Energy Saving and Reliable Data Reduction Techniques for Single and Multi-Modal WSNs

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***Abstract*—Wireless Sensor Networks (WSNs) suffer from many limitations such as the computing capabilities, and the allocated bandwidth. However, the limited energy source is the dominant factor where energy starvation occurs due to the large number of messages that need to be transferred through the network. In this paper, we propose new protocols to save the nodes energy as well as prolonging the overall network lifetime. Not like other protocols proposed in the literature, our protocols consider the accuracy/ reliability of the reported data to the sink node. Our first approach considers different types of wireless sensor networks including single and multimodal wireless sensor networks. Our second protocol utilizes the concept of distributed fuzzy logic agents for energy saving in wireless sensor network. Our approaches are extensively tested using simulation as well as real data captured from MIT WSN laboratory. In addition, the paper introduces a WSN prototype based on our data saving approaches. Our conclusion reveals promising results.**

***Keywords*—Wireless Sensor Network, Data Reduction technique, Reliability, Multimodal WSN, Fuzzy Logic, WSN Prototype, and Exponential Smoothing**

I. Introduction

The need for a new technology model that collects and analyzes data from the surrounding environment has led to the emergence of Wireless Sensor Networks. WSN is a collection of battery-powered sensors that monitor our environment. These sensors suffer from limited communication and sensing ranges, limited processor capability, and small memory footprint [1]. However, nodes could be responsible for sensing and transmitting its own sensed data as well as other sensors messages. Therefore, energy consumption is one of the important challenges in WSNs. Due to the fact that the radio transceiver consumes the most of the sensors' energy, reducing the number of exchanging messages among the sensors is one of the WSNs requirements. For instance, Verdone in [2] found that the energy cost of transmitting 1 KB of information a distance of 100m is approximately the same as executing 3 million instructions. Consequently, many devices such as Mica2 and MicaZ with two AA batteries may live only for a few days if no power management schemes are used.

On the other hand, due to the usage of WSNs in many of the critical applications, data accuracy and reliability represent a key challenge in WSNs. For instance, WSNs are used in battle fields [3] and health care [4]. Therefore, it is a tradeoff between reducing the number of messages to be exchanged among the sensors as well as between the sensors and the sink node and sending reliable data. This situation became more challengeable when introducing the concept of multimodal WSNs. In a multimodal WSNs, sensors may sense multiple features such as temperature, humidity, and pressure at the same time. A node might need to send each feature in a single message or send all sensed features collectively in one message. Our work in this paper introduces new techniques for reducing energy consumption in WSN by minimizing the amount of data to be transferred among the sensor nodes as well as between the sensors and the sink. We introduce two smart approaches where the first utilizes the concept of data prediction techniques and the second is based on the concept of fuzzy logic.

The paper is organized as follows: the following section elaborates on the related work; section III overviews some of similar protocols and ideas; section IV shows the details of our prediction algorithms simulation results; section V explains the idea behind the usage of fuzzy logic and its efficiency; section VI examines the performance of our approaches through WSN prototype; finally, the paper concludes in section VII.

II. Overview

For the paper to be self-contained, this section provides a short review on some of the important techniques used for energy saving in WSNs. In addition, we introduce some of the methodologies that will be used later in this paper.

Energy saving in WSNs could be classified into two classes; the first class focuses on the energy saving in sensors hardware while the other class concentrates on developing efficient protocols for sensors operation. In the first class, sensors lifetime was maximized by reducing the power consumed in the different operations inside the sensor node through using: 1) the dynamic voltage scaling [5], 2) dynamic frequency scaling [6], 3) asynchronous processors [7], 4) ultra wideband for radio communication [8], and 4) CMOS low voltage and low power wireless Integrated Circuit (IC) [9]. Other techniques try to benefit from the surrounding environment by converting the ambient energy such as solar, vibration, and wind energies into electricity to power the sensor nodes as described in [10] and [11].

The second class for energy saving in WSNs attracted many of the researches. The literature under this class could be simply categorized, as shown in Fig. 1, into algorithmic and prediction protocols. Further, the prediction methods could be divided into stochastic, time series, and heuristic methods.

Algorithmic methods are usually handled in scheduling, routing, and clustering protocols. For instance, Hnin Yu, et al [12], enumerate four techniques for energy saving. The first one utilizes the sensors scheduling concept where sensors alternate between sleeping and waking. The waking sensors sense events in their environments and the sleeping sensors avoid idle listening and overhearing. The second one aggregates several events into a single event at intermediate nodes to reduce transmissions. Network coding is the third technique in which the collected data are mixed at intermediate node then encoded packets are sent instead of sending individual packets. In the last one, data collision is avoided to reduce the retransmission of packets due to scheduling nodes onto different sub-channels that are divided either by time, frequency or orthogonal codes. Other protocols such as routing and clustering are heavily introduced in the last few years such as the ones reported in [13], [14], [15], and [16]. The major disadvantage of the algorithmic approach is the overhead introduced along with each protocol as well as implementation issues where most of them either implemented on a small network prototype or tested by simulators.

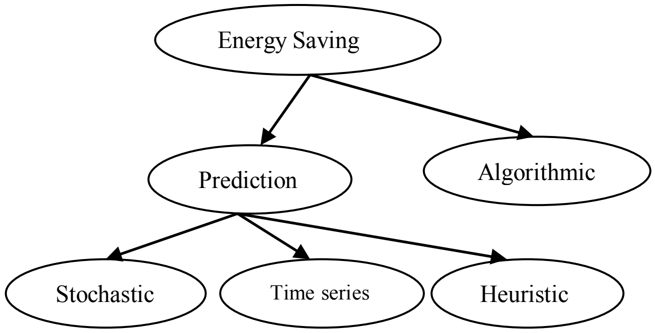

Figure 1. Energy saving approaches in WSNs

On the other hand, prediction techniques are also used in WSNs for energy saving and data reduction. Such techniques evolve some of the stochastic, time series, and heuristic methods. Stochastic methods are usually based on probabilistic models such as correlation [17], Kalman filter [18] and Dynamic Probabilistic Model (DPM) [19]. Such techniques are used in many other systems and proved to be efficient in most of the cases including WSNs. Time series techniques are utilized by Santini, et al. in [20] where they tried to reduce the amount of data to be transferred among the nodes by implementing the Least Mean Square (LMS) adaptive algorithm on the senor nodes. The LMS is an adaptive algorithm with very low computational overhead and memory footprint. It also does not require a priori knowledge or modeling of the statistical properties of the observed signals. Nicholas Paul, et al [21] implemented this algorithm on FPGA kit where they showed that this method managed to increase the network lifetime by almost 18,962.5 % when compared to an always on solution. However, sensors' data usually have a trend and might be seasonal that can benefit from. As can be seen, the prediction algorithms could be efficient in saving the sensors' energy and reducing the transferred messages; however, another factor which is the data reliability is ignored during the implementation of such techniques. There are some other heuristics that are not widely used due to the centralized implementation such as PREMON and buddy protocols [22].

A. Single Exponential Smoothing (SES)

Robert G. Brown [23] proposed this idea of SES in 1944 while he was working for the US Navy as an operations research analyst. This method is used when the data have a *mean* that is either stationary or changes slowly with time which is usually the case of WSNs data. The simplest form of exponential smoothing is given by the formulae [23].

$$F_{t+1} = \alpha y_t + (1-\alpha) F_t \tag{1}$$

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:

$$F_{t+1} = \alpha y_t + \alpha(1-\alpha) y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} + \dots + (1-\alpha)^{n+1} F_{t-n} \tag{2}$$

as time passes the smoothed statistic F_t becomes the weighted average of a greater and greater number of the past observations y_{t-n}, and the weights assigned to previous observations are in general proportional to the terms of the geometric progression $\{1, (1-\alpha), (1-\alpha)^2, (1-\alpha)^3, \dots\}$.

The smoothing constant must satisfy the following inequality $0 < \alpha < 1$, if α is chosen close to 1, it will have less of a smoothing effect and give greater weight to recent changes in the data. On the other hand, values of α closer to zero have a greater smoothing effect and are less responsive to recent changes. For higher accuracy, the value of α which satisfies the smallest Mean Squared Error (MSE) is chosen for use in producing the future predictions. The initial value of F_t plays an important role in computing all the subsequent values. One option is to assign the first observation as an initial value. However, we can get more accurate initialization by averaging the first five observations.

B. Double Exponential Smoothing (DES)

During the 1950s, Charles C. Holt [23] developed a method for exponential smoothing of additive trends. The predictor's operation is initiated by decomposing the data under consideration into level and trend signals. Afterwards, these signals are smoothed using (3) and (4) while the predicted values are found using equation (5).

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

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta) b_{t-1} \quad (4)$$

$$F_t = L_t + m b_t \quad (5)$$

Where L_t is the estimate of the level at time t, y_t is the actual value of series in period t, α is the data smoothing factor, $0 < \alpha < 1$, β is the trend smoothing factor, $0 < \beta < 1$, b_t is the estimate of the slope of the series at time t, and m is the period to be predict into the future. In equation (3) L_t is adjusted directly for the trend of the previous period, b_{t-1}, by adding it to the last smoothed value, L_{t-1}. This helps to eliminate the lag and brings L_t to the appropriate base of the current value. Afterwards, equation (4) evaluates the trend at time t, which is expressed as the difference between the last two values. Equation (4) is similar to equation (1), but here applied to the updating of the trend. The smoothing constants α and β are chosen independently between 0 and 1, where their values must satisfy the smaller MSE. To start the process, both L_1 and b_1 must be initialized by setting $L_1 = y_1$ 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 $F_1 = y_1$.

The work in this paper focuses on utilizing the concepts of single and double exponential smoothing techniques smartly in WSNs for data reduction. At the same time, our approach takes into consideration the tradeoff between data reduction and the data reliability. Moreover, up to our knowledge, this is the first work that mull over data reduction in multimodal WSNs. Nevertheless, we introduce another fuzzy logic based data reduction approach and test it against real and simulated data.

III. METHODOLOGY

As mentioned, the problem that we want to tackle in this paper is energy saving by data reduction in WSNs. For better understanding, the problem is mathematically formulated as Integer Linear programming (ILP) as follows:

$$min \sum_{t=0}^{L} \sum_{s=1}^{n} M_{st} X_{st} \qquad \forall_{s,t} \quad (6)$$

Provided that:

$$L_{st} \geq \mu \qquad \forall_s \quad (7)$$

$$| T_{st} - T_{s(t-1)} | \leq \gamma \qquad \forall_s \quad (8)$$

$$X_{st} \ [0,1] \quad (9)$$

Equation (6) tries to minimize the number of messages M_{st} that can be sent by a sensor s starting from $s=1$ to n at any time t. At the same time, a sensor s is considered died when its lifetime or residual energy L_{st} is reached a certain threshold μ as stated in (7). X_{st} is a binary variable that is set to 1 when a message is to be sent and 0 otherwise as given in equation (9). On the other hand, it is necessary to maintain the accuracy of the data T_{st} sent by a sensor s at time t high and suitable for the application's requirements as described in (8). However, the data reliability, in this case, depends on the threshold value defined by the WSN user (γ *in our case*). The sink node will be working on values other than the original readings of the sensor nodes. Therefore, it is obvious the reliability and data reduction are contradicting terms since the reliability requires sending every piece of information to the sink node; while the data reduction and energy conservation require the minimization of the number of messages that are received by the sink node for other nodes.

Thus, this paper smartly tries to use very simple predictors in terms of their memory footprint and required processing but efficient in terms of data reliability. Single and/or double exponential prediction algorithms are supposed to be implemented on both sensors and sink nodes. Node's predictor is 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 (a sensor and the sink) is canceled, 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.

Throughout the next section, we experiment the performance of the proposed algorithms based on two categories of experiments. The first category of experiments utilizes a simulation of 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. Secondly, we test the exponential smoothing predictors on a real WSN where National Instruments (NI) WSN kit is used to examine the effectiveness of our approach.

IV. SINGLE AND DOUBLE SMOOTHING RESULTS

This section starts by the describing the environment set followed by the simulation of both single and multimodal WSNs.

A. Environment Setup

A WSN simulator is developed 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 simulator developed by David J. Stein [24]. The simulator is 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. Sensors decisions in sending and/or forwarding messages are based on their residual energy as proposed in [25]. 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.

For the purpose of accuracy, we implemented a similar energy model to the one used in [26]. The first order radio model stated that the energy for transmitting 1 bit data over distance d is:

$$E_t = a_1 + a_2 * d^k \quad (10)$$

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.

Our simulator runs on machine with 2.13 GHz processor and 2 GB RAM with Windows 7 operating system. 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 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 that 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 reach the sink node. In the following subsections, the influence of the data reduction technique based on exponential smoothing predictors is tested.

B. Data Reduction Technique Based On Exponential Smoothing Predictors

In this section, both single and double smoothing predictors for both single modal and multimodal WSN are experimented with. However, one of the requirements of these predictors is to set the smoothing constant presented in equations (4), (6), and (7) by appropriate values. We believe that such constants will be determined once we know them and can be used in different WSNs applications. Therefore, the following set of experiments tries to find such constants.

1) Predictors' parameters and reliability test

Although single and double smoothing algorithms are not new and heavily used in many applications, their reliable constants could differ based on the type of used data. Therefore, in these set of experiments, the exponential smoothing predictors were tested on a set of real world data which are publicly available at [27]. In these data, every 31 seconds, humidity, temperature, light intensity and voltage values were collected from 54 Mica2Dot sensor nodes [28] that were deployed in the Intel Berkley Research Lab between February 28th and April 5th, 2004. The indicator used in these experiments to identify the best constants values is Mean Square Error (MSE). The results given in Figs. 2 and 3, show that the larger the smoothing constant the lower the MSE. In addition, it has been noticed that MSE in case of temperature values is smaller than that in the case of humidity.

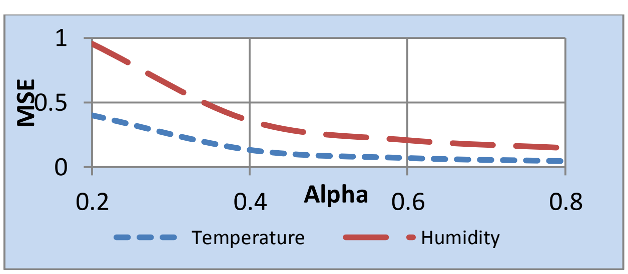

Figure 2. MSE decreases as α increase.

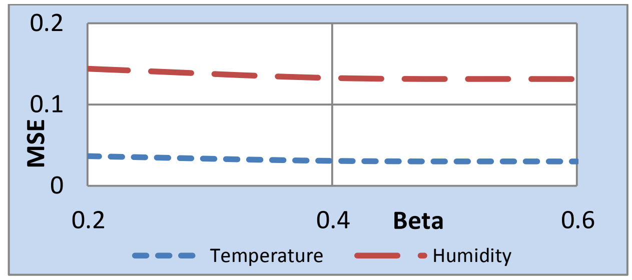

Figure 3. MSE decreases as β increase.

As can be seen in Figs. 2 and 3, starting from β=0.4 the MSE values are almost the same. Consequently, β is selected 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 Fig. 3, is that based on our observation in DES, MSE is approximately constant beyond α=0.6. Therefore, to standardize our experiments, we set α to 0.6. Also, the MSE in case of temperature values seems to be smaller than that in case of humidity based on the used data. Therefore, we can initially conclude that exponential smoothing predictors are more accurate if the data under consideration represents temperature values rather than humidity values.

The reliability of the measurements and the predictions are estimated based on the Standard Deviation (SD). It is sometimes evaluated as a percent of the mean; in such case it is known as a Coefficient of Variation (CV). When the measurements of a single subject are repeated to determine the mean and SD, the resulting coefficient of variation could be considered as an important measure of reliability. As shown in Fig. 4, CV readings are linearly proportion to the smoothing constant (Alpha) in case of SES. So we can conclude that the lower the smoothing constant the higher the data reliability if the SES is used; on the other hand, the higher the smoothing constant the higher the data reliability if the DES is used.

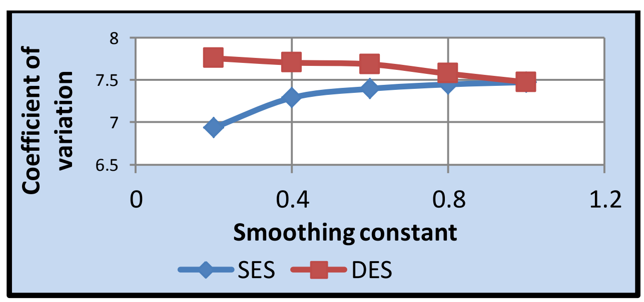

Figure 4. Coefficient of variation in case of humidity readings

2) Single and Multimodal Simulation results

In this subsection, different set of experiments are used to examine the performance of our proposal for reliable data reduction approach. In addition, the effect of our data reduction technique on the WSN lifetime is investigated. The first set of experiments target a single modal WSN while the second set considers multimodal WSN. The smoothing constants are set to α = 0.6, β = 0.4 according to the results obtained from previous sections. In addition, the threshold varies from 0.0 to 2, so the sensors will not send its readings as long as the error signal is smaller than the given threshold.

The results presented in this section is the average values over 1000 runs with different settings including different network topologies. Simulated WSNs in these following experiments consider flat network where no clustering is used. Input of the simulator is the real data captured from [27]. Nevertheless, the presented results in the following experiments use the logarithmic scale for comparisons.

a) Single Modal Experiments

The naïve algorithm to send the data in a flat WSN is to use a multi hop transmission from the source to the sink node. This naïve algorithm is compared to SES and DES algorithms in terms of network lifetime as shown in Fig. 5. As can be seen in the figure, different threshold values are used within the range of 0 and 2. From the results, it can be noticed that the SES over performs DES for low threshold values. However, both of the algorithms produce almost the same performance for high threshold values. At the same time, both of them over perform the naïve modal for all threshold values. This means that predictors' error is small relative to the threshold value. In addition, with increasing the threshold value, it is obvious that the lifetime of the network increases since there is no need for sensors to flood the network with messages. However, the increasing of the network lifetime with large threshold was not expected to be that high. On the other hand, the reliability of the data will be degraded.

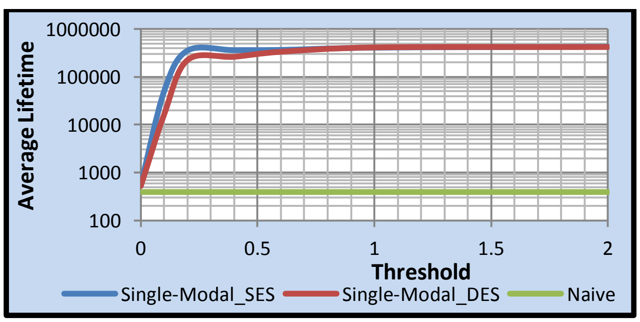

Figure 5. Lifetimes in Single Modal WSN (Logarithmic scale)

b) Multi-modal WSN

In this set of experiments, multimodal sensors have been used where a sensor may report more than one feature from the monitored field. There are two settings that are proposed to examine the multimodal WSN which are: 1) every sensor sends each measured feature in a separate message, 2) all of the sensor's features will be sent collectively in one message. For single packet settings shown in Fig. 6, SES, DES, and the Naive algorithm are compared in terms of the network lifetime. As can be seen, SES and DES seem to perform the same with different threshold values. At the same time, their performances tend to be much better than the naive model. In fact, the lifetime increases almost linearly after the threshold reaches 0.3.

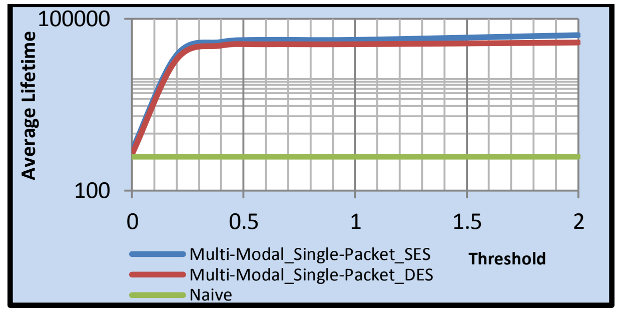

Figure 6. Lifetimes in Multi-Modal WSN using real sensor readings (Single-packet settings).

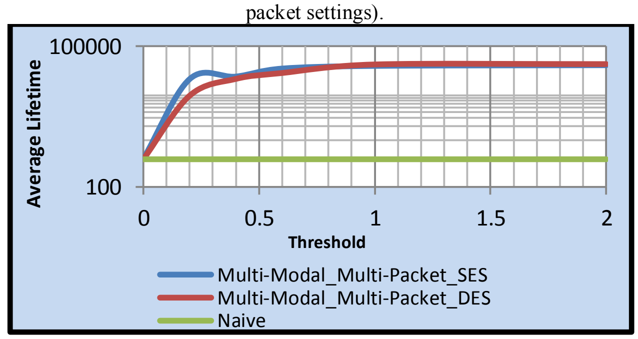

Figure 7. Lifetimes in Multi-Modal WSN using real sensor readings (Multi-packet settings)

In the second setting, shown in Fig. 7, a multimodal WSN is simulated with sending all of sensed features collectively in a message when it is needed. The performance of our approach in terms of lifetime is similar to the one presented in Fig. 7 except the fact that SES over performs DES for threshold values below 0.4

V. Data Reduction Based on Fuzzy Logic Algorithm

Lotfi A. Zadeh proposed the concept of fuzzy logic in 1965 [29]. Fuzzy logic is a multi-valued logic, where it formalizes reasoning when dealing with vague terms. The decisions are not limited to either true or false, or as with Boolean logic either *0* or *1*. Therefore, fuzzy logic algorithms take into consideration the degrees of truthfulness and falsehoods. For instance, the Boolean logic is not only *0* and *1* but also all the numbers that fall in between.

Fig. 8 shows that the crisp set of input data are gathered and converted to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms and membership functions; this step is known as fuzzification. Afterwards, an inference is made based on a set of rules. Finally, the resulting fuzzy output is mapped to a crisp output using the membership functions in the defuzzification step as shown in Fig. 8.

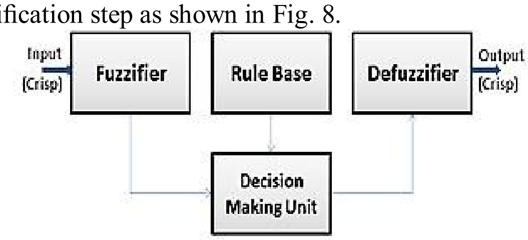

Figure 8. A Fuzzy logic System [30].

Linguistic variables are a representation for the system's input or output variables where they convert the numerical values into words or sentences from a natural language. The membership functions are used in the fuzzification and defuzzification processes of a fuzzy logic to map the non-fuzzy input values to fuzzy linguistic terms and vice versa. Therefore, our proposal is apply fuzzy logic on every sensor and the sensor sends only its decision to the sink node. The inputs to the fuzzy logic algorithm are the temperature, humidity, and light intensity values, for instance, at a certain area. These values will be transformed to linguistic variables in order to be processed using the fuzzy logic. The output of the fuzzy logic algorithm is a value that represents the probability of certain event to occur. Therefore, sensor nodes will not turn on its transceiver unless this probability exceeds a threshold set by the user. Fuzzy logic is used as an alternative solution to the problem of power consumption in WSNs through minimizing the number of messages sent to the end user. In this case, sensor nodes can turn off their transceivers until a real danger probably exists. This danger is sensed based on temperature, humidity and light intensity measurements.

To test the fuzzy logic approach, temperature and humidity data collected from [27] are used as input to the fuzzy logic controller. The temperature and humidity are mapped, as shown in Figs. 9 and 10, to "*Low*", "*Medium*" and "*High*" linguistic input variables. "*Very Low*", "*Low*", "*Medium*", "*High*" and "*Very High*" terms are also used as output linguistic variables which represent the probability of fire in our example. On the other hand, the fuzzy rules are set empirically. For instance, table 1 shows sample of the fuzzy rules used in the defuzzification process to determine the probability of fire. In addition, the center of gravity for singletons method is used to determine the output (probability of fire occurrence).

TABLE 1: SAMPLE FUZZY RULES

Temperature	Humidity	Light Intensity	Output
L	H	L	VL
L	M	H	L
H	M	M	H
H	L	H	VH
:	:	:	:

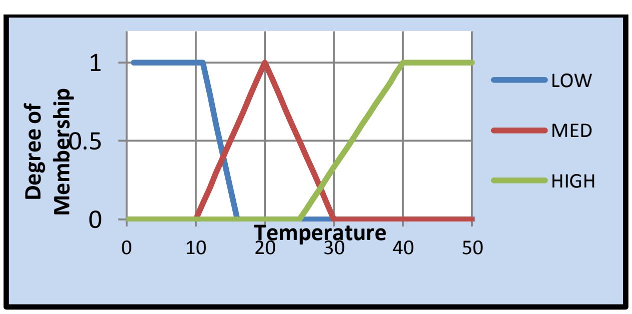

Figure 9. The membership function for the input variable

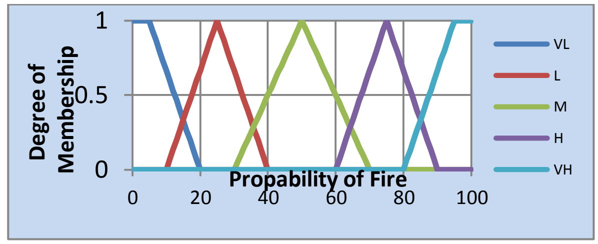

Figure 10. The membership function for the output variable

The same simulator parameters and the energy model used in the previous section experiments are also used in this set of experiments. Fig. 11 examines the effect of the fuzzy logic approach on the WSN lifetime against the probability of fire decisions in each node. As can be seen, the average lifetime of the WSN increases as the probability of fire increase except for the range between 55% and 59%, the lifetime is approximately constant.

In order to compare the fuzzy logic efficiency, the WSN lifetime is compared against the adaptive filter, SES, and DES. The adaptive filter technique presented in [21] used to maximize the lifetime of the WSN is implemented in our simulator for the purpose of comparison. As depicted in Fig. 12, it seems that the average lifetime of the WSN based on fuzzy logic system at 60% probability of fire is fairly double that of the single modal WSN. In addition, it is approximately 17 times better than the adaptive filter as well as other approaches when multi modal is configured.

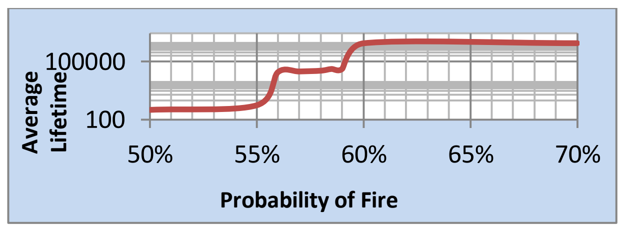

Figure 11. The average lifetime of WSN for different probability of fire

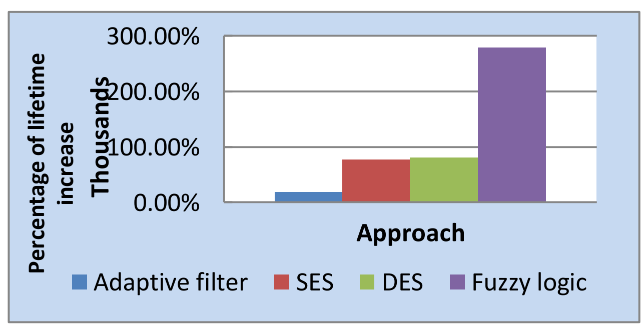

Figure 12. The comparison of results

VI. EXPERIMENTAL RESULTS

In this section, we present some other experiments that show the efficiency of the proposed energy saving and data reduction techniques presented in this paper. Our proposed approaches are implemented on a real wireless sensor network. SES and DES are implemented on National Instruments (NI) WSN kit [31], where its sensor nodes are programmable. The kit contains an NI WSN-9791 Ethernet gateway, two battery powered programmable nodes (NI WSN-3202 ±10 V analog input node, and NI WSN-3212 thermocouple input node). The gateway works as a bridge between the IEEE 802.15.4 wireless network and the wired Ethernet network. The default behavior of an NI node is to sample all channels and transmit every sample acquired to the gateway. However, we added intelligence for the nodes to increase their lifetime by extending the transmit interval which is equal to the time period between the successive transmissions of a certain sensor node.

NI LabVIEW [32] is used to program the sensing nodes. As shown in Fig. 13 the Virtual Instrument (VI) block diagram for DPS predictor is presented which is set on the sensor nodes; at the same time, an identical predictor is running on the host controller. The lifetime of the node is determined based on the sample interval, and the transmit interval. In these experiments, the sampling rate is set to a constant value, 5Hz; while the transmit interval is adaptive where this period is determined based on the error between the actual measurements and the predicted values. For example, if the error signal is below 0.5 degree, the transmit interval is set to 5000 second. If the error signal is below 1 degree, the transmit interval is reduced to 50 second. However, if the error increased beyond 1 degree, nodes will transmit every 1 second.

It has been reported that based on LabVIEW WSN pioneer performance benchmark, the lifetime of the nodes is 5.3 months when the transmit interval is set to 5 seconds. Compared to this performance, our approaches were able to increases the lifetime to 27 months for transmission interval of 5000 second. However, we can obtain longer lifetime if we extend the transmit interval beyond 5000 second.

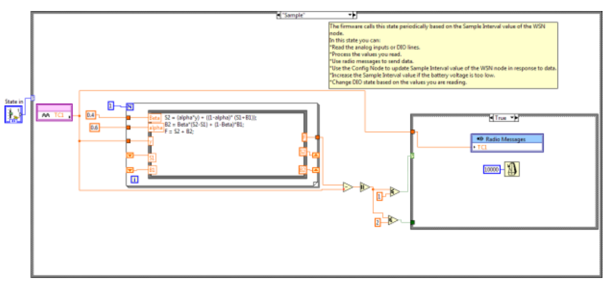

Figure 13. Controlling the transmit time by the DES predictor (VI)

VII. Conclusion

In this paper, the impact of applying the data reduction techniques on the lifetime of WSNs was investigated. The approaches utilized single and double exponential predictors, fuzzy logic algorithm, and threshold and tolerance approaches to reduce the number of messages transmitted between the nodes and their neighbors as well as between the nodes and the sink node. Our approaches also targeted the reliability enhancement in sensors data. We tested the performance of our approaches compared to the naïve model where each sensor sends its sensed data in a separate message to the sink node. The simulation results showed that such approaches will increase the lifetime of the network up to 100s' of times consequently the in-network traffic is minimized. In addition, the practical experiment confirmed the results obtained from the simulation. Moreover, the results showed that the data reduction based on fuzzy logic algorithm provides the maximum savings in the nodes' power. In the future work, we will add clustering and routing algorithms to our proposed technique. Moreover, we will investigate the use of fuzzy logic type II for the data reduction technique instead of fuzzy logic type I.

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