

PERFORMANCE OF VARIOUS FORECASTING ALGORITHMS TO REDUCE
THE NUMBER OF TRANSMITTED PACKETS BY SENSOR NODE IN
WIRELESS SENSOR NETWORKS

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A project report submitted in partial
fulfilment of the requirement for the award of the
Degree of Master of Electrical Engineering

Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia

June 2018

ACKNOWLEDGEMENT

Deep and humble gratitude to ALLAH Almighty for providing the opportunity and giving me the strength to complete this project.

I want to pay tribute to the countless contributions of my supervisor and mentors and the support of my family and friends. To my supervisors Assoc. Prof. Dr. Jiwa bin Abdullah, thank you for your continued supervision and endless patience in completing this project. To my parents Ihsan Husni Ali and Suhaila Taqi, thank you for giving me freedom and opportunity to pursue my studies, and forgive me for not being there when you protested me. To Mr. Nayef Abdulwahab Alduias, thank you for your help and available comments.

My sincere thanks to the staff of Faculty of Electrical and Electronic Engineering (FKEE), Universiti Tun Hussein Onn Malaysia (UTHM). Thanks for providing me with an excellent research environment and the necessary resources to undertake this project.

I would like to thank a person who contributes to complete my final project report directly or indirectly. I would like to acknowledge him/her helps, which was necessary to complete this.

Mohammed Ihsan Husni

June 2018

ABSTRACT

The development of wireless sensor networks originated in military research and the application of monitoring conflict areas. One of the main features of WSNs is the limited energy of their wireless sensor nodes. Energy consumption is an important issue in WSN. Reducing the number of transmission packet messages for sensor nodes is one of the techniques. Furthermore, forecasting is one of the most common solutions to reduce them. Therefore, the main contribution of this thesis is to study the performances of different algorithms that can reduce the number of data packets transmitted by sensor nodes within the WSN. The simulation experiments are done using MATLAB software for a variety of algorithms. The selected algorithms for the reduction algorithm in the transmissions include Move Average algorithm (MA), Autoregressive all-pole model parameters — Burg's algorithm. (AR-B), Autoregressive all-pole model parameters — Yule-Walker algorithm (AR-YW) and an Efficient Data Collection and Dissemination Algorithm (EDCD1). The data has been extensively gathered at 500 data points. The performance comparison shows that the on the basis of reduction in the data packet transmissions from the source to the sink EDCD1 algorithm shows the maximum reduction of 92% while a minimum reduction of 23% is shown in case of MA and the reduction of AR-B and AR-YW are 58% and 56, respectively. Moreover, in term of overall performance for reduction in a number of data transmission reduction EDCD1 algorithm shows the highest ratios. Additionally, in terms of absolute error in the data at the sink, the EDCD1 algorithm shows the best performance with less average error at 2.2803 for all sensors compared to others algorithms.

ABSTRAK

Pembangunan Rangkaian Sensor Wayarles (WSN) bermula sebagai suatu keperluan penyelidikan yang berasaskan ketenteraan dan berbagai aplikasi pemantauan di kawasan terdapatnya konflik. Salah satu ciri WSN yang utama ialah simpanan tenaga yang terhad bagi nod sensor wayarles. Penggunaan tenaga ini menjadikan ia isu paling utama WSN. Oleh itu mengurangkan bilangan penghantaran paket maklumat bagi nod sensor merupakan kaedah utama. Seterusnya ramalan adalah satu lagi kaedah biasa yang mudah dilaksanakan bagi mengurangkan paket maklumat. Oleh itu sumbangan utama tesis ini adalah untuk mengkaji prestasi pelbagai algoritma yang bertujuan untuk mengurangkan bilangan paket maklumat yang dipancarkan oleh nod sensor dalam WSN. Penyelidikan dilaksanakan menggunakan perisian Matlab bagi pelbagai algoritma. Algoritma yang di pilih untuk pengurangan bilangan paket maklumat adalah Algoritma Gerak Purata (MA), Algoritma Autoregres parameter model semua kutub – Algoritma Burg (AR-B), Algoritma Autoregres parameter model semua kutub – Algoritma Yule-Walker (AR-YW) dan Algoritma Kutipan Data dan Agihan (EDCD1). Data telah dikumpulkan secara ekstensif pada kedudukan 500 point data. Perbandingan prestasi tersebut menunjukkan bahawa algoritma EDCD1 mencapai sehingga maksimum 92% pengurangan paket maklumat dan pengurangan minimum adalah 23% bagi MA sementara pengurangan yang melibatkan algoritma AR-B dan AR-YW adalah masing-masing 58% dan 56%. Seterusnya, dalam istilah prestasi menyeluruh bagi pengurangan bilangan paket maklumat penghantaran data, algoritma EDCD1 menunjukkan nisbah yang tinggi. Tambahan lagi, dalam sebutan ralat absolut algoritma EDCD1 menunjukkan prestasi yang terbaik dengan ralat purata adalah 2.2803 bagi semua sensor berbanding dengan algoritma lain.

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LIST OF SYMBOLS AND ABBREVIATIONS

WSNs	-	Wireless sensor networks
BS	-	Base station
CH	-	Cluster head
OP	-	Operating System
PC	-	Personal Computer
E_{total}	-	Total energy for frame
E_{BF}	-	Energy for beamforming
RT%	-	Ratios of reducing the number of packets transmissions,
N_{tran}	-	Total number of transmitted messages
$N_{samples}$	-	Total number of samples
AR-B	-	Autoregressive - Burg's algorithm
AR-YW	-	Autoregressive -Yule-Walker algorithm
EDCD1	-	Efficient Data Collection and Dissemination Algorithm1
MA	-	Move average Algorithm

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CHAPTER 1

INTRODUCTION

In the recent years, wireless sensor networks (WSN) have attracted worldwide attention due to the importance of monitoring in hazardous environments. The development of wireless sensor networks originated in military research and the application of monitoring conflict areas. Nowadays, they are widely used for natural and human environmental monitoring and protection. Specifically, wireless sensor networks are used to monitor atmospheric data collection of large-scale fires, industrial air pollution, industrial water levels, humidity, pressure, temperature, and wild animal protection zone monitoring [1].

In this chapter the background of the project is defined. In addition, the objectives of the project, problem statement, and scopes of project are elaborated

1.1 Background of Project

Wireless sensor nodes (sensor nodes, for brevity) are small computing devices with low production costs, equipped with a radio antenna and sensors that are capable of sensing one or more environmental parameters [2]. Thanks to their portable size, sensor nodes are often densely deployed in areas that may not be humanly accessible [3]. Hence, one of the biggest challenges of working with battery equipped sensor nodes has been their limited energy availability [4], which is compounded by the fact that (1) radio transmissions are the operations that consume the most energy and (2) Wireless Sensor Networks (WSNs) are mainly data-oriented networks; that is, their most valuable asset is the data that sensor nodes can produce.

As described in [3], the same algorithm is used for the prediction model (ie, the same prediction method). The term prediction may refer to a process of deducing missing values in a dataset based on statistical or empirical probabilities, or estimating future values based on historical data. The prediction method (P) is a function that produces a prediction based on two input values: a set of observations (X) and a set of parameters (θ). The prediction model (p) is an example of the prediction method P such that $p\theta(X)=P(X,\theta)$; that is, each prediction model is deterministic, and its output depends only on the set of observations. The value of θ can be selected based on the evaluation provided by the utility function, which can measure the accuracy of the prediction, the complexity of the model, and the loss of information.

The prediction method may require some information about the data to be predicted, for example, assuming the values will be normally distributed. In some cases, this knowledge is already owned by the user before deploying the WSN and can be applied to statistical methods such as linear regression. The positive aspect of statistical methods is that the system's output can be estimated in advance. For example, based on assumptions about the normality of data, the probability of making an accurate prediction can be used to calculate whether the benefits that the system can achieve are worth investing in.

1.2 Problem statement

One of the main characteristics of WSNs is the limited energy of their wireless sensor nodes. Battery efficiency is a key issue because sensor nodes in wireless sensor networks are typically driven by non-renewable batteries. Meanwhile, it is a challenge for researchers and developers to achieve continued running hours without decreasing the WSN performance. Furthermore, the problem is that current algorithms for reducing the number of packets transmitted from sensor nodes to base stations cannot be used for different types of sensors. These algorithms have different performance depending on the type of sensor. Therefore, in the case of considering a set of

performance measurements, choosing a better algorithm that can work for different types of sensors is a problem that needs to be studied.

1.3 Project Objectives

The objectives of this project are:

- I To identify various algorithms that reduce the number of transmitted messages from sensor node to fusion center.
- II To evaluate the performance of these algorithms using a set of performance metrics through various simulation experiment.
- III To perform the comparison analysis of the algorithms.

1.4 Project scopes

This project is concerned with the scopes as follows:

1. Study different algorithms to reduce the number of transmitted messages. The study algorithms are to be considered: (i) Move average Algorithm (MA), (ii) Autoregressive all-pole model parameters — Burg's algorithm. (AR-B) (iii) Autoregressive all-pole model parameters — Yule-Walker algorithm (AR-YW) and (iv) an Efficient Data Collection and Dissemination Algorithm (EDCD1).
2. Evaluate methods by applying them to various types of sensors (Temperature/ Relative humidity / light) separately.
3. The performance comparison of these algorithms using a set of performance metrics, including energy consumption, accuracy and ratio of reduce number of transmitted messages reduction.
4. The MATLAB program is used to study and analyze the different scenarios.

1.5 The report structure outline

This project report consists of five chapters as the follows:

Chapter 1 discusses the background of the research. In addition, the problem statement, objectives of project, scopes of study and report structure outline are presented.

Chapter 2 contains literature review discussing the application of WSNs, the various algorithms for reduce number of transmissions in wireless sensor networks along with their corresponding routing protocols, energy radio model and performance metrics.

Chapter 3 argue about the way that used to improve the project, including the tools, equipment's, procedures and processes involved in the software improvement and accomplishment of the project. In addition, the flowchart of study, the system structure assumption is presented.

Chapter 4 will discuss simulation model parameters and experimental results reported for evaluating and analysing different algorithms for reduce the number of transmitted packets by sensor node in wireless sensor networks.

Finally, Chapter 5 will cover the conclusions and recommendations of future work.

CHAPTER 2

LITERATURE REVIEW

This chapter summarizes the information of the related previous studies on WSNs. In addition, the chapter covers types of most WSN, the related algorithms to reduce number of transmissions, performance metrics and the simulation environment. These reviews done based on materials from journals, conference proceeding and books.

2.1 Wireless Sensor Networks

Wireless sensor network (WSN) has emerged as one of the most promising technologies for the future. This has been enabled by advances in technology and availability of small, inexpensive, and smart sensors resulting in cost-effective and easily deployable WSNs [5]. WSN is constituted by spatially distributed autonomous devices communicating wirelessly, gathering information and detecting certain events of significance in the physical and environmental conditions. Each of these devices is capable of concurrently sensing, processing and communicating. Having these capabilities on a sensor device offers a vast number of compelling applications [6-9].

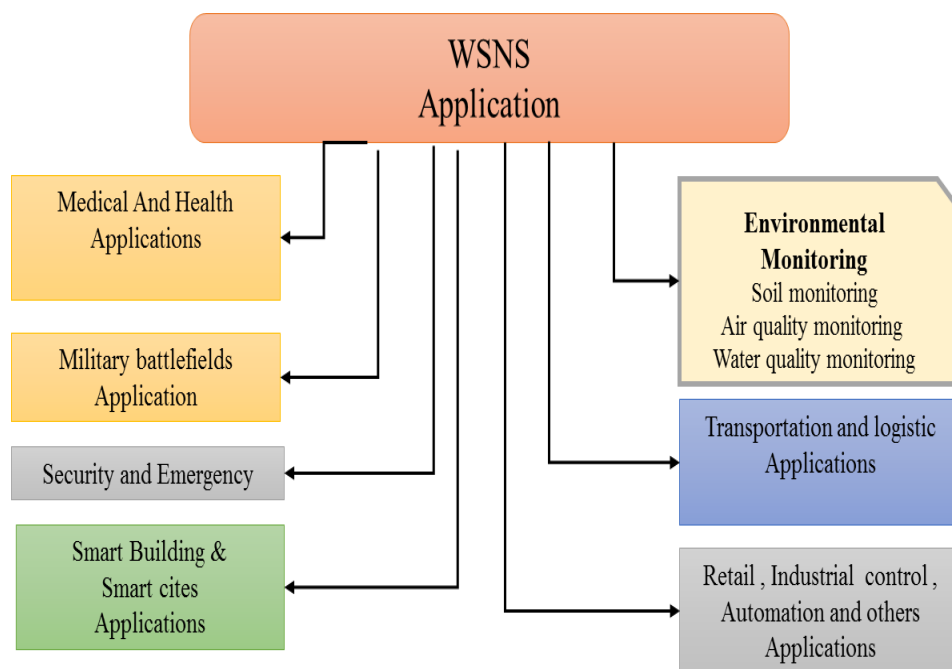


Figure 2.1: WSN Applications

2.2 Challenges in WSN

WSN have tremendous potential because they will expand our ability to monitor and interact remotely with the physical world. Sensors have the ability to collect vast amounts of unknown data. Sensors can be accessed remotely and placed where it is impractical to deploy data and power lines. To exploit the full potential of sensor networks, we must first address the peculiar limitations of these networks and the resulting technical issues. Although data fusion requires that nodes be synchronized, the synchronization protocols for sensor networks must address the following features of these networks. WSNs to become truly ubiquitous, a number of challenges and obstacles must be overcome. In [11-15], the works have been discussing many issues related to WSN challenges.

Energy: The first and often most important design challenge for a WSN is energy efficiency. Power consumption can be allocated to three functional domains: sensing, communication, and data processing, each of which requires optimization. The sensor node lifetime typically exhibits a strong dependency on battery life. The

constraint most often associated with sensor network design is that sensor nodes operate with limited energy budgets [15].

Power efficiency, the ability of the network to operate at extremely low power levels, also plays an important role. A typical method for designing a low-power sensor network is to reduce the duty cycle of each node. The drawback is that wireless as the wireless sensor node stays longer in sleep mode to save power, there is less chance that the node can communicate with its neighbor's. This decreases the network responsiveness, and also lowers reliability due to the lack of the exchange of control packets and delays in packet delivery. In addition, a more complicated synchronization technique will be necessary to keep more nodes in low duty cycle, which may also affect scalability [1].

2.3 Reduce number of transmissions algorithms

The main drawback of generating prediction models independently was addressed in [16] [17]: approaches that rely on predefined prediction methods can lead to poor prediction performances if the model choice is not accurately done. The authors decided to generate prediction models in sensor nodes. However, a new responsibility is assigned to sensor nodes: after collecting local measurements, they must fit a prediction model to the real data and communicate any occasional change to their CHs. Fitting a prediction model means finding the model that best summarizes the real measurements. Hence, this mechanism requires much more computing power from the nodes than the other approaches (both to store more data and to choose the prediction models) and the savings depend on the predictions' accuracy, which may vary according to the sensed phenomenon and the data sampling rate. Moreover, the choice of the prediction method is restricted by the memory and processor power limitations of the sensor nodes. In [16] tested how better AR models can improve the WSN lifetime in comparison with constant prediction models. The results of the simulations using real data from WSNs showed that the adaptive approach could reduce the number of data transmissions with neither exceeding the constrained memory nor the computational resources of common wireless sensor nodes. With identical architectures, Li and Wang [18] chose the traditional ARIMA and McCorrie et al. [19]

the ES method to predict temperatures in the environment and in aircraft engines, respectively.

2.3.1 Burg's Method

This section describes Berger's method. As explained in [20-24], Berg's idea is very simple, but there is no explanation and sometimes hidden behind unnecessary confusion and vocabulary, or is often buried underneath unnecessary grid filtering theory. In 1975, they used Levinson-Durbin recursion. Ideally, you wanted to find a solution with similar computational requirements but no instability. This is another constraint that Burg completed by reusing Levinson-Durbin recursion. In the original Levinson-Durbin recursion, coefficients

Stored in a vector $A_k = \begin{bmatrix} 1 \\ a_1 \\ a_2 \\ \vdots \\ a_k \end{bmatrix}$ and an inverted order vector $V_k = \begin{bmatrix} 0 \\ a_k \\ \vdots \\ a_2 \\ a_1 \\ 1 \end{bmatrix}$ (2.1)

The recursion formula is therefore the following

$$A_{k+1} = A_k + \mu V_k \quad (2.2)$$

With μ computed so that to respect the initial problem conditions as detailed in Collomb (2009). Burg's idea was simply to change the way μ is computed, so that not to fit the initial problem conditions, but to instead minimize the total sum of $F_k + B_k$ introduced in (2.1) and (2.2). That is it, that was not too complicated, was it? Now it is time to derive the

Formulas. Before going further, it is better to prepare by changing few notations to make the next steps easier. Reworking equation (2.1) by defining $a_0 = 1$ gives

$$F_k = \sum_{n=k}^N \left[a_0 x_n + \sum_{i=1}^k a_i x_{n-i} \right]^2 = \sum_{n=k}^N \left[\sum_{i=0}^k a_i x_{n-i} \right]^2 = \sum_{n=k}^N (f_k(n))^2 \quad (2.3)$$

With

$$f_k(n) = \sum_{i=0}^k a_i x_{n-i} \quad (2.4)$$

Similarly , reworking equation (2.2) gives

$$B_k = \sum_{n=k}^N \left[a_0 x_n + \sum_{i=1}^k a_i x_{n+i} \right]^2 = \sum_{n=k}^N \left[\sum_{i=0}^k a_i x_{n+i} \right]^2 = \sum_{n=k}^N (b_k(n))^2 \quad (2.5)$$

With

$$b_k(n) = \sum_{i=0}^k a_i x_{n+i} \quad (2.6)$$

Finally writing A_{k+} as the vector of the coefficients , using (2.3) and the fact that V_k is simply the inverted of A_k , and defining $(a_n)_{n \in \llbracket 1, k+1 \rrbracket}$. Solving for μ , Assuming that have been found the value of A_k , in order to find μ , need to use (2.4) and (2.6), and simply need to minimize

$$F_{k+1} + B_{k+1} = \sum_{n=k}^{N-k-1} (b_{k+1}(n))^2 + \sum_{n=k}^N (f_{k+1}(n))^2 \quad (2.7)$$

From (2.4) and (2.7) derive

$$f_{k+1}(n) = \sum_{i=0}^{k+1} a_i x_{n-i} \quad (7)$$

$$f_{k+1}(n) = \sum_{i=0}^{k+1} a_i x_{n-i} + \mu \sum_{i=0}^{k+1} a_{k+1-i} x_{n-i} \quad (8)$$

$$f_{k+1}(n) = f_k(n) + \mu \sum_{i=0}^{k+1} a_j x_{n-k-1+i}$$

Hence ,

$$f_{k+1}(n) = f_k(n) + \mu b_k(n - k - 1) \quad (2.8)$$

From (2.6) and (2.8) derive

$$b_{k+1}(n) = \sum_{j=0}^k a_i x_{n+j}$$

$$b_{k+1}(n) = \sum_{i=0}^{k+1} a_i x_{n+i} + \mu \sum_{i=0}^{k+1} a_{k+1-i} x_{n+i}$$

$$b_{k+1}(n) = b_k(n) + \mu \sum_{i=0}^{k+1} a_j x_{n+k+1-i} \quad (2.9)$$

Carry on Equation (2.8) and (2.9) into (2.10) gives

$$b_{k+1}(n) + f_{k+1}(n) = b_k(n) + \mu \sum_{i=0}^{k+1} a_j x_{n+k+1-i}$$

$$+ f_k(n) + \mu \sum_{i=0}^{k+1} a_j x_{n-k-1+i} \quad (2.10)$$

This can be minimized by simply finding when the derivative of the μ variable is zero.

Therefore, need to find μ so that

$$\frac{\partial(F_{k+1} + B_{k+1})}{\partial \mu} = 0 \quad (2.11)$$

$$0 = \frac{\partial(b_k(n) + \mu \sum_{i=0}^{k+1} a_j x_{n+k+1-i} + f_k(n) + \mu \sum_{i=0}^{k+1} a_j x_{n-k-1+i})}{\partial \mu}$$

Extracting μ is now simple and gives

$$\mu = \frac{\sum_{n=k+1}^N f_k(n)b_k(n-k-1) + \sum_{n=0}^{N-k-1} f_k(n+k+1)b_k(n)}{\sum_{n=0}^{N-k-1} f_k(n+k+1)^2 + \sum_{n=k+1}^N b_k(n-k-1)^2} \quad (2.12)$$

2.3.2 Moving average Algorithm(MA)

This method is appropriate when there is not a significant trend (fast up or downtrend) or seasonal characteristics. It is used only to smooth out the randomness of the data. This method is very simple to compute and requires one decision: the number of time periods to consider n . The larger the number of time periods considered, the smoother the forecast. The moving average forecast of order k , which we write as $MA(k)$, is defined as

$$F_{t+1} = \frac{1}{k} \sum_{i=t-k+1}^t Y_i \quad (2.13)$$

This forecast is only useful if the data does not contain a trend-cycle or a seasonal component. In other words, the data must be *stationary*. Data is said to be stationary if Y_t , which is a random variable, has a probability distribution that does not depend on t . A convenient way of implementing this forecast is to note that

$$F_{t+2} = \frac{1}{k} \sum_{i=t-k+2}^{t+1} Y_i = F_{t+1} + \frac{1}{k} \sum_{i=t-k+1}^t (Y_{i+1} - Y_{i-k+1}) \quad (2.14)$$

This is known as an updating formula as it allows a forecast value to be obtained from the previous forecast value by a simpler calculation than using the defining expression.

The only point of note is that moving average forecasts give a progressively smoother forecast as the order increases, but a moving average of the large order will be slow to

respond to real but rapid changes. Thus, in choosing k , a balance has to be drawn between smoothness and ensuring that this lag is not unacceptably large.

2.3.3 The Yule-Walker Method

Autoregressive modeling of noise data is widely used for system identification, surveillance, malfunctioning detection and diagnosis. Several methods are available to estimate an autoregressive model. For more information about Autoregressive model and other methods to determine its parameters has been described in [25]. Furthermore, the Yule-Walker Method has been explained in detail in [26]. Table 2.1 shown a compares the features of the various Algorithms to reducing the number of transmissions message.

Table 2.1: Compares the features of AR-B , AR-YW, MA and EDCD1 algorithms

	Burg AR algorithm [27]	Yule-Walker AR algorithm [27]	Moving Average [29]	EDCD1 [28]
Characteristics	Does not apply window to data Minimizes the forward and backward prediction errors in the least squares sense, with the AR coefficients constrained to satisfy the L-D recursion	Applies window to data Minimizes the forward prediction error in the least squares sense (also called “autocorrelation method”) Always produces a stable model.	Moving Average is calculated by taking the arithmetic mean of a given set of values.	This method compares the current sensed data to the last transmitted data. The idea behind the node will not send the data if the relative change is low than specified threshold selected by the fusion center

Advantages	Always produces a stable model		More benefit for correlated data.	Simple and adaptive
Disadvantage		Performs relatively poorly for short data records	High sensed data effect in the estimating value for the next period.	

2.3.4 Algorithm to Reduce the Number of Packet Transmissions During data Collection for single sensor (EDCD1)

In this part describe the EDCD1 algorithm as explained by authors in [28], Saving energy and prolonging the lifetime of the sensor node battery are the biggest challenges in IOT based WSN technology. One method to achieve low energy consumption – for WSN is by controlling the operations of Radio Frequency (RF) transmit On/Off, by observing state of the current measuring sensor value ($S_{V(t)}$) and the previous measuring sensor value transmitted ($S_{V(t-1)}$) for a sensor. In other words, the idea is to let the sensor node transmit the packets - only when changing the sensing measuring value. As we discussed in the introduction and related works section, some approaches have been made to decrease the energy utilization. One of them used (E_s) method as defined in Eqn. (2.15), to compare the current and last sensor measuring values. However, it is not feasible to update data due to the sensor node physical features. In addition, it is a rare event that the current sensor measured value has the same as previous sensor measured value in a given time interval.

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