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Applying Machine Learning Technology to Optimize the Operational Cost of the Egyptian Optical Network

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Abstract

The Optical Network is considered an important asset to any telecom operator. One of the most critical issues to the operators is how they can maximize the Return of Investments (ROI) by optimizing the operational costs in the optical network. In this paper for the first time we propose an Intelligent Universal Platform (IUF) to manage and optimize the operational tasks in the optical network. the proposed platform drives the supervision of the network to the automation, and is formed by the integrations between four models, the 1'st one is the energy model and built according to the variations in the power consumptions and it proposes the recommended actions to optimize the energy consumption by swapping the cooling system between two system types (air-conditions and fan units) according to the temperature degrees , also the model learns from the variations in the heat dissipation according to the busy and the idle modules and it can transform the unused hardware to the sleeping mode, the 2'nd model is the fault localizations and is built by the practical experiments of the faults recovery and forms its expert system to predict the mean time to repair (MTTR), the 3'rd model is the network performance and is built by monitoring the optical signal to noise ratio (OSNR) and provides the recommended corrective actions to keep the same level of the performance, the 4'th model is the configuration management and it suggests the best routes in the network. The paper studied four use cases in two situations As-Is and To-Be, the cases are about the energy consumptions, the fault locations, the circuit creations and finally the variation in the signal to noise ratio. the results shows that by using the machine learning in our platform the time of the fault location is reduced from 40 min to 3 min, the efforts to create one circuit is reduced by 30.87%, the number of the complaints are reduced by 30% per year, and the response time to the complains is decreased from 55 min to 5 min. This indicates that in the near future the machine techniques will play a significant role in monitor, detect, localize faults, and finally optimize the resources of optical network, all without human intervention.

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1- Introduction

Working in the operational tasks of the optical network by the traditional methods is very expensive and directly affects the net profits of any telecom operator. To optimize the operational costs in a huge optical network such in Egypt there are many tasks should be done in an intelligent way by using the suitable machine learning technique. The most important factors which affect the cost of the operations in any optical network are how they can monitor and control the energy consumptions, reduce the time of the fault localization, monitor the quality of the transmission links in a periodic way and finally choosing the best routes for the creations of the new circuits to reduce the waste of the rare network resources. The previous studies indicates that The artificial intelligence and the machine learning techniques have the promising future in the automations and the smart applications in many fields such the optical network, as the previous studies investigated separately one factor only from all of the operation factors such that: many studied introduced the AI to predict the energy consumption by using artificial neural Network (ANN) and support vector machine (SVM) in the renewal energy field [1]. Other studies explained how to use the different machine learning techniques in the forecasting of the energy consumption in the electricity market by using multi-objective genetic algorithms (MOGAs) [2]. Few studies investigated how to optimize the energy consumption in the Data centers by using the AI forward and back propagations techniques [3]. Many different studies explained how to use machine learning algorithms to predict the fault location in the optical network by using double-exponential smoothing and support vector machine (DES-SVM) algorithm [4]. Other investigations used the graph-based correlation (GBC) heuristic in defining the fault location in the optical network [5]. A long short-term memory (LSTM) network with the deep learning technique was introduced by certain studies as a solution to continually estimate the optical signal to noise ratio (OSNR) [6]. Few previous studies were done about how to use the AI techniques in the configurations management of optical network to automate the creation of the new circuits on the optical network one of these studies explored how to use the dynamic routing and the spectrum assignment with the hold time between the different nodes in the optical network to define the best routes in the Dense Wave Division Multiplexing (DWDM) network [7]. The paper proposes for the first time universal platform to derive the important operation factors in the optical network to the automation, and this done by the interactions between four different proposed models to automate the executions of the operation tasks in the network. The Four models of the operation tasks in the optical network are introduced and implemented by the different techniques of the Artificial Neural Network (ANN) to reduce the human interventions in the executions of these factors and at the same to optimize the waste of the resources in the optical network.

The paper is organized as following: Section 2 introduces the existing challenges in the operations of the optical network; Section 3 introduces the proposed Machine Learning Models of the operational tasks in the optical network; sections 4 discuss the expected results and finally Section 5 provides the conclusion.

2- Challenges in the operations of the optical network

The optical transmission network is considered the core infrastructure of the communication industries in Egypt. This network was built over many years and it is still extending over the time in all country area. One of the most important challenges in this network is the enormous diversity in its resources, as an example of this diversity it consists of many different vendors equipment, different transmission technologies from the synchronous digital hierarchy (SDH) to the Optical Transport Network (OTN) with the Core DWDM technology, and different spans in the fiber cables of the network. As a result of this diversity in such huge amount of optical network resources many network management systems (NMS's) were used to manage it (one NMS for every vendor equipment type), and this makes the executions of the operational tasks by the human interventions between these different NMS's very difficult and expensive, at the same time the energy consumptions over all the network of these NMS's is not controlled by centralized management system. The results of the pervious situations are high costs of the operations, huge efforts and resources with long time to meet the target of the Operations key performance indexes (OKPI) over the entire optical network. Figure 1 shows an example of the optical network with many vendors and NMS's.

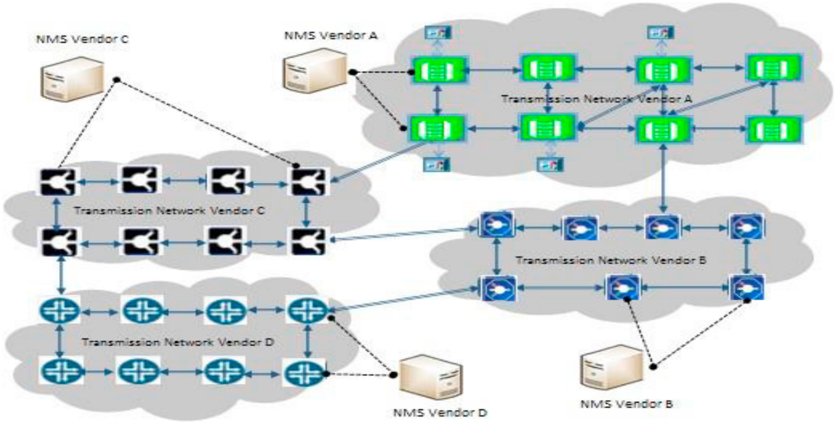

Fig. 1. Example of the Transmission Network with Multi-Vendor

As shown from figure 1 the executions of the operational tasks in the network of different vendors are very complex. In this paper we study only four Use-Cases in the operations task of the optical network with different vendors and different NMS's to illustrate 4 challenges in the network.

2.1 Monitor the total Energy consumption over all optical networks

One of the most important challenges in the optical network is how to optimize the energy consumption especially with the huge rise in the cost of providing it from other parties. The AS-IS case in monitoring the energy consumptions is built upon every owner of the network element stations calculates the consumption of the power according to his perceptions and the following equations:

$$P_{DC}(NE)= I * V \quad (1)$$
$$P_{AC} = \sqrt{3}\, I * V * \cos \emptyset \quad (2)$$
$$P_{TL}=N * LAMP\ WAT \quad (3)$$

Where	
$P_{DC}(NE)$	The DC power consumptions for one Network element
P_{AC}	The power consumptions by the cooling systems
P_{TL}	The power consumptions by the lighting system
N	The number of lighting unit
$cos\ \emptyset$	Power factor
I	consumed current
V	Power Voltage Value

As we can see from the previous equations there is no relations between the power consumed by the network elements and the power consumed by the infrastructures such cooling systems and lighting systems, also there is no relations between the estimations of the power consumptions in one stations to the remaining part of the optical network which is associated with the loaded services on the optical network elements.

Challenge no.1: *There is no centralized system can be used to monitor and control the performance of the total power consumptions (the 's consumptions and infrastructure consumptions) and the relations between these consumptions with the total loaded services in the network elements over the entire optical network.*

2.2 The time of the fault localizations

The supervision of the optical network with such complexity and heterogeneity as shown in figure 1 is limited by the manual administrations of the operational tasks, and the probability of the risks in the optical network increases with the complexity of the network and how much the execution of the operational tasks is done by the human interventions. One of the most important challenges in the supervision of the optical network is how to find the location of the faults and how to easy define the root cause of any affected traffic within the suitable time [8]. In the traditional methods the fault localization depends only on the observations of the different alarm lists from many NMS's by the responsible persons which may contain hundreds of the records. The time consumed in the fault localization phase and the quality of performing this task depends mainly on the experience of the responsible persons. This method of the fault recovery affects directly the operational cost by increasing the mean time to repair (MTTR) and may be violating the service level agreements (SLA) with the customers.

Challenge 2: *There is no automated process to faster the fault localizations time and find the root cause problem to minimize the mean time to repair over the entire optical network*

2.3 The Optical performance monitoring

The quality of the transmission network depends mainly on the proactive maintenance in the network. Monitoring the quality of the transmission links over the time is an important task in the operations of the optical network. One of the important factors which used to measure the performance of the optical network is the optical signal to noise ratio (OSNR) [6]. The traditional method in monitoring the optical signal to noise ratio is done by the observations of many lists which contain thousands of the laser power measurements in the different NMS's systems. It takes long time and huge efforts to keep in track with the dynamic changes in the power measurements in all the optical ports of the network. The quality of performing this task depends only on the experiences and the commitment of the responsible persons. Any improvement in performing this task will affect in a positive way the number of complaints from the bad quality of the network and affects directly the operational cost of the optical network.

Challenge 3*: There is no automated process to perform the performance monitoring task and notifies by the needed proactive actions in the optical network*

2.4 configuration management

One the most critical issues in the optical network are the utilization of the optical network. To create new circuit in multivendor network with the traditional way it will take long time to complete the route creation. The quality of the network configuration is varied according to the performance of the creations and the existing gap between the high level of the requirements and the low level of the configuration methods [8]. The quality of the network configurations affects directly the operational costs in a negative way such that in case of bad quality will make waste of the expensive resources. The time consumed in different steps in the new creation process in the optical network depends on the type of the customer request. The time consumed in the implementation of the customer request in the network is the longest time in all creation period. In case of the creation will be done over multi- vendor network the time and the efforts will be doubled according to the number of the vendors in the network.

Challenge 3: *There are no automated tools to perform complete provisioning of the all resources in the optical network and to maximize the return of the investments in these resources.*

3- The Proposed Solution for Smart Operations in the Optical Network

From the previous investigation we found that the artificial inelegance is the best solution to perform smart optical network. The proposed solution to overcome the pervious challenges in the optical network is to design Intelligent Universal Platform (IUP) in upper layer than the NMS layer. The proposed platform is done to transform the operational tasks in the optical network to be more automated and is working as robots instead of human interventions. One of the important functions of the proposed platform is to predict the optimal solution to execute the operational tasks. The IUP consists of the interactions between 4 proposed models to perform the optional tasks in the optical network. Every model is designed by using machine learning technique or the deep learning techniques to reduce the human interventions in the processes of the operations especially in monitoring and predicting the optimal solutions of performing the operational tasks. The design of every model and the complete solution model are explained in the following subsections.

3.1 The Power Consumption Model

The model consists of machine learning algorithm that learns from the actual power consumptions in some sites in the network. The he training data of the system is raised from m optimal sites as following equations [10 -11]:

$$PUE=\frac{\text{Total Facilities Power}}{\text{Optical Network Equipment Power}}=\frac{FP}{EP}=\frac{F_0+\sum_{J=1}^{n}(a_j)+\sum_{p=1}^{c}(b_p)}{\sum_{l=1}^{p}(E_l)+\sum_{i=1}^{k}w_i(m_i+s_i)} \tag{4}$$

Where

PUE	The Power usage effectiveness in the Optical Network
F_0	The initial power consumption for the facilities in one site
a_j	The power consumption by the cooling system with n air conditions in one site
b_p	The power consumptions by the others facilities for c units (lighting – measurement equipment – fans)
E_l	The power consumptions by p empty optical network shelfs
m_i	The power consumptions by inserted i modules in the total number of shelfs
s_i	The power consumptions by the implemented services on the i modules
w_i	The weight of the power consumption for i modules with its services

The proposed model of power consumption consists of 3 layers of the Artificial Neural Network (ANN) which are used to form simple prediction model of the power consumptions performance in the optical network as shown in figure 3 [9].

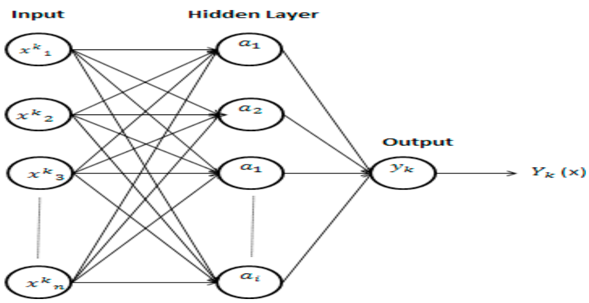

Fig. 2. The Proposed Artificial Neural Network for power consumption model

- The first layer is assigned for the input variables of the different parameters in the optical network such cooling, air-conditions, lighting, modules, number of the network elements in the same network elements, and any other variables with n number of variable's. k number of training examples

- The 2'nd layer is the hidden layer which used to find the relations between the output and the input variables with total number of i coefficients
- The 3'rd layer is the output layer which explores the value of the optical network in one site.

The deployment of the model is done in 3 steps:

- The learning phase: where the output ( ) and the input are known from the training data with the following equation which explains the nonlinear relationship between the outputs and the inputs [9-10]

$$Y_k = Y(x^k{}_n\, ; a_i) = \sum_{i=1}^{i=h} a_i f\left(\sum_{n=1}^{n=m} a_i x^k{}_n\right) \quad (5)$$

Where k expresses of the site number during the training phase and a_i is estimated coefficient function to perform the relation between inputs and outputs

- The generalization phase in this phase is evaluating the machine learning algorithm to generalize it on all network by testing the expected outputs $\hat{Y}_{\bar{k}}$ in site $\bar{k}$ with the unseen examples in the training phase as the following equations:

$$\hat{Y}_{\bar{k}} = \sum_{i=1}^{i=h} a_i f\left(\sum_{n=1}^{n=m} a_i x^{\bar{k}}{}_n\right) \quad (6)$$

To evaluate the algorithms the root mean square errors (RMSE) will be used as the following:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{\bar{k}=1}^{\bar{k}=N} (\hat{Y}_{\bar{k}} - Y_{\bar{k}})^2}$$

(7)

Y_k	The actual output of the learning data set
$x^k{}_n$	The n input variables for k training samples
a_i	The coefficient functions of every neural cell
$f(x)$	Each of the hidden units are related to the tangent function such $(e^x - e^{-x})/(e^x + e^{-x})$
$\hat{y}$	The expected output of the testing data set

- The last phase in the implementation phase to the monitor and test the consumption power over all the network stations and alert with the extreme values in the consumptions.

3.2 Fault localization model

The Fault localization model is designed for any optical network which includes different types of vendors and technologies, the design of the machine learning model is done according to the assumptions of the optical transmission network which consists of the core transmission network with dense wave division Multiplexing (DWDM) and optical transport network (OTN) technologies as shown in figure 1. As shown in figure 3 the faults of the optical network are classified in 2 categories the secondary alarms which are raised from the loaded traffic of the circuits on the network and the primary alarms which are raised from the modules and cards of network elements [12]. To formulate the training data of the machine learning algorithm there are many correlation rules between all the alarm types should be formulated first. The correlation rules are built according to the time factor as the secondary and primary alarms are raised to the Network Management System (NMS) at nearly the same time, these rules are depended on the mean time between consecutive incidents (MTBCI) which is very small for the same root cause incident in the optical network, by considering the primary alarms which express the network alarms is time independent and the secondary alarms are time dependent. According to the Weibull distribution the localization of the failure links depends on the correlations between the different variables of the alarm lists which stored in the change management data base (CMDB) the different NMS's. The data set which used in the learning model was created from the past practical experience according to the following techniques [13 - 14]:

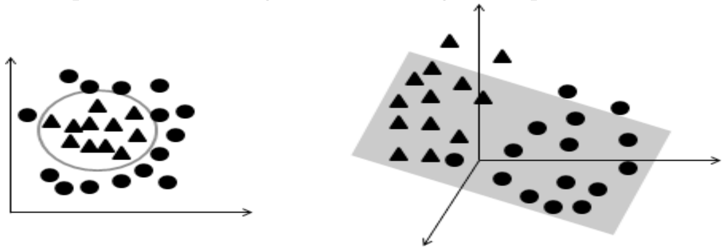

Fig. 3 The Types of the data in the alarm list of the NMS

- The affected equipment raises abnormal conditions to the NMS with many records in the list of alarms ( ) which consist of two groups of data secondary alarms ( ) and Primary alarms ( ) where ( ) ( ) ( ) as shown in figure 3.The secondary alarms are associated with certain links in the optical networks by the Vector failure links (i) (i) (i) … D ( ) can be determined as following [13]:

$$X_j(i) = \begin{cases} \frac{S_j(i)}{A(i)}, & D \geq j \geq 1, X_j \in S(i) \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

(i) is the distribution vector of the failure links from total number of links in the optical network L.

- The root cause of the faults incidents is the link failure in the optical network which is one link from the Vector (i) and determined as following equation:

$$Y_j(i) = \frac{P_j(i)}{X_j(i)}, \qquad X_j(i) \subset X(i) \tag{9}$$

- If $_k$ (i) is equal to any positive value then the link with name k is the root cause of the total failure in incident i. The implementation algorithm in the machine learning consists of 3 layers as shown in figure 4 the first layer is the input of all alarm lists the 2'nd and 3'rd layers is the definitions of the relations between the failure links and the alarm lists the 4'th is the outputs of the failure link. The prediction algorithms is implemented according to the nonlinear regressions between inputs and output as the following equation:

$$Y_k = Y(x^k{}_n ; a_i ; b_j) = \sum_{i=1 \& j=1}^{i=h \& j=d} a_i\, b_j\, f\left(\sum_{n=1}^{n=m} a_i\, b_j\, x^k{}_n\right) \tag{10}$$

The root mean square errors (RMSE) is used to test the validity of the system by calculating the errors between the actual results of the model $_k$ and the result of the unused test examples in the training phase.

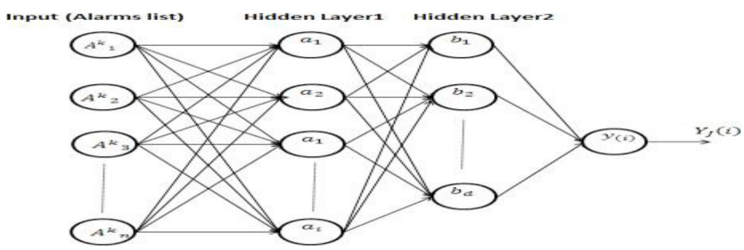

Fig. 4. The Proposed Artificial Neural Network for fault localization model

3.3 The optical network performance model

The model is as intelligent optical performance monitoring (IOPM); it covers all the OSNR Monitoring tasks for the high rate of the wavelengths in multi-vendor DWDM network. Also it supervises the end to end optical layer performance in the whole optical network. The training data is used from the change management database (CMDB) of the NMS systems and are classified according to every Optical port type in the NE as following: Transmit power, Receive power, Error rates, Receive End of Live power (EOL), Optical Fiber span attenuation and ONSR. Table 1 illustrates the different types of the data which is used as input or output in IOPM model for Every NE [15 -16].

Table 1. Variables of IOPM.

Parameter	Transmitter port	Receiver Port	Amplifier card
Optical power	Input	Input	input
BER		Output	
OSNR	Output	Output	output
Amplifier Gain			input
Fiber Span Attenuations		Input	
Line Rate	Input	Input	

The first phase of building the model is the learning phase and the data set in this phase is obtained from the CMDB of the NMS for every NE with optical ports bit rate 10 Gb/s or more. There are linear relations between output factors (OSNR & BER) and the input factors as following [17]:

$$OSNR = 10\frac{S}{N} \tag{11}$$

$$10\, log_{10}(BER) = 10.7 - 1.45\,(OSNR) \tag{12}$$

Where S represents the linear optical signal power, N represents the linear optical noise power.

The model consists of 3 layers one layer for input parameters which consists from n variables and d ports and the 2'nd layer from the relation between input and output with m coefficient and third layer is the output layer as shown in figure 5[18].

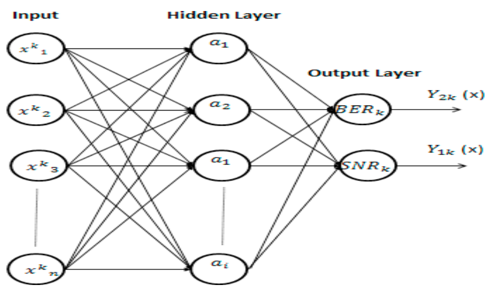

Fig. 5. The Proposed Artificial Neural Network for Optical Performance model

$$Y_{1k}(x) = f\left(\sum_{n=1}^{n=d}\sum_{i=1}^{i=m} a_i x_n^k + w_0\right) \tag{13}$$

$$Y_{2k}(x) = f\left(\sum_{n=1}^{n=d}\sum_{i=1}^{i=m} a_i x_n^k + w_1\right) \tag{14}$$

Where
$Y_{1k}(x)$ The expected output of the OSNR in the port number k
$Y_{2k}(x)$ The expected output of the BER in the port number k

a_i	The coefficient functions of the hidden layers
f(x)	Each of the hidden units are related to the tangent function
x_n^k	The input of n variables for port number k in the network
w_0	The fixed weight between input variables and output OSNR
w_1	The fixed weight between the input variables and the output BER

3.4 The configuration model

In the configuration model a combinations between the Artificial Bee Colony Algorithm (ABC) and the ANN is used where the model consists of Artificial Neural Network (ANN) which uses input topology, physical layer characteristics, Optical port status, capacity, source and distention to be implemented according to the ABC technique in 5 steps [19]:

- Step 1 generates a list of paths randomly between every node as a source and all possible destinations by the process of the search paths and the spanning tree control to form the routing table for all networks and update the external archive in the data base of the model.
- Step 2 produces a new solution for every created route in step1 by using Greedy Selection Process (GEP).
- Step 3 Search for new multicast tree from the source node the destination nodes.
- Step 4 Choose the best probability for the routes from the sources and destinations according the one with smaller D value has a higher choosing probability as the following equations [20 - 21]:

$$p(\theta_i) = \frac{1}{R(\theta_i)+D(\theta_i)} \quad where\ \theta_i \in S \tag{15}$$

$$D(\theta_i) = \frac{1}{2+\sum_{k=1}^{\sqrt{|S \cup Arch|}} \|f(\theta_i) - f(a_k)\|}, \qquad a_k \in S \cup Arch \tag{16}$$

$$R(\theta_i) = \sum_{\beta \prec \theta_i} \{w | \beta \prec w \wedge w \in S\} \tag{17}$$

Where

$p(\theta_i)$	The chosen probability for route θ_i
S	The set of the routes from one source to the possible destinations
$D(\theta_i)$	The candidates density around θ_i based on $\sqrt{\|S \cup Arch\|}$ nearest neighbors
$R(\theta_i)$	The importance of θ_i terms of how many candidates are dominated

- Step5 Produce new alternatives according to the current probability and update the archive data
- Step 6 The terminations are not achieved go to step 2

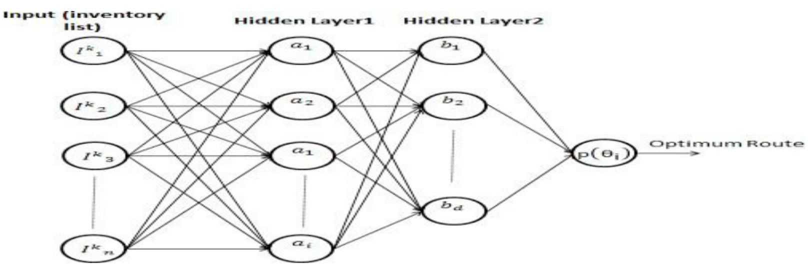

Fig. 6. The Proposed Artificial Neural Network for the configuration model

Figure 6 show the design of the model by using 4 layers of the ANN model. The first layer is the input variables which are the inventory database from the CMDB of the NMS of the optical network with many input variables such number of available ports, nodes , capacity of every optical link , existing routes ,available frequencies, topologies of networks, types of every node, the sources, destinations and the cost of every link. The 'nd layers are the hidden layers which will be used to find the relations between the input and the output, the final layer is the output layer. The implementation of the model is the same as equation (10).

3.5 The Total Proposed Platform

From the previous subsections we found that there are direct relations between the different variables of every model with the other. Table 2 illustrates the relations between the inputs variables and the output variables for the all models in one site of the optical network, as all variable are extracted from the CMDB of the different NMS's.

Table 2. Total Variables of the universal platform

Input Variables		Output Variables			
		PUE	Fault Location	OSNR Performance	Optimum Route
Number of N 's	NE	■			
Traffic weight	TW	■			■
Power consumed for one NE	PN	■			
Power Consumed for cooling system	PC	■			
Power Consumed for other infrastructure systems	PI	■			
Capacities of every optical link	CO		■		■
Transmit Laser Optical power for every port	TL		■	■	
Receive Laser Optical power for every port	RL		■	■	
Bit Error Rate for every link	BER		■	■	
ONSR for every link	OSNR		■	■	
Secondary Alarm lists	SA		■		
Primary Alarm Lists	PA		■		
Number of the optical links	NL	■	■	■	■
Topology of the network	TN				■
Cost factor of optical links	CF				■
Source	S				■
Distention	D				■
NE Vendor Type	NV	■	■	■	■

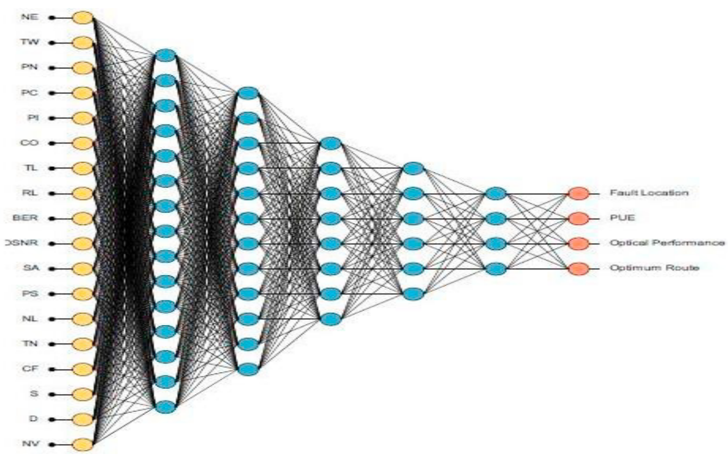

Fig. 7. The Proposed Artificial Neural Network for the General Model

Figure 7 illustrated the proposed complete model by using ANN technique to execute the operational tasks in the optical network. The general model consists of 6 layer the first layer for the input variables as shown in table 2, and source of the input data set comes from the CMDB of the multi-vendor NMS's, the 'nd layer is the first hidden layer and consists of m neural cells which are connected with all the input variables, the 3'rd layer is hidden layer with k neural cells, and it sorts the input variables according to the output types, the 4'th layer is hidden layer with n neural cells and it makes more classifications to the variables according to the output types, the 5'th layer is the last hidden layer and consists of q neural cells and it determines the different forms of the outputs, and finally the last layer is the outputs. The general model is represented by the following equation [22 – 23].

$$Y_k = Y\left(x^k{}_n\,;\; w_f\,; a_i\,; b_j;\; c_l\,;\; d_r\;\right) \;=\; \sum_{f=1}^{m}\sum_{i=1}^{k}\sum_{j=1}^{n}\sum_{r=1}^{z}\sum_{l=1}^{q}\; w_f\, a_i\, b_j\, c_l\;\; d_r\, f\left(\,\sum_{n=1}^{n=m} a_i\, b_j\, x^k{}_n\right) \tag{18}$$

Y_k	The chosen output of the model
$x^k{}_n$	The data set of the inputs
$w_f\,; a_i\,; b_j;\; c_l\,;\; d_r$	The coefficient functions of hidden layer respectably

4. Results & discussion

Neural designer Simulator and Statistical Package for the Social Sciences (SPSS) are used to implement the test and the validity of our model. Due the complexity the test is done on 2 models only as the following:

4.1 The Test and the results of Power consumption model

The data set consists of 500 records for 7 variables from actual experimental data. The data set is sorted as 5 inputs (N Number of NE elements, PN Power consumed by NE, PI Power consumed by Infrastructures , PC Power consumed by cooling system , S weight of the services on the NE) and 2 outputs (T total consumed power and PUE power effective units). Table3, 4 illustrate the results of the test model for the correlations between the Input and Total Power output and the coefficients of the linear regression model with case summery of the processing model.

Table 3 Correlations between the input variables (N, NE, PN ,PI and PC) with T output

		T	N	PN	PI	PC	S
Pearson Correlation	T	1.000	1.000	1.000	.953	-.200	1.000
	N	1.000	1.000	.	.952	-.199	.
	PN	1.000	.	1.000	.952	-.199	.
	PI	.953	.952	.952	1.000	-.255	.952
	PC	-.200	-.199	-.199	-.255	1.000	-.199
	S	1.000	.	.	.952	-.199	1.000
Sig. (1-tailed)	T	.	.000	.000	.000	.000	.000
	N	.000	.	.000	.000	.000	.000
	PN	.000	.000	.	.000	.000	.000
	PI	.000	.000	.000	.	.000	.000
	PC	.000	.000	.000	.000	.	.000
	S	.000	.000	.000	.000	.000	.
N	T	498	498	498	498	498	498

N	498	498	498	498	498	498
PN	498	498	498	498	498	498
PI	498	498	498	498	498	498
PC	498	498	498	498	498	498
S	498	498	498	498	498	498

Table 4.b illustrates the coefficient of the model

		Unstandardized Coefficients	
Model		B	Std. Error
1	(Constant)	2.355E-11	.000
	PI	.102	.000
	PC	-8.956E-14	.000
	S	.552	.000

Table 4.b Case Processing Summary

		N	Percent
Sample	Training	345	99.7%
	Testing	1	.3%
Valid		346	100.0%
Excluded		152	
Total		498	

The Output model of the estimated total power consumption in the optical network according to the test model is dependent on the power of the infrastructure, power of the cooling system and consumed power for services in the N ’s as the following equation.

Figure 8.a, 8.b shows the relations between prediction values of the total power consumption with the actual values and the residual values from the test model.

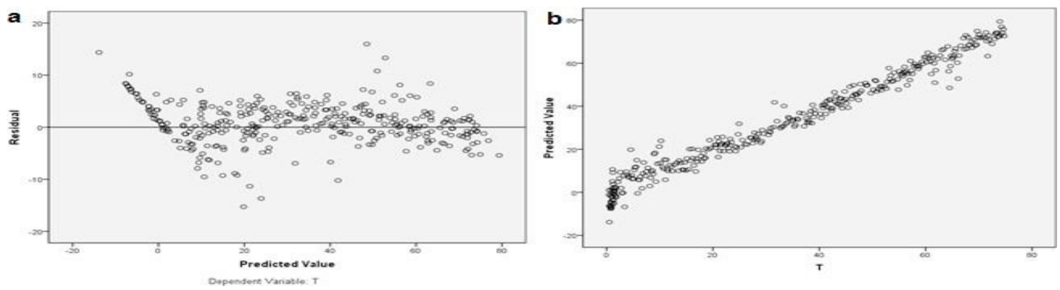

Fig. 8. The Relation between the Prediction Values and the Actual of the total power consumptions with the residual

For the output PUE, table 5 shows the coefficient and the model summery of the linear regression in case and the case summery the of output model .The following equation indicates the prediction model of PUE in the optical network. Figure 9 shows the linear regression between the protected values and the actual PUE

$$\hat{T} = 2.355E\text{-}11 + .102 * PI - 8.956E\text{-}14\ PC + .552\ S \quad (19)$$

Table 5. the Coefficients and model summery of the PUE Test Model

Model	Unstandardized Coefficients		Model Summary			
	B	Std. Error	R	R Square	Adjusted R Square	Std. Error of the Estimate
(Constant)	.357	.104				
PI	.421	.032				
PC	.001	.000	.622	.386	.383	.40324
S	-.023	.001				

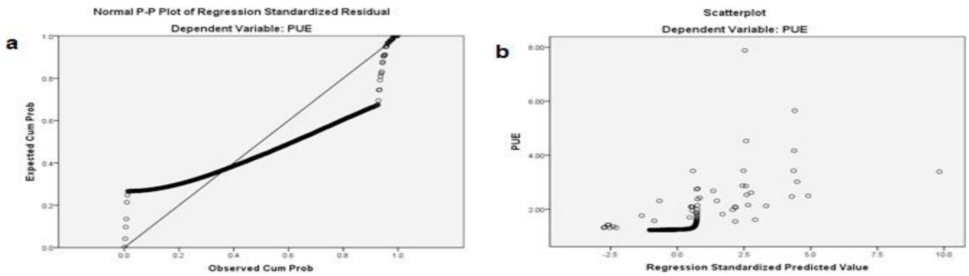

Fig. 9. The regression relation between the Prediction Values and the Actual PUE

4.2 *The test and the results of the Performance model*

The system is designed by using ANN and actual experimental input data of 500 records with 5 input variables (TX transmit power, Rx receive power, ER error rates, OSNRt, and OSNRt) and 2 output variables (BER and FL fault location), table 6 illustrates the correlations between the variables

Table 6. The Correlations between the different variables

		FL	Tx	Rx	SNRt	SNRr	BE
Pearson Correlation	FL	1.000	.	.	.	.	.
	Tx	.	1.000	.816	-.826	.746	.838
	Rx	.	.816	1.000	-1.000	.411	.997
	SNRt	.	-.826	-1.000	1.000	-.412	-.999
	SNRr	.	.746	.411	-.412	1.000	.412
	BE	.	.838	.997	-.999	.412	1.000

Table 7. The Test Model **Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.623E-9	.000		.291	.771
	BE	1000.000	.000	1.000	5090700.061	.000
2	(Constant)	1.856E-5	.000		5.153	.000
	BE	999.977	.004	1.000	227553.304	.000

SNRt	-4.776E-7	.000	.000	-5.152	.000

From Table 7 the following equations illustrates the prediction model of BER

$$\widehat{BER} = 0.357 + 999.977{*}ER + -4.776E\text{-}7\,OSNRt \quad (20)$$

Figure 10 Shows the Regression between the predicted values and the actual BER

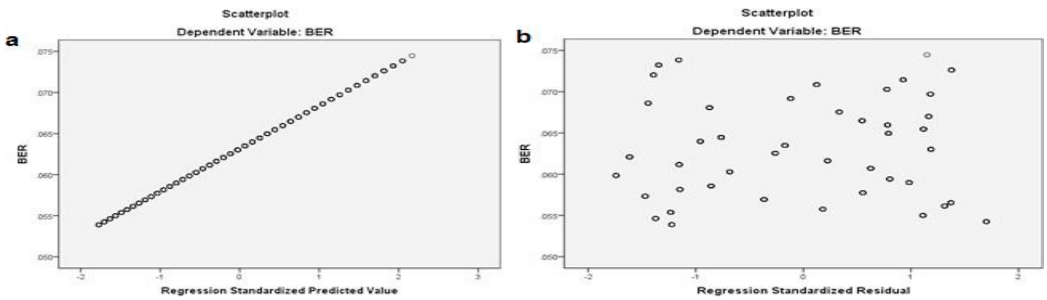

Fig. 10. The regression relation between the Prediction Values and the Actual BER

From The previous results the estimated values of BER and power consumptions can be calculated by equations 19, 20 and the same test model can be implemented for the other outputs such fault localization and the configuration management. We can see that the implementation of the total model is applicable by using the ANN technique. Figure 11 shows the output from an empirical study in the optical network of the benefits from using the machine learning techniques in the operational tasks and the compares between AS-IS and TO-BE use cases.

Fig. 11. An example about the benefits from using AI in the Optical Network

5. Conclusion

For the first time we propose an Intelligent Universal Platform (IUF) to manage and optimize the operational tasks in the optical network. the proposed platform drives the supervision of the network to the automation, and is formed by the integrations between four models, the 1'st one is the energy model and built according to the variations in the power consumptions and it proposes the recommended actions to optimize the energy consumption by swapping the cooling system between two system types (air-conditions and fan units) according to the temperature degrees , also the model learn from the variation in the heat dissipation according to the busy and the idle modules and it can transform the unused hardware to the sleeping mode, the 2'nd model is the fault localizations and is built by the practical experiments of the faults recovery and forms its expert system to predict the mean time to repair (MTTR), the 3'rd model is the network performance and is built by monitoring the optical signal to noise ratio (OSNR) and provides the recommended corrective actions to keep the same level of the performance, the 4'th model is the configuration management and it suggests the best routes in the network. The paper studied four use cases in two situations As-Is and To-Be, the cases are about the energy consumptions, the fault locations, the circuit creations and finally the variation in the signal to noise ratio. the results shows that by using the machine learning in our platform the time of the fault location is reduced from 40 min to 3 min, the efforts to create one circuit is reduced by 30.87%, the number of the complaints are reduced by 30% per year, and the response time to the complains is decreased from 55 min to 5 min. This indicates that in the near future the machine techniques will play a significant role in monitor, detect, localize faults, and finally optimize the resources of optical network, all without human intervention.

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