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Automation of Switching in COADM using Machine Learning Algorithm

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***Abstract:** In this paper a Machine Learning (ML) algorithm has been proposed based on application in field of Optical Network, where in it makes use of large data set to learn, train the switching nodes and predicts the traffic in the network. Configurable Optical Add-Drop Multiplexer (COADM) are used as the switching nodes. Once prediction is done, the traffic at the node is directed to the next node automatically. This improves the performance in terms of efficiency and reduces the delay in the network due to automation.*

***Keywords:** Machine Learning (ML), Support Vector Machine (SVM), Random Forest, k Nearest Neighbors (kNN), Configurable Optical Add-Drop Multiplexer (COADM).*

I. INTRODUCTION

As the communication technology is gaining the importance which demands for the increase in number of users. As the users are increasing in a very large number, the amount of data generated every minute is very large and demand for Quality of Service (QoS) is also increasing [1].

Automation in the networking filed has gained lot of importance, so that the operation and maintenance of the network can be handled by machines rather than human beings [2]. ML algorithms are applied to the networks for various applications like intrusion detection [2], traffic classification [3], and cognitive radios [4].

Optical network are deployed over large area world wide as it provides high capacity, low cost [1]. This paper is constrained to the optical networks. The research to improve the performance of the optical network carried out to investigate on wavelength assignment, survivability, traffic grooming and routing [5], [6].

The main disadvantage of Fixed Optical Add Drop Multiplexer (FOADM) was that it could not be used for different Wavelength Division Multiplexing (WDM) technologies. , thus to overcome this problem Configurable Optical Add Drop Multiplexer (COADM) were developed, which is an all- optical equipment, that is used for adding or dropping of wavelengths based on network services. It gives flexibility in routing of optical streams by bypassing the faulty connections and allows for minimal disruption in services. It can adapt and do upgrades [7].

The most needed advantage of Reconfigurable Optical Add Drop Multiplexer (ROADM) is that it will allow single wavelength operation or a wavelength group, working through a fixed port. There is no need for the repeated conversions between the electrical signals and optical signals. It consists of WDM and Optical switches [7]. The other way to efficiently manage the optical network resources and provide better spectrum utilization is by deploying Elastic Optical Networks (EONs), which addresses intractable Routing and Spectrum Allocation (RSA) problem [8].

Artificial Intelligence (AI) is the science to automate and make machines capable of intelligently taking decisions based on the previously available data in the network [9]. ML is a subset of AI which enables learning paradigm [10,11]. The

Research is trending of making use of ML algorithm to optic networks.

ML algorithm is used for laser characterization [12], predictive maintenance [13], and failure localization [14, 15], to erbium-doped fiber amplifier (EDFA) equalization [16].

The major challenge with today's growing demand is that the bandwidth requirements has grown from 8-16 wavelengths to 48-96, thus increasing the work of the Network operators for adding and changing and dropping of the wavelengths. This scenario is possible by efficient use of the data that is generated in the network by predicting the traffic using ML algorithm and switch the traffic using COADM.

The rest of the paper is organized as follows. In Section II, the overview ML algorithms, focusing on ML methods, Generative or Discriminative, loss function, Decision boundary, parameter estimation algorithm, model complexity reduction and to decide best suitable ML algorithm based on the processed data. In Section III, the simulated results of various ML algorithms are compared in terms of efficiency for the optical network data base. In Section IV, the COADM of different configurations are implemented and Random Forest algorithm is used to train and select the frequencies in COADM. In Section V, the conclusions are discussed based on the obtained results.

Machine Learning algorithms

The performance of the ML algorithms is based on an automatic procedure for selecting the best based on the training and estimation on the available data to predict the scenario. The ML algorithms are further classified as supervised learning, unsupervised learning, Semi-supervised, Reinforcement learning and Overfitting, underfitting and model selection [1]. In this paper, the work is based on supervised learning algorithms which are SVM, Random Forest and kNN. As the data for training is always labelled data thus only supervised learning algorithm has been considered.

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The dataset for this simulation experiment has been taken from UCI Machine Learning Repository.

A. k Nearest Neighbors (kNN): It is one of the simplest algorithms for classification. It depends on the distance between the different data points of the training set and groups together the points that are closer by and label them [17]. When an unknown instance of data is given, it will consider a radius around it in such a way that the circle will include k number of points nearest to it. Note that here k value must always be odd number. The class of the given instance is decided based on most of the points included in that circle as shown in Fig 1.

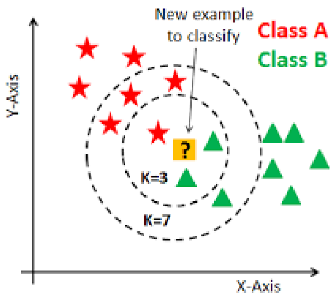

Fig. 1. Representation of kNN [17]

B. Random Forest: it is one of the most powerful and popular supervised learning algorithms used for classification. It works by creating forest with number of decision trees. It can be said as an advanced application of Decision tree algorithm, where in it creates multiple decorrelated trees. Different features are extracted from the groups to create this forest. More the number of trees more accurate the decision as shown in Fig 2. Once the subsets are classified using decision trees, the unknown instance is ran through it and the class is predicted. The same is repeated for all the subset decision trees developed, the majority voting of these prediction is taken as the result classification [18].

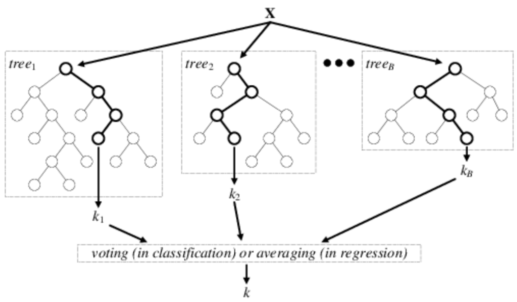

Fig. 2. Representation of Random Forest [18]

C. Support Vector Machine (SVM): it is one of the best classifier algorithms. It is a supervised learning algorithm, where in all the labelled data is represented as points in n-dimensional plane with 'n' number of features of classification as shown in Fig 3. A hyper-plane is used to segregate the different classes in the n-dimensional plane. The hyper- plane is decided such that it maximises the distance (Margin) between the nearest data points and the hyper- plane. And penalty parameter is added for data points that lie in the coordinates of wrong class [19].

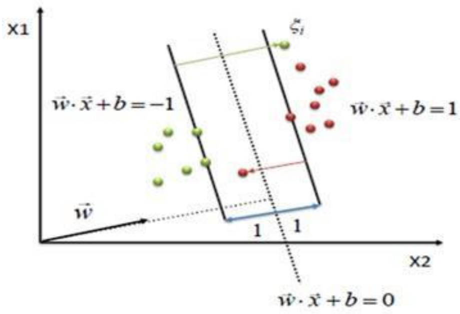

Fig. 3 Representation of SVM [19]

II. METHODOLOGY

The ML algorithms are simulated in Python to analysis the database for Burst Header Packet (BHP) flooding attack on Optical Burst Switching (OBS) Network data set. The steps of implementation are discussed in the following way.

A. Implementation of the ML algorithms:

1. Read the data.
2. Store the parameters mentioned
3. Separate input and output data (Y dependent on X)
4. Divide the data into two parts, 70% as training data and 30% as testing data.
5. Normalize the data of the parameter considered.
6. Apply the algorithm to the data considered.
7. Predict the output for the test data for validation.
8. Find the accuracy of the algorithm by comparing the predicted data with the stored data.
9. Give unknown values of parameters to predict the output for testing
10. All the steps are carried out using Python language using libraries from Scikit-learn tool
11. The classes considered is whether the given link can be used or not depending on the loss of this particular link and that of other links leaving the same node.
12. If the link can be used than further, it is used to implement at the node to switch to that link before the transfer of the actual data.

The simulated result for various algorithms is tabulated in Table 1 for 70% training data and 90% training data. The approximate accuracy of the algorithms is given below:

Table 1. Accuracy results of the algorithms

Algorithm	Training data %	Accuracy
kNN	70%	0.851
	90%	0.990
Random Forest	70%	0.990
	90%	0.990
SVM	70%	1.0
	90%	1.0

The conclusions drawn from the Table 1 are:

- SVM is the best for the given dataset for classification
- More the training data more the accuracy.
- With less testing data, the validation of the algorithm cannot be guaranteed.
- Processing time for SVM is large, reducing the over-all efficiency for large data, thus Random Forest is used for all further implementation.

The main component is COADM is designed using WDM adders and optical switches. Using the controls, the main wavelength are selected or the other added wavelength. The chosen wavelength is obtained in output fibre and other set in dropped wavelengths. The wavelength switching in COADM is discussed below:

B. Implementation of Switching in COADM:

1. Two control switches are considered, which takes input as '1' or '0', dependent on the ML classification results.
2. The input frequencies can be a set of wavelengths generated for the source nodes or input taken from previous node.
3. The added frequencies are another set of wavelengths that is added or dropped depending on the ML results.
4. The Output from Opti-System is in Noise Figure in dB, it has been mapped to the Packets lost given in the Training Data for ML to help in prediction.
5. Python code is written such that it can read the results of the ML output and accordingly, generate python script that will create the Opti-System project, such that if control is given as '0' if the input frequencies will not cause blocking or otherwise given as '1' to choose the added frequencies.
6. Once the python script is generated, it can be run to open the Opti-System project and creates all the layout, links and controls and can be further tested to get the output.

Internal design of a COADM that can be used as node in a network is shown in figure 4.

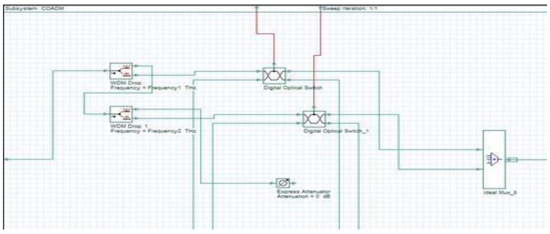

Fig. 4. COADM sub-component

The following figure 5 shows the Opti-System implementation for 3 COADM, with equivalent number of control signals. It has 6 input frequencies consisting of 190 THz, 192 THz, 194 THz, 202 THz, 204 THz and 206 THz while 6 other frequencies can be added as optional depending on the losses. The frequencies that can be added are 196 THz, 198 THz, 200 THz, 208 THz, 210 THz and 212 THz. These frequencies are selected because they lie in the operating wavelength window of 1580 nm for the optical fibre. The below figure 5 and 6 shows the internal design and whole topology for 3 COADM.

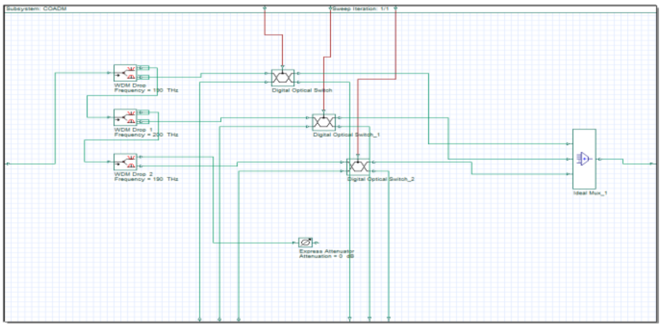

Fig. 5 Internal design of 3 switching COADM

For the implementation of larger topology and for the analysis of results as the number of nodes increases, 2 COADM was considered and the number nodes was increased from six nodes to ten nodes that were added for extension. The Fig. 6 shows the external connections present in the 6 node COADM network. Here the first two nodes taken as source nodes.

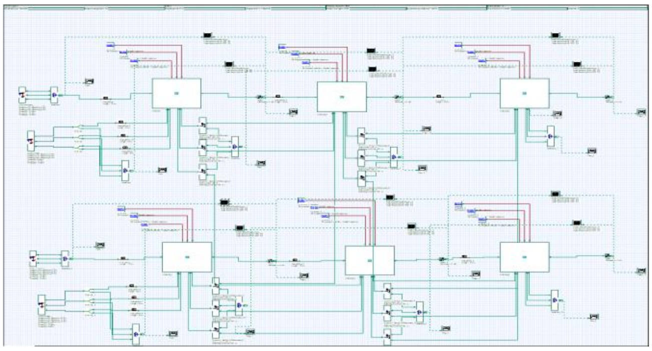

Fig. 6. 6 nodes network of 3 COADM

III. RESULTS

The integration of the two phases means that the Machine Learning is implemented to each and every node and the output links from the node will be predicted. Here in Optical topology the links are in the form of Frequency carriers thus, it will give rise to Frequency re-use concept. It can be observed that with integration of machine learning, the algorithm by itself will select the frequency as per the re-use concept. As use of the same frequency in different nodes will lead to congestion which will be predicted by the algorithm. Table 2 shows the noise figure in 2 COADM network at various nodes without and with Random Forest (RF) algorithms respectively. It can be observed that there is reduction in Noise Figure after the application of the Random Forest algorithms in 2 COADM network compared to 2 COADM network without Random Forest Algorithm in the network as shown in the Table 3.

Table 2. Noise Figure in 2 COADM without RF (Itr. 0) with RF (Itr. 1, 2)

Nodes	Frequency	Iteration 0	Iteration 1	Iteration 2
Node 3	194	100	42.008	35.97
	196	176.54	41.99	1.91
Node 4	202	169.19	41.99	35.97
	204	170.512	42.00	35.97
Node 5	190	100	73.45	71.41
	192	88.17	0.035	95.62
Node 6	194	122.46	40.37	83.16
	198	95.61	2.00	1.97

Table 3. Performance (difference in Noise Fig.) in 2 COADM

Nodes	Frequency	Loss 1	Loss 2
Node 3	194	57.99	6.02
	196	134.54	40.08
Node 4	202	127.19	6.08
	204	128.51	-6.02
Node 5	190	26.54	2.03
	192	88.13	-95.58
Node 6	194	82.08	-42.78
	198	93.61	0.02

The above noise figures have been graphically represented for the selected frequencies in the following figure 7.

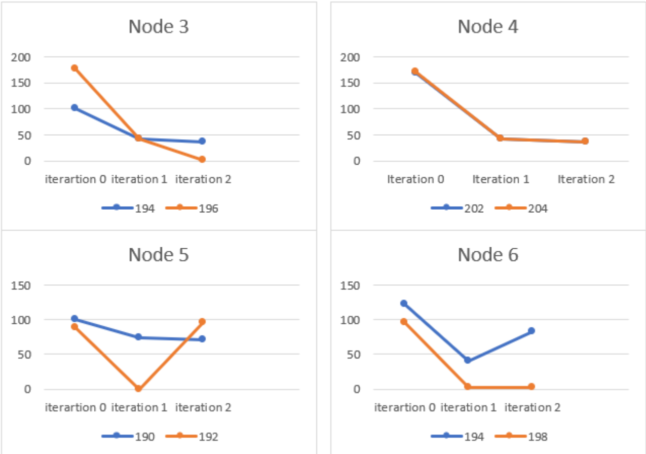

Fig. 7 Noise Figures for the selected frequencies.

Similarly, Table 4 and Table 5 shows the noise figure in 3 COADM network at various nodes without and with Random Forest algorithms respectively.

Table 4. Noise Figure in 3 COADM without RF (Itr. 0) with RF (Itr. 1, 2)

Nodes	Frequency	Iteration 0	Iteration 1	Iteration 2
Node 3	196	63.91	62.79	61.79
	198	100	73.13	77.14
	200	80.89	1.96	1.90
Node 4	208	71.03	68.55	54.37
	210	163.76	1.95	1.89
	212	163.21	1.95	1.90
Node 5	190	46.22	5.32	23.57
	192	93.87	83.16	80.17
	194	82.64	77.62	77.60
Node 6	194	48.5	36.04	34.79
	202	89.16	0.738	2.16
	204	44.16	5.99	1.92

Table 5. Performance (difference in Noise Fig.) in 3 COADM

Nodes	Frequency	Loss 1	Loss 2
Node 3	196	1.12	0.99
	198	26.86	-4.01
	200	78.92	0.06
Node 4	208	2.48	14.17
	210	161.81	0.05
	212	161.25	0.05
Node 5	190	40.89	-18.25
	192	10.70	2.99
	194	5.01	0.023
Node 6	194	12.53	1.25
	202	88.42	-1.42
	204	38.17	-0.02

The above noise figures have been graphically represented for the selected frequencies in the following figure 8.

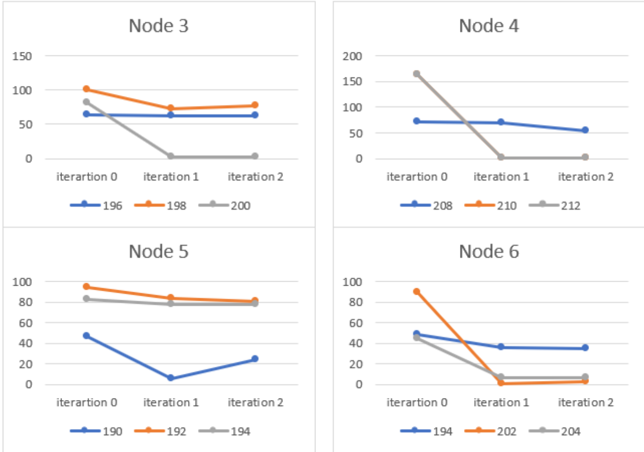

Fig. 8 Noise Figures for the selected frequencies.

Similarly, Table 6 and Table 7 show the noise figure in 4 COADM network at various nodes without and with Random Forest algorithms respectively.

Table 6. Noise Figure in 4 COADM without RF (Itr. 0) with RF (Itr. 1, 2)

Nodes	Frequency	Iteration 0	Iteration 1	Iteration 2
Node 3	196	63.91	62.79	61. 79
	198	100	73.13	77.14
	200	80.89	1.96	1.90
Node 4	208	71.03	68.55	54.37
	210	163.76	1.95	1.89
	212	163.21	1.95	1.90
Node 5	190	46.22	5.32	23.57
	192	93.87	83.16	80.17
	194	82.64	77.62	77.60
Node 6	194	48.58	36.04	34.79
	202	89.16	0.73	2.16
	204	44.16	5.99	6.01

Table 7. Performance (difference in Noise Fig.) in 4 COADM

Nodes	Frequency	Loss 1	Loss 2
Node 3	196	1.12	0.99
	198	26.86	-4.01
	200	78.92	0.06
Node 4	208	2.48	14.17
	210	161.81	0.05
	212	161.25	0.05
Node 5	190	40.89	-18.25
	192	10.70	2.99
	194	5.01	0.02
Node 6	194	12.53	1.25
	202	88.42	-1.42
	204	38.17	-0.02

The above noise figures have been graphically represented for the selected frequencies in the following Fig 8.

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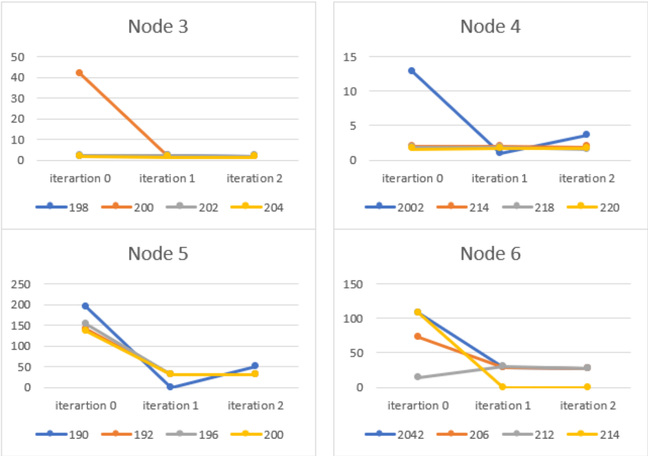

Fig.8. Noise Figures for the selected frequencies.

IV. CONCLUSIONS

This paper proposes the selection of ML algorithm to predict the traffic for a defined set of database and switches the traffic using COADM. Here supervised learning has been used for the defined dataset. Selection of algorithms depends completely on the type of training data and its application. Here the machine learning algorithms are used to predict the future traffic so that by the time the actual data traffic comes, the network will know the links to forward it. Three of the ML algorithms were used for the experiment, testing which: SVM is the best algorithm with 100% accuracy but takes large amount of time to learn the data and reduces the over-all performance of the network. kNN, though is simple cannot classify if any part of the data is missing. Thus, Random Forest can be concluded to be the most optimistic algorithm for the given dataset and given scenario. The algorithms were applied twice for the dataset, and the results were tabulated for 3 iterations (1 without ML and 2 with ML) which gives the performance observed based on the reduction in Noise Figure. This Noise Figure is improved by 42% and 35% in iteration 2 and 3 compared to iteration1 and around 15% from iteration 3 compared to iteration 2 taken from Table 2. When ML algorithm is applied to the Node the Noise Figure will reduce it also depends on the traffic at that link at a given time. It has been observed that as number of frequencies increases, efficiency of ML decreases. This when applied to every node of the network will improve the over-all performance of the network.

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