Using Bayesian Belief Networks for Burst Detection in Ethernet Passive Optical Networks

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Abstract- The Ethernet Passive Optical Networks (EPONs) have been considered as a promising candidate for the next generation wired access networks for quite some time. In EPONs bandwidth requests and bandwidth allocations are critical issues which need to be addressed efficiently in order to guarantee the End-to-End (ETE) Quality of Service (QoS) for diverse classes of services. In this paper, we discuss the application of a statistical prediction technique based on the Bayesian Belief Networks (BBNs) which provides real-time decision support to the EPONs Dynamic Bandwidth Allocation (DBA) function. We show that in situations of burst traffic it helps the DBA to predict additional bandwidth requirements.

Keywords: EPON, BBN, DBA

I. INTRODUCTION

The volume of the Internet traffic which has in consistence pattern is increasing every year. Every day new subscribers who are facing the risk of missing out online services such as health, financial services, etc., register to the different Internet Service Provider (ISP), while the current subscribers upgrade their Internet services to a better one which has faster connectivity and 24/7 availability. The Digital Subscriber Line (DSL) and Cable Modem (CM) networks are the most deployed telecommunication infrastructures for broadband access networks. Their problem domains could be categorised as physical location, upgradability and traffic growth. For instance they are unable to support subscribers located more than 5.5 km from the central office (CO). They also cannot provide enough bandwidth for ongoing demands for more sophisticated services and bandwidth hungry applications. The Optical Network (ON) is a solution for the DSL and CM problem domains by providing higher bandwidth and supporting subscribers located more than 20 km from the CO. The ON can also be upgraded to the higher bit rate or even additional wavelength easily. The Passive Optical Network (PON) is the most promising candidate among other ON solution as it eliminates the necessity of installing active component such as the multiplexer and a de-multiplexer in the splitting point between the local exchange and the local loop [6]. The PON is a point-to-multipoint fibre infrastructure including the Optical Line Terminal (OLT) in the CO, the Optical Network Units (ONUs) near customer premises as well as the 1:N passive splitter/combiner with the split range of 16, 32 or 64 fibres [3]. The Ethernet-based Passive Optical Network (EPON, IEEE 802.3ah) appears to be the preferred choice among the other PON’s major data-link technologies such as the SONET-based PON (SPON) and ATM-based PON (APON). For instance in APON [19] the IP packets should be broken into cells at the source and then reassembled at the destination which adds extra cost and complexity to the network. The SPON is also too expensive for the local loop and not suitable for the data traffic [6]. On the other hand, the Ethernet is an inexpensive, ubiquitous and scalable technology. It is also interoperable with a variety of legacy equipment with adopt quality of service (QoS). The EPON seems to be the most promising candidate among the other wired broadband access network technologies [4] with the Time Division Multiplexing (TDM), Wavelength Division Multiplexing (WDM) and Code Division Multiplexing (CDM) as possible media-access technologies with different challenges. For instance the WDM provides higher bandwidth rather TDM however, it is a costly technique as it needs the ONUs that can work in different wavelengths. On the other hand, the TDM is least costly techniques as it only needs one transmitter at the OLT no matter how many ONUs are connected. However, the TDM is a complex method as it needs synchronisation between the OLT and the ONU. In this paper, we consider the TDM in our implementation as a cost-aware technique. Allocation and arbitration of the up-stream bandwidth that is shared between a different number of the ONUs is a critical issue which needs to be considered efficiently in order to provide sufficient QoS for different service classes. Many bandwidth allocation algorithms, particularly Dynamic Bandwidth Allocation (DBA) algorithms have been proposed in the literature for the EPONs. Most of the proposed DBA algorithms address bandwidth allocation issues between the ONUs (inter-ONUs schemes) [8-11] in EPONs. In this paper, we propose the Bayesian Belief Networks (BBNs) as the burst detection method to improve the bandwidth request within each ONU in an EPON. The OPNET [2] and HUGIN Lite [1] tools have been used to conduct initial experiments. A burst is a large number of events occurring within a certain time window. Many data stream applications require the detection of bursts across a variety of window sizes. For example, stock traders may be interested in bursts having to do with institutional purchases or sales that are spread out over minutes or hours [20]. The remainder of this paper is organized as follows. In section II we review the related work with regard to the DBA in EPON. In section III we briefly discuss the bandwidth negotiations in EPON and then follow by problem definition in section IV. Section V covers the proposed burst detection algorithm using BBNs. Initial implementations are detailed in section VI and the paper is concluded in section VII including the work in progress.

II. RELATED WORK

The IEEE 802.3ah provides the framework to support dynamic bandwidth allocation (DBA) in EPON environments.
To date the wide range of bandwidth allocation algorithms has been proposed in order to provide high bandwidth utilization towards up-link fibre and support the ETE QoS in EPONs. The overview of some of the EPON up-stream DBA can be found in [18]. The Interleaved Polling with an Adaptive Cyclic Time (IPACT) algorithm was proposed in [10]. The IPACT is placed inside the OLT (CO) and pools the ONUs in a round-robin fashion then grants time-slot dynamically to each with regard to the reported queue length from the ONU. The IPACT works efficiently, but it does not support the QoS for different traffic classes. The IPACT with Grant Estimation (IPACT-GE) was proposed in [13] in which the ONU estimates the amount of the packets arriving between two consecutive time slots. It reduces average packet delay and queue length when the network is lightly loaded compared with the plain IPACT, but it does not support the QoS. In order to facilitate the IPACT with the QoS provisioning, the IPACT with MPCP was proposed in [12]. The IPACT with MPCP can support up to three priority queues defined for EPONs: Expedited Forwarding (EF), Assured Forwarding (AF) and the Best Effort (BE), by using the Jackson’s queuing network. For an inter-ONU scheduling scheme, the Broadcast Polling (BP) algorithm was proposed in [16] in order to allocate the bandwidth among different number of ONUs based on EPON traffic types. Although the BP algorithm considers the QoS for different traffic types, there is no bandwidth limitation for the first-class of traffic (EF). In order to use the excessive unused bandwidth from the lightly-loaded ONUs which requested bandwidth less than their minimum guaranteed bandwidth, the authors in [15] proposed a mechanism to collect the excess bandwidth from lightly-loaded ONUs and distribute them among the heavily-loaded ONUs that is able to provide higher bandwidth utilization towards up-link fibre. However, in [15] the ONU can receive bandwidth more than that requested. A weight-base DBA (W-DBA) was proposed in [14] in which different weight is allocated to each buffer and then the excess bandwidth from lightly-loaded ONUs will be distributed among the heavily-loaded ONUs based on the weight of each buffer. The W-DBA provides fairness among different priority queues and is considered as a solution for the problem in [15]. To address the problems mentioned above and with regard to the lack of the intelligent algorithms in EPONs as well as the lack of the techniques to guarantee the network efficiency under the bursty nature of the Internet traffic pattern we propose the Bayesian Belief Networks (BBNs) approach, which is a promising candidate among decision making methods and prediction techniques as a part of the intra-ONU scheduling algorithm. In this paper, the main purpose of using BBNs is to reduce the queuing delay and queue length for the packets inside the ONU’s buffer.

III. EPON BANDWIDTH NEGOTIATIONS

The Multi Point Control Protocol (MPCP) (IEEE 802.3ah) supports bandwidth negotiations (requests and grants) in EPONs by using the REPORT and GTAE messages [4]. The MPCP includes three types of messaging formats: the Auto-discovery messages (REGISTER_REQ, REGISTER and REGISTER_ACK), REPORT messages and the GATE messages. The MPCP starts working when a new ONU joins the network by sending the REGISTER_REQ message, which is processed by the OLT and is replied by using REGISTER message. The ONU uses REGISTER_ACK messages as a confirmation to the OLT after receiving a REGISTER message from OLT. When the auto-discovery procedure is finished, the ONU should request bandwidth from the OLT by sending the REPORT messages reporting its buffer lengths at the end of each allocated time slot. These messages are tools which are provided in IEEE802.3ah for bandwidth negotiations between the ONUs and OLT for EPONs. There is no specific algorithm for bandwidth allocation in IEEE 802.3ah. In our previous work [4] we investigated the different techniques for multiple accesses to the up-link share fibre. The OLT-based Dynamic Bandwidth Allocation (DBA) based-on the time division multiple access (TDMA) technique is a promising candidate as the OLT knows about the state of the entire network. It is also inexpensive technique as the ONUs do not need to connect and communicate with one another.

IV. PROBLEM DEFINITION

The EPON uses Multi Point Control Protocol (MPCP) defined in IEEE 802.3ah for bandwidth negotiations between the OLT and the ONU. At the end of each time slot, which is allocated by the OLT to correspondent ONU, the ONU should report its current buffer length and should wait for the next time slot to arrive. Between the two consecutive time slots (e.g. Tn and Tn+1) due to the network traffic patterns, the number of the packet arrivals may vary. These new arrivals will be reported after the arrival of the next allocated time slot (Tn+1) and will be transferred in slot (Tn+2) therefore, they should wait two time slots to get transferred towards up-stream shared fibre. Generally speaking, newly arrived packets between two consecutive time slots experience two time slot delays and may be dropped due to the buffer occupancy and bursty nature of the Internet traffic pattern. In this paper a burst is a large number of the data arriving within a certain time window inside the ONU’s buffer which can degrade the QoS by causing packet drop, long queuing delay or by increasing queuing delay if it does not get handled efficiently. However, if the traffic pattern can be predicted, the QoS degradation will be diminished and the performance (essentially, queue length and queuing delay) can be improved for the packets arriving between two consecutive time slots. Most of the available prediction methods use time series approach and some of them use neural networks. Among the existing uncertainty reasoning methods, the Bayesian network is the only one that directly grounded in probability theory. The Bayesian network approach is mainly used as a prediction tool for representing and reasoning about the uncertain domain [7]. It has been used successfully in many fields such as speech recognition, industrial control, economic forecasting, etc. Recently with the development of the Data Mining, the learning about the Bayesian networks attracted more attention. In this paper, we consider the Bayesian Belief
Networks (BBNs) approach as a traffic pattern predictor particularly burst detection mechanism inside the ONU. A low-level scheduler is located inside the ONU and works in two different directions: up-stream, to request bandwidth from the OLT and down-stream, to distribute the allocated bandwidth between priority queues. In our proposed scheme the BBN has been used in cooperation by the low-level scheduler inside the ONU in an EPON scenario.

V. PROPOSED BURST DETECTION MODEL

A. Bayesian Belief Networks (BBNs) Theory

The BBNs is a probabilistic graphical model, Directed Acyclic Graph (DAG), which includes a network structure $\mathcal{S}$ that encodes the set of parameters (variables) $V$ and a set $\rho$ of local probability distributions related to each parameter [5][17]. For each node $X \in V$ there is a conditional probability distribution $P(X | pa(X)) \in \rho$ where the $pa(X)$ are the parents of the $x$ in the DAG. Therefore, a Bayesian network is an efficient representation of a joint probability distribution $P(V)$ which factorises as:

$$P(V) = \prod_{x \in V} P(X | pa(X))$$

Fig. 1 is an example of BBN in the parent-child (cause-effect) order in a sample problem domain. It is equivalent to the following functional decomposition for the joint probability:

$$p(A, B, C, E, D) = p(A) p(B) p(C) p(D | A, B, C) p(E | D)$$

which is then equivalent to the following set of the conditional independence statements where $X \perp Y$ is $X$ and $Y$ are independent and $X \perp Y \perp Z$ is $X$ and $Y$ are independent given $Z$:

$$B \perp A, C \perp A, C \perp B, E \perp (A, B, C) \mid D$$

Fig. 1. A sample structure of the BBN

The BBN can be in the format of the single-evidence, multiple-evidence and multiple-layer probabilistic relationship among the variables (parameters) which relates only the neighbouring nodes [5]. The Conditional Probability Table (CPT) which is attached to each node of the network represents the effect that each parent has on a single node (child). The Structural Learning and Parameter Learning are two of the learning methods during which the BBNs can estimate the behaviour of each node and the relationship between one another. The former helps build the structure of the BBN model including the BBN nodes and a set of links which connect pairs of nodes together in parent-child order while the latter uses the historical data to learn the CPT of each node.

B. BBN in the context of the burst detection model

The BBN in the burst detection model specifies the dependency relations between a set of burst indicators. Fig. 2 describes dependence relations between the burst, packet drop, queuing delay, queue length, traffic out and traffic in for a sample queue. This model computes the probability of burst given information on the input traffic characteristic and buffer behaviours. In the BBN burst detection model, each node can be specified either as target node or indicator node. The target node is the hypothesis variable which reveals whether the input traffic is bursty or not. In Fig. 2 the burst is the target (hypothesis) variable and the rest of the nodes are indicator variables. The BBN burst detection model is constructed with the expert knowledge and experience (historical data), or a combination of both elements. Its implementation process includes the following steps: data collection, network structure and specification, parameter estimation based on expert knowledge or experience and historical data and finally model evaluation.

C. BBN in the context of the scheduler inside ONU

The burst detection process is started by receiving the traffic flows from the sub-nets and classifying each in an appropriate queue using the CLASSIFIER. The CLASSIFIER is implemented inside the ONU and is responsible to receive, classify and then direct the data traffic from the associated sub-nets into three queues provided for three service classes in EPON: EF, AF and the BE. Fig. 3 depicts the BBN model in the context of the SCHEDULER inside the ONU. The SCHEDULER is the most important module inside the ONU which arbitrates access to the up-stream shared bandwidth between three priority queues. It is the only component that receives the allocated time slot from the OLT towards the down-link fibre in the form of the GATE message and then shares it between three priority queues. The scheduler allows the traffic transmission only after receiving the GATE message in which the start time and the length of the time during which the scheduler has access to the up-stream fibre are addressed. The scheduler inside the ONU has full control of EPON’s three priority queues and has comprehensive knowledge and real-time information about the status of each queue. Information such as: the rate of the input traffic, packet drop, queuing delay, queue length and the output traffic on each priority queue. This information is captured by the scheduler on a regular basis and fed into the BBN model to support the decision on whether to acknowledge the currently received traffic flow as the burst or to acknowledge it as normal flow. The scheduler then can benefit from the decision made by the BBN model by requesting more bandwidth from OLT in advance to avoid or reduce packet drop, queuing delay and long queue length.

D. Proposed algorithm inside the ONU in assistance with BBN

Let the $ONU_i^{th}$ be the granted time slot from the OLT to the correspondent $ONU_i$, $Q_j^{length}$ and $K_j$ be the queue length and the estimated queue lengths in the $j^{th}$ queue, respectively in $T_n$
time slot. Therefore, the following algorithm has been proposed for the bandwidth request inside the ONU.<br>

**Algorithm for the scheduler inside the ONU**

1. capture the allocated time slot from the OLT ($ONU_{i}^{prt}$)<br>
2. start sending packet till the end of the allocated time slot<br>
3. capture the current queue length for the three priority queues: $Q_{length} = \sum_{j=1}^{3} Q_{j}^{length}$<br>
4. connect to the BBN model<br>
5. if the probability of being bursty for three priority queues is FALSE, $ONU_{i}^{req} = Q_{length}$ and go to 8<br>
6. otherwise: Estimate the prediction queue length for three priority queues: $Q_{E_{i}}^{length} = \sum_{j=1}^{3} K_{j}$<br>
7. $ONU_{i}^{req} = Q_{total,i}^{length} + Q_{E_{i}}^{length}$<br>
8. send the $ONU_{i}^{req}$ to the OLT and go to 1

**VI. INITIAL IMPLEMENTATIONS**

In order to show how the proposed burst detection model differentiates the bursty input traffic from the normal traffic pattern, we have developed two network domains. The first domain is the data domain including a sample EPON scenario which was implemented from the scratch based on the IEEE 802.3ah standards and protocols, Fig. 4. The second domain is the decision domain, which is developed based on the BBNs approach and computes the probability of the burst given information on the characteristic of the input traffic and buffer behaviour, Fig. 2. The required information for each BBN node is captured from the EPON data domain during the simulation. The OPNET Modeler [2] and HUGIN Lite [1] were the tools which are used to conduct initial simulation experiments for the data domain and decision domain, respectively.

**A. Data Domain Implementation**

In our implementation phase the top-level scheduler, which is placed at the OLT, is responsible for the time slot allocation between 16 ONU nodes near the customer premises. The allocation of the time slot is done by using the DBA algorithm in which the length of the allocated time slot by the OLT to each ONU varies from cycle to cycle. The actual need of the ONU, which is captured from the ONU’s latest REPORT messages, will affect the time slot allocation length over different cycles. The allocated time slot from the OLT will be distributed by the low-level scheduler inside the ONU between queues. Table I indicates the parameters of the EPON simulation scenario, used in the data domain.

<table>
<thead>
<tr>
<th>TABLE I: THE EPON SIMULATION PARAMETERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of ONUs: 16</td>
</tr>
<tr>
<td>Splitter – ONU’s and OLT-ONU distance: 5 km, 20 km</td>
</tr>
<tr>
<td>Packet size, Traffic type: Exponential (1024 byte), Burst</td>
</tr>
<tr>
<td>Packet Interarrival time: Exponential (1.0)</td>
</tr>
<tr>
<td>ON and OFF time for bursty sources: Exponential (90.0), (10.0)</td>
</tr>
<tr>
<td>Number of sub-nets and buffer per ONU: 3, 3</td>
</tr>
<tr>
<td>Supported service classes, Buffer size: 3 (EF, AF and BE), 8 Mb</td>
</tr>
<tr>
<td>Uplink fibre, Max bandwidth per ONU: 1 Gbps, 65 Mbps</td>
</tr>
<tr>
<td>Cycle Time, Guard time: 2ms, 1 μs</td>
</tr>
</tbody>
</table>

In our implementation we assumed 16 ONUs each supporting three classes of services. Each ONU is connected to three sub-nets and has a buffer capacity of 8 Mb per priority queue. We ran the EPON simulation 20 times for one hour with a seed of 128 and 100 values per statistic.

**B. Decision Domain Implementation**

The decision domain specifies the relation between the input traffic and a set of bursty indicators including the buffer behaviours and characteristics, Fig. 2. The Conditional Probability Tables (CPTs) are needed to specify a probability distribution based on the network at each node. These tables can
be specified in any forms: implicitly by some parametric probability distribution, or explicitly as tables [7]. In our implementation, the decision model (burst detection model) is implemented manually by considering all the parameters which can indicate the bursty traffic from normal traffic pattern. We also need to indicate the CPT of the packet_drop, queueing_delay, queue_length, traffic_out and traffic_in given the variable Burst. The entries of each CPT can either be assessed from the domain expert knowledge or estimated from historical data or combinations of both. Table II indicates the variables defined for each node in BBN burst detection model.

### Table II : Parameters for each node in BBN model

<table>
<thead>
<tr>
<th>BBN Node</th>
<th>State</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burst</td>
<td>[True, False]</td>
</tr>
<tr>
<td>Packet Drop</td>
<td>[very_low, low, medium, high, very_high]</td>
</tr>
<tr>
<td>Queuing Delay</td>
<td>[very_low, low, medium, high, very_high]</td>
</tr>
<tr>
<td>Queue Length</td>
<td>[very_low, low, medium, high, very_high]</td>
</tr>
<tr>
<td>Traffic Out</td>
<td>[very_low, low, medium, high, very_high]</td>
</tr>
<tr>
<td>Traffic In</td>
<td>[very_low, low, medium, high, very_high]</td>
</tr>
</tbody>
</table>

In order to distinguish between the bursty traffic and normal traffic, parameters such as packet_drop, queueing_delay, queue_length, traffic_out and traffic_in have been collected from a sample ONU in EPON scenario (data domain) and then discretised into five levels of very_low, low, medium, high and very_high. There are 5^5 possible conditions for all five indicator nodes {packet_drop, queueing_delay, queue_length, traffic_out, traffic_in} in BBN model which form the rule table for the decision domain. Table III reveals a group of compositions in which the BBN model acknowledges the input traffic flow as Burst where VL=very_low, L=low, M=medium, H=high and VH=very_high. For instance when the packet_drop is either high or very_high the BBN model acknowledges the current traffic flow as Burst regardless of the state of the other nodes (row 1). Moreover, when the traffic_out is either low or very_low and traffic_in is either high or very_high in spite of the condition of the other nodes, the current traffic flow will be acknowledged as Burst (row 2), etc. The CPT which shows the strength of the relationship between probabilities of traffic being burst (either True or False) and the state of each node should also be calculated.

### Table III : The rule table for burst detection model

<table>
<thead>
<tr>
<th>#</th>
<th>Packet Drop</th>
<th>Queueing Delay</th>
<th>Queue Length</th>
<th>Traffic Out</th>
<th>Traffic In</th>
<th>Burst?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>... H or VH</td>
<td>... ... ... ...</td>
<td>... L or VL</td>
<td>H or VH</td>
<td>... True</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>... ... ... H or VH</td>
<td>... ... ...</td>
<td>... ...</td>
<td>... ... ...</td>
<td>... True</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>... ... ... H or VH</td>
<td>... ... ...</td>
<td>... ...</td>
<td>... ... ...</td>
<td>... True</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>... ... ... H or VH</td>
<td>... ... ...</td>
<td>... ...</td>
<td>... ... ...</td>
<td>... True</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>... ... ... ... ... ...</td>
<td>... ... ...</td>
<td>... ...</td>
<td>... ... ...</td>
<td>... True</td>
<td></td>
</tr>
</tbody>
</table>

### VII. Conclusion and Work in Progress

The EPON has been considered as one of the promising candidates for the next generation wired access networks for quite some time to provide inexpensive, high-speed and high-capacity services. The bandwidth request and allocation are the critical issues in EPON which need to be addressed efficiently in order to provide the ETE QoS for different service classes. In this paper, we have proposed a novel approach for the burst detection inside the ONU priority queues using the Bayesian Belief Networks (BBNs) theory to improve the bandwidth request in a typical EPON environment. The initial experiments reveal that the proposed scheme can estimate the bursty nature of the input traffic. The decision, which is made by the BBN model, can be used in cooperation by the low-level scheduler inside the ONU by requesting more bandwidth from the OLT in advance in order to improve the QoS metrics such as queue length and queuing delay. Our future work will further explore the use of the decision made by the BBN in cooperation with the bandwidth request algorithm in an EPON scenario.

### Acknowledgment

The authors would like to acknowledge the support of University of Ulster for providing VCRS scholarship and IU-ATC for funding the joint work with BT.

### References

2. OPNET Modeler 16.0, available at: www.opnet.com