Traffic estimation in high-speed communication networks using fuzzy systems

E. Magaña Lizarrondo
Dpt Automática y Computación
Universidad Pública de Navarra
Campus de Arrosadía
31006 – PAMPLONA (SPAIN)
eduardo.magana@unavarra.es

J. Villadangos Alonso
Dpt Automática y Computación
Universidad Pública de Navarra
Campus de Arrosadía
31006 – PAMPLONA (SPAIN)
jesusv@unavarra.es

J. J. Astrain Escola
Dpt Matemática e Informática
Universidad Pública de Navarra
Campus de Arrosadía
31006 – PAMPLONA (SPAIN)
josej.astrain@unavarra.es

Abstract

We present a practical application of fuzzy systems in communication networks. In this case a fuzzy relational model is developed to estimate the bytes transferred every time unit over a communication link. Such estimation is useful to provide an algorithm to dynamically reserve resources in order to guaranty the quality of service of the communications. In order to evaluate the fuzzy estimator we apply the information about the whole IP packets received at the router of the Public University of Navarra along two months. The estimator predicts the load of the communication link 1, 2, 4 and 6 hours before. The results show that the estimator can be used to dynamically assign bandwidth for communication services.

Keywords: traffic estimation and forecasting, fuzzy relational model

1 Introduction

Nowadays, the Internet access and backbone are suffering a continuous upgrade process in order to provide users with higher bit rates. An access router serves as the internetworking unit between the access subnetwork and the Internet backbone, providing address translation functions and others such as policing and accounting functions in order to shape user traffic to the access link. In fact, due to the increase in network bandwidth at both access and backbone network the access link bandwidth is the most valuable resource, with strong impact in the ISP benefits.

Usually, an operator is responsible of such access link or, being the operator an ISP itself. Service providers establish a flat rate scheme for billing access bandwidth. Namely, regardless of the traffic volume the ISP will be charged for a fixed amount of bandwidth with no time of day variation. Such fixed amount of bandwidth is normally approximated with the aid of network measurements. Since Internet traffic shows an extreme burstiness a constant bandwidth allocation is clearly inefficient. On the other hand, even if a constant bandwidth allocation scheme is adopted it turns out that in most cases the absolute value of such constant bandwidth is determined with heuristics, that treat to maximize statistical multiplexing gain while providing a good quality of service to the end users and are normally based on ISP experience.

Due to the strong input traffic variability, which complicates matters for off-line link dimensioning, dynamic bandwidth allocation schemes seem better suited to optimize bandwidth usage at the access link. Such dynamic bandwidth allocation schemes can be classified as pro-active or reactive. Both schemes are complementary since the performance of reactive schemes, such as for instance the ATM Available Bit Rate service class, is highly independent on the input traffic burstiness and propagation delay in the link. A pro-active scheme, which adapts the network resources to a traffic prediction may serve to the purpose of reducing uncertainty to the bandwidth allocator, which anticipates resource usage before the actual traffic is produced.

There are several proposals that applies fuzzy logic to handle different problems in communication networks: call admission control [1], traffic policing [2] and parameter estimation [3, 4].

In this work, based on the proposal of the fuzzy relational model [5], we build a traffic estimator to predict the load of the communication link that connects the Public University of Navarra with the Spanish Internet service provider for the research community (RedIris). The main goal of the system is to predict as accurate as possible the load of the communication network. The results show that the estimator provides an accurate prediction of the average consumed bandwidth several hours ahead. Moreover, the system provides a better prediction for lower time horizons (predictions for the next 1 and 2 hours).

Following, in section 2 we describe the fuzzy relational model that we use to build the traffic estimator. In section 3 we provide the results obtained when applied the estimator to predict the communication link load 1, 2, 4 and 6 hours ahead. Conclusions and references end the paper.

2 Fuzzy relational models

This section proposes fuzzy relational structures as a basis for fuzzy predictive models. The problem of conversions between the numerical quantities provided and required by the model and the fuzzy quantities processed by the structure are addressed. Conceptually, a dynamic relational model has three blocks [5]: A numeric/linguistic or input interface, which transforms the input information into a linguistic format (i.e. fuzzy sets). A linguistic processing block where the linguistic relationships between input and output fuzzy sets are captures. A linguistic/numeric or output interface, which converts the output linguistic information produced by the processing block back to numerical data.

2.1 I/O interface

Fuzzy discretization provides the same basic framework for construction of both input and output interfaces. Both interfaces are based on a class of n referential fuzzy sets providing a linguistic description for the numerical I/O variables. In this sense, the problem of an interface design is to reduce the problem of selection n referential fuzzy sets and n itself.

In this paper, the I/O interface consider as input variables the hour of the day (HourDay) defined by 24 linguistic terms, the day of the week (WeekDay) defined by 7 linguistic terms and past values of bytes per hour or link load (Bph) defined by 8 linguistic terms. These properties are defined considering triangular membership functions, which are tuned with a training process based on the backpropagation algorithm.

2.2 Linguistic processing block

Modelling dynamic systems can be described as a non-linear static mapping between input and output spaces. The dynamic is then brought into the model externally using tapped delay lines. In this paper, we consider the numeric feedback (NF) topology [5]. In the NF configuration the numeric prediction is fed back into the N/L interface and then into the relational structure. This topology allows considering different number of linguistic terms at model output and input [5].

The representation of the linguistic processing block model can be expressed by

$$\begin{aligned} Y(k+p) &= U(k) \circ U(k+1) \circ . \circ U(k+q-1) \circ Y(k) \circ \\ &\quad Y(k+1) \circ ... \circ Y(k+p-1) \circ R, \text{ i.e.} \\ Y(k+p) &= U(k) \circ U(k+1) \circ ... \circ U(k+q-1) \circ . \circ \\ &\quad L(N(Y(k))) \circ ... \circ L(N(Y(k+p-1))) \circ R, \end{aligned} \quad (1)$$

Where q and p are integers referring to the model order, Y(k) and U(k) are the linguistic representations of numeric output and control of the model at the k sampling time instant (y(k) and u(k) respectively). Thus, $Y(k) \in [0, 1]^m$ (i.e. $Y(k) = [Y_1(k) \dots Y_2(k) \dots Y_m(k)]$) and $U(k) \in [0, 1]^n$. The fuzzy relation *R* deals with the dynamics of the fuzzy model and is defined as follows:

$R : U \times \dots \times U \times Y \dots Y \to [0, 1]$, where the symbol x represents the Cartesian product of fuzzy sets, and o in (1) denotes max-τ composition, τ being a triangular norm. The operators *L* and *N* denote the mapping realized by the N/L and L/N interfaces, respectively, being defined as follows:

$L : B \to [0, 1]^m$ and $N : [0, 1]^n \to A$, with both A and B compact sets in *R*.

The fuzzy relation (1) represented in a distributed way forming a relational network structure where each weight is an element of the tensor representing *R*. In this structure the weights are computed through a parametric and supervised learning scheme, where the minimization criteria was to minimize the mean square error.

3 Experimental scenario

In this work we present the results to estimate a traffic trace from the Public University of Navarra. The data consists on the captured IP packets that arrive to the router of the Public University of Navarra during 2 months. It was possible by using the IPmiser monitoring tool developed at the same University. From the captured trace we evaluate the load of the communication link in intervals of one hour for each hour and day of the week along two months. The collected data corresponding to the first month are used to identify off-line the parameters of the system (membership functions of the I/O interfaces and the rules of the fuzzy estimator). The rest of the data are used to validate the system.

The measured link load is showed in Figure 1, that is the objective to be predicted. We present the results for the fuzzy estimator in different figures due the resulting confusing view if we plot altogether.

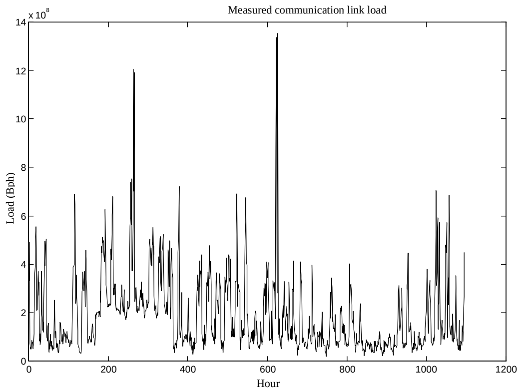

Figure 1 : Measured link load

Next figures 2-5 show the prediction realized by the fuzzy estimator for 1, 2 4 and 6 hours ahead. These figures show that the prediction with an anticipation of 1, 2 and 4 hours is very similar to the objective. It is showed that in all cases the average load along the time is similar and that the traffic peaks are present at the same instant. Only the case of the prediction with a time horizon of 6 hours presents a clear difference with the objective.

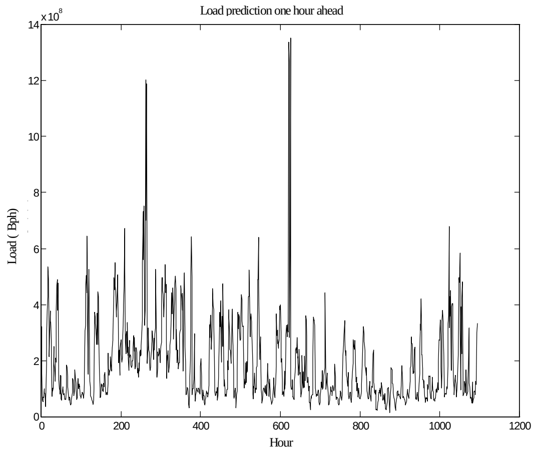

Figure 2 : Prediction one step ahead

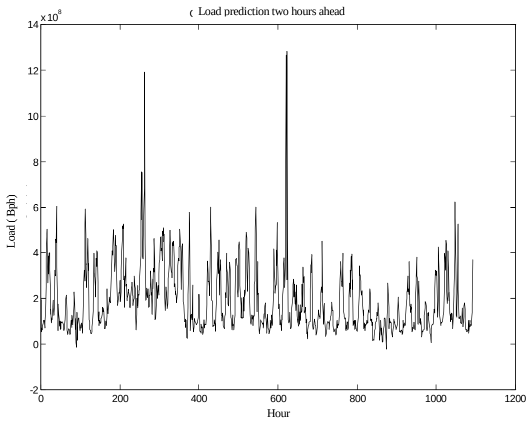

Figure 3 : Prediction two steps ahead

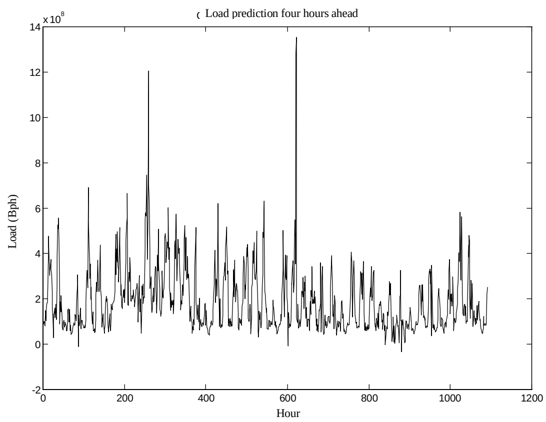

Figure 4 : Prediction four steps ahead

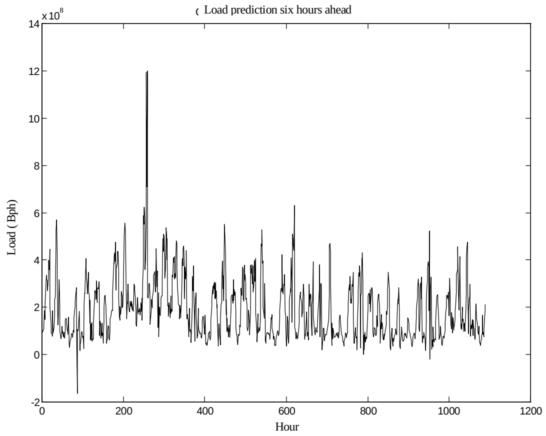

Figure 5 : Prediction six steps ahead

In order to provide a more precise view of the performance we present a zoom of the measured and predicted link load. In figure 6 and 7 we present the measured and the predicted communication link load, respectively. These figures show that the fuzzy estimator developed follows the objective and has a very similar behaviour to the real load. That is, by using the developed estimator a service provider can evaluate accurately and one hour before the required bandwidth necessary to provide service for its users.

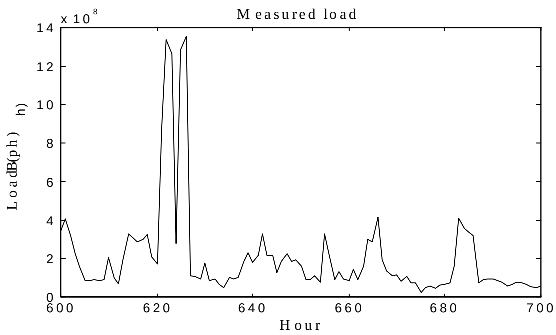

Figure 6 : Zoom of the measured link load

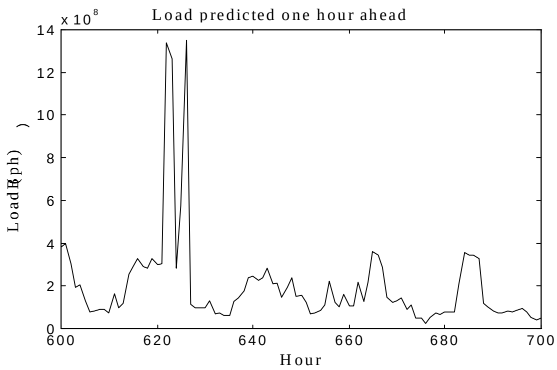

Figure 7 : Zoom of the predicted load

Conclusions

In this paper we have developed a fuzzy relational estimator to predict the communication link load with different time horizons. The estimator has been evaluated with real traffic from the ATM link of the Public University of Navarra. The evaluation shows that the estimator can predict with an anticipation of several hours the average load to be consumed by the whole users of the university community. Then, the estimator can be an element to be used to dynamically establish and negotiate the parameters of the communication. For example, to reserve the necessary bandwidth to satisfy users demands for the next hour.

References

[1] K. Uehara, K. Hirota; *Fuzzy Connection Admission Control for ATM Networks based on Possibility Distribution of Cell Loss Ratio*. IEEE JSAC v. 15, n. 2, 1997

[2] A. Pitsillides, Y.A. Sekecioglu, G. Rammurthy; *Effective Control of Traffic Flow in ATM networks using Fuzzy Explicit Rate Marking (FERM)*. IEEE JSAC v. 15, n. 2, 1997

[3] H.R. Mehvar, T. Le-Ngoc; *Fuzzy Logic in Estimation of Traffic Burstiness for Admission Control in Broadband Networks*. Proc ICC’97, June 1997

[4] P.K. Dash, A.C. Liew, S. Rahman; *Peak Load Forecasting using a Fuzzy Neural Network*. Electric Power Systems Research, 32, 1995

[5] J. Valente de Oliveira, J.M. Lemos; *Long-range predictive adaptive fuzzy relational control*. Fuzzy Sets and Systems, 70, 1995.