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Cooperative Neuro-evolution of Elman Recurrent Networks for Tropical Cyclone Wind-Intensity Prediction in the South Pacific Region

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***Abstract*—Climate change issues are continuously on the rise and the need to build models and software systems for management of natural disasters such as cyclones is increasing. Cyclone wind-intensity prediction looks into efficient models to forecast the wind-intensification in tropical cyclones which can be used as a means of taking precautionary measures. If the wind-intensity is determined with high precision a few hours prior, evacuation and further precautionary measures can take place. Neural networks have become popular as efficient tools for forecasting. Recent work in neuro-evolution of Elman recurrent neural network showed promising performance for benchmark problems. This paper employs Cooperative Coevolution method for training Elman recurrent neural networks for Cyclone wind-intensity prediction in the South Pacific region. The results show very promising performance in terms of prediction using different parameters in time series data reconstruction.**

I. Introduction

COOPERATIVE COEVOLUTION (CC) is an evolutionary computation method that divides a problem into subcomponents that are similar to the different species in nature [1]. CC has been effective for neuro-evolution of feedforward and recurrent neural networks [2], [3], [4], [5], [6], [7]. 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 that are training cooperatively and collectively [2].

Cooperative coevolution problem decomposition method is defined by structural properties of the neural network that contains inter-dependencies [8]. 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) [9], [10], [11] and neuron level (NL) [12], [8] methods. Cooperative coevolution has been been used for neuro-evolution of recurrent neural networks for time series problems [11], [13] and it has been shown that the perform better compared to several methods from literature.

A tropical cyclone is one of the most common and devastating natural disasters that impact coastal and tropical countries [14]. It involves air-sea interaction over warm waters of the tropics with an organized surface circulation, and frequently occurs during boreal summer (April to November) in the Northern Hemisphere [1] and austral summer (November to April) in the Southern Hemisphere [2]. Tropical cyclones get considerable scientific and social attention due to their (i) disaster impacts, (ii) regional rainfall impacts due to inter-annual variations, and (iii) relation to global warming due to changes in frequency, intensity, numbers, and tracks [14].

In light of the warming of climate system, several studies have been conducted on the variations of sea-surface temperature, sea-level rise, precipitation, and drought, with the aim to understand the extreme weather events in the South Pacific Ocean [14], [15]. For instance, a study on climate change impacts on tropical cyclones and extreme sea-levels show that the most extreme sea-level in the South Pacific Ocean is generated by tropical cyclones occurring in that region and also from the swells generated by distant storms [16].

A study of the dynamics of variability of tropical cyclone activities has been one of the biggest challenges for charting climate change projections [14]. For the case of the South Pacific Ocean, the intensity of the strongest tropical cyclones is expected to increase. The future projection of tropical cyclone numbers, frequency and intensity will lie in the quality of available historical (observed) data sets and high-resolution dynamical climate models [14]. The availability of reliable data sets provides the basis for simulating realistic climate change projections that in turn assist in understanding future occurrences of tropical cyclones. In the case of smaller islands, scientists encounter some of the major challenges in the acquisition of reliable data especially because the oceanographic data for the entire region are sparse as compared to the North Pacific region, where the spatial resolution of available data is considered higher [16].

Tropical cyclone intensity forecast skills lag that of the

[1] www.nhc.noaa.gov
[2] www.bom.gov.au

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track forecast [17], [18], [19]. The models (numerical and dynamical) used for intensity forecast, discussed in detail later, are showing modest improvement in the forecast skill, however, the struggle remains due to many factors including deficiencies in systematically collecting inner core data in the real-time. Given different approaches in previous studies, there has not been much work done using computational intelligence methods to forecast cyclone intensity, especially with neural networks.

This paper presents an application of cooperative neuro-evolution of recurrent neural networks for cyclone wind-intensity prediction in the South Pacific region. We use cyclone wind-intensity data from past 3 decades for training and testing. We employ Taken's theorem to reconstruct the cyclone wind-intensity time series data in 4 different sets that is used to for neuro-evolution using Neuron and Synapse level problem decomposition methods. The Elman recurrent neural networks [20] is used for prediction. The performance of the different reconstructed data sets and problem decomposition methods are compared and a discussion for real-time cloud based prediction system using neuron-evolution is also given.

The rest of the paper is organized as follows. A brief background on tropical cyclones is given in Section 2 and Section 3 gives details of the proposed method using cooperative neuro-evolution of recurrent neural networks for cyclone wind-intensity prediction. Section 4 presents a background on the given chaotic time series problems, 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

The official tropical cyclone guidance track and intensity forecast is assigned to the designated regions around the world. For the South Pacific, the Fiji Meteorological Service (FMS) in Nadi Fiji is a World Meteorological Organisation (WMO) recognised Regional Specialised Meteorological Centre (RSMC) who is responsible for the southwest Pacific Ocean [3]. In addition to FMS, the Australian Bureau of Meteorology (BoM), a Tropical Cyclone Warning Center (TCWC), is also responsible for the far southwest Pacific Ocean basin [4]. While the U.S naval Joint Typhoon Warning Centre (JTWC) [5] is not a WMO recognised RSMC or TCWC, it however also issues cyclone warnings for various ocean basins, including northwest Pacific, North Indian, Southwest Indian, Southeast Indian/Australian, and the Australian/Southwest Pacific basins [Central Pacific Hurricane Centre] [6].

B. Related work in Cyclone Wind-Intensity Prediction

When the satellite era began, the intensity of tropical cyclones was estimated using satellite images [21], where methods involving cloud features with conventional estimates of cyclone strengths were devised for estimating the intensity [22], [23]. Dvorak (1975) used a technique to combine meteorological analysis of satellite imagery with a model consisting a set of curves that depicted cyclone intensity change with time and cloud feature descriptions of the cyclone at intervals along the curves [24]. Since then this technique is known as the Dvorak technique and has been used extensively in tropical cyclone forecasting. Tropical cyclone track forecasting has shown steady improvement over the past three decades with the availability of better observations and state-of-the-art numerical models [25]. By contrast, in spite of sophisticated numerical model applications, there has been comparatively little improvement in cyclone intensity prediction (by maximum surface wind speed) [25]. The three-dimensional coupled and numerical models would lead to better understanding of the cyclone intensity changes, however, the intensity change has non-trivial dependence on the horizontal resolution even at small grid spacing [26], making it difficult to obtain best approximate of the intensity. Fortunately, the statistical models are able to provide the best intensity forecast today [27]. It is also important to note that cyclone intensity change is caused by the atmospheric and ocean environmental factors. Given that, the best statistical model prediction schemes account for pre-storm sea surface temperature and vertical wind shear [28].

There are only a few models that forecast cyclone intensity change. Statistical Hurricane Intensity Forecast (SHIFOR), is a multiple regression statistical model that uses various climatological and persistence of the intensity parameters to forecast the intensity of a cyclone 12-hourly out to 72 hours. The predictor variables that SHIFOR model utilizes are: Julian day, current storm intensity, intensity change in the past 12 hours, initial storm location (latitude and longitude), and zonal and meridional component of storm motion. The historic cyclone data from the period 1900-1972, cyclones at least 30 nautical miles from the land, was used to develop the original SHIFOR equation [29]. The current SHIFOR5 equation uses 1967-1999 cyclone data with a minimum requirement that each cyclone intensifies into tropical storms. To maintain the continuity in the model runs, the parameters included in the prediction equation at a particular forecast time are preferred in the subsequent forecast time [30].

Statistical Hurricane Intensity Prediction Scheme (SHIPS), is a statistical-dynamic intensity prediction model that has been available since mid-1990s [27]. SHIPS model was developed using the standard multiple regression techniques where predictors were climatological, persistence and numerical model forecasts. The cyclone intensity forecasts are made for 12-hour periods out to 120 hours. The initial SHIPS equations were developed using 49 storms that were at least 30 nautical miles from land during the period 1982-1992. These equations are updated annually and the recent versions of SHIPS have significant skill at least out to 72 hours. In addition to the five predictors used in SHIFOR, SHIPS uses divergence of winds at 200 hPa, intensification potential, vertical shear of the horizontal winds between 850-200 hPa levels, average 200 hPa temperature, average 850 hPa vorticity, average 500-300 hPa layer relative humidity, cloud top temperature measured

[3] www.met.gov.fj
[4] www.bom.gov.au
[5] http://www.usno.navy.mil/JTWC/
[6] http://www.prh.noaa.gov/cphc/pages/FAQ/Forecasting.php

by GOES satellite and oceanic heat content from altimeter measurements. A drawback of SHIPS model in cyclone intensity forecast is that it is not suitable for cyclones near the coasts as the SHIPS equations were developed using storm data over the ocean [31].

The Southern Hemisphere Statistical Typhoon Intensity Prediction Scheme (SH STIPS) model, a consensus-based method based on multiple linear regression equations for each forecast time, was desinged in 2005 to make statistical forecasts on intensity using environmental forecast information [32]. This model, mirrors similar capabilities as its counterpart used in the western North Pacific [33] , uses optimal combination of factors related to climatology and persistence, intensification potential, vertical wind shear, atmospheric stability and dynamic intensity forecasts. Based on the performance statistics, the SH STIPS is one of the better models making intensity forecasts in the Southern Hemisphere basins [32].

Before discussing the focus of this study, it is important to understand the wind structure of a tropical cyclone. Schematic shown in Figure 1 is the typical wind strength distribution across the cross section of a cyclone. The yellow curve indicates the wind speed profile where maximum wind speeds are in the eye-wall and lowest in the eye of the cyclone. The measured intensity of the cyclone as in the data set is defined by the maximum mean winds near the centre at the standard 10m height above the ocean or flat open land.

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

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*. In our past works, we have investigated about the depth of search and effects of different problem decomposition methods [35], [8] and the performance of cooperative neuro-evolution in time series prediction problems [11].

Recurrent neural networks have been an important focus of research as they can be applied to difficult problems involving time-varying patterns. They are suitable for modelling temporal sequences. First-order 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 [20] 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).

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

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.

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 [36]. k is equal to the total number of hidden, context and output neurons. Each subcomponent 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 [37].

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

A major concern in this 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 [1]. 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 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.

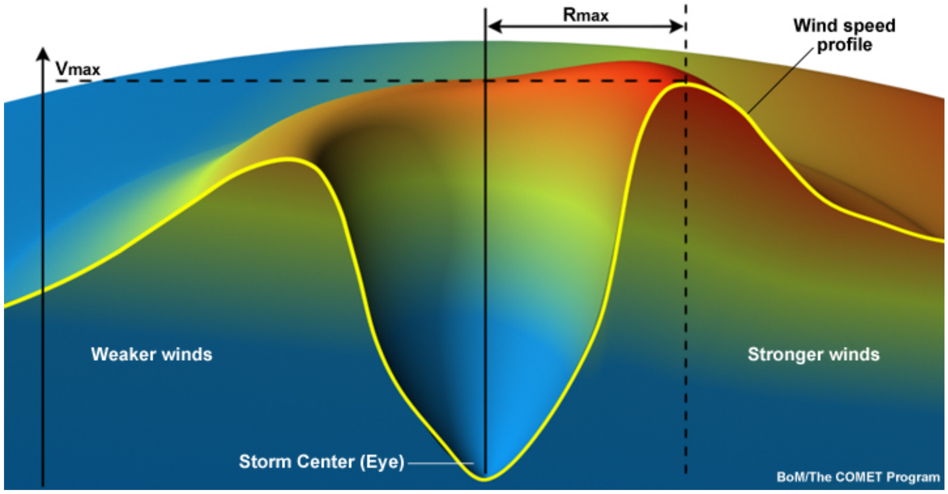


Fig. 1. Wind intensity structure of a tropical cyclone [34]

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: Initialise 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

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).

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

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

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 order to effectively use neural networks for time series prediction, measures need to be taken to pre-process the raw time series data and arranged in a specific way so that it can be used to train the Elman recurrent network. In the cyclone wind-intensity data, a number of missing values were present for cyclones before 1985 and therefore, we tool values afterwards. We used Taken's theorem to reconstruct the time series data in stats-space vector. In this way, there is over-lapping 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 [38]. Taken's theorem expresses that the vector series reproduces many important characteristics of the original time series. The right values for D and T must be chosen in order to efficiently apply Taken's theorem [39]. Taken's proved that if the original attractor is of dimension d, then $D = 2d+1$ will be sufficient to reconstruct the attractor

[38].

The reconstructed vector is used to train the recurrent network for one-step-ahead prediction where 1 neuron is used in the input and the output layer. The recurrent network unfolds k steps in time which is equal to the embedding dimension D. Similar setup was used in our previous work [11].

IV. Simulation and Analysis

This section presents an experimental study of using co-operative coevolution for training the Elman recurrent neural network on cyclone wind-intensity time series problem.

The behaviour of the respective methods are evaluated on different recurrent network topologies which are given by different numbers of hidden neurons and difference problem decomposition methods in cooperative neuro-evolution given by neuron level (NL) [11] and synapse level (SL) [11] problem decomposition methods.

A. Experimental set-up

The Elman recurrent network employs sigmoid units in the hidden, context and output layer of the network. The experiment set-up is similar to our previous works [11]. The RMSE and MAE given in Equation 2 and Equation 3 are used as the main performance measures of the recurrent network.

In the proposed cooperative neuro-evolution of recurrent networks shown in Algorithm 1, each sub-population is evolved for a fixed number of generations in a round-robin fashion. This is considered as the *depth of search*. We used 1 as the depth of search in all the experiments as also done in our previous works [11]. Note that all sub-populations evolve for the same depth of search.

The termination condition of the all the problems and recurrent network training methods is when a total of 50 000 function evaluations has been reached by the respective cooperative co-evolutionary methods (NL and SL).

We used the following combinations of dimension and time lag using Taken's theorem [38] for state-space reconstruction of the time series that 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 of Southern Hemisphere [40]. The data set contained readings taken at every 6 hours during the course of the tropical cyclone.

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

B. Results and discussion

This section reports the performance of CICC for training the Elman recurrent network for predicting tropical cyclones wind-intensity for one-step ahead prediction.

The results in terms of RMSE and MAE are shown in Table I to Table IV with different sets of configuration from (Configuration A - Configuration D) which was specified in previous subsection. The mean and 95 % confidence interval is given from 30 experimental runs. Due to the use of evolutionary algorithm, each run approximately took 1 hour 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 different number of hidden neurons test robustness of the proposed algorithm in different network topologies while the different sets of configuration shows scalability as they contain varied data set sizes.

In Table I to Table IV, the results from the four different configurations in general show that the two methods that report the accuracy of the results (MAE and RMSE) lead to similar conclusions about the best results. This shows that both these methods of reporting accuracy are similar.

Moreover, synapse level problem decomposition (SL) shows to give good or best results with lower number of hidden neurons (H) when compared to neuron level (NL). In some situations, the training performance does not lead to the best generalization performance which implies over training.

In general, NL has been more robust in giving similar performance even though there is major changes in the number of hidden neurons when compared to SL where the results deteriorate as the number of hidden neurons increases.

Overall, the best performance was given by Configuration B (D5-T3) by NL method shown in Table II.

Figure 2 gives a typical experimental run performance taken from one of the best performance from Configuration B.

C. Discussion

The proposed method with different sets of configuration in time series data reconstruction has given very promising performance. Overall, it can be said that NL gives the better performance than SL in terms of RMSE for training and testing for Configuration A - C. In Configuration D, both methods have competing performances. The error rate in terms of RMSE for training can be further decreased by using competitive cooperative coevolution method [41] that can be focus of future research.

Although SL and NL were given the same optimisation time in terms of number of function evaluations, we note that SL takes long than NL in the initialisation state as it has significantly higher number of subcomponents. A comparison of initialisation time has been done in our previous work where it shows that NL is faster [36] in the initialisation stage. Taking the time and performance into account, we recommend NL problem decomposition method to be used in future works.

TABLE I. RESULTS FROM THE PROPOSED METHOD FOR CONFIGURATION A

M	H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
NL	3	3.10E-02 ±2.79E-04	3.23E-02 ±3.21E-04	**2.99E-02**	3.56 ±5.03E-02	3.96 ±4.29E-02	**3.70**
NL	5	3.04E-02 ± 8.08E-05	3.22E-02 ± 2.25E-04	3.10E-02	3.48 ± 1.48E-02	3.93 ± 2.24E-02	3.80
NL	7	**3.03E-02 ± 1.33E-04**	**3.21E-02 ± 2.69E-04**	3.06E-02	**3.47 ±1.83E-02**	**3.91 ± 2.24E-02**	3.81
NL	9	3.09 E-02 ± 1.04E-03	3.24E-02 ± 8.08E-04	0.03046	3.60 ± 1.79E-01	3.99 ± 1.30E-01	3.74
SL	3	3.16E-02 ±5.38E-04	3.27E-02 ±4.55E-04	3.03E-02	3.65 ±9.54E-02	3.97 ±6.04E-02	3.70
SL	5	**3.10E-02 ±2.61E-04**	**3.27E-02 ±3.62E-04**	**3.07E-02**	**3.58 ±4.84E-02**	3.99 ±3.638E-02	3.82
SL	7	3.19E-02± 6.60E-04	3.37E-02 ±9.89E-04	3.07E-02	3.77 ±1.27E-01	4.24 ±1.82E-01	3.68
SL	9	3.35E-02 ± 1.72E-03	3.59E-02 ± 2.17E-03	3.04E-02	4.15 ± 0.356778	4.71 ± 4.22E-01	3.77

TABLE II. RESULTS FROM THE PROPOSED METHOD FOR CONFIGURATION B

M	H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
NL	3	3.06E-02± 2.91E-04	2.92E-02 ±3.40E-04	2.77E-02	3.61 ±5.09E-02	3.72± 5.18E-02	3.58
NL	5	3.01E-02 ±3.09E-04	2.90E-02 ±2.65E-04	**2.75E-02**	3.54 3.10E-02	3.70 ±4.22E-02	**3.45**
NL	7	**2.98E-02 ± 1.49E-04**	**2.87E-02 ± 1.86E-04**	2.79E-02	**3.51 ± 2.55E-02**	**3.64 ±3.00E-02**	3.49
NL	9	2.99E-02 ± 2.46E-04	2.90E-02 ±2.50E-04	**2.75E-02**	3.55 ±4.19E-02	3.70 ±4.55E-02	3.49
SL	3	**3.11E-02± 5.32E-04**	**2.97E-02 ±6.02E-04**	**2.78E-02**	**3.68± 9.08E-02**	**3.79 ±1.07E-01**	**3.44**
SL	5	3.22E-02 ±2.22E-03	3.12E-02± 2.41E-03	2.78E-02	3.91 ±4.30E-01	4.06 ±4.52E-01	3.51
SL	7	3.15E-02 ±8.56E-04	3.10E-02 ± 1.26E-03	2.72E-02	3.85 ± 1.73E-01	4.09 ±2.46E-01	3.43
SL	9	3.77E-02 ± 3.87E-03	3.82E-02 ± 4.16E-03	2.77E-02	5.06 ± 7.46E-01	5.44 ± 7.82E-02	3.50

TABLE III. RESULTS FROM THE PROPOSED METHOD FOR CONFIGURATION C

M	H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
NL	3	3.07E-02 ±2.39E-04	3.61E-02 ± 3.72E-04	3.38E-02	3.59 ±4.87E-02	4.40 ±3.88E-02	4.20
NL	5	3.00E-02 ± 1.26E-04	**3.56E-02 ±2.86E-04**	**3.37E-02**	**3.46 ±1.80E-02**	**4.33± 3.24E-02**	**4.17**
NL	7	2.99E-02 ± 1.27E-04	3.58E-02 ± 5.26E-04	3.39E-02	3.47 ± 2.54E-02	4.35 ± 2.93E-02	4.23
NL	9	**2.98E-02 ± 1.33E-04**	**3.56E-02 ± 3.18E-04**	3.39E-02	3.47 ± 2.08E-02	4.35 ± 3.17E-02	4.22
SL	3	3.20E-02± 7.25E-04	**3.60E-02± 5.69E-04**	**3.22E-02**	3.78± 1.06E-01	**4.41 ±6.26E-02**	4.17
SL	5	**3.12E-02 ± 5.44E-04**	3.63E-02 ± 5.43E-04	3.41E-02	**3.65 ± 1.00E-01**	4.46 ± 9.68E-01	**4.15**
SL	7	3.19E-02 ± 1.21E-03	3.70E-02 ± 1.19E-03	3.34E-02	3.86 ± 2.33E-01	4.66 ± 2.29E-01	4.17
SL	9	4.22E-02 ± 6.29E-03	4.87E-02 ± 6.70E-03	3.34E-02	5.88 ± 1.18	6.89 1 ± 1.25	4.13

TABLE IV. RESULTS FROM THE PROPOSED METHOD FOR CONFIGURATION D

M	H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
NL	3	3.04E-02 ± 3.29E-04	3.15E-02 ± 3.34E-04	3.02E-02	3.62 ± 4.46E-02	3.89 ± 5.86E-02	3.38
NL	5	2.94E-02 ± 2.40E-04	**3.09E-02 ± 2.92E-04**	2.98E-02	3.51 ± 3.05E-02	3.80 ± 3.99E-02	3.62
NL	7	**2.90E-02 ± 2.33E-04**	**3.09E-02 ± 3.25E-04**	**2.92E-02**	**3.48 ± 2.71E-02**	**3.80 ± 3.30E-02**	**3.58**
NL	9	2.95E-02 ± 2.26E-04	**3.09E-02 ± 3.88E-04**	2.99E-02	3.53 ± 3.45E-02	3.83 ± 4.40E-02	3.67
SL	3	3.03E-02 ± 3.45E-04	**3.09E-02 ± 3.49E-04**	**2.91E-02**	**3.59 ± 4.67E-02**	**3.80 ± 4.20E-02**	3.61
SL	3	3.03E-02 ± 5.81E-04	3.15E-02 ± 3.99E-04	2.91E-02	3.63 ± 9.42E-02	3.89 ± 7.38E-02	**3.58**
SL	7	**2.97E-02 ± 6.09E-04**	3.19E-02 ± 1.05E-03	2.93E-02	3.61 ± 9.96E-02	3.95 ± 1.50E-01	3.65
SL	9	3.91E-02 ± 5.19E-03	4.17E-02 ± 5.99E-03	2.99E-02	5.35 ± 9.58E-01	5.84 ± 1.09	3.65

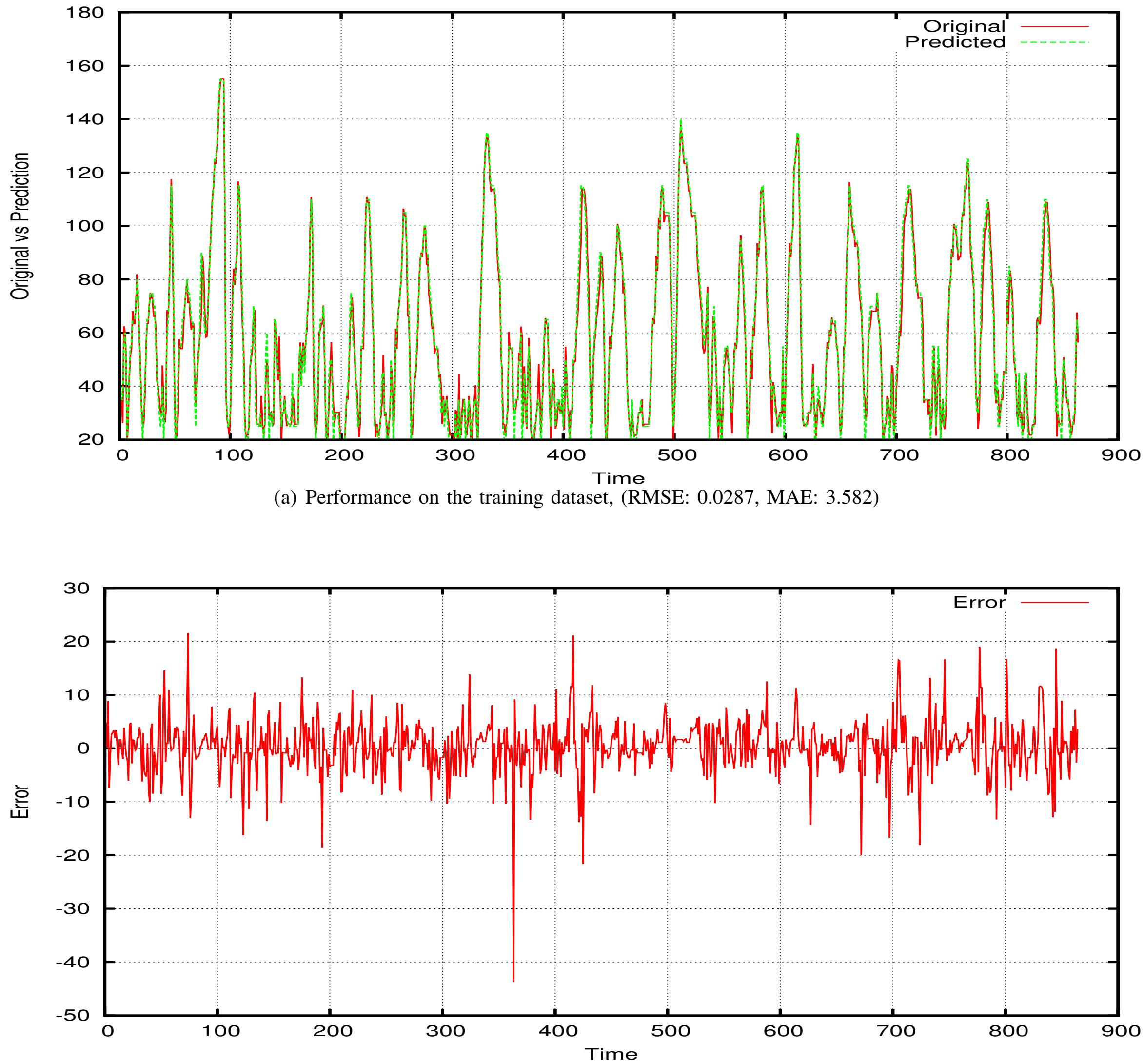
The way ahead is to implement this system as a web service or website that employs cloud computing infrastructure and users can use it to predict future cyclones. Along with the wind-intensity, cyclone track prediction is also important can can be used to develop a better system for disaster forecasting and management.

Tropical cyclone wind intensity prediction is complex in nature as it is affected by various surrounding factors and processes that are not well understood to this day. Therefore, an important concern that may arise out of this study is how the prediction skill would change if those factors are also incorporated into the experiment. Since the current study is designed to predict a single dimensional time series, ie., maximum wind speed, a multi-dimensional time series approach is needed that can account for various parameters which will act as predictors for the wind intensity forecast that meteorological offices around the world can adapt.

V. CONCLUSIONS AND FUTURE WORK

This paper presented an application of state-of-art neuro-evolution method for prediction of wind-intensity for tropical cyclones in the South Pacific region. The method employed data from cyclone wind-intensity taken for the last three decades. The results show promising prediction performance with low error rates that makes it feasible for real time implementation.

In future work, the implementation of the proposed method for cyclone wind-intensity prediction can be done using cloud computing methods and a web service can



(a) Performance on the training dataset, (RMSE: 0.0287, MAE: 3.582)

(b) Error on the training dataset

Fig. 2. Typical prediction performance of a single experiment given by CCRNN for Cyclone test data set (2006 - 2013 tropical cyclones)

also be created. The method can also be used to predict cyclone wind-intensity from other regions and extension of the method to use clone tracks can give more information about the future track of the cyclone which can be very beneficial for disaster management.

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