An Efficient Data Reduction Technique for Single and Multi-Modal WSNs

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Abstract. Intelligent environments, in general, represent the future evolutionary development step for the real world environment. However, to achieve their aims, an intelligent system is required to collect data from the surrounding environment. Wireless Sensor Networks (WSN) is one of the technologies that extensively used to collect such data. It has been used in many applications such as surveillance, machine failure diagnosis, weather forecast, intelligent environments, intelligent campuses and chemical/biological detection. Nonetheless, their nodes suffer from energy starvation due to the large number of messages need to be transferred through the network. The purpose of this paper is to investigate new approaches for data reduction in single and multimodal WSN. The proposed approaches are based exponential smoothing predictors . At the same time, we believe that such approaches will enhance the reliability of the sensed data. Through large number of experiments, we test our approach through real data as well as through simulation.

Keywords. Smart/Intelligent environment, Wireless Sensor Network, Data reduction technique, multimodal WSN, and Exponential Smoothing

Introduction

Mark Weiser defined the smart/intelligent environment [1] as a physical world that is richly and invisibly interwoven with sensors, actuators, displays, and computational elements, embedded seamlessly in the everyday objects of our lives. However, the smartness of the environment is mainly based on information collected from its surroundings. The data is usually collected and handled by a network of wireless sensors. At the same time, the internal work of the network in terms of number of messages and processing plays an important role in the smart system performance.

With the recent advances in micro-electro-mechanical systems, digital electronics, and wireless communications have led to the emergence of Wireless Sensor Networks (WSNs). A WSN is an infrastructureless network made of hundreds to thousands of devices using sensors/nodes to monitor different conditions including temperature, vibration, pressure, motion, or pollutants, at different locations. These sensors are scattered throughout the monitored field. They cooperate together, establish a routing topology, and transmit data back to a collection point for automatic control or human evaluation. If one of the nodes fails, a new topology would be selected and the overall network would continue to function.

Sensor nodes are self-contained units equipped with a radio transceiver, a small microcontroller, and an energy source. A sensor node suffers from many restrictions such as: 1) small bandwidth, 2) small battery, and 3) limited computation capabilities. Consequently, sensor networks experience the same limitations in addition to the ad-hoc routing, self-configuration, reliability, and self healing requirements. These requirements force the network to exchange large number of overhead messages along with the data messages. Our work in this paper focuses on the sensed data reduction not on the overhead data reduction since it has the major effect on the lifetime of the WSN. We consider two different types of WSNs which are single and multi modal. In single modal networks, each sensor is assumed to measure only one feature from the sensed environment while in multimodal WSNs, a sensor may sense multiple features at the same time such as temperature, humidity, and pressure. Nowadays, new smart sensors are used to sense multiple features and report them in one message. These sensors help to provide fast and accurate readings to the monitoring environment and eliminate redundant hardware. For example, in BioControl [15] lighting multi variable platform sensor (MVP) is used to measures quality indicators, such as Adenosine Triphosphate (ATP), PH and temperature which allows fast decision to be made. Data reduction is a mandate in multimodal WSN due to the huge data need to be sent throughout the network.

Due to the importance of data reduction techniques, there are many techniques have been proposed. Santini, et al [2] proposed data reduction technique that uses Least Mean Square (LMS) adaptive algorithm. The LMS is an adaptive algorithm with very low computational overhead and memory footprint that provides excellent performance. It also does not require a priori knowledge or modeling of the statistical properties of the observed signals. Nicholas Paul, et al implemented this algorithm on FPGA kit where they shown that this method manages to increase the network life time by 18,962.5 % when compared to an always on solution [3]. However, sensors' data usually have a trend and might seasonal information that we can benefit from.

The problem of WSN lifetime maximization, in general, has been addressed in several other works which are not related to data reduction only. Hnin Yu, et al [4], for instance, listed four approaches for saving energy . The first one is the use of sensors' scheduling by which sensors alternate between sleeping and waking; the waking sensors sense events in their environments and the sleeping sensors avoid idle listening and overhearing. The problem with such approach is that it requires synchronization among sensors which generates overhead messages to do so. In addition, it might not possible to do synchronization especially in mobile WSN. The second lifetime maximization technique is the in-network processing where intermediate nodes may aggregate several events into a single event to reduce transmissions. Again, this technique is perfect only when sensors' readings do not vary and readings accuracy is not that important.

Network coding is the third lifetime maximization technique in which the collected data are mixed at intermediate node then encoding packets are sent instead of sending individual packets; consequently reducing the traffic. In the fourth approach, data collision are avoided to reduce the retransmission of packets; this is achieved by employing communication protocols including Time division multiple access (TDMA), frequency division multiple access (FDMA) and code division multiple access (CDMA). Their basic idea is to avoid interference by scheduling nodes onto different sub-channels that are divided either by time, frequency or orthogonal codes. Other approaches were proposed such as the dynamic voltage scaling, dynamic frequency scaling, energy efficient routing, asynchronous processors, nodes partitioning (clustering), the use of ultra wideband for radio communication and the use of CMOS low voltage and low power wireless IC.

Time series prediction is one type of the prediction techniques that heavily used in many applications including as Inventory Control Applications, tracking, and other Applications in Finance. Also, it may be used for saving the handover' latency in WiMAX applications as proposed in [5]. Throughout this paper, we experiment the performance of the time series prediction algorithms based on two categories of experiments. In the first category of experiments, we apply real collected data available at [6]. This experiments a sample of intelligent environment WSN where the data was collected by indoor sensors in the Intel Berkley Research Lab. The second category of experiments utilizes a simulation to WSN based on different network topologies as well as communication ranges and sensing ranges. Such experiments simulate outdoor WSN suitable for critical applications such as battle field and habitat monitoring.

The paper is organized as follows: the following section elaborates on the problem definition; section 2 explains the main idea behind time series prediction techniques used in this paper; section 3 shows the details of our experiments; finally, the paper concludes in section 4.

2. Problem definition

As mentioned, one of the basic problems in WSN is the network lifetime. Network lifetime can be defined as the interval of time, starting with the first transmission in the wireless network and ending when the percentage of nodes that have not terminated their residual energy falls below a specific threshold, which is set according to the type of application (it can be either 100% or less) [7] .Computation of node lifetime requires knowledge of the time spent in the various states including transmission, reception, listening, and sleeping. It is well known that the energy cost of transmitting 1 Kb of information a distance of 100 m is approximately the same as that for the executing 3 million instructions by 100 million instructions per second/W processor [8]. For this reason, energy efficient models have to be employed to reduce the wasteful power that is consumed in the radio communication. As a conclusion, the transceiver is the part responsible for the consumption of most energy, so data communication is very expensive in terms of power consumption. It is therefore mandatory to minimize the data items that need to be transmitted to the base station. Based on our knowledge, sudden changes in sensors' readings are not a common feature of WSN; therefore, utilizing this feature might increase the overall lifetime of the WSN. Some of the proposals in this regard forces the sensors to send only the abrupt change based on a threshold value. However, the data reliability, in this case, depends on the threshold value defined by the WSN user. Our proposal in this paper considers both the data reliability as well as the data reduction for the purpose of maximizing the overall network lifetime.

2. Our Approach

In this section, we present our proposed method for data reduction in WSN. Our approach utilizes the time series prediction algorithms; especially the exponential smoothing prediction algorithms. The name "exponential smoothing" reflects the fact that the weights decrease exponentially as the observations get older. Robert G. Brown proposed this idea in 1944 while he was working for the US Navy as an Operations Research analyst. During the 1950s, Charles C. Holt [14] developed a similar method for exponential smoothing of additive trends and an entirely different method for smoothing seasonal data In 1960, Winters tested Holt's methods with empirical data, and they became known as the Holt–Winters forecasting system. Throughout the next sections, we briefly describe the three different exponential smoothing methods.

2.1 The simplest exponential smoothing method

The simplest exponential smoothing method is the single smoothing (SES) method, and it called "Single" since only one parameter needs to be estimated. This method is used when the data has mean that is either stationary or changes only slowly with time. In other words, for higher prediction accuracy the data must not have trend or seasonality. Mathematically this model appears in the form [9]:

$$F_{t+1} = \alpha\, y_t + (1 - \alpha)\, y_t \qquad (1)$$

Where F_{t+1} is the prediction for the next period, α is the smoothing constant, y_t is the measured value in period t, and F_t is the old forecast for period t. If we recursively apply the smoothing equation to F_{t+1}, we get:

$$F_{t+1} = \alpha\, y_t + (1 - \alpha)\, y_{t-1} + \alpha\,(1-\alpha)^2\; y_{t-2} + \alpha\,(1-\alpha)^3 y_{t-3} + \cdots + \alpha\,(1-\alpha)^{t-1}\, y_1 \qquad (2)$$

So, SES is a weighted sum of all the previous observations. It is obvious that such a weighting scheme places much higher weights on more recent observations and the fluctuations from the mean also will be weighted heavily.

The smoothing constant must satisfy the following inequality $0 < \alpha < 1$, if α is chosen close to 1, more weights are put on recent values, and the model becomes more responsive to structural changes in the data stream. While if α is chosen close to 0, distant values are given weights comparable to recent values, and the model will have more ability to smooth out random fluctuations. For higher accuracy, the value of α which satisfies the smallest Root Mean Squared Error (RMSE) is chosen for use in producing the future predictions. The initial value of Ft plays an important role in computing all the subsequent values. Setting it to y1 is one method of initialization. Another possibility would be to average the first four or five observations.

2.1 Holt's method

Holt's method makes use of two different parameters, so it is called Double Exponential Smoothing (DES), and allows forecasting for series with trend. Mathematically this model appears in the form [9]:

The exponentially smoothed series or current level estimate:

$$L_t = \alpha\, y_t + (1 - \alpha)\,(L_{t-1} + b_{t-1}) \tag{3}$$

The trend estimate:

$$b_t = \beta\,(l_t - L_{t-1}) + (1 - \beta)\, b_{t-1} \tag{4}$$

Forecast m periods into the future:

$$F_{t+1} = L_t + mb_t \tag{5}$$

Where L_t is the estimate of the level of the series at time t, α is the smoothing constant for the data, y_t is the new observation or the actual value of series in period t, β is the smoothing constant for trend estimate, b_t is the estimate of the slope of the series at time t, and m = periods to be forecast into the future. The constants α and β are chosen between 0 and 1, where their values must satisfy the smaller RMSE. To start the process, both L_1 and b_1 must be specified. Possible starting values are $L_1 = y_1$ and $b_1 = y_2 - y_1$. Thus, no forecasts can be made until y_1 and y_2 have been observed. By convention, we let $F_1 = y_1$.

2.3 Holt-Winter's method

Holt-Winter's method involves three smoothing parameters to smooth the data, the trend, and the seasonal index. We will not mention the mathematical model since it is only suitable for data stream with trend and seasonality. We limit the research in this paper to the previous two prediction methods since the real data that we have has no seasonal features. However, we plan to study the Holt-Winter's method when we got access to sensors' seasonal data.

The main idea behind utilizing these predictors in sensors' data reduction is to use typical predictors on sensor nodes as well as on the sink node as shown in Figure 1. In a clustered network, the same predictor will be running on the cluster heads as well. Predictors running on sensors are used to predict the sensor's readings, where the predictor on the sink node is initialized after the sensor node sends a number of readings to it. Therefore, on the sensor, we have two values, the sensor's reading and the predicted value. If the difference between these two values, which is called the error signal, is lower than a certain threshold value then the transmission between the two nodes is canceled as given in Figure 1, and the sink node stores the predicted value generated from its own predictor as the sensor reading at this time. On the other hand, if the error signal is greater than this threshold, then the sensor reading is transmitted to the sink node, and the sink node uses this value to update its predictor.

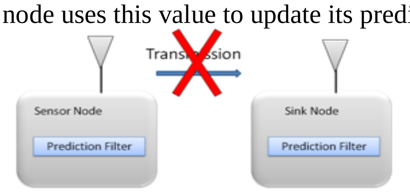

Figure 1. Transmission is canceled when the error signal is lower than the threshold

We selected these types of predictors due to their simplicity. They also require small memory footprint, and they have high degree of accuracy. Moreover, we will investigate the lifetime of the sensor network in three modes of operations:

1. Normal mode where no power saving technique is used in the WSN (naive method) .

2. Single modal in which the sensors will collect only one environmental phenomenon such as temperature or humidity. This model will be tested twice one of these tests using SES while the other using DES.

3. Multimodal WSN where the sensors will collect multiple phenomena such as temperature, humidity and pressure. There are two techniques to send these measurements from the sensor node to the sink nodes, either using one data message for all measurements or using multiple messages to send each phenomenon in a separate message. Each case will be tested along with SES and DES.

3. Experimental and Simulation Results

In this section, we test our data reduction proposal based on single and multiple smoothing predictors for both single modal and multimodal WSN. Our experiments are categorized into two categories which are experimental category based on real data and simulation results based on simulation to the WSNs environment. Throughout the next sections, we will elaborate more on these categories.

3.2 Experimental Results

In the first set of experiments, the exponential smoothing-based data reduction strategy was tested on a set of real world data which is publicly available at [6]. Every 31 seconds, humidity, temperature, light and voltage values were collected from 54 Mica2Dot sensor nodes [10] that were deployed in the Intel Berkley Research Lab between February 28th and April 5th, 2004. A file which contains a log of about 2.3 million readings collected from the 54 sensor nodes was downloaded from [6]. Our experiments started by determining the best predictors' constant values to be used throughout the rest of the experiments. As shown in Figure 2, these experiments try to determine the best α value for the used data. As can be seen, the larger the smoothing constant the lower the Mean Square Error (MSE). In addition, we noticed that the MSE in case of temperature values is smaller than that in case of humidity.

In addition, DES requires some other constants that need to be adjusted such as α and β. Therefore, we tend to experiment with large number of values for α and β and study the predictor conversion in each case using MSE as shown in Figure 3. It turns out that MSE decreases as β increase; however, starting from β=0.4 the MSE values are almost the same. Therefore, we selected β to be 0.4 and α to be 0.6. The reason behind choosing α to be 0.6 not 0.8, as given in Figure 2, is that based on our observation in DES, it produces better MSE when α=0.6 not 0.8. Therefore, to standardize our experiments, we set α to 0.6.

Now, the temperature and humidity values are used to test the SES as shown in Figures 4 & 5, respectively. The figures show that the predictors' data are very close if not the same as the actual data and the predictors' convergence are very fast. For instance at epoch number 1000 in both figures, the predicted data is the same as the real data.

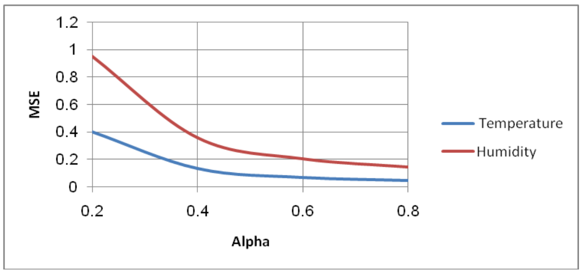

Figure 2. MSE decreases as α increase.

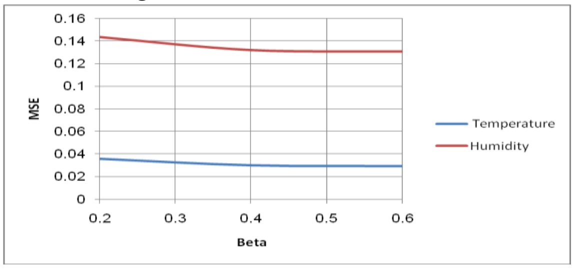

Figure 3. MSE decreases as β increase.

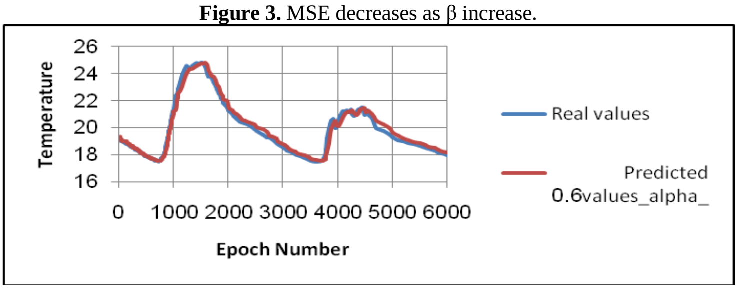

Figure 4. Actual temperature readings and the predicted values using SES

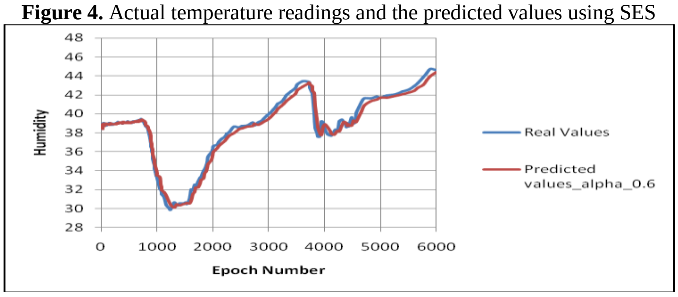

Figure 5. Actual humidity readings and the predicted values using SES

In Figures 6 & 7, the performance of DES is tested for both temperature and humidity values respectively. The results show that the predictors' data are also very close to the actual data and the predictors' convergence are fast. However, Figure 6 shows that the MSE in case of temperature values is smaller than that in case of humidity. Therefore, we conclude from these experiments that, DES is more accurate if the data represent temperature values based on the provided data from [6].

3.2 Simulation Results

In the previous section, we tested our proposed data reduction techniques on real data. However, this real data does not actually measure the effect of our reduction techniques on sensors and WSNs energy. Therefore, we developed a simulator to investigate how our reduction techniques reduce the transmitted data among the sensors as well as between the sensors and the sink node. We modified the WSN simulator developed by David J. Stein [11]. It is a very simple simulator that is written in C# and used to detect and report certain events across certain areas. The author simulated the WSN as a connected graph and sensors always transfer their data towards the sink node (data collector). Sensors decisions in sending and/or forwarding messages are based on their residual energy as proposed in [12].

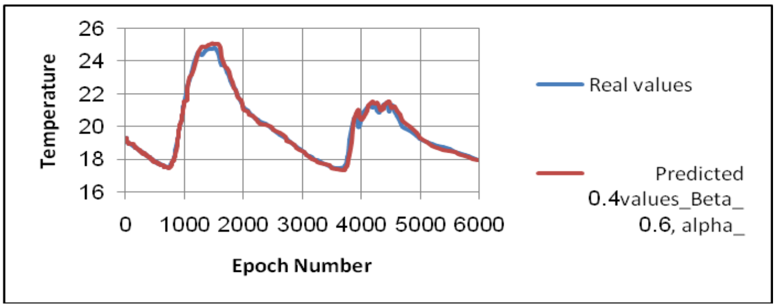

Figure 6. The actual temperature readings and the predicted values using DES

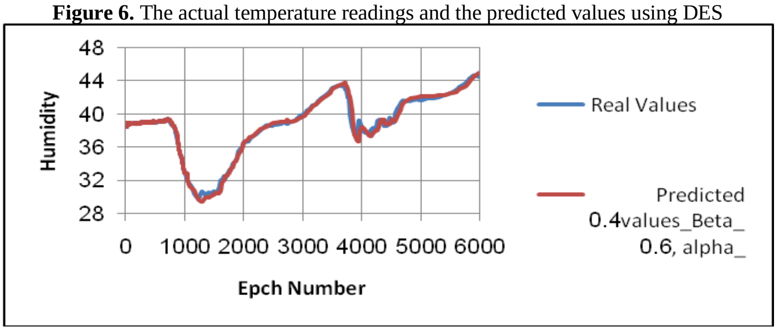

Figure7. The actual humidity readings and the predicted values using DES

The simulator is modified to cope with our desired mission, where the event is changed from detecting moving objects to sensing environmental phenomena such as temperature, humidity, or pressure. In addition, the data reduction technique is implemented based on SES and DES in both single and multimodal WSNs. In a multimodal WSN, it is assumed that each sensor is able to report multiple phenomena from the monitored field. For the purpose of accuracy, we implemented a similar energy model to the one used in [13]. The model assumes that the radio channel is symmetric such that the energy required to transmit a message from node A to node B is the same as the energy required transmitting a message from node B to node A for a given Signal to Noise Ratio (SNR). In addition, all sensors are assumed to be sensing the environment at a fixed rate and thus always have data to send to the end-user.

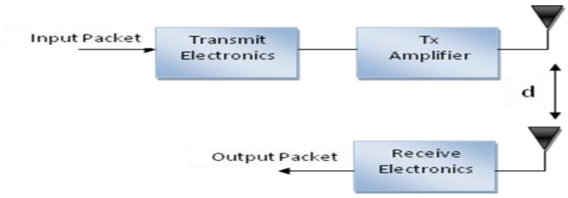

Figure 8. The First order radio model

As given in Figure 8 and Eq. (1), the first order radio model stated that the energy for transmitting 1 bit data over distance d is:

$$E_t = a_1 + a_2 * d^k \quad (6)$$

Where a_1 is the energy spent by transmitter electronics (a_1 = 50 nJ/bit), a_2 is the transmitting amplifier (a_2 = 100 pJ/bit/m^2), and k is the propagation loss exponent, while the energy for receiving 1 bit data E_r is equal to the energy spent by receiver electronics (a_3 = 50 nJ/bit). This model is used throughout all of our experiments.

3.2.1 Simulation Setup

Our simulator runs on a Windows 7 laptop machine with 2.13 GHz processor and 2 GB RAM. 35 nodes are randomly deployed in an area of 460 X 300 cm. It is assumed that nodes are equipped with a 1 cm^3 of non-rechargeable lithium battery (at maximum energy density of 2880 J/cm3 or 800 watt hour per liter) were to consume 100 µW of power on average. The smoothing constants are set to $\alpha = 0.6$, $\beta = 0.4$ according to the results obtained from previous sections. In addition, the threshold varies from 0.00 to 0.6 , so the sensors will not send its readings as long as the error signal is smaller than the given threshold . The lifetime of the WSN is considered as the period between the start of simulation process till the depletion of at least one sensor node from its energy. In our experiments, we believe it will not be practically to consider the network lifetime as the running time of the simulator until a node's energy is depleted. Thus, we count the lifetime based on the number of iterations that the simulator takes till a node dies. The iteration is described as a complete pass over all the nodes having data to be sent and/or forwarded till their data reaches the sink node. The results presented in this section is the average values over 1000 runs to the simulator with different settings including different network topologies. WSNs used in our simulator are considered to be flat where no clustering techniques are used. Also, since our approach is over performing the naive model with 1000's of times, we will use the logarithmic scale for comparisons and the list of the lifetimes in numbers is presented in Table 1.

3.2.2 Case Study One: Single Modal WSN

Here, we compare our reduction approaches to the naïve communication method between the sensors and the sink node where each sensor sends its information or forward others information in a separate message. Also, we assume that each sensor senses only one phenomenon from the monitored environment, where the measurements are simulated based on a random distribution as shown in Figure 10. As can be seen in the figure, the fluctuation of the input values is high which might affect the operation of the predictors as we given in Figure 10.

Figure 10 depicts the comparison among three different algorithms which are the naïve, SES, and DES. The three algorithms are compared in terms of their lifetimes with different threshold values. As can be seen in the Figure, DES performs almost the same as the naive model when the threshold is very low. At the same time, SES over performs the naïve model by small percentage when the threshold is low. This means the predictors' error is high relative to the threshold value. However, with increasing the threshold value, the lifetime of the network increases with large percentage since there is no need for sensors to flood the network with messages. Moreover, we noticed that the DES over performs the SES due to the high fluctuations in the sensors readings.

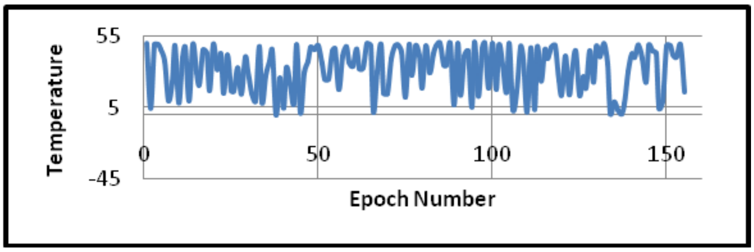

Figure 9. The sensor nodes' readings

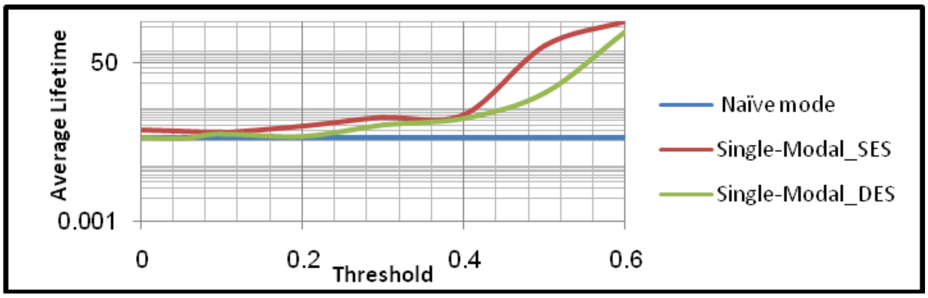

Figure 10. Lifetimes in Single Modal WSN. (Logarithmic scale)

3.2.3 Case Study Two: Multi-Modal WSN

In these set of experiments, the performance of our data reduction techniques are measured according to the concept of multi-modal WSNs. For the multimodal WSN, in which multiple environmental phenomena are collected. We test our approaches with two different settings which are single packet and multi packet; in single-packet settings, the monitored data are collected and sent all together in one packet to the sink/cluster head node. While in multimodal multi-packets, each measured phenomenon is sent within a separate packet to the collector node.

Again, the SES and DES were tested with different threshold values as given in Figures 11 and 12. For single packet settings given in Figure 11, the predictors seem to perform the same as the naive model. However, after certain threshold (0.2) their performances tend to be much better than the naive model. In fact, the lifetime increases almost linearly when predictors' are used.

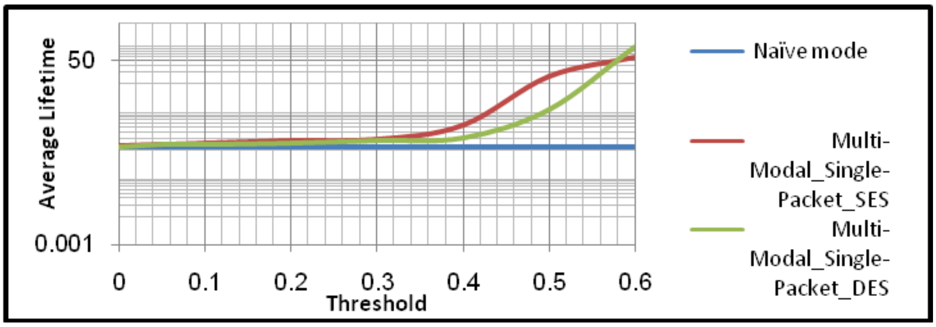

Figure11. Lifetimes in Multi-Modal WSN (Single-packet settings). (Logarithmic scale)

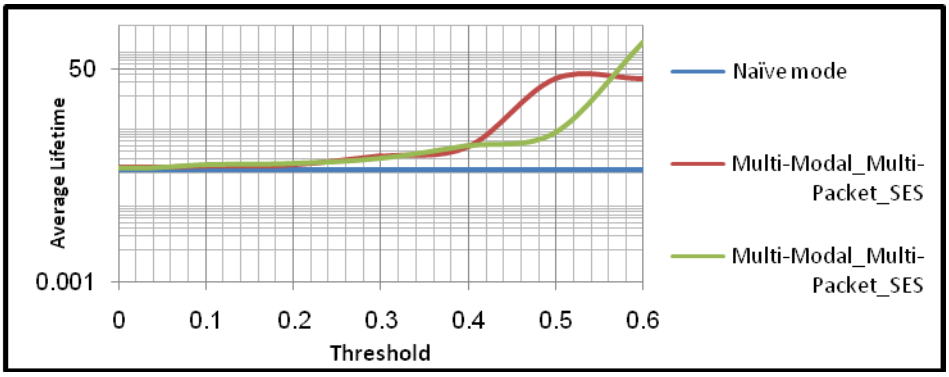

Figure 12. Lifetimes in Multi-Modal WSN (Multi-packet settings). (Logarithmic scale)

While in the second setting as shown in Figure 12, a multimodal WSN is simulated with sending the sensed features in separate messages when it is needed. We allowed different thresholds to be used and the WSN lifetime with each threshold is recorded. The performance of our approach is similar to the one presented in Figure 11.

Table 1. Lifetimes versus threshold values

	Threshold/Lifetime							
	0	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**
Naive	309	309	309	309	309	309	309	309
Single-Modal_SES	515	484.2	456.8	698.8	1248.4	1559.6	164068	902792
Single-Modal_DES	310.6	301.6	415	340.2	730	1211	6855.8	428508
Multi-Modal Single-Packet_SES	344.6	366.8	386.6	460.8	495.8	1118.2	19732.8	60539.6
Multi-Modal Single-Packet_DES	311.4	355.2	355	386.4	446.2	515.4	2820.8	108392.5
Multi-Modal Multi-Packet_SES	341.4	335.2	366.6	379.4	611.6	996.2	30320	30138
Multi-Modal Multi-Packet_DES	328.6	335.8	389.2	410	530	1002.2	2034.4	206377

4. Conclusion

In this paper, we introduced a new approach for data reduction in WSN. The approach utilizes single and double exponential predictors to reduce the number of messages transmitted between the nodes and their neighbors as well as between the nodes and the sink node. Our approach also targeted the reliability enhancement in sensors data. We tested the performance of our approach compared to the naïve model where each sensor sends its sensed data in a separate message to the sink node. Our results showed that such approaches will increase the lifetime of the network up to 100s' of times when the used threshold is large. In our future work, we will implement our proposal in this paper on a real network that will arrive to our lab in the next few days.

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