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Machine Learning-Based Queueing Time Analysis in XGPON

N. A. Ismail[1,2], S. M. Idrus[1*], F. Iqbal[1], A.M.Zin[1,2], F. Atan[1,2] and N. Ali[3]

[1]School of Electrical Engineering, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia
[2]College of Engineering, Universiti Teknologi MARA, Cawangan Johor, 81750 Johor, Malaysia
[3] Faculty of Electronic Engineering Technology, Universiti Malaysia Perlis, 02600, Perlis, Malaysia

ABSTRACT

Machine learning has been a popular approach in predicting future demand. In optical access network, machine learning can best predict bandwidth demand so as to reduce delays. This paper presented a machine learning approach to learn queueing time in XGPON given the traffic load, number of frames and packet size. Queueing time contributes to upstream delay and therefore would improve the network performance. Output R acquired from the trained ANN is close to value 1. From the trained ANN, mean squared error (MSE) shows significantly low value and this proves that machine learning-based queueing time analysis offers another dimension of delay analysis on top of numerical analysis.

Keywords: ANN, DBA, machine learning, queueing time, XGPON

1. INTRODUCTION

Communication networks are rapidly evolving over the years from web browsing in the 1990s to Internet-of-Things (IoT) that the world is experiencing currently. With the current pandemic COVID-19 that affects worldwide, people are spending most of the time at home working, streaming videos, online gaming, video calling, etc. Thus, according to The Global Internet Phenomena Report [1] internet usage grows to almost 40% within the month of February and April 2020. As the population of internet users are growing, the demand for high-speed stable internet connection is increasing too. Passive optical network (PON) has the criteria for both speed and stable connection in addition to its low power consumption. PON consists of optical terminal unit (OLT), optical network units (ONUs) and an optical splitter. The three elements are connected in the formation of tree topologies, where a single OLT is connected with numbers of ONUs via optical splitter. The splitter receives signal from aggregated switch, then the mirrors and glass in the splitter component split the signals requiring no power and therefore, the network is termed passive.

According to International Telecommunication Union (ITU-T) recommendation [2], downstream and upstream rate of 10G-PON (XGPON) is 10Gbps and 2.5Gbps respectively. The downstream frame and upstream frame are synchronized and has a fixed size of 125μs. During downstream transmission, data is being broadcasted by OLT to ONUs, while upstream transmission uses time division multiplexing (TDM) method. Each ONU is given time slot to avoid collision when sending upstream data which being controlled by medium access (MAC) controller in the OLT. Dynamic bandwidth allocation (DBA) algorithm is used to assign timeslots for each ONU in the network. DBA for GPON/XGPON is not specified in the ITU-T recommendations and is left for network operators to optimize it.

*sevia@utm.my

ITU-T categorized network traffic in terms of traffic container (T-CONT); T-CONT type 1 has fixed bandwidth, T-CONT type 2 has assured bandwidth, T-CONT type 3 has assured and non-assured bandwidth and T-CONT type 4 has best effort bandwidth. Quality of Service (QoS) for guaranteed service is specified by maximum delay, peak information rate and peak burst size. Reducing upstream delay is important to ensure no service disruption especially for T-CONT with assured bandwidth. Technically, queueing time for each polling cycle contributes to upstream delay and therefore reducing queueing time will improve upstream delay.

1.1 Background of Study

ITU-T supports mainly two polling mechanisms, status reporting (SR) and non-status reporting (NSR) also known as traffic monitoring. The key advantage of SR polling is accuracy of grant allocation as compared to NSR due to the reported buffer occupancy status from each ONU, thus SR is widely chosen in DBA algorithm. There are two stages of DBA mechanism for XGPON, assured and surplus bandwidth allocation according to ITU-T. Initially, OLT sets up the network by doing ranging process due to distance inequality between ONUs and OLT. During downstream, OLT broadcast frames to all ONUs and collects bandwidth requests from ONUs. Dynamic bandwidth report upstream (DBRu) is a transmission slot of a queue of an ONU assigned by OLT. ONUs report their buffer status in BuffOcc field and a bandwidth map (BWmap) is transmitted to ONU at the start of next DS transmission. Each ONU has a number of Allocation-ID (Alloc-IDs) that represent every T-CONT coming from the said ONU. OLT produces DBA results in the fixed frame duration of 125μs. A parameter called service interval (SI) to indicate one XGPON cycle is represented in the unit of 125μs. After a fixed period of time according to SI, the counter for allocation size is recharged to its initial values. This method is seen to be bandwidth efficient as it uses as much allocation granted for that period of SI. Consequently, it minimizes upstream delay as polling of Alloc-IDs is also reduced. These DBA algorithms [1]–[3] choose value of SI value between five and ten depending on types of T-CONT. Previous works for GPON/XGPON DBA [4]–[8] are extended work of GigaPON Access Network (GIANT) [2] where improvements had been done to ensure bandwidth utilization is efficient enough to reduce bandwidth waste.

Delay components are very important role in determining performance of DBA schemes, thus delay analysis in PONs is critical in designing DBA algorithm. Studies in [9]–[17] proposed analytical model based on mean packet delays for DBA in PONs. The mean upstream delay consists of cycle time, queueing time and grant time [18]. One cycle time, Tc is the time interval between consecutive transmissions from ONU [19]. It determines the network average US delay. Polling mechanism for XGPON illustrated in Figure 1 shows how OLT and ONU transmit downstream and upstream frame respectively. Only one ONU is shown as the ranging protocol in GPON/XGPON provides all ONUs with a unique equalization delay (EqD) which results in all ONUs being the same virtual transmission distance from the OLT. The dotted lines represent empty frames. During the first cycle C1, OLT sends downstream frame contains BWmap and set DBRu flag as 1, ONU then sends upstream frame after its response time, T_{ONU} to prepare upstream frame in C2. Based on the reported queue, OLT prepares the allocated grant using BWmap to be transmitted downstream after T_{OLT}. The time taken by OLT from the first downstream frame transmission in C1 and after receiving ONU's queue report can be referred as T_{Grant}. Table 1 summarizes delay analysis for TDM PONs especially EPON. From the analysis, closed-form expressions are obtained for mean packet delay and mean packet length distribution. In general, these analyses are based on Markov chain queueing model that utilizes Poisson arrival process at the ONUs. In recent study, a machine learning-based delay analysis presented in [20] shows that delay analysis can also be done by learning from data. Therefore, this paper is taking machine learning as means to learn packet queueing time obtained from simulation results in XGPON testbed.

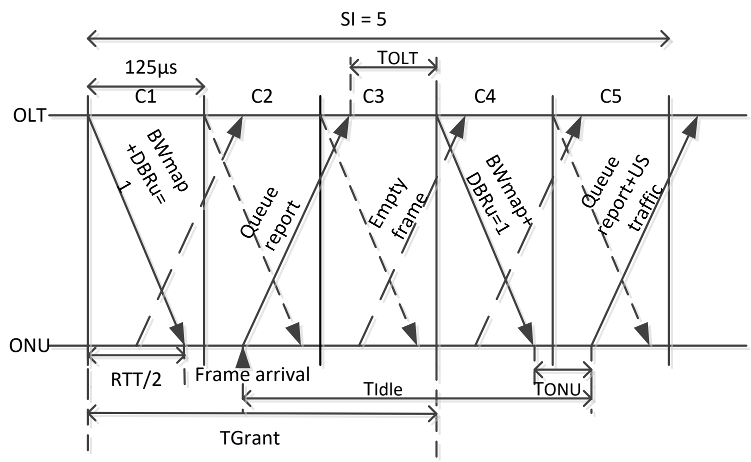

Figure 1. Polling mechanism for XGPON

Surveys presented in [21] proved that numerous works in optical networks that utilized machine learning as research methodology. A multilayer perceptron or artificial neural network (ANN) is chosen in this paper as a preliminary study using machine learning which in our case, we can use and learn from data that is already available. The proposed solution of this paper is to predict queueing time of XGPON frames categorized by T-CONT using ANN. Allocation ID (Alloc-ID) in XGPON is used to distinguish T-CONT coming from different ONUs, and EPON traffic characterization is different of that XGPON. Thus, to the best of our knowledge, the proposed solution is a new approach for XGPON.

Table 1.1 Summary of delay analysis in PON

Type of Service	**Key Features**	**Type of PON**	**References**
Gated	Determination of queue length distribution based on packet mean waiting time – derived from switchover time. Assumes Poisson arrival process with two-stage buffer at ONUs.	EPON	[17]
	Determination of grant size equation using recursive formula to form relationship between transmission time, queue length and grant size. Assumes average traffic arrival rate is fixed – only applicable to Poisson not self-similarity traffic (gives an error to the equation).	EPON	[16]
	Mean grant size and mean cycle length are evaluated to yield mean upstream delay equation. For the case of multiple ONUs, approximation of delay is obtained based on Poisson arrival process – inaccurate results.	EPON	[13]
Gated and limited	Mean packet delay is based on residual time, service time and reservation time. Additional reservation time for packets that arrive during an ONU’s reservation time due to residual time is already reservation time for a packet.	EPON	[14]

Priority-based	Network based on two queueing models; one for the batches (M/D/1) and one for individual packets (M/D/m). Mean end-to-end packet delay consists of mean queueing time, transmission time and propagation delay.	TDM PON	[22]

2. SIMULATION AND PERFORMANCE EVALUATION

Simulation data attained from OMNET++ with the same simulation setup in [23] is used to train the ANN. The inputs to ANN are traffic load, number of frames received at ONU and packet size. All data are collected at each ONU for traffic load 0.3 and 0.6. Packet size selection is based on triangular distribution, with variations of 64, 600 and 1500 bytes. Every simulation runs for one hour to get variations of number of frames, hence reliable trained network. MATLAB neural network tool is used to train the ANN. A total of 96 samples are collected from XGPON OMNET++ simulation with normalized traffic load varying from 0.1 to 1.4. The XGPON consists of one OLT and 16 ONUs with uplink capacity of 2.5 Gbps and ONU to OLT link rate is 200 Mbps. Each simulation ran for one hour to achieve 95% confidence interval of the mean inter-arrival time variation. From the raw data collected, upstream arrival rate, packet lengths and upstream delay are chosen as input features for ANN because they have strong correlations to queueing time, the target variable. We use *nftool* for curve fitting. The dataset is divided to 70% training, 15% test and 15% validation. Matlab has built-in function *fminmax* that suits the purpose of data optimization. After standardization of dataset, training or learning process of the ANN takes place. The number of hidden neurons is set to 10 and training algorithm Levenberg Marquardt (LM) is used.

Different trained network is created for each T-CONT 2, T-CONT 3 and T-CONT 4. T-CONT 1 is not considered because it has fixed bandwidth assignment. The proposed ANN is to predict queueing time for each T-CONT. With predicted queueing time, the DBA performance can be optimized. Upstream delay (Dus) consists of idle time ($Tidle$) and queueing time (Tq)as shown in Eq. 1, where $Tidle$ is waiting time after DBRu is sent to OLT before getting the grant and Tq depends on the DBA process.

$$Dus = Tidle + Tq \tag{1}$$

For the trained ANN, the best regression plot consists of training, validation and testing is captured in Figure 2 with coefficient of correlation, R approaching to 1. Figure 3 presents the queueing time attained using the trained ANN and target queueing time for each T-CONT. For testing purpose, input data of traffic load 0.9 is used. The trained ANN queueing time for T-CONT 3 is very similar to target. The trained ANN queueing time values for T-CONT 4 shows a significant difference to its target values. It is worth noting that T-CONT 4 has surplus bandwidth which means it is expected to have high queueing time. The trained network for T-CONT 4 has been retrained for numbers of time as compared to T-CONT 2 and 3 due to its fluctuating target data. However, the trend for trained ANN values follows target queueing time. It can be highlighted from the results that at higher traffic load (i.e. 0.9), it is more suitable to use trained ANN with high traffic load range (e.g. 0.7 to 1.0) to achieve high prediction accuracy.

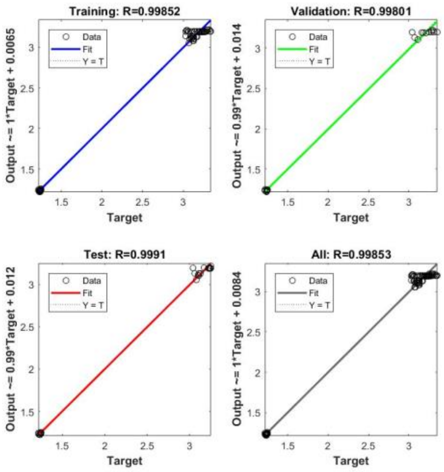

Figure 2. Regression coefficient of the trained ANN

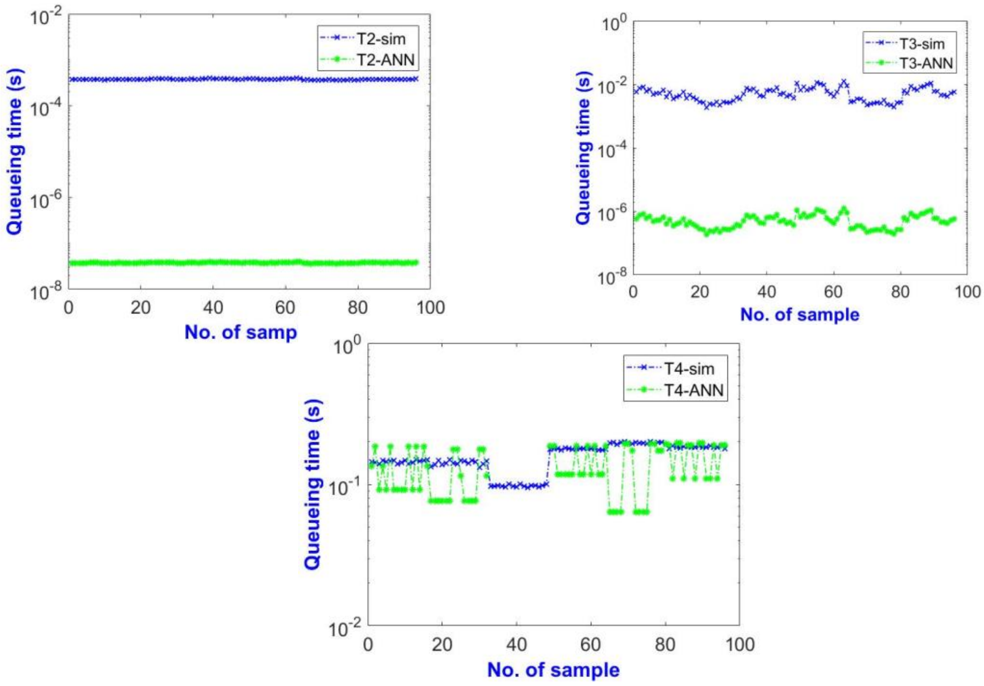

Figure 3. Queueing time comparisons of simulation and using ANN for T-CONT 2, 3 and 4.

2.1 Model Evaluation

The model is learned using the LM algorithm as mentioned previously in section 2. Based on the learning history, it is estimated whether the model is capable of predicting queueing time. The learning process of the model takes 95 epochs to evaluate the accuracy and loss of the model. Mean squared error (MSE) is used as loss function of the model and the value obtained is 5.6117e-10 as shown in Figure 4. The significantly low value proves that machine learning-based analysis offers another dimension to delay analysis on top of numerical analysis as discussed in section 1.1.

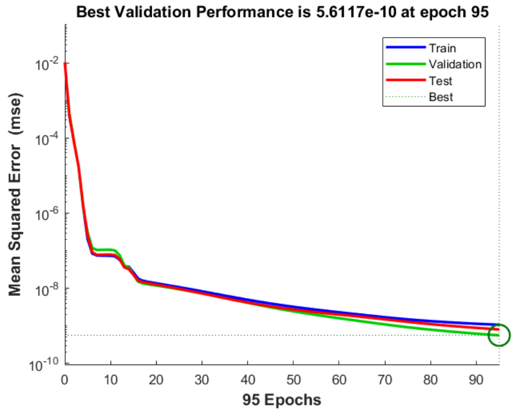

Figure 4. Loss of the trained ANN

3. CONCLUSION

This paper presents a machine learning technique specifically ANN to predict queueing time of ONUs. ANN is a great prediction method because it learns from a lot of input and target samples fed to the network. Results show that the trained ANN T-CONT 3 queueing time has the highest accuracy as compared to T-CONT 2 and 4. The model evaluation shows a good fit which supports the relevance of the trained ANN model. Furthermore, the dataset can be used for other machine learning model to compare which gives better prediction in terms of loss and accuracy. The demonstrated trained ANN will be improved for thorough delay analysis in XGPON and further enhance DBA performance.

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