A Hybrid Time Series Forecasting Model for Disturbance Storm Time Index using a Competitive Brain Emotional Neural Network and Neo-Fuzzy Neurons

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Abstract: The Disturbance storm time (Dst) index is an important indicator of the occurrence of geomagnetic storms, which can damage communication and power systems, as well as, affect Astronauts performance. Such potential consequences of this fatal event has challenged researchers to develop Dst predictors, with some success. This paper presents the design of a computationally fast, neuro-fuzzy network to forecast Dst activity. The proposed network combines a class of emotional neural networks with neo-fuzzy neurons and is named, Neo-fuzzy integrated Competitive Brain Emotional Learning (NFCBEL) network. Equipped with five competing units, the hybrid model accepts only the past two samples of Dst time series, to predict future values. The model has been tested in the MATLAB programming environment and has been found to offer superior performance, as compared to other state-of-the-art Dst predictors.

Keywords: geomagnetic storms; Dst time series; emotional neural networks; neo-fuzzy neurons; MATLAB

1   Introduction

Geomagnetic storms are the result of interactions between the solar winds and the earth's magnetic field. During this interaction, energy is transferred from the magnetic field carried by solar winds to the Earth's magnetosphere which gives rise to increased electric currents inside the magnetosphere and ionosphere. This enhanced electrical activity further results in the modification of the magnetosphere's magnetic field and can lead to geomagnetic storms. These storms can cause disruptions in electrical power systems, radio communication systems, satellites and navigation systems [1].

The presence of the geomagnetic storms is dictated by the disturbance storm time index which is an estimate of the variation in the horizontal component of Earth's magnetic field and is measured with the help of magnetometers placed at four different stations near the Earth's equator. No geomagnetic storm is reported if these measurements fall between +20 to -20 nT while the storm is classified as moderate, intense and super if these measurements lie in the range of -50 to -100 nT, -100 to -250 nT and lower than -250 nT respectively [2]. Two intense geomagnetic storms have already hit the earth in 1859 and 1989 besides other intense and moderate storms. The Dst index was measured to be roughly -1760 nT during an 1859 storm, named 'Carrington Event', which caused the disruption of telegraph services across the United States and Europe [3], while it was estimated to be -589 nT during an 1989 storm, which resulted in the collapse of Hydro-Quebec power grid, leaving six million people without power for nine hours [4]. To prevent such disaster events, it is important to have a good prediction model of the Dst index.

Several studies have reported the one step ahead prediction model for the Dst index, based on the differential equations and intelligent networks [5]. The first mathematical model appeared in [6], which describes the time variation of Dst index having a constant decay rate through a first order differential equation which is driven by a linear function of the interplanetary electric field's dawn-dusk component. This earlier model was modified [7], by adding the solar wind pressure to the source term and reducing the decay rate, to predict high geomagnetic activities. The constant decay rate was made variable, in another study [8], to predict the low and high geomagnetic activities.

Amongst the intelligent networks, recurrent type neural networks have been widely studied to predict the Dst index because of their capability of implicit implementation of time dynamics [9]. In [10], a recurrent type neural network is presented to predict the Dst index using the interplanetary magnetic field (IMF) and the plasma parameters of the solar wind. However, when the plasma parameters of the solar wind are either not available or inaccurately measured by the relevant instruments, the performance of the prediction model is degraded.

To overcome this drawback, another recurrent neural network is proposed in [11] which can provide better predictions of the Dst index using only the IMF data.

More recently, brain emotional learning (BEL) networks are explored, to forecast the geomagnetic activity indices [12]-[16]. These neural network models are based on the mechanism employed by the limbic system of the mammalian brain in processing the stimuli and differ only in the generation of reinforcement signal during learning. The emotional networks in [12], [13] used a specially designed reward signal to predict the geomagnetic activity index. Although the network predicted the peak points well, the performance of the network degraded for predicting the valley points which is the case for Dst index, where the valley points are an indicator of the strength of geomagnetic storms. A modification to this network is presented in [14], [15] where the reinforcement signal is set to be the target value and a decay rate is introduced in the learning rules, thereby, enabling the network to learn through the input-target samples in a supervised fashion. The modified network is named as ADBEL and has shown superior performance in predicting the valley points in Dst profile. A fuzzy model of ADBEL network is presented afterwards [16] where the weights of the network are kept as fuzzy numbers and the predicted value is generated through the defuzzification process.

Neuro-fuzzy networks form another class of intelligent algorithms which have been studied for the prediction of Dst index. A locally linear neuro-fuzzy model combined with a recursive locally linear model tree algorithm is proposed in [17] to predict the Dst index along with other space weather indices. The recursive modification allows the online adjustment of neuro-fuzzy parameters so as to cope with the time varying nature of geomagnetic activity indices. In another study, authors have presented a novel neuro-fuzzy model named NFADBEL network which has shown superior performance as compared to BEL network in forecasting the chaotic Dst index along with some other benchmark time series [18]. The network works in an online fashion, to predict the next value based on the past four occurrences of the time series data.

The present work also deals with the design of a neuro-fuzzy network for the prediction of Dst index by combining the recently proposed competitive brain emotional learning (CBEL) network [19] with neo-fuzzy neurons [20]. To the best of the authors' knowledge, such a hybrid model is proposed for the first time. The proposed network is named as NFCBEL and uses only past two samples of the Dst time series to predict its future value. It employs five competitive units each comprising of a BEL network fused with neo-fuzzy (NF) neurons. The fusion of neo-fuzzy neurons takes place in the orbitofrontal cortex which is the knowledgeable part of the BEL network. The proposed network is trained on the Dst dataset acquired from [15] and the test results reveal its superior performance as compared to some of the current Dst predictors, in terms of the normalized mean square error (NMSE) criterion.

This paper is structured as follows: Brain emotional learning and neo-fuzzy networks are briefly reviewed in Sections 2 and 3 respectively, the proposed network is described in Section 4 and results are presented in Section 5 followed by conclusions.

2   Brain Emotional Learning Network

First proposed by C. Lucas et. al [21], brain emotional learning network is the computational model of the emotional processing in the mammalian brain based on the work of Moren and Balkenius. The model generates a response to the stimulus based on the interaction of two parts of the brain namely orbitofrontal cortex and amygdala. Amygdala quickly responds to the stimulus owing to its close proximity to thalamus and sensory cortex which are the carriers for stimulus. The response generated by amygdala is then inhibited by orbitofrontal cortex based on the context. During this interaction, reward signals are generated and the weights of the network are adjusted. The generation of these reward signals has been the point of discussion in the literature. Further, the computational model developed by Lucas cannot be adjusted by pattern-target samples. To address this limitation, a supervised version of brain emotional learning network is proposed by E. Lotfi et. al which has been shown to perform well for time series prediction and pattern classification tasks [14] [15]. A competitive version of the network is also proposed in which a particular block of the network is triggered to produce output response based on the proximity of stimulus to that block [19]. One such block of the competitive brain emotional learning network is shown in Figure 1.
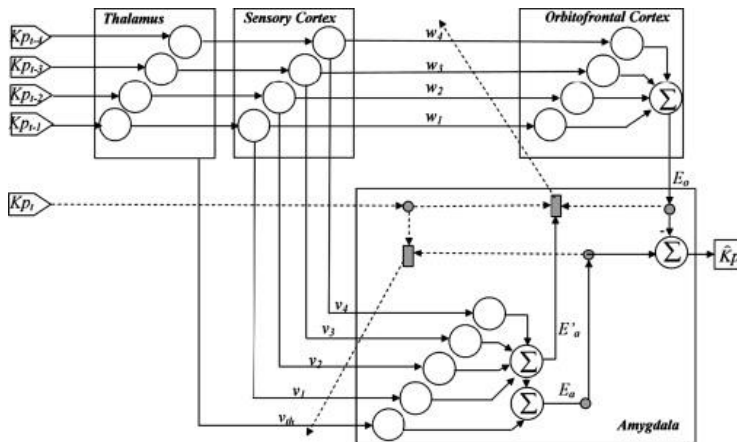

Figure 1

Brain emotional learning network for DST prediction [15]

3   Neo-Fuzzy Network

Neo-fuzzy neurons are characterized by their transparent structure, simplicity and effectiveness in time series prediction, classification and control tasks. Constructed from triangular membership functions (μ_{ij}), a neo-fuzzy neuron has a nonlinear synapse and can map the input-output data by adjusting its weights through gradient descent technique. The network constructed from neo-fuzzy neurons has also been shown to possess generalization ability. One such network is shown in Figure 2, where past samples of the time series are used to perform one step ahead prediction task.
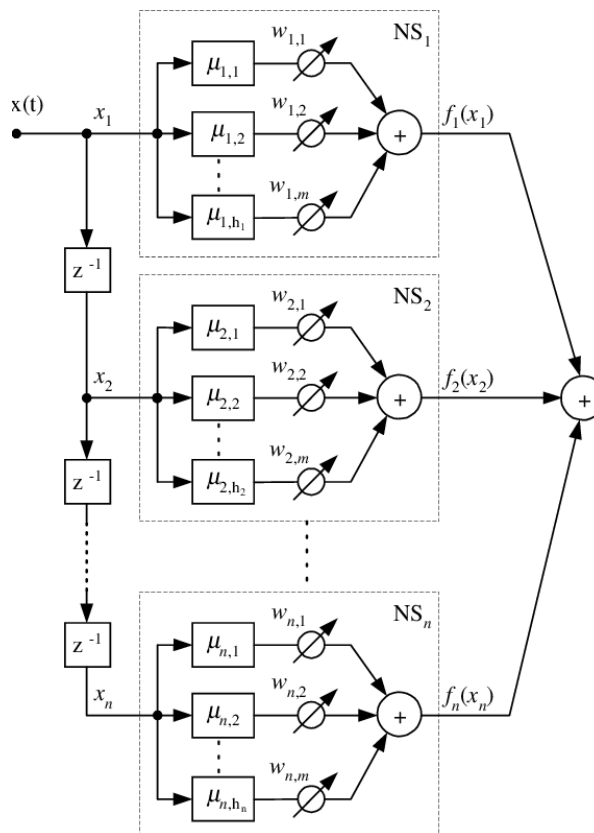

Figure 2
Neo-fuzzy network [20]

4   Proposed Hybrid Dst Predictor

The proposed Dst predictor is constructed from competitive brain emotional learning neural network and neo-fuzzy neurons. It is a single layer network with two inputs and one output as shown in Figure 3. The inputs are the past two samples in Dst time series while output is the one hour ahead predicted Dst value. The network has five competing units and only one of them is active at any time. The activation of a particular unit is based on the Euclidean distance between the input sample and the weights associated with that competing unit. The unit offering the least distance to the input sample is selected:

$$i* = \arg\min_i \left(\left\| c_i - y_t \right\| \right), i = 1, 2, 3, 4, 5 \tag{1}$$

Where $c_i = \begin{pmatrix} c_{1i} & c_{2i} \end{pmatrix}^T$ is the weight vector associated with i^{th} unit, $y_t = \begin{pmatrix} y_{t-1} & y_{t-2} \end{pmatrix}^T$ is the input sample containing past two Dst values and $i*$ is the winner unit. The output from the winner unit is the predicted value of Dst which can be given as:

$$y(t) = f \left(v_i^* y_{te} - w_i^* h_i^* \right) \tag{2}$$

Where f is the log-sigmoid function and other winner-unit's entries in (2) are given as:

$$
\begin{aligned}
v_i^* &= \begin{pmatrix} v_{1i}^* & v_{2i}^* & v_{3i}^* \end{pmatrix} \\
w_i^* &= \begin{pmatrix} w_{1i}^* & w_{2i}^* & w_{3i}^* & w_{4i}^* & w_{5i}^* & w_{6i}^* \end{pmatrix} \\
y_{te} &= \begin{pmatrix} y_{t-1} & y_{t-2} & \max \begin{pmatrix} y_{t-1} & y_{t-2} \end{pmatrix} \end{pmatrix}^T \\
h_i^* &= \begin{pmatrix} h_{1i}^* & h_{2i}^* & h_{3i}^* & h_{4i}^* & h_{5i}^* & h_{6i}^* \end{pmatrix}^T
\end{aligned} \tag{3}
$$

Where v_i^* and w_i^* are the weights associated with the amygdala and orbitofrontal cortex sections of the winner unit respectively while y_{te} and h_i^* are the expanded inputs to the amygdala and orbitofrontal cortex sections respectively. The first three entries of h_i^* are computed as:
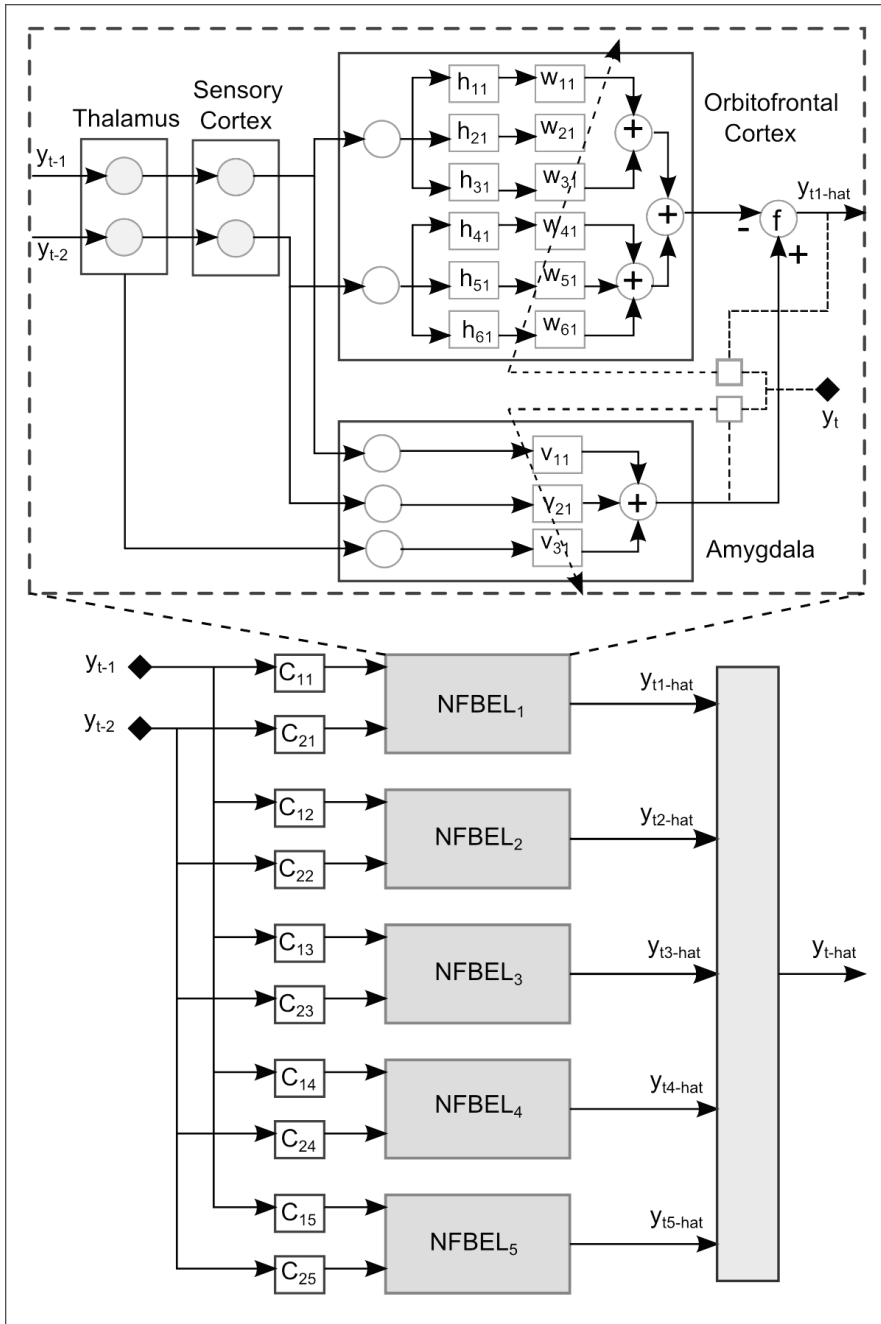
Figure 3
Proposed Dst index predictor

$$h_{1i}^* = \begin{cases} -2y_{t-1}+1, & 0 \leq y_{t-1} < 0.5 \\ 0, & y_{t-1} \geq 0.5 \end{cases}$$

$$h_{2i}^* = \begin{cases} -2y_{t-1}, & 0 \leq y_{t-1} < 0.5 \\ -2y_{t-1}+2, & 0.5 \leq y_{t-1} \leq 1 \end{cases} \tag{4}$$

$$h_{3i}^* = \begin{cases} 2y_{t-1}-1, & 0.5 < y_{t-1} \leq 1 \\ 0, & y_{t-1} \leq 0.5 \end{cases}$$

The last three entries of (3) can be computed by replacing y_{t-1} with y_{t-2} in (4). We now compute the prediction error as:

$$e(t) = y(t) - y(t) \tag{5}$$

With the knowledge of (5) and the expanded inputs of (3), the weights of the winner unit of the proposed Dst predictor are adjusted in the following way:

$$w_i^*(t+1) = w_i^*(t) - \beta e(t) h_i^{*T} \tag{6}$$

$$v_i^*(t+1) = v_i^*(t) - \gamma v_i^*(t) + \alpha \max\left(y(t) - v_i^*(t) y_{te}, 0\right) y_{te}^T \tag{7}$$

Where α and β are constants representing the learning rates of amygdala and orbitofrontal cortex respectively while γ is the decay rate. The complete algorithm is shown in Figure 4.

Remark 1: In the proposed hybrid model, neo-fuzzy neurons are only utilized in the orbitofrontal cortex sections of competitive emotional neural network. This is done purposefully as orbitofrontal cortex is believed to have more knowledge of the underlying process. Thus, more degrees of freedom are available in the proposed neuro-fuzzy hybrid model.

Remark 2: The integration of neo-fuzzy network in the amygdala section can also be considered but it will increase the computational complexity of the resulting hybrid model.

Remark 3: In the proposed hybrid model, learning laws for the amygdala sections are the same as in case of competitive emotional neural networks. However, learning laws for orbitofrontal cortex sections are changed to incorporate fuzzified stimuli.
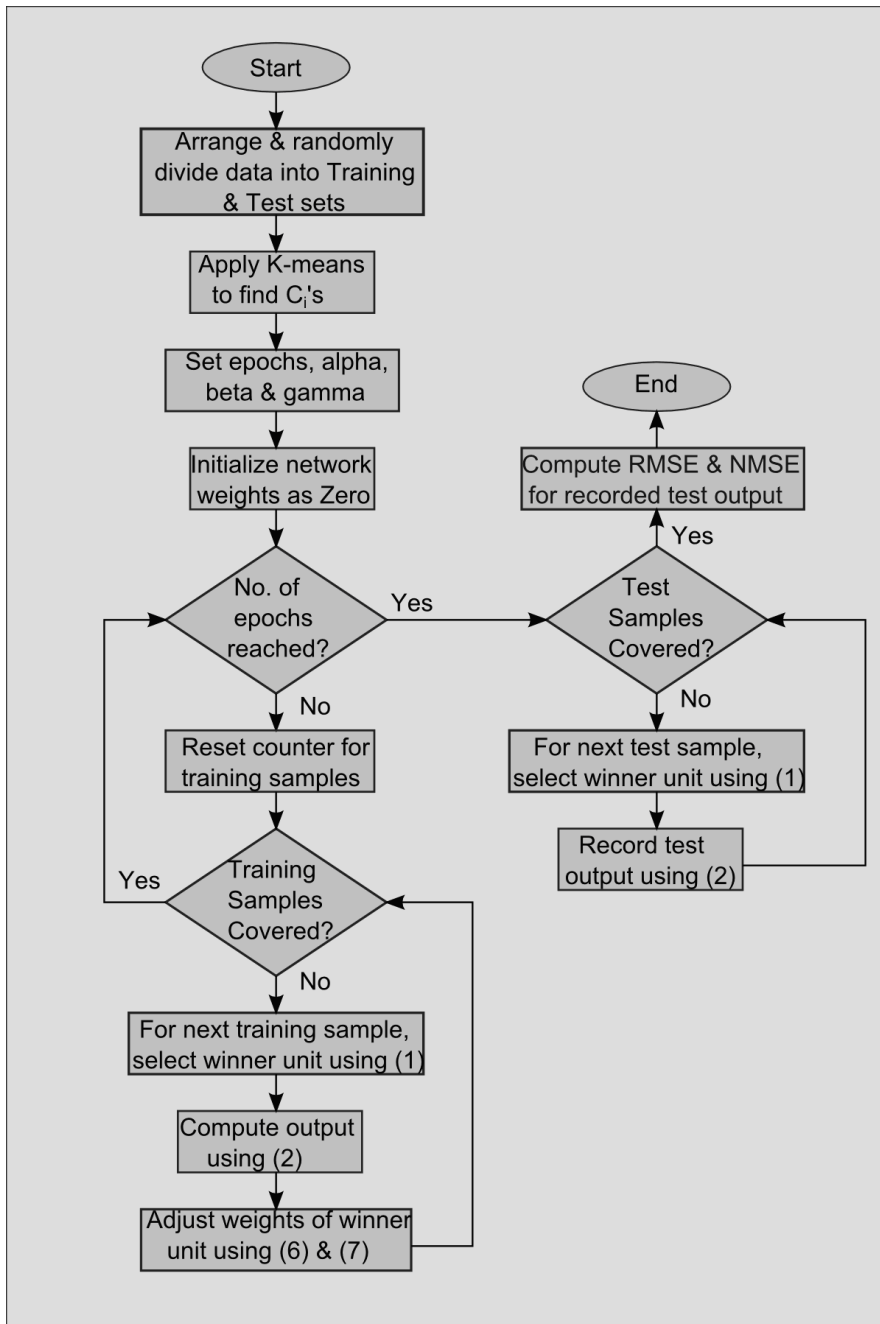
Figure 4
Flow chart of proposed Dst predictor

5   Results & Discussion

The proposed Dst predictor is implemented in the MATLAB programming environment and its performance is evaluated on the dataset obtained from [15] which contains the hourly Dst measurements between the years 2000 and 2008. At first, these 78912 Dst samples are arranged as input-output pairs where each input pair $\left(Dst_{t-1}, Dst_{t-2} \right)$ contains the past two Dst values while output is the current value Dst_t. The resulting 78910 patterns are scaled between 0 and 1 and the scaled dataset is then randomly divided in the ratio 70:30 where 70% of the dataset (55237 patterns) is used for training the proposed model while 30% (23673 patterns) is used for accessing its performance in terms of Root Mean Square Error (RMSE) and Normalized Mean Square Error (NMSE) as defined below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y - y \right)^2} \tag{8}$$

$$NMSE = \frac{\sum_{i=1}^{n}\left(y - y \right)^2}{\sum_{i=1}^{n}\left(y - \overline{y} \right)^2} \tag{9}$$

Where n is the number of test samples and $\overline{y}$ is average of the recorded output Dst values in the test sequence. By setting the parameters as given in Table 1, the proposed predictor is first trained under varying epochs. It is found that the network performance is improved when the number of epochs are increased. The trained network is then deployed to forecast the hourly Dst values and its performance is recorded on the test dataset as shown in Table 2. The predicted values for the first 200 hours in Dst test dataset are plotted in Figure 5. It can be observed that regions of low Dst activity are well-recognized by the proposed model which play vital role in the prediction of geomagnetic storms. Regression analysis of the developed predictor is also performed on the test dataset as depicted in Figure 6 which shows a good amount of correlation between the target and predicted values.

Table 1

Parameters of NFCBEL Dst predictor

Parameters	Description	Values
n_{nf}	Number of neo-fuzzy neurons	2
n_{mfs}	Number of membership functions for one neuron	3
n_{cu}	Number of competing units	5
α	Amydala learning rate	0.1
β	Orbitofrontal cortex learning rate	0.3
γ	Decay rate associated with Amygdala	0.0001
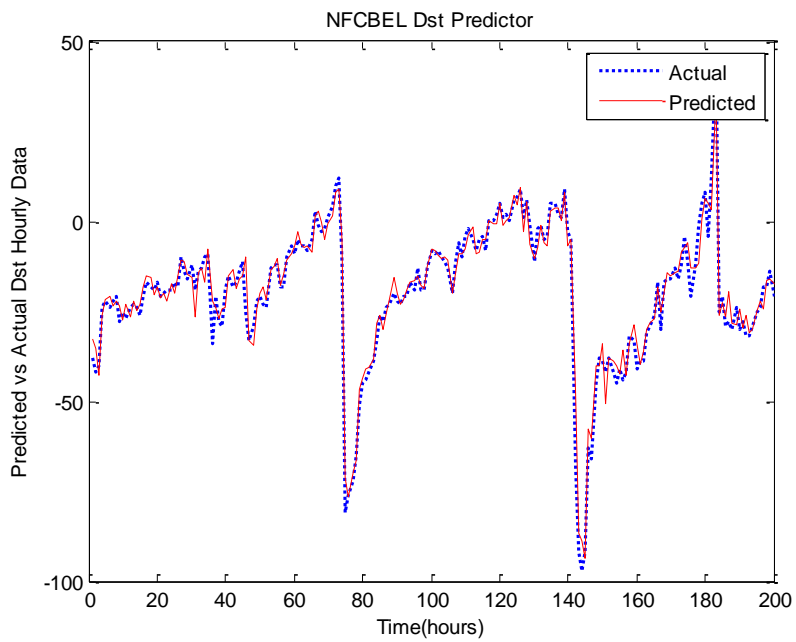
Figure 5

NFCBEL Dst predictor on test dataset

Table 2

Performance of NFCBEL Dst predictor

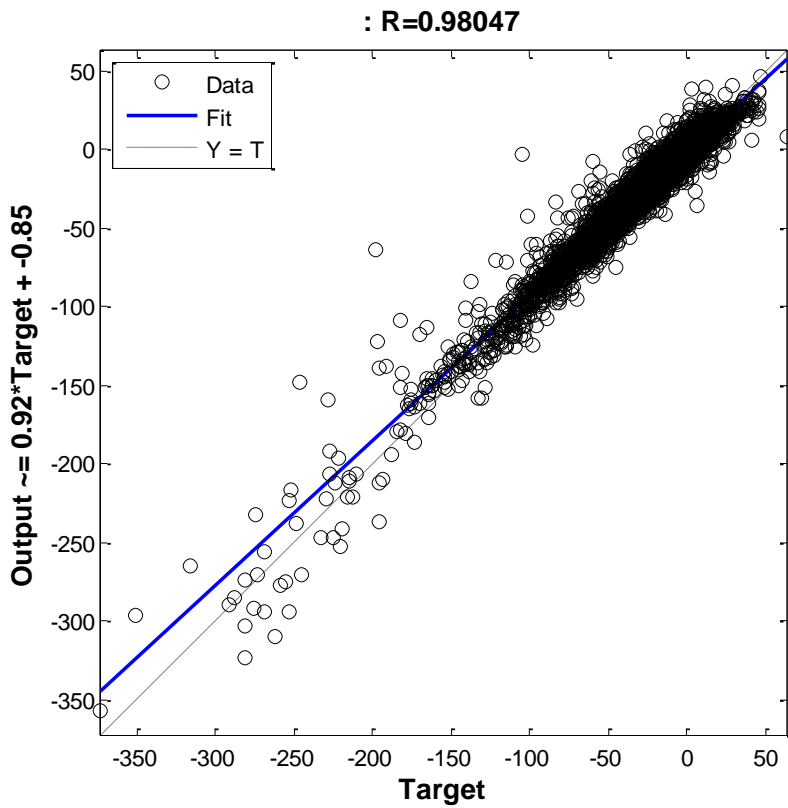| Epochs	RMSE	NMSE	COR
10	4.9578	0.0436	0.97932
25	4.8040	0.0409	0.98032
50	4.7694	0.0404	0.98047

Figure 6

Regression analysis of proposed Dst predictor

The proposed hybrid NFCBEL model is also compared with some state of the art Dst predictors. Following the lines of [15], [18], NMSE is chosen as the basis of comparison for the Dst data between the years 2000 and 2006 which are approximately 61392 patterns. The network with the previously learned weights is deployed to forecast a total of 61392 target Dst values and NMSE is recorded. It is found that the proposed model offers the lowest NMSE as shown in Table 3 which shows its superior performance as compared to other Dst predictors. Further, the predicted Dst values are also plotted for some critical hours when considerable geomagnetic activity is observed. These results are shown in Figures 7 through 9. It can be observed that predicted values are in close agreement with their actual values which validates the good performance of the proposed Dst predictor.
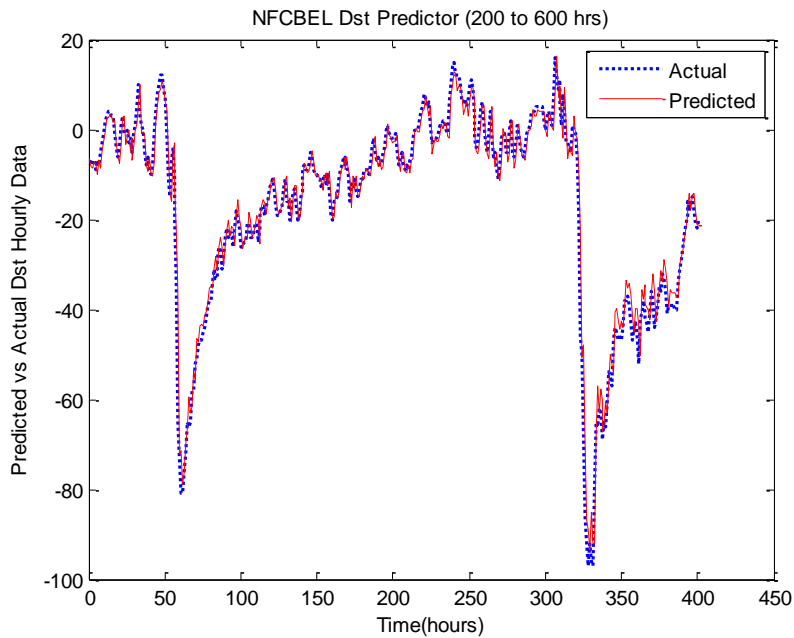

Figure 7
Result of the proposed Dst predictor for the hours 200 to 600 during the years 2000-2006

Table 3

Comparison of Dst predictors based on NMSE between 2000 & 2006

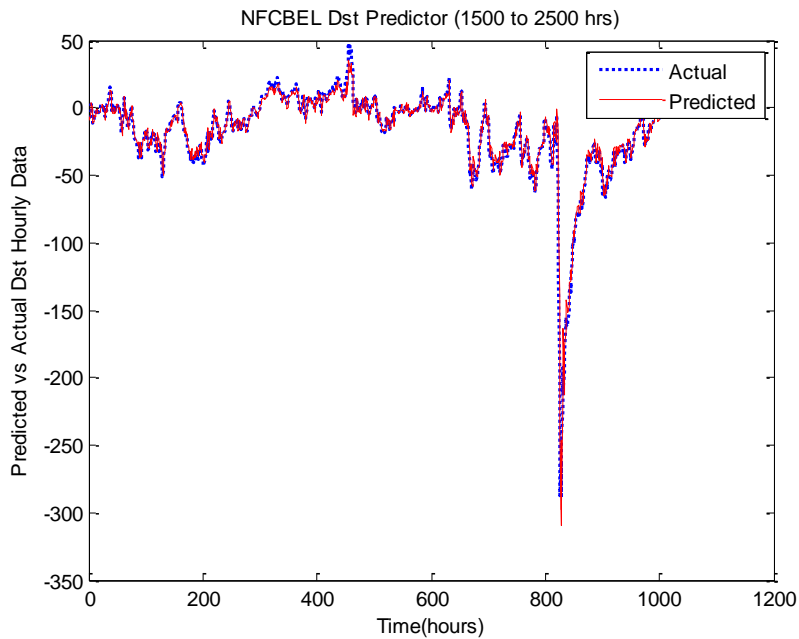| Algorithm	Learning	NMSE
LLNF	LoLiMoT	0.5348
Adaptive LLNF	RLoLiMoT	0.0968
ADBEL	Emotional Decaying	0.1123
Proposed NFCBEL	Emotional Decaying	0.0400

Figure 8

Result of the proposed Dst predictor for the hours 1500 to 2500 during the years 2000-2006
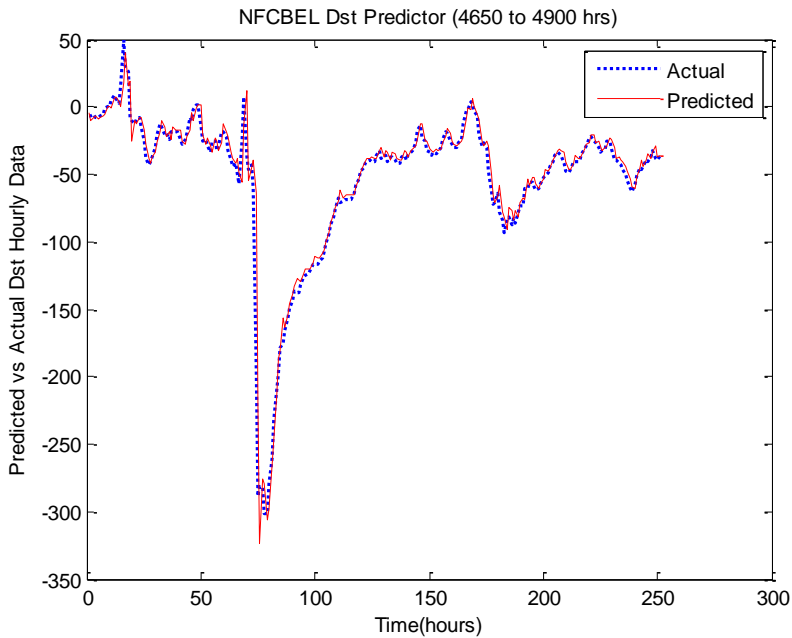
Figure 9
Result of the proposed Dst predictor for the hours 4650 to 4900 during the years 2000-2006

Conclusions

This paper presents the design of a novel hybrid model for the hourly forecast of the Disturbance Storm Index, which is an important parameter for predicting geomagnetic storms. The model combines competitive emotional neural networks with neo-fuzzy neurons to yield an effective Dst predictor which offers features such as, low computational complexity and fast learning. Low complexity is the result of fewer inputs, neo-fuzzy neurons and competing units, while fast learning is the result of employing emotion processing mechanism of the mammalian brain. The proposed model is trained offline and then deployed for the hourly prediction of Dst activity. The performance of the model is also evaluated in terms of RMSE, NMSE and COR. The comparison of the proposed model with some state-of-the-art predictors, reveals its superior performance, as the model offers the lowest NMSE. Future work involves determining model parameters, like optimal number of neo-fuzzy neurons, competing units and weighting through metaheuristic algorithms.

Acknowledgement

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