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Real-Time Prediction of RTT Based on Holt-Winters Method for Internet-Based Teleoperation

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Abstract – *The teleoperation of complex systems became possible and cheaper by the adoption of Internet network as a communication channel. This induces specific problems due to the constraints of communications such as round trip time delay (RTT), bandwidth limitation, channel congestion, availability and transmitted information losses or errors. All these parameters are attributes of the Quality of Service (QoS) offered by the communication network. Predicting the RTT plays a major role in the dynamic enhancements for many applications such as telemedicine or mobile telerobotics.*
So the ideal approach concerning this important parameter in internet must be strictly studied. This paper proposes to use the Holt-Winters method to explore real-time predicting of RTT. This technique is largely used for the analysis and treatment of time series data. Real measurements of the RTT were taken between 4 geographically distant nodes. The obtained results confirm the efficiency and precision of the proposed method. ***Copyright © 2015 Praise Worthy Prize S.r.l. - All rights reserved.***

Keywords*: Quality of Service (QoS), Round Trip Time (RTT), Prediction, Holt-Winters Method, Teleoperation*

Nomenclature

b_t	Secular trend
h	The horizon of the time series
L_t	Cyclical variation
t	Measurement period (or frequency)
S_t	Seasonal variation
s	Number of samples
SSD	Sum of squared difference
x_t	Observer value of the series X_t
X_t	Random variable representing the time series
α	Smoothing parameter of the level
β	Smoothing parameter of the trend
γ	Smoothing parameter of the seasonality

I. Introduction

Internet is a communication support without QoS. When used as data link for the remote control of robotic structures, we are confronted to a various difficulties that could reduce the performance of the remote task [1], [2] such as system unavailability, imprecision and instability.

The major problem in this case is the RTT. It is mainly due to two causes: one is the long distance between the two sites (master site and slave site) and the other is due to network congestion. For tasks that require very fast response, studies have found that the performance of the human operator begins to decrease if the RTT exceeds 180 milliseconds [3].

Knowing that it is impossible to reduce this delay, a widely used solution is to make a real time prediction of the RTT then to consider the predicted value in the remote control model of teleoperated system.

II. Related Work

The communication delay parameter estimation has attracted the attention of the scientific community [4]-[9].

Many researchers have found that knowing the delay in advance in internet based control systems could be useful: J.W. Park *et al.* [10] explore the characteristics of the data transmission and propose a data transmission model for their teleoperation system. H.Y. Li *et al.* [11] use the autoregressive (AR) method to predict the time induced by the network. X.

Tu [12] had presented a method to predict the internet based delay on the data waveform as well as the impartial grey model transformation method (UGM) to demonstrate that this method has a higher predictive precision than the AR method. There are also researchers who used the methods of prediction based on the machine learning algorithm and the artificial neuron networks (ANN) which are the most representative of machine learning methods: M. Yang *et al.* [13] adopt the prediction of internet delay. S. Ganjefar *et al.* [14] and K.T. Chong *et al.* [15] use the multi-layer perceptron (MLP) networks which help to measure time data by searching the prediction of the RTT. S. Belhaj *et al.* [16] propose an approach based on the artificial neuron enhancement.

This approach helps to model and predict the RTT from a long distance using recurrent neuron networks (RNN). S. Hanlin *et al.* [17] present a neuron network based on the theory of chaos. This work is based on a large number of probing data sets; the model of chaos could be used to predict the jitter in which the neuron network is used for learning the evolution of chaos system. However, artificial neural networks require an extensive training and the convergence of the training process is uncertain. Moreover, network architectures are difficult to choose.

Other researchers proposed various methods to predict the RTT. Y. Yang *et al.* [18] propose a sparse matrix based on kernel regression (SMKR). The use of this method to predict the RTT can result in more accurate prediction than the use of the method sparse multivariate linear regressive (SMLR) [19].

P. Calyam *et al.,* and Z. Bo *et al.* [20], [21] use the model of autoregressive integrated moving average (ARIMA) which is the mostly used method nowadays for the modelling of the temporal chaotic series.

S. Yantai et al. [22], C. Chen et al. [23] have shown that the ARIMA model could be used to predict the internet traffic. However, the traditional ARIMA model is not adapted to predict the delay due to the instability and non linearity of internet delay [24].

This paper suggests a new approach for real-time prediction of “end-to-end” delay based on Holt-Winters method [25]. A time measure of the RTT between four nodes was made. These involved the University of Sciences and Technology of Oran web site (USTO - Algeria), the University of Brest web site (UoB - France), the University of Mohamed Khider - Biskra web site (UMKB - Algeria) and Ahwaz Newnet Internet Service Provider of Iran (ANISP-Iran).

These measures were next stored in a data base in order to analyze them and predict the next RTT. The process of measurement occurs every 2 seconds.

Fig. 1 shows the proposed architecture of our real-time prediction system.

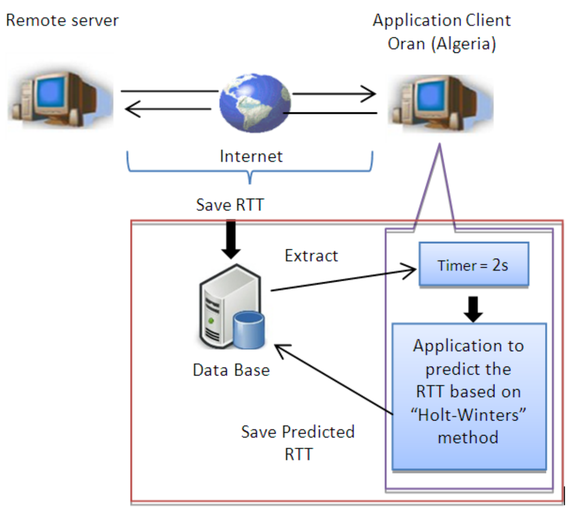

Fig. 1. The architecture of the teleoperation system

This paper is organized as follows: in section III, we emphasize on the “end-to-end” delay problems in internet. The collection of data and their pre-treatment are described in section IV. The Holt-Winters method is presented in Section V. In Sections VI and VII, we present the procedures for initializing smoothing parameters and the adopted prediction equations. Section VIII is devoted to the experimental validation and discussion of results.

Finally, conclusions and perspectives are presented in section IX.

III. The “End-to-End” Delay on Internet

Today, internet is a gigantic network. The transmission process is dynamic with congestion phenomena that vary depending on the time of the day. Since transmission through such a network does not provide QoS, IP packets can be erroneous, duplicated, delayed, altered, un-sequenced, presented at random order, or they do not reach their destination. In fact, IP protocol neither provides a reliable connectionless service nor a warranty datagram delivery. Moreover, the quality of service offered by IP is called "best effort"; that is to say, the network is best to route packets. In other words, no warranty on the transmission delay “end-to-end” is available [26].

The “end-to-end” time delay on Internet varies randomly. Indeed, the total delay experienced by an IP packet is the sum of several delays introduced by each intermediate node traversed from the sender to the recipient. These are:

– The time of treatment in a node (which depends on used protocols);
– The time of queue (which depends on the load in a node);
– The time of packet injection on the physical support (which depends on the capacity of the link);
– The time of spread (which varies according to distance).

The RTT is often used to study the dynamics of internet network [27]. The next section deals with a preliminary study on RTT data collection.

IV. Preliminary Study

IV.1. Data Collection

We conducted a comparison measure of “End-to-End” time between four nodes: the University of Sciences and Technology of Oran Web site (USTO, Algeria), the University of Brest Web site (UoB, France), the University of Mohamed Khider-Biskra website (UMKB, Algeria) and Ahwez Newnet Internet Service Provider in Iran (ANISP-Iran) during 16 days (from March 1st to 15th, 2014).

The data in this study are collected between the source node and three destination nodes using the network Ping tool (Packet InterNet Groper) [28].

Fig. 2 shows the graphical interface of the RTT measure software: the transmitter (USTO) sends a fixed size packet to the target hosts. These hosts respond using another packet.

The protocol used to measure the "End-to-End" time is the TCP protocol [29]. The nodes are as follows:

- Client:
  IP address: 193.194.88.4 / University of Sciences and Technology of Oran (USTO, Algeria);
  [www.univ-usto.dz];
- Server 1:
  IP address: 195.83.247.125 / University of Brest (UoB, France);
  [www. univ-brest.fr];
- Server 2:
  IP address: 193.194.69.98 / University of Mohamed Khider - Biskra (UMKB, Algeria);
  [www.univ-biskra.dz];
- Server 3:
  IP address: 85.185.225.39 / Ahwaz Newnet Internet Service Provider (ANISP - Iran);
  [www.newnetisp.com].

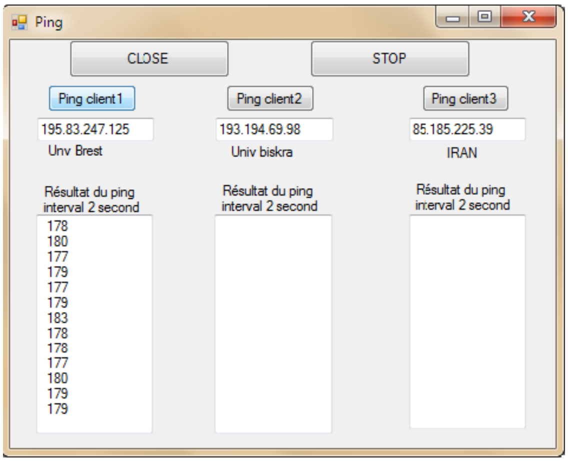

Fig. 2. The designed software package used for measuring RTT between three internet nodes, based on TCP Protocol

We have chosen three different days for realizing the experiment. Fig. 3 shows the RTT measures for the 1st day: the horizontal axis contains 600 points with 2 seconds sampling interval, the vertical axis indicates the RTT in milliseconds.

The first measure was taken on the March 8th, 2014; the second one was taken on the March 10th, 2014 and the third was taken on the March 15th, 2014.

IV.2. Data Pre-treatment

We consider the measured RTT as a time series which is regarded as the realization of a random process during time (X_t). For each t, (X_t) is a random variable on which we have a realization [30].

Fig. 3 shows the jitter series between Client (USTO-Algeria) and server 3 (ANISP-Iran) on March 8th, 2014 from 17:00 to 17:25.

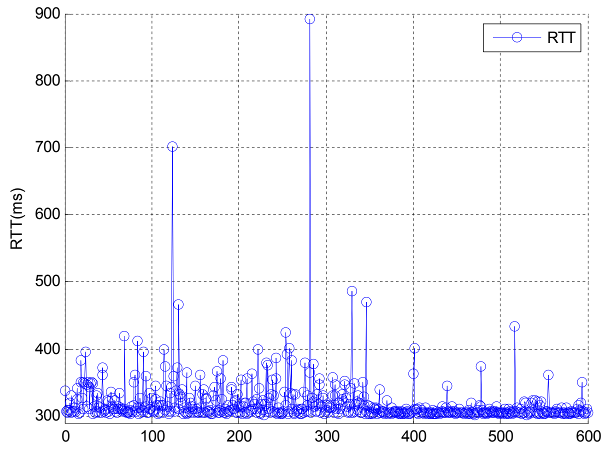

Fig. 3. The RTT between the Client and Server 3 with a 2 seconds pace - Day: March 8th, 2014 from 17:00 to 17:25.

In our case, the proof 't' represents the number of samples (t = pace = 2seconds). We can have daily, weekly, monthly or quarterly data according to our needs. In all cases, 't' represents the number of the observation, but the time unit is different.

The temporal relationship can take different shapes and it usually takes a form of chronological series which are regularly repeated or varied randomly. This variation is due to the random factor. In our case, the factors are the network load and the routing.

The temporal series analysis is the identification of the main components of this series which are:

- Secular Trend (b_t)
- Seasonal Variations (S_t)
- Cyclical Variations (L_t)

This analysis is discussed in the next section.

V. Holt-Winters Method

The Holt-Winters (H-W) method is mostly favoured among the exponential smoothing techniques in the case of observation series which have secular trend and seasonality.

They operate simultaneously the smoothing of three terms corresponding to the local level estimates of the seasonally adjusted series (L_t), the slope of the pattern (b_t), and the seasonality (S_t).

We can mention at least two methods; one of them is suitable for series admitting a multiplicative decomposition and the other corresponding to the additive decomposition [31].

V.1. The Additive Version of Holt-Winters Method

Let us note 's' being the natural frequency of the series.

The system of equations is given by [31]:

- Smoothing of the level:

$$L_t = \alpha(x_t - S_{t-s}) + (1-\alpha)\cdot(L_{t-1} + b_{t-1}) \qquad (1)$$

- Smoothing the trend:

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta) \cdot b_{t-1} \quad (2)$$

- Smoothing the seasonality:

$$S_t = \gamma \cdot (x_t - L_t) + (1-\gamma) \cdot S_{t-s} \quad (3)$$

where:
- L_t : The smoothed level of the series in t;
- x_t: The observer value of the series in t;
- S_t: The seasonal coefficient in t;
- b_t: The estimated tendency in t;
- α, β, γ: The smoothing parameters.

V.2. The Multiplicative Version of Holt-Winters Method

The equations are as follows [31]:
- Smoothing of the level:

$$L_t = \alpha \cdot \frac{x_t}{S_{t-s}} + (1-\alpha) \cdot (L_{t-1} + b_{t-1}) \quad (4)$$

- Smoothing of the trend:

$$b_t = \beta \cdot (L_t - L_{t-1}) + (1-\beta) \cdot b_{t-1} \quad (5)$$

- Smoothing of the seasonality:

$$S_t = \gamma \cdot \frac{x_t}{L_t} + (1-\gamma) \cdot S_{t-s} \quad (6)$$

The Holt-Winters model has the advantage of incorporating a seasonal component and thus achieves the calculation of the prediction in a single treatment.

Three separate smoothing are performed:
- Smoothing of the level with a smoothing parameter $\alpha \in [0,1]$;
- Smoothing of the trend with a smoothing parameter $\beta \in [0,1]$;
- Smoothing of the seasonality with a smoothing parameter $\gamma \in [0,1]$.

To obtain a good result of prediction, it is necessary to carefully choose these coefficients.

In order to choose between the two versions (multiplication or additive), we have tested the two techniques to predict the RTT by using real measurements. Fig. 4 shows the comparison results.

We also calculated the relative error for the two versions for comparison purposes (see Table I).

By analyzing the results, our choice was quickly oriented toward multiplicative version of Holt-Winters.

TABLE I
PREDICTION ERROR DISTRIBUTION (IN %) FOR "HOLT-WINTERS" ADDITIVE VERSION VS. MULTIPLICATIVE VERSION

H-W Version	≤ 2ms	≤ 3ms	≤ 5ms	≤ 10ms	>10ms
Addit. ver. - %	61.6	68	76	88.4	10.8
Multipl. ver. - %	68.4	74.4	81.6	93.2	6

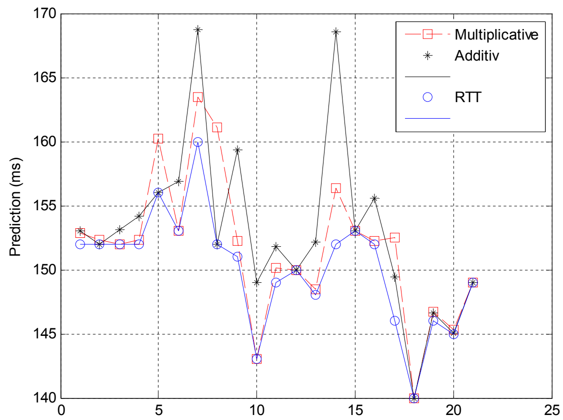

Fig. 4. Comparison between the additive version and the multiplicative version results

VI. Choice of Smoothing Parameters

To start the smoothing process, we must select a value for the constant α. This choice is very important because it determines the future prediction through the degree of weight that is assigned to the recent past and the farthest one. Various estimation procedures have been established. The most classic one is to retain the value of α that minimizes the difference between the prediction and the realization of the known part of the chronologic series. Another approach is to develop procedures for regulation and control of the constant change of smoothing. Thus, in case of systematic prediction divergence, α is automatically adjusted to fit this change in structure. The most commonly used principle of the calculation technique is as follows:

For a given range of values of α, ß and γ with a "pace" close enough to "0.05", the predictions are simulated and the sum of squared error prediction is calculated. We retain the value of α which gives the minimum sum of squared deviations (SSD). This technique can be generalized to determine the three parameters α, ß and γ.

The retained value of the coefficient is that which corresponds to the minimum of the term:

$$SSD = \sum_{t=1}^{s} (x_t - S_t)^2 \quad (7)$$

VII. The Prediction

The Holt-Winters method helps in realizing predictions from historical data. This technique allows giving great importance to the closest historical data and less importance to furthest ones. The prediction of the horizon 'h' is given by the Eq. (8):

$$\hat{x}(t,f) = (L_t + h \cdot b_t) \cdot S_{t-s+h} \quad (8)$$

The initialization of the algorithm requires knowledge of the initial values $L_1, \dots, L_s$, $b_1, \dots, b_s$, and $S_1, \dots, S_s$.

In this article, we took into consideration the first six values of RTT known in advance (s = 6), and the initial estimates of the values are given by the following equations:

$$L_t = \frac{x_1 + \cdots + x_s}{s} \tag{9}$$

$$b_t = \frac{1}{s} \cdot \left[\frac{x_{1-s} + \cdots + x_1}{s} + \ldots + \frac{x_{2s} + \cdots + x_s}{s} \right] \tag{10}$$

$$S_t = \frac{x_t}{L_t} \tag{11}$$

VIII. Validation

We measured the RTT between four nodes. Each measure contains 600 points with a sampling interval of 2 seconds. In this section, we show the obtained results.

Fig. 5, Fig. 6 and Fig. 7 show the modelling of RTT by the Holt-Winters method. When we have good models we get good prediction results, because the predicted value has a relationship with the last value of S_t as shown in Eq. (8). The prediction accuracy is related to the amplitude of the variation of the measured RTT. To refine our observation, we decided to analyze the two following cases:

- The slight variation of RTT;
- The abrupt (sudden) variation of RTT.

VIII.1. Prediction of the RTT with the Slight Variation

According to the previous experiments, Fig. 8 and Fig. 9 shed light on the prediction results between client (USTO) and two nodes “Server 1” on March 13th, 2014 and “Server 2” on March 2nd, 2014 respectively. Those results have shown that the proposed method is capable of predicting the RTT with higher precision. Table II shows the distribution of the prediction error that is the absolute value of the difference between the real and the predicted value. The distribution of prediction errors between “client” and “server 1” is less than 3ms which represents 89.55% while it is 2.15% for values higher than 10ms.

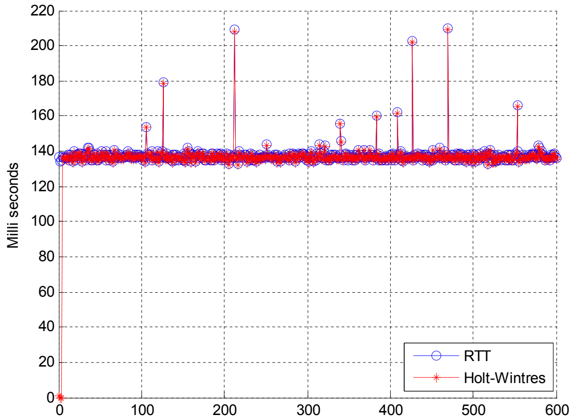

Fig. 5. RTT modelling by Holt-Winters between Client (USTO-Algeria) and Server 1 (UoB- France) on March 3rd, 2014 during 11:00-11:20

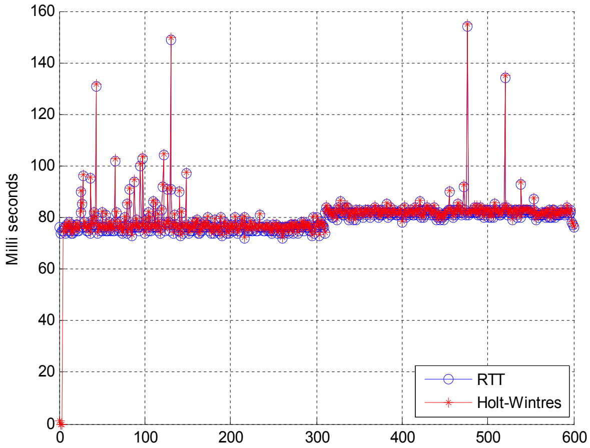

Fig. 6. RTT modelling by Holt-Winters between Client (USTO-Algeria) and Server 2 (UMKB-Algeria) on March 2nd, 2014 during 12:00-12:20

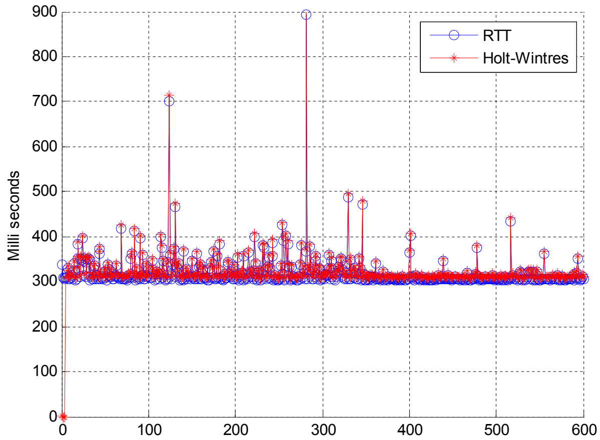

Fig. 7. RTT modelling by Holt-Winters between Client (USTO-Algeria) and Server 3 (ANISP-Iran) on March 5th, 2014 during 17:00-17:20.

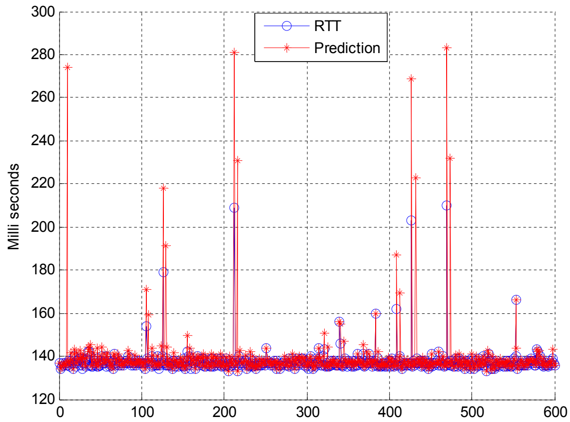

Fig. 8. The prediction of RTT by Holt-Winters between Client (USTO-Algeria) and Server 1 (UoB-France) on March 3rd, 2014 during 11:00-11:20

Regarding the distribution of “server 2”, prediction errors are less than 3ms which represents 91.39% while it is 1.98% for values higher than 10ms. The remaining results, presented in Table I show that the majority of errors are less than 3ms.

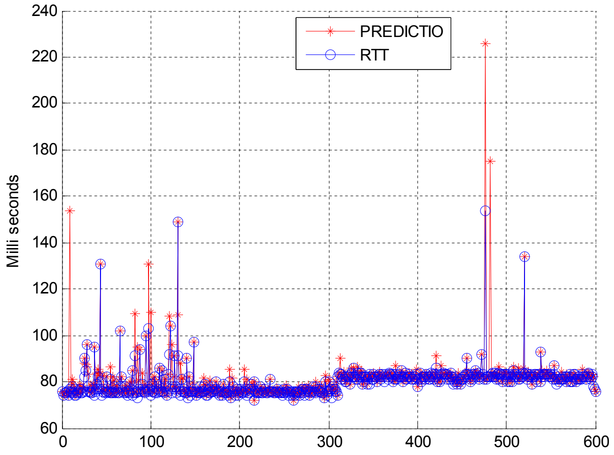

Fig. 9. The prediction of RTT by Holt-Winters between Client (USTO) and Server 2 (UMKB-Algeria) on March 2nd, 2014 during 12:00-12:20

TABLE II
RTT PREDICTIVE PRECISION (IN %) FOR THREE TYPICAL PERIOD OF TIME BETWEEN CLIENT (USTO-ALGERIA) AND THE 3 SERVERS

Nodes	≤ 1ms	≤ 2ms	≤ 3ms	≤ 5ms	≤ 10ms	>10ms
Server1	77.28	84.74	89.55	95.85	97.84	2.15
Server2	76.65	84.10	91.39	95.52	98.01	1.98
Server3	70.26	73.75	75.91	80.39	86.04	13.95

Fig. 10 and Fig. 11 confirm the results presented above in the sense that the prediction error is smaller when the variation of RTT is slight. In this case, the Holt-Winters method is able to accurately predict the RTT.

VIII.2. Prediction of RTT with a Brusque Variation

In Fig. 12, we notice that the RTT variation between “Client” and “server 3” is brusque, thus affecting the accuracy of the prediction. Table I gives the distribution of the prediction error. We notice that most of the errors are less than 5ms with a total of 80.39% and 13.95% for errors higher than 10ms. These values are lower in accuracy than the previous values (slight variation) due to the sudden change of RTT.

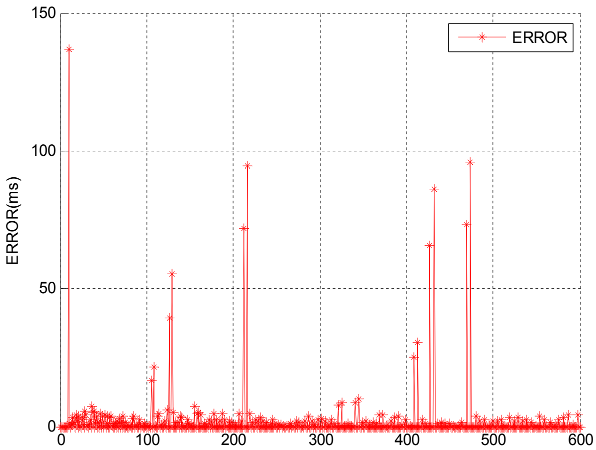

Fig. 10. The prediction error between Client (USTO-Algeria) and Server 1 (UoB-France) on March 3rd, 2014 during 11:00-11:20

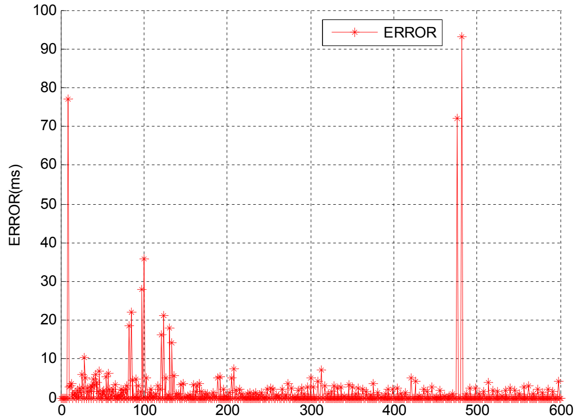

Fig. 11. Prediction error between Client (USTO-Algeria) and Server 2 (UMKB-Algeria) on March 2nd, 2014 during 12:00-12:20

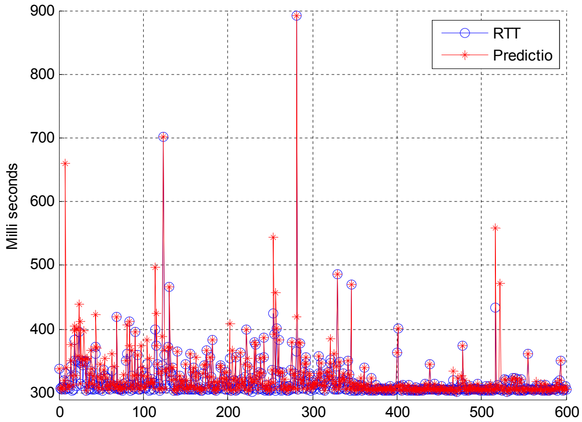

Fig. 12. Prediction of RTT by Holt-Winters between Client (USTO-Algeria) and Server 3 (ANISP-Iran) on March 5th, 2014 during 17:00-17:20

Therefore, the Holt-Winters method can predict the RTT but the prediction accuracy is affected by its real variation (brusque or slight).

Fig. 13 shows that the RTT varies initially between 300ms and 400ms randomly. This reduces the accuracy of prediction, and then the RTT is stabilized with some sudden change resulting in good prediction accuracy.

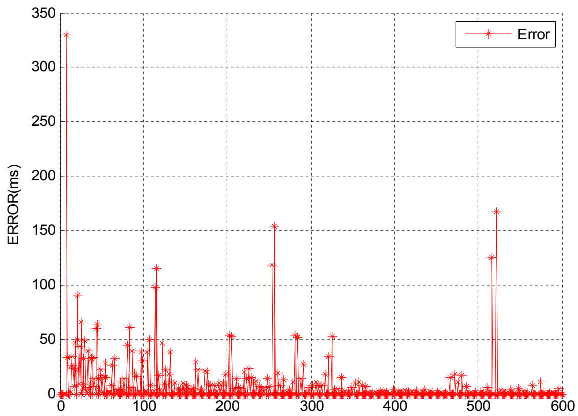

Fig. 13. Prediction error for the nodes: Client (USTO-Algeria) and Server 3 (ANISP-Iran) on March 5th, 2014 during 17:00-17:20

To evaluate the implemented method, we carried out a series of measures in real-time of the RTT between 4 distant nodes (Algeria - France - Iran). The obtained results of prediction by the Holt-Winters method are more than encouraging.

IX. Conclusion

The time delay on internet is one of the greatest obstacles of numerous real-time applications. This is particularly true for the internet based control systems. ù

In this work, a new approach is proposed to predict the RTT. The holt-winters method was adopted for the prediction of RTT.

The proposed predictor has been evaluated on online data between four different nodes.

The prediction results show that the proposed method is able to predict the RTT, but the accuracy of prediction is related to the variation of jitter.

As future work, it would be interesting to improve the performance of "Holt-Winters" algorithm by refining the choice of smoothing parameters in order to obtain good prediction accuracy regardless of changes in the RTT.

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