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Neo-Fuzzy Integrated Adaptive Decayed Brain Emotional Learning Network for Online Time Series Prediction

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ABSTRACT Adaptive decayed brain emotional learning (ADBEL) network is recently proposed for the online time series forecasting problems. As opposed to other popular learning networks, such as multilayer perceptron, adaptive neuro-fuzzy inference system, and locally linear neuro-fuzzy model, ADBEL network offers lower computational complexity and fast learning, which make it an ideal candidate for the time series prediction in an online fashion. In fact, these prominent features are inherited from the mechanism employed by the limbic system of the mammalian brain in processing the external stimuli, which also forms the basis of the ADBEL network. This paper aims at further enhancing the forecasting performance of the ADBEL network through its integration with a neo-fuzzy network. The selection of the neo-fuzzy network is made as it offers features required for online prediction in real time environments including simplicity, transparency, accuracy, and lower computational complexity. Furthermore, this integration is only considered in the orbitofrontal cortex section of the ADBEL network and only three membership functions are employed to realize the neo-fuzzy neuron. Thus, the resultant neo-fuzzy integrated ADBEL (NF-ADBEL) network is still simple and can be deployed in online prediction problems. Few chaotic time series namely the Mackey glass, Lorenz, Rossler, and the Disturbance storm time index as well as the Narendra dynamic plant identification problem are used to evaluate the performance of the proposed NF-ADBEL network in terms of the root mean squared error and correlation coefficient criterions using MATLAB®programming environment.

INDEX TERMS Brain emotional decayed learning, neo-fuzzy network, chaotic time series, dynamic plant identification, MATLAB.

I. INTRODUCTION

Brain emotional learning (BEL) networks are the computational models mimicking the method employed by the mammalian brain in processing of the emotional stimuli as described by LeDoux [1], [2]. According to him, the emotional stimuli are processed faster than the normal stimuli due to the existence of shorter paths in a part of brain known as the emotional brain, which has a psychological description as well [3]. The parts of the emotional brain responsible for processing the emotional stimuli include thalamus, sensory cortex, amygdala, orbitofrontal cortex and hippocampus. The process is initiated after the emotional stimulus is received by the thalamus which submits imprecise information regarding the stimulus to the amygdala. The stimulus is also propagated to amygdala through sensory cortex which forms a longer path than the path between thalamus and amygdala. Further, the sensory cortex also passes on the stimulus information to the orbitofrontal cortex. Amgdala responds to the received emotional stimulus quickly and produces an emotional response. Amygdala also submits this emotional response to the orbitofrontal cortex which evaluates this response and rectifies it with the help of context provided by the hippocampus. This emotional process is depicted in Fig. 1.

The aforementioned emotional process in the mammalian brain forms the basis of the computational models of the emotional brain. The first such model appeared in [4] and [5]. In this model, the imprecise information submitted by the

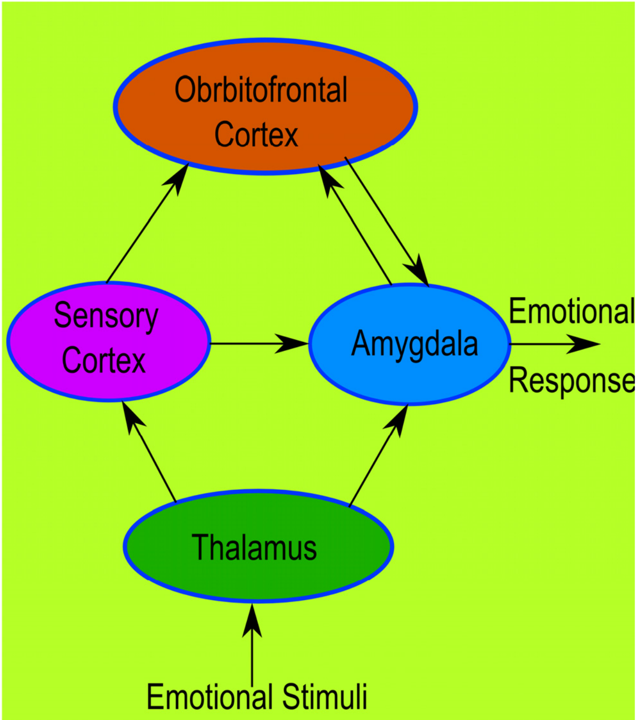

FIGURE 1. Generation of emotional response by the emotional brain.

thalamus to amygdala is the maximum value of the stimulus and the rectifying operation of the orbitofrontal cortex is achieved using the suppression operator i.e., the output from the BEL model is the emotional response of the amygdala minus the output from the orbitofrontal cortex. A reinforcement signal R_o is also computed for the model to learn, which is given as [20]:

$$R_o = \begin{cases} \left(\sum a_i - rew\right)^+ - \sum o_i, & rew \neq 0 \\ \left(\sum a_i - \sum o_i\right)^+, & otherwise \end{cases} \tag{1}$$

Where $\sum a_i$ represents the amygdala output while $\sum o_i$ is the orbitofrontal cortex output. This reinforcement signal is used to adjust the weights of the BEL model to improve its response. Thus through a history of input rewards and punishment signals, the model is made to learn the desired response to the emotional stimuli. However, it is not clear how the value is assigned to '*rew*' signal in the learning process. In other BEL models [6]–[18], this signal is computed as the weighted combination of a set of reinforcement factors related to a process [20]:

$$rew = \sum w_j r_j \tag{2}$$

The special way of computing '*rew*' signal as in (2) makes the model less efficient in learning opposite behaviors but works well for a specific problem. The BEL models with '*rew*' given by (2) have shown great success in various real time applications including home appliances [7], robotics [8]–[10], electrical drives [11]–[13] and other industrial systems [14]–[16]. These models have also been used for time series prediction problems [17], [18] where their performance in predicting the peak points are excellent but not for all points especially the performance is poor at valley points in the time series data. In order to improve the performance of these BEL models, supervised BEL models are proposed in [19] and [20]. These models employ the pattern-target samples in a supervised fashion for their learning and assign target values to '*rew*' signal during the learning process [20]:

$$rew = t \tag{3}$$

The benefit of using target-pattern samples is that the model can be adjusted to follow peak or valley points in the time series data while the shortcoming is that the model can only yield good results for the recent inputs and the performance is degraded for the case of distant examples. A decay rate is added in the BEL model to overcome this weakness which has a neurobiological basis [21] also. The resulting BEL model is named as ADBEL and has shown good performance for online time series forecasting as reported in [19] and [20].

This paper considers the integration of neo-fuzzy network [22]–[25] with ADBEL network to yield a new NF-ADBEL network with improved forecasting performance. Both the ADBEL and neo-fuzzy networks share important features of simplicity, accuracy and lesser computational complexity which are very much desired for online forecasting problems. Thus, it is natural to investigate a hybrid forecasting model based on these two networks. To the best of author's knowledge, no such hybrid model has yet been explored in the literature. The proposed NF-ADBEL network is simulated in MATLAB (R2009b) programming environment to forecast a number of chaotic time series in an online mode including Mackey Glass, Lorenz, Rossler, Narendra and Disturbance Storm Time index. The comparison of prediction performance of both the networks in terms of RMSE and COR criterions reveals the superiority of the proposed NF-ADBEL network in online forecasting problems. Please note that the comparison of NF-ADBEL network with the popular networks like MLP, ANFIS and LLNF will not be produced here as ADBEL network has already been shown to perform better than these networks [19], [20] for online time series forecasting problems. Also, both ADBEL and the proposed NF-ADBEL networks are not trained prior to perform predictions while other aforementioned networks need to be trained before they can be deployed to do predictions.

We start by reviewing ADBEL and neo-fuzzy networks in section II and III respectively. The proposed neo-fuzzy integrated ADBEL network is presented in section IV followed by simulation results in section V. Conclusions are drawn in section VI.

II. REVIEW OF ADBEL NETWORK

ADBEL network is proposed in [19] and [20] for the time series prediction in a supervised way. It is different from other BEL models as it can be used in an online fashion and no prior

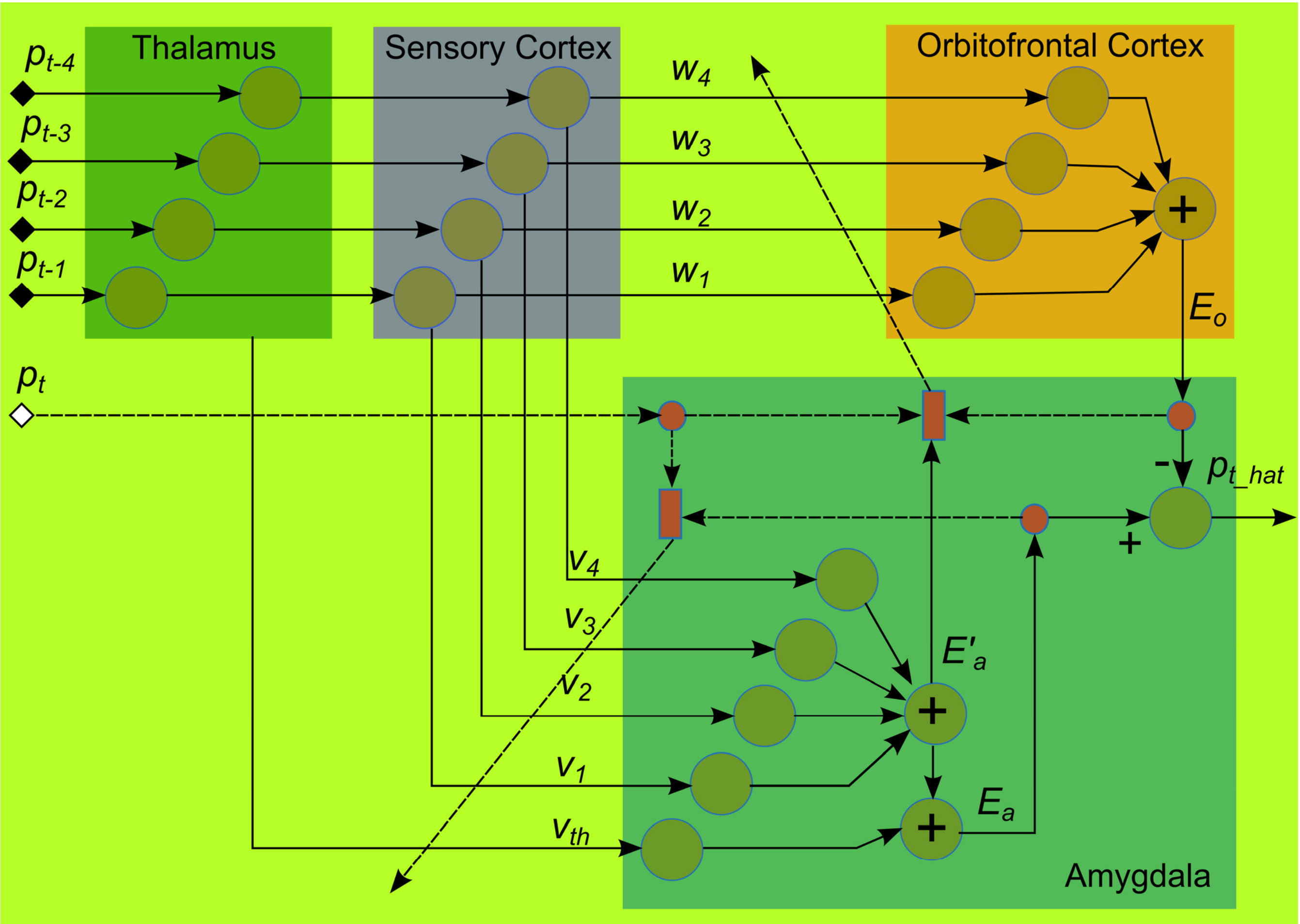

FIGURE 2. **ADBEL network.**

training is required before using the network. In fact, ADBEL network trains itself in online mode using an internal reward signal. As opposed to other BEL models, ADBEL network uses a decay rate which has a neurobiological basis and serves to improve the performance of the network. A schematic representation of the network is given in Fig. 2.

ADBEL network has four inputs $(p_{t-4}, p_{t-3}, p_{t-2}, p_{t-1})$ and one output (p_t), as can be seen from Fig. 2. The four inputs are actually the time series values at previous four time instants while the output is the predicted value of the time series at the current time instant. This mapping can be given as:

$$\hat{p}_t = f\left(p_{t-4}, p_{t-3}, p_{t-2}, p_{t-1}\right) \tag{4}$$

The working of ADBEL network is such that after the inputs are presented to the network, a maximum value is computed by the thalamus (m) which then submits it to the amygdala. The inputs are then transferred to the sensory cortex which submits these inputs to the amygdala and orbitofrontal cortex through the weights v_j's and w_j's respectively. Amygdala after receiving the five inputs produces two outputs, E_a and E'_a as:

$$\begin{aligned} E_a &= E'_a + v_{th} m \\ E'_a &= \sum_{j=1}^{4} v_j p_{t-j} \\ m &= \max_{j=1}^{4} \left(p_{t-j}\right) \end{aligned} \tag{5}$$

Similarly, orbitofrontal cortex produces an output, E_o as:

$$E_o = \sum_{j=1}^{4} w_j p_{t-j} \tag{6}$$

The final output from ADBEL network i.e., the predicted value of the time series at the current time stamp is found as:

$$\hat{p}_t = E_a - E_o \tag{7}$$

The step (5)-(7) are termed as prediction steps in [20]. After the prediction stage, ADBEL network is trained with the help of signals E_a, E'_a, E_o, p_t and constant parameters α, β, γ. The output from amygdala, E_a in conjunction with the current time series value p_t and decay rate γ is used to adjust the amygdala weights in the following way:

$$v_j(t+1) = (1-\gamma)\,v_j(t) + \alpha \max(p_t - e_a, 0)\,p_{t-j}, \quad j = 1,2,3,4$$
$$v_{th}(t+1) = (1-\gamma)\,v_{th}(t) + \alpha \max(p_t - e_a, 0)\,m \qquad (8)$$

To adjust the weights of orbitofrontal cortex, an internal reward signal is first computed as:

$$R_o = \begin{cases} \max\left(E_a' - p_t, 0\right) - E_o, & p_t \neq 0 \\ \max\left(E_a' - E_o, 0\right), & \textit{otherwise} \end{cases} \qquad (9)$$

Based on this reward signal, the weights of the orbitofrontal cortex are updated as:

$$w_j(t+1) = w_j(t) + \beta R_o p_{t-j}, \quad j = 1,2,3,4 \qquad (10)$$

As can observed from the prediction and learning stages of ADBEL network, it presents a simple way of time series prediction in an online mode as opposed to the other popular networks used for forecasting such as ANN with back error propagation algorithm and ANFIS which cannot be used to predict time series with shorter update intervals due to their computational complexity. It is also to be noted that there are three constant positive parameters α, β, γ which are used in the learning stage of the network and need to be tuned for best network's performance. The range of these parameters is reported to be [20]:

$$\begin{aligned} \alpha &\le 1 \\ \beta &\le 1 \\ 0 \le \gamma &\le 0.2 \end{aligned} \qquad (11)$$

III. REVIEW OF NEO-FUZZY NETWORK

Neo-fuzzy is a multi-input, single-output network which employs nonlinear synapses to generate the mapping between input and output data. An n-input neo-fuzzy network is depicted in Fig. 3. The working of the network is such that each input presented to the network is fuzzified using 'k' triangular membership functions. Each degree of belongingness thus computed is further weighted and all such weighted degrees are summed to generate the output. Mathematically, the process can be given as:

$$y_{nf} = \sum_{i=1}^{n} f_i(x_i) \qquad (12)$$

Where $f_i(x_i)$ is the response of the i^{th} neo-fuzzy neuron in the final network output and is given as:

$$f_i(x_i) = \sum_{j=1}^{k} h_{ij}(x_i)\,w_{ij} \qquad (13)$$

Where $h_{ij}(x_i)$ is the degree of membership of i^{th} input over j^{th} membership function and w_{ij} is the corresponding weight which needs to be determined for mapping input-output data. Please note that the membership functions are fixed, complementary and are equally spaced to cover the universe of discourse. The overlapping parts of neighboring membership functions therefore can be described as:

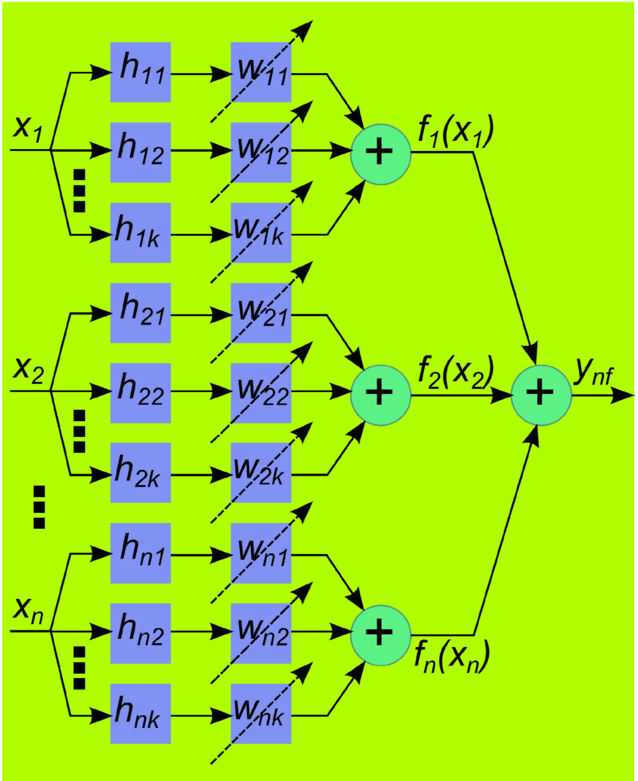

FIGURE 3. Neo-Fuzzy network.

$$\left.\begin{aligned} h_{ij+1}(x_i) &= \frac{x_i - c_j}{c_{j+1} - c_j} \\ h_{ij}(x_i) &= 1 - h_{ij+1}(x_i) \end{aligned}\right\} x_i \in \left[c_j, c_{j+1}\right], \quad j = 1,2,\ldots,k-1 \qquad (14)$$

Where c_j is the center of the j^{th} membership function and can be easily computed using the knowledge of uniform spacing, d between the membership functions as:

$$\begin{aligned} c_{j+1} &= c_j + d, \quad j = 1,2,\ldots,k-1 \\ c_1 &= x_{\min}, \quad c_k = x_{\max} \\ d &= \frac{x_{\max} - x_{\min}}{k-1} \end{aligned} \qquad (15)$$

Please note that the unknown parameters in the neo-fuzzy network are the weights on the membership degrees while the membership functions are fixed for all the neurons defining the network. This is in contrast to classical neuro-fuzzy system where membership functions are adjusted during learning process. To compute the adjustable weights, error function is defined as:

$$E = \frac{1}{2}\left(y_{nf} - y_d\right)^2 \qquad (16)$$

The minimization of this quadratic error function through gradient descendent method yields the following parameter

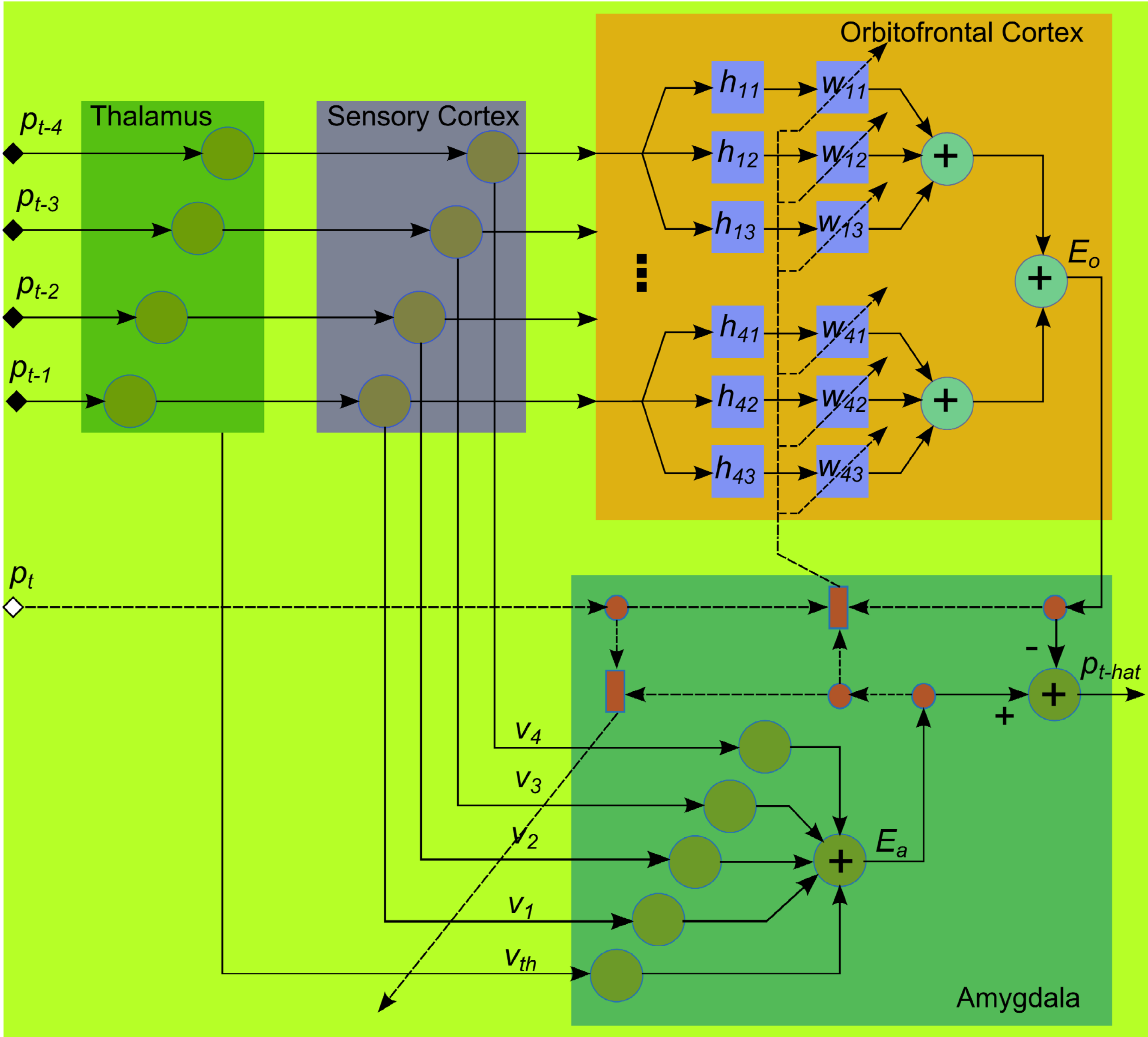

FIGURE 4. Proposed Neo-Fuzzy integrated ADBEL network.

adjustment rule:

$$w_{ij}(t+1) = w_{ij}(t) + \beta\left(y_{nf}(t) - y_d(t)\right) h_{ij}(x_i) \tag{17}$$

Where, β is a positive constant and is defined as the learning rate of neo-fuzzy network.

IV. NEO-FUZZY INTEGRATED ADBEL NETWORK

Inspired by the common features offered by ADBEL and Neo-Fuzzy networks, this work considers a hybrid model named as NF-ADBEL to further improve the forecasting accuracy of the ADBEL network. Although all the neurons in different sections of ADBEL network can be replaced by neo-fuzzy neurons, we have only considered replacing the neurons in orbitofrontal cortex section of ADBEL network with neo-fuzzy neurons. This is done purposefully i.e., the hybrid network can still be used in an online mode for time series prediction. The resulting network is shown in Fig. 4. The working of NF-ADBEL network is similar to ADBEL network in a broad sense i.e., output response of NF-ADBEL network is the difference between the amygdala and orbitofrontal cortex outputs' after the input stimuli are fed to these sections through thalamus and sensory cortex. The difference lies in the construction of orbitofrontal cortex section and its learning as can be observed by comparing Figs. 2 and 4 (the dashed lines in these figures represent the learning of the network). The neo-fuzzy neuron for orbitofrontal cortex is realized with three triangular membership functions and the universe of discourse is selected to be

[0,1] for all the inputs which is in fact the normalized limit for the time series data points. Thus the output of the proposed integrated NF-ADBEL network can be given as:

$$\hat{p}_t = \sum_{j=1}^{4}\sum_{k=1}^{3}\left(v_j p_{t-j} - w_{jk}h_{jk}\right) + v_{th} \times m \tag{18}$$

The unknown weights of amygdala and orbitofrontal cortex in (18) are adjusted in an online manner using the laws in (8) and (17) respectively. Please note that the proposed NF-ADBEL network does not have any knowledge about the time series just as the case with ADBEL network. Previous works on neo-fuzzy networks consider training the network with the time series data and then the trained network is deployed to do future predictions [26]–[30]. However, in this work no prior training of neo-fuzzy network is assumed.

V. RESULTS AND DISCUSSIONS

The proposed fuzzy integrated ADBEL network is tested in MATLAB (R2009b) programming environment for online forecasting of chaotic time series including Mackey glass, Lorenz, Rossler, Narendra and Disturbance Storm Time index. Performance of the neo-fuzzy based ADBEL network is accessed in terms of root mean squared error and correlation coefficient criterions. A comparison is also made with ADBEL network driven by the optimal set of parameters where percentage improvement index is used as a basis for comparison. These performance indices are defined as:

$$RMSE_k = \sqrt{\frac{1}{n_e - n_s + 1}\sum_{i=n_s}^{n_e} e_{ki}^2} \tag{19}$$

$$COR_k = \frac{\sum_{i=n_s}^{n_e}\left(\hat{p_{kti}} - \underline{\hat{p_{kt}}}\right)\left(p_{ti} - \underline{p_t}\right)}{\sqrt{\sum_{i=n_s}^{n_e}\left(\hat{p_{kti}} - \underline{\hat{p_{kt}}}\right)^2}\sqrt{\sum_{i=n_s}^{n_e}\left(p_{ti} - \underline{p_t}\right)^2}} \tag{20}$$

$$PI = \frac{PC_w - PC_f}{PC_w} \times 100 \tag{21}$$

Where, $RMSE_k$ is the root mean squared error and subscript 'k' can be either 'f' denoting neo-**f**uzzy ADBEL network or 'w' representing ADBEL network **w**ithout neo-fuzzy neuron, 'n_e' is the number of samples, 'n_s' indicates the start of steady state period, COR_k is the correlation coefficient obtained using k^{th} network, $\hat{p_{kti}}$ is the predicted value with k^{th} network, $\underline{\hat{p_{kt}}}$ is the mean of the predicted values with k^{th} network, p_{ti} is the target value, $\underline{p_t}$ is the mean of the target samples, PC_k is the performance criterion which can be either $RMSE_k$ or COR_k, and index 'PI' is the percentage decrease with respect to the ADBEL network if low root mean squared error is achieved by neo-fuzzy based ADBEL network which can be treated as percentage improvement with respect to the neo-fuzzy integrated ADBEL network.

To run the simulations, the time series data is first normalized to the range [0,1]. The normalized data is then arranged in such a way that the first four samples form the inputs while the fifth sample forms the output. By following this method, the size of input data for time series is set as $4 \times n_e$ while the size of output data is set as $1 \times n_e$. Please note that the number of samples n_e can be different for different time series depending upon the availability. After running the ADBEL and neo-fuzzy ADBEL algorithms, the predicted time series data is de-normalized. In order for a fair comparison between the two networks, all the network weights are initialized as zeros instead of assigning them random values. This will also help in running the simulations only once and no averaging of the results is required as the networks will yield the same performance every time. Further, the learning parameters of the networks namely α, β and γ are selected after extensive experimentation to yield the best possible prediction performance in each case.

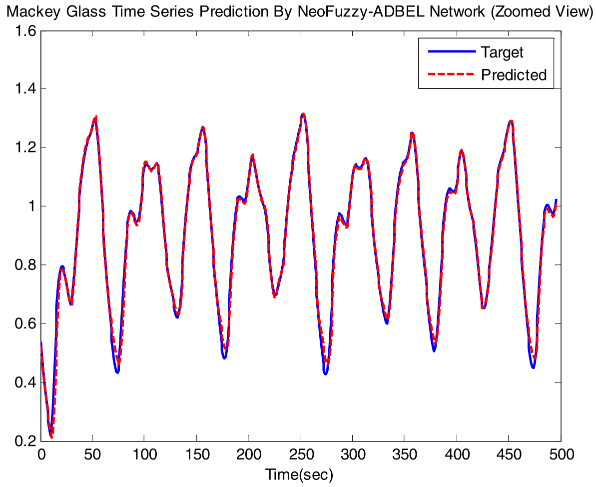

FIGURE 5. Mackey-Glass time series as predicted by NF-ADBEL network.

Let us first predict the time series data generated from a time delayed Mackey-Glass nonlinear differential equation which has been used as a bench mark by the researchers for validating their prediction algorithms [31]–[33]. The series can be defined as:

$$\dot{x}(t) = \frac{0.2x(t-\tau)}{1 + x(t-\tau)^{10}} - 0.1x(t) \tag{22}$$

With the initial conditions as $x(t) = 0, t < 0; x(0) = 1.2$ and by setting the time delay as $\tau = 17$, (22) is simulated in MATLAB programming environment to generate the time series data which can be observed to be non-periodic and non-convergent. A total of $n_e = 1200$ points are generated for testing the networks. By setting the learning parameters to be $\alpha = 0.5, \beta = 0.2, \gamma = 0.03$, neo-fuzzy integrated ADBEL network is first deployed to predict this time series and the steady state result over a pre-defined time window is depicted in Fig. 5. The same time series is also predicted with ADBEL network using the learning parameters as $\alpha = 0.5, \beta = 0.8, \gamma = 0.03$. The prediction error is recorded in both the cases and analysis shows that the transient period in both the cases remains the same ($\leq$5s). Thus the steady state starting index is set to be

$n_s = 5$ in both the cases for the purpose of computing the performance indices. Figure 6 shows the zoomed view of the error in steady state as yielded by both the ADBEL and NF-ADBEL networks in predicting the Mackey Glass time series. It can be observed that NF-ADBEL network has performed better than the ADBEL network as lower peaks in the prediction error are observed in case of NF-ADBEL network. Further, root mean squared error and correlation coefficient are also determined for both the networks using the relations (19) and (20). The computed values are shown in Table 1. It can be seen that lower root mean squared error and higher correlation coefficient are offered by NF-ADBEL network for predicting Mackey Glass time series as compared to ADBEL network. A good amount of percentage improvement is also obtained as found through (21).

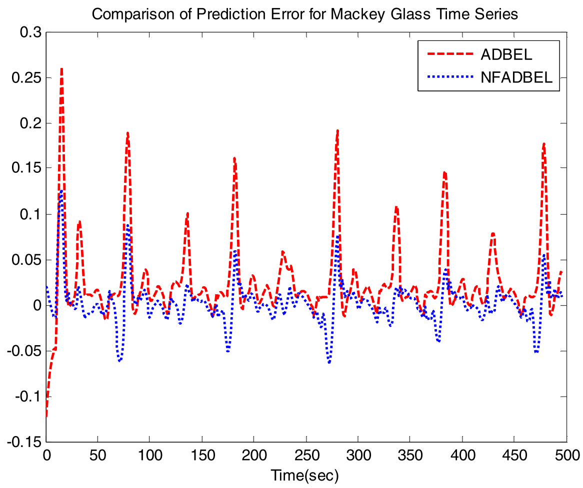

FIGURE 6. Error comparison in predicting Mackey-Glass time series by ADBEL and NF-ADBEL networks.

Neo-fuzzy integrated ADBEL is also simulated to predict the x-dynamics of the Lorenz chaotic time series. This series has also been used in various studies to verify the performance of prediction algorithms [34], [35]. The series is generated from the following coupled differential equations with $a = 10$, $b = 28$ and $c = 8/3$:

$$\begin{aligned} \dot{x}(t) &= a\,(y(t) - x(t)) \\ \dot{y}(t) &= x(t)\,(b - z(t)) - y(t) \\ \dot{z}(t) &= x(t)\,y(t) - cz(t) \end{aligned} \tag{23}$$

For the generated Lorenz time series having $n_e = 16380$ data points, we first evaluate the prediction performance of NF-ADBEL network with the learning parameters set as: $\alpha = 0.8$, $\beta = 0.2$, $\gamma = 0.01$. Figure 7 shows few data points of Lorenz time series as predicted by NF-ADBEL network. It can be observed that the prediction result of NF-ADBEL network for Lorenz time series is better as compared to its result for Mackey Glass time series as it is almost difficult to distinguish the predicted Lorenz time series from the original one. For the purpose of comparison, ADBEL network is also simulated to predict the Lorenz time series. The best learning parameters for ADBEL network in predicting the Lorenz time series are found to be the same as that of NF-ADBEL network i.e., $\alpha = 0.8$, $\beta = 0.2$, $\gamma = 0.01$. By recording and analyzing the prediction error in both cases, it is found that the transient

TABLE 1. RMSE & COR for time series prediction & dynamic plant identification by ADBEL and NF-ADBEL networks.

Time Series		Prediction Network	RMSE	COR	PI (%)
Mackey Glass		ADBEL	0.04727	0.98952	61.92
		NF-ADBEL	0.0180	0.99706	
Lorenz		ADBEL	0.55635	0.99827	68.98
		NF-ADBEL	0.1726	0.99976	
Rossler		ADBEL	1.5014	0.99224	80.03
		NF-ADBEL	0.2999	0.99929	
DST Index	APR 2000	ADBEL	14.6540	0.94165	37.99
		NF-ADBEL	9.0874	0.9706	
	JUL 2000	ADBEL	19.3543	0.91827	42.95
		NF-ADBEL	11.0409	0.96731	
	MAR 2001	ADBEL	22.2816	0.91529	41.44
		NF-ADBEL	13.0485	0.96437	
	OCT 2003	ADBEL	26.8221	0.90121	47.70
		NF-ADBEL	14.0290	0.96724	
	JUL 2004	ADBEL	14.0976	0.95256	48.71
		NF-ADBEL	7.2304	0.9821	
Narendra Plant		ADBEL	0.07556	0.9980	78.49
		NF-ADBEL	0.01625	0.99987	

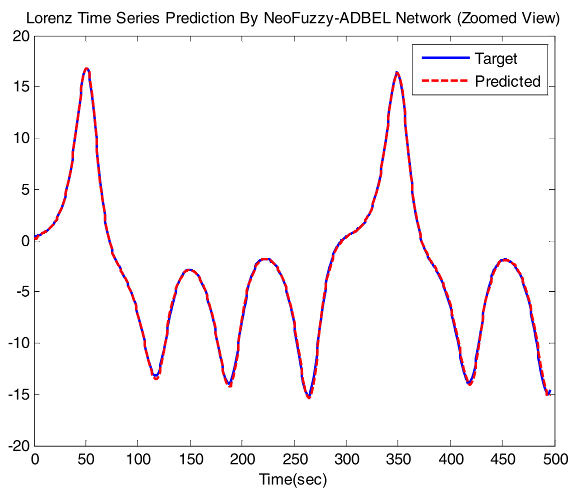

FIGURE 7. Lorenz x-time series as predicted by NF-ADBEL network.

period is less than 5s and therefore the steady state starting index is taken as $n_s = 5$. A zoomed view of the prediction error as returned by both the networks in steady state is shown in Fig. 8. It is evident that the proposed NF-ADBEL network has offered lower error in predicting the Lorenz time series as compared to the existing ADBEL network. The prediction performance in both the cases is also analyzed in terms of root mean squared error (19) and correlation coefficient (20) criterions. The results for this analysis are included in Table 1 and show the superior performance of NF-ADBEL network due to the lowered root mean squared error, higher correlation coefficient and significant percentage improvement as offered by this network.

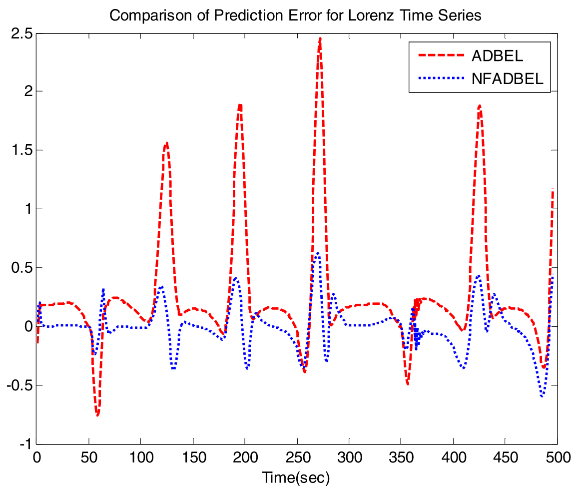

FIGURE 8. Error comparison in predicting Lorenz x-time series by ADBEL and NF-ADBEL networks.

We have also used neo-fuzzy integrated ADBEL network in predicting the Rossler chaotic time series as it has been used in literature to evaluate the performance of prediction algorithms [36], [37]. The time series is generated through the following differential equations with the constants selected to be $a = 0.15$, $b = 0.2$, $c = 10$:

$$\begin{aligned} \dot{x}(t) &= -y(t) - z(t) \\ \dot{y}(t) &= x(t) + ay(t) \\ \dot{z}(t) &= b + z(t)(x(t) - c) \end{aligned} \tag{24}$$

A total of $n_e = 8188$ samples are generated for Rossler time series. To simulate the proposed NF-ADBEL network for predicting this time series, the learning parameters are selected to be $\alpha = 0.5, \beta = 0.5, \gamma = 0.08$ and the zoomed view of the predicted time series in steady state is shown in Fig. 9. ADBEL network driven by the parameters $\alpha = 0.8, \beta = 0.2, \gamma = 0.05$ is also simulated to forecast the Rossler time series and the comparison of the two networks in terms of the prediction error is displayed in Fig. 10. Please note that the prediction error for both the networks is shown for a finite duration in steady state. The transient period happens to be the same as in case of Mackey Glass and Lorenz time series i.e., $n_s = 5$. It can be seen that the amplitude of

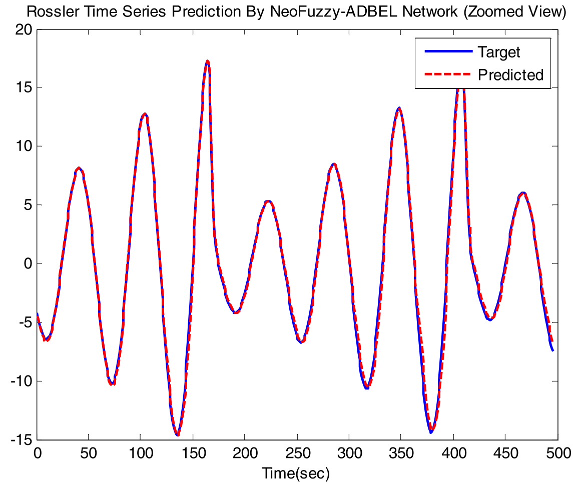

FIGURE 9. Rossler x-time series as predicted by NF-ADBEL network.

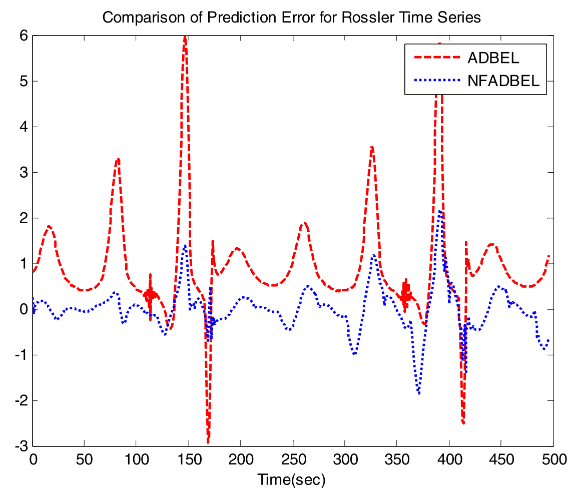

FIGURE 10. Error comparison in predicting Rossler x-time series by ADBEL and NF-ADBEL networks.

error signal for NF-ADBEL network is lower as compared to ADBEL network. This shows the better prediction accuracy of NF-ADBEL network. Analysis of the predicted results for Rossler time series in terms of the root mean squared error and correlation coefficient criterions, as listed in Table 1, also reveal the superiority of NF-ADBEL over ADBEL network. Finally, a good amount of percentage improvement is yielded by NF-ADBEL network for predicting the Rossler time series as can be seen from Table 1.

Neo-fuzzy integrated ADBEL network is also used to predict the disturbance storm time index which is an hourly indictor of geomagnetic storms. The negative values in this index are vital as they indicate the weakening of earth's magnetic field leading to geomagnetic storms which can disrupt the radio communications, damage satellites and cause power system outages. Various models based on differential equations and neural networks have been proposed in the literature for predicting the disturbance storm time index [38]–[43]. Recently, ADBEL network is proposed to

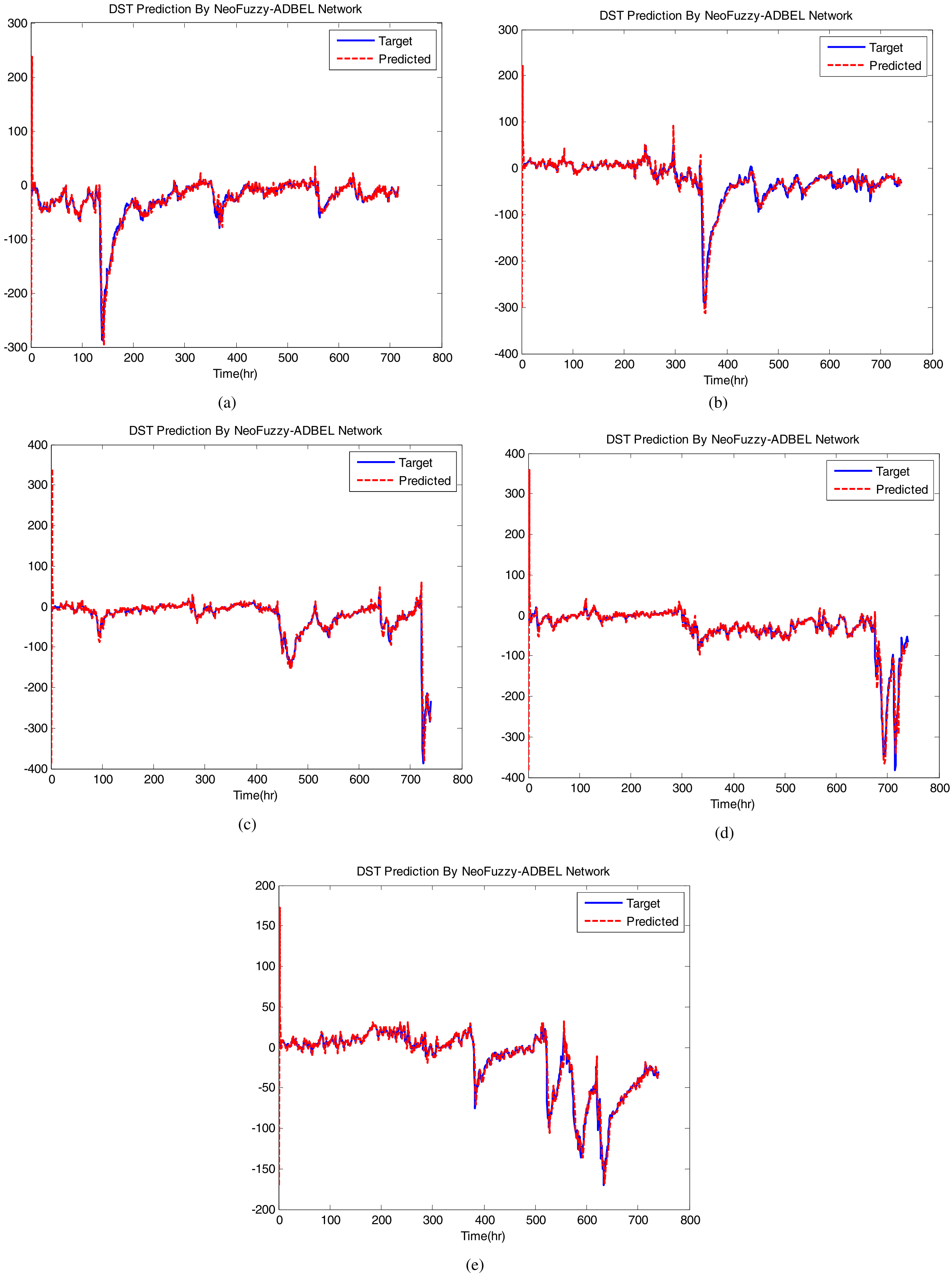

FIGURE 11. Disturbance storm time series as predicted by NF-ADBEL network (a) April 2000 (b) July 2000 (c) March 2001 (d) Oct 2003 (e) July 2004.

predict this important index [20] which has been modified in the present work to yield a new NF-ADBEL network. Here we simulate NF-ADBEL network to predict DST time series for few months when considerable geomagnetic activity was observed. The data for these months is downloaded from the website of "WDC for Geomagnetism, Kyoto".

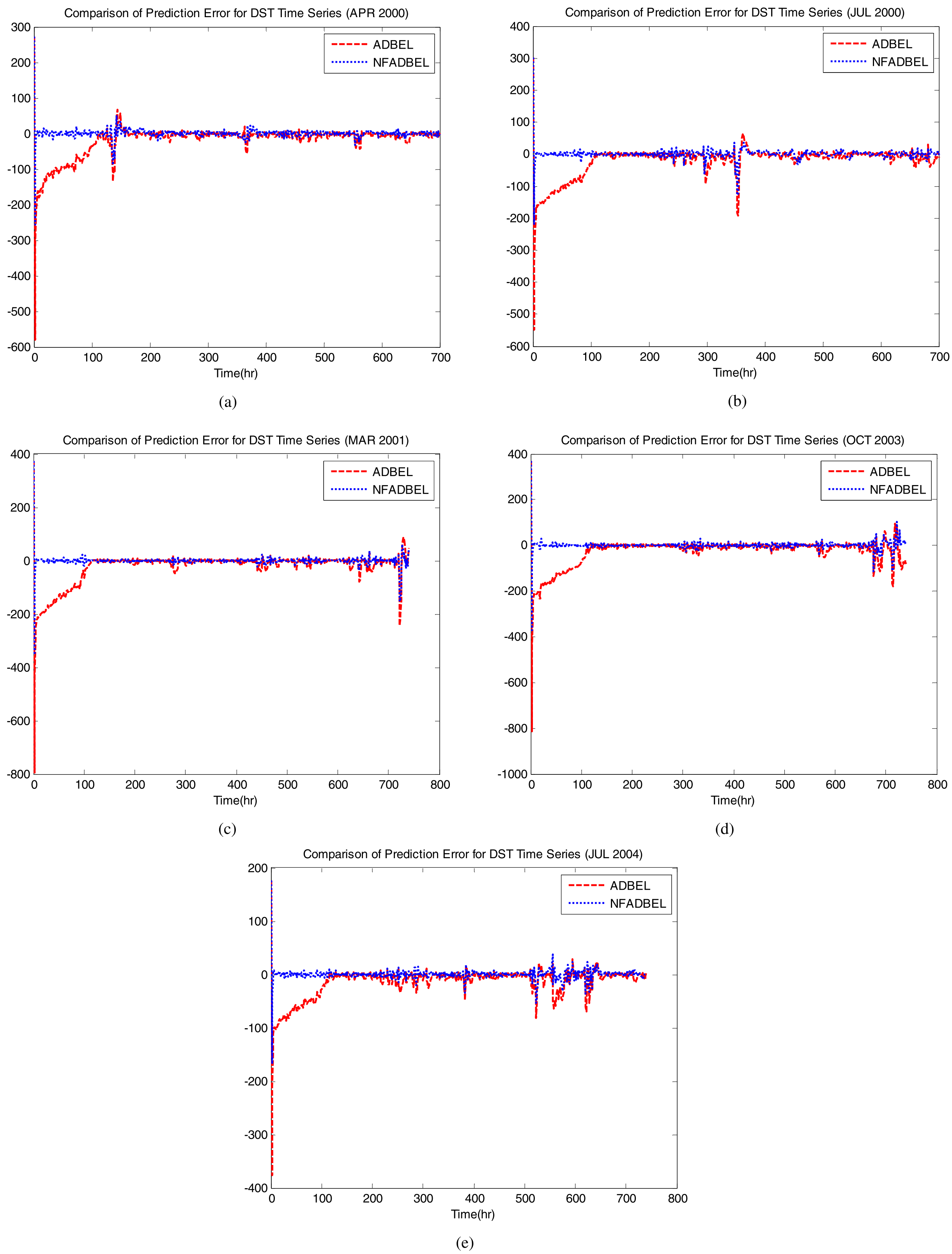

FIGURE 12. Error comparison in predicting Disturbance storm time series by ADBEL and NF-ADBEL networks.

With the learning parameters set to be $\alpha = 0.3$, $\beta = 0.3$, $\gamma = 0.01$, NF-ADBEL network is deployed to predict the DST index for the months of April 2000, July 2000, March 2001, October 2003 and July 2004 where the number of samples are $n_e = 716$ for April 2000 and $n_e = 740$ for all other months. The predicted results by NF-ADBEL network in all these cases are shown in Fig. 11. The transient period of NF-ADBEL network for all the reported cases is found to be 10hrs which becomes the steady state starting index i.e., $n_s = 10$. It can be observed that despite the high initial transients, NF-ADBEL network is able to follow the DST time series in steady state and the important valley points are also well predicted which actually points towards the possible occurrence of geomagnetic storms. In order to draw a comparison, existing ADBEL network is also used to predict the DST time series. For this purpose, the learning parameters of ADBEL network are assigned the values of $\alpha = 0.8, \beta = 0.2, \gamma = 0.01$. The result of this comparison in terms of the prediction error is displayed in Fig. 11. It can be observed that the ADBEL network has offered long transient period as compared to NF-ADBEL network which is found to be 110hrs and acts as the steady state staring index for the ADBEL based DST prediction analysis i.e., $n_s = 110$. It can also be seen that the initial transients in case of ADBEL network have high amplitudes as compared to NF-ADBEL network. Further, the response of NF-ADBEL network in steady state is also better than ADBEL network. This is also supported by the lower root mean squared error, higher correlation coefficient as obtained for NF-ADBEL network for predicting the DST time series. Table 1 lists these performance indices for both the ADBEL and NF-ADBEL networks. It can be observed that a fair amount of percentage improvement can be obtained by deploying the proposed NF-ADBEL network in predicting the DST time series.

We have also simulated the NF-ADBEL network for the online identification of Narendra dynamic plant which is described by the following discrete equation [44]:

$$y(t+1) = \frac{y(t)}{\left(1+y^2(t)\right)} + f(t)$$
$$f(t) = \begin{cases} \sin^3\left(\dfrac{\pi t}{250}\right), & t \leq 500 \\ 0.8\sin\left(\dfrac{\pi t}{250}\right) + 0.2\sin\left(\dfrac{\pi t}{25}\right), & t > 500 \end{cases} \tag{25}$$

With an initial condition of $y(1) = 0.5$, a total of $n_e = 1996$ samples are generated according to (25). NF-ADBEL network is first employed to identify the dynamic plant using the learning parameters as $\alpha = 0.3$, $\beta = 0.5, \gamma = 0.01$. A zoomed view of the identification result in steady state is shown in Fig. 13 where the steady state starting index is taken to be $n_s = 5$. It can be seen that NF-ADBEL network is able to identify the dynamic plant. Narendra plant is also identified using ADBEL network for the purpose of comparing its identification performance with NF-ADBEL network. The simulation is run with the learning parameters for ADBEL network being set as $\alpha = 0.5$, $\beta = 0.5, \gamma = 0.01$ and identification error is recorded. The transient period for ADBEL network is found to be the same as that of NF-ADBEL network. However, NF-ADBEL network has shown better performance as compared to ADBEL

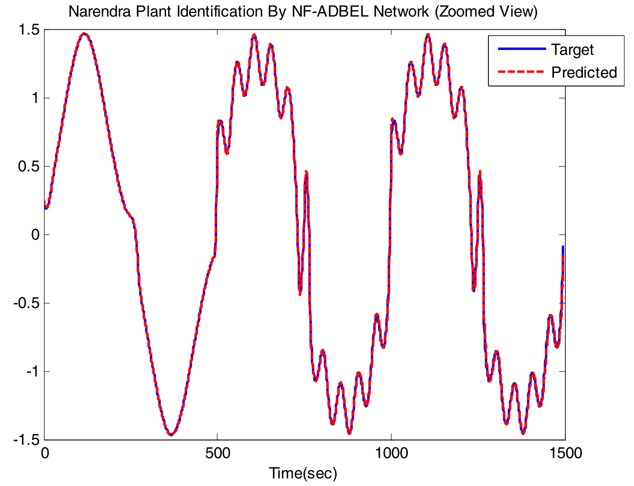

FIGURE 13. Narendra plant as identified by NF-ADBEL network.

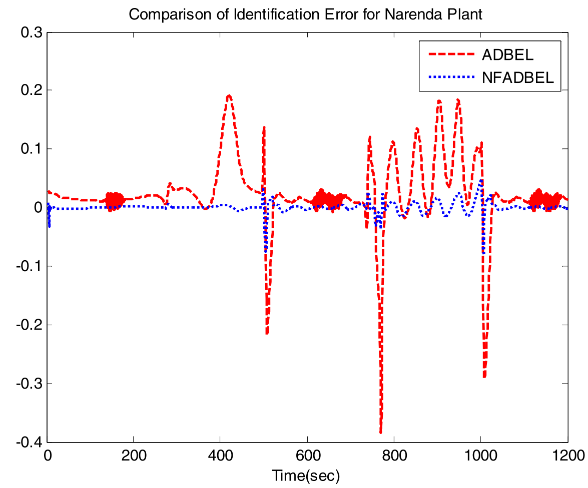

FIGURE 14. Error comparison for Narendra plant identification problem by ADBEL and NF-ADBEL networks.

network owing to the lesser identification error being offered by this network during steady state as can be seen from Fig. 14. A lower root mean squared error, higher correlation coefficient and sufficient percentage improvement as yielded by NF-ADBEL network validate its superior performance over ADBEL network in identifying Narendra plant (Table 1). Besides plant identification, other important fault diagnosis problems can also be considered [45]–[48].

VI. CONCLUSIONS

The design of a neo-fuzzy integrated ADBEL network is presented in this work for the time series forecasting in an online mode. Although all the sections of ADBEL network can be integrated with neo-fuzzy network, the integration is only considered in the orbitofrontal cortex section in order to retain the simplicity and quickness of the proposed NF-ADBEL network. The selection of few membership functions for implementing the neo-fuzzy neurons further help in keeping the computational complexity of the proposed network at minimum. To demonstrate the effectiveness of the proposed network, simulations are carried out in MATLAB programming environment to predict a number of chaotic time series including Mackey glass, Lorenz, Rossler and Disturbance storm time index. Simulations are also conducted to identify a dynamic Narendra plant model by deploying the proposed NF-ADBEL network. The performance of the proposed forecasting network is evaluated in terms of root mean squared error and correlation coefficient criterions. In order to draw a comparison, ADBEL network is also simulated to forecast the same time series with optimal parameters. A percentage improvement index is defined to compare the performance of both the networks. Simulation results show the superiority of the proposed NF-ADBEL network as lower root mean squared error and high correlation coefficient is obtained in comparison with ADBEL network. A fair amount of percentage improvement is also observed in all cases when NF-ADBEL network is used to predict the time series data.

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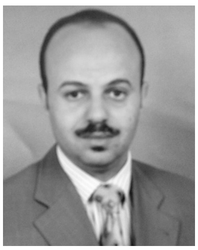

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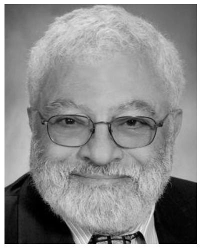

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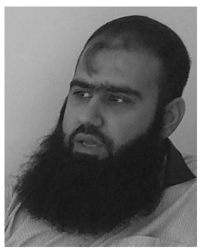

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