Splice Fault Position Detection of Single Mode Fiber Using Feed-Forward Neural Networks

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Abstract

The purpose of this work is to detect the splice fault that decrease the signal level of single mode optical fiber for a length of 10 Km by using an optical source of 1550 nm wavelength, the principle of work depends on the comparison between fiber undefected and fiber that contains defect which are its signal were taken by optical time domain reflectometer (OTDR), this comparison was operated by artificial neural networks, it is found that the splice fault location inside the optical fiber can be detected with high speed using feed-forward neural (FFN) networks, the proposed Mean Square Error (MSE) is ($10e^{-7}$) to check the performance of (FFN), the results that obtained by using MATLAB programming were with high accuracy .

Keywords: *Single Mode Fiber, Splice Location, Feed-Forward Neural Networks*.

الكشف عن موقع عيوب اللحيم في الليف الضوئي أحادي النمط باستخدام الشبكات العصبية الاماميه

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الخلاصة

الغرض من هذا البحث هوالكشف عن عيب اللحيم الذي يقلل مستوى الاشاره في الليف أحادي النمط ذو الطول 10كم باستخدام مصدر ليزري بطول موجي 1550 نانومتر ، مبدأ العمل يعتمد على المقارنة بين الليف الخالي من العيوب والليف الذي يحتوي على العيوب والذي تؤخذ إشارتهما بواسطة جهاز الانعكاس البصري الزمني(OTDR) ، هذه المقارنة تقوم بها ألشبكة العصبية الذكية ، لقد وجد إن العيوب في الليف الضوئي تكتشف بسرعة عالية باستخدام الشبكة العصبية الامامية (FFN) ، إن متوسط مربع الخطأ هو ($10e^{-7}$) في أداء ألشبكة العصبية (FFN) ، هذه النتائج تم الحصول عليها بواسطة استخدام برنامج الماتلاب وبدقة عالية .

1. Introduction

A single fiber is an optical fiber that only propagates one light mode (one light ray path down the centre of the fiber). This occurs because of the core size (diameter) of single mode fibers is small (7 to 10 μm) and near the wavelength of the light, approximately 1260 to 1600 μm [1,2]. The loss of power in light in an optical fiber is measured by decibels (dB). Fiber optic cable specifications express cable loss as attenuation per 1-km length as dB/km. This value is multiplied by the total length of optical fiber in kilometers to determine the fiber's total loss in dB. Optical fiber light loss is caused by a number of factors that can be categorized into extrinsic and intrinsic losses. Extrinsic losses can be divided into three types, Splice, Connector and Bending Loss. Meanwhile Intrinsic losses include also three types which are Loss inherent to fiber, Loss resulting from fiber fabrication and Fresnel reflection[1]. The attenuation of the optical fiber is a result of two factors; absorption and scattering shown in figure (1). Absorption factor is caused by the absorption of the light and conversion to heat by molecules in the glass. Primary absorbers are residual OH^+ and dopants used to modify the refractive index of the glass. This absorption occurs at discrete wavelengths, determined by the elements absorbing the light. The OH^+ absorption is predominant, and occurs most strongly around 1000nm, 1400nm, and above 1600nm [3].

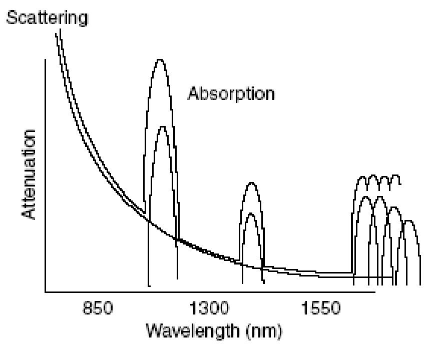

Figure 1. Fiber loss mechanisms [3].

The largest cause of attenuation is scattering. Scattering occurs when light collides with individual atoms in the glass and it is anisotropic. The Light that is scattered at angles outside the critical angle of the fiber will be absorbed into the cladding or scattered in all directions, even transmitted back toward the source. Scattering is also a function of wavelength, proportional to the inverse fourth power of the wavelength of the light. Thus, if the wavelength of the light is double, the scattering losses will be reduced by 2^4 or 16 times. Therefore for long distance transmission, it is advantageous to use the longest practical wavelength for minimal attenuation and maximum distance between repeaters. Together, absorption and scattering produce the attenuation curve for a typical glass optical fiber shown in figure (1). Fiber optic systems transmit in the windows between the absorption bands at 850nm, 1300nm and 1550nm, where physics also allows one to fabricate lasers and detectors easily[3]. Silica glass has two low loss windows, one around the wavelength λ=1300nm and one around λ=1500nm, which both are used for optical fiber communication. The popular single-mode fiber has a loss of about 0.25dB/km at the 1500nm. A third wavelength window around λ=850nm, where the loss is about 2.5dB/km, is used for short-reach (data) communication applications, mostly because low-cost optical sources and detectors are available for this wavelength[3]. In this paper we study the splice fault that decrease the signal level of single mode fiber for a length of 10 Km by using optical time domain reflectometer (OTDR) and artificial neural networks.

2. Splice losses (Lateral displacement)

Single-mode fibers have core diameters on the order of 9µm. Owing to this microscopic size, mechanical misalignment is a major challenge in joining two fibers by connector or splice. Power losses result from misalignments because the radiation cone of the emitting fiber does not match the acceptance cone of the receiving fiber. The magnitude of the power loss depends on the degree of misalignment. Lateral displacement results when the axes of the two fibers are offset by a distance (d). The misalignment to which a connection is most sensitive is lateral displacement, shown in figure (2). The losses of lateral displacement misalignment for (d « $\bar{\omega}_o$) are given by the following equation: [4].

$$L_{Lat}(dB) = -10\log_{10}\left(\exp -\left(\frac{d}{\bar{\omega}_o}\right)^2\right) \text{..... (1)}$$

The ($\bar{\omega}_o$) is the spot size of the fundamental mode. The spot size is usually defined as the width to (1/e) intensity to the (LP_{01}) mode, or in terms of the spot size of an incident Gaussian beam which gives maximum launching efficiency. However, the spot size ($\bar{\omega}_o$) for the (LP_{01}) mode corresponding to electric and magnetic field (HE mode) may be obtained from the empirical formula given by Marcuse [5] .

$$\bar{\omega}_o = b\left(0.65 + 1.619V^{-3/2} + 2.879V^{-1}\right) \text{ ... (2)}$$

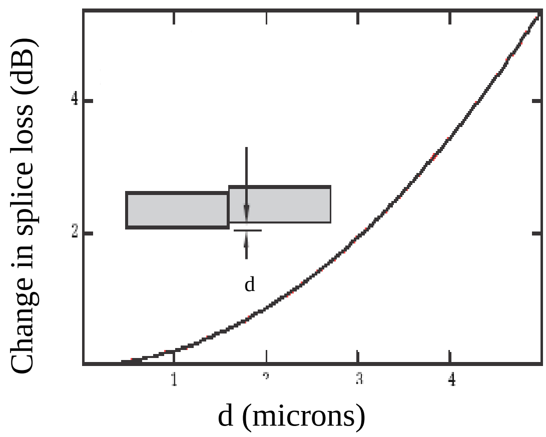

Figure 2. Coupling loss in single-mode fiber as a function of lateral [5].

Where (b) is the radius of the core in single-mode optical fiber, (V) is the normalized frequency. A pulse with power (P_o) and pulse duration (τ_ω) shall be launched into the fiber from attenuation of fibers, at a distance (z) from the fiber input the transmitted pulse power P_t (z) is attenuated to [5]:

$$P_t(Z) = P_o . 10^{-\alpha Z/10dB} \qquad \text{..... (3)}$$

3. Artificial Neural Networks (ANNs)

Humans are able to adapt new situations and learn quickly when given the correct context. ANN work by simulating the structure of the human brain. At their basic level they consist of a network of neurons connected by synapses. Neurons are the basic element of an ANN. Neurons accept inputs from other connections and produce an output by firing their synapse. Neurons typically perform a weighted sum on all of their input connections and then pass it through a transfer function to produce its output [6]. A typical network is composed of a series of interconnected nodes and the corresponding weights between them. It aims at simulating the complex mapping between the input and output. The training process is carried out on a set of data including input and output parameters. The learning procedure is based on the training samples and the testing samples are used to verify the performance of the trained network. During the learning process, weights in a network are adapted to optimize the network response to a presented input. The way in which these weights are adapted is specified by the learning rule.

The most common rules are generalizations of the Mean Square Error (MSE) rule. Equation (4) being the generalized delta rule or back propagation, it is most frequently used for supervised learning in feed forward neural networks. In supervised learning, the accuracy of the response is measured in terms of an error *E* defined as the difference between the current Y_k and desired T_k output as in equation (4) [7] [8].

$$MSE = \sqrt{\frac{\sum_{j=1}^{n}\sum_{k=1}^{m}\left(T_{j,k} - Y_{j,k}\right)^2}{nm}} \qquad \text{.................................. (4)}$$

Where n represents the number of training patterns, m is the number of outputs, T is the target value and Y is the actual value.

4. Back propagation (BP) learning algorithm

The back propagation (BP) algorithm was proposed in 1986 by Rumelhart, Hinton and Williams for setting weights and hence for the training of multi-layer perceptrons [9]. A three layers feedforward network also called the perceptrons or the universal approximation is shown in figure (3). The BP algorithm propagates backward the error between the desired signal and the actual network output through the network. After providing an input pattern, the output of the network is then compared with a given target pattern and the error of each output unit calculated. [9] .

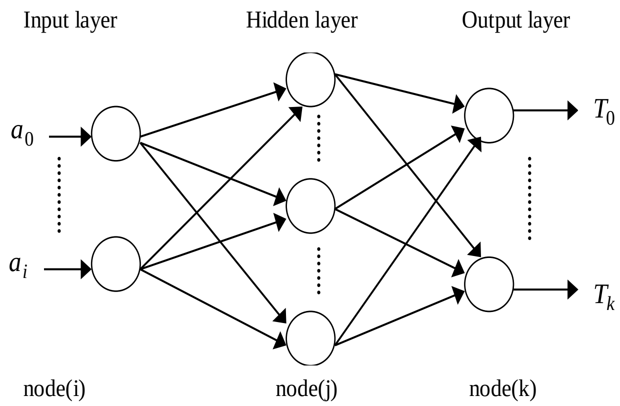

Figure 3. Multi-Layer Perceptrons .

This error signal is propagated backward, and a closed-loop control system is thus established. The weights can be adjusted by a gradient-descent-based algorithm. In order to implement the BP algorithm, a continuous, nonlinear, monotonically increasing, differentiable activation function is required. The two most-used activation functions are the logistic function equation (5) and the hyperbolic tangent function equation (6), and both are sigmoid functions [10].

$$F(net) = \frac{1}{1+e^{-net}} \qquad \text{……. (5)}$$

$$F(net) = \frac{e^{net} - e^{-net}}{e^{net} + e^{-net}} \qquad \text{……. (6)}$$

Where net is determined by using equation (7) and $F(net)$ represent the actual output [11].

$$net = \theta_j + \sum_{i=1}^{n} a_i w_i \qquad \text{..….. (7)}$$

Where a_i is the input training vector, θ_j is the bias of hidden node j, w_i is the input weight. Back-Propagation algorithm (BP) can then be used to adjust connection weights in the ANN iteratively in order to minimize the error calculated by equation (4) [12]. The error is propagated backwards from the output to the input layer. Appropriate adjustments are made, by slightly changing the weights in the network. After weights have been adjusted, patterns are presented all over again. Error is calculated weights adjusted, and so on, until the current output is satisfactory, or the network cannot improve its performance any further [8].

Based on the previous discussion, backpropagation training algorithm can be summarized as below:

1- Initialize network weight value.

2- Repeat the following steps until some criterion is reached (for each training pair).

3- Sum weighted input and apply activation function to compute output of hidden layer.

$$h_j = f\left(\sum_i a_i w_{ij} + \theta_j\right) \quad \text{.... (8)}$$

w_{ij} is the weight connected between input node i and hidden node j ,and h_j is the output of hidden node j .

4- Sum weighted hidden layer and apply activation function to compute output of output layer.

$$y_k = f\left(\sum_j h_j w_{jk} + \theta_k\right) \quad \text{.... (9)}$$

Where w_{jk} is the weight connected between hidden node j and output node k . θ_k is the bias of output node k and y_k is the output of output node k .

5- Compute back propagation error.

$$\delta_k = (t_k - y_k) f'\left(\sum_j h_j w_{jk}\right) \quad \text{.. (10)}$$

Where t_k is the desired output at node k and δ_k is the error at node k .

6- Calculate weight correction term.

$$\Delta w_{jk}(n) = \eta \delta_k h_j + \gamma \Delta w_{jk}(n-1) \quad \text{....... (11)}$$

Where γ is the momentum coefficient. η is the learning rate and Δw_{jk} is The weight adjustment between hidden node j and output node k .

7- Sum delta input for each hidden unit and calculate error term.

$$\delta_j = \sum_k \delta_k w_{jk} \; f'\left(\sum_i a_i w_{ij}\right) \quad \text{... (12)}$$

Where Δw_{ij} is the weight adjustment between input node i and hidden node j and δ_j is the error at node j .

8- Calculate weight correction term.

$$\Delta w_{ij}(n) = \eta \delta_j a_i + \gamma \Delta w_{ij}(n-1) \quad \text{... (13)}$$

9- Update weights.

$$w_{jk}(n) = w_{jk}(n-1) + \Delta w_{jk}(n) \quad \text{... (14)}$$

$$w_{ij}(n) = w_{ij}(n-1) + \Delta w_{ij}(n) \quad \text{.... (15)}$$

10- Test for stopping condition (maximum number of iterations or met the lowest learning error. [11]

5. Fault Position Detection Using Feed-Forward Neural Network

In this article, the optical time domain reflectometer (OTDR) positioned at the front end of SMF can receive and save the signal of optical power returned from the defective fiber (splice fault) at 3Km which is shown in figure(4). FNNs will be trained to learn and save the OTDR signal by use Backpropagation training algorithms where the fault position was detected at 3Km. The training process for this scheme is shown in figure (5). Then the neural network used again to read and save the optical power in the existence of splice in this time at 3km distance. After that, a Matlab program was implemented using a neural network; its function is to subtract the defective signal from the non-defective one. The result that obtained represents the optical power according to algorithm declared in section (3) at 3km distance which is an indicative sign of a faulty position of splice. Practically, for suggested approach after recording and saving the signal of optical power from the undefective SMF using OTDR as mentioned above, then FNN can be implemented according to the weights obtained from the simulation results from the proposed scheme by use of Field Programmable Gate Array (FPGA).

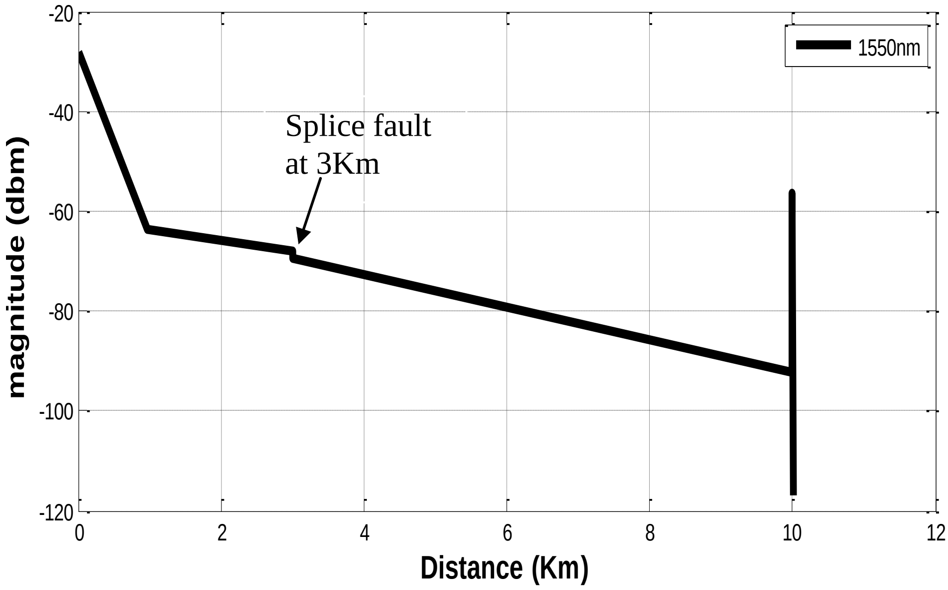

Figure 4. The output signal of OTDR which fed to FNN.

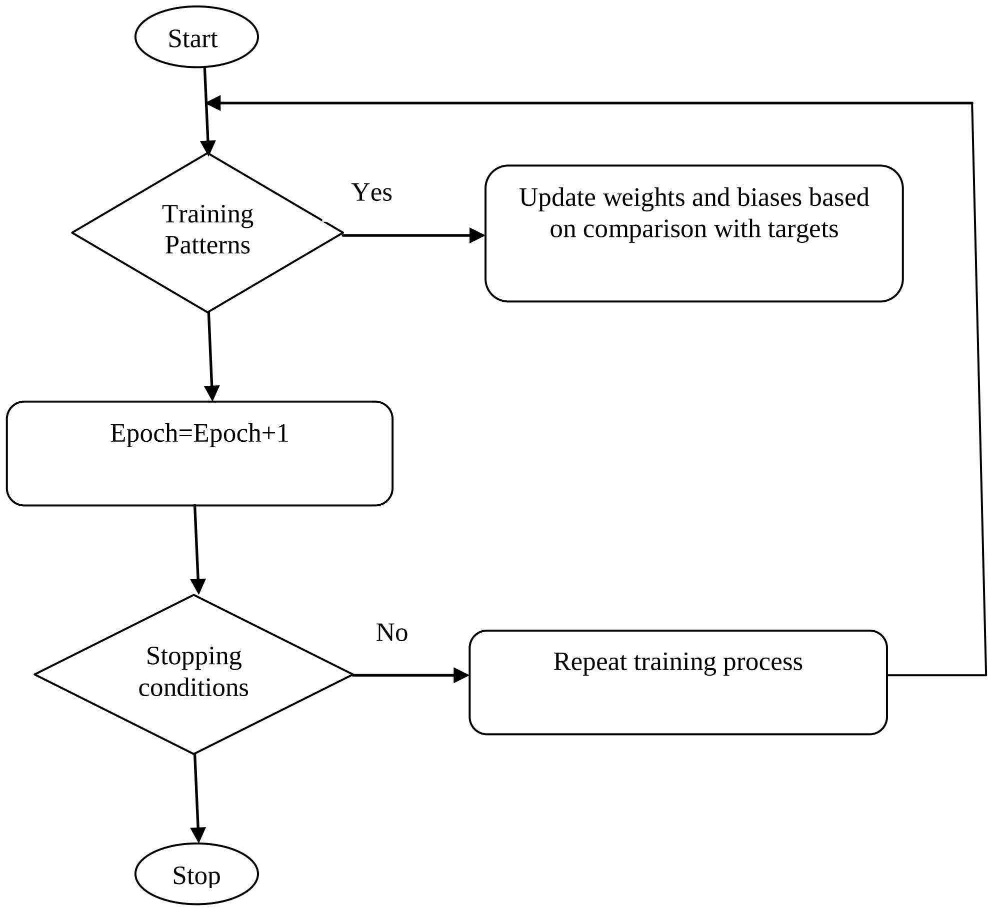

Figure 5. Backpropagation training algorithms

6. Computer Simulation and Results

Feedforword Neural Network structure of two input neurons, five hidden neurons with tan sigmoid activation function and one output neuron with log sigmoid activation function was chosen to implement detection circuit as shown in figure(6). Before training process, The parameters of Back-propagation algorithm are set to the momentum coefficient γ=0.9 and the learning rate η=0.5. The initial weights and biases are randomly generated between [-0.5, 0.5]. The maximum number of iterations (epoch) =100 and Mean Square Error (MSE=10e-7) . Learning Rate is the training parameter which controls the size of weight and bias changes during learning. The real domain of learning rate is [0, 1]. However, Momentum coefficient simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is

too low cannot reliably avoid local minima, and can also slow down the training of the system.
All the data were calculated by Mean Square Error equation (MSE), which was dependent on vary low value of error ratio according to normalization.
The number of patterns equal to the number of points into the distance matrix which is from (0 to 10000m). Patterns number was chosen according to equation (3) in section (2.1 Splice losses (Lateral displacement)).

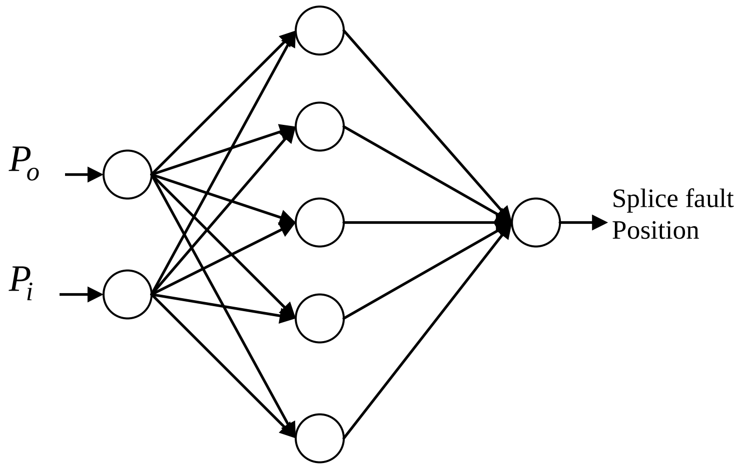

Figure 6. Neural Network Structure of detection circuit.

The output power of single mode fiber is shown in figure(7), which is represent the non defective single mode optical fiber. The attenuation that appears in the signals is due to attenuation in the input signal along optical fiber which is 0.25 dB/Km.

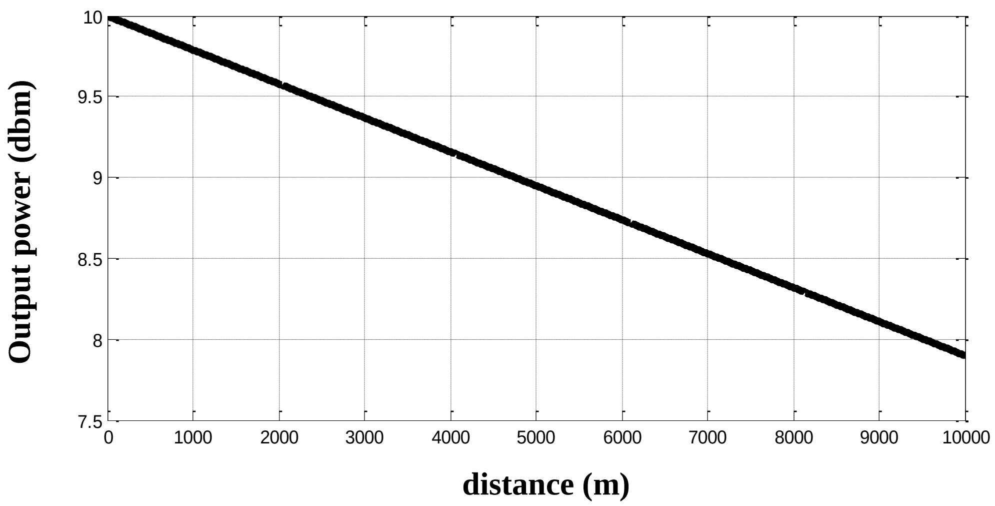

Figure 7. The output power of non defect optical fiber (without Splice fault)

But if a splice is added to the single mode fiber at distance 3 Km, the output power will be decrease with shift equal to L (splice losses) according to equation (1), and the output power which is defected signal is shown in figure(4). The performance of feedforward neural network training is shown in figure (8). Where the goal is 10 e^{-7} , and the relationship between desired and actual output is linear as shown in figure (9). Subtracting the signal shown in Fig.(4) from the signal shown in Fig.(7), the signal shown in Fig.(10) was obtained , from which y-axis of the ANN output signal represents the magnitude of the losses caused by splice, meanwhile the x-axis represents the location of splice fault along SMF. It seems from Fig.(10) that the splice loss equal zero before the position of splice fault (3000m). At position (3000m) the splice loss became greater due to the existing of the splice at this point.

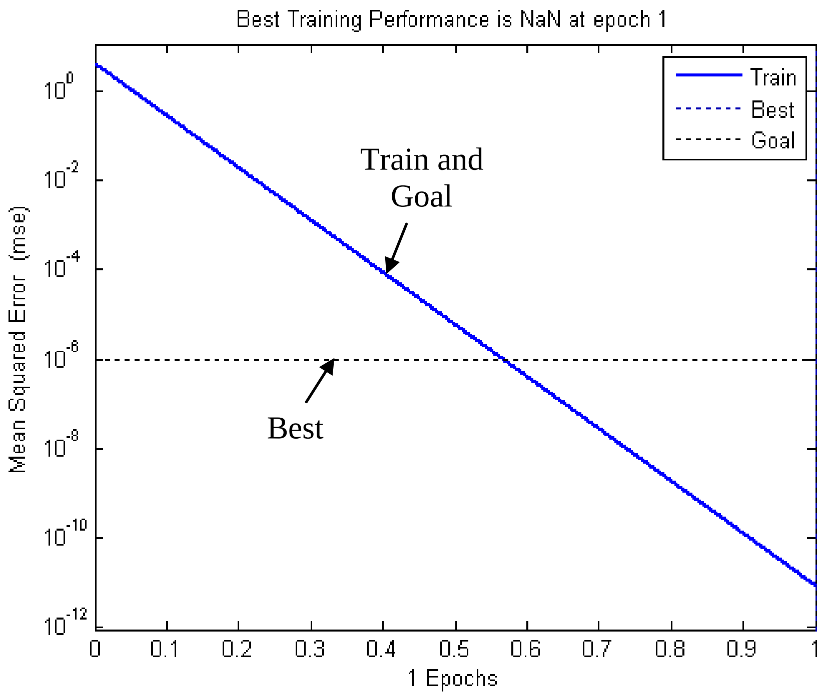

Figure 8. The performance of feed forward neural network.

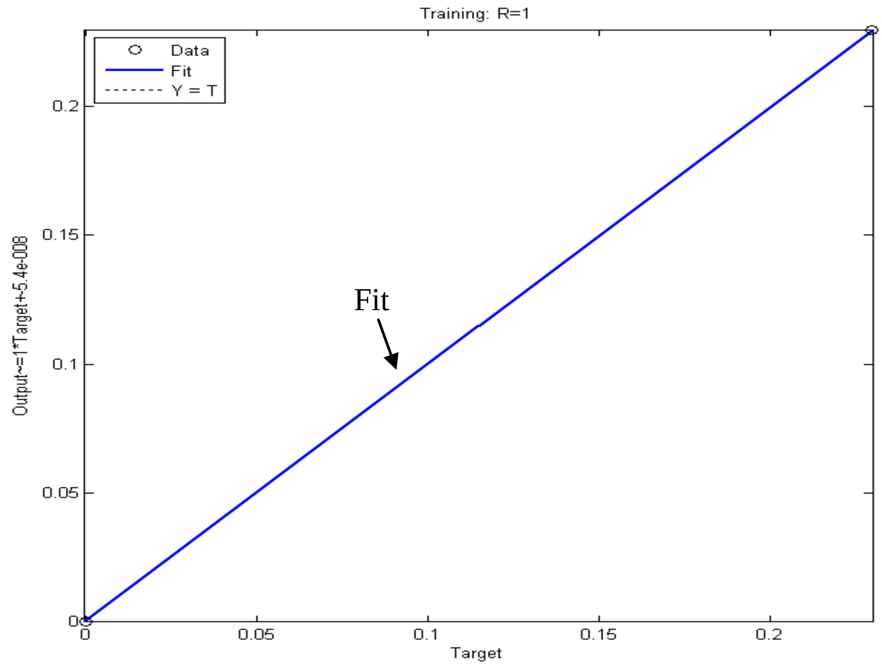

Figure 9. The relationship between desired and actual output

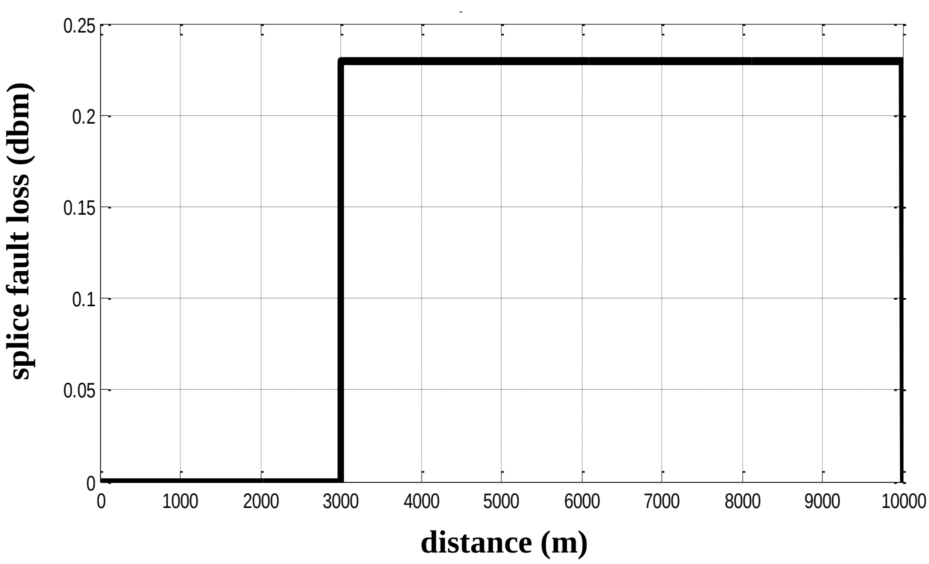

Figure 10. The output signal of ANN.

7. Conclusions

In this research, we concluded that:

1- It is possible to find the location and value of splice fault and any type of faults through the use of feed-forward neural (FFN) networks and

OTDR, in this research the value of the splice fault loss was 0.27dbm at 3Km.

2- By Subtracting the signal of fig.4 from the signal of fig. 7, the signal of fig. 10 was obtained. from position 3km to 10km. The splice loss became greater due to the existing of the splice at position 3km.

3- Feed forward Neural Network is a powerful technique for fault position detection with a suitable accuracy.

4- It is possible to use FNN in the rear end of SMF to detect the fault position depending on the information recorded by OTDR.

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