

Determination of optimized sleep interval for 10 gigabit-passive optical network using learning intelligence

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Article Info

Article history:

Received Dec 31, 2020

Revised Jan 1, 2022

Accepted Jan 15, 2022

Keywords:

10 gigabit-passive optical network

Artificial neural network

Cyclic sleep

Energy efficient

Sleep interval

ABSTRACT

The overall aim of this project is to investigate the application of a machine learning method in finding the optimized length of asleep time interval (T_{AS}) in a cyclic sleep mechanism (CSM). Since past decade, the implementations of CSM in the optical network unit (ONU) to reduce the energy consumption in 10 gigabit-passive optical network (XG-PON) were extensively researched. However, the newest era sees the emergence of various network traffic with stringent demands that require further improvements on the T_{AS} selection. Since conventional methods utilize complex algorithm, this paper presents the employment of an artificial neural network (ANN) to facilitate ONU to determine the optimized T_{AS} values using learning from past experiences. Prior to simulation, theoretical analysis was done using the M/G/1 queueing system. The ANN was then trained and tested for the XG-PON network for optimal T_{AS} decisions. Results have shown that towards higher network load, a decreasing T_{AS} trend was observed from both methods. A wider T_{AS} range was recorded from the ANN network as compared to the theoretical values. Therefore, these findings will benefit the network operators to have a flexibility measure in determining the optimal T_{AS} values at current network conditions.

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1. INTRODUCTION

With its cost-efficient and multigigabit transmission, the time division multiplexed passive optical networks (TDM-PONs) have been providing broadband connectivity to customers for many years. However, reports show that massive deployment of optical access networks (OANs) have consumed power that equals 2% of global carbon dioxide (CO₂) emission [1]. This figure is projected to be 4% in the year 2025 [2]. These numbers are predominantly contributed by billion optical network unit (ONU) devices residing in the OAN, which use 60 % of total energy consumption in PON [3]. In turn, cyclic sleep mechanism (CSM) is ratified as the ONU power saving method, which was esteemed from its widespread implementations in wireless communication [4]. In the 10 Gigabit-PON (XG-PON), the international telecommunication union-telecommunication (ITU-T) sector has specified the CSM operational procedures for controlling ONU active/asleep modes in [5], [6]. Basically, CSM has a simple operation, only uses timers to set the ONU active/ON or asleep/OFF period. Nevertheless, CSM employment has imposed challenges on both hardware and algorithm design in PON [7], [8].

Dealing with those challenges, improving the sleep control scheme is the most preferred approach. This only requires an algorithm modification in the optical line termination (OLT) or in the ONU. In CSM, the period of ActiveHeld (T_{AH}), ActiveFree (T_{AF}), SleepAware (T_{SA}), and Asleep (T_{AS}) in the ONU state

machine are determined by the network operators' algorithm. Generally, a longer period of asleep or sleep time interval (T_{AS}) promotes high power reduction but, with an increase in the network delay [7]–[9]. In XG-PON standard, the end-to-end delay limit is 56 ms, the end-to-end round-trip delay for voice and video conference is 150ms, and jitter for interactive video should not exceed 30 ms [9]–[11]. However, the industrial revolution (IR) 4.0 with the internet-of-everythings, are demanding for stringent 1 to 10 ms end-to-end delay [12]. Furthermore, an inevitable surge of bandwidth needs due to the current COVID-19 pandemic requires a rethinking of network operational strategy when most home-based working with various real-time applications are practiced. Therefore, further investigations of proper T_{AS} selection are also crucial.

Using a fixed T_{AS} is not favorable because it does not allow ONU to sleep longer at high network load. This limits the energy savings or lessens the network efficiency [13]. Thus, an adaptive or dynamic T_{AS} is more feasible to support unpredictable network changes [14]. The computation of the adaptive T_{AS} can be done by monitoring both OLT and ONU buffer status, as reported in [11], [13], [15]–[17]. The improvement from this method include the service-based sleep with quality of service (QoS) limitations which has a strict/small T_{AS} on high priority or stringent delay traffic (e.g. Traffic Class T1 and VoIP) such as presented in [9], [18], [19].

Methods on determining T_{AS} mentioned above mostly comprise a complex algorithm, and various control packets exchanged between the OLT-ONU to activate/deactivate the sleep mode. This complexity could increase the network processing load and degrade the overall network performance [11], [20]. Thus, an improved and robust method in determining T_{AS} is needed. If an ONU can decide its own sleep interval and OLT have known the sleep pattern of a particular ONU, the complexity will be largely reduced. To the best of our knowledge, this method is given a low attention by the research community. Furthermore, the energy efficiency research in optical networks using learning intelligence is quite new. Thus, for this direction, we present our exploratory works of using a machine learning (ML) technique for the CSM improvement scheme.

In this work, we have applied the widely recognized artificial neural network (ANN) to assist ONUs to determine the T_{AS} values according to current network conditions. Therefore, our work is presented as follows: section 2 reviews, discusses, and analyzes the existing research efforts on the T_{AS} selection in PONs. Section 3 describes the theoretical analysis of the T_{AS} computation using the M/G/1 modelling approach. Then, in section 4, we present our proposed work in determining T_{AS} using ANN. We then evaluate and compare both methods in section 5. Finally, we end our paper with the concluding remarks in section 6.

2. LITERATURE REVIEW

A passive optical network (PON) is a low-cost, simple, and flexible point-to-multipoint access network architecture [21]. In PON, OLT which is located in the central office (CO) is connecting to a number of ONU (8/16/32) at remote nodes via the passive optical splitters. PON transmits multiple services such as data, voice, and video. There is no external power within PON distribution network, reducing its operational cost. With high guaranteed bandwidth and long-reach capability, XG-PON from the ITU-T is the most preferred as a global PON access network architecture.

XG-PON is recognized by its unique multi-layered XG-encapsulation method (XGEM) that encapsulates data into a varying size of XGEM frames. This method provides XG-PON with higher capacity and more robust data security as compared to 10G-EPON [6]. XG-PON classifies subscribers' services into different transmission containers (T-CONTs) through the XGEM PortID numbers. These T-CONTs are then given unique Alloc-ID numbers from OLT upon upstream bandwidth access transmission. In XG-PON upstream direction, the OLT allocates ONUs the bandwidth using the allocation structures sent in the BWmap within the downstream frame. This BWmap contains the StartTime and GrantSize for each Alloc-ID number for the next polling cycle transmission timeslots. XG-PON has a fixed 125 us polling cycle. In the downstream transmission, the OLT broadcasts the data packets to all ONUs. Each ONU filters and only accepts packets with its MAC addresses. Therefore, ONUs have to remain active to continuously listen and inspect the downstream traffic, even there is no incoming traffic. This is significantly wasting energy. In reducing the energy consumption in PON, sleep mode, adaptive link rate (ALR), and hybrid mechanisms were proposed in [22]. Among these methods, sleep mode is widely accepted technique due to its simple operation, only turning off various unused components in ONU when there is no traffic on the link [1]. As a result, the determination of ONU sleep/asleep duration is extensively researched.

The implementation of an adaptive T_{AS} is achieved by monitoring both OLT and ONU buffer status [15], [16], [23], [24]. Then, the calculation of the next cycle T_{AS} is made based on these buffer queue lengths. Since the queue length for the downstream transmission is already known by OLT, for upstream direction, ONU reports its queue length in the dynamic bandwidth report upstream (DBRu) header in the upstream payload. Therefore, all decisions to activate/deactivate sleep mode are made by OLT. To determine the ONU

buffer size required during sleeping, work in [23] has proposed an analytic model for incoming traffics from a user. It was based on the state stationary probabilities which depend on buffer sizes, sleep periods, and arrival rates. They discover that a T_{AS} over 40 ms or 50 ms does not effectively reduce the consumed power if the buffer size of the ONU system with CSM is enough to queue all incoming traffics from UNI. Elrasad *et al.* [15] present a sleep time sizing and scheduling framework based on an analytical probability according to data or control packets or both types of packet arrivals. However, the relationship between queue length and T_{AS} was not clearly stated. Work in [16] has modelled PON as an N-user M/G/1 queue with reservations and vacations where the sleep mode between 1 to 10 ms off was activated based on the upstream queue length. They continue for both downstream and upstream directions in [24] but simply assumed that T_{AS} is the minimum between downstream and upstream sleep intervals. The effort in [17] proposes two predefined/fixed sleep times: a long or short T_{AS} for the OLT to calculate whether the accumulated packet delay was due to the sleep time. However, a maximum of 8 ms and minimum 1 ms sleep times were simulated, which this range is too small for energy savings. A CSM framework based on sleep buffer has been proposed in [11] which includes a DBA scheme that contains all traffic classes T1, T2, T3 and T4. They have delayed the ONU wake-up indications to maximize energy savings but with higher downstream and upstream delays than a quick-released sleep method. Work in [22] proposes a CSM controller using a feedback control technique. They observe the downstream queue length and determine T_{AS} in proportional to the difference between the target and the monitored queue lengths.

Service-oriented improves the buffer-oriented method by including the QoS limitations in T_{AS} decisions. In this method, most of the works consider the traffic priorities, such as in [9], [18], [19], [25]. Shi *et al.* [25] present the service-level-agreement (SLA)-based scheduling scheme for PON, in which the OLT can adjust the sleep time, and ONU can quit sleep mode to send high-priority packets. However, only a maximum T_{AS} of 50 ms was used. Work in [9] proposes a variable sleep period with a tolerable delay for different services. A maximum T_{AS} of 217 ms was simulated with a delay of 110 ms for web browsing traffic. Work in [18] develops an adaptive delay-aware energy efficient (ADAEE) algorithm to meet the upstream strict delay and relaxed delay requirement, where the OLT decides the maximum and minimum T_{AS} and informs the ONU. They continue with energy-efficient uplink and downlink delay aware (EUDDA) algorithm in [26] to meet both downlink and uplink delay requirements. However, both ADAEE and EUDDA are quite complex, which could increase the network processing time. The effort in [19] utilizes a cognition method by looking at the Ethernet header in EPON and at parts of the payload to adjust the ONU sleep time dynamically. They focused on energy minimization first by applying the buffer-oriented approach and then, the buffer limit was decreased/increased to meet the service delay requirements.

Most of the literature works discussed above exploit some complexity in the model/algorithm design, which needs regular modifications to adapt to the network changes. Thus, the latest technology scheme should set idle ONUs in enough sleep period adaptively and can learn from each ONU's behavior or learn from past experiences. Thus, the adoption of intelligence in PON is promising to increase the CSM capability. Among many intelligence-based technologies, ML techniques are widely used for learning, classification, identification, and prediction. It can learn from input sets and historical events to classify/identify test objects and predict the future. In fact, the ML techniques are now adopted in optical networks, as extensively reviewed in [27] and [28]. Sarigiannidis *et al.* [14] determine the T_{AS} using the learning automata (LA) scheme by increasing the probability of the learning feedback. The LA produces a random variable based on the probability vector, which corresponds to specific sleep duration. They continue in [29] by using an exponential smoothing technique in ONU to forecast the XG-PON dynamic traffic patterns. Bhar *et al.* [30] have designed a green ONU using autoregressive moving average (ARMA)-based traffic prediction. In this work, they predicted the ONU buffer fill-up time to decide the energy-efficient mode with different energy ratings and duration. Then, the buffer was continuously observed to determine the wake-up decisions. The learning from ANN is also adopted in PON, such as the effort in [31]. They propose an adaptive control scheme to control the transition from full power to power saving state and use a burst transmission scheme to determine the sleep period for ONU.

Table 1 compares the methods of computing an adaptive T_{AS} studied above in which learning from experience is the best approach. However, none of the related work using ML considers the XG-PON practical network environment parameters. Thus, we continue the CSM improvement scheme by utilizing an XG-PON simulation test-bed in [1]. We employ the ANN to find the optimal T_{AS} for energy savings because ANN can learn how to react to the network inputs through the learning process [32], [33]. Accordingly, we aim at achieving the following objectives. Firstly, we want to analyze the existing technique theoretically prior to the ANN network design. Our second objective is to find the optimized T_{AS} using the ANN method. Finally, we aim to validate the ANN model by comparing the T_{AS} values from both approaches.

Table 1. Comparison analysis between the methods of computing an adaptive T_{AS}

Method	Ref.	Features	Comment
Buffer-based	[11], [15]–[17], [23], and [24]	T_{AS} is based on the utilized buffer queue length. It is simple to implement. It has options of quick or delayed wake-up indications.	Only suitable when QoS level for different traffic types or services are not considered.
Service-based	[9], [18], [19], [25], and [26]	T_{AS} depends on the different delay requirements for each service type and can have a maximum and minimum T_{AS} .	Some of the algorithms are quite complex such as ADAEE and EUDDA. To maximize energy savings, maximum delay is considered but with lower QoS experienced by users.
Intelligence-based	[14], and [29]–[31]	Newest technology adopted in network communications. Using a learning from experiences approach to support ONU to take the best possible T_{AS} based on current network status.	Most of the works rely on the simulation data because unavailability of real-data traffic due to confidentiality. However, none of the reviewed work above considers the XG-PON practical network environment parameters.

3. THEORETICAL ANALYSIS

The XG-PON system with CSM energy conservation scheme can be modelled as an M/G/1 queueing system with T_{AS} is represented by the time a server on vacation period [11]. Besides, the work in [16] has produced a relationship between the maximum target delay and the selection of T_{AS} by using both vacation and reservation intervals. Following both approaches in [11] and [16], we extend the analysis by including all T-CONT traffic classes T1, T2, T3 and T4 and compute the average performances. All of the traffic classes are randomly generated based on their percentages as in [34]. Figure 1 shows the example of traffic generated for the different classes and their distribution in 0.1 sec timeframe at 0.5 network load. For a queueing system, the sleep/vacation interval depends on the number of frames and the frame arrival rate. Thus, our analysis firstly performs a simulation framework in the OMNeT++ software to monitor the frame arrivals at the ONU within 1 sec timeframe [1]. Assuming fixed reservation interval in XG-PON because all packet headers are transmitted within the upstream and downstream payload; and vacation intervals are varied, thus (1) and (2) can be used to determine the T_{AS} for XG-PON [6]. Hence, we can get the reservation period using $\bar{V} = \frac{n}{\lambda}$. By using this \bar{V} , we can calculate the probability of ONU in sleep using (1). All of this value is then applied in (2), to observe the trend of T_{AS} over network load. Other network parameter values are defined in Table 2.

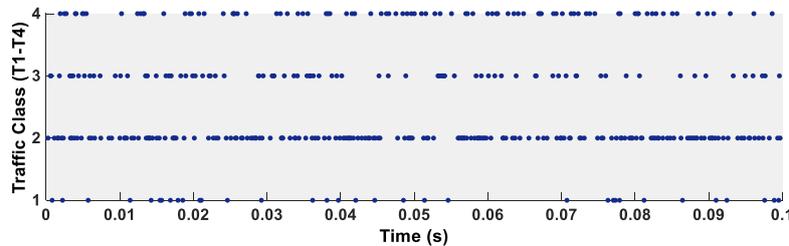


Figure 1. Traffic distribution for T1-T4 classes in 0.1 sec

Table 2. Network parameters

Parameter	Notation	Value
Number of ONUs	N	8, 16, 32
Number of frames	n	
Frame arrival rate	λ	ρ/X^-
Service time	X^-	125 μ s
Probability of ONU in sleep	q	
Network load	ρ	0.1-0.9
Maximum allowable delay	W_{max}	10-50 ms

Figure 2 illustrates the calculated T_{AS} values with an increasing network load, ρ for the practical number of ONU applied in real-network, which are 8, 16 and 32. As can be seen from this figure, the T_{AS} decreased with increasing ρ thus indicating that ONU was not allowed to sleep longer under heavy traffic. A lower T_{AS} was recorded for 32 ONUs as compared to 16 and 8 ONUs due to the existence of a high volume

of traffic. Figure 3 depicts the T_{AS} value for 16 ONUs with varying target delays, W . It shows that a high delay limit allows a longer sleep as plotted by $W=50$ ms, 40 ms, and 30 ms and this is slowly reduced with the increasing of ρ . It was observed that at a low network load, it was not possible for an extremely low value of W to give the same trend of T_{AS} but would still be able to achieve the same trend at a high network load. At $\rho=0.9$, a T_{AS} of 50 ms was recorded when the target delay was 50 ms.

$$q \approx \sqrt[N]{1 - \rho - \frac{Nn}{\lambda T_{AS}}} \tag{1}$$

$$T_{AS} \approx \frac{W_{max}}{\frac{q^N}{N(1-\rho)} + \frac{N-1}{N}(q - q^{N+1} + q^N)} \tag{2}$$

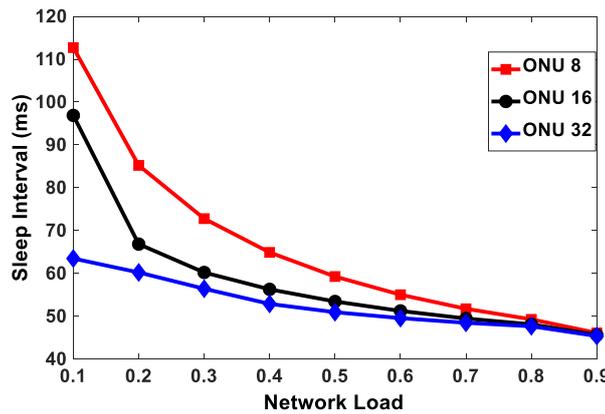


Figure 2. Sleep interval for different number of ONU

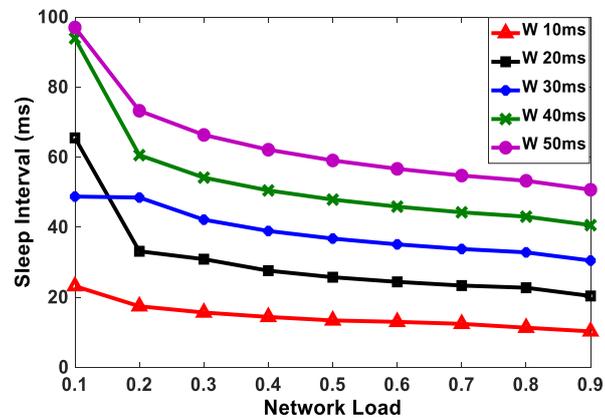


Figure 3. Sleep interval for ONU=16 with varying delay

4. SLEEP INTERVAL OPTIMIZATION USING ANN

For the T_{AS} optimization, we present an exploratory work of using a feedforward ANN in the MATLAB software. The ANN consists of training, validation and testing phases. During the supervised training phase, the ANN is trained by a selection of network features as input and the known targets as output. To implement the supervised training, we have collected a training set, $S = \{(x_i, y_i) | i = 1, 2, \dots, k\}$ from the XG-PON test-bed that was developed in section 3 which uses the event-driven packet-level simulations in OMNeT++. The traffic packets are randomly generated by individual users who follow a Poisson distribution with packet sizes are 64, 600, and 1518 bytes and include all traffic classes. For simplicity, we assume one user is connected to an ONU. The ANN network then learns the association between both upstream and downstream delays, W_{DS} and W_{US} performances, network load, ρ , and frame arrival, λ as inputs, x_i with the sleep interval, T_{AS} as the target output y_i . For a given x_i , the y_i was obtained by measuring the average T_{AS} over a 1 second of network runtime. Note that in this phase, we choose the practical number of ONU, N of 16

for evaluation. The procedure of collecting (x_i, y_i) is repeated until more than 1000 samples are collected. When the supervised training is completed, the trained ANN is used to predict T_{AS} corresponding to the testing inputs.

In the ANN network, we have used 67% of data for training and the remaining 33% for validation and testing [32]. The ANN model consists of an input layer, a hidden layer with 10 blocks, and an output layer. To highlight the accuracy of the data, Figure 4 illustrates the near similar trends of mean square errors (MSEs) obtained during training, validation, and testing. Figure 5 depicts the linear regression profile of the ANN network for all progressing states which all of the regression, R values are very close to 1. From these figures, it also can be seen that most output numbers are fit to the targeted values.

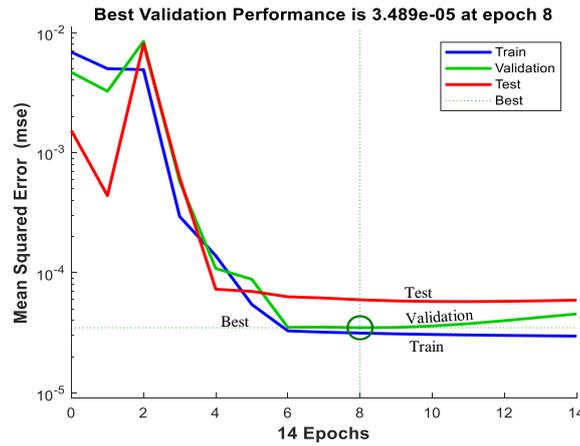


Figure 4. MSE performance of the ANN network

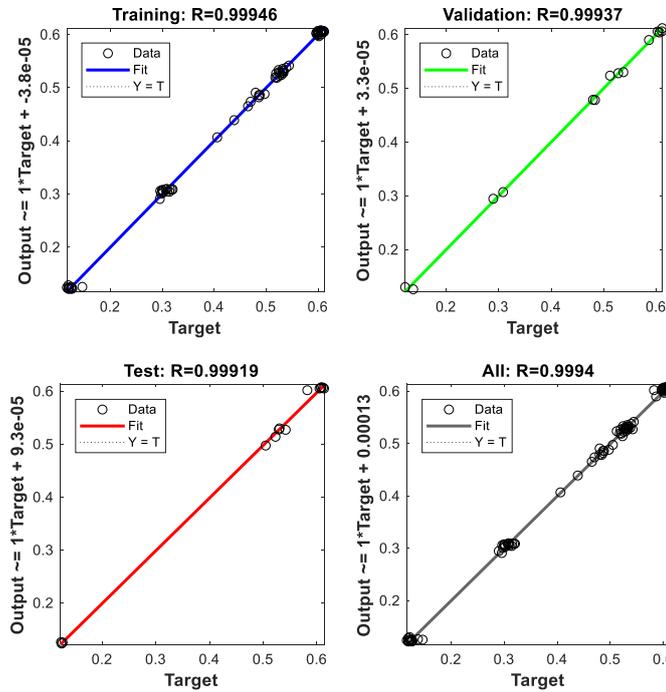


Figure 5. Regression profiles during training, validation, testing and all

5. PERFORMANCE EVALUATION

The objective of our learning using ANN intelligence is to determine an optimized output value of T_{AS} . This section discusses the results from the ANN and then, will be compared with the theoretical results

in section 3 for validations. Accordingly, the ANN network has been tested to produce the optimized sleep time for traffic distribution as shown in Figure 6. Since T-CONT Class 1 (T1) traffic is treated as the highest priority in XG-PON, we assume that it will largely determine the amount of T_{AS} experienced by the network. As can be seen in Figure 6, following the distribution of traffic T1 plotted in the x-axes, the T_{AS} values produced by the ANN are in trend with the expected T_{AS} . Supported these results, a low mean error of ± 0.41 are recorded in this ANN simulation.

Figure 7 plots the value of T_{AS} versus network load for both the trained ANN and from the theoretical calculations. Generally, as compared to calculation values which have a gradually decreasing trend over network load, the trained ANN produces a fluctuating and decreasing T_{AS} trend. Between network loads of 0.1 to 0.4, both methods produce T_{AS} values of approximately between 50 to 60 ms, in which the trained ANN has higher T_{AS} values at most of the points. At higher traffic load, specifically at the network load of 0.6, the trained ANN resulted in a lower and strict T_{AS} value which is about 13 ms as compared to T_{AS} of 45 ms from the calculation. This shows a 71% of difference. This high discrepancy value is because the ANN was trained, validated, and tested using the practical simulation data of an XG-PON network. The data that were inserted into the ANN network simulation includes XG-PON processing features such as a control message between OLT-ONU. Besides, a high number of traffic queued in the buffer during high network load is not allowing an ONU to sleep longer.

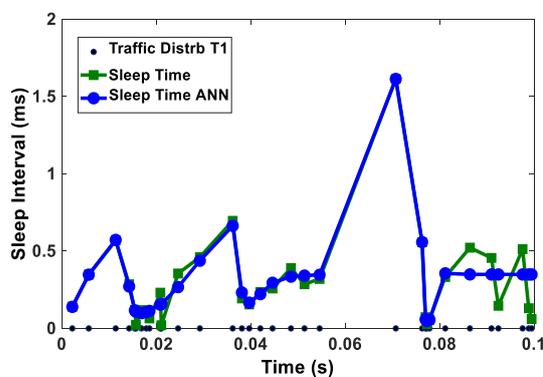


Figure 6. Comparison of expected T_{AS} values and from ANN over time

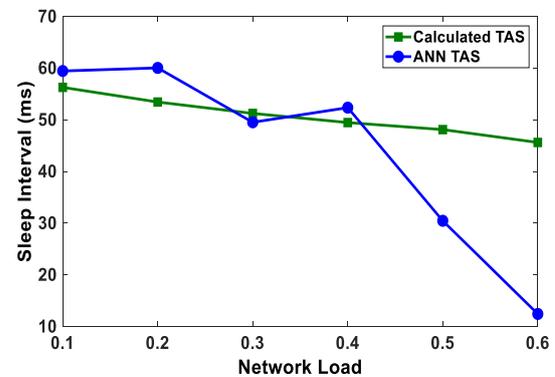


Figure 7. T_{AS} values from the theoretical calculation and from ANN over network load

6. CONCLUSION

We have presented the work in determining an optimized T_{AS} for energy-efficient XG-PON. We have proposed the exploitation of using ANN in estimating the T_{AS} values. A theoretical analysis also has been done for comparison. With the training and validating processes performed, we have comprehensively produced T_{AS} values associated with the network load and delay requirements. Supported by the ANN's intelligence, simulation results have shown that the proposed work is in line with theoretical performances at a low network load but having strict values at a higher network load. In the end, the ANN network have produced a wider T_{AS} range, which promotes more flexibility to the network operators in determining the optimal T_{AS} at the current network requirements. Furthermore, the ANN network is also able to produce an optimized T_{AS} when tested for traffic class T1. In our future work, we will extend this work using real-data traffic and investigate its capability in operating the network intelligently. More advanced learning such as recurrent neural network and deep learning are also considered.

ACKNOWLEDGEMENTS

We express our acknowledgements to Universiti Teknologi Malaysia (UTM) Johor Bharu, Malaysia for providing the research funding and facilities under the Transdisciplinary Research Grant (TDR) 05G80 and Universiti Teknologi MARA, Malaysia for the financial support to the first author.

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