

Design Passive Optical Network Using Multiclass Classification Neural Network

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Abstract: To require the order of last mile and the increasing demands of high quality of internet, the network architecture of FTTH (Fiber to the Home) has been chosen by numerous ISP (Internet Service Provider). Poor planning does not only increase the infrastructure costs, but it also increases maintenance costs. In this study, the authors focus on the design of passive optical network by using multiclass classification [9] in backpropagation neural network to shorten the FTTH network planning based on passive optical network design to determine final splitter type which refers to the feasibility of QoS (Quality of Service) and Cost Efficiency. Dataset in this study utilizes GIS (Geographic Information System) report with 33 sub-districts in Malang Regency in 2019 data layer. As a result, after 7300 epoch, the accuracy training was 99.99% and the splitter classification accuracy was 98.76%.

Keywords: PON; QGIS; multiclass-classification; quality-of-service

1. INTRODUCTION

Fiber optic (FO) is a current transmission medium that has the reliability of passing data with a large data capacity, has the characteristics of large bandwidth, high transmission speed in gigabit units and has low attenuation. Optical fiber has been widely used in various fields of technology, one of which is in the field of telecommunications networks [1].

With the rapid use of fiber optics in the telecommunications sector, internet penetration in Indonesia increased by 8.9% in 2019 compared to 2018. The data was released by the Indonesia Survey Center through APJII (Association of Indonesian Internet Service Providers) [2]. In addition, APJII also continues to improve the availability of access infrastructure by collaborating with network providers through a member-neutral FTTH program [3].

ISP (Internet Service Provider) as an internet network provider as well as a member of APJII has a pivotal role in increasing internet penetration and equity in Indonesia by carrying out the commitment of 5 cities in the first 5 years on the principle license period. This is in accordance with the statement of the chairman of APJII, Jamalul Izza, in discussing the RPM controversy (Draft Ministerial Regulation) regarding to the prohibition on the operation of internet access services outside the scope of its service area. This is also published in PERMENKOMINFO No.7 of 2015 [4]. The commitment of regional services has implications on the broad reach of ISPs in developing internet business.

To meet the increasing demand for last mile (end user) as well as the demands of internet service quality, the FTTH (Fiber to the Home) network architecture has been chosen by many ISPs. However, poor network planning can not only lead to very high infrastructure installation costs, but it can also increase high maintenance costs. This encourages researchers to perform optimizations using

various methods. One of the FTTH architectures that is often studied is PON (Passive Optical Network).

PON is an optical fiber-based broadband access network architecture that uses optical passive devices, so it can be used in point-to-multipoint configurations and can increase access speeds from 155 Mbps to 2.4 Gbps and even up to 5 Gbps for GPON. The elements used in PON are passive optical elements such as passive splitters, fiber optic cables and splices so that this technology can simplify the network, simplify protocol synchronization between interconnection devices and reduce costs in terms of network construction [5].

To get quality of service (QOS) optimization, FTTH network planning must notice to several parameters including the total demand in the cluster, bandwidth requirements, OLT placement, splitter placement, and the cable length. The increasing number of ISP operators available in the certain areas can also provide effectiveness in determining the topology and use of the final infrastructure [6]. Apart from the above parameters, device specifications such as the power emitted on the OLT, the power sensitivity of the ONT, the spectral width of the laser are also needed to consider. Feasibility parameters such as rise time, SNR (Signal to Noise Ratio), and BER (Bit Error Rate) are the output of the feasibility parameters.

A related research previously conducted by Mateusz Zotkiewicz in 2018 entitled "Classifiers Applied to Dimensioning of Splitters in PON Design" compares the PON classification using a neural network and a decision tree. The use of a neural network is better than using a decision tree [7]. Dataset is adapted from Kaltham Al Romaiti in 2020 entitled "Optimization of Multilayer Design for FTTH Networks Based on Geographical Information" [8]. We utilizes QGIS with OSM (Open

Street Map) as basic map to provide road and demand data which processed using geoAI/ grass, also using k-means to provide clustered demand and route line. Random OLT point determination is required to process the potential node middle splitter and final splitter and the various report attributes therein. The complete process of collecting dataset in QGIS is explained in section 2. Dataset in this study is generate from 33 sub-districts in Malang Regency in 2019 data layer. The purpose of this research is to shorten design of passive optical network to determine final splitter type which refers to the feasibility of optical transmission QoS (Quality of Service) and Cost Efficiency in FTTH planning.

2. METHOD

The concept of the method in this study is shown in Figure 1 below:

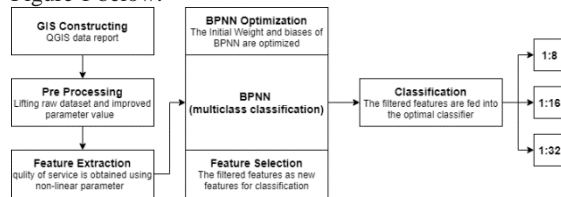


Figure 1. (Research Method)

2.1 Passive Optical Network

PON (Passive Optical Network) in this paper are used GPON parameters shown in Table 1 below:

ITU-T G.652			
652.D (Uplink)	0.4	dB/km	
652.D (Downlink)	0.3	dB/km	
Chromatic Dispersion (Tmat) SMF	12	ps/nm.km	
Intermodal Dispersion (Tmod) MMF	0	ps/nm.km	
Optical Interface			
Sensitifity Receiver	-27	dBm	
Risetime Receiver	200	ps	
Risetime Transmitter	150	ps	
Passive Component			
Splitter 1:4 Loss	7.25	dB	
Splitter 1:8 Loss	10.38	dB	
Splitter 1:16 Loss	14.1	dB	
Splitter 1:32 Loss	17.45	dB	
Connector Loss	0.5	dB	
Redaman Splicing	0.1	dB	

Table 1. Passive Optical Specification

The parameters are used to calculate the feasibility of SNR and BER at each potential node, with minimum standard of $SNR > 21.5$ dB and $BER > 1 \times 10^{-9}$. The total loss parameter is calculated by using the general link budget in equation 1-12 to ensure the power received is not less than the minimum receiver sensitivity. The risetime budget in this study uses an NRZ type encoding that can carry a large bandwidth.

$$t_{sys} = (t_x^2 + t_{chromatic}^2 + t_{modal}^2 t_x^2)^{1/2} \quad (1)$$

$$D_t = D(\lambda) \cdot S \cdot L \quad (2)$$

$$D(\lambda) = \frac{S_0}{4} \left(\lambda - \frac{\lambda_0^4}{\lambda^3} \right) \quad (3)$$

$$t_{sys} < t_r \quad (4)$$

$$t_r = \frac{0.7}{Br} \quad (5)$$

Quality-of-service also involves SNR and Q factor parameters.

$$\left(\frac{S}{N} \right) = \frac{Signal\ Power}{Shot\ Noise\ Power + Amplifier\ Noise\ Power} \quad (6)$$

$$Signal\ Power = 2 \left(2P_{opt} \frac{\eta q}{\eta v} \right)^2 M^2 \quad (7)$$

Noise:

$$Noise\ Dark\ Current\ i_{ND}^2 = 2q i_D B \quad (8)$$

$$Thermal\ Noise = \frac{4k T_{eff} B}{R_{eq}} \quad (9)$$

$$Shot\ Noise = 2q \left(2P_{opt} \frac{\eta q}{\eta v} \right)^2 B M^2 F(M) \quad (10)$$

To calculate BER, Q factor needs to be calculated with the following equation:

$$(S/N)_{pk/rms} = 20 \log 2Q \quad (11)$$

$$BER = Pe(Q) = \frac{1}{\sqrt{2\pi}} \cdot \frac{e^{-Q^2}}{Q} \quad (12)$$

2.2 Dataset

The data used in this research are the QGIS parameter reports which were processed to produce SNR and BER values. From 33 sub-districts, the data collected is 2727 clusters with various customer capacities for each cluster. From 2727 clusters, 41801 potential node final splitters were produced with a splitter ratio parameter of 1:8, 1:16, and 1:32.

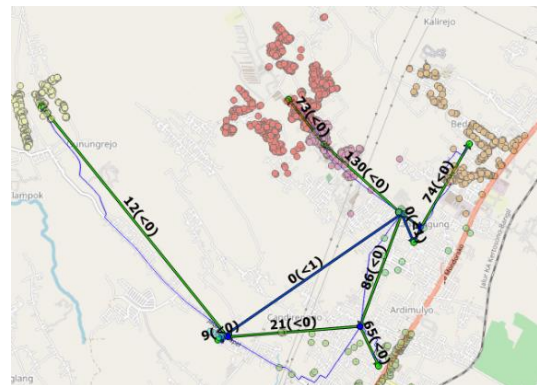


Figure 2. QGIS Design Network

In addition to parameters of power transmission, bitrate and wavelength are required to design the QoS (Quality of Service) ODN (Optical Distribution Network). The transmission power scenario uses 1.5, 3, 5 dB, bitrate from 10-100 Mbps, wavelengths of 1490 (dual play), and 1550 (triple play). To build a classification model, we use three stages: 1) GIS constructing, 2) Design of QoS (Quality of Service), 3) Determine the passive optical network class label on ODN.

1) *Gis Constructing*: we make the use of hierarchical features and k-means algorithm provided by the GNI planner of QGIS. Experiments were carried out several times to produce an even distribution of demand in each cluster. After the clusters are generated, we repeated this step to produce several distribution variations in the same district. From the distribution of demand in each cluster, a potential node was generated in the form of a middle splitter and final splitter as well as a rough calculation of loss. Report parameters in GIS was selected to be used as the system training input.

- 2) *Design Quality of Service*: This stage adopts 1-12 equations and aims to produce training data matrices that are in accordance with the feasibility of Quality of Service. The amount of data used has as many as matrices (1048575, 83)
- 3) *Classification of Training*: To determine the training data, we calculate Design Quality of Service first, then select which index or parameter is suitable to be used as training data (eg: BER replaced by Q factor) because it has a very small value.

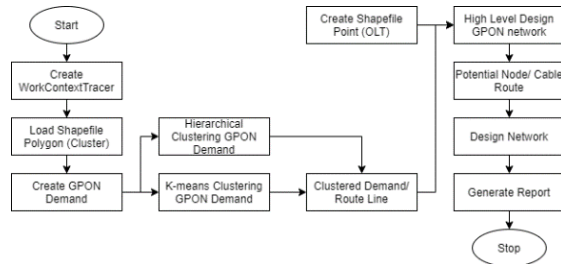


Figure 3. GIS Constructing

id	s	w	hdd	l	p	c	rdl	sdh	qdl	k	testing
1	0	1	0.57	4.7021815	0	57	0.2620012	781.91801	13.981398	1	
3	0	1	0.69	10.791893	0	69	0.3080037	222.75678	7.4625193	1	
5	0	1	0.97	9.8789222	0	97	0.2995688	188.06218	6.8567883	1	
6	0	1	0.77	4.5569913	0	77	0.2612853	590.48283	12.149926	1	
7	0	1	1.93	2.0275388	0	193	0.3252245	399.61709	9.9952125	1	
9	0	1	1.45	7.5612436	0	145	0.2799795	189.53917	6.8836613	1	
10	0	1	0.73	7.8712315	0	73	0.2823593	377.58645	9.7157919	1	
11	0	1	1.64	6.2036849	0	164	0.2705465	211.33357	7.2686582	1	
14	0	1	2.17	4.212662	0	217	0.2596765	209.83052	7.2427639	1	
15	0	1	1.98	6.8887327	0	198	0.2751144	145.41756	6.0294602	1	
19	0	1	2.4	2.8284628	0	240	0.2544077	262.93922	8.1077004	1	
20	0	1	1.84	3.5206422	0	184	0.2567968	298.06378	8.6322619	1	
21	0	1	1.97	2.0839265	0	197	0.2524022	354.66384	9.4162603	1	
24	0	1	1.32	0.2227212	0	132	0.2590276	818.75646	14.306786	1	
25	0	1	1.12	1.2998123	0	112	0.2599373	760.59036	13.789474	1	
27	0	1	0.02	12.601642	0	2	0.3265453	5723.4139	37.826624	1	
29	0	1	0.9	8.2265417	0	90	0.2851448	266.24904	8.1585697	1	
30	0	1	0.64	6.9726996	0	64	0.2757016	487.3306	11.037783	1	
31	0	1	1.91	5.4838524	0	191	0.2661905	200.28195	7.0760904	1	
32	0	1	1.1	7.6674498	0	110	0.280781	235.21963	7.6684357	1	

`sf_train.drop(sf_train[sf_train.k < 1].index,inplace=True)`
(123001, 11)

Table 2. Dataset using dataframe.drop

2.3 Network Architecture

We used 3 layers of MLP (Multi-Layer Perceptron) in this study. In Figure 2, the input layer has eight nodes in the form of wavelength, bitrate, length, capacity, tx, risetime, SNR, and BER. Those eight layers in the hidden layer are for adding non-linear parameters into the model resulting in three output layer nodes as the final splitter multiclass classification [9] based on the quality-of-service feasibility value.

We did an experiment using several hidden layer models and a different number of neurons and got a fit model using a hidden layer 8,8. The architecture above was chosen because it produces minimal loss and results in a fairly effective training process compared to the combination of hidden layers and other neurons.

Algorithm for the proposed system:

1. Initiation of weights using small random numbers

2. Feed Forward

- Each input unit ($x_i, i=1, \dots, n$) was passed to the hidden layer
- Each hidden layer ($z_j, z=1, \dots, p$) added the weight of the input signal $Z_in_{jk} = V_{0j} + \sum_{i=1}^n x_i v_{ij}$, by applying the activation function $Z_j = f(Z_in_j)$

- For example, the activation function used is sigmoid $y = f(x) = \frac{1}{1+e^{-x}}$, then this signal was sent to all output units.
- Each output unit ($y_k, k=1, \dots, m$), added up the input and weight $Y_in_k = w_{0j} + \sum_{k=1}^p z_j v_{jk}$ by applying the activation function $Y_j = f(Y_in_k)$

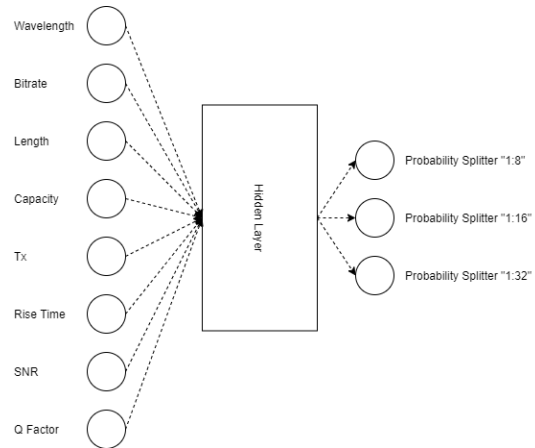


Figure 4. Neural Network Architecture

3. Backpropagation

- Each output unit ($y_k, k=1, \dots, m$) received the training input by calculating the error $\delta_k = (t_k - y_k) f'(y_in_k)$
- Calculating the correction for weight and bias $\Delta w_{jk} = \alpha \delta_k x_j, \Delta w_{0k} = \alpha \delta_k$
- Each hidden layer ($z_j, z=1, \dots, p$) added up the input delta $\delta_in_j = \sum_{k=1}^m \delta_k w_{jk}$ and calculated the error $\delta_j = \delta_in_j f'(x_in_j)$
- Calculating weight and bias correction $\Delta v_{ij} = \alpha \delta_j x_i$

4. Fixing the weight and bias

- Each output unit ($y_k, k=1, \dots, m$) updated the weight and bias ($j=0, 1, \dots, p$)
- $w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk}$
- Each hidden layer unit ($z_j, z=1, \dots, p$) updated the weight and bias ($i=0, 1, \dots, n$)
- $v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij}$

5. Training stopped

2.4 Implementation

We conducted an experiment using several hidden layers and hyperparameter model. The input feature will be streamed to all hidden layer neurons where each feature will be multiplied by weight and added bias at the same time, as well as the output from the hidden layer to the output layer. After the feature reach the output layer, the classification loss will be calculated using Categorical Cross-Entropy (CCE) loss. The target for multi-class classification is a one-hot vector, meaning has one on a single position and 0's everywhere else [10] [11].

$$\text{Loss CCE} = - \sum_x p(x) \cdot \log q(x) \quad (13)$$

$p(x)$ = Probability of class x in the "target" matrix

$q(x)$ = Probability of class x in the "predict" matrix

The training process uses Early Stopping parameters with Patient (Number of epochs with no improvement after which training will be stopped) [12] after the 1000th epoch and Model Checkpoint monitoring Val accuracy mode 'max' to avoid overfitting during training. Training stopped at the 7300th epoch of the 20,000 epochs specified. MLP used 5 neurons in the hidden layer with the sigmoid activation function and three neurons in the output layer with the SoftMax activation function [10] [11]. The author also conducted an experiment using hyperparameter [citation]. This experiment aims to find a neural network model that produces the best accuracy.

es = EarlyStopping (monitor = 'val_loss', mode = 'min', verbose = 1, patience = 1000)

mc = ModelCheckpoint ('best_model.h5', monitor = 'val_accuracy', mode = 'max', verbose = 1, save_best_only = True)

3. RESULT AND DISCUSSION

3.1 Training Result

After 7300 epochs, we evaluate the model using the test data. The training accuracy is around 99.99% and the testing accuracy is around 98.76%.

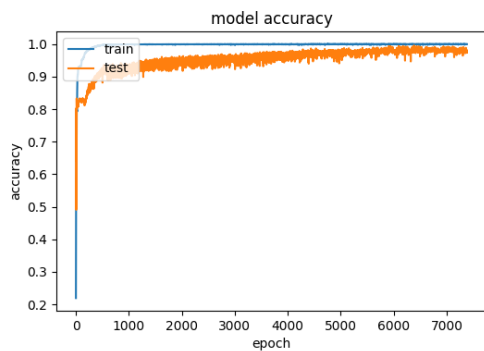


Figure 5. Training and Testing Accuracy Result

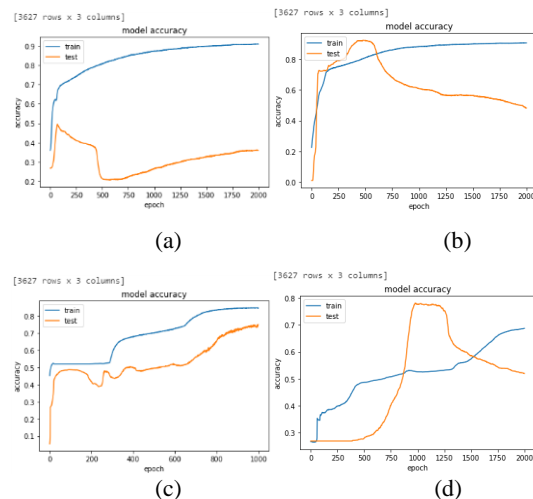


Figure 6. Overfit (a) relu 8 batch-size 64, adam 0.00001 (b) relu 7 batch-size 64, adam 0.00001 (c) 4 relu, 8 sigmoid, batch-size 16, sgd 0.0001 (d) 7 relu, 5sigmoid, 32, 0.00001

Epoch 07299: val_accuracy did not improve from 0.99559

Epoch 7300/20000

116/116 [=====] - 0s
 1ms/step - loss: 5.2663e-04 - accuracy: 0.9997 - val_loss: 0.1006 - val_accuracy: 0.9876

3.2 One-hot Encoding

The target for multi-class classification is a one-hot vector, meaning has 1 on a single position and 0's everywhere else [13].

Layer (type)	Output Shape	Param #
input_23 (InputLayer)	[(None, 8)]	0
dense_44 (Dense)	(None, 5)	45
dense_45 (Dense)	(None, 3)	18

Figure 7. Neural Network Model

	1:8	1:16	1:32
8226.0	1.000000	1.181006e-08	2.144990e-29
3990.0	1.000000	1.302063e-08	2.111058e-29
4013.0	1.000000	1.302063e-08	2.111058e-29
5186.0	1.000000	2.197091e-08	4.575406e-29
5209.0	1.000000	2.197091e-08	4.575406e-29
2016.0	1.000000	8.022938e-10	3.542995e-31
2030.0	1.000000	8.022938e-10	3.542995e-31
2884.0	1.000000	1.227288e-09	6.593431e-31
2898.0	1.000000	1.227288e-09	6.593431e-31

Figure 8. Multiclass Classification Result (One-hot Encoding)

Some classifications resulted in inaccurate predictions of final splitter ratios. However, the classification results produced the optimum final splitter in FTTH network planning by prioritizing the cost efficiency factor without eliminating the QoS factor.

3893.0	0.013101	9.868993e-01	1.065835e-16
5089.0	0.003422	9.965783e-01	2.124624e-16

Figure 9. Cost Efficiency Result

3.3 Loss CCE

On the section 2.4, it has been explained that the implementation of training used *Categorical-CrossEntropy*. loss CCE is calculated using equation 13 [13]:

Sample (id 3893)

0 0.003422 Loss 1:8?
 Target = 1, Prediction = 0.9868998 Loss 1: 16?
 0 2.12 - 16 Loss 1: 32?

$$\begin{aligned} \text{Loss 1:8} &= -p(1:8) \cdot \log q(1:8) \\ &= -0.003422 \cdot \log(0.003422) \\ &= 0 \end{aligned}$$

$$\begin{aligned} \text{Loss 1:16} &= -p(1:16) \cdot \log q(1:16) \\ &= -1 \cdot \log(0.9868998) \\ &= 0.0057269 \end{aligned}$$

$$\begin{aligned} \text{Los 1:32} &= -p(1:32) \cdot \log q(1:32) \\ &= -0 \cdot \log q(2.12E-16) \\ &= 0 \end{aligned}$$

3.4 QoS (Quality of Service)

The data testing id 3893 will be tested using the equation in section 2.1. The parameter of testing data are as follows:

Parameter:
 $s = 1 (1:8)$

w = 1 (1550 nm)
 p = 2 (5 dB)
 b = 10 Mbps
 c = 1
 l = 2.35801132506869 Km

Final splitter planning using 1: 8 resulted in a QoS calculation that was in excellent status where the risetime budget was 0.2530716, SNR 55.757096, and BER 0. Multiclass Classification predicted that the final splitter ratio was possible to use a larger ratio, namely 1:16 which resulted in risetime as 0.253072, SNR 48.43843, and BER 0. This showed that the feasibility of QoS can still be reduced to the minimum standard limits of SNR and BER to produce cost efficiency in network planning. This simplifies the QoS input parameters without calculating manually to produce optimal FTTH network planning (QoS and cost efficiency). The following is a comparison table of 1: 8 and 1:16:

rt	SNR(dB)	Q	BER	QoS
1:8	0.2530716	55.757096	306.77841	0 yes
1:16	0.2530716	48.438427	132.09651	0 yes

Table 3. Quality of Service id 3893

The authors tried to prove that by adjusting the QoS parameter to the standard value of feasibility, it can result in cost efficiency optimization. In this experiment, we used data testing id 3893 by changing the parameter of the capacity to be 100 homepassed, SNR using a minimum standard of 21.5 and BER 1E10-9. Following are the prediction results:

1s 2ms/step - loss: 0.0014 - accuracy: 0.9998 - val_loss: 0.0480 - val_accuracy: 0.9876

[[2.0661601e-26 2.6315628e-03 9.9736845e-01]]

Referring to the clarification system result, the authors calculated manually using final splitter ration 1:32. The results are as follows:

rt	SNR(dB)	Q	BER	QoS
1:32	0.2530716	35.7571	30.6778	5.629E-207 yes

Table 4. Quality of Service id 3893 1:32

4. CONCLUSION

4.1 Conclusion

From the results of the research, several conclusions can be drawn:

1. The design of passive optical network (final splitter) can be done using the Multiclass Classification method with a multilayer perceptron Neural Network.
2. The val accuracy of 98.76% can produce QoS (Quality of Service) feasibility in the design of passive optical network FTTH network.
3. The final splitter determination using Multiclass Classification can increase the cost efficiency of FTTH network development because the increased capacity of the splitter ratio can reduce the need for distribution cables.

4.2 Suggestions

Design Passive Optical Network using Multiclass Classification can utilize the ISP dataset such as ONMS (Optical Network Monitoring System) and CRM (Customer Relationship Management) to be applied in network expanding.

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