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Dynamic Bandwidth Allocation for OFDMA-PONs Using Hidden Markov Model

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ABSTRACT Accurate prediction of traffic conditions on orthogonal frequency division multiple access passive optical networks is important because of its vital role in network resource management and efficient bandwidth allocation. Given the dynamic and stochastic nature of network traffic, our proposed algorithm conducts a probabilistic approach by using the hidden Markov model (HMM). The HMM defines traffic states with two parameters: the mean and contrast of the bandwidth request observations. Simulation results demonstrate the performance comparison between with and without the prediction method in terms of throughput and end-to-end delay. As a result, the throughput improves 15% and the saturation offered load of the delay for the prediction and non-prediction is 0.8 and 0.7, respectively.

INDEX TERMS OFDMA-PONs, hidden Markov model, dynamic bandwidth allocation.

I. INTRODUCTION

An orthogonal frequency division multiple access passive optical networks (OFDMA-PONs) provides considerably higher data rates in support of the ever-increasing bandwidth demand for various types of multimedia traffic with stringent quality of service (QoS) requirements in the access network [1]–[4]. Naturally, the technique of the bandwidth management in the circumstance of high capacity request significantly influences the network performance such as the network throughput and packet delay. Therefore, to improve the efficiency of the resource assignment, numerous approaches regarding the bandwidth allocation were suggested.

Reference [1], the elastic bandwidth allocation was studied to compensate the difference in losses experienced by the users in the OFDMA-PONs. Reference [1] experimentally validates a statistical multiband OFDM-PON with two optical network units (ONUs) in both downstream and uplink considering flexible bandwidth allocation. Reference [2] proposed a randomized dynamic bandwidth allocation algorithm for upstream access in OFDMA-PON system. The bandwidth allocation in [2] is determined by the data length information of each ONU and the estimation of the data arriving rate of each ONU during the trip time between the ONU and the optical line terminal (OLT). Reference [3] presented a heterogeneous, optical/wireless bandwidth allocation framework, exhibiting intelligent traffic queuing for controlling the QoS of mobile traffic, backhauled via OFDMA-PONs. In addition, inter-ONU algorithms were developed, based on the distribution of weights to allocate subcarriers to both cellular base station/ONUs and residential ONUs, sharing the same infrastructure.

In particular our published paper [4] proposed dynamic bandwidth allocation that considers both time slots and subcarriers in OFDMA-PONs. Reference [4], the ONUs are classified either as heavily loaded or as light loaded based on a simple comparison between their current bandwidth request and guaranteed bandwidth. Only heavily loaded ONUs share the surplus bandwidth. Although this process reduces the computation burden of the OLT, it can cause inefficient resource management because the network traffic variation was not sufficiently considered. To overcome this problem, the proposed algorithm incorporates a traffic prediction technique on the dynamic bandwidth allocation. Due to the stochastic variation of traffic behavior, the Hidden Markov Model (HMM) was utilized to predict this traffic condition. It should be noted that as a consequence of the traffic prediction with the HMM algorithm the OLT experiences more computational load compared to [4].

II. HMM BASED DBA

A. HMM STATES

The OFDMA-PON has N ONUs with each ONU classified into one of three service level agreement (SLA) grades. Although the ONU's traffic states are not directly visible to the OLT, this problem can be efficiently modelled by the HMM. Despite the hidden traffic condition, the OLT can effectively make an estimation of these states by exploiting the bandwidth request messages that are being reported by each ONU. Let $R_t^{i,s}$ denote the requested bandwidth of i ONU for the t polling cycle where s is the index of SLA, $s = \{\text{indexofSLA}|1, 2, 3\}$. $R_t^{i,s}$ is used to determine an observation symbol in HMM as follows

$$o_t = \left\lfloor \frac{R_t^{i,s}}{C_{max}^{i,s}} \times 100 \right\rfloor \%. \quad (1)$$

where $C_{max}^{i,s}$ is the maximum queue capacity of i ONU with s SLA and $\lfloor\cdot\rfloor$ is a floor function. Due to the floor function on the calculation of o_t, the observation symbol is expressed as a positive integer in the range of 0 to 100. The observation sequence is $O = \{o_1, o_2, \ldots, o_T$ and T denotes the length of the sequence.

To accurately reflect the traffic condition, the HMM state is constructed with two parameters: the mean(μ) and contrast (φ) of the observation. The mean represents the central tendency of the observation. To emphasise heavily loaded traffic, we divided the mean into four ranges: $\mu < 55\%, 55\% < \mu < 70\%, 70\% < \mu < 85\%$ and $85\% < \mu < 100\%$. The contrast characterises the degree of traffic variation and is defined by:

$$\varphi = \sum_{\forall o_i} \sum_{\forall o_j} \left(o_j - o_i\right) \left|o_j - o_i\right| h_{o_i,o_j}, \quad (2)$$

$$h_{o_i,o_j} = \frac{P_{o_i,o_j}}{P_{total}}, \quad 1 \le i, j \le T, \ i < j. \quad (3)$$

where $P_{o_i,o_j}$is the number of pairs between o_i and o_j and P_{total} is the total number of possible pairs in O. A negative φ means that the volume of the arrived data in the ONU queue is decreasing, and vice versa. Thus, to efficiently distribute the bandwidth to heavily loaded ONUs, positive φ was mainly considered in our algorithm. In addition, to reduce the computational cost, φ was divided into four ranges: $\varphi < 0$, $0 < \varphi < 10$, $10 < \mu < 20$ and $\varphi > 20$. Each of the positive ranges indicates small, moderate, and large increases in traffic respectively. By combining the mean and contrast, a total of 16 traffic states was obtained, as shown in Table 1. Surplus bandwidth is mostly needed for the ONU in state 16 because of the queue occupancy being more than 85% together with the rapid increase in traffic. On the other hand, the ONU in state 1 has the lowest priority in the surplus bandwidth allocation.

TABLE 1. Description of 16 traffic states.

Mean (μ)	Contrast (φ)			
	< 0	0 to 20	10 to 20	> 20
< 55	1	2	3	4
55 to 70	5	6	7	8
70 to 85	9	10	11	12
85 to 100	13	14	15	16

B. CONSTRUCTION OF HMM

An HMM is specified by three probability matrices, (i) state transition matrix $\mathbf{A}$ (ii) emission matrix $\mathbf{B}$ and (iii) prior probability matrix $\boldsymbol{\pi}$. With three matrices, an HMM, denoted by $\boldsymbol{\Theta}$, can be defined as $\boldsymbol{\Theta} = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$ [5]. $Q = \{q_1, q_2, \ldots, q_T\}$ is the hidden state sequence where the state of the traffic condition at any polling cycle t is represented by q_t. O_t is used to model the observation based on the bandwidth requests reported by the ONUs at polling cycle t. $O = \{o_1, o_2, \ldots, o_T$ is the observation sequence, which is a subset of all possible observations, $V = \{v_1, v_2, \ldots, v_M\}$. We define $S = \{s_1, s_2, \ldots, s_K$ as the set of traffic states and K with a constant value of 16. The state transition matrix is defined as $\mathbf{A} = \{a_{ij}\}$ where $a_{ij} = P(q_t = s_j|q_t{-}1 = s_i)$, $1 \le i, j \le K$. For the emission matrix, we define $\mathbf{B} = \{b_{jm}\}$ where $b_{jm} = P(o_t = v_m|q_t = s_j)$, $1 \le j \le K$, $1 \le m \le M$ is the probabilities to observe v_m if the current state is $q_t = s_j$. Fig 1 illustrates the mapping of ONU's traffic variation problem into HMM.

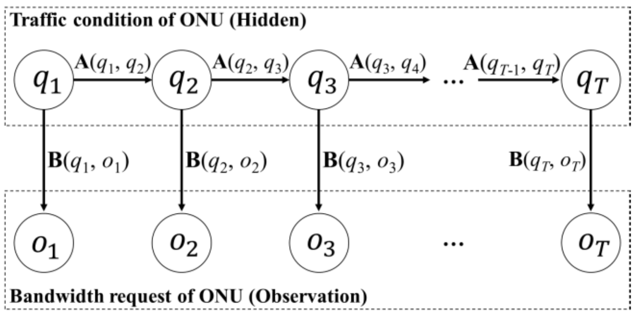

FIGURE 1. Mapping ONU's traffic variation problem into HMM.

The Baum–Welch algorithm [6] is adapted to determine the HMM parameters, $\mathbf{A}$, $\mathbf{B}$, and $\boldsymbol{\pi}$ using the maximum likelihood method. In the procedure of iterative updates and modifications of HMM parameters, two variables, $\xi_t(i, j)$ and $\gamma_t(i)$ are used.

$$\xi_t\,(i, j) = P\left(q_t = s_i, q_{t+1} = s_j \,|\, O, \boldsymbol{\Theta}\right) \quad (4)$$

$$\gamma_t\,(i) = P\left(q_t = s_i \,|\, O, \boldsymbol{\Theta}\right) \quad (5)$$

$\xi_t\,(i, j)$ represents the state transition probability of ONU's traffic condition from state s_i at polling cycle t, to state s_j at polling cycle $t + 1$. $\gamma_t(i)$ is the posterior probability of the traffic condition being in state s_i at polling cycle t, given the model $\boldsymbol{\Theta}$ and the history of bandwidth request. After every iteration, the re-estimated $\mathbf{A}$, $\mathbf{B}$, and $\boldsymbol{\pi}$ are defined as:

$$\hat{\pi}_i = \gamma_1(i), \quad 1 \le i \le K \tag{6}$$

$$\hat{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)}, \quad 1 \le i,\ j \le K \tag{7}$$

$$\hat{b}_{jm} = \frac{\sum_{t=1, o_t = v_m}^{T} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(j)}, \quad 1 \le j \le K,\ 1 \le m \le M. \tag{8}$$

C. OPTIMAL STATE SEQUENCE

Incorporating several previous bandwidth request observations, a sequence of the traffic condition can be formed. Furthermore, to find the optimal hidden traffic state, we operate the Viterbi algorithm using the maximum likelihood with regard to a given observation. The Viterbi algorithm has two variables, $\delta_t(i)$ and $\psi_t(i)$. $\delta_t(i)$ is the highest likelihood of a single path among all paths that finish in state s_i at polling cycle t and it is defined as

$$\delta_t(i) = \max_{q1,q2,\cdots,qt-1} P(q_1, q_2, \ldots, q_t = s_i, o_1, o_2, \ldots, o_t | \Theta) \tag{9}$$

$\psi_t(i)$ is exploited to track the best path that finish in state S_i at time t and it is defined as

$$\psi_t(i) = \arg\max_{q1,q2,\cdots,qt-1} P(q_1, q_2, \ldots, q_t = s_i, o_1, o_2, \ldots, o_t \,|\, \Theta). \tag{10}$$

In the process of searching for the optimal state, the Viterbi algorithm performs four steps recursively.

Step 1 (Initialization):

$$\begin{aligned} \delta_t(i) &= \pi_i \cdot b_{i,q_1}, \quad 1 \le i \le K \\ \psi_t(i) &= 0 \end{aligned} \tag{11}$$

Step 2 (Recursion):

$$\begin{aligned} \delta_t(i) &= \max_{1 \le i \le K} (\delta_t(i) \cdot a_{i,j}) \cdot b_{j,q_t}, \quad 2 \le t \le T,\ 1 \le j \le K \\ \psi_t(i) &= \max_{1 \le i \le K} (\delta_{t-1}(i) \cdot a_{i,j}), \quad 2 \le t \le T,\ 1 \le j \le K \end{aligned} \tag{12}$$

The recursive procedure finds the maximum likelihood based on the best likelihood of the former phase.

Step 3 (Termination):

$$\begin{aligned} P^*(O \,|\, \Theta) &= \max_{1 \le i \le K} \delta_T(i) \\ q_T^* &= \arg\max_{1 \le i \le K} \delta_T(i) \end{aligned} \tag{13}$$

Step 4 (Backtracking):

$$\begin{aligned} Q^* &= \{q_1^*, q_2^*, \ldots, q_T^*\} \\ q_t^* &= \psi_{t+1}\left(q_{t+1}^*\right), \quad t = T-1,\ T-2, \ldots, 1 \end{aligned} \tag{14}$$

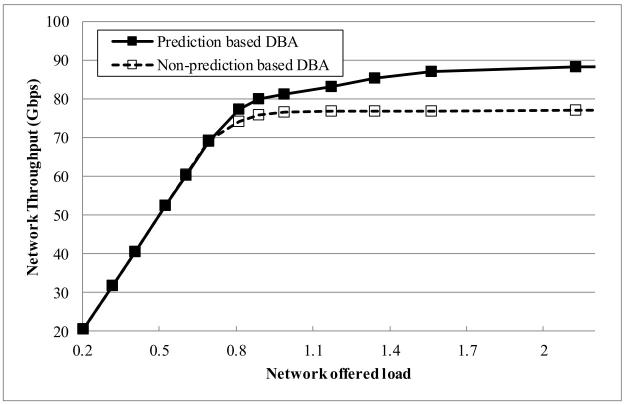

FIGURE 2. **Network throughput results with prediction and non-prediction based scheduling.**

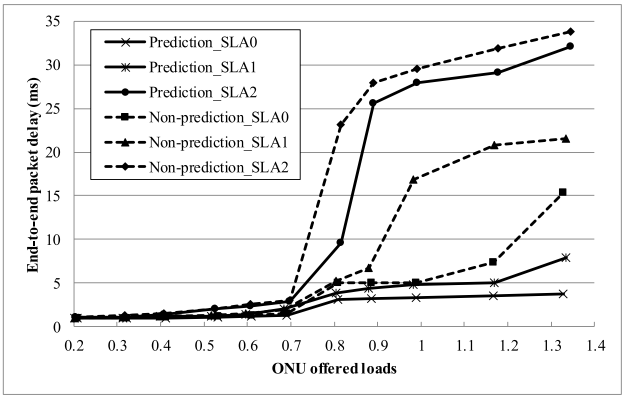

FIGURE 3. **End-to-end packet delay for both algorithms and different SLAs.**

III. SIMULATION RESULTS

Simulation results for the performance comparison between the prediction and non-prediction based DBA in terms of the throughput and end-to-end delay are presented. Note that [4] was conducted as a reference model for the non-prediction approach and all simulation parameters follow [4]. The characteristics for the network throughput against offered load in Fig. 2 confirms that prediction based DBA achieves increased throughput. The resulting 88.5 Gbps exhibits an improvement in throughput rate by 15%, compared to the non-prediction scheme that stalls at around 77 Gbps. Furthermore, Fig. 3 displays the end-to-end delay for all three SLAs against the ONU offered load. It can be observed that the threshold ONU loadings for the non-prediction and prediction schemes to achieve the saturation are 0.7 and 0.8, respectively, because the low level SLA (SLA2) delays of the non-prediction and prediction schemes dramatically increase after these loads. Above 90% of the ONU offered load, the results show the superior performance of the prediction based over the non-prediction based algorithm. For SLA0 and SLA1, the delay using the prediction based algorithm is consistently less than 5 ms, even with an ONU traffic load of 1.0. In particular the performance improvement of SLA1 is more significant than that of SLA0 and SLA2. The main advantage of the prediction based DBA algorithm is to significantly improve the efficiency of sharing the surplus bandwidth by accurately separating the heavily loaded ONUs and light loaded ONUs. The condition of the highest priority SLA0 ONUs often stays in the light loaded one because the guaranteed bandwidth sufficiently supports the SLA0 ONUs. In that sense, the middle priority SLA1 ONUs receives the most benefit of the surplus bandwidth because the surplus bandwidth is assigned in order of the priority. Therefore, the delay of SLA1 is much more improved than the others.

IV. CONCLUSION

To improve the efficiency of bandwidth allocation in OFDMA-PON a prediction based DBA algorithm is proposed. An HMM scheme was exploited to predict the traffic conditions of the ONUs with the HMM state expressed as a two-dimensional degree with mean and contrast. The observation in HMM is calculated with the bandwidth request of ONU and it is represented in the range of 0 to 100%. Simulation results of the throughput and end-to-end delay are compared with the non-prediction DBA algorithm and the performance evaluation figures confirm that the prediction approach improves bandwidth management.

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