Optimal Backhaul Resource Management in Wireless-Optical Converged Networks

Ioannis Loumiotis(✉), Evgenia Adamopoulou, Konstantinos Demestichas, and Michael Theologou

National Technical University of Athens, Athens, Greece
i_loumiotis@cn.ntua.gr

Abstract. The introduction of the new 4G technologies promises to satisfy the increasing demands of the end-users for bandwidth consuming applications. However, the high data rates provided by 4G networks at the air interface raise the need for more efficient management of the backhaul resources. In the current work, the authors study the problem of the efficient management of the backhaul resources at the side of the base station. Specifically, a novel scheme is proposed that, initially, predicts the forthcoming demand using artificial neural networks and, then, based on the prediction results, it proactively requests the commitment of the appropriate resources using linear optimisation techniques. The experimental results show that the proposed scheme can efficiently and cost-effectively manage the backhaul resources, outperforming the traditional flat commitment approaches.

Keywords: Resource management · Backhaul network · Artificial neural networks

1 Introduction

During the last few years there has been a tremendous growth of bandwidth consuming mobile applications [1], resulting in an increasing demand for higher data rates at the access network. The introduction of the new 4G technologies promises to address this demand by offering increased capacity and extremely high data rates to the end-users. Towards this direction, the integration of the wireless access network with a passive optical network (PON) at the backhaul has been proposed. The high capacity of the PON can satisfy the increasing demand at the access network and provide Quality of Service (QoS) to the end-users. However, there are open issues in the proposed convergence regarding the allocation of the backhaul resources to the base stations (BSs).

Traditionally, network planning has been performed statically and it has been based on empirical methods, which led to a fixed, flat commitment of the resources. Though this method yielded satisfactory results in the previous communication standards, it cannot be implemented within a converged optical-wireless network, especially if the PON belongs to a different operator. As a result, the necessary resources should be calculated and committed dynamically to each BS.

R. Giaffreda et al. (Eds.): IoT360 2014, Part II, LNICST 151, pp. 254–261, 2015.
DOI: 10.1007/978-3-319-19743-2_36

The problem of backhaul resource management has been widely studied in the literature. However, the majority of these works, e.g. [2], investigate on the backhaul resource allocation problem only at the air interface and they cannot be implemented within a converged network. There are only a few studies in the literature that consider the resource allocation problem in a converged network architecture. In [3], the authors propose a resource allocation mechanism for a converged network infrastructure that improves the QoS performance, based on the forecasting of near future packet arrivals.

In the current work, the authors propose a novel algorithm for the optimal management of the backhaul resources that can provide QoS to the subscribers, while minimising the operational expenditure (OpEx) of the mobile operator (MO). The proposed scheme can be used in conjunction with software defined solutions in order to provide the appropriate resources to a Software-Defined network controller as proposed in [4]. Specifically, the algorithm consists of two phases. In the first phase, the BS predicts the forthcoming demand based on the collected historical data, using artificial neural networks (ANNs), and in the second phase, it requests the commitment of the appropriate information rates (IRs) from the PON operator. Specifically, in the second phase, a linear programming problem is formulated, based on the prediction results, that allows the BS to minimise the leasing cost (OpEx), while guaranteeing the QoS provisioning to its customers. Finally, for the validation of the proposed scheme, the authors use real data collected by fully operational BSs.

2 Backhaul Resource Management

The deployment and the configuration of the backhaul network is an issue that concerns only the MO. However, the Next Generation Mobile Networks (NGMN) Alliance has defined a set of high-level backhaul requirements in order to support the requirements of 4G networks and beyond. According to the NGMN Alliance, the backhaul network should provide a peak information rate (PIR) and a committed (average) information rate (CIR) in a flexible and granular way. Specifically, it is recommended that the CIR and PIR should be configurable in increments of 2 Mbps between rates of 2–30 Mbps, 10 Mbps between rates of 30–100 Mbps and 100 Mbps for rates beyond 100 Mbps, offering a “pay as you grow” model [5].

On the other hand, the PON itself provides the necessary mechanism for dynamic bandwidth allocation (DBA). In the downstream direction, it is the responsibility of the optical line terminal (OLT) to provide QoS-aware traffic management based on the respective service specifications and the dynamic traffic conditions. On the other hand, for the upstream direction, each queue in the optical network unit (ONU) can be provided with three different information rates; a fixed information rate (FIR), an assured information rate (AIR) and a maximum information rate (MIR). The part of the bandwidth above the AIR may be either non-assured or best-effort with the latter experiencing the lowest priority. It is noted that according to the G.984.3 standard, the sum of the FIR and the AIR should be typically equal to the CIR, while the MIR should not be higher than the PIR of the BS [6].

Therefore, in the context of an optical-wireless converged infrastructure, the BS should request the commitment of the appropriate IRs by the PON operator. These IRs can be variable with respect to time based on the BS's needs, and should be defined in a formal agreement between the two parties, called service level agreement (SLA). In the rest of the paper, it is considered that the BS requests for a FIR, an AIR and a non-assured IR in order to satisfy its subscribers' demands.

3 Intelligent Base Station

The efficient management of the backhaul resources requires BSs with enhanced processing capabilities. In the current approach, the authors consider the deployment of appropriate agents that offer to the BSs the necessary intelligence, as it can be seen in Fig. 1. Specifically, these intelligent agents are located at the side of the BSs and should be enhanced with processing capabilities that allow them to monitor, store and process the traffic demand statistics. Based on the collected data, the intelligent agents should be able to learn the traffic pattern and predict the forthcoming demand. To this end, the agents employ ANN schemes that can accurately predict the network traffic. The accurate prediction will allow the intelligent agent to proactively request the appropriate resources from the PON operator, exploiting the DBA mechanism described above and ensuring the QoS provisioning to its customers in an efficient and cost-effective way.

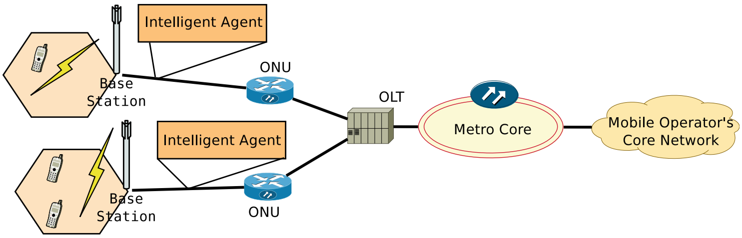

Fig. 1. Proposed network architecture.

4 Measurements and Traffic Characteristics

A key feature for the accurate prediction of network traffic is the identification of its inherent characteristics. There are many works in the literature which argue that network traffic has non-linear characteristics, and as a result, traditional methods of linear regression analysis cannot be efficiently implemented [7]. In order to identify the special characteristics of the traffic pattern, the authors use a set of 2464 data[1] collected by a fully operational BS located in the centre of Athens, capital of Greece. The collected data are hourly averaged measurements and refer to a period of 4 months. The BS provides High Speed Packet Access+ (HSPA+) connectivity and serves an area of 9 cells, providing 42 Mbps for the downlink case and 5.8 Mbps for the uplink case at each cell site. It is noted that a traditional resource allocation scheme would require the flat commitment of the resources by the MO, i.e. a bandwidth of 378 Mbps for the downlink case and 52.2 Mbps for the uplink case.

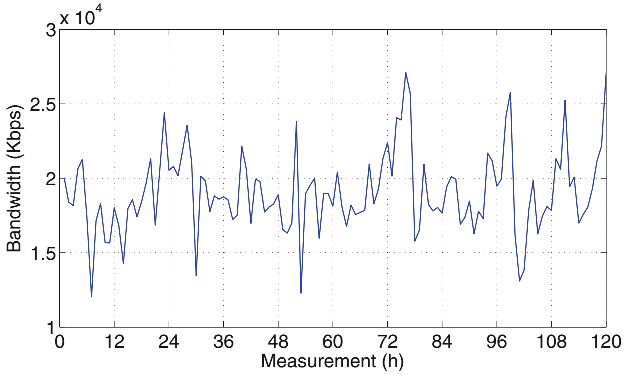

Fig. 2. Downlink traffic demand.

It is expected that the traffic pattern of the BS will experience certain periodicities due to the habitual behaviour of the users. As can be seen in Fig. 2, the traffic pattern experiences a peak during the rush hours in the morning and in the evening, while the demand is reduced during the night. As a result, the set of inputs for the ANN consists mainly of the day and time in which the measurements were collected and the output is the hourly-based averaged bandwidth demand. Assuming that $\mathbf{x}$ is a vector variable that denotes the input of the ANN and y is a scalar variable that denotes the output of the ANN, i.e. the estimated bandwidth, it holds that

$$\mathbf{x} = (day, month, date, hour, event) \tag{1}$$

where *day* is the specific day of the measurement (e.g. Monday), *month* is the month of the collected measurement, *date* is the sequence number of the day (e.g. 25), *hour* is the hour of the day and *event* is a binary variable that designates a holiday, which can potentially have an influence on the prediction process.

[1] The collected data are the aggregated demand experienced by the BS and correspond to a mixture of services requested by the subscribers.

5 Proposed Algorithm

The proposed algorithm consist of two phases. In the first phase the agent uses an ANN in order to predict the forthcoming demand and in the second phase, based on the prediction results, it calculates the appropriate IRs and requests their commitment from the PON operator.

5.1 Prediction Phase

It can be easily understood that the efficiency of the proposed scheme depends on the accuracy of the prediction results. For the implementation of the prediction process, the authors evaluate several ANNs and they compare their performance with the traditional linear regression model. In particular, a multilayer perceptron (MLP) neural network [8], a general regression neural network (GRNN) [9], and a group method for data handling (GMDH) neural network [10] have been used. The optimal parameters for the MLP neural network were calculated by constructing multiple networks, which were evaluated using 4-fold cross validation, while for the case of the GRNN the conjugate gradient algorithm was used. For the case of the GMDH neural network a 64th order polynomial was constructed.

In order to evaluate the performance of the prediction model, the authors used the first 2392 data. Specifically, the 10-fold cross validation technique is employed, whilst the mean absolute percentage error (MAPE) is used to compare the performance of the different models. The results are depicted in Table 1.

Table 1. Results of the validation process.

Prediction method	Downlink MAPE	Uplink MAPE
MLP	12.034	20.354
GMDH	11.561	18.786
GRNN	10.422	15.229
Linear regression	13.1068	20.793

It can be easily seen that the GRNN outperforms the other types of ANNs providing a MAPE of 10.42 % for the downlink case and 15.22 % for the uplink case. Based on these results, and the capability of GRNN networks to handle sparse data in real-time environments [9], it can be concluded that they constitute an ideal choice for the implementation of the prediction process.

Furthermore, it should be noted that the uplink traffic experiences a higher MAPE than the downlink traffic for all the above models. Hence, it becomes apparent that the uplink traffic is more difficult to be accurately predicted. This inefficiency lies in the fact that the subscribers of the BS contribute mainly to the downlink traffic, averaging the aggregated demand, and thus, the throughput experiences less variability [11]. On the other hand, only a few users have a notable contribution to the uplink traffic (the average uplink traffic is 1.5 Mbps), which experiences significant variations that constitute its prediction more challenging.

5.2 Resource Request Phase

In the resource request phase of the algorithm, the intelligent agent performs a prediction about the forthcoming demand using a GRNN and based on the derived results, it requests the appropriate resources that are consistent with the specifications of the NGMN Alliance [5].

For the validation of the second phase of the algorithm, the GRNN is trained using the first 2392 data, and then it predicts the demand for a period of three days (72 h) over new unseen data. The results of the prediction process are shown in Fig. 3.

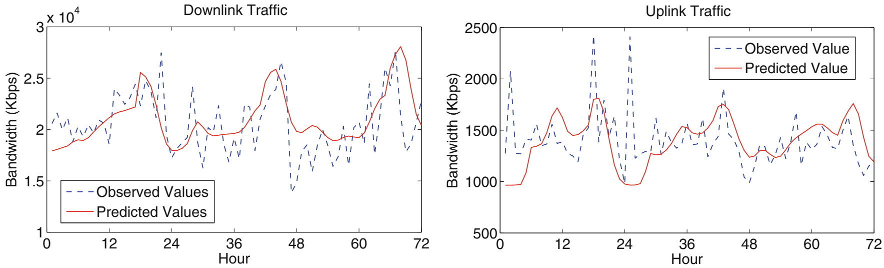

Fig. 3. Prediction of downlink and the uplink bandwidth.

Based on the prediction results, the BS should calculate the appropriate IRs and request their commitment from the PON operator. Undoubtedly, in order for the BS to guarantee the QoS provisioning to its subscribers, it should overdimension the estimated traffic demand by requesting a high percentage of the prediction results. Assume that I^F, $\mathbf{I}^A$, $\mathbf{I}^{NA}$ denote the FIR, AIR and non-assured IR that are requested by the BS. It is noted that according to the recommendation, the FIR is constant, and thus, I^F is a scalar variable, while $\mathbf{I}^A$ and $\mathbf{I}^{NA}$ are vector variables with 72 elements that correspond to every hour within the predicted period $\mathcal{T}$ (3 days). Furthermore, each IR requested by the BS has a different leasing cost for the MO. Let C_F, C_A and C_{NA} denote the leasing cost per capacity metric for the case of FIR, AIR and non-assured IR, respectively. It is expected that a FIR would be more expensive than the AIR, while the non assured IR should be the least expensive. Thus, it holds that $C_F > C_A > C_{NA}$.

As mentioned above, I^F, $\mathbf{I}^A$ and $\mathbf{I}^{NA}$ should be based on the prediction results of the first phase of the proposed algorithm. Specifically, certain percentages of the prediction results are considered essential in order for the BS to provide QoS to its subscribers. Let δ_1, δ_2 and δ_3 denote the QoS parameters that specify the threshold values of the necessary resources as a proportion of the prediction results. Thus, the intelligent agent should calculate the proper IRs in order to provide an enhanced QoS to the BS's subscribers in a cost efficient way.

The problem of the backhaul resources management is now formed as a linear optimisation problem:

$$\begin{array}{ll}
\underset{I^F, I^A, I^{NA}}{\text{minimize}} & I^F C_F + \sum_{i \in \mathcal{T}} I_i^A C_A + \sum_{i \in \mathcal{T}} I_i^{NA} C_{NA} \\
\text{subject to} & \\
\text{(C.1)} & I^F \geq \delta_1 \min y \\
\text{(C.2)} & I^F + I_j^A \geq \delta_2 y_j, \ j \in \mathcal{T} \\
\text{(C.3)} & I^F + I_j^A + I_j^{NA} \geq \delta_3 y_j, \ j \in \mathcal{T}
\end{array}$$

where y_i, $i \in \mathcal{T}$, denotes the result of the prediction process. Constraint (C.1) implies that the requested FIR is at least equal to a percentage δ_1 of the minimum predicted value, while constraint (C.2) denotes that the summation of FIR and AIR, which corresponds to the guaranteed IR should be at least equal to a certain percentage δ_2 of the predicted value. Similarly, constraint (C.3) express that the summation of the IRs, which corresponds to the MIR, should be at least equal to a certain percentage δ_3 of the predicted value. The problem described above is a simple optimisation problem which can be easily solved using traditional linear programming techniques (i.e. simplex method).

One key feature in the optimisation problem is the selection of the quality parameters. If the parameters are high, then there will be an overdimensioning of the resources, ensuring the QoS to the end-users at the expense of a high leasing cost. Hence, there is a tradeoff between QoS provisioning and cost-efficiency.

It should be noted that there is not a single optimal choice for the quality parameters. Each BS should select the appropriate values of δ_1, δ_2 and δ_3 based on its own needs. For instance, an urban BS, which serves many subscribers with high demands, should prefer to overdimension the available resources in order to guarantee the QoS provisioning.

The results of the proposed scheme for a choice of $\delta_1 = 0.6$, $\delta_2 = 1$ and $\delta_3 = 1.4$ and leasing costs $C_F = 80$, $C_A = 70$ and $C_{NA} = 50$ are depicted in Fig. 4. From this figure, it becomes apparent that the proposed algorithm can satisfy the requested demand, providing an efficient and cost-effective way for the management of the backhaul resources.

According to the above results, the accurate prediction of the forthcoming demand improves the utilisation of the resources. In contrast to the proposed scheme, a traditional allocation method of the backhaul resources would require the flat commitment of 378 Mbps for the downlink case and 52.2 Mbps for the uplink case, so as to satisfy a worst case scenario, constituting, thus, the bandwidth allocation process in next generation mobile networks highly inefficient.

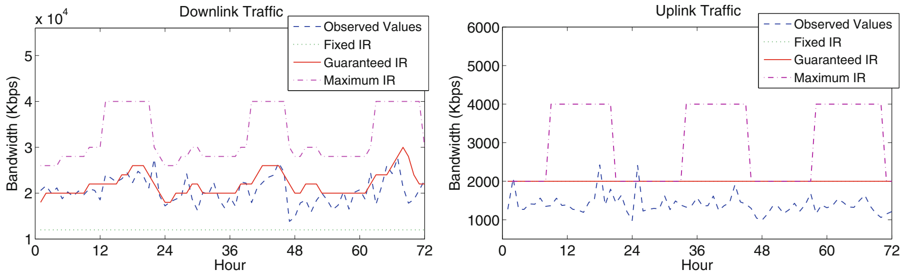

Fig. 4. Requested IRs by the BS.

6 Conclusion

In the current paper, the problem of backhaul resource management in a wireless-optical converged network is studied. The authors exploit the DBA mechanism offered by the PON and propose a scheme that allows the efficient and cost effective management of the backhaul resources. Specifically, intelligent agents at the side of the BSs are used to predict the forthcoming demand using the historical traffic data, and based on the prediction results, they request the commitment of the necessary IRs from the PON. The experimental results show the appropriateness of the GRNN for the prediction process and the efficiency of the proposed scheme.

References

1. Cisco: Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2013–2018. White paper (2014)
2. Yi, S., Lei, M.: Backhaul resource allocation in LTE-Advanced relaying systems. In: Wireless Communications and Networking Conference, pp. 1207–1211 (2012)
3. Ranaweera, C., Wong, E., Lim, C., Nirmalathas, A., Jayasundara, C.: An efficient resource allocation mechanism for LTE-GEPON converged networks. J. Netw. Syst. Manage. **22**(3), 437–461 (2014)
4. Riggio, R., Gomez, K., Goratti, L., Fedrizzi, R., Rasheed, T.: V-Cell: going beyond the cell abstraction in 5G mobile networks. In: IEEE Network Operations and Management Symposium, pp. 1–5 (2014)
5. NGMN: Optimised Backhaul Requirements. White paper (2008)
6. ITU-T G.984.3: Gigabit-capable Passive Optical Networks (G-PON): Transmission convergence layer specification. Recommendation (2008)
7. Zhang, P.: Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing **50**, 159–175 (2003)
8. Mitchell, T.: Machine Learning. McGraw-Hill, Maidenhead (1997)
9. Specht, D.: A general regression neural network. IEEE Trans. Neural Netw. **2**(6), 568–576 (1991)
10. Farlow, S.: The GMDH algorithm of ivakhnenko. Am. Stat. **35**(4), 210–215 (1981)
11. NGMN: Guidelines for LTE Backhaul Traffic Estimation. White paper (2011)