Application of Cooperative Neuro-evolution of Elman Recurrent Networks for a Two-Dimensional Cyclone Track Prediction for the South Pacific Region

Rohitash Chandra * † Kavina Dayal ‡ † Nicholas Rollings § †
* School of Computing Information and Mathematical Sciences
University of the South Pacific, Suva, Fiji. http://scims.fste.usp.ac.fj/
† Artificial Intelligence and Cybernetics Research Group, Software Foundation,
Nausori, Fiji. http://aicrg.softwarefoundationfiji.org/ Email: c.rohitash@gmail.com
‡ Pacific Centre for Environment and Sustainable Development
University of the South Pacific, Suva, Fiji. Email: kavinadayal@gmail.com
§ Geospatial Science with the School of Geography, Earth Science and Environment
University of the South Pacific, Suva, Fiji. Email: nicholas.rollings@usp.ac.fj

***Abstract*—This paper presents a two-dimensional time series prediction approach for cyclone track prediction using cooperative neuro-evolution of Elman recurrent networks in the South Pacific region. The latitude and longitude of tracks of cyclone lifetime is taken into consideration for past three decades to build a robust forecasting system. The proposed method performs one step ahead prediction of the cyclone position which is essentially a two-dimensional time series prediction problem. The results show that the Elman recurrent network is able to achieve very good accuracy in terms of prediction of the tracks which can be used as means of taking precautionary measures.**

I. Introduction

Recurrent neural networks have been an important focus of research as they can be applied to difficult problems involving time-varying patterns [1], [2], [3]. Their architecture makes them suitable for modelling temporal sequences and they have shown to be effective for time series prediction [4].

Cooperative coevolution (CC) is a neuro-evolution method that divides a problem into subcomponents that are similar to the different species in nature [5] and has been effective for time series prediction [4], [6] . Problem decomposition is an important procedure in cooperation coevolution that determines how the subcomponents are decomposed which actually means dividing the neural network into smaller regions [7]. It has been shown that the problem decomposition method is dependent on the particular neural network architecture and training problem [8]. The two major established problem decomposition methods are synapse level (SL) and neuron level (NL) methods. In synapse level problem decomposition, the subcomponents are defined by the weight connection which is known as synapse [2], [9], [4]. In neuron level problem decomposition, the neural network gets decomposed by use of neurons in the network [10], [8].

The forecast for future tropical cyclone track is considered extremely important for avoiding casualties and mitigating damage to properties [11], [12]. Cyclones behave differently in different ocean basins, hence meteorological offices around the world adapt to a combination of techniques to predict several interrelated features of the cyclone, including tracks, intensity, induced storm surges, and accompanying rainfall to achieve highest level of accuracy and reliability [11], [13], [14], [15]. There has been a number of cyclone track prediction methods and models developed for various ocean basins [13], discussed in detail later. However, computational intelligence methods such as neural networks has not been widely used in cyclone track forecasting, hence there is a scope for its application.

We employ a two-dimensional time series prediction approach for cyclone track prediction in the South Pacific region. The latitude and longitude of tracks of cyclone lifetime is taken into consideration for past three decades. We use cooperative neuro-evolution of Elman recurrent networks to build a robust forecasting system that can perform one step ahead prediction of the cyclone position. We employ cooperative neuro-evolution using Neuron and Synapse level problem decomposition methods. We reconstruct two-dimensional time series data in 4 different sets using Taken's theorem [16]. The performance of the different reconstructed data sets and problem decomposition methods are compared and a discussion for real-time system is also given.

The rest of the paper is organised as follows. A brief background on tropical cyclones is given in Section 2 and Section 3 gives details of the proposed method for cyclone track prediction. Section 4 gives experimental results and discussion. Section 5 concludes the work with a discussion on future work.

II. Background and Related Work

A. Background on Tropical Cyclones

A tropical cyclone is a low pressure system with a warm core which is characterised by cyclonic tangential and inflowing radial winds [17]. The six major conditions necessary but not limited to the formation of tropical cyclones are: (1) warm sea surface temperature ($> 26^\circ$ C) to accumulate heat that supplies the energy necessary for cyclone formation, (2) a pre-existing disturbance, (3) moist mid-troposphere to promote large scale thunderstorm activity, (4) location of low pressure zone away from the equator to sustain the system through Coriolis force, (5) sufficient vorticity (amount of rotation of air) and convergence (inflow of air), and (6) weak vertical shear of the horizontal winds between 850- and 200-mb pressure levels [18], [19].

Once a cyclone is formed, it usually moves over the ocean in the direction away from the equator and lasts a few days to sometimes 2-3 weeks [20]. A cyclone can travel hundreds of kilometres during its lifetime and the actual path of the cyclone's eye is known as the cyclone's track. A cyclone forecast consists of cyclone track, intensity, induced storm surges, rainfall and threat to coastal areas [12]. The direction of cyclone movement is the most important feature in the forecast as it helps the inhabitants to prepare ahead of time, thus minimise damage to life and property. For this reason, forecasting cyclone track is considered extremely important forecast function by scientists and meteorological agencies around the world [11].

The precise observational data of the ongoing cyclone and a high quality historical data that reveals typical behavioural patterns in the cyclone movement are very crucial in making accurate cyclone track forecast [21], [11], [22], [23]. A number of cyclone track forecast techniques are being employed by various tropical cyclone forecasting centres, such as: averaging across occurrences, statistical forecasting techniques, dynamical and numerical forecasting techniques, statistical-dynamical techniques and hybrid forecasting techniques [21]. The current cyclone track forecasting techniques are based on four factors: (1) averaging across previous cyclones, (2) statistical modelling of previous cyclones, (3) numerical and dynamical modelling of physical forces affecting cyclones, and (4) considering past data by detection of reoccurring behaviour patterns [14], [15]. Detailed description of the listed techniques is discussed in Roy and Kovordanyi (2012) [13].

B. Related work on Cyclone Track Prediction

In the South-west Pacific, region of focus in this study, the techniques used for cyclone forecasting are just a few. Fiji, for example; uses a subjective assessment of synoptic reasoning, evaluation of the cyclone's steering current and expected changes in the large-scale surrounding flow fields. In addition to subjective assessment, Darwin and Brisbane in Australia utilise three other techniques for cyclone track forecasting [11]. (1) Analog forecast that takes into account features of the cyclone (eg., latitude, longitude, intensity, maturity, and past motion) and compared with those of previous cyclones in the same region so that one or more analogues can be selected. The cyclone movement is then derived from the previous analogues. (2) Steering current technique that involves analysis of winds at specified points and altitudes around the cyclone. According to Bureau of Meteorology Research Centre (2000) [24], the actual forecast using steering current technique can be based either on simple regression analysis or on analysis of the advection and propagation of winds, incorporating linear interactions between the cyclone vortex and the background absolute vorticity. (3) Statistical forecasting techniques are based on regression analysis [11].

Artificial neural networks has been applied to cyclone track forecasting based on satellite images [21] where a multi-layer neural network was used to forecast the movement of cyclones based on NOAA-AVHRR satellite images. The trained neural network produced directional forecast with 98% of the test images, adding to the confidence that neural networks can be developed into effective tool for cyclone track forecasting.

Understanding the geographical distribution and movement pattern of tropical cyclones is crucial for studying the topic. Figure 1 shows the climatology of tropical cyclone genesis and tracks in the South Pacific Ocean. The genesis location is the first point (longitude,latitude) of each recorded cyclone that reached the depression stage, when maximum surface wind speed upgrades to >20-knots, and the track is the actual path the cyclone has taken during its lifetime. As seen in the figure, the favourable region for tropical cyclone formation is between 5°S-20°S clustered mainly in the south-west Pacific. The movement of the cyclone is poleward, or away from the equator, and is affected by the Coriolis and steering flow.

III. Cooperative Neuro-evolution of Recurrent Networks for Cyclone Track Prediction

Recurrent neural networks use context units to store the output of the state neurons from computation of the previous time steps. The context layer is used for computation of present states as they contain information about the previous states. The Elman architecture [1] employs a context layer which makes a copy of the hidden layer outputs in the previous time steps. The dynamics of the change of hidden state neuron activation's in Elman style recurrent networks is given by Equation (1). The Elman network is used for prediction of latitude and longitude to determine the cyclone path as shown in Figure 2. The context layer and weights in in Figure 2 are used to propagate information from previous time step that corresponds to previous data point of the time series.

$$y_i(t) = f\left(\sum_{k=1}^{K} v_{ik}\, y_k(t-1) + \sum_{j=1}^{J} w_{ij}\, x_j(t-1)\right) \quad (1)$$

where $y_k(t)$ and $x_j(t)$ represent the output of the context state neuron and input neurons respectively. v_{ik} and w_{ij} represent their corresponding weights. $f(.)$ is a sigmoid transfer function.

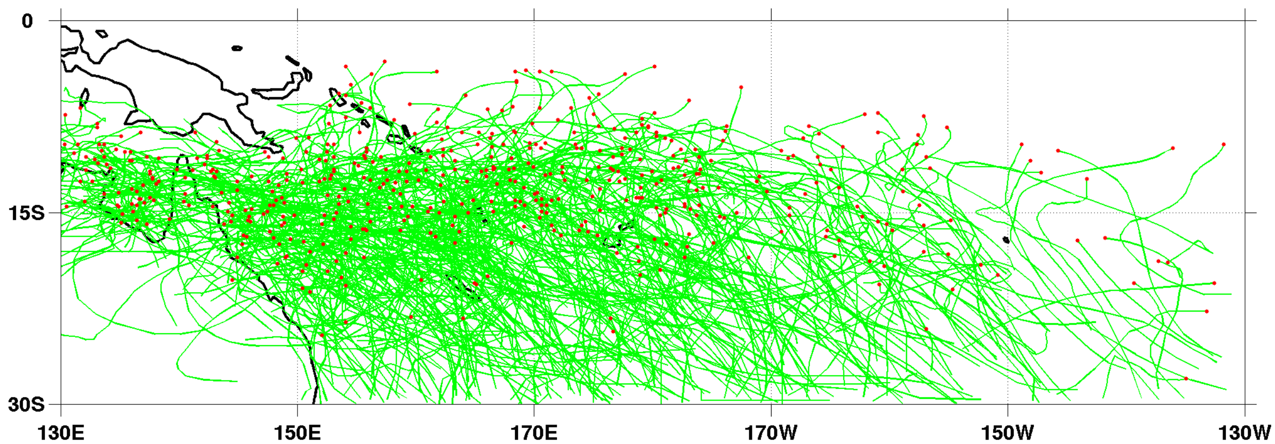


Fig. 1. Climatology of tropical cyclone genesis location (red dots) and track (green) from 1970-2013 in the South Pacific Ocean.

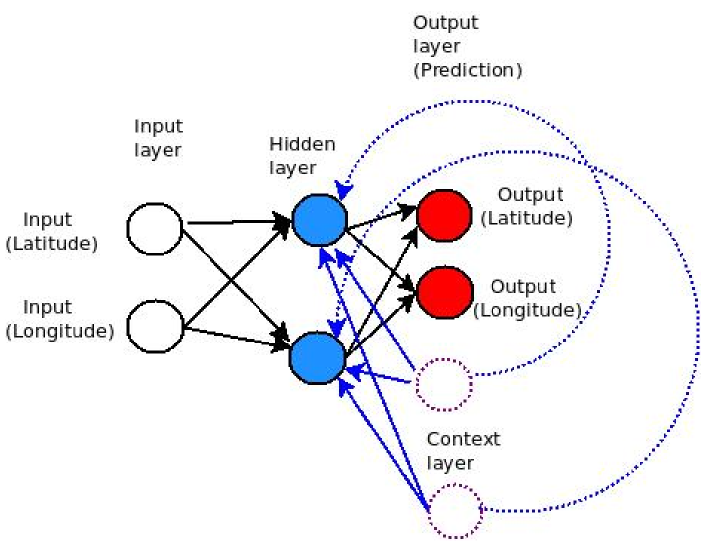


Fig. 2. Elman recurrent neural network used for prediction of latitude and longitude to determine the cyclone path which becomes a two dimensional time series problem. The context layer and weights are used to propagate information from previous time step that corresponds to previous data point of the time series.

In cooperative neuro-evolution of recurrent networks, problem decomposition determines how the problem is broken down into subcomponents that involves weights in the neuro-evolution problem. The subcomponents are implemented as sub-populations that are evolved in a *round-robin* fashion for a given number of generations known as the *depth of search*.

The general cooperative neuro-evolution method for training Elman recurrent neural networks is given in Algorithm 1.

In Algorithm 1, the recurrent neural network is decomposed in k subcomponents using neural level problem decomposition method [3]. k is equal to the total number of hidden, context and output neurons. Each subcomponents contains all the weight links from the previous layer connecting to a particular neuron. Each hidden neuron also acts as a reference point for the recurrent (state or context) weight links connected to it. Therefore, the subcomponents for a recurrent network with a single hidden layer is composed as follows:

1) Hidden layer subcomponents: weight-links from each neuron in the $hidden(t)$ layer connected to all $input(t)$ neurons and the bias of $hidden(t)$, where t is time.
2) State (recurrent) neuron subcomponents: weight-links from each neuron in the $hidden(t)$ layer connected to all hidden neurons in previous time step $hidden(t-1)$.
3) Output layer subcomponents: weight-links from each neuron in the $output(t)$ layer connected to all $hidden(t)$ neurons and the bias of $output(t)$

.

The subcomponents are implemented as subpopulations that employ the generalised generation gap with parent-centric crossover operator genetic algorithm [25].

A *cycle* is completed when all the subpopulations are evolved for a fixed number of generations.

A major concern in the proposed method is the cooperative evaluation of each individual in every subpopulation. There are two main phases of evolution in the cooperative coevolution framework. The first is the *initialisation phase* and second is the *evolution phase*.

Cooperative evaluation in the initialisation phase is given in Step 3. In the initialisation stage, the individuals in all the subpopulations do not have a fitness. In order to evaluate the ith individual of the kth subpopulation, arbitrary individuals from the rest of the subpopulations are selected and combined with the chosen individual and cooperatively evaluated. The best individual is chosen once fitness has been assigned to all the individuals of a particular subpopulation [5]. Cooperative evaluation in the evolution phase is shown in Step 3 (ii). This is done by concatenating the chosen individual from a subpopulation k with the single best individual from the rest of the subpopulations. The algorithm halts if the termination condition is satisfied. The termination criteria is a specified fitness is achieved which

Alg. 1 Cooperative Neuro-Evolution of Elman Recurrent Networks

Step 1: Decompose the problem into k subcomponents according to the number of Hidden, State, and Output neurons
Step 2: Encode each subcomponent in a subpopulation in the following order:
i) Hidden layer subpopulations
ii) State (recurrent) neuron subpopulations
iii) Output layer subpopulations
Step 3: Initialize and cooperatively evaluate each subpopulation
for each *cycle* until termination **do**
  for each Subpopulation **do**
    for n Generations **do**
      i) Select and create new offspring
      ii) Cooperatively evaluate the new offspring
      iii) Add the new offspring to the subpopulation
    end for
  end for
end for

is given by mean absolute error on the validation data set. Another termination condition is when the maximum number of function evaluations has been reached.

A. *Performance Evaluation*

The root mean squared error (RMSE) and mean absolute error (MAE) are used to evaluate the performance of the proposed method for cyclone wind-intensity prediction.

These are given in Equation 2 (RMSE) and Equation 3 (MAE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (2)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(y_i - \hat{y}_i)| \quad (3)$$

where y_i and $\hat{y}_i$ are the observed and predicted data, respectively. N is the length of the observed data. These two performance measures are used in order to compare the results with the literature.

B. *Data Pre-processing and Reconstruction*

In the cyclone wind-intensity data, a number of missing values were present for cyclones before 1985 and hence we took values afterwards. The data contained track position in terms of latitude and longitude and the wind-intensity of the cyclones. We combined all the cyclones into a training and test data set.

We used Taken's theorem [16] to reconstruct the time series data in stats-space vector. In this way, there is overlapping information about the time series data at different windows taken at equally spaced time lags.

Given an observed time series $x(t)$, an embedded phase space $Y(t) = [(x(t), x(t-T), ..., x(t(D-1)T)]$ can be generated, where, T is the time delay, D is the embedding dimension, $t = 0, 1, 2, ..., N - DT - 1$ and N is the length of the original time series.

In the above case, only one dimensional time series is considered. Our problem had two dimensions (latitude and longitude) and hence Taken's theorem was extended for two dimensions.

The reconstructed vector is used to train the recurrent network for one-step-ahead prediction where two neurons are used in the input and the output layerto represent the latitude and the longitude. The recurrent network unfolds k steps in time which is equal to the embedding dimension D [26], [27], [4].

IV. Simulation and Analysis

This section presents an experimental study of the proposed system that employs recurrent neural networks for cyclone track prediction. The neuron level (NL) [4] and synapse level (SL) [4] problem decomposition methods are used for training.

A. *Experimental set-up*

The Elman recurrent network employs sigmoid units in the hidden and output layer.

The termination condition is when a total of 50 000 function evaluations has been reached by the cooperative coevolutionary method (NL and SL).

The time series data contained 6000 points in the training set (Tropical Cyclones from 1985 - 2005) and 2000 points in the test set (Tropical Cyclones from 2006 - 2013) taken from JTWC data set which had readings taken at every 6 hours during the course of the tropical cyclones [28].

We used Taken's theorem [16] for state-space reconstruction. The data set contained time series of wind-intensity along with their position (latitude and longitude). We approached it as a two dimensional time series problem that included the latitude and longitude that defines the tracks of all the cyclones in the last three decades. We combined all the cyclones together and performed data pre-processing by considering the position in the southern hemisphere and converting all into one region. The conversion of latitude was done by multiplying the original latitude by -1 to accomodate for South in the southern hemisphere. The longitudes with

East (E) coordinates remained unchanged while the West (W) coordinates were subtracted from 360° to define all points in terms of East coordinates for easier plotting of cyclone tracks on spatial map.

We used the following combinations of dimension and time lag using Taken's.

- Configuration A: $D = 4$ and $T = 2$, reconstructed dataset contains 3417 samples in training set and 1298 samples in test set.
- Configuration B: $D = 5$ and $T = 3$, reconstructed dataset contains 2278 samples in training set and 865 samples in test set.
- Configuration C: $D = 7$ and $T = 3$, reconstructed dataset contains 2277 samples in training set and 865 samples in test set.
- Configuration D: $D = 7$ and $T = 4$, reconstructed dataset contains 1708 samples in training set and 649 samples in test set.

We employed three neurons in the input and output layer of the Elman recurrent network as shown in Figure 2. We experimented with different number of hidden neurons.

B. *Results and Discussion*

As specified in previous subsections, we used RMSE and MAE as main performance measures with fixed training time. The results are shown in Table I to Table IV. The mean and 95 % confidence interval is given from 30 experimental runs. Each run approximately took about 1.5 hours of computation time in 3.0 Giga hertz Intel Processor. The best results are shown with least values of RMSE and MAE and given in bold. The test for robustness of the proposed algorithm is done using different sets of configuration shows scalability as they contain varied data set sizes.

Overall, the best performance was given by NL method (3 Neurons) in Configuration D where D of 7 and T of 4 was used as shown in Table IV. The results by SL method in this configuration is also close. We note that the training performance is lower in Configuration D when compared to rest of the configurations. It seems, that in the rest of configurations, there is over-fitting of data as lower better training performance (in terms of lower values of RMSE and MAE) have not been able to give better testing or generalisation performance.

In general, NL problem decomposition method in co-operative neuro-evolution has outperformed SL in all the configurations.

Figure 3 and Figure 4 gives a typical experimental run performance by NL method taken from Configuration B.

C. *Discussion*

Although a two-dimensional time series problem is generally difficult, the results have shown that the proposed method has been very well able to give good prediction performance which has been visualised in Figure 3 and 4.

The goal of this research was to develop a system for prediction of the track of cyclones. We have not taken into account the speed which can also be an attribute in building a better system. The prediction of wind-intensity is also important and a three-dimensional approach can predict both the track and wind-intensity. Statistical techniques can be used to determine the relationship between the track and the wind intensity, i.e it would be interesting to find if there is significant change or curvature in the track when the wind intensity reaches a certain level. It would be interesting to find the correlation of wind-intensity and track.

Figure 5 gives a map for the visualisation of the cyclones and their tracks predicted by the proposed system. The randomly chosen 10 cyclones that had more than 15 predicted points, less first and last points, are used for plotting the track. The first and last coordinate points were removed for each cyclone as they had large (>5°) errors in the x-coordinate (longitude). In general, the error in predicted longitude is reasonably large compared to the error in predicted latitude from the original values, as illustrated in the figure. Although the prediction is close to the actual track, it can be further improved in future research. Mixture of experts can be used to build a combined prediction model, i.e. a separate neural network is assigned for wind-intensity and another one is assigned for track prediction. Moreover, other forms of neural network training method can be used that include hybridisation of gradient based methods with cooperative neuro-evolution. Feature extraction in multi-dimensional time series prediction can also be further explored.

V. Conclusions and Future Work

We presented a novel method that employed state-of-art techniques in neuro-evolution for evolution Elman recurrent networks for cyclone track prediction which was essentially a two-dimensional time series prediction problem. The results have shown to be very promising and a real-time implementation can be developed using web services and cloud computing infrastructure.

In future work, other computational intelligence methods can be used to compare with these results in order to build a robust system for tropical cyclone track prediction. Neuro-evolution and gradient based algorithms can be hybridised and used for training and further improving the results. The system can be extended to predict wind-intensity for tropical cyclones and data outside the South Pacific region can also be used for testing the method.

References

[1] J. L. Elman, "Finding structure in time," *Cognitive Science*, vol. 14, pp. 179–211, 1990.

[2] F. Gomez, J. Schmidhuber, and R. Miikkulainen, "Accelerated neural evolution through cooperatively coevolved synapses," *J. Mach. Learn. Res.*, vol. 9, pp. 937–965, 2008.

[3] R. Chandra, M. Frean, M. Zhang, and C. W. Omlin, "Encoding subcomponents in cooperative co-evolutionary recurrent neural networks," *Neurocomputing*, vol. 74, no. 17, pp. 3223 – 3234, 2011.

[4] R. Chandra and M. Zhang, "Cooperative coevolution of Elman recurrent neural networks for chaotic time series prediction," *Neurocomputing*, vol. 186, pp. 116 – 123, 2012.

TABLE I. RESULTS FROM THE PROPOSED METHOD FOR CONFIGURATION A

M	H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
NL	3	0.0508 ± 0.0010	0.0484 ± 0.0010	0.0455	9.718± 0.520	8.581± 0.496	6.981
NL	5	0.0493 ± 0.0006	0.0471 ± 0.0006	0.0447	8.943± 0.342	7.930± 0.323	6.882
NL	7	0.0492 ± 0.0007	**0.0471± 0.0006**	**0.0448**	8.826 ± 0.374	**7.830 ± 0.337**	**6.645**
SL	3	0.054± 0.0012	0.0504± 0.0012	0.0460	11.554± 0.687	10.274± 0.635	7.951
SL	5	0.053± 0.0012	**0.0495± 0.0011**	**0.0452**	10.850± 0.699	**9.633± 0.731**	**7.253**
SL	7	0.068± 0.0101	0.0656± 0.0103	0.0460	18.747± 4.329	17.814± 4.410	7.915

TABLE II. RESULTS FROM THE PROPOSED METHOD FOR CONFIGURATION B

M	H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
NL	3	0.0526 ± 0.0014	0.0481± 0.0013	0.0432	10.906± 0.714	9.197± 0.675	6.549
NL	5	0.0506± 0.0007	0.0462± 0.0008	0.0430	9.715± 0.401	8.168± 0.385	6.656
NL	7	0.0497± 0.0006	**0.0456± 0.0006**	**0.0425**	9.314± 0.304	**7.804± 0.279**	**6.367**
SL	3	0.058± 0.0035	0.0527± 0.0032	0.0436	13.616± 1.521	11.822± 1.426	7.698
SL	5	0.054± 0.0013	**0.0491± 0.0012**	**0.0434**	11.862± 0.811	**10.334± 0.755**	**6.729**
SL	7	0.062± 0.0048	0.0569± 0.0051	0.0435	15.831± 2.509	14.283± 2.562	6.945

TABLE III. RESULTS FROM THE PROPOSED METHOD FOR CONFIGURATION C

M	H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
NL	3	0.0530± 0.0010	0.0485± 0.0011	0.0448	10.695± 0.593	9.586± 0.559	6.877
NL	5	0.0504± 0.0007	**0.0468± 0.0006**	**0.0448**	9.415± 0.408	**8.621± 0.366**	**7.143**
NL	7	0.0501± 0.0006	0.0472± 0.0007	0.0445	9.328± 0.410	8.447± 0.356	6.924
SL	3	0.057± 0.0016	0.0514± 0.0015	0.0449	12.563± 0.944	11.401± 0.840	7.535
SL	5	0.055± 0.0016	**0.0507± 0.0013**	**0.0452**	12.169± 0.920	**10.997± 0.855**	**8.050**
SL	7	0.069± 0.0110	0.0656± 0.0112	0.0454	19.059± 4.483	18.180± 4.549	7.411

TABLE IV. RESULTS FROM THE PROPOSED METHOD FOR CONFIGURATION D

M	H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
NL	3	0.0578 ±0.0010	0.0334 ± 0.0014	0.0282	11.828 ±0.574	8.340± 0.567	**5.690**
NL	5	0.0554 ±0.0007	**0.0308 ±0.0007**	0.0284	10.582 ±0.338	**7.160± 0.318**	5.964
NL	7	0.0553 ±0.0006	0.0318± 0.0010	**0.0278**	10.815 ±0.374	7.512± 0.379	5.686
SL	3	0.062± 0.0020	0.0402± 0.0028	0.0301	14.535± 1.186	11.225± 1.139	7.168
SL	5	0.060± 0.0021	**0.0387± 0.0031**	**0.0293**	13.310± 0.957	**10.068± 0.899**	**6.911**
SL	7	0.069± 0.0052	0.0522± 0.0066	0.0318	19.451± 2.689	16.613± 2.797	7.792

[5] M. Potter and K. De Jong, "A cooperative coevolutionary approach to function optimization," in *Parallel Problem Solving from Nature PPSN III*, ser. Lecture Notes in Computer Science, Y. Davidor, H.-P. Schwefel, and R. Mnner, Eds. Springer Berlin Heidelberg, 1994, vol. 866, pp. 249–257.

[6] R. Chandra, "Adaptive problem decomposition in cooperative coevolution of recurrent networks for time series prediction," in *International Joint Conference on Neural Networks (IJCNN)*, Dallas, TX, USA, Aug. 2013, pp. 1–8.

[7] M. A. Potter and K. A. De Jong, "Cooperative coevolution: An architecture for evolving coadapted subcomponents," *Evol. Comput.*, vol. 8, no. 1, pp. 1–29, 2000.

[8] R. Chandra, M. Frean, and M. Zhang, "On the issue of separability for problem decomposition in cooperative neuro-evolution," *Neurocomputing*, vol. 87, pp. 33–40, 2012.

[9] C.-J. Lin, C.-H. Chen, and C.-T. Lin, "A hybrid of cooperative particle swarm optimization and cultural algorithm for neural fuzzy networks and its prediction applications," *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, vol. 39, no. 1, pp. 55–68, Jan. 2009.

[10] R. Chandra, M. Frean, M. Zhang, and C. W. Omlin, "Encoding subcomponents in cooperative co-evolutionary recurrent neural networks," *Neurocomputing*, vol. 74, no. 17, pp. 3223 – 3234, 2011.

[11] "Tropical-cyclone forecasting: a worldwide summary of techniques and verification statistics," *Bulletin of American Meteorological Society*, vol. 68.

[12] G. Holland, "Global guide to tropical cyclone forecasting. bureau of meteorology research center, melbourne, australia," http://cawcr.gov.au/publications/BMRC_archive/tcguide/, 2009, accessed: January 21, 2015.

[13] C. Roy and R. Kovordnyi, "Tropical cyclone track forecasting techniques - a review," *Atmospheric Research*, vol. 104-105, pp. 40–69, 2012.

[14] J. Hope and C. Neumann, "A survey of worldwide tropical cyclone prediction models," vol. Volume of Conference Papers, 11th Technical Conference on Hurricane and Tropical Metreorology, December 1316, Published by Amer. Meteorl. Soc., Boston,, pp. 375–380, 1977.

[15] "Models for the prediction of tropical cyclone motion over the north atlantic: an operational evaluation," *Monthly Weather Review*, vol. 109.

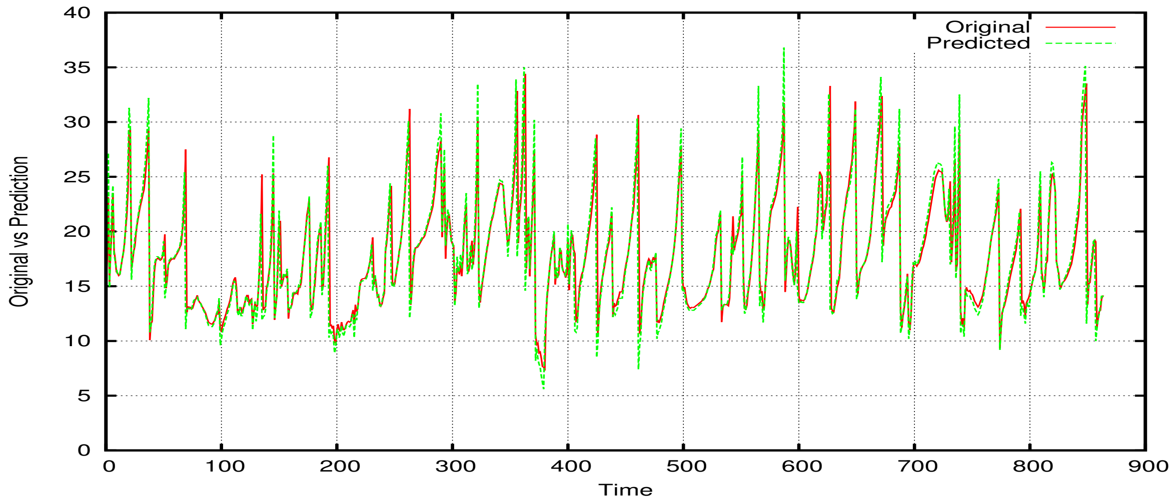
[16] F. Takens, "Detecting strange attractors in turbulence," in *Dynamical Systems and Turbulence, Warwick 1980*, ser. Lecture Notes in Mathematics, 1981, pp. 366–381.

[17] J. P. Terry, *Tropical Cyclone Structure*. Springer New York, 2007.

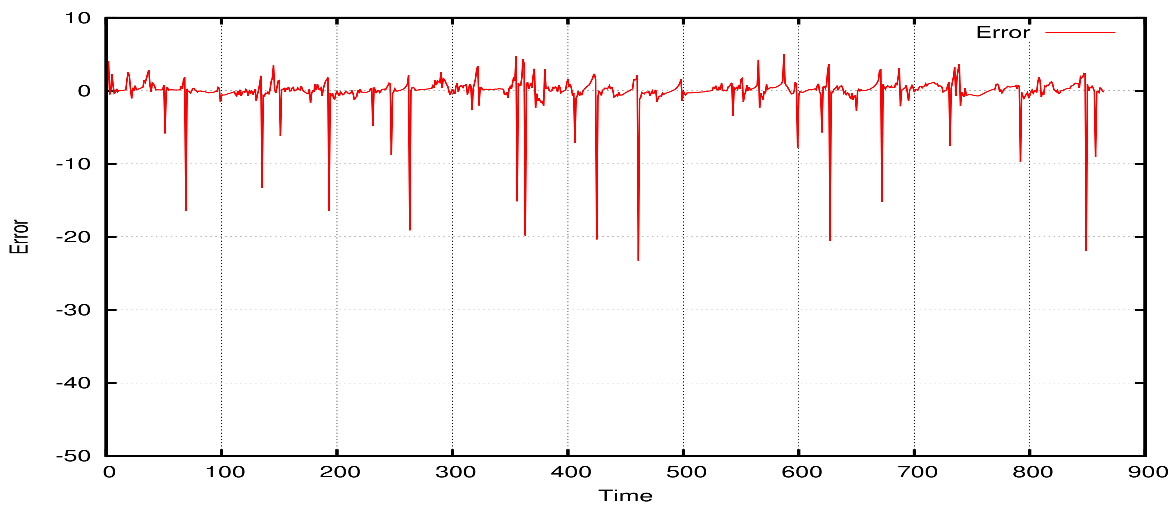
[18] M. G. William, "Global view of the origin of tropical disturbances and storms," *Monthly Weather Review*, vol. 96, pp. 669 – 700, 1968.

[19] ——, "Hurricanes: their formation, structure and likely role in the tropical circulation," *Royal Meteorological Society*, vol. RG12 1BX, pp. 155 – 218, 1979.

[20] S. Debsarma, "Cyclone and its warning system in bangladesh," National Disaster Reduction Day, 2001.



(a) Performance of latitude prediction the test data set, (RMSE:0.0439, MAE:7.365)



(b) Corresponding error of latitude prediction

Fig. 3. Typical prediction performance of a single experiment given by CCRNN for **Cyclone track latitude** test data set (2006 - 2013 tropical cyclones)

[21] R. Kovordnyi and C. Roy, "Cyclone track forecasting based on satellite images using artificial neural networks," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 64, pp. 513–521, 2009.

[22] R. A. Anthes, *Tropical Cyclones: Their Evolution, Structure and Effects*. Amer Meteorological Society; 1st edition (June 1982), 1982.

[23] V. Dvorak, "Tropical cyclone intensity analysis and forecasting from satellite imagery," *Monthly Weather Review*, vol. 103, pp. 420–430, 1975.

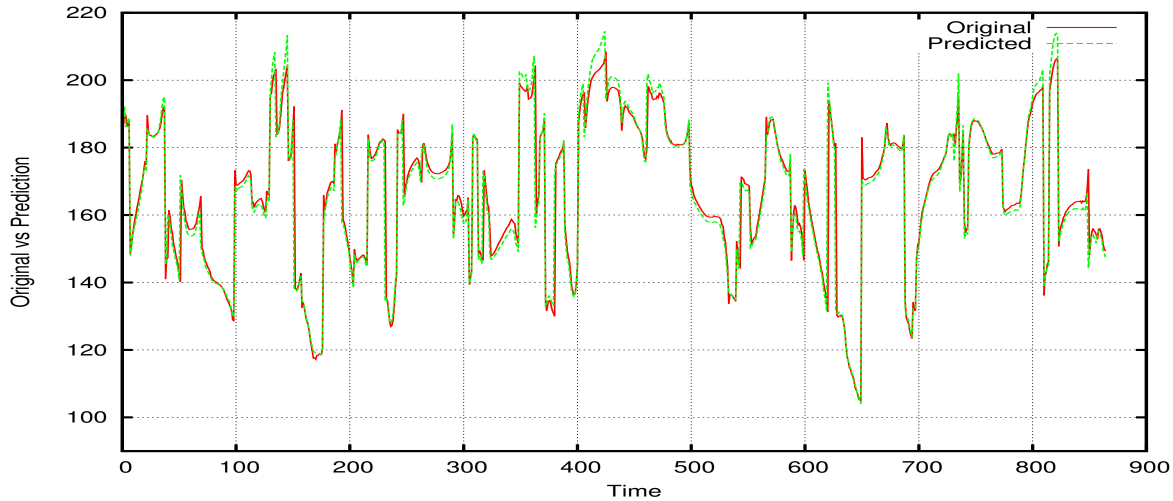
[24] (2000) Bureau of meteorology research centre. Accessed: January 21, 2015.

[25] K. Deb, A. Anand, and D. Joshi, "A computationally efficient evolutionary algorithm for real-parameter optimization," *Evol. Comput.*, vol. 10, no. 4, pp. 371–395, 2002.

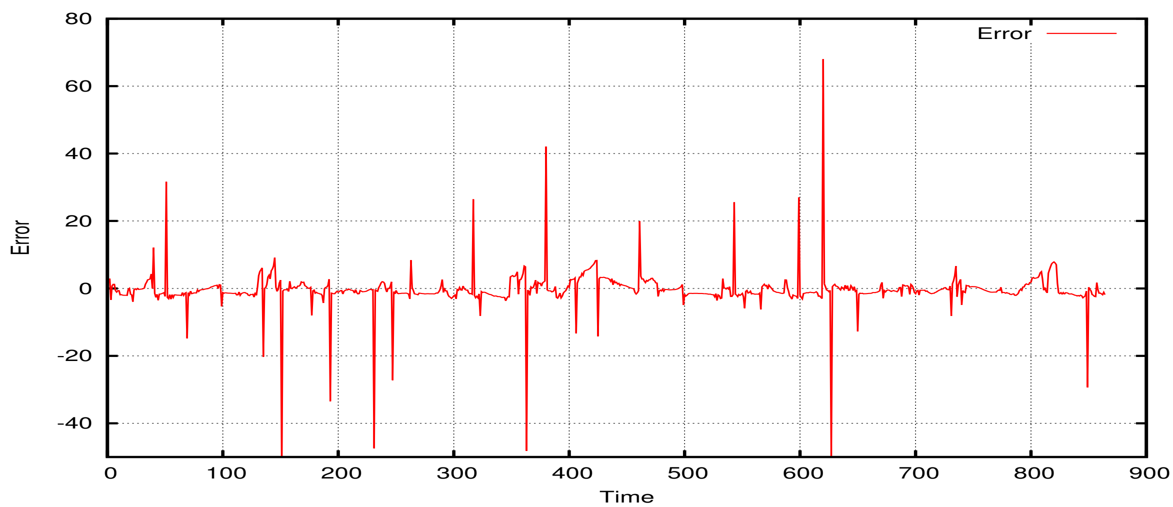
[26] T. Koskela, M. Lehtokangas, J. Saarinen, and K. Kaski, "Time series prediction with multilayer perceptron, FIR and Elman neural networks," in *In Proceedings of the World Congress on Neural Networks*, San Diego, CA, USA, 1996, pp. 491–496.

[27] D. Mirikitani and N. Nikolaev, "Recursive bayesian recurrent neural networks for time-series modeling," *Neural Networks, IEEE Transactions on*, vol. 21, no. 2, pp. 262 –274, Feb. 2010.

[28] "JTWC tropical cyclone best track data site," 2015. [Online]. Available: http://metocph.nmci.navy.mil/jtwc/best_ tracks/



(a) Performance of longitude prediction the test data set, (RMSE:0.0439, MAE:7.365)



(b) Corresponding error of longitude prediction

Fig. 4. Typical prediction performance of a single experiment given by CCRNN for **Cyclone track longitude** test data set (2006 - 2013 tropical cyclones)

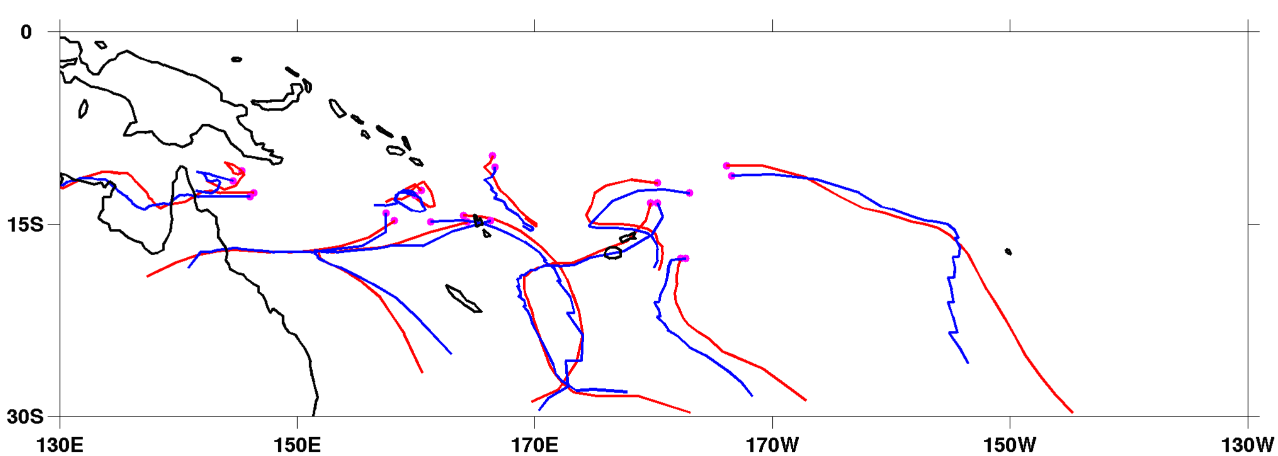


Fig. 5. Randomly chosen 10 tropical cyclone tracks. The red tracks correspond to original cyclone tracks while blue tracks correspond to predicted cyclone tracks. The magenta coloured dots are the start location of the tropical cyclones.