The Use of Linear Time Series for Prediction of Congestion Detection in Wireless Sensor Networks

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Abstract— *A Wireless Sensor Network (WSN) is developed with large number of sensor nodes. Packet transfer in this network presents a range of challenges to protocol designers due to resource constrains, limited battery power, processing power, memory and storage capacity of sensor nodes in WSN. The applications that produce high volumes of data which require high transmission rates, may cause congestion in the sensor node and leading to packet loss and impairments in the quality of service (QOS) as well as throughput of networks. If data transmission to the network is not controlled, congestion status can arise and decrease network lifetime. Therefore, we need various congestion detection mechanisms to identify congestion. In this paper, we present a Prediction based Congestion Detection (P-CD) technique in order to identify congestion before congestion occurrence. These techniques use queue length as a parameter to recognition congestion. The introduced technique has better prediction accuracy.*

Keywords— Wireless Sensor Networks (WSNs), Congestion detection, Queue length, Prediction, ARIMA model

1. INTRODUCTION

A typical Wireless sensor networks (WSNs) consists of a base station (sink node) and large number of sensor nodes. Sensor nodes in WSNs can organize themselves to monitor around environment and report conditions. When sensor nodes are densely distributed and/or reporting conditions operate under heavy load, congestion can occur. Congestion may consequence to packet loss and increase transmission delay, energy consumption and hence decreases overall performance as well as QOS. Therefore, solution of congestion problem has many challenges due to

limited battery power and storage capacity of sensor nodes in WSNs.

There are two methods in order to resolve congestion problems. The First method is congestion control which system does not perform any response until congestion state occurrence. The system attempts to solve congestion just after this incidence. The second method is congestion avoidance that system tries to detect congestion occurrence before conditions happen. In second method, an estimation of time in case of situations that may occur in future is required. Congestion control is conducted in three steps: congestion detection, congestion notification, and rate adjustment. All congestion control techniques have the same basic manners: they investigate the network to detect congestion, notify the other nodes of the congestion status, and reduce the congestion and/or its impact using rate adjustment methods. Congestion control protocols differ in the way that they detect congestion, notice congestion information and adjust traffic rate. In this paper, we focus on congestion detection that is the first step of congestion control and can propose as a method for congestion avoidance. In order to detect congestion, there are three different ways [1]: buffer occupancy, channel load and reporting rate. Buffer occupancy-based methods consider the queue length of nodes while channel load and reporting rate provide more accurate information in some cases. In this paper, a simple yet scheme to address congestion detection is proposed. The scheme use prediction methods for recognition congestion proactively. Also congestion detection method considers queue length of sensor nodes. The reminder of this paper is organized as follows: section 2 presents various congestion detection techniques in congestion control protocols for WSNs. Section 3 explains employed prediction and also details of ARIMA method as well as Congestion detection based on ARIMA model. Finally, some concluding remarks and future works are presented in conclusion part.

2. RELATED WORK

In traditional TCP protocol, congestion is detected at the end nodes based on a timeout or redundant acknowledgments. Generally, link-by-link congestion detection in sensor networks has better performance than traditional end-toend congestion detection using timeout or duplicate acknowledgment. Thus, TCP protocol has good performance in wired networks and cannot be suitable implemented for WSN [2]. Therefore, in sensor networks, proactive methods are used based on some forms of congestion indicator. Different congestion indicators have been proposed such as queue length, channel load, packet service time or the ratio packet service time to packet inter arrival time at the intermediate nodes.

Different protocols have been proposed for congestion detection in WSNs which are using one parameter. Choosing this parameter is based on various criterions, for example: QOS or type of network applications, network resources, data transmission rate and network structure. In [3], CODA, an efficient congestion control protocol for sensor networks was proposed. CODA detects congestion based on queue length as well as channel load at intermediate nodes. Also Fusion [4], Siphon [5], ESRT [6] and STCP [7] use measurement of queue length in each sensor node in order to congestion detection. In CCF [8], author proposed congestion detection based on service time to deduce the current congestion state in each intermediate sensor node. In [9], congestion is detected based on packet service rate and packet scheduling rate in all sensor nodes. PCCP [10] uses packet inter arrival time and packet service time in order to produce a parameter to detect congestion. Also RCRT, for congestion detection technique, uses per-flow list of out-oforder which presents the number of packets have been received after the first unrecovered packet loss and how much time has passed since the first unrecovered loss.

3. ARIMA MODEL

If packets arrival rate exceeds processing rate, then queue length will arise. In this case, many packets may dropped because of overflow or the delay in their processing reach to a level, in which packets will be useless; that we called this state congestion. As we know, Congestion is one of the critical conditions in the networks that needs to avoidance or control.

Congestion usually happens in network bottleneck. Bottleneck is a place that many packets will pass this point for arriving to their destination. Congestion in bottleneck causes strong falls in network performance. Therefore, we need a better method to congestion detection in the network properly.

a. Introduction to ARIMA model

In the analysis of time series, ARIMA Model [11] [12] is an integrated automated moving average which is a linear prediction method and more extensive than ARMA Model [11]. ARIMA model is useful for describing the behavior of many time series. ARIMA is a linear time series model.

ARIMA model is one of the most important methods for box–Jenkins [13] which is the combination of the moving average (MA) and auto regressive (AR). ARIMA models defined as ARIMA (p, d, q) that p is auto regressive order, q is moving average order, and d is differential order of the raw data for usage in ARIMA model [11] [12]. P and q are computedthrough auto correlation function (ACF) and partial auto correlation function (PACF), respectively. ACF is a method to recognize the relationship between time–series observations. Therefore, correlation between current observation (Y_t) and P periods before the current observation must be measured. We can determine the moving average (MA) parameter's order q straight. Because of the characteristics of the PACF which describes the correlation between the current states' innovation of the time series with the past, we can determine the auto regressive (AR) parameter's order p directly.

For constructing an ARIMA model a four-step process is performed as Fig. 1. First of all, using graphs, ACFs, PACFs and difference determine an experimental model through analysis of historical data (identification step). Then the unknown model parameters are estimated (estimation step). The error test runs to verify the suitability of model. If the model was confirmed, it can be set as the basis for predicting future behavior of that series otherwise repeat the steps (diagnostics step). In the last, forecasting the data (forecast step).

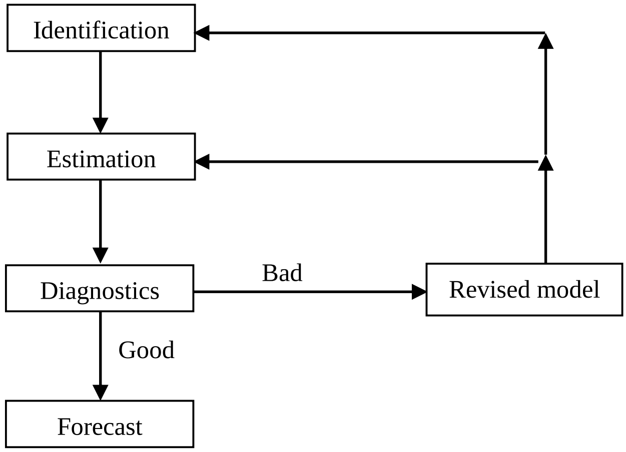


Fig. 1 The diagram of procedure ARIMA model

The ARIMA model can be described by Eq. (1). In the Eq. (1), available variable amounts are polynomial functions which presented in Eqs. (2) and (3) from p and q order, respectively.

$$\emptyset(B) * \nabla^{d} * X_{t} = \theta(B) * \alpha_{t} \tag{1}$$

Also X_t is defined as a time–series in which t is an integer index and X_t are real numbers. α_t is a white noise with an average 0 and a variance σ^2. We define the lag-1 difference operator ∇ by Eq. (4). Also B is a backward shift operator that power of B presents the number of backward times in which t-power (B) indicates the time that X data are accessible. ∇^d which is defined in Eq. (5) [13], is a differential operator calculated by HURST parameter H. In order to calculate H, Abry-Veitch (AV) Wavelet method is used [14].

$$\emptyset(B) = 1 - (\emptyset_1 B + \emptyset_2 B^2 + \cdots + \emptyset_p B^p) \tag{2}$$

$$\theta(B) = 1 + (\theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q) \tag{3}$$

$$(1 - B)X_t = X_t - X_{t-1} \tag{4}$$

$$\nabla^d = (1 - B)^d = \sum_{k=0}^{\infty} \binom{d}{k} (-1)^k B^k \tag{5}$$

The estimation of the $\emptyset$ parameter values are based on the calculation of auto–covariance matrix and solving the Yule Walker equations. Then by using these estimated coefficients, observed series are being filtered to obtain an appropriate moving average process. Finally, a sequence of auto covariance of the moving average process is being calculated and will be used in estimation of moving average coefficients (θ) [15]. All the zeros of ∅(B)and θ(B) are outside the unit circle. In Eq. (5), (d¦k) value equals to Eq. (6).

$$\binom{d}{k} = \left(d!/_{k!\,(d-k)!}\right) = \left(^{\Gamma(d+1)}/_{\Gamma(k+1)\Gamma(d-k+1)}\right) \tag{6}$$

b. PREDICTION METHOD OF ARIMA MODEL

One of the usages of ARIMA model is to predict time–series. The mathematical terms of ARIMA model are being used for predicting one step forward and K steps forward. Let〖 X〗_tto be the time series that we want to predict, then K steps forward prediction can be defined with (X_(t+k))̂.To have Kth step, we use the one step forward prediction recursively [16].

ARIMA model uses lagged queue length values to predict one step forward in different time scaling. By increasing K, predictions close to K encounter more errors to the other predictions close to t. For prediction, Eq. (1) is being used.

4. EXPERIMENTAL RESULTS

One of the most important issues in congestion detection is queue length that influences the performance of the network. Many of protocols use queue length as a parameter to congestion detection. Also ARIMA model as a prediction model can improve methods such as congestion detection and flow control by predicting state of the queue in the networks. This prediction method can run in each sensor node. Therefore, congestion detection method that is proposed in this paper, can located in each sensor node. This method that is applicable to all nodes is more flexible since it is possible to determine time of congestion occurrence in each sensor node.

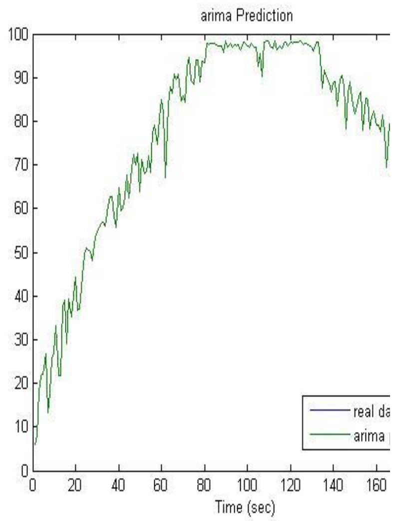
The mainstream prediction methods can present us with an approximate time estimation through which critical conditions commence, according to input queue lengths records in past and the threshold of the queue length. This approximation will be conducted based on the modeling input data. System will try to prognosticate the future conditions time periods.

c. Congestion prediction based on ARIMA model

In this section, we apply the ARIMA model that is described in previous section to predict the real queue length values. In the prediction procedure, we use one-step-ahead prediction and extend it to k-step-ahead prediction, where “step” means the time unit. All the models use the lagged queue length values to predict one-step-ahead traffic value. We notice that the nature of the queue length trend plays a significant role in the congestion prediction performance.

Figs. 2 and 3 show the predicted values of queue occupation when we apply the ARIMA prediction model and provide a comparison to original data in data with a change of behavior and also without any change. The used scheme illustrates the queue length to hover around any undesired value by increasing time, so it detects buffer overflow and congestion occurrence. It also contributes to estimate the network utilization and avoid congestion.

In Figure2, it is necessary to note that ARIMA method has identified a descending model at the time 128 exactly. Therefore, the identification process has been corrected and descending behavior of the data continues. In Figure 3, ARIMA method identified ascending model from historical data and its prediction is based on ascending model.



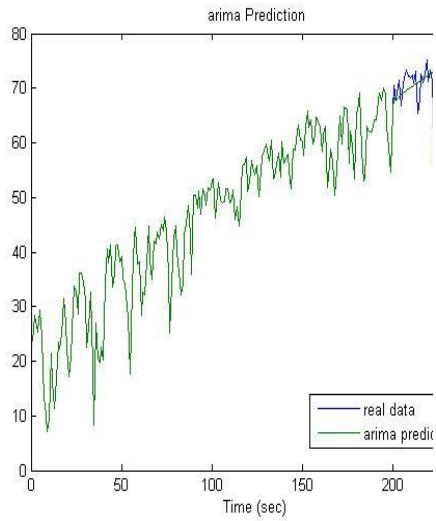


Figure 2. The comparison of ARIMA (3,1,4) method with real data in data with various changes

Figure 3. The comparison of ARIMA (1,1,4) with real data in data with perpetual behavior change

5. CONCLUSION

Predicting the queue length is important and of great interest because successful prediction of queue length may promise attractive benefits in detecting congestion occurrence in future. It affects decisions of sender nodes by increasing or decreasing transmission rate. We apply ARIMA model to predict one-step-ahead and k-step-ahead queue length values. It is tested on two different queue length data series by changing in trend and without changing. Based on experimental results, show that ARIMA method has been able to obtain a correct model of data and the performance of queue length prediction can be significantly enhanced. Therefore ARIMA prediction model can be highly efficient in prediction of queue behavior. Upon detecting congestion occurrence in future, sender nodes can adjust their rate to congestion avoidance.

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