step in an open loop configuration. Because under normal operating conditions the power system behaves in a quasi-static manner, a simplified model of the dynamic behavior of the power system states is considered. Two different ANN models have been used for these two steps of power system state forecasting problem. For the filtering step, a functional link network (FLN), and for the forecasting step, a time delay neural network (TDNN) have been used to simulate the dynamic behavior of the power system states. The proposed method has been tested on two IEEE test systems, and a practical Indian system and results have been compared with an extended Kalman filter (EKF) based technique [Leite da Silva et al., 1983].

1 Introduction

Electrical power systems are complex dynamic systems in which system characteristics fluctuate with various loads and generation schedules. Over time, the operating point (state vector) of a power system changes. Real-time monitoring of an electric power system is performed at energy control centers in order to ensure its secure operation. The monitoring function involves estimation of the state vector of the power system. The state vector, which consists of voltage magnitudes and phase angles at all the nodes, varies with time, owing to the dynamic nature of the system loads. Therefore it is necessary to establish a dynamic model for the time behavior of the power system states, whereas the dynamic modeling and detailed representations of power plants are outside the scope of the state forecasting problem [Rousseaux et al., 1990].

The power system state forecasting problem consists of prediction of the state vector based on their past estimations, followed by a filtering process performed

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when a new set of measurements is available. It is extremely useful for security assessment of electric power system, as it gives the system operator a longer decision time.

In the literature the dynamic behavior of the power system states (x) has been modeled in three different ways [Rousseaux et al., 1990; Rousseaux et al., 1988]. The first model directly uses the dynamic modeling of the conventional state variables. In the second model the dynamic modeling is based on the load prediction. The third model uses hierarchical state estimation to overcome the dimensionality problem.

[Debs and Larsen, 1970] considered an oversimplified dynamic linear model of system state (x)

$$x(k+1) = x(k) + w(k), \tag{1}$$

where the system evolution is taken into account via the system noise vector $w(k)$. [Nishiya et al., 1976] introduced a trend component $c(k)$ to estimate the state

$$x(k+1) = x(k) + c(k) + w(k), \tag{2}$$

where $c(k) = (\hat{x}(k/k) - \hat{x}(k-1/k-1))$,

$\hat{x}(k/k) =$ estimated value of states at time step k.

[Leite da Silva et al., 1983] arrived at a more appealing dynamic modeling

$$x(k+1) = F(k)x(k) + e(k) + w(k), \tag{3}$$

where $e(k) =$ control vector,

$F(k) =$ diagonal Jacobian matrix of state transition function with respect to x.

[Mallieu et al., 1986] solved prediction step on the basis of nodal power injections rather than the conventional state variables (x) consisting of bus voltages. The state forecasting problem has been solved using two steps, viz., state forecasting and state filtering. In the first step, the forecasted state vector and its covariance matrix were evaluated using linear exponential smoothing principle. Once a new set of measurements is available, in the second step the state vector is filtered based on a weighted least squares method, where the squared residues of the predicted state vector and the measurement vector are weighted by their covariance matrices. To overcome dimensionality problems, hierarchical dynamic state estimators were proposed [Bahgat et al., 1989]. It uses the decomposition of the overall system into small subsystems, which are easier to handle.

Neural network models are providing new approaches to problem solving [Mori et al., 1992; Vankayala et al., 1993]. Artificial neural networks can achieve high computational speed by employing a massive number of simple processing elements arranged in parallel with a high degree of connectivity between the elements. The dynamic behavior of neural networks exhibits stable states that act as a basin of attraction toward which neighboring states develop in time. In practice, most of the real-world problems of power system are time varying in nature. Hence, static neural nets cannot be used, and dynamic neural networks should be used for such time varying systems.

An attempt has been made in this paper to apply a dynamic neural network model to solve the state forecasting problem probably for the first time. A TDNN based on back propagation algorithm (BPA) has been used for the state forecasting step, and an FLN has been used for the state filtering step. The ANN-based state forecasting problem has been tested on IEEE 14-bus, IEEE 57-bus, and a practical 19-bus Indian system, and results have been compared with those obtained from an EKF-based model [Leite da Silva et al., 1983].

2 State Forecasting in Electric Power System

A power system is considered to be in quasi-static state, and its state estimation is carried out at present at time intervals of few minutes (time samples). At each time sample (k), the state $x(k)$ is estimated from measurements $z(k)$ using the dynamic behavior of power systems states (x).

The measurements used for real-time monitoring basically consists of real and reactive power bus injections, line flows, and bus voltage magnitudes. The measurements are related to the state vector by the nonlinear equation:

$$z(k) = h(x(k)) + v(k) \tag{4}$$

where

$z(k) =$ m-dimensional measurement vector,
$h(\bullet) =$ m-dimensional nonlinear vector function relating z to x,
$v(k) =$ m-dimensional measurement error vector.

The power system state dynamic model is of the following general form:

$$x(k+1) = f(x(k), w(k), k), \tag{5}$$

where

$x =$ n-dimensional state vector,
$f =$ n-dimensional nonlinear state transition function,
$w(k) =$ system noise vector.

Most of the algorithms of dynamic state estimation are based on EKF [Rousseaux et al., 1990], which provides a linear minimum variance estimate of the state vector (x). Some of the features of the EKF method are as follows:

(i) The EKF consists of alternate sequences of prediction and filtering steps.
(ii) The filtering step uses the measurement model equation (4), which naturally involves the conventional state vector (x).
(iii) The prediction step uses the system state dynamic model equation (5).

The EKF method given in [Leite da Silva et al., 1983] uses system state dynamic model

$$x(k+1) = F(k)x(k) + G(k) + w(k), \tag{6}$$

where $F(k) =$ nonzero diagonal matrix with dimension $(n \times n)$

$G(k) =$ nonzero vector with dimension $(n \times 1)$.

The parameters $F(k)$ and $G(k)$ are defined according to Holt's 2-parameter linear exponential smoothing method of forecasting. The following models have been used for state forecasting and state filtering steps [Leite da Silva et al., 1983].

State Forecasting Step

If $x(k)$ and $\Sigma(k)$ are estimates for the state vector and its covariance matrix, respectively, at time k, be performing the conditional expectation operator on equation (6), the forecasted state vector $\tilde{x}(k+1)$ with its covariance matrix $M(k+1)$ are given by

$$\tilde{x}(k+1) = f(k)\hat{x}(k) + G(k), \tag{7}$$

$$M(k+1) = F(k)\Sigma(k)F^T(k) + Q(k), \tag{8}$$

where $Q(k) =$ covariance matrix of $w(k)$ and $\hat{x}(k)$ in the predicted value of states for interval k.

State Filtering Step

When a new set of measurements $z(k+1)$ is available, the predicted state vector $\tilde{x}(k+1)$ can be filtered and a new estimate $\hat{x}(k+1)$ is then obtained, together with its error covariance $\Sigma(k+1)$. This considers the following objective function for the filtering process at time $(k+1)$:

$$J(x) = [z - h(x)]^T R^{-1}[z - h(x)] + [x - \tilde{x}]^T M^{-1}[x - \tilde{x}]. \tag{9}$$

To simplify the notation, the time index $(k+1)$ has been omitted from all variables in equation (9). The approximated filtering state vector can be written as follows:

$$\hat{x}(k+1) = \tilde{x}(k+1) + K(k+1)v(k+1), \tag{10}$$

where

$$v(k+1) = z(k+1) - h(x(k+1)) = \text{innovation vector},$$

$$K(k+1) = [H^T R^{-1} H + M^{-1}]H^T R^{-1} = \text{gain matrix}.$$

3 Proposed ANN-Based State Forecasting

To capture the dynamics of the power system states, a nonlinear temporal dynamic model of ANN is required for the state forecasting. Memory structures are an important component of dynamic neural networks. In fact, a dynamic neural network can be thought of as a static model network extended with a short-term memory. There are two ways of incorporating time information into ANNs [Kung, 1993]. The first technique is to use a spatial representation of time, such as TDNNs. In these ANNs, time information is represented spatially across the network input, and the ANNs compute a static mapping from the input to output. In the second technique, time is represented implicitly by using a recurrent ANN architecture, that is, the effect of temporal evolution are captured in the state of the network. In this paper, TDNN has been used for the forecasting step.

[Vinod Kumar et al., 1996] developed four different ANN models based on multilayer perceptron, FLN, counterpropagation network (CPN), and Hopfield network to solve the static state estimation problem. Out of these four models, FLN was found to be most suitable for static state estimation. Moreover, it was established that the FLN model has superior inherent filtering capability for bad data in the measurement set, compared with other neural network models. Also, the FLN-based

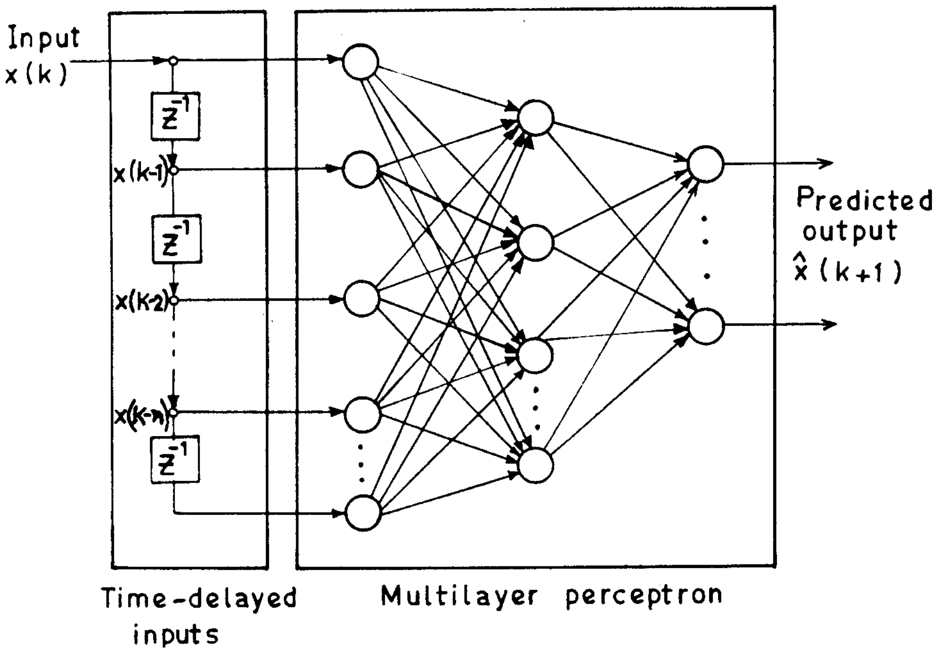

Figure 1. Time-delay neural network.

static state estimator provides system states in one forward pass and does not involve any iterative process. Hence, the FLN has been used in the present work for the state filtering step. The TDNN and FLN neural network models are briefly described below.

3.1 Time-Delay Neural Network

The most common feed forward networks are static, having no internal time delays and responding to a particular input by immediately generating a specific output. Static networks can respond to temporal patterns if the network inputs are delayed samples of the input signals, i.e., time is treated as another dimension in the problem. An architecture like this is often referred to as a TDNN. These networks, trained with standard back propagation algorithm, have been used as adaptive filters for noise reduction and echo canceling and for chaotic time series prediction [Hush and Horne, 1993].

The TDNN consists of an input layer with delay units, one hidden layer (neurons with sigmoidal activation function), and an output layer (neurons with summation function). The TDNN is nonrecurrent and copes with time alignment by explicitly delaying the signal waveform by a fixed time span. In this, the basic units are modified by introducing delays, as shown in Figure 1. The inputs to such a unit are multiplied by several weights, one for each delay and one for the undelayed input. For example, if a TDNN consists of 2 delays ($D = 2$) and 16 inputs ($I = 16$), 48 weights will be needed to compute the weighted sum of the 16 inputs, with each input now measured at three different points in time. In this way, a TDNN unit has the ability to relate and compare current input to the past history of events.

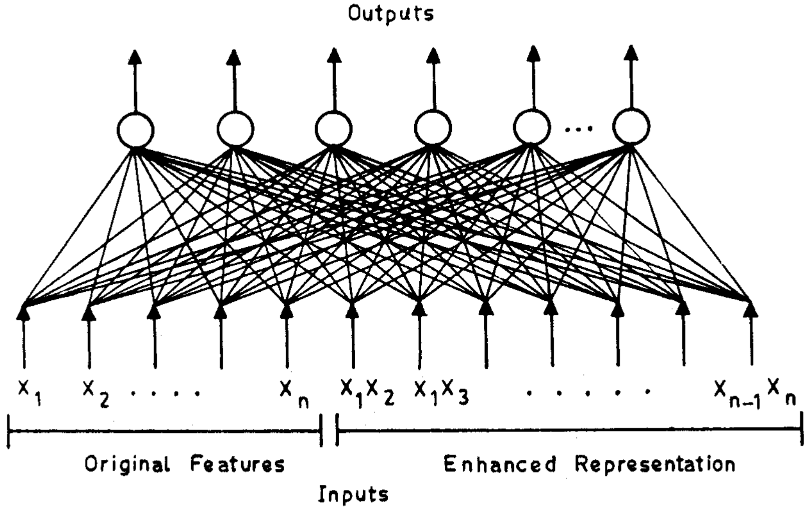

Figure 2. Functional link network.

TDNN is capable of modeling systems where the output has a finite temporal dependence on the input, that is

$$x(k+1) = F\,[x(k), x(k-1), \ldots x(k-n)], \tag{11}$$

where $F(\bullet)$ is the nonlinear function.

Back propagation algorithm has been used as the learning procedure [Rumelhart et al., 1987], which works well for classification, prediction, function estimation, and time series tasks [Hammerstrom, 1993].

3.2 Functional Link Network

In FLN, [Yoh-Han, 1989], the input patterns are enhanced by means of functional transformations before feeding to the input layer of the actual network. An enhanced input/output pair is learnt with a flat net, that is, a net with no hidden layer. Problems that might be difficult in the original pattern space generally become quite straightforward in the enhanced representation space. There is mathematical basis, as well as pragmatic evidence, that supervised learning can be achieved exceedingly well with a flat net and delta rule if the enhancements are done correctly. The flat architecture of the FLN exhibits highly desirable learning capabilities and, in some applications, drastically reduces the convergence time. The benefit of the FLN, when applied to mathematical modeling, is the increased accuracy of mapping through the expansion of the basic set. The functional link network is illustrated schematically in Figure 2.

There are two models of the FLN: a tensor (or outer product) model and the functional expansion model. In this paper, supervised tensor model of FLN has been used. In the tensor model, each component of the input pattern multiplies the entire input pattern vector. The functional link in this case generates an entire vector from each of the individual components using transformation, such as

$$\{x_i\} \Rightarrow \{x_i, x_ix_j\} \Rightarrow \{x_i, x_ix_j, x_ix_jx_k\} \Rightarrow \ldots. \tag{12}$$

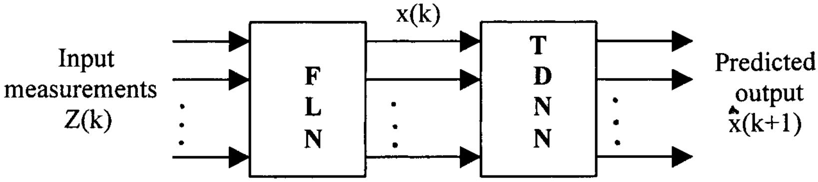

Figure 3. ANN-based state forecasting model.

The idea of FLN is very close to that of series expansion. In the present work, only second-order models have been used. Because functional link networks do not have a hidden layer, simple delta rule [Rumelhart et al., 1987] has been used for training.

4 Development of ANN-Based State Forecasting Model

The state forecasting and filtering steps have been attempted by using FLN and TDNN, respectively. Past history of state variables up to time (k) has been used to forecast the states at time $(k + 1)$.

The inputs to the FLN are real-time measurements consisting of real and reactive power bus injections and line flows, whereas the desired outputs are the state variables. The output of the FLN computed for time (k) has been used as the input to the TDNN, which forecasts the system states for time $(k + 1)$. A block diagram for the ANN-based state forecasting model is shown in Figure 3, and a general state forecasting model in an open loop configuration is shown in Figure 4.

The time evolution of the operating states of a power system is basically determined by the continuous variation of the system loads. In daily operation, the loads vary according to cyclic patterns superimposed by small, random fluctuation. Training patterns for the state forecasting were generated for a base case using a load flow program considering an assumed linear variation of loads.

5 Simulation Results

The training and testing of ANNs have been carried out on DEC Alpha Workstation and HP9000 computer for IEEE 14-bus, IEEE 57-bus, and a 19-bus practical Indian system. The 19-bus Indian system represents a 400-kV network of Uttar Pradesh State Electricity Board (UPSEB), presently being monitored through telemetry link.

The load curve at each bus is composed of a linear trend plus a random fluctuation (jitter). The linear trend for the load curve is adopted to take into account the previous history of the state vector. Even though loads at each bus is varied randomly, training of the neural networks can be done similar to the proposed one.

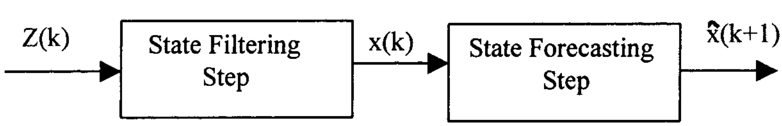

Figure 4. State forecasting model in an open loop configuration.

Table 1
Comparison of accuracy of state forecasting models

Test system	Maximum absolute error in voltage magnitude (p.u.)		Maximum absolute error in phase angle (rad.)	
	ANN model	EKF model	ANN model	EKF model
IEEE 14-bus system	0.0015	0.0067	0.0026	0.0570
IEEE 57-bus system	0.0032	0.0365	0.0043	0.0729
19-bus practical system	0.0029	0.0992	0.0058	0.1185

Table 2
Comparison of CPU time (in seconds)

Model	IEEE 14-bus system	IEEE 57-bus system	Practical 19-bus system
ANN	0.04860	0.17844	0.07153
EKF	3.00000	120.51000	6.40000

Training patterns were generated for base case using a load flow program by varying the loads at each bus linearly, covering the whole range of operating conditions from 20% to 120% of the base case load curve for the IEEE 14-bus and IEEE 57-bus systems, whereas for the 19-bus practical Indian system, loading conditions were varied linearly from 20% to 110% of the base case. Beyond 110% loading, the load flow did not converge for the practical 19-bus Indian system. The jitter was represented by a normal distribution random number with zero mean and standard deviation as 3% of the actual physical value of the measurements.

The two ANN models, viz., FLN and TDNN were trained separately for the training patterns generated from the load flow. For training the FLN, 1000 patterns were generated by varying the loads at each bus covering the whole operating range of the base case load curve, out of which 800 patterns were used for training and 200 patterns were used for testing.

The inputs to the FLN for IEEE 14-bus, IEEE 57-bus, and 19-bus Indian system were 68, 274, and 88, respectively. These measurements consist of real and reactive power line flows and bus injections. The FLN-based filter had voltage magnitude and phase angle at all the buses as outputs. Hence, output nodes of the FLN for the IEEE 14-bus, IEEE 57-bus, and 19-bus Indian system were 28, 114, and 38, respectively. The learning rate (η) and momentum (α) for the three systems were taken as 0.8 and 0.3 for the first 100 iterations, and 0.65 and 0.35 in subsequent iterations. The change in (η) and (α) values after 100 iterations helped in accelerating the convergence. After training, the FLN-based filter was tested for the novel input patterns corresponding to different loading conditions. It was established in [Vinod Kumar et al., 1996] that the FLN can solve static state estimation with less than 1% error.

Table 3
EKF results for IEEE 14-bus system

Bus No.	Voltage magnitude (true value)	Phase angle (true value)	Voltage magnitude (EKF results)	Phase angle (EKF results)	Voltage magnitude (absolute error)	Phase angle (absolute error)
1	1.0600	0.0000	1.0665	0.0000	0.0065	0.0000
2	1.0450	−0.0870	1.0504	−0.1056	0.0054	0.0186
3	1.0100	−0.2223	1.0161	−0.2708	0.0061	0.0485
4	1.0155	−0.1795	1.0104	−0.2156	0.0051	0.0361
5	1.0183	−0.1529	1.0127	−0.1834	0.0056	0.0305
6	1.0700	−0.2482	1.0765	−0.2998	0.0065	0.0516
7	1.0605	−0.2328	1.0588	−0.2796	0.0017	0.0468
8	1.0900	−0.2328	1.0967	−0.2796	0.0067	0.0468
9	1.0550	−0.2604	1.0504	−0.3127	0.0046	0.0523
10	1.0502	−0.2632	1.0462	−0.3163	0.0042	0.0531
11	1.0565	−0.2580	1.0569	−0.3107	0.0004	0.0527
12	1.0551	−0.2631	1.0581	−0.3176	0.0030	0.0545
13	1.0502	−0.2644	1.0516	−0.3189	0.0014	0.0545
14	1.0349	−0.2796	1.0292	−0.3366	0.0057	0.0570

Table 4
ANN-based state forecasting for IEEE 14-bus system

Bus No.	Voltage magnitude (true value)	Phase angle (true value)	Voltage magnitude (ANN results)	Phase angle (ANN results)	Voltage magnitude (absolute error)	Phase angle (absolute error)
1	1.0600	0.0000	1.0603	0.0000	0.0003	0.0000
2	1.0450	−0.0870	1.0455	−0.0882	0.0005	0.0012
3	1.0100	−0.2223	1.0115	−0.2229	0.0015	0.0006
4	1.0155	−0.1795	1.0158	−0.1815	0.0003	0.0020
5	1.0183	−0.1529	1.0195	−0.1555	0.0012	0.0026
6	1.0700	−0.2482	1.0711	−0.2491	0.0011	0.0009
7	1.0605	−0.2328	1.0607	−0.2332	0.0002	0.0004
8	1.0900	−0.2328	1.0910	−0.2336	0.0010	0.0008
9	1.0550	−0.2604	1.0551	−0.2618	0.0001	0.0014
10	1.0502	−0.2632	1.0512	−0.2639	0.0010	0.0007
11	1.0565	−0.2580	1.0570	−0.2596	0.0005	0.0016
12	1.0551	−0.2631	1.0558	−0.2652	0.0007	0.0021
13	1.0502	−0.2644	1.0513	−0.2654	0.0011	0.0010
14	1.0349	−0.2796	1.0353	−0.2817	0.0004	0.0021

Table 5
EKF results for IEEE 19-bus practical system

Bus No.	Voltage magnitude (true value)	Phase angle (true value)	Voltage magnitude (EKF results)	Phase angle (EKF results)	Voltage magnitude (absolute error)	Phase angle (absolute error)
1	1.0300	0.0000	1.0363	0.0000	0.0063	0.0000
2	1.0300	0.0162	1.0363	0.0145	0.0063	0.0017
3	1.0300	0.0166	1.0363	0.0146	0.0063	0.0020
4	1.0300	0.0252	1.0363	0.0247	0.0063	0.0005
5	1.0274	−0.0732	1.0217	−0.0821	0.0057	0.0089
6	1.0245	−0.0913	1.0159	−0.1012	0.0086	0.0099
7	1.0266	−0.0855	1.0217	−0.0959	0.0049	0.0104
8	1.0260	−0.0759	1.0194	−0.0848	0.0066	0.0089
9	1.0030	−0.2320	0.9734	−0.2595	0.0296	0.0275
10	1.0086	−0.2819	0.9717	−0.3171	0.0369	0.0352
11	1.0172	−0.3887	0.9624	−0.4435	0.0548	0.0548
12	1.0510	−0.6260	0.9550	−0.7407	0.0960	0.1147
13	1.0652	−0.6401	0.9660	−0.7586	0.0992	0.1185
14	1.0548	−0.6231	0.9574	−0.7368	0.0974	0.1137
15	1.0270	−0.3726	0.9743	−0.4242	0.0527	0.0516
16	1.0275	−0.3674	0.9756	−0.4180	0.0519	0.0506
17	1.0617	−0.5448	0.9867	−0.6341	0.0750	0.0893
18	1.0647	−0.5301	0.9882	−0.6154	0.0765	0.0853
19	1.0564	−0.6110	0.9592	−0.7208	0.0972	0.1098

For training and testing the TDNN, 200 patterns were generated. Out of these, 160 patterns were used to train the neural network, and the remaining 40 patterns were used to test the accuracy and robustness of the ANN. The inputs to the TDNN for the IEEE 14-bus, IEEE 57-bus, and 19-bus Indian systems were twice the number of buses (voltage magnitude and phase angle at each bus) in the respective power systems. Therefore, the input nodes to the multilayer perceptron for IEEE 14-bus, IEEE 57-bus, and 19-bus Indian systems were 28, 114, and 38, respectively. The sliding window consisted of three time delay units for each input. The outputs of the TDNN were the predicted values of the state variables. Hence, the output nodes were the same in number as the input nodes. The number of hidden nodes for the IEEE 14-bus, IEEE 57-bus, and 19-bus practical Indian systems were 50, 135, and 60, respectively, which was decided based on hit and trial. The learning rate (η) of 0.002 and momentum (α) of 0.1 were taken for all three systems. For training, a convergence criterion of 0.001 p.u. and maximum number of iterations of 15,000 were used for all the three systems.

The state forecasting problem was also solved using EKF [Leite da Silva et al., 1983] for all three systems. The results of the ANN-based state forecasting and EKF model were compared with those obtained from the load flow for the known load patterns and maximum absolute error in voltage magnitude (p.u.) and phase angle (radians), and are presented in Table 1. The CPU time required for finding the state forecasting solution using the proposed ANN-based and EKF model are given

Table 6
ANN-based state forecasting results for 19-bus practical system

Bus No.	Voltage magnitude (true value)	Phase angle (true value)	Voltage magnitude (ANN results)	Phase angle (ANN results)	Voltage magnitude (absolute error)	Phase angle (absolute error)
1	1.0300	0.0000	1.0304	0.0000	0.0004	0.0000
2	1.0300	0.0162	1.0308	0.0168	0.0008	0.0006
3	1.0300	0.0166	1.0306	0.0165	0.0006	0.0001
4	1.0300	0.0252	1.0310	0.0291	0.0010	0.0039
5	1.0274	−0.0732	1.0282	−0.0790	0.0008	0.0058
6	1.0245	−0.0913	1.0261	−0.0952	0.0016	0.0039
7	1.0266	−0.0855	1.0295	−0.0897	0.0029	0.0042
8	1.0260	−0.0759	1.0285	−0.0784	0.0025	0.0025
9	1.0030	−0.2320	1.0048	−0.2364	0.0018	0.0044
10	1.0086	−0.2819	1.0097	−0.2848	0.0011	0.0029
11	1.0172	−0.3887	1.0188	−0.3922	0.0016	0.0035
12	1.0510	−0.6260	1.0535	−0.6292	0.0025	0.0032
13	1.0652	−0.6401	1.0671	−0.6444	0.0019	0.0043
14	1.0548	−0.6231	1.0564	−0.6269	0.0016	0.0038
15	1.0270	−0.3726	1.0292	−0.3751	0.0022	0.0025
16	1.0275	−0.3674	1.0286	−0.3684	0.0011	0.0010
17	1.0617	−0.5448	1.0627	−0.5467	0.0010	0.0019
18	1.0647	−0.5301	1.0664	−0.5348	0.0017	0.0047
19	1.0564	−0.6110	1.0581	−0.6142	0.0017	0.0032

in Table 2. It is seen from Tables 1 and 2 that the ANN-based model has provided state forecasting results with much less error, compared with EKF model, and its takes approximately 0.20 seconds CPU time for all three systems, compared with much larger time required by the EKF method. The state forecasting results for the IEEE 14-bus system and for the 19-bus practical system using the EKF method and using the proposed ANN model are given in Tables 3 and 4 and Tables 5 and 6, respectively.

6 Conclusions

This paper has presented a new model of state forecasting based on ANNs. The FLN model was used for the filtering step, and the TDNN model was used for the forecasting step. The results presented for the three systems reveal that

(i) The ANN-based state forecasting model predicts the system states more accurately, compared with the EKF model. The maximum absolute error in voltage magnitude with the ANN model was about 0.33% for 57-bus system, whereas with the EKF model it went up to 9.5% for the 19-bus system. The maximum absolute error in phase angle with the ANN model was 0.0058 radians, whereas with the EKF model it was 0.1185 radians for the 19-bus system.

(ii) The CPU time for solving the state forecasting problem based on EKF model increases as the number of buses in the system increases, whereas with the ANN model, CPU time required is less than 0.20 seconds for all the three systems, which is much less compared with the EKF model.

Results could not be tested on the real-time system data, however, as these are not available for the practical system considered. It is envisaged that the proposed model of ANNs for the state forecasting will also work effectively with the real-time data.

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