# A Novel Soft Failure Diagnosis System in Optical Spectrum Using Neural Network Classifier

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***Abstract*— As a result of the huge amount of traffic, failure detection is critical in optical network communication. Therefore, the source of failure needs to be identified so that failed resources can be eliminated from the calculation of restoration paths. In this paper, several machine learning approaches for soft-failure detection and identification are explored. Three different solutions for the most common filter-related soft-failures; filter shift and tight filtering which noticeably deform the expected shape of the optical spectrum are presented here. Filter cascading is similar to filter tightening as it affects the shape of the optical spectrum. To improve the classification accuracy, a neural network is used as a classifier in all three approaches. So classification outcome for all features of the input spectrum is obtained and this will improve the detection performance of the fault detection system. The proposed solutions for filter related soft-failures are: i) multi-classifier approach, which uses features directly extracted from the optical spectrum ii) single-classifier approach, which uses pre-processed features to compensate for filter cascading, and iii) residual-based approach, which uses a residual signal calculated from subtracting the signal acquired by OSAs from a synthetically generated expected signal.**

***Keywords*—Optical Spectrum Analyzer (OSA), Optical Performance Monitoring, Soft-Failure Detection and Identification.**

## I. INTRODUCTION

Optical communication is the most modern and advanced mode of data communication in which light is used to carry the signal instead of electrical current. Optical communication uses optical fibers to carry signals to their destinations. It is used in a wide variety of applications such as network, defense, medical, etc. The main advantages of optical communication include high bandwidth, exceptionally low loss, great transmission range, transmission security, and no electromagnetic interference. Optical communication has seen tremendous growth over the last decade which is mainly due to the incessant and continuous demand for high capacity. The optical networks architectures are becoming more complex, transparent and dynamic in nature. These high-capacity fiber-optic networks are vulnerable to several transmission impairments which can alter over time due to the dynamic nature of these networks. The optical connections support a large amount of traffic. So failure detection and identification are essential in optical networks.

In order to reduce operational cost and repair time of optical networks, continuous monitoring of network performance is necessary [2] and it is a key enabler for failure detection and identification, and it is referred to as optical performance monitoring (OPM). Optical Spectrum Analyzer (OSA) is a precision instrument used in the optical nodes as monitoring devices acquiring the optical spectrum of outgoing links. By analyzing the optical spectrum, specific soft-failures that affect the shape of the spectrum can be detected.

Soft failures degrade the quality of transmission and sometimes these soft failures lead to hard failures. Several soft failures that affect the quality of transmission (QoT) of the signal are laser drift, filter shift, and filter tightening. The most common filter-related soft failures are Filter Shift and Filter tightening. When considering the optical spectrum of lightpath, if a signal is properly configured, its central frequency should be around the center of the assigned spectrum slot to avoid filtering effects, and it should be symmetrical with respect to its central frequency. In the case of Filter shift the optical spectrum becomes asymmetrical and in the case of filter tightening the edges of the optical spectrum get noticeably rounded are shown in figure 1. These changes help to differentiate optical spectra suffering from filter related soft-failures from the properly configured ones. Hence, a substantial mechanism for soft failure detection and identification is essential, as it may be used by operators to perform re-routing of traffic and fast failure recovery.

To detect degradations and identify failures the optical spectrum features can be exploited by machine learning-based algorithms. Machine learning is a branch of artificial intelligence and it provides machines the ability to learn automatically and improve from experience without being explicitly programmed.

This paper is divided into six sections, the first section is the introduction. Section II is the literature review of this topic. Section III gives a brief idea about different machine learning approaches for the detection and identification of filter-related soft-failures. Probabilistic neural network classifier is presented in section IV. Simulation results are given in section V. Finally, conclusions are drawn in section VI.

## II. LITERATURE REVIEW

To locate single and multiple failures in transparent optical networks failure location algorithm is introduced in [3]. This algorithm is used to find four types of failures: power, IBJ, wavelength misalignment, and out-band jamming.

The author studied four failures affecting the signal quality of an optical connection such as signal overlap, tight filtering gradual drift and cyclic drift and proposed algorithms BANDO and LUCIDA to detect and identify the most probable failure [5].

Machine learning (ML) algorithms can help in the process of detecting and identifying soft-failures. The performance of two different algorithms, DTs and SVMs, in terms of their accuracy in the detection of the failures are presented in [7].

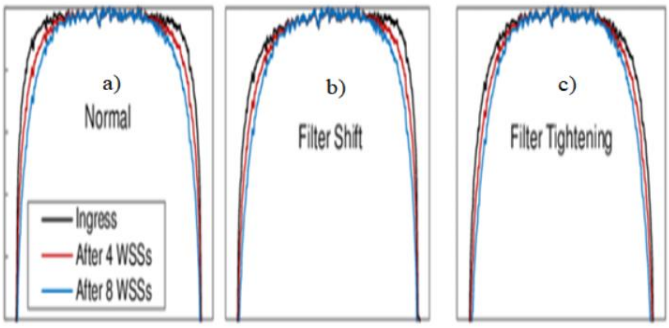



Fig.1. The shape of the optical spectrum: a) Normal signal b) Filter shift c) Filter tightening

## III. MACHINE LEARNING APPROACHES FOR FILTER RELATED SOFT-FAILURES

Three different machine learning approaches are used to detect the filter-related soft failures. They are shown in figure 2. These approaches deal with filter cascading effects individually allowing the development of more powerful solutions. The approaches are based on a set of classifiers. The approaches can be classified into two groups:

### *A. Feature-Based Approaches*

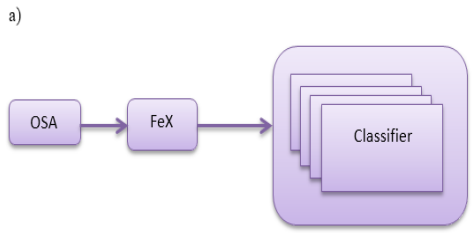
The feature-based approaches use optical spectrum features for classification. Two different approaches are considered in feature-based approaches. They are:

#### *1) Multi-Classifier Approach*

In the multi-classifier approach, a set of classifiers are needed in every intermediate node. When an optical spectrum is acquired, the appropriate classifier is used. Based on the features obtained directly from the acquired optical spectrum, the selected classifier decides failures. This approach does not need any kind of feature pre-processing. To train all the classifiers, a very large dataset of optical spectra with different levels of filter cascading is required. This is the main drawback of this approach.

#### *2) Single-Classifier Approach*

As a result of filter cascading, some of the features that a classifier uses for prediction are changes. Some pre-processing is done to avoid multiple classifiers. So one single classifier can be used to avoid the problems of filter cascading. The features of a signal acquired after passing N filters can be compensated by subtracting/adding the differences between the values of a perfectly configured signal at that node w.r.t. those just after the transponder. A vector called correction mask is used to store these differences. Different correction masks are required for different levels of filter cascading.



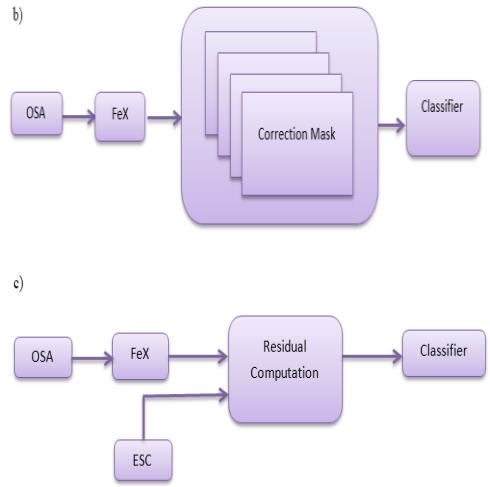




Fig.2. Machine learning approaches a) Multi-classifier b) Single-Classifier c) Residual computation.

### *B. Residual-Based Approach*

A residual-based approach is a new approach in which it analyzes the optical spectrum in a distinct way. The received signal is pre-processed using a theoretically computed expected signal and it uses a single-classifier. Feature extraction module (FeX) is not used in this approach. The residual computation module and Expected Signal Calculation (ESC) module are required to compute the residual signal. The ESC module generates a theoretically-calculated optical spectrum emulating a properly configured lightpath. The function of the ESC module is to reproduce a noise-free version of the optical signal. When a new spectrum is obtained from an OSA, the residual computation module subtracts it from the expected signal.

## IV. PROBABILISTIC NEURAL NETWORK

Probabilistic Neural Network was introduced by D.F. Specht in the early 1990s. PNN is a feedforward neural network which provides a general solution to pattern recognition and classification problems. PNN is a type of ANN. To classify data this type of network adopts the probabilistic method. The PNNs are effective discriminative classifiers with several outstanding characteristics. It was derived from the Bayesian network and a statistical algorithm called Kernel Fisher discriminant analysis. The main advantages of PNN are fast training, good accuracy, coverage to an optimal classifier as the size of the representative training set increases and negligible retraining time. The architecture of PNN is illustrated in Figure 3.

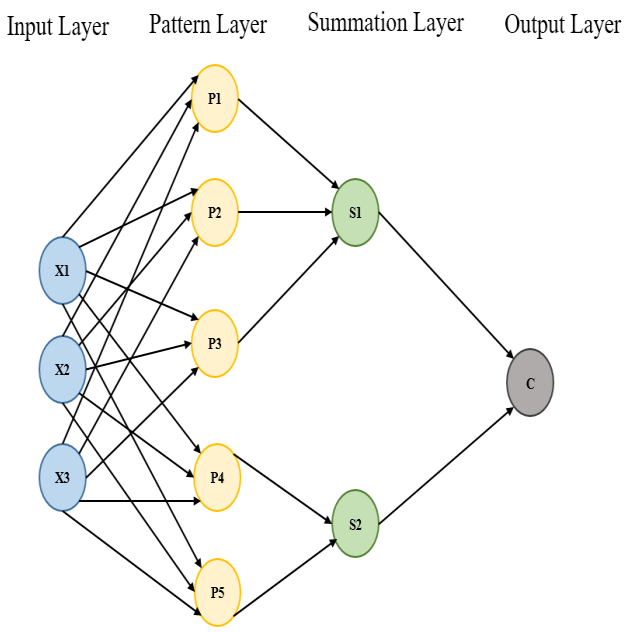



Fig.3. Architecture of PNN

The PNN has four layers: the input layer, pattern layer, summation layer, and output layer. There are three input nodes in the input layer. Two classes in the pattern layer with three training samples in class1 and two training samples in class 2. The input layer contains the neurons with a set of feature values. The input layer supplies these values to the hidden layer. The pattern layer contains one neuron for each training case in the training data set and the neurons are divided into different classes. Each pattern layer neuron computes the distance between the input vector and the training example represented by that pattern neuron and applies a weighting function and yields the activation value of each neuron. The summation layer contains one neuron for each class. The summation layer neuron adds the contributions for each class. The output layer compares the results from the summation neurons layer and uses the largest value to predict the class.

## V. SIMULATION RESULT

In this section, we compare the performance of the residual-based, multi-classifier and single-classifier approaches in terms of accuracy.

Filter shift accuracy of residual-based, multi-classifier and single-classifier approaches are shown in figure 5. The residual-based approach reaches 100% accuracy for 2 GHz FS magnitude. The single-classifier attains 100% accuracy for 6 GHz FS magnitude and multi-classifier attains 100% accuracy at 7 GHz. The multi-classifier based approach shows the lowest overall accuracy for FS failures.

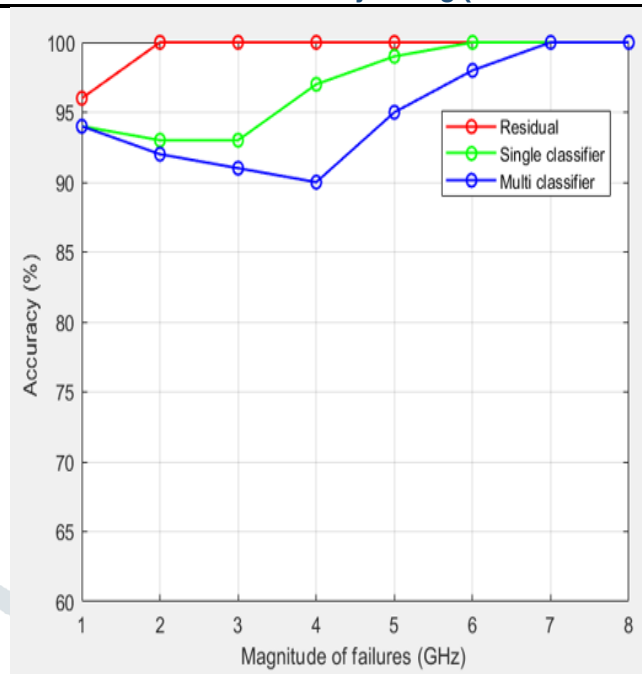



Fig.4. Filter shift accuracy for different approaches

The difference between the ideal bandwidth of the filter and its actual bandwidth during the failure is called the magnitude of FT. Figure 6 shows that the residual-based approach reaches 100% accuracy for 7 GHz FT magnitude. The multi-classifier reaches 100% accuracy for 8 GHz FT magnitude and single classifier attain 100% accuracy for 10 GHz FT magnitude. In the case of filter tightening the multi-classifier approach performs better than the single-classifier approach.

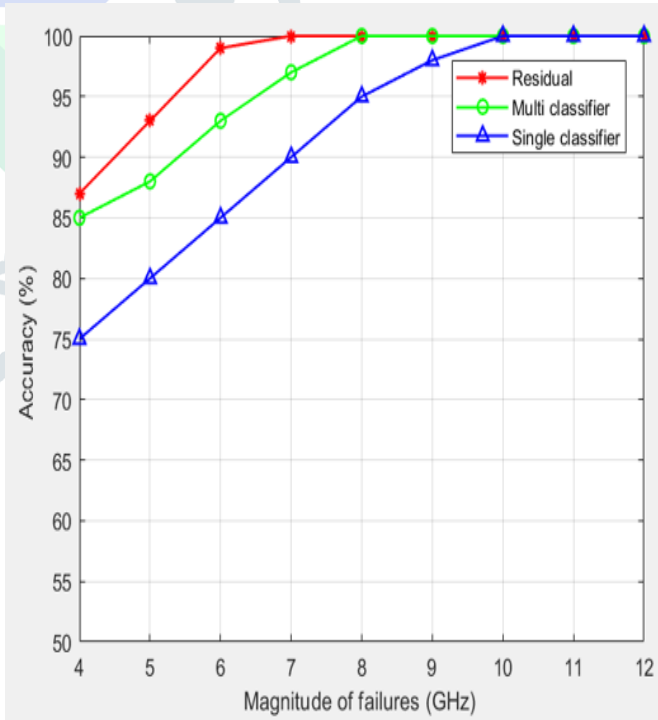



Fig .5. Filter tightening accuracy for different approaches

The residual-based approach performs better than feature-based approaches for the detection of filter shift and filter tightening.

## VI. CONCLUSION

The performance of three different machine learning approaches for filter-related soft-failure detection and identification was compared in terms of accuracy by using the PNN algorithm. The training of a multi-classifier approach requires a large dataset. The single-classifier approach requires N times fewer data compared to the multi-classifier approach. But it requires the calculation of the correction masks. The residual based approach uses a single classifier, performs better than the feature-based approaches and it brings down the complexity of training compared to the multi-classifier approach.

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