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Network Device Status Detection using ANFIS-based Classification for ISP Networks Upgrade Planning

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Abstract
With recent advances in technology, a lot of network equipment is always being brought and replaced as per needs. So the management of the networking equipment is a significant challenge in terms of operational cost and manpower. Many software are available to monitor the network health, but for the replacement of networking equipment, there is no mechanism developed till now. In this study, an adaptive neuro-fuzzy inference system was developed (ANFIS), based on input parameters such as based on input parameters like throughput, CPU usage, memory, end of life [EoL], end of support [EoS], and energy consumption to predict replacement of network devices like router and switch. This research will help internet service providers to decide whether to replace or upgrade equipment to ensure proper network infrastructure is functional. The simulation result shows that ANFIS gives a better result in terms of root mean square error. In case of router best ANFIS model was with gaussian membership function (gauss MF) having input membership function 2*2*2*2*2 and output membership function constant with testing RMSE of 0.1288. In case of switch best ANFIS model was with gaussian membership function (gauss MF) having input membership function 2*2*2*2*2*2 with output membership function constant with testing RMSE of 0.23663. ANFIS approach is very much useful and easy to implement. The evaluation showed the superiority of the proposed expert-based approach using ANFIS with hybrid learning for the prediction of the replacement of networking equipment.

Keywords
ANFIS, ISP network, router, switch, replacement planning

Information is the building block for smooth communication. The company's productivity depends on its capability to deliver useful information through proper communication. The systems and infrastructure used to ensure the proper communication requires constant maintenance to reduce the downtime and make the system running and operational. Small business and ISP owners spend a lot of money annually in devices to make networking systems operate efficiently, and then forget about them before something goes wrong. With time as the device starts to age, the performance starts degrading, and there might be a breakdown. In this situation, replacement of the hardware is the best possible solution instead of investment in repair. It is important to predict how long does the hardware of networking systems lasts. Managing thousands of networking devices is time-consuming and costly. If devices are not properly managed, then this leads to their rapid obsolescence. Without creating any replacement plan, if we replace old equipment, this might lead to complications [1]. We might face several critical issues with the compatibility of the newer device with the existing system. Newly purchased equipment requires extra cost for purchase, and some equipment might require extra cost for staff training. Good maintenance management will substantially reduce operational costs. Hence, it is imperative to provide a methodology to prioritize all networking equipment for replacement.

In this paper, we propose the network device replacement plan to identify the parameters to develop and establish a knowledge-based reasoning engine and to model the device status detection system based on a fuzzy inference system, and to provide the recommendations based on the decisions obtained from the inference engine. ANFIS is used for classification [2] for device replacement planning. While making device status prediction regarding upgrade or replace the proposed approach should possibly try to answer the following questions:

1. How can we predict the status of equipment for an annual replacement plan?
2. Which parameters are useful to determine the replacement plan?
3. Is there enough support and end of life left of equipment for it to be upgraded?

For this study, the model developed is only applicable for CISCO products, i.e. switches, and routers. For other products like Juniper, Huawei products, ZTE, Raiscom, ISCOM, Extreme, Summit need different preprocessing and modeling.

1. Related works

In recent years, a great deal of work has been done in various fields related to the replacement using fuzzy logic [3]. Type-2 [4] fuzzy sets let us the model and minimize the effects of uncertainties in rule base fuzzy logic systems. However, these fuzzy sets are challenging to understand for a variety of reasons, which we enunciate. Mendel [5] strived to overcome the difficulties by establishing a small set of terms that help communicate easily about type-2 fuzzy sets and also defined such sets very precisely, presented a new representation for type-2 fuzzy sets, and used this new representation to derive formulas for the union, intersection, and complement of type-2 fuzzy sets.
Suresh et al. [6] proposed a model that described a fuzzy-set model for the maintenance policy of multistate equipment. The model extended to maintenance planning for the entire life of the equipment. The result proved useful for both replacement and inventory control decisions.

Rajasekaran [7] developed an automated equipment replacement planning system (ERPS) to identify equipment most in need of replacement in order to optimize the utilization of capital budget resources, the attention to patient safety, and efficiency of the healthcare process. Rules were developed to assist in determining which equipment should be prioritized for replacement. The ERPS consisted of a skeleton database in which the replacement rules have been programmed. Mummolo et al. [8] proposed a model which considered both linguistic and quantitative parameters, estimated accurately, in order to include many of the factors that influence replacement decisions with an approach that is unique yet simple to use in the healthcare context.

Sinha [9] proposed a method in which for ANFIS, the evaluation was done with different input configurations by varying the number and type of membership functions using ANFIS. The model evaluation attempted to analyze the effect of parameter tuning using ANFIS on the decision-making capability of fuzzy agents in reinforcing consumer relations management. The simulation result shows that changing numbers and member function types affect the performance of the model, and the ANFIS model gives a better root mean square error result, thereby enhancing the decision-making capability of fuzzy agents. The research showed that parameter tuning using ANFIS could provide an opportunity to optimize the model's design with the best input configuration to evaluate the overtime consumer response effectively .

From the previous works, it is found that fuzzy logic and neural networks stand as suitable methodologies dealing with these uncertainties but it lacks when it comes in terms of learning. ANFIS algorithm has a hybrid learning approaches in its structure. This helps the algorithm to be faster and more precise in terms of efficiency to model for the device replacement plan. As Opeyemi [10] reported, the ANFIS method provides a fuzzy modeling method for learning data set information to calculate membership function parameters that allow the associated fuzzy inference system to track the data relationship between input and output.

In summary, current literature is mostly limited to replacement planning done in the medical field and very limited research for the replacement of networking devices. Therefore a new intelligent approach to device status prediction using ANFIS is proposed to address this problem. For this study, certain assumptions are made that small business and ISP maintains a spreadsheet of inventory items or have inventory advisory to store information about all the equipment which forms the network infrastructure. From inventory advisory, input parameters can be identified. Using knowledge-based logic based on expert suggestions, rules will be formed. After that, rules will then apply to input parameters, and after applying rules, we will get predicted results. After that, the predicted output for status prediction is fed into ANFIS.

1.1 Neuro-fuzzy systems

The Neuro-Fuzzy Systems(NFS) [11] uses a combination of the paradigms of fuzzy logic and Artificial Neural Networks (ANN). Meantime, the FIS allows expressing the knowledge of an expert human being by simple If-then rules described in natural language. The NFS arose from the need to obtain and adjusting the FIS parameters, either their sets or rules, through a formal method not just based on human knowledge or trial and error. The hybrid-type NFS presents a unified architecture, being its foundation the interpretation of the rule base in terms of an ANN [12]. For their application, a set of membership functions and initials fuzzy rules must be available, and also an error boundary that allows stopping learning.

1.1.1 ANFIS structure

For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs and one output. The rule base contains the fuzzy if-then rules of Takagi and Sugeno's [13] type as follows: If x is A and y is B, then z is f(x,y) where A and B are the fuzzy sets in the antecedents, and z = f(x, y) is a crisp function in the consequent. Usually, f(x, y) is a polynomial for the input variables x and y. But it can also be any other function that can approximately describe the system's output within the fuzzy region as specified by the antecedent.

When f(x,y) is a constant, a zero-order Sugeno fuzzy model is formed, which may be considered to be a particular case of the Mamdani fuzzy inference system where each rule consequent is specified by a fuzzy singleton. If f(x,y) is taken to be a first-order polynomial, a first-order Sugeno fuzzy model is formed. For a first-order two rule Sugeno fuzzy inference system, the two rules may be stated as

Rule 1: If x is A_1 and y is B_1 then

$$f_1 = p_1x + q_1y + r_1 \tag{1}$$

Rule 2: If x is A_2 and y is B_2 then

$$f_2 = p_2x + q_2y + r_2 \tag{2}$$

In this inference system the output of each rule is a linear combination of the input variables. The final output is the weighted average of each rule's output. The corresponding equivalent ANFIS structure is shown in figure 1.

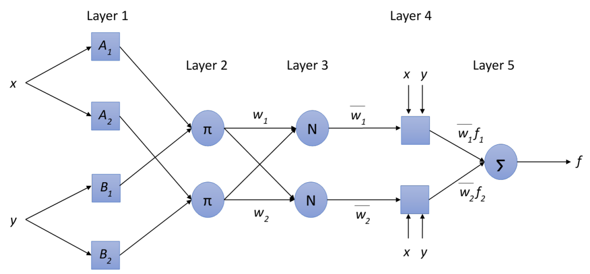


Figure 1: ANFIS architecture for two inputs and two rules based on the first-order Sugeno model

The individual layers of this ANFIS structure are described below:

Layer 1: Every node i in this layer is adaptive with a node function

$$O_i^1 = \mu_{A_i}(x) \tag{3}$$

where, x is the input to node i, A_i is the linguistic variable associated with this node function and μ_{A_i} is the membership function of A_i . Usually $\mu_{A_i}(x)$ is chosen as

$$\mu_{A_i}(x) = \frac{1}{1+[((x-c_i)/a_i)^2]^{(b_i)}} \tag{4}$$

where x is the input and a_i, b_i, c_i is the premise parameter set.

Layer 2: Each node in this layer is a fixed node which calculates the firing strength w_i of a rule. The output of each node is the product of all the incoming signals to it and is given by,

$$O_i^2 = w_i = \mu_{A_i}(x) * \mu_{B_i}(y), i = 1,2 \tag{5}$$

Layer 3: Every node in this layer is a fixed node. Each i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of firing strengths of all the rules. The output from the i^{th} node is the normalized firing strength given by

$$O_i^3 = \overline{(w_i)} = \frac{w_i}{(w_1+w_2)}, i = 1,2 \tag{6}$$

Layer 4: Every node in this layer is an adaptive node with a node function given by

$$O_i^4 = \overline{(w_i)} f_i = \overline{(w_i)}(p_i x + q_i y + r_i), i = 1,2 \quad (7)$$

where w_i is the output of Layer 3 and p_i, q, r_i is the consequent parameter set.
Layer 5: This layer comprises of only one fixed node that calculates the overall output as the summation of all incoming signals, i.e

$$O_i^5 = overall output = \sum_i \overline{(w_i)} fi = \frac{(\sum_i w_i f_i)}{(\sum_i w_i)} \quad (8)$$

1.1.2 Learning algorithm: hybrid

In ANFIS, using hybrid learning algorithm if values of premise parameters are given, the final output can be expressed as a linear combination of the consequent parameters. Consider the two rules ANFIS with two inputs x and y and one output f. Let the premise parameters be fixed. ANFIS output is given by linear combination of consequent parameters p, q and r. The output f in fig. 1 can be written as

$$f = \frac{w_1}{(w_1 + w_2)} f_1 + \frac{w_2}{(w_1 + w_2)} f_2 \quad (9)$$

$$\begin{aligned} &= \overline{(w_1)} f_1 + \overline{(w_2)} f_2 \\ &= ((\overline{w_1})x)p_1 + ((\overline{w_1})y)q_1 + ((\overline{w_1}))r_1 \\ &\quad + ((\overline{w_2})x)p_2 + ((\overline{w_2})y)q_2 + ((\overline{w_2}))r_2 \end{aligned}$$

where f is linear in the consequent parameters $(p_1, q_1, r_1, p_2, q_2, r_2)$.

2. Methodology

In this study, an integrated framework is proposed for predicting the status of network devices for replacement based on several criteria and parameters. The block diagram of the system is presented in figure 2.

For this study, the assumption is made that ISPs have the details of networking equipment kept in their inventory advisory. From the inventory advisory, we identify some input parameters. After parameter selection, preprocessing is carried out on input parameters. After preprocessing, knowledge-based

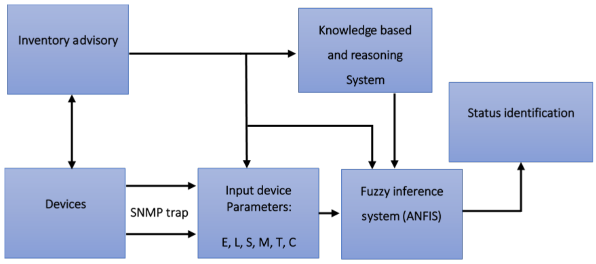


Figure 2: model of network device replacement plan

rules are to be formed, and these rules are based on expert suggestions. These rules then need to be applied to input data parameters and fed to ANFIS to predict the device's status for replacement planning.

2.1 Data preparation and preprocessing

The extraction of some essentials parameters is also taken from device specifications and some parameters are extracted from SNMP. The dataset is prepared for switch and router using different CISCO product models. The input parameters for routers and switches are throughput, CPU usage, memory, end of life, end of support, energy consumption, which can be seen from table 1 and table 3.

Initially weights are assigned to input parameters based on their priorities of being replaced. So a scoring system, as well as a weightage system, is introduced. Negative scoring is introduced, as shown in table 2 and table 4. The predicted output is calculated by summation of the multiplied product of weights of each parameter to the score of each parameter.

Table 1: Input variables of router

Variable Name	Unit	Description
L	Years	End of life converted into several years
S	Years	End of support converted into several years
m	MB	Unused memory of device during operation
Me	MB	Extra memory slot size
M	MB	Total memory to be after upgrade
T	Mbps	Device throughput
C	Percentage	CPU usage ratio

Table 2: Scoring assigned for router

L		S		M		T		C	
Value range	Score L_s	Value range	Score S_s	Value range	Score M_s	Value range	Score T_s	Value range	Score C_s
<0	-9	<0	-9	$<=$ 128	-9	$<$ 100	-9	$>$ 80	-9
0-2	2	0-3	2	128-512	2	100-1k	2	60-80	2
2-4	3	3-6	3	512-1024	3	1k-5k	3	40-60	3
>4	4	>6	4	$>$ 1024	4	$>$ 5k	4	$<$ 40	4

Table 3: Input variables of switch

Variable Name	Unit	Description
L	Years	End of Life converted into number of years
S	Years	End of support converted into number of years
M	MB	Total used memory during operation
T	Mbps	Device throughput
C	Percentage	CPU usage ratio
E	Watt	Total energy consumption per port

Table 4: Scoring assigned for switch

L		S		M		T		C		E	
Value range	Score L_s	Value range	Score S_s	Value range	Score M_s	Value range	Score T_s	Value range	Score C_s	Value range	Score E_s
≤ 0	-12	≤ 0	-12	0-100	-12	0-25	-12	>80	-12	>50	-12
0-2	2	0-3	2	100-200	2	25-50	2	60-80	2	30-50	2
2-4	3	3-5	3	200-400	3	50-75	3	40-60	3	15-30	3
>4	4	>5	4	>400	4	>75	4	0-40	4	0-15	4

2.2 Knowledge based rules(KBR)

The total weighted score is the summation of all the input parameters weighted values. After considering all the possible best and worst case scenarios based on input parameters used for replacement, a weightage value is chosen as a threshold value (T), which provides the base for replacement rule. The threshold value found for router and switch are 2.15 and 2.4 respectively.
Case 1: If total weighted score$\leq T$ than go for replacement.
Case 2: Else go for an upgrade.

2.3 Model output comparisons

ANFIS is then applied onto the experimental dataset and the system is trained, tested and evaluated. Experiments are conducted using different number of membership functions, different shapes of member functions and with different output membership function (μ). For evaluation, the model is configured and tested for 2, 3, and 4 membership function value for each of 5 input variables in case of router and 6 variables in case of switch on different epochs 20 and 50 respectively.

2.4 Tools and Software

All the simulation, runs in a terminal with a Window 10, i7 10^{th} generation 2.3 GHz processor, 16 GB of RAM and in MATLAB version R2016a.

3. Result and Analysis

3.1 Experimental setup

The training dataset for router is obtained from 40 different CISCO product models [14] referring to CISCO 800, 1700, 1800, 1900, 2600 and 2900 series routers. The training dataset for switch is obtained from 68 different CISCO product models referring to CISCO series of SG200, SG250, SF200, SF350, Catalyst 3750X, Catalyst 3760X, Catalyst 3560 Catalyst 2960S, C1000, series switches.

For router and switch out of 500 data samples, 70% (350 samples) for training, 20% (100 samples) for testing and 10% (50 samples) for checking/validation are taken. Prepared dataset is used to train the test and validate ANFIS model. The model is trained using MATLAB fuzzy logic toolbox by choosing hybrid learning algorithm on different models with different membership functions and different membership value types trained at different number of epochs.

3.2 Procedures in ANFIS model design

The steps done in the ANFIS model design are as follows:

1. **Generate FIS:** This ANFIS model uses grid partition method for FIS generation.
2. **Train FIS:** In this step, the hybrid optimization method is used. It a combination of least-squares and back propagation gradient descent method. In hybrid method, model tunes with two pass: forward pass and backward pass. Process stops whenever the maximum epoch number is reached or the training error goal is achieved.
3. **Test FIS** After FIS training, validation of the model is done using testing or checking data that differed from the one used for training the FIS.

3.3 Training the ANFIS model

In case of router, ANFIS model for gauss MF with input mf of 2*2*2*2*2 for output MF constant 32 rules are formed as mentioned in figure 4. In case of switch, ANFIS model for gauss MF with input mf of 2*2*2*2*2*2 for output MF constant 64 rules are formed as mentioned in figure 5.

Surface plots: In case of router, 10 different relationships are found among L, S, M, T, C keeping 3

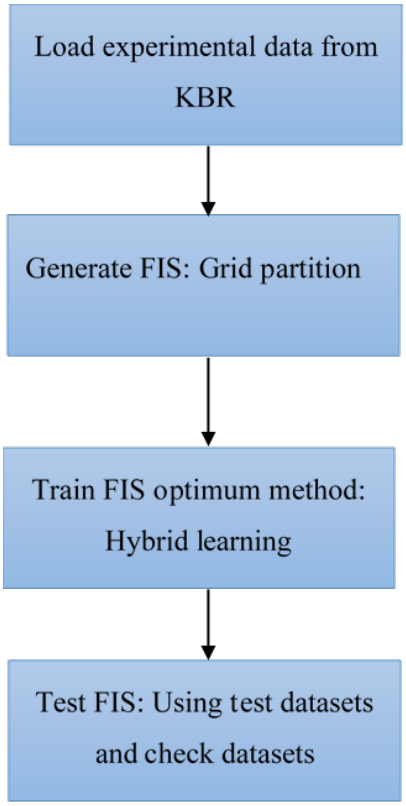


Figure 3: ANFIS system flow diagram

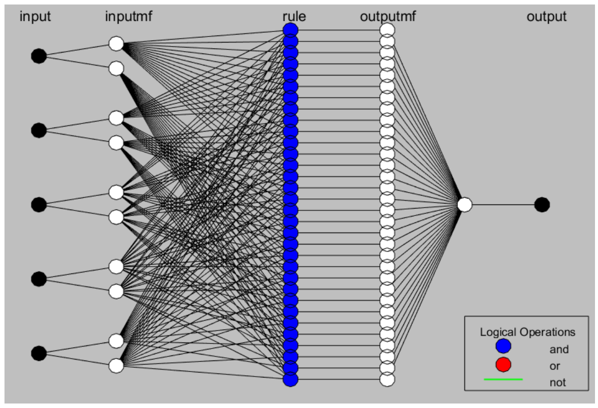


Figure 4: ANFIS model of router with 32 rules, 5 input and 1 output

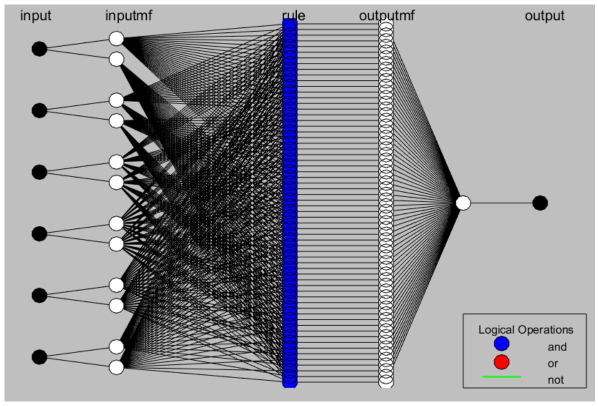


Figure 5: ANFIS model of switch with 64 rules, 6 input and 1 output

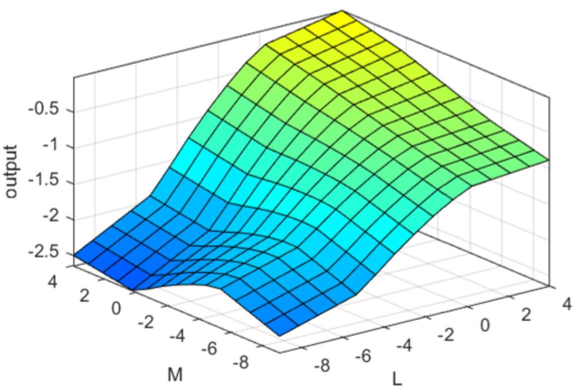
variables as reference inputs. The surface plots of the relationship is obtained from FIS toolbox for gauss MF 2*2*2*2*2 for epochs 50 for output membership constant. In case of switch, 15 different relationships were found among E, L, S, M, T, C keeping 4 variables as reference inputs. Surface plots of the relationship were obtained from FIS toolbox for gauss MF 2*2*2*2*2*2 for epochs 50 for output membership constant.

The surface plots of router for L and M with respect to output with ref input [S,T,C]= [2.5,-3,-2.5], for L and C with respect to output with ref input [S,M,T]= [-2.5,-2.5,-3] and surface plots for L and S with respect to output with ref input [M,T,C]= [-2.5,-3,-2.5] is shown in figure 6. The three-dimensional surface view provides the relation of two input parameters concerning the corresponding output. From the surface plots, it can be seen that the value of output is lower if the input parameter value is low. Similar surface plots for other parameters for router and switch can be obtained.

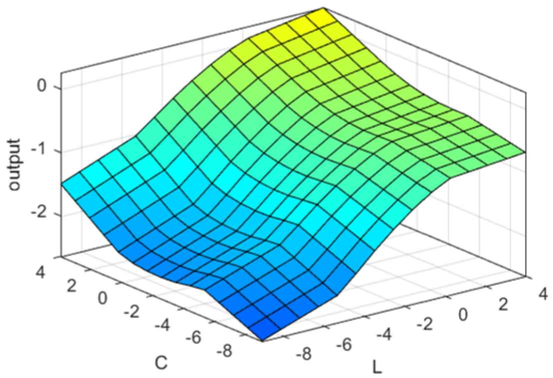
3.4 Performance evaluation

Performance evaluation are done based on RMSE values obtained from ANFIS training, testing and validation done on different models having different membership value of input for different membership function as well as for different output membership function for switch as well as router. The evaluation is done for the prediction performance of ANFIS models using RMSE. In case of router from the comparison based on RMSE, best results is obtained with gauss MF having input MF 2*2*2*2*2 and output mf constant. The testing RMSE obtained is 0.1288. In case of switch from the comparison based on RMSE, the best results is obtained with gauss MF with input MF 2*2*2*2*2*2 with output MF constant. The test RMSE obtained is 0.23663.

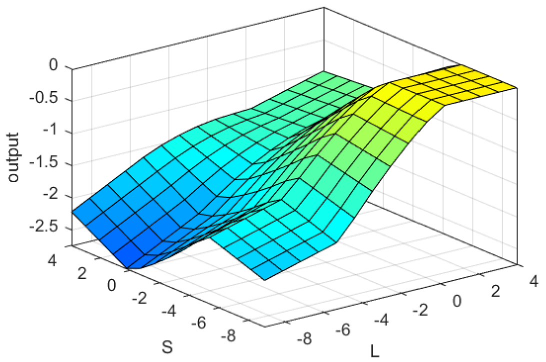
Figure 7 and figure 8 presents the expected and observed output with error difference during validation test. Output threshold 2.15 and 2.4 is defined for the decision making for router and switch respectively. Output value greater than 2.15 for router and 2.4 for switch indicates the device upgrade, otherwise the device should be replaced. The expected and observed output graphs of validation data almost overlapped with considerable error



(a)



(b)



(c)

Figure 6: (a) Surface view of L and M with respect to output with ref input [S,T,C]= [2.5,-3,-2.5] (b) Surface view of L and C with respect to output with ref input [S,M,T]= [-2.5,-2.5,-3](c) Surface view of L and S with respect to output with ref input [M,T,C]= [-2.5,-3,-2.5]

difference and providing optimal values.

4. Conclusion and future works

In this paper, an intelligent replacement plan is proposed to model the device status detection system

L		S		M		T		C	
Value range	Score L_s	Value range	Score S_s	Value range	Score M_s	Value range	Score T_s	Value range	Score C_s
<1	-9	<=0	-9	<=128	-9	<100	-9	>80	-9
1-2	2	0-3	2	128-512	2	100 – 1k	2	60-80	2
2-4	3	3-6	3	512-1024	3	1k-5k	3	40-60	3
>4	4	>6	4	>1024	4	>5k	4	<40	4

Figure 7: Expected vs observed plot of router

L		S		M		T		C		E	
Value Range	Score L_s	Value Range	Score S_s	Value Range	Score M_s	Value Range	Score T_s	Value Range	Score C_s	Value Range	Score E_s
<0	-12	<0	-12	0-100	-12	0-25	-12	>80	-12	>50	-12
0-2	2	0-3	2	100-200	2	25-50	2	60-80	2	30-50	2
2-4	3	3-5	3	200-400	3	50-75	3	40-60	3	15-30	3
>4	4	>5	4	>400	4	>75	4	0-40	4	0-15	4

Figure 8: Expected vs observed plot of switch

based on fuzzy inference system. The model is designed in order to be suitable for service providers as well as small and medium-sized enterprises or small and medium-sized businesses to conduct maintenance and upgrade plans. The performance of ANFIS is evaluated, which showed relationship between actual and predicted outcomes. The problem that is encountered during this study is to have good dataset.

Future research needs to be done to revise the rules, inputs, number and type of membership functions, the epoch numbers used, and training sample to further refine the ANFIS model. Work also needs to be done to assess the accuracy of the proposed ANFIS using different classification algorithms for proper and better validation.

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