Adaptive Model for Network Resources Prediction in Modern Internet Service Providers

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***Abstract*—Nowadays, Internet became a crucial tool for service delivery, enhancing network requirements. In this new scenario, through Internet Service Providers (ISPs) tend to evolve to Modern Internet Service Providers (MISPs), addressing situations such as elastic network resource demand that may cause problems of slowness, service interruption and constant disconnections. A promising approach to deal with elastic services is the usage of a network traffic prediction model, but traditional models do have all the necessary features to it. Within this context, this paper presents an adaptive network prediction model for MISPs that adjusts seasonality and trend and removes time series error cycles according to the behavior observed in network traffic. The results, using a real bandwidth data set, suggest that the proposed model improves the existing prediction models.**

***Index Terms*—Modern Internet Service Providers, Elastic Demand, Prediction Model.**

I. Introduction

Recently, the Internet arose as the main way for modern computational services (for example, content sharing, intelligent systems, task automation and others), becoming a crucial entity in our modern lives. Most of these services are based on Internet Access Service (IAS) through an Internet Service Provider (ISP). Thus, ISPs expanded their service delivery, giving different wired and wireless alternatives to access Internet for their clients, such as residences, companies, universities, etc [1].

Regardless the type of access network, all of them need to address key features: low delay, flexibility, resilience, compatible Capital Expenditure (CAPEX) and Operational Expenditure (OPEX). These features influence the Quality of Service (QoS) and Quality of Experience (QoE) of the final users [2].

This new scenario creates the idea of Modern Internet Service Providers (MISPs), that need to evolve the resource management, network flexibility and the behavior customization of the network infrastructures. One promising approach for MISPs is the deployment of network slices, i.e., the splitting of network resources into logical isolated network on the top of the network infrastructure. Each network slice can have the most suitable configuration to better meet the client's requirements [1].

In the same way, an important point for MISPs to keep the quality of IAS is the elastic demand for network resources throughout the day, which occurs because of the human mobility within cities [3]. In this scenario, MISPs need to expand or to shrink the bandwidth allocation dynamically (elastic behavior), allowing a suitable on demand IAS. This behavior, when not treated properly, may cause problems of slowness, service interruption and constant disconnections, resulting in the frustrate users and break in requirements of Service Level Agreement (SLA) [4].

A promising approach to deal with elastic services is the usage of a network traffic prediction model [5]. Network traffic prediction model allows the understanding of the network behavior, through previous observations of network resource usage (history), and to predict future values of network demand, enabling the application of proactive tasks to avoid the previous mentioned problems and to plan the network infrastructure.

Traditional approaches do not model the time series to minimize the low amplitudes of regular cycles, using only automatic reductions based on the moving average of the own prediction models. In this way, these traditional prediction models lack from adaptability to follow the changes in the behavior of the observations, since they originally do not perform adjustment in the seasonality and do not remove possible error cycles [6]. This fact difficulties the usage of this existing models in MISPs to address the elastic demand situation due to the variability of the clients behavior during time (whether during the day, week or month). Therefore, the MISPs need a solution to perform an adaptive prediction.

Within this context, this paper presents an adaptive network prediction model, called *ANP*, to allow suitable network resource allocation and an strategic planning of the network infrastructure. The proposed adaptive model adjusts the seasonality and remove error cycles in the time series, through Auto-Regressive Integrated Moving Average (ARIMA) and Neural Network Auto-Regressive (NNAR) techniques, according to the observed network traffic behavior. We varied the structure of the training series from 24 (1 cycle) to 1440 (3 cycles) samples, representing 1 and 3 days of observation, respectively. As consequence, the redundancy and the variation of the cross-validation methods, as well as the adjustment in low low amplitudes of regular cycles, were crucial to minimize the error rate.

Experiments were performed using a real bandwidth demand dataset of the State University of Ceara (UECE - Brazil). This dataset has the average bandwidth utilization to

TABLE I
RELATED WORK

Reference	Context	Strategy	Focus
Bayati et al. [5]	High Speed Networks	Timescales using GPR	Multiple-step-ahead Traffic Prediction
Hou et al. [2]	Tactical Internet	Neyman-Pearson method	Bandwidth reservation
Ruan et al. [7]	Optical-Wireless Networks	Predictive Bw Allocation	Minimization of Upstream Delay
Wang et al. [8]	SDN	ARIMA and ARCH	DoS Mitigation
Yoo et al. [9]	SNMP based Networks	ARIMA and STL	Resource Utilization and Scheduling
Aldhyani et al. [10]	Generic Networks	Soft Clustering and Time Series	Network Traffic Forecasting
Katris et al. [11]	Generic Networks	FARIMA and GARCH with neural networks	Video Traffic prediction
Harstead et al. [12]	Fixed Access Networks	Statistical Techniques for Quantification	Network infrastructure planning
Our proposal	MISP	Adaptive model	Elastic Resource Demand Prediction

Internet of every hour of the first six months of 2019. The results indicate that the proposed adaptive prediction model minimizes the error rate of predicted values, reaching 30% of improvement when compared to existing network prediction models (such as reference [9]).

The remainder of this paper is organized as follows: Section II presents the existing related work. Section III introduces the proposed adaptive prediction model, while Section IV describes the results of the experiments performed. Finally, Section V concludes the paper and presents future work.

II. RELATED WORK

This section describes key related work about resource demand and prediction strategies for computer networks. Table I summarizes these existing work in the literature, highlighting the differences to our proposal, where the *Context* column presents the environment where the related work acts, while the *Approach* and *Goal* columns inform the strategy applied and the goal of the paper, respectively.

Bayati et al. [5] proposed an algorithm, for high-speed networks, to model different timescales using Gaussian process regression (GPR), addressing the error propagation in the multiple-step-ahead traffic prediction. The prediction at a timescale is made using the data of that timescale as well as the prediction results at larger timescales. However, this algorithm does not consider an adaptive approach to deal with the elastic resource demand behavior.

Hou et al. [2] apply Neyman-Pearson method to classify the arrival process of each user, designing burstiness aware bandwidth reservation for Tactile Internet scenarios. The authors differentiates the users in high and low traffic states and then optimize reserved bandwidth to meet latency and reliability requirements. Nevertheless, the approach applied by the users considers only the packet arrival according to the burst behavior, limiting its applicability in MISPs.

Ruan et al. [7] present a machine learning approach to predict bandwidth demand over heterogeneous optical-wireless networks in Tactical Internet, called MLP-DBA. The MLP-DBA focus on the minimization upstream delay requirements through predictive bandwidth allocation according to the status of each optical network unit. However, the application of the MLP-DBA in MISPs is compromised by its restriction to optical-wireless networks information.

Wang et al. [8] propose BWManager, which mitigates the Denial-of-Service (DoS) attacks in the controller of SDN networks. Basically, the BWManager forecasts the bandwidth consumption of users to determine the users trust values and the priority queues for protection. The forecasting engine predicts bandwidth utilization for each user based on historical data of the switches byte counter, analyzing difference at two time points through ARIMA and AutoRegressive Conditional Heteroskedasticity (ARCH) techniques.

Yoo et al. [9] developed a model to forecast expected bandwidth utilization on high-bandwidth wide area networks, aiming to improve the efficiency of resource utilization and scheduling of large-scale scientific data movements. The forecast model is based on Seasonal Decomposition of Time Series by Loess (STL) and ARIMA on Simple Network Management Protocol (SNMP) path utilization data. The developed model works specifically with SNMP protocol data, i.e., it is limited to SNMP based network. This fact compromises the application of the developed model in MISPs.

Aldhyani et al. [10] propose a forecasting model that combines time series models with soft clustering approaches (such as Fuzzy C-Means - FCM and Rough K-Means - RKM) to enable bandwidth allocation and congestion control. This integrated model avoids the nonlinear and volatile data to affect the choices performed by the forecasting models. However, this integrated model does not perform an adaptive approach to address the elastic resource demand requirements.

Katris et al. [11] implemented time series models to video traffic as part of three dynamic bandwidth allocation schemes. The authors attempt to improve the accuracy of video traffic predictions by using Fractionally integrated AutoRegressive Integrated Moving Average (FARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) with neural networks. The traffic forecasts applies a nonlinearity selection method to be combined with the model. The usage of the implemented forecasting model is specific to video traffic, since it considers buffering and utilization rate information. From this fact, the its application in MISP context is limited.

Harstead et al. [12] describe a model that forecasts bandwidth demands of aggregated subscribers on residential fixed access networks. The model allows network operators to dimension their networks and make the correct investments for the future. The authors used statistical techniques to quantify the number of concurrent video streams, the shifting mix of standard definition, high definition, and ultra high definition resolutions, multicast gain, and the trend from multicast to unicast delivery of these streams.

To the best of our knowledge, no paper in the literature focused on the design of an adaptive bandwidth prediction model for elastic demand in MISPs, which is the focus of this paper. Our proposal performs several task to enhance the prediction process: data processing, seasonal adjustment, errors cycles removal, trend analysis, residual checking and amortization of irregular cycles. All these additional tasks create a standardized sample model that evolves the prediction process of the existing techniques, reducing the computational time to create the models as well as their accuracy.

III. Proposal

This section describes the proposed adaptive network prediction model (ANP). The ANP model aims to adjust the data regarding bandwidth usage to elastic demand scenarios, allowing a better performance of the existing prediction techniques. These techniques deal with seasonality and trend issues, but usually they do not attain suitable correction factors, failing to predict the data behavior properly, specially in elastic demand situations.

The ANP model performs the following tasks sequentially: (1) Data decomposition; (2) stationarity test; and (3) cycles removal. After being preprocessed by the ANP model, data may be processed a chosen prediction technique.

In the fist step, the ANP model receives, analyzes, and adaptively adjusts the original bandwidth usage data. The original data—without adjustments—is partially shown in Figure 1.

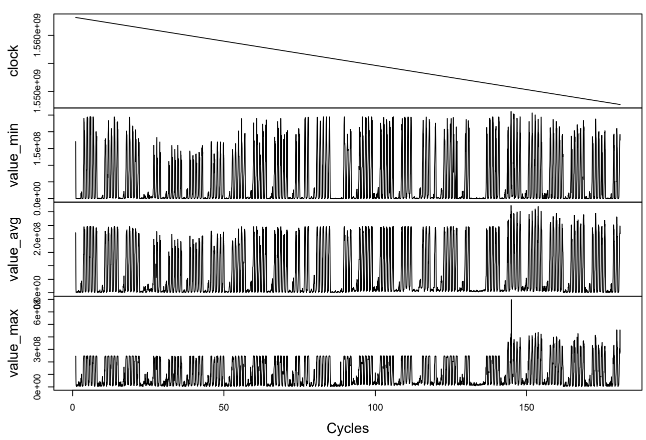

Fig. 1. Original data of Bandwidth usage: clock, minimum, mean and maximum.

The following subsections detail each task performed by the ANP model: Data decomposition (Subsection III-A), stationarity test (Subsection III-B), and cycles removal (Subsection III-C). Section III-D presents the role of the prediction techniques, as well as their interaction with the proposed ANP model.

A. Data Decomposition

The data decomposition task aims to decompose the time series Z_t, with $t \in \{1, \ldots, N\}$, into its seasonality (S_t), trend (R_t), and cycle error (a_t, with zero mean and constant variance) additive components:

$$Z_t = S_t + R_t + a_t \,.$$

Seasonality in a time series reflects the oscillations occurring in specific regular intervals of the year, month, week, or day. The *trend* highlights the long term behavior of a time series, i.e., the incremental, decremental, or stable behavior of the time series as well as the frequency of these changes. *Cycles* are characterized by the oscillations of up and down of the time series. The periodically occurrence is called regular cycle component, while irregular fluctuations can be treated as irrelgular variations. Figure 2 illustrates an example of *seasonality* and *trend* in temporal series of the bandwidth usage from the data shown in Figure 1.

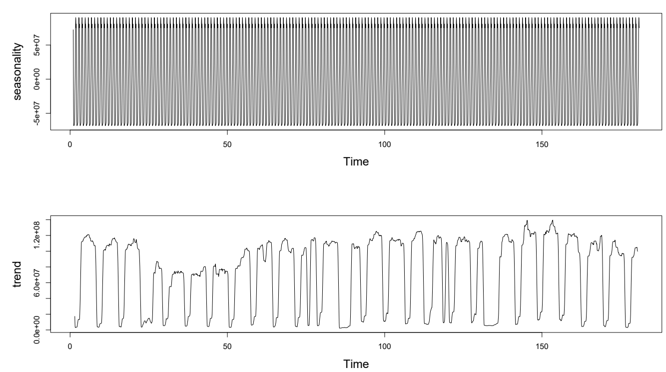

Fig. 2. (a) Original *Seasonality* Data; (b) Original *Trend* Data.

After the identification of these three data features, it is possible to find the *error* component, i.e., information not encompassed by *seasonality* and *trend*. These *errors* are found through the determination of a trend component using a moving mean approach. Next, the seasonal value is calculated by the mean in each time unit and through all periods, centralizing the seasonal component. Finally, when the *Seasonality* and *Trend* are removed from the original data, it possible to identify the *Erros*. From this knowledge (*Seasonality*, *Trend*, *Cycles* and *Errors*) the proposed ANP model goes to next task of *Stationarity Test*.

B. Stationarity Test

The *Stationarity Test* aims to check the long time behavior of the time series of the data. This behavior may be exponential or regular [13]. In specific cases, the time series may or may not be stationary, implying a change of the slope level in short or long periods. This fact affects directly the prediction capability of certain prediction techniques [14].

The *Stationarity Test* used in the ANP model is based on Kwiatkowski-Phillips-Schmidt-Shin (KPSS) [15], which checks the stationary hypothesis for the data. The test assumes that the time series of the bandwidth (X_i, for $i = 1, 2, \ldots, n$) may be represented as the sum of the deterministic trend (T_i), a random walk (W_i), and the stationary error (E_i), according to Equation 1.

$$X_i = T_i + W_i + E_i \,. \tag{1}$$

The random walk, by its turn, follows Equation 2:

$$W_k = W_{k-1} + U_k \,, \tag{2}$$

where U_k is a collection of Independent and Identically Distributed (IID) random variables with zero mean and variance σ^2.

From these determinations, the stationary hypothesis is $\sigma^2 = 0$, since it is assumed that E_k is stationary about the null hypothesis that X_i has stationary tend. Therefore, the result of KPSS revels the stationary factor of the time series in all cycles of the set, not rejecting the null hypothesis[16].

In order to increase the reliability of the model and the standardization of the samples, the proposed stationarity test is applied in the training set, accepting the stationarity hypothesis and evaluating the presence of the unit square as null. This evidence is obtained when the hypothesis test values of the time series are lower than 0.383, which is considered critical for a confidence level of joint confirmation [15]. After the stationary evidence, it is possible to remove the cycle errors that disturb the prediction ability.

C. Removal of Cycle Errors

In regular days, the bandwidth demand average reaches higher values than irregular days (weekend, holiday, events, etc.), due to the characteristics of bandwidth usage in elastic demand situations. In this type of situation, the prediction techniques may not distinguish the low amplitude signals in cycles of irregular days.

These low amplitude cycles interfere with the analysis of trend and seasonality. Thus, an efficient prediction approach should remove these error cycles. In the proposed ANP model, a moving mean based technique is applied in order to remove the samples related to low amplitude cycles (considered as errors). However, the application of this approach is not enough to remove all the errors in the time series.

Additionally, the proposed model executes a seasonal and trend decomposition using *Loess* [17] to estimate the relation between nonlinear variables (missing values), removing the existing outliers. The change in the time series configuration after the ANP (without low amplitude cycles) in front of the original time series of the data is shown in Figure 3.

Figure 3(a) illustrates the original time series (without adjustments). From the data in Figure 3(b), it is possible to observe the effect of the low amplitude cycles remotion (cycle errors) in the time series. In Figure 3(c), the time series appears almost without cycle errors when submitted to the removal of cycle errors task. Finally, from the data presented in Figure

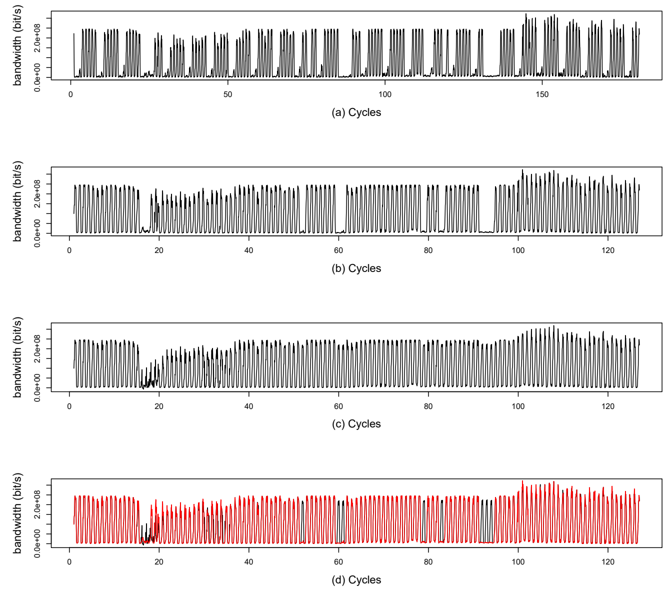

Fig. 3. Evolution of the irregular cycles correction.

3(d), one may notice that the removal of cycle errors fills the gaps of the original time series. Once the low amplitude cycles were removed, the ANP model can continue to analyze the data that has been decomposed.

Once the decomposition was completed, an adaptive model shall relate non-observed components (atypical or fortuitous facts) with the samples that will be created for by the prediction model are constant and regular. This adaptive model was chosen due to its capacity to identify that the seasonality and the trend fluctuates (do not vary according to the level of the time series). Otherwise, a multiplicative model could be applied. This process is represented in Equation 3, where L_t is the data at time t, with $t \in \{1, \ldots, T\}$, S_t is the seasonal component, R_t is the trend, and N_t is the random noise with zero mean and constant variance. Figures 4(a) and 4(b) show the seasonality and trend, respectively, of the adjusted data (without the error cycles).

$$L_t = S_t + R_t + N_t \,. \tag{3}$$

D. Prediction Techniques

In general, prediction techniques estimate future steps based on past samples. These techniques try to follow the seasonality and trend, but they have limitations in their ability to correctly deal with the time series when it does not have well define patterns. Examples of popular prediction techniques are Autoregressive Integrated Moving Average (ARIMA) [18] and Neural Network Auto-Regressive (NNAR) [19].

ARIMA is a classic model of statistics that deals with seasonality in the model $(p, d, q)(P, D, Q)$ (the lowercase letters refers to non seasonal operators and the uppercase letters the seasonal variables), where p is the autoregressive

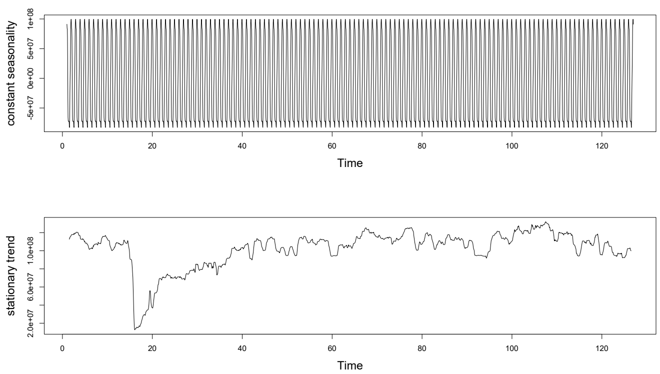

Fig. 4. Seasonality and Trend in the adjusted time series.

part, d is the differentiation degrees and q is the moving mean order. As for NNAR (p, P, K), it is a prediction model based on mathematical models for the brain, allowing nonlinear relations between the answer variables and its predictors. NNAR works similarly to ARIMA, but it does not considers linear relations.

IV. Results

This section presents the results obtained from the analysis of the experiments performed using a real dataset. The dataset used described the bandwidth usage (traffic volume) of the central backbone of the State University of Ceará (UECE). The data was collected through real time network monitoring during six months, providing minimum, maximum and mean values calculated every 60 minutes. A period of 24 hours defines a cycle, so, all the dataset is composed by 4320 cycles.

The technique Time Series Cross-Validation (TSCV) was applied due to the dependency of the time series [19]. In both prediction techniques (ARIMA and NNAR), it was used TSCV to model the samples in order to input them for prediction (i.e., the next 24 hours of bandwidth usage). Through the *HoldOut* method, the subsets of *Training* (used to create the model) and *Test* (utilized for validation) were selected since the high amount of data. Thus, we applied first 72 samples as training set, second 144 samples for the training and so on $(72, 144, 216, \dots)$.

The proposed ANP model is used as previous step to the application of the prediction technique. Thus, in order to measure the benefits of the ANP in the modeling and prediction capacity of the existing techniques (ARIMA and NNAR), we compared the performance of these prediction techniques with and without the application of ANP model.

The metric used to evaluate the performance of the proposal in a period T is the Root mean squared error (RMSE), which follows Equation 4, where $\hat{y}_t$ is the predicted value and y_t is the real values of bandwidth usage in time t.

$$\mathrm{RMSE}(T) = \frac{1}{\sqrt{T}} \left(\sum_{t=1}^{T} (\hat{y}_t - y_t)^2 \right)^{\frac{1}{2}}. \tag{4}$$

Figure 5 presents the results of RMSE for the prediction of 1 cycle using the proposed ANP model and the existing prediction techniques (ARIMA and NNAR) isolated (without the ANP model). Similarly, Figure 6 illustrates the behavior of the predictions performed by the ANP model for determined cycles.

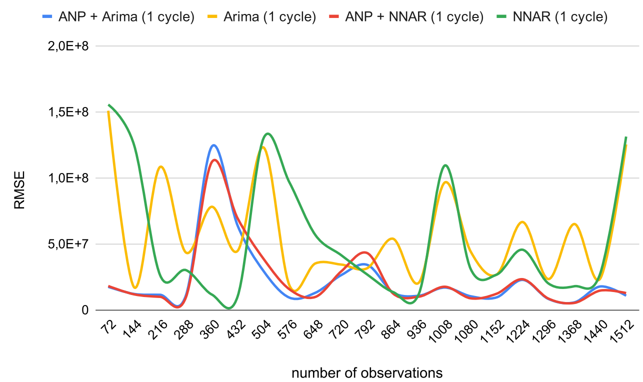

Fig. 5. Prediction Errors (RMSE) with and without the ANP model.

According to Figure 5, ARIMA and NNAR reach high values of RSME in several moments, representing the impact of the elastic demand situation in the prediction capacity of both techniques. On the other hand, when ARIMA and NNAR techniques are applied together with the proposed ANP model (represented as "ANP+ARIMA" and "ANP+NNAR", respectively), the performance of both techniques increase (lower prediction errors), reaching similar values. The highest RSME values (in samples 360 and 432) are effect of the not enough corrections due to big fluctuations in the time from 16 to 19 (illustrate in Figure 3). In this way, it is possible to conclude that the proposed ANP model is flexible and independent of the prediction technique applied, allowing the evolution of these techniques in front of the elastic demand situation.

As can be seen in Figure 6, the ANP model can accompany the samples of the time series of the dataset, following the seasonality and amplitude fluctuations, giving the importance of the samples variation (with approximately 2, 4, 6 and 8 weeks).

Moreover, the ANP model reduced the computational processing for the training phase (parameters estimation) in around 85% using ARIMA and 12% applying NNAR. This situation occurs because the ANP model removes the low importance variables during the removal of cycle errors. This fact indicates that the ANP model is capable to reduce the processing time for the prediction techniques, enabling its application in real time prediction scenarios.

V. Conclusion

The Internet became a crucial tool to network service delivery. The ISPs tend to evolve to MISPs, in order to deal with situations that can affect the QoS of service delivery. One

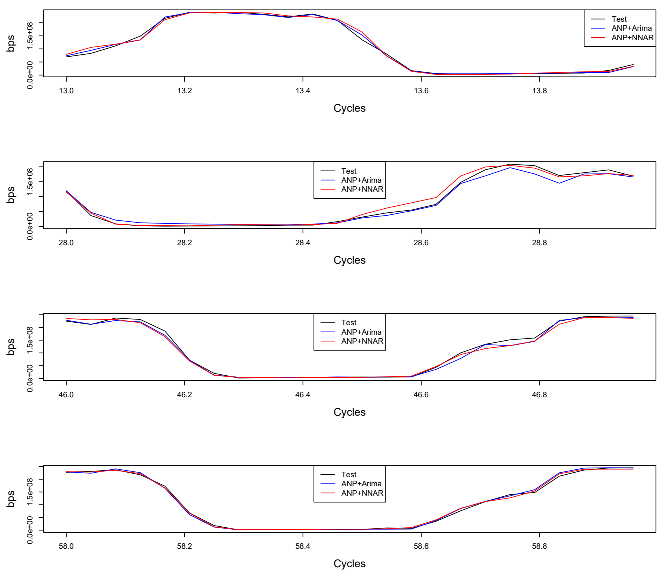

Fig. 6. Relation between real and predicted values.

of these situations that commonly happen in the cities is the elastic demand of network resources, that can cause problems of slowness, interruption and constant disconnections.

In this paper, we presented an adaptive network prediction model (ANP) to improve the existing prediction techniques, turning them in a efficient approach to overcome situations of elastic demand of network resources. The proposed model adapts the utilization of distinct means of bandwidth for cycles intervals. Additionally, the proposed ANP performs a sequence of adjustments to reach suitable values of generalization.

The experiments performed, based on a dataset of real traffic behavior, show that the application of the proposed model together with a prediction technique evolved the prediction capacity of these techniques when compared to isolated case (only the prediction technique, i.e., without the ANP model). The usage of ANP model reduces, around 30%, the RMSE error rate. Moreover, the results of RMSE demonstrates a proximity between the existing prediction techniques. This fact does not occurs when these techniques are applied isolated, indicating the flexibility of the ANP model and its independence regarding the prediction technique used.

As future work, we pretend to extend the prediction approach, including issues related to independent variables, which can generate a higher capacity of knowledge about the elastic demand behavior.

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