Dynamic backhaul resource allocation in wireless networks using artificial neural networks

I. Loumiotis, T. Stamatiadi, E. Adamopoulou, K. Demestichas and E. Sykas

The increasing bandwidth demand of end-users renders the need for efficient resource management more compelling in next generation wireless networks. In the present work, a novel scheme incorporating the deployment of an intelligent agent capable of monitoring, storing, and predicting the forthcoming needs for resources of a base station (BS) is proposed. In this way, the BS can in advance commit the necessary resources for its backhaul connection, guaranteeing the end-user's quality of service. The prediction process is performed using machine learning techniques.

Introduction: The mobile communications landscape is characterised by the continuous growth of new services, the provision of which poses the need for higher data rates to guarantee the quality of experience for the end-users. The advent of fourth-generation (4G) networks [1] promises to encounter this demand by offering increased capacity, high data rates, seamless mobility and robust reconfiguration abilities. However, these can only be achieved through the convergence of the wireless network with a wired optical network (xPON) [2]. Furthermore, the trend towards self organisation [3] in communication networks introduces the need of base stations (BSs) with enhanced processing capabilities in contrast to the traditional scheme of a central authority responsible for the functionality of the entire network. Such intelligent BSs will continuously monitor their environment and adapt their behaviour when needed, providing robustness against failure.

The main concern of network operators in order to provide quality of service is the proper allocation of resources at the BS. Traditionally, the planning of the network was made by a person and it was based on empirical methods which led to a flat commitment of the resources. However, such an approach is prohibited in self-organised networks. Thus, models based on prediction schemes have been proposed. In [4], the authors used ARIMA models for the prediction of network traffic. A wavelet multiresolution analysis was presented in [5]. Artificial neural networks have been used only by few approaches in the literature [6]. In the current Letter, the authors propose a dynamic scheme for resource management in the backhaul connections of 4G networks. The proposed scheme consists of an intelligent agent located at the BS that will be able to monitor its environment and predict the forthcoming resources' demands using machine learning techniques [7]. Subsequently, the BS is able to commit in advance the calculated resources for the backhaul network guaranteeing appropriate quality of service and experience for the end-users. In this framework, the resource allocation decision is taken in a distributed manner, thus complying with the self-organisation principle of next generation wireless networks.

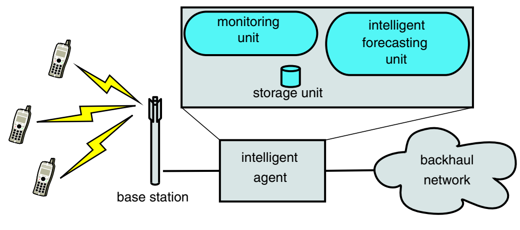

Fig. 1 *Intelligent agent scheme*

Intelligent agent: The intelligent agent proposed in this Letter is located at the side of the BS and is able to monitor its environment, store and process data that enable it to properly manage the corresponding backhaul network resources. Specifically, the agent monitors the aggregated demand of the BS at discrete time intervals, and based on the collected historical data, makes predictions for the forthcoming demand. Consequently, the agent may request the commitment of the necessary backhaul resources in advance, improving the perceived service quality of the end-users.

A graphical representation of the proposed scheme is depicted in Fig. 1. The intelligent agent located at the BS observes the traffic load and properly stores traffic statistics needed for the training process of an artificial neural network. After the training process is completed, the agent performs a prediction concerning the forthcoming demand of a period T_p, and requests the necessary backhaul resources from the backhaul network.

Furthermore, through continuous monitoring, the agent ensures that the committed resources suffice to provide proper service quality to the end-users. In case the agent observes that the committed resources are not consistent with the true traffic load of the BS, then it dynamically adapts its behaviour and requests more resources for a short-term period T_{st} (adapted short-term prediction).

Forecasting model: As explained above, the main challenge of the proposed intelligent agent is the prediction of the forthcoming resources' demand in a real-time environment. Specifically, the intelligent agent should be able to process large amounts of sparse data for the learning process within a short period of time. To cover these requirements, a general regression neural network (GRNN) algorithm has been implemented. GRNN is a one-pass neural network used for estimation of continuous variables. Its fast learning ability and the convergence to the optimal regression surface are its main advantages, and thus it has been widely used for forecasting purposes. In brief, assuming that the input data consist of pairs of ($\mathbf{x}$, y), where $\mathbf{x}$ is a vector random variable and y a scalar random variable, the resulting estimation is given by

$$\widehat{Y}(\mathbf{X}) = \frac{\sum_{i=1}^{n} Y^i exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} exp\left(-\frac{-D_i^2}{2\sigma^2}\right)} \tag{1}$$

$$D_i^2 = (\mathbf{X} - \mathbf{X}^i)^T(\mathbf{X} - \mathbf{X}^i) \tag{2}$$

where $\mathbf{X}$ is a particular measured value of the random variable $\mathbf{x}$, n is the number of sample observations, $\mathbf{X}^i$ and Y^i are sample values of the random variables $\mathbf{x}$ and y, and σ is the smoothing parameter. Further information about the algorithm can be found in [8].

The output $\widehat{Y}(\mathbf{X})$, given by (1) can be interpreted as a weighted average of the observed values Y^i, where each Y^i is weighted exponentially according to its Euclidean distance from $\mathbf{X}$.

One challenging issue is the choice of the smoothing parameter σ. If σ is made large then the estimated density is smooth and in the limiting case becomes a multivariate Gaussian. On the other hand, if σ is made small, then the estimated density has non-Gaussian shapes, but at the risk that distant points may have a great effect on the estimate.

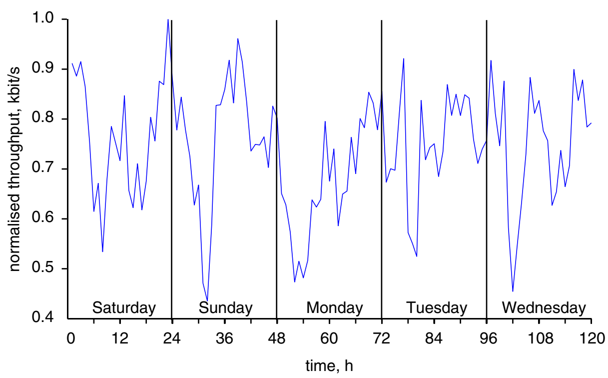

Fig. 2 *Traffic load pattern*

Measurements: For the training process of the GRNN, the authors used a set of real input and output data collected by a major mobile network operator in Greece. The collected data refer to a period of approximately four months and they consist of hourly-based averaged measurements. The data refer to the traffic load of a BS in the centre of Athens, Greece, supporting high speed packet access (HSPA) connectivity. Due to the periodicity exhibited by the traffic load pattern, the input data of the neural network should be time-associated. For instance, as can be seen in Fig. 2, a high load demand occurs during the rush hour both in the morning and in the evening. Also, the traffic pattern during the weekend differs from that of a typical working day. As a

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result, the set of inputs for the neural network consist mainly of the day and time in which the measurements were collected and the output is the hourly-based averaged bandwidth demand. Furthermore, special days (holidays, other special events) that may affect the load demand were also taken into consideration for the training process.

Specifically, the input variable **x** is defined as

$$\mathbf{x} = (day, month, hour, date, special\ event) \tag{3}$$

where *day* is the name of the day (e.g. Monday), *month* is the name of the month, *hour* is the time of the hour of the day, *date* is the sequence number of the day of the month (e.g. 25) and *special event* is used to designate any special occasion concerning the day.

Experimental results: To demonstrate the appropriateness of the general regression neural network, the authors compared the result of the validation process of the GRNN ($\sigma = 0.14$) with two other types of neural networks, namely a simple three-layered perceptron network [7] and a group method of data handling (GMDH) polynomial neural network [9]. Specifically, the designed three-layered perceptron network is a 5-3-1 feedforward network, while the polynomial neural network employing a quadratic function was used with two variables. The input data in the training process for all of the three neural networks were the same as described above. For the scoring process of the neural networks, a random 15% of the input data were retained, and after the training process, these data were used to calculate the validation error of the model (mean absolute percentage error (MAPE)). The comparison results of the validation process are depicted in Table 1. It is clear that the GRNN network outperforms both the three-layered perceptron network, and the GMDH polynomial neural network, making it highly suitable for traffic load prediction. Furthermore, the effect of the smoothing factor σ of the GRNN to the MAPE is depicted in Fig. 3. It can be observed that for values of σ in the range of $0.05 < \sigma < 0.4$, the GRNN network always provides better results than the other two types of neural networks.

Table 1: Results of validation process

Neural network	MAPE
3-layered NN	12.2777
GMDH	10.5629
GRNN	9.6573

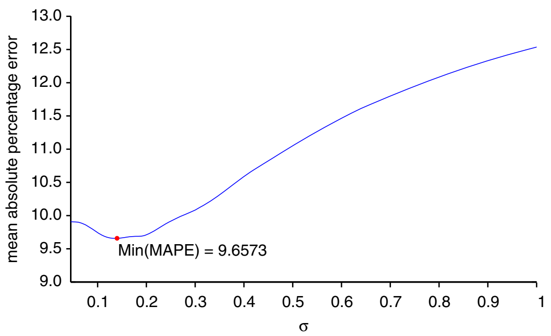

Fig. 3 *Mean absolute square error for GRNN with respect to σ values*

Conclusion: In the current Letter, a dynamic backhaul resource management scheme for next-generation wireless networks is proposed. According to this scheme, an intelligent agent located at the BS monitors its environment and stores traffic-related data. In conjunction with context parameters (e.g. time) these data then serve as the basis for estimating the forthcoming resources' needs and for requesting *a priori* their commitment from the backhaul network. To validate the proposed prediction process, an artificial neural network was designed and implemented, based on the GRNN algorithm. The validity of the proposed scheme was studied and a σ analysis of the GRNN algorithm is presented. Results show that backhaul resource requirements can effectively be predicted through the proposed method with an average error of below 10%. A comparison with alternative prediction methods was also carried out.

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One or more of the Figures in this Letter are available in colour online.

I. Loumiotis, T. Stamatiadi, E. Adamopoulou, K. Demestichas and E. Sykas (*Institute of Communication and Computer Systems, National Technical Univerity of Athens, Greece, GR15780*)

E-mail: i_loumiotis@cn.ntua.gr

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