Optimizing LSTM* RNNs† Using ACO‡ to Predict Turbine Engine Vibration

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ABSTRACT

This work presents the use of an ant colony optimization (ACO) based neuro-evolution algorithm to optimize the structure of a long short-term memory (LSTM) recurrent neural network (RNN) for the prediction of aircraft turbine engine vibrations. It expands upon previous work using three different LSTM architectures, with the new evolved LSTM cells showing an improvement of 1.35%, reducing prediction error from 5.51% to 4.17% when predicting excessive engine vibrations 10 seconds in the future. These results were gained using MPI on a high performance computing cluster, evolving 1000 different LSTM cell structures using 168 cores over 4 days.

CCS CONCEPTS

•**Applied computing → Aerospace; Engineering;**

KEYWORDS

Ant Colony Optimization, ACO, Long Short Term Memory Recurrent Neural Network, LSTM, RNN, Aviation, Turbine engine vibration

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AbdElRahman ElSaid, Brandon Wild, Fatima El Jamiy, James Higgins, and Travis Desell. 2017. Optimizing LSTM[1] RNNs[2] Using ACO[3] to Predict Turbine Engine Vibration. In *Proceedings of GECCO '17 Companion, Berlin, Germany, July 15-19, 2017,* 2 pages.
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[1]Long Short Term Memory
[2]Recurrent Neural Network
[3]Ant Colony Optimization

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1 INTRODUCTION

Initial work examined building viable Recurrent Neural Networks (RNN) using Long Short Term Memory (LSTM) neurons to predict aircraft engine vibrations [3]. The different networks were trained on time series flight data records obtained from a regional airline containing flights that suffered from excessive vibration. The structure of the used LSTM Recurrent Neural Network used in this study is shown in Figure 3. After selecting an initial set of 15 relevant parameters, these LSTM RNNs were able to predict vibration values for 1, 5, 10, and 20 seconds in the future, with 2.84% 3.3%, 5.51% and 10.19% mean absolute error, respectively.

2 IMPLEMENTATION

This study expands on the previous work by optimizing the structure of the cells used in the previous LSTM architecture. An ant colony optimization (ACO) based algorithm was chosen for this, as it has shown prior success in evolving evolving general RNNs for time series data prediction [2].

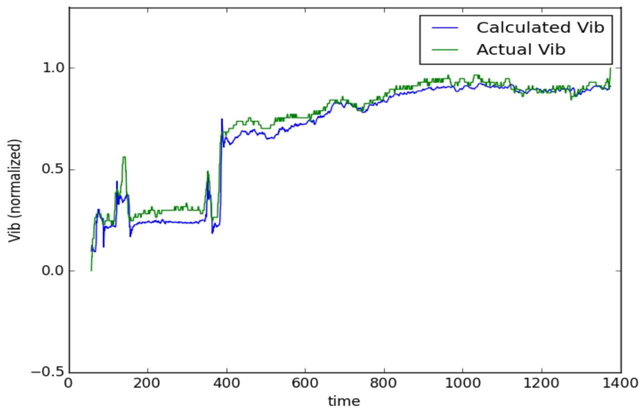
An MPI[4] version of the ACO algorithm was developed and compared to the fixed topology examined in previous work[3]. The optimization process targeted the structure of the **"M1"** LSTM cells as shown in Figure 3 based on predicting vibration for 10 seconds in the future. The goal of the method was to optimize the connections between the nodes. Worker processes used Theano [1] to train the LSTM RNNs with the evolved cell structures.

The first stage of the optimization process started by generating a fully connected network that is used by the ants to generate new paths for new cell structure designs. Paths are selected by the ants based on the value of pheromones on edges; each connection in the network has a pheromone value that determine its probability to be chosen as a path. Given a number of ants, each one will select one path from the fully connected network as shown in Figure 2. All the paths selected from all the ants are then collected, duplicated paths are removed and a network cell is generated.

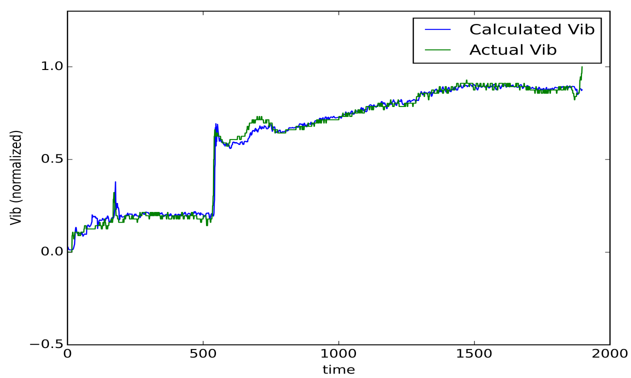
3 RESULTS

The algorithm was run using 168 cores on a high performance computing cluster where 1,000 different cell structures were evolved

[4]Message Passing Interface



(a) Unoptimized



(b) Optimized

Figure 1: Plotted results for predicting ten seconds in the future for one test flight.

over the course of 4 days. Worker processes requested different cell structures from the master process, and then trained the LSTM RNNs using those cell structures for 575 epochs.

The LSTMs with evolved cell structures have shown an 1.35% increase in performance (5.51% – 4.17% mean absolute error for 10 seconds prediction in the future). Plots for results of unoptimized and optimized predictions for one test flight are shown in Figures 1.

4 DISCUSSION

These neural networks provide a promising means for the future development of warning systems so that suitable actions can be taken before the occurrence of excess vibration to avoid unfavorable situations during flight. Future work involves using ACO to evolve the overall structure of the RNN, as well as optimizing the cells independently.

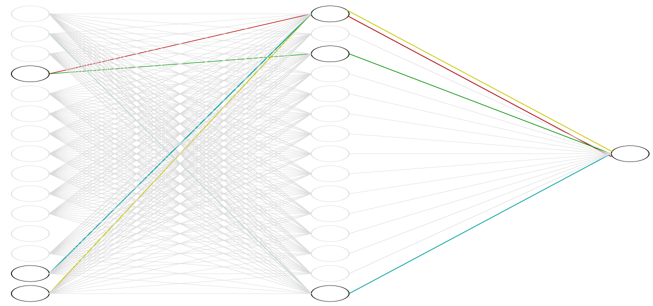


Figure 2: Ants' paths through the network (schematic)

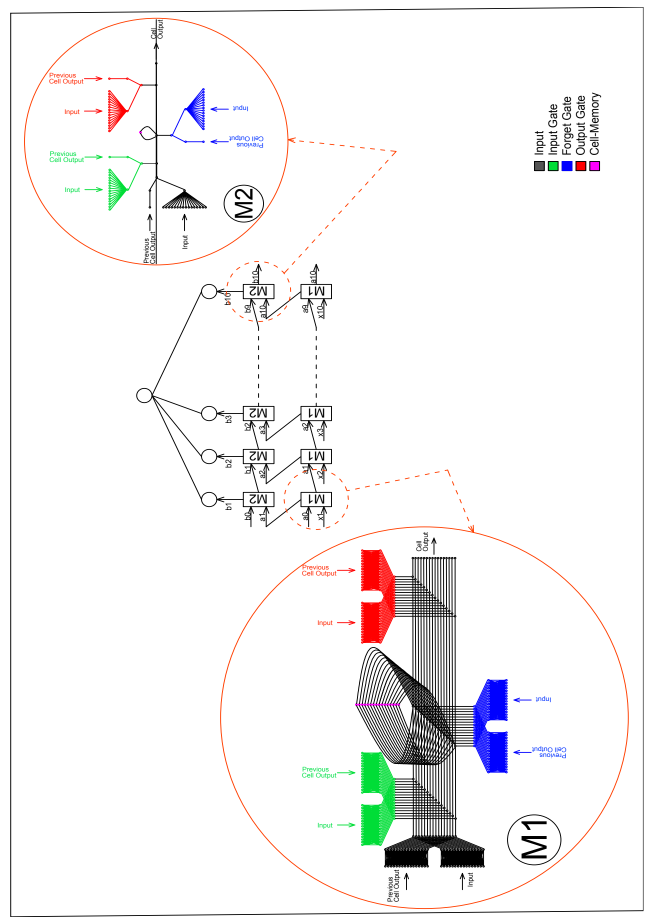


Figure 3: Neural Network Structure

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