Coevolutionary Recurrent Neural Networks for Prediction of Rapid Intensification in Wind Intensity of Tropical Cyclones in the South Pacific region

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Abstract. Rapid intensification in tropical cyclones occur where there is dramatic change in wind-intensity over a short period of time. Recurrent neural networks trained using cooperative coevolution have shown very promising performance for time series prediction problems. In this paper, they are used for prediction of rapid intensification in tropical cyclones in the South Pacific region. An analysis of the tropical cyclones and the occurrences of rapid intensification cases is assessed and then data is gathered for recurrent neural network for rapid intensification predication. The results are promising that motivate the implementation of the system in future using cloud computing infrastructure linked with mobile applications to create awareness.

Key words: Cooperative coevolution, neuro-evolution, recurrent neural networks, tropical cyclones, rapid intensification.

1 Introduction

Rapid intensification occurs when a tropical cyclone intensifies dramatically within a short period of time [1]. Previous studies have shown that operational forecasting models are more skillful in predicting tropical cyclone tracks whereas predicting cyclone intensity remains one of the major challenges in tropical weather forecasting [2]. Forecasting rapid intensification has been another challenge, which is partly due to our limited understanding of the physical mechanisms of tropical cyclone intensity change in general [2], [3]. Previous efforts in studying individual tropical cyclone have identified some conditions that are favourable for rapid intensification. For instance, in efforts to understand change in tropical cyclone intensity, it has been shown that warm ocean temperatures [4], [5] and warm-ocean eddies [6] influence the rapid intensification of tropical cyclones.

The existing literature defines rapid intensification in various ways. For instance, [1] defined rapid deepening of tropical cyclones when the systems pressure drops by $\geq$42 millibar in 24-hours. The rapid intensification for Northern Hemisphere tropical cyclones according to National Hurricane Centre is an increase in the maximum sustained winds of a tropical cyclone by at least 30-knots in a 24-hour period. This definition has been employed in [7] who define rapid intensification as an approximate of the 95th percentile of all 24-hour over-water intensity change of tropical cyclones in the North Atlantic basins by 30-knots over 24-hour period.

Cooperative coevolution (CC) is a evolutionary computation method which divides a large problem into subcomponents and solves them using evolutionary algorithms [8]. CC has been effective for neuro-evolution of feedforward and recurrent neural networks [9–13]. Problem decomposition is an important procedure in cooperation coevolution that determines how the subcomponents are decomposed [9]. Cooperative neuro-evolution of recurrent neural networks have given very promising performance for time series problems [13, 14] and also have been successfully applied for cyclone wind-intensity and track prediction problems for the South Pacific Ocean [15, 16].

In this paper, cooperative neuro-evolution of recurrent networks is applied for prediction of rapid intensification in tropical cyclones in the South Pacific region. Rapid intensification cases are detected and collected for recurrent neural network for training and testing. We capture the time series during the cyclone for one and two days ahead that led to rapid intensification cases. Although other machine learning methods can be used, we specially chose coevolutionary recurrent neural networks as they showed promising performance in cyclone wind-intensity and track prediction [15, 16].

The rest of the paper is organised as follows. Section 2 gives background in cyclone wind-intensity prediction and computational intelligence methods for time series prediction. In Section 3, the proposed method is discussed in detail while in Section 4, experiments and results are given. Section 5 concludes the paper with discussion of future work.

2 Coevolutionary Recurrent Networks for Rapid Intensification

2.1 Recurrent Network Architecture

Recurrent neural networks are suitable for modelling temporal sequences. Elman recurrent neural networks use context units to store the output of the state neurons from computation of the previous time steps [17]. The context layer is used for computation of present states as they contain information about the previous states as shown in Figure 1. The dynamics of the change of hidden state neuron activation's in Elman style recurrent networks is given by Equation (1).

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

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.

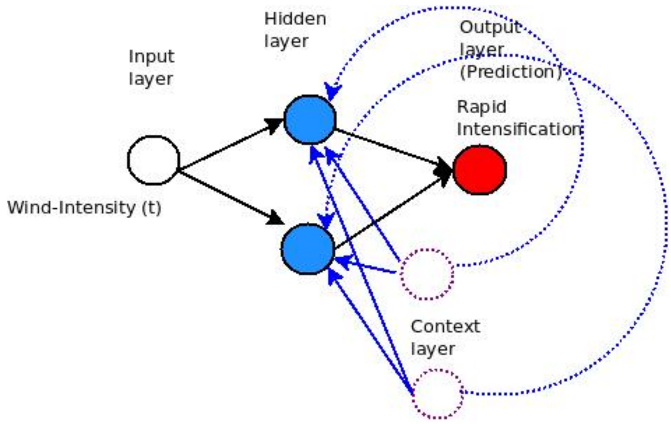

Fig. 1. Elman recurrent neural network used for prediction of rapid intensification in cyclones. We use the wind-intensity to predict the strength of rapid intensification. The recurrent neural network has 1 neuron in the input layer and 1 output neuron assigned for the prediction of rapid intensification.

2.2 Cooperative Neuro-Evolutionary Recurrent Networks

Algorithm 1 gives details for the cooperative neuro-evolution method used for training Elman recurrent neural networks shown in Figure 1.

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 sub-population in the following order:
i) Hidden layer sub-populations
ii) State (recurrent) neuron sub-populations
iii) Output layer sub-populations
Step 3: Initialise and cooperatively evaluate each sub-population
for each *cycle* until termination **do**
  for each Sub-population **do**
    for n Generations **do**
      i) Select and create new offspring
      ii) Cooperatively evaluate the new offspring
      iii) Add the new offspring to the sub-population
    end for
  end for
end for

In Algorithm 1, the recurrent neural network is decomposed in k subcomponents using neural level problem decomposition method [13]. 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 $output(t)$

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The subcomponents are implemented as sub-populations that employ the generalised generation gap with parent-centric crossover operator genetic algorithm [18]. A *cycle* is completed when all the sub-populations are evolved for a fixed number of generations.

A major concern in this proposed method is the cooperative evaluation of each individual in every sub-population. 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 sub-populations do not have a fitness. In order to evaluate the ith individual of the kth sub-population, arbitrary individuals from the rest of the sub-populations 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 sub-population [8]. Cooperative evaluation in the evolution phase is shown in Step 3 (ii). This is done by concatenating the chosen individual from a sub-population k with the single best individual from the rest of the sub-populations. 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.

The G3-PCX (generalised generation gap with parent-centric crossover operator) algorithm is used in the sub-populations of cooperative coevolution [18].

G3-PCX has been used in sub-populations of cooperative coevolution methods in our past research that includes cooperative coevolutionary recurrent neural networks for time series prediction [13], memetic cooperative coevolution [11] and competitive cooperative coevolution for time series prediction [14] and also application for cyclone wind-intensity prediction [15]. It gave promising results when compared to related methods from the literature.

2.3 Application Problem: Rapid intensification in Cyclones

The case of rapid intensification involves data pre-processing where the wind-intensity of all the tropical cyclones in a region is examined. The definition in literature for rapid intensification is when there is an increase in wind-intensity by 30 knots in 24 hours [7]. In order to make our proposed prediction method more robust, we catered for other cases of rapid intensification by the following rules:

- Case 1: Between 20 - 30 knots
- Case 2: Between 30 - 40 knots
- Case 3: More than 40 knots

The cyclones are from the South Pacific and Indian Ocean region [19] and contains the wind-intensity and cyclone track information in terms of the longitude and latitude.

We pre-processed the cyclone data taking into account two major configurations in order to investigate if the track information of cyclones has major impact in terms of determining rapid intensification. The purpose of this approach is to find out if the track information is important in order to determine cases of rapid intensification.

We used 30 hours, 5 data points - i.e., take 5 previous points when the rapid intensification is detected. Therefore, the recurrent neural network would be able to predict rapid intensification when 5 readings (every six hours are given).

3 Experiments and Results

This section presents the results of experiments for cooperative neuro-evolution of recurrent neural networks for prediction of rapid intensification in tropical cyclones in the South Pacific region. Initially, an analysis of the tropical cyclones and the occurrences of rapid intensification cases is assessed and then data is collected for recurrent neural networks training and testing.

3.1 Analysis of the Dataset

We implemented an algorithm that checked the occurrences of the cases of rapid intensification. The definition of rapid intensification from literature is when a tropical cyclones changes its speed by more than 30 knots in 24 hours [7].

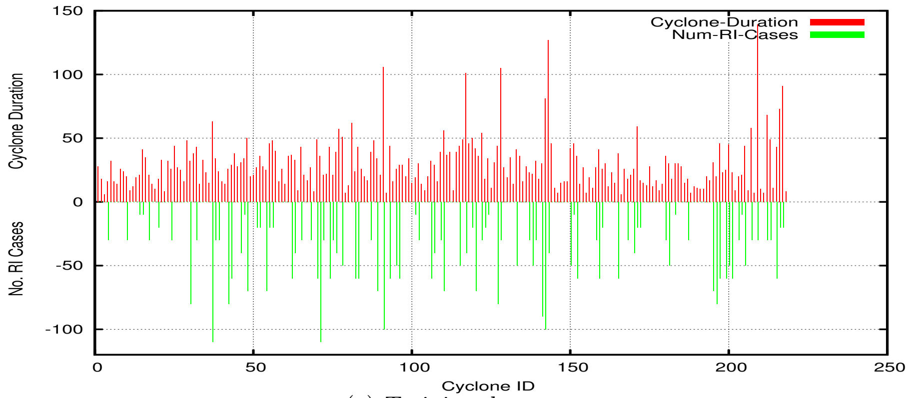
The Southern Hemisphere tropical cyclone best-track data from Joint Typhoon Warning Centre [19] recorded every 6-hours are used. Only the austral summer tropical cyclone season, November to April, from 1980 to 2012 data is analysed in the current study. The South Indian basin domain is taken to be 0-30°S, 30°E-130°E and South Pacific domain is 0-30°S, 130°E-130°W.

We divided the original data of tropical cyclone wind intensity in the South Pacific [19] into training and testing set as follows:

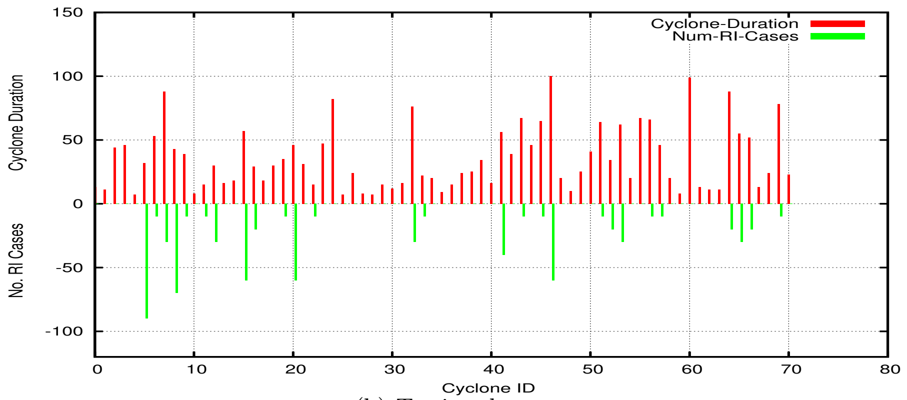
- Training Set: Cyclones from 1985 - 2005 (219 Cyclones)
- Testing Set: Cyclones from 2006 - 2013 (71 Cyclones)

Table 1 gives the details about the occurrences of different cases of rapid intensification in each dataset.

Figures 2 show the details of the duration of each cyclone in the training and testing dataset for different cyclones given by their identification number (ID) in the x axis. Note that each point of duration in the y axis represents 6 hours. The negative bars in the histograms shows the number of cases of rapid intensification for the corresponding cyclones. Note that for visualisation purpose, we multiplied each of the case by a factor of 10. For instance, if there is a cyclone ID that shows -50 on the y axis, it represents 5 rapid intensification cases.



(a) Training dataset



(b) Testing dataset

Fig. 2. Number of Rapid Intensification cases (x 10) and duration of each cyclone over the cyclone identification number (ID). Each point of cyclone duration in y axis represents 6 hours. In certain cyclones, there is no case of rapid intensification.

3.2 Data Pre-processing

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

Table 1. Cases of Rapid Intensification in the South Pacific

Dataset	Case-1	Case-2	Case-3	Total
Testing Set	66	6	1	73
Training Set	259	103	52	414

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 the year 1985. The set of experiments in this paper used cyclones from the year 1985 and onward.

3.3 Results

The performance and results of the method were evaluated by using different number of hidden neurons (H) and compared with standalone cooperative co-evolution.

The maximum training time was given by number of function evaluations by cooperative coevolution (20 000). The G3-PCX evolutionary algorithm [18] was used in sub-populations of cooperative coevolution with fixed parameters such as population size (200), 2 offspring and 2 parents for parent centric crossover operator as used in previous works [13]. 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.

The results are given in Table 2 where the RMSE and MAE have been used as the main performance measures. We observe that there is larger training error than the prediction. The large training error is due to possible inconsistencies and noise in the time series analysis of the rapid intensification dataset snapshot taken for the last 30 hours (5 points).

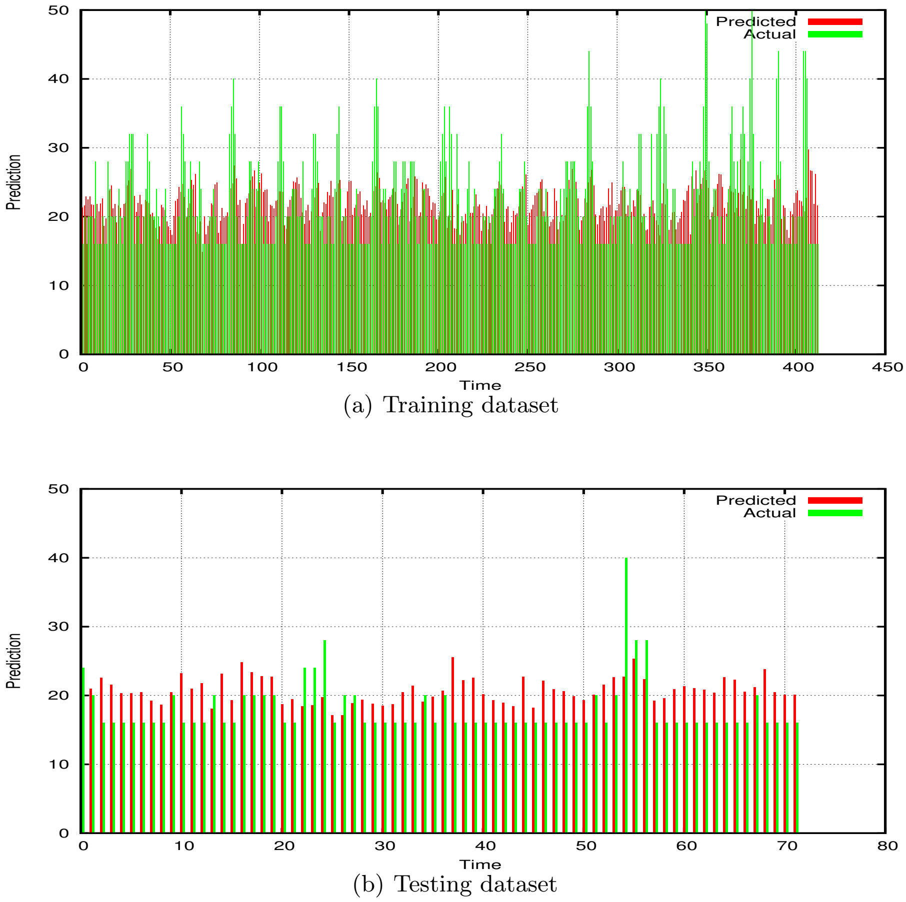
A typical performance on the training and test set is given in Figure 3. We can observe that the recurrent neural network has good performance for most of the cases except for the extreme cases of rapid intensification where the wind-intensity change is more than 30 knots in 24 hours.

3.4 Discussion

Although the results are promising, they need to be improved further as the training errors are quite high which suggests that the data sets have noise or

Table 2. Results: Wind-Intensity for Rapid Intensification in South Pacific

H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
3	0.1621 ±0.0005	0.1237 ±0.0036	0.1112	4.8979 ±0.0221	4.2122 ±0.1576	3.6593
5	0.1612 ±0.0006	0.1205 ±0.0014	0.1132	4.8613 ±0.0253	4.0401 ±0.0659	3.7008
7	0.1615 ±0.0005	0.1227 ±0.0019	0.1160	4.8808 ± 0.0219	4.1652±0.0857	3.8001
9	0.1614 ±0.0005	0.1214 ±0.0016	0.1089	4.8812 ± 0.0239	4.1032 ±0.0755	3.6841



(a) Training dataset

(b) Testing dataset

Fig. 3. Rapid Intensification prediction for all cyclones in the South Pacific

contractions and hence the recurrent neural network had difficulty to converge to lower errors. There seems to be local convergence in the training as there is not significant changes to the error after 1000 function evaluations in all the experiments. The maximum time was 20 000 function evaluations. One problem is the lack of the past data points. We only considered 5 data points which is taken every 6 hours and spans for 30 hours. We can have better convergence when more data points are given, i.e., if readings are taken every 3 or 2 hours, we will have more information and hence the recurrent neural network can resolve contractions and go towards better convergence and prediction.

Further information along with the wind-intensity can also be incorporated into the system, i.e., if more features of the cyclone is recorded such as humidity, pressure and sea surface temperature, then the system could be more accurate.

The knowledge gained from current analysis can be used to improve our understanding of the process of rapid intensification by identifying useful predictors, hence help improve seasonal and intra-seasonal prediction of rapid intensification activity. Moreover, online web services and mobile applications can be developed for awareness and warning.

We concentrated on predicting the intensity of rapid intensification which is essentially a time series prediction problem. The problem can also be viewed as pattern classification problem, where instead of the intensity, the occurrence of rapid intensification could be predicted. This means that the system would be able to determine if a cyclone will rapidly intensify and the one proposed in this paper will predict the intensity.

4 Conclusions and Future Work

We have been successful in providing an analysis of the number of cases and types of rapid intensification in the South Pacific region over the last three decades. The proposed system based on co-evolutionary recurrent neural networks has been able to give prediction with reasonable errors between actual and predicted wind intensity change. However, more accuracy is desired in order for full implementation.

In future work, we would like to use more data points in terms of readings about the cyclones and features in order to build a more accurate system. We would also like to check other data readings such as the sea surface temperature, humidity and pressure levels and check their relationship with the cases of rapid intensification. Other neural network architectures such as feedforward networks can also be used for prediction of rapid intensification with different training algorithms. The rapid intensification problem can also be approached as a pattern classification problem where the occurrence of rapid intensification is predicted rather than its value of intensification.

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