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An ANNs Based Failure Detection Method for ONOS SDON Controller

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Motivation

Network reachability is an important factor of an optical telecommunication network. In a wavelength-division-muliplexing (WDM) optical network, any failure can cause a large amount of loss and disruptions in network. Failures can occur in network elements, link, and component inside a node or etc. Since major network disruptions can caused network performance degradations, it is necessary that operators have solutions to prevent such those failures. This work examines a prediction model in optical networks and propose a protection plan using a Machine Learning (ML) algorithm called Artificial Neural Networks (ANN) using Mininet emulator. ANN is one of the best method which applied for failure prediction and identification in optical networks. The simulation result show the advantages of using ANN method. Also, it has proved that the prediction accuracy was greater than 90 %. on the ONOS controller.

Introduction

With capacity growth of optical transport networks, internet traffic increases. With continuous increase traffic, network resilience take an important place. A failure of any network elements such as a switch, splitter, and etc can lead an immense loss of data[1-3]. To reduce the damage, many protection algorithms have been proposed such as shared-path protection (SPP)[2], best-effort shared risk link group (SRLG) failure protection[3]. These algorithms can protect the damage after failure happens. In this case, because of time delay of protection and recovery, a part of data will be lost. Therefore, we need a proactive protection algorithm to prevent damage from any failures. In this work, We investigate the use of simple and fast-training feed-forward artificial neural networks (ANN) that predicts the failure for unknown device parameters faster than some other machine learning method. We simply trained a model to classify equipment status to show the accuracy of the ANN for predicting of failure. The data set is used during the training of the model contains the network equipment information with corresponding labels. These information were obtained from daily monitoring of the network management system in an actual wavelength division multiplex (WDM). During a real test, we didn't pass the corresponding labels for each data set. Essentially, we were passing our unlabeled test data to our model and having our model predict on if the information shows equipment failure or not. In this method the predictions are occurring based on what the model learned during training. Our simulation results demonstrate how well ANN method performs on data it hasn't seen before. This process will also give us some insight on what our model has or hasn't learned. In this work we made sure that our training and validation sets are representative of the actual data we want our model to be predicating on it. We aggregated multiple simulations to guarantee a 95% confidence. Our simulation results demonstrate that ANN method can predict an equipment failure with about 95.59 %.

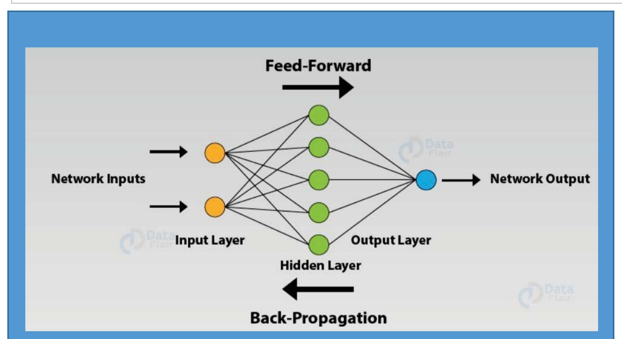

Figure 1. ANN Model Component

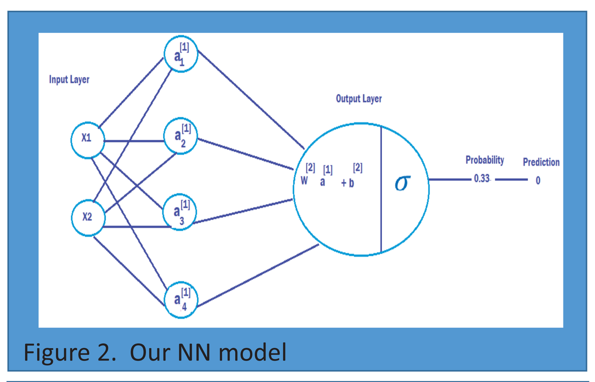

Figure 2. Our NN model

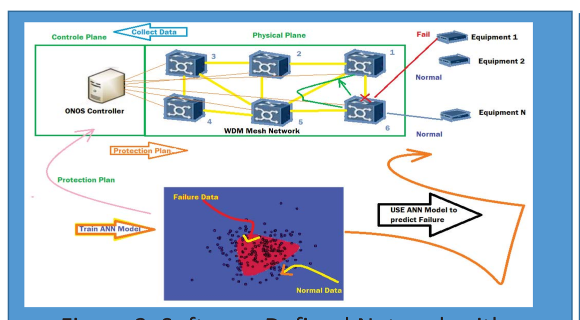

Figure 3. Software Defined Network with Prediction model

Lable Name	Units
Input Optical Power	dbm
Output Optical Power	dbm
Laser Bias Current	LBC
Laser Temperature	C
Envirnomental Temperature	C

Figure 4. The Labels used to train test data

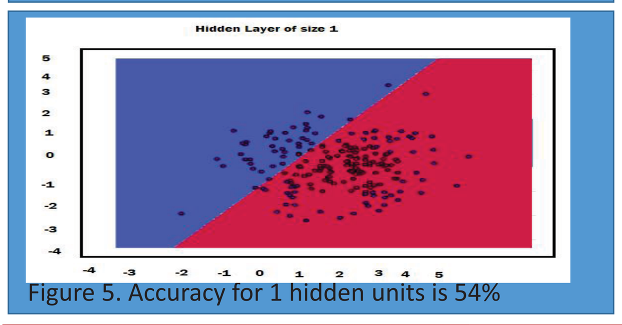

Figure 5. Accuracy for 1 hidden units is 54%

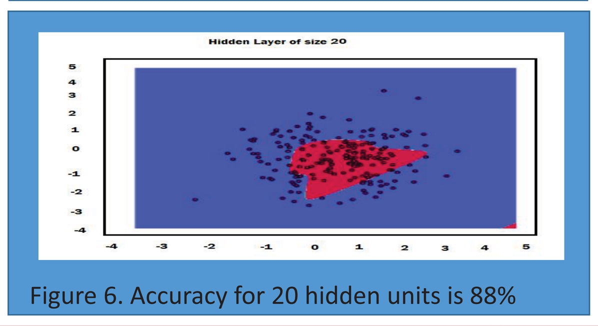

Figure 6. Accuracy for 20 hidden units is 88%

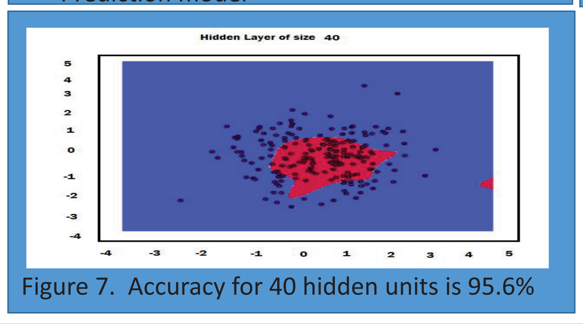

Figure 7. Accuracy for 40 hidden units is 95.6%

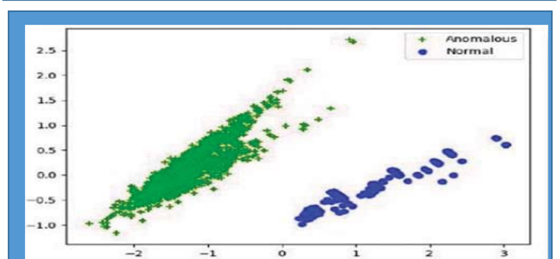

Figure 8. Ann classifier result

Experiment

We use Java-based open source controller ONOS. ONOS provides its own set of high-level abstractions and models. Mininet creates SDN elements such as controller, switches, and hosts and can share them with the other networks. In this work, we build a NN with 1 hidden layer with 4 neurons (Figure 2). Input layer will have 2 nodes as our data has two features (X1 and X2) and output layer will have one node , based on the probability threshold we will classify the output as either white or black (0 or 1). First, we defined our network structure based on the number of input units and number of hidden units. Then we initialize the model's parameters (Figure 4). Perform the below steps in loop until we get minimum cost/optimal parameters.

- Implement forward propagation
- Compute loss
- Implement backward propagation to get the gradients
- Update parameters

Then we merge all the above steps into one function. This function called SDN_NN model. The second step we made is to learn the right parameters. The parameters were used are shown in Figure 4. Afterward we made predictions on new data. Compare with some other machine learning algorithms such as SVM. We found that ANN is a better framework in terms of predicting on failure equipment.

Results

- An ANN prediction method can predict the board failure in a WDM network.
- ANN is proven to be very efficient as a classifier (Figure 8).
- Services can be protected from data loss before a network failure occurs.
- Since ANN has nonlinear nature, then it is more suitable for failure prediction in Optical Network devices.
- Environmental temperature was the first labels which helped for board failure. It was about 78.38%.
- According to the experiment data, the accuracy of the ANN prediction method was 95.59% on average, which meant the failure state of 96% of the boards could be correctly predicted.
- Another advantage of ANN implementation scenario is monitoring optical performance. This features is not accessible in SVM.
- The results of performance monitoring might be used in designing optical devices.
- Estimation maximization of the optical link capacity can be achieved in ANN method. Such as a linear or nonlinear optical signal to noise ratio (OSNR).

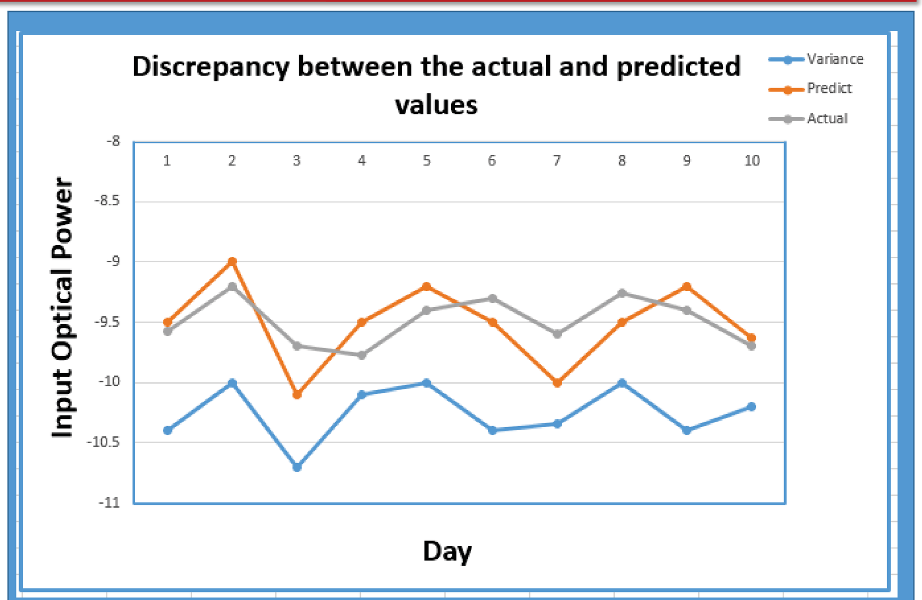

Figure 9. Comparison between actual and predicted for the label of "Input Optical power"

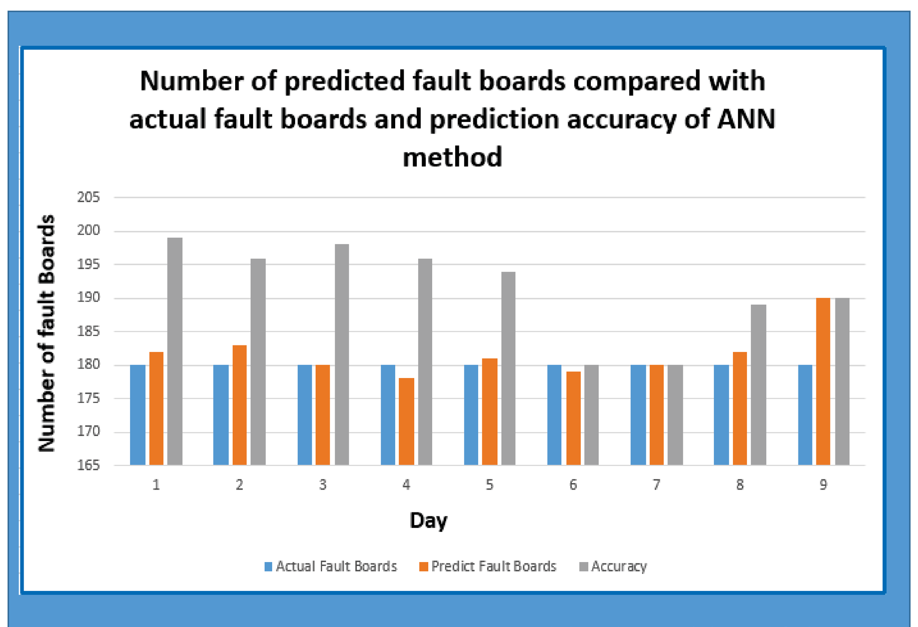

Figure 10. Comparison Between Prediction model and Actual board failure

Figure 10 shows the predication of board failure during the 40 days. With our ANN prediction method, most of these fault boards were correctly predicted; the prediction accuracy was greater than 90%.

Conclusion

Results indicate:

- This work aimed to predict optical equipment's failure.
- The observation period was 44 days.
- Data in the first 20 days were used to train the ANN model.
- We observed that if the number of normal data and fail data were balanced, the result of the predication model was more accurate (Figures 5, 6 and 7).
- A central controller (ONOS) collects the operation and maintenance data from all WDM nodes and then analyzes the data before providing instructions (Figure 3).
- The controller collects data from the network management log to train the prediction model and predict an equipment failure.
- Once the controller identifies a potential equipment failure by the ANN prediction model, it will send the control messages to all WDM nodes.
- These nodes switch the services to a safe path to prevent data loss.

Future Work

- Detection and mitigation of soft failure in optical networks.
- Implement Decision Tree which is another machine learning algorithm to identify failure.
- Work on different deployment approaches like central and tree topology in our testbed.

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