Coevolutionary Recurrent Neural Networks for Prediction of Rapid Intensification in Wind Intensity of Tropical Cyclones

by

Rohitash Chandra

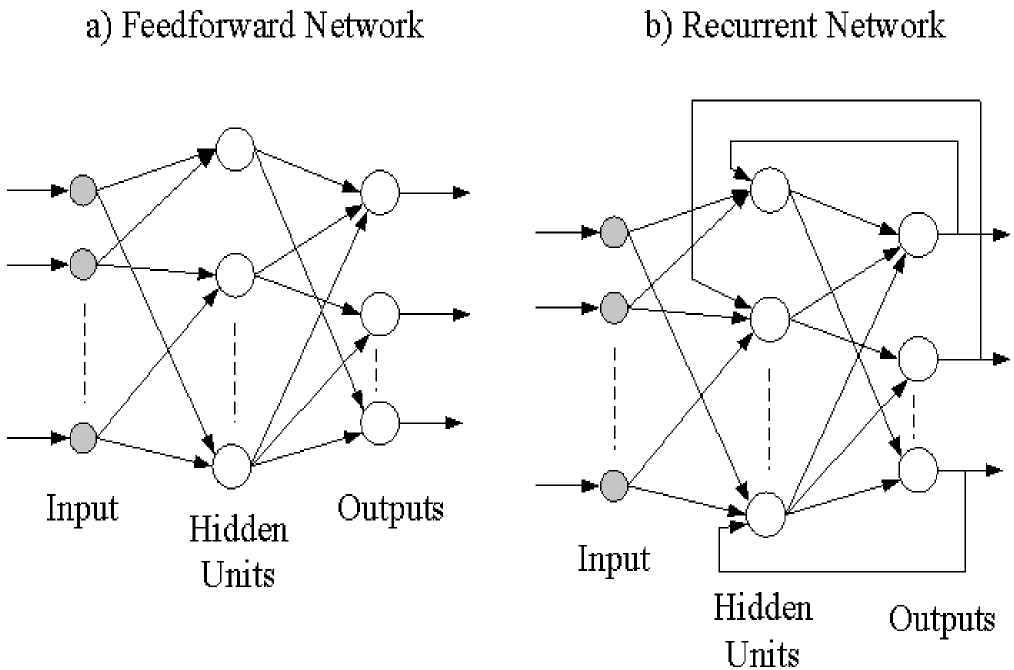
School of Computing, Infomation and Mathematical Sciences
University of the South Pacific
Suva, Fiji

Outline

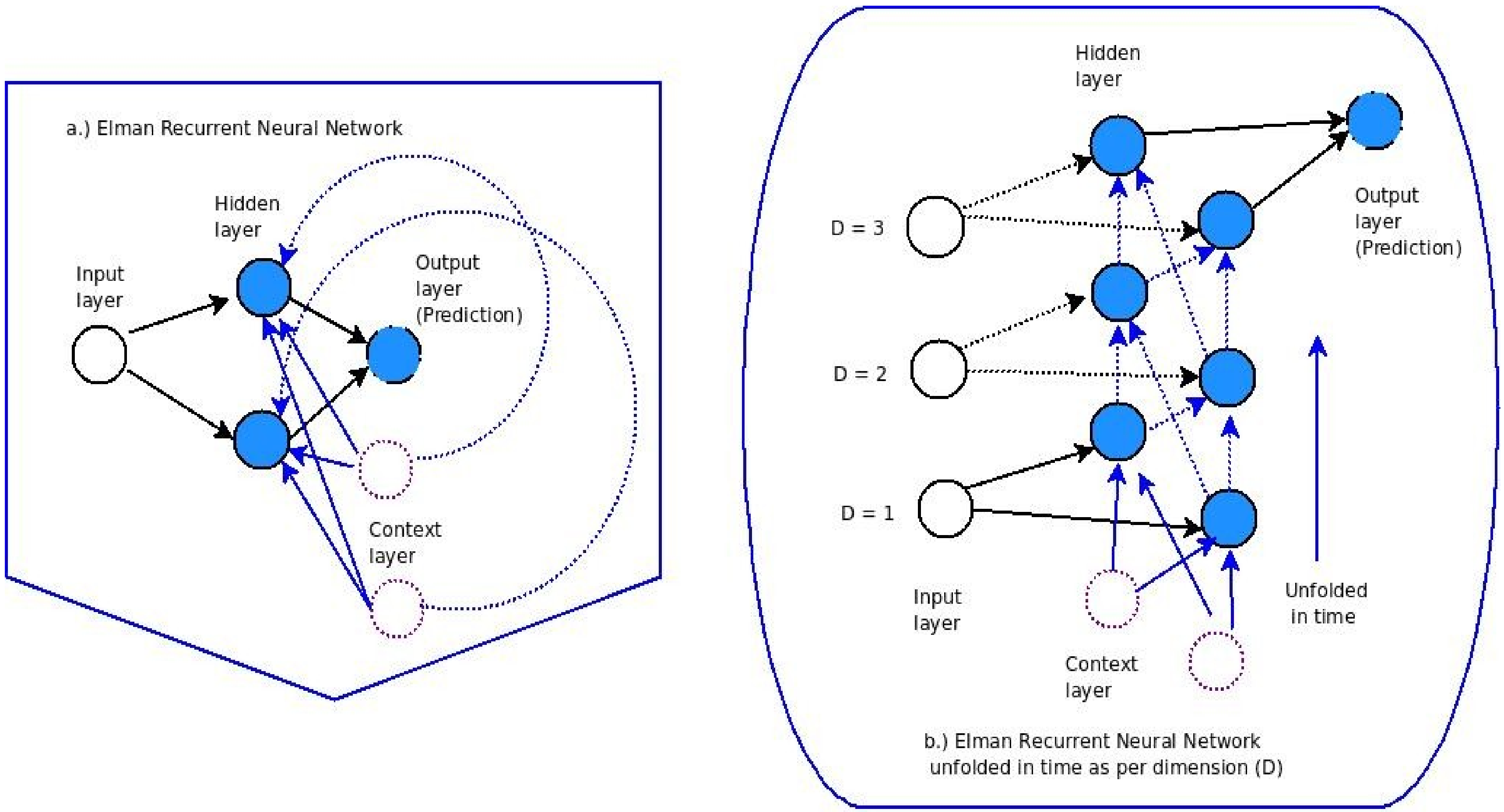
1. Recurrent Neural Networks (RNN)
2. Cooperative Neuroevolution
3. Tropical Cyclones and Rapid Intensification (RI)
4. Methodology: RNN for RI
5. Results
6. Discussion and Conclusion

Recurrent Neural Networks

- Recurrent neural networks use context units to store theoutput of the state neurons from computation of the previoustime steps
- Applications: Speech recognition, gesture recognition, financial prediction, signature verification and robotics control
- Dynamical systems whose next state and output depend on the present network state and input; they are particularly useful for modelling dynamical systems.



Unfold RNN in time



Neuro-evolution (NE)

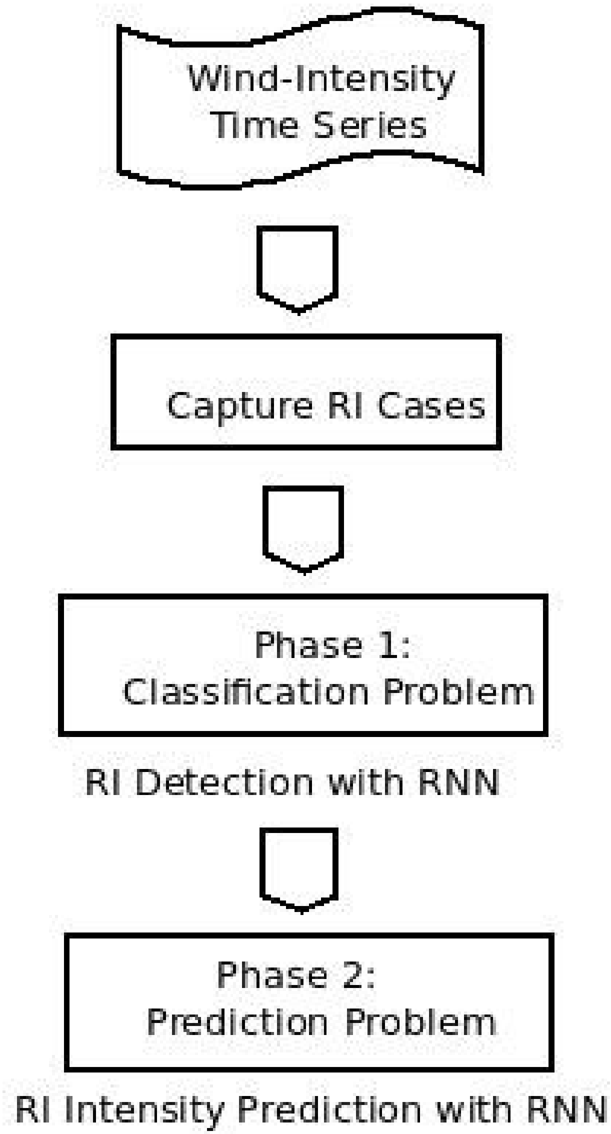
- The search for its optimal training algorithm is still an open problem.
- Gradient descent based training paradigms are unable to guarantee a good or acceptable solution in difficult problems and those involving long-term dependencies.
- Neuro-evolution employs evolutionary algorithms --> handle the global search problem.
- Easily deployed in any neural network optimisation problem → without being constrained to a particular network architecture.
- Used for evolving feedforward and recurrent network

Cooperative Neuro-evolution

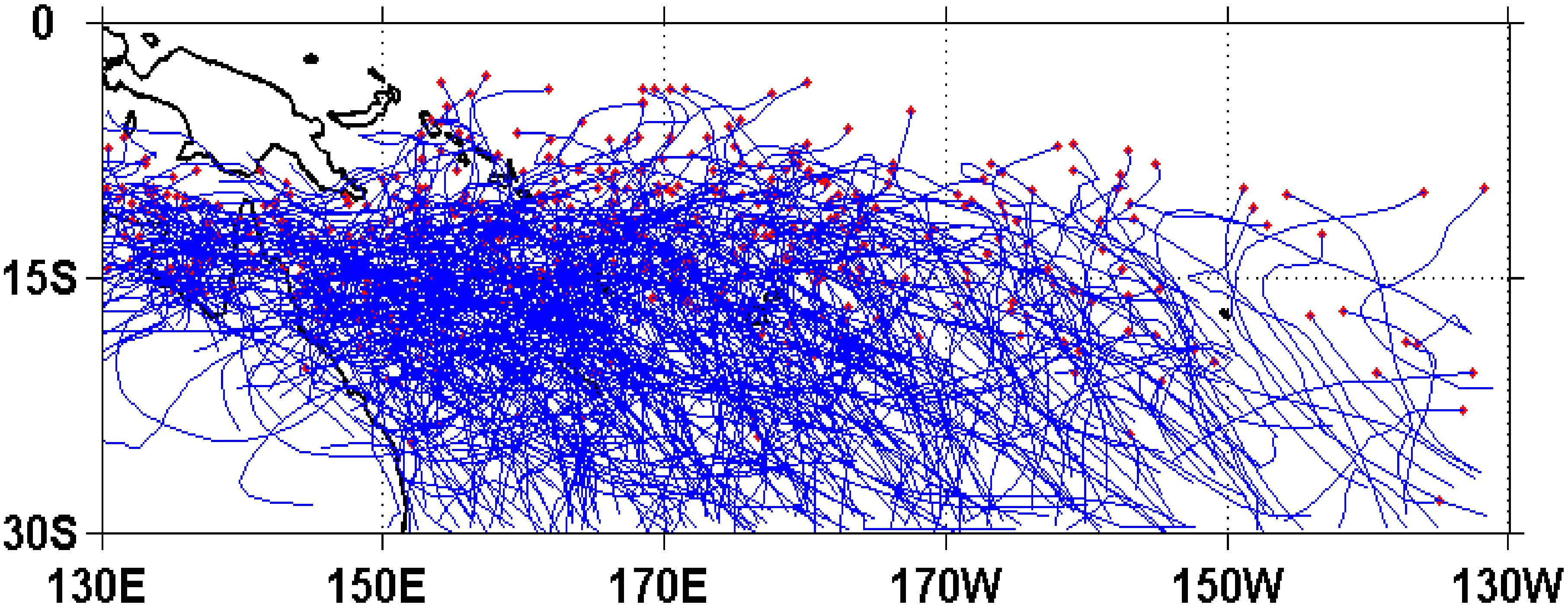
- Cooperative coevolution (CC) decomposes a bigger problem into smaller subcomponents and employs standard evolutionary optimisation in solving those subcomponents in order to gradually solve the bigger problem.
- The subcomponents are also known as species or modules and are represented as subpopulations.
- The subpopulations are evolved separately and the co-operation only takes place for fitness evaluation for the respective individuals in each subpopulation.
- Applications: optimization, large scale function optimization, training neural networks, training recurrent neural networks

Cooperative Neuro-evolution for Time Series Prediction

- Cooperative Coevolution methods have shown promising performance in time series prediction problems.
- Some methods include:
- 1. Synapse level and Neuron level problem decomposition (Chandra and Zhang, Neurocomputing 2012)
- 2. Adaptive Cooperative Coevolution Methods (Chandra, IJCNN 2013)
- 3. Competitive Island Based Cooperative Coevolution (Chandra, IJCNN 2014; Chandra, TNNLS 2015)
- 4. Multi-Objective Cooperative Neuro-Evolution (Chand and Chandra, IJCNN 2014; Chandra, CEC 2015)


Wind-Intensity Time Series
Capture RI Cases
Phase 1: Classification Problem
RI Detection with RNN
Phase 2: Prediction Problem
RI Intensity Prediction with RNN

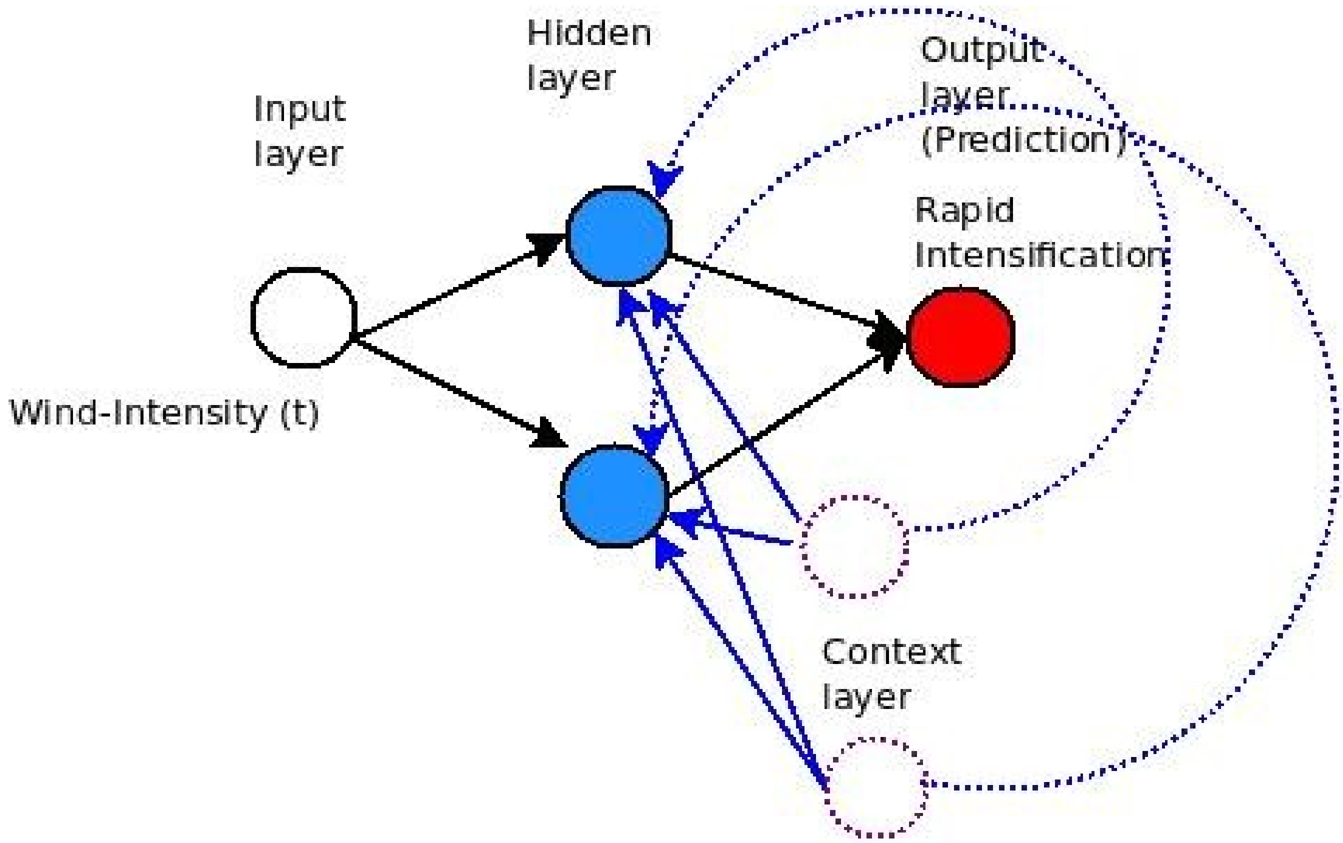
Tropical Cyclones in South Pacific Region – Climatology from 1980-2012

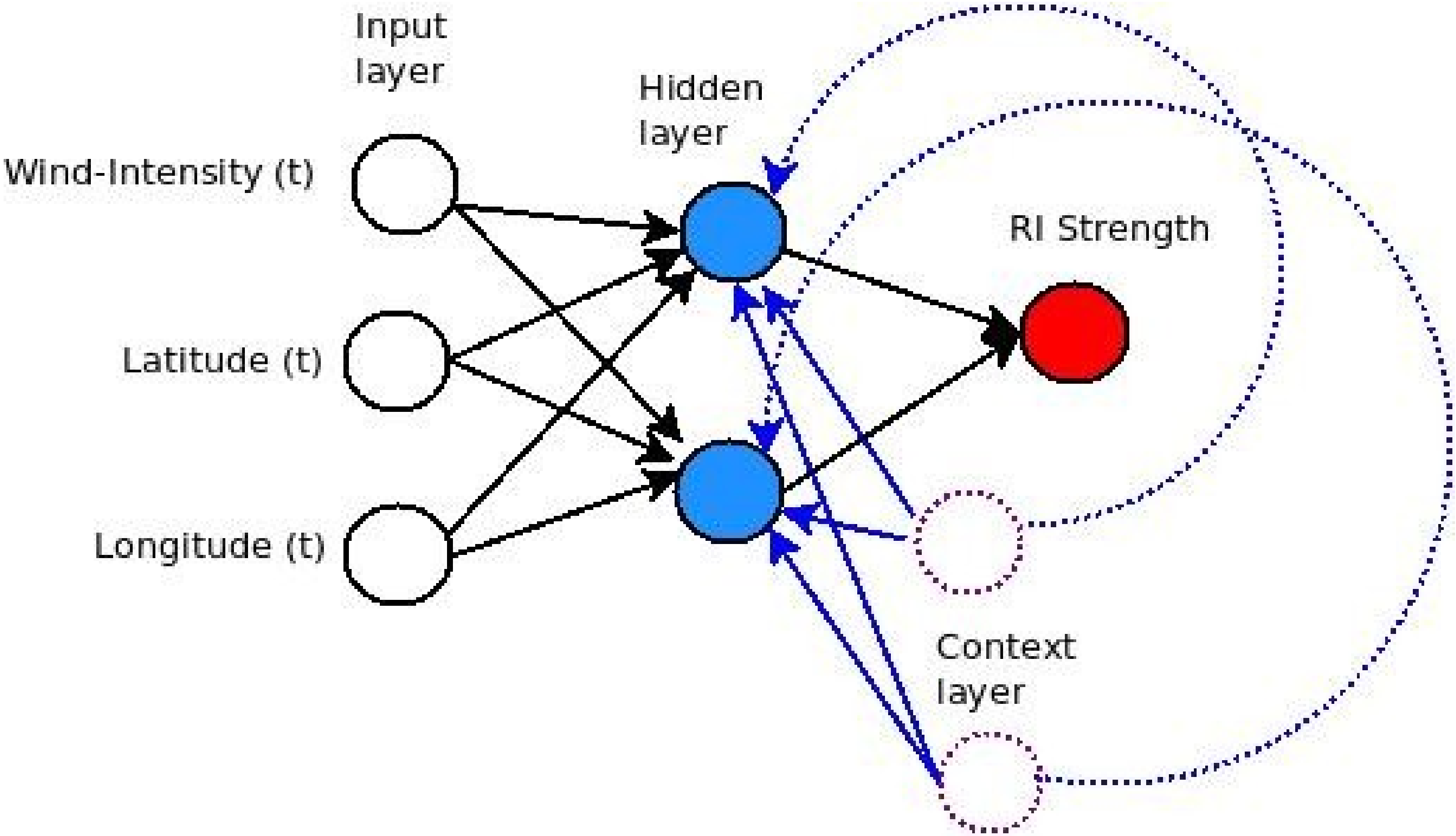


Rapid Intensification in Wind-Intensity

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.

Method: Coevolutionary Recurrent Neural Networks for Rapid Intensification in Cyclones




Input
layer
Hidden
layer
Wind-Intensity (t)
Latitude (t)
Longitude (t)
RI Strength
Context
layer

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

Experimental Set-up

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 $\circ$ S, 30 $\circ$ E-130 $\circ$ E and South Pacific domain is 0-30 $\circ$ S, 130 $\circ$ E-130 $\circ$ W.

We divided the original data of tropical cyclone wind intensity in the South Pacific into training and testing set as follows:
– Training Set: Cyclones from 1985 - 2005 (219 Cyclones)
– Testing Set: Cyclones from 2006 - 2013 (71 Cyclones)

Smart Bilo: Computational Intelligence Framework

- Neural Computation (Feedforward and Recurrent Neural Networks)
- Evolutionary Cmputation (Cooperative Cevolution, Neuroevolution)

http://smartbilo.aicrg.softwarefoundationfiji.org/

Performance Evaluation

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.

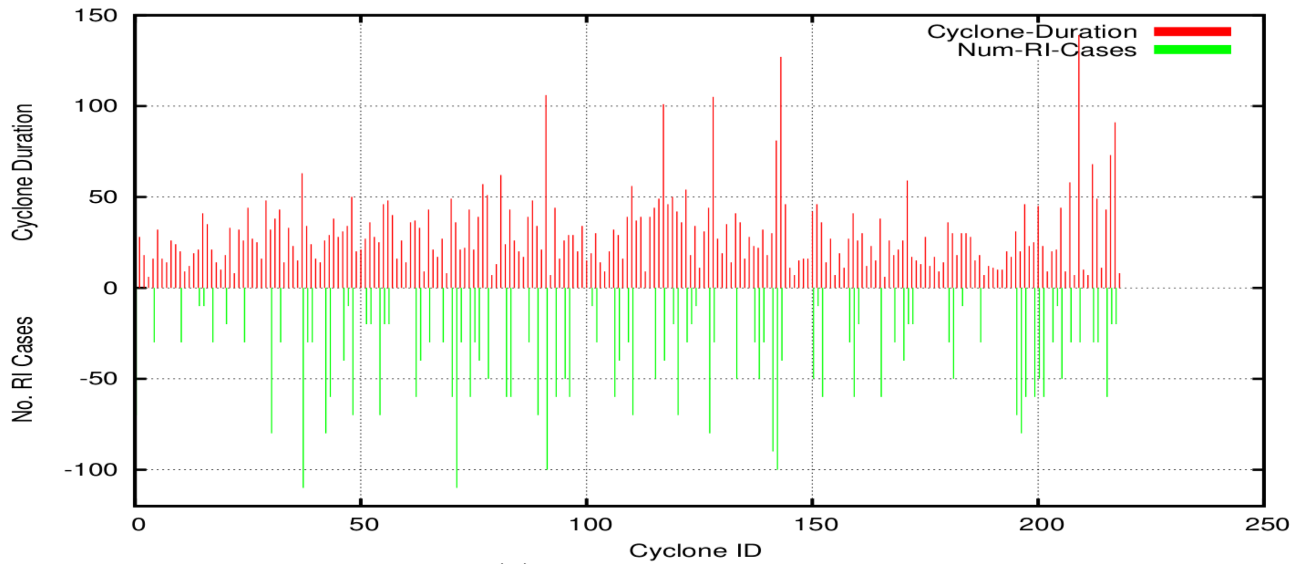
These are given in Equation 2 (RMSE) and Equation 3 (MAE).

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

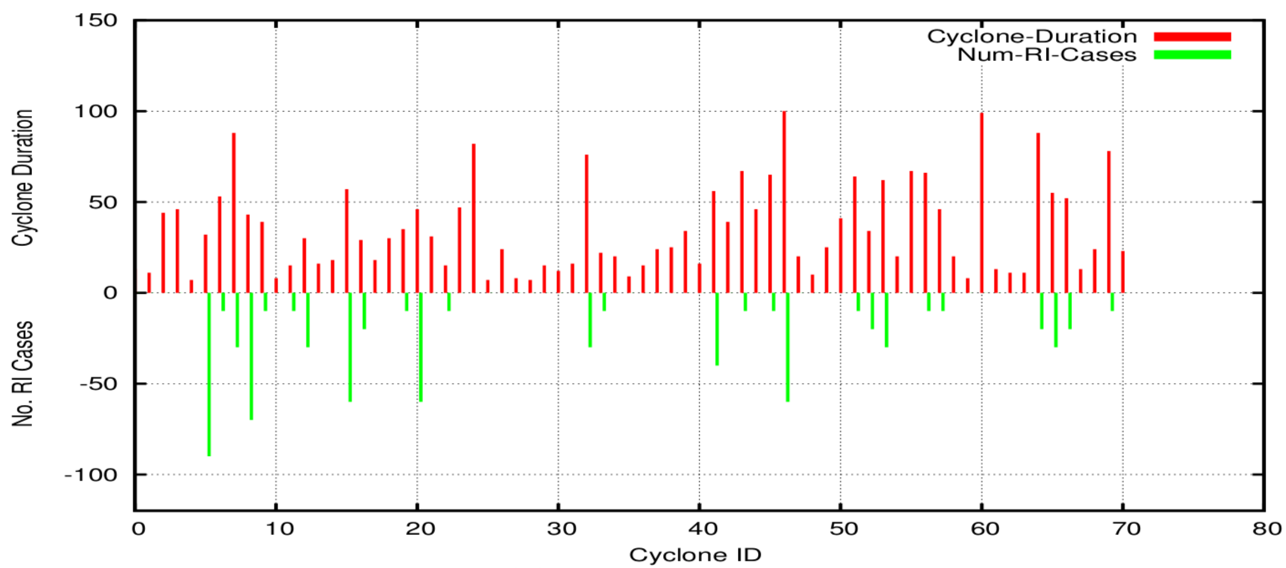
$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(y_i - \hat{y}_i)| \tag{3}$$

Table 3: Prediction of Occurrence for RI

Problem	Hid.	Percentage (Train)	Percentage (Test)
Indian Ocean	5	98.707 ± 0.037	97.390 ± 0.008
	7	98.789 ± 0.085	97.375 ± 0.023
	9	98.774 ± 0.021	97.366 ± 0.020
	11	98.794 ± 0.040	97.375 ± 0.013
South Pacific	5	99.788 ± 0.013	97.214 ± 0.013
	7	99.711 ± 0.010	97.278 ± 0.009
	9	99.677 ± 0.008	97.266 ± 0.011
	11	99.721 ± 0.011	97.212 ± 0.015



(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.

Table 4: Prediction of Intensity of RI in the South Pacific

Method	H	RMSE (Train)	RMSE (Test)	Best	MAE (Train)	MAE (Test)	Best
Wind	3	0.1621 $\pm$0.0005	0.1237 $\pm$0.0036	0.1112	4.8979 $\pm$0.0221	4.2122 $\pm$0.1576	3.6593
	5	0.1612 $\pm$0.0006	0.1205 $\pm$0.0014	0.1132	4.8613 $\pm$0.0253	4.0401 $\pm$0.0659	3.7008
	7	0.1615 $\pm$0.0005	0.1227 $\pm$0.0019	0.1160	4.8808 $\pm$ 0.0219	4.1652$\pm$0.0857	3.8001
	9	0.1614 $\pm$0.0005	0.1214 $\pm$0.0016	0.1089	4.8812 $\pm$ 0.0239	4.1032 $\pm$0.0755	3.6841
Wind and Track	3	0.1633 $\pm$ 0.0005	0.1274$\pm$ 0.0034	0.1170	4.9286 $\pm$0.0234	4.3122 $\pm$ 0.1371	3.8888
	5	0.1626$\pm$ 0.0005	0.1231$\pm$ 0.0011	0.1171	4.8895 $\pm$0.0210	4.1413$\pm$ 0.0472	3.9312
	7	0.1626$\pm$ 0.0003	0.1232 $\pm$0.0013	0.1152	4.9004 $\pm$0.0162	4.1492 $\pm$ 0.0524	3.8874
	9	0.1626$\pm$ 0.0004	0.1241 $\pm$0.0011	0.1184	4.8918 $\pm$0.0178	4.1854 $\pm$0.0578	3.9227
Wind and Month	3	0.1626 $\pm$0.0006	0.1419 $\pm$0.0035	0.1228	4.9544 $\pm$ 0.0292	4.8515 0.1680	3.9695
	5	0.1613 $\pm$0.0004	0.1388 $\pm$ 0.0032	0.1202	4.9188 $\pm$0.0280	4.7080 $\pm$0.1686	3.8868
	7	0.1616 $\pm$ 0.0005	0.1403 $\pm$ 0.0025	0.1266	4.9618 $\pm$0.0303	4.8246 $\pm$ 0.1291	4.0151
	9	0.1641 $\pm$0.0024	0.1339 $\pm$ 0.0040	0.1124	4.9462 $\pm$0.0183	4.5574 $\pm$0.1886	3.6111

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
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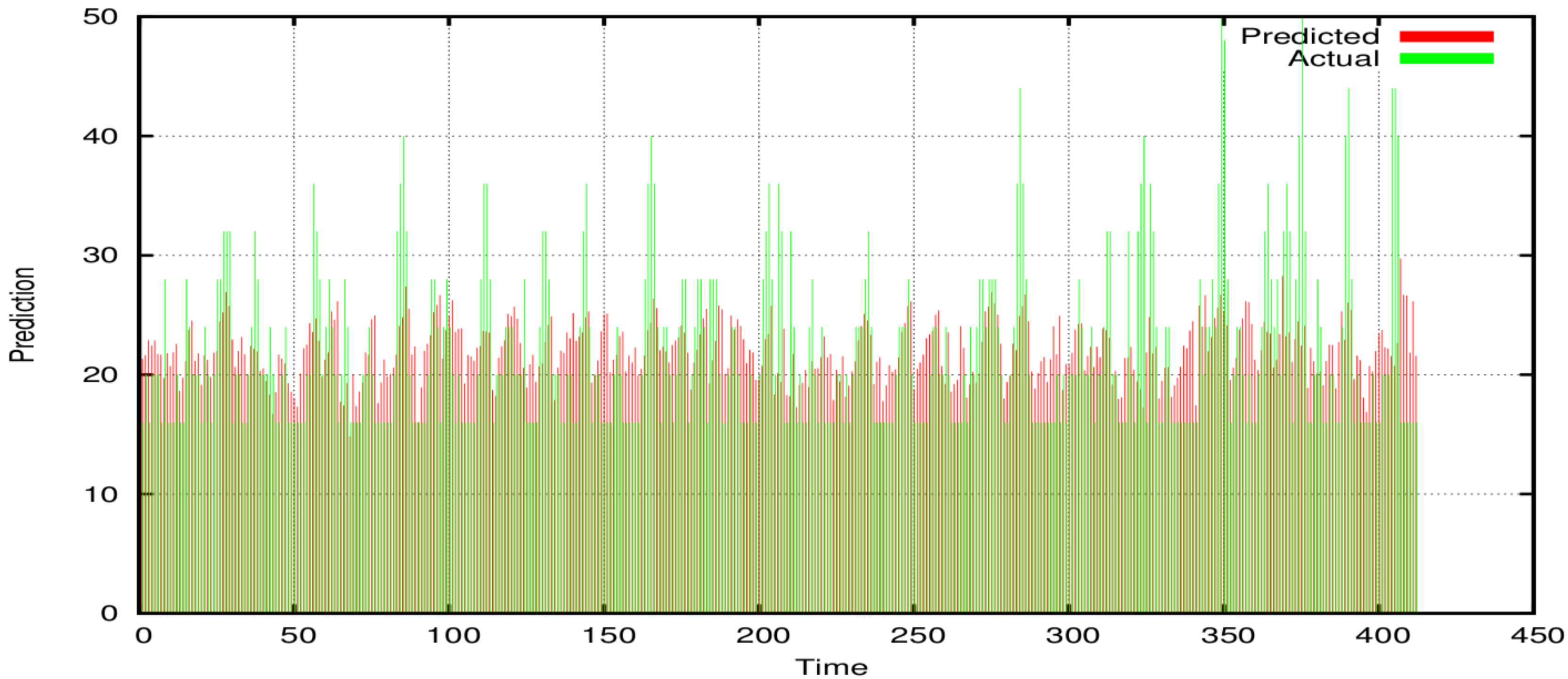
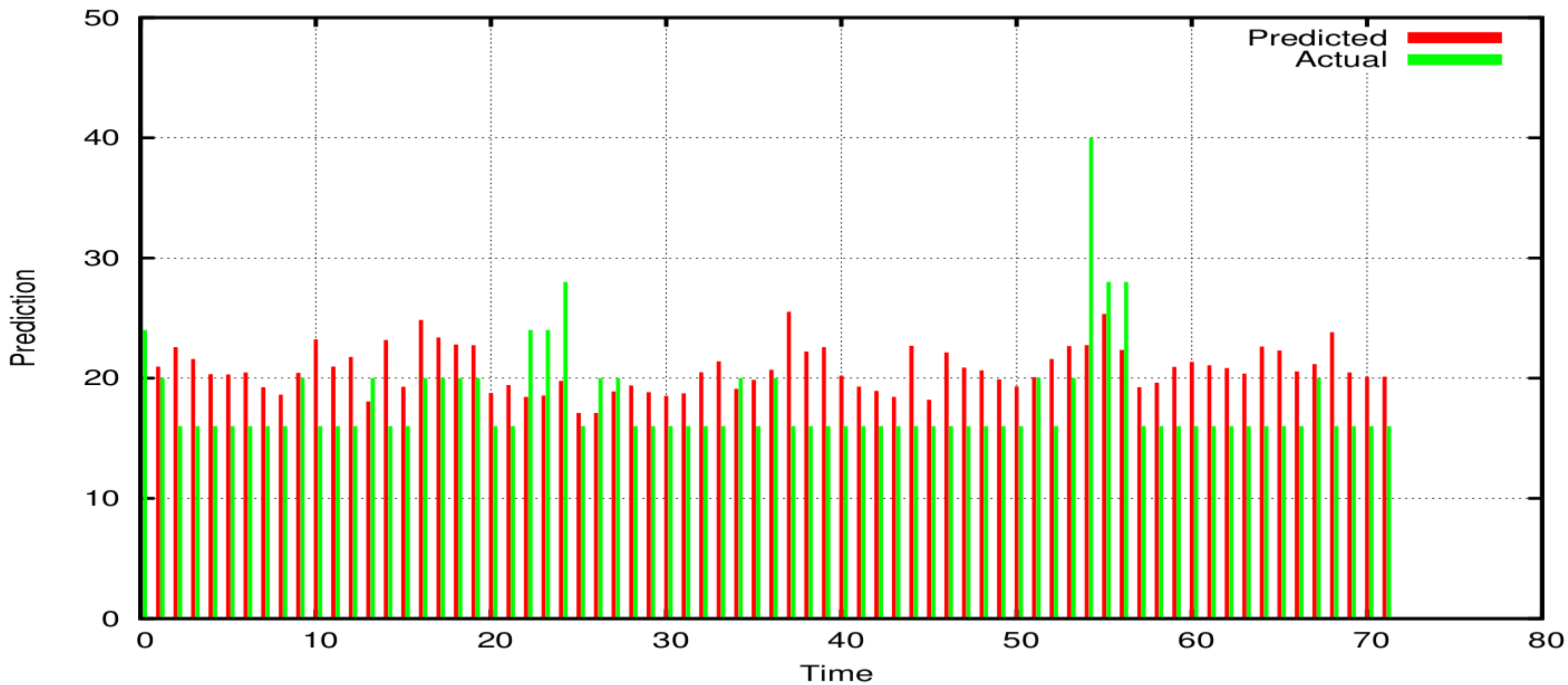


(a) Training dataset



(b) Testing dataset

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

Discussion

- We could 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.
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- 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.

Conclusions and Future Work

- 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.
- 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.

Future Work

- 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.

Publication

1) R. Chandra and K. Dayal, International Conference on Neural Information Processing, Istanbul, November 2015, Springer LNAI, In Press (Available through ResearchGate)
2) R. Chandra and K. Dayal, IEEE Transactions on Geoscience and Remote Sensing, Under Review, 2015.

Vinaka and Dhanyavaad

rohitash.chandra@usp.ac.fj