Data Window Aggregation Techniques for Energy Saving in Wireless Sensor Networks

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***Abstract*—Redundant data transmissions are likely to happen repeatedly in Wireless Sensor Networks (WSNs). According to the literature survey, energy-efficiency predominately relies on data aggregation rather than routing or duty-cycling approaches. As data redundancy dominates the power usage in communication costs, in order to identify and reduce the redundant data transmissions by individual nodes, we propose a hybrid data aggregative window function (DAWF) algorithm for exploiting both spatial and temporal data redundancies in WSNs. Furthermore, the proposed novel approach aims to process the hybrid filtration using both compressive and prediction-based techniques in sensor nodes (SN) as well as in cluster-head (CH) nodes. In this regard, the experimental study case of this work show that the DAWF mechanism can suppress a huge amount of temporal redundant data transmissions in sensor nodes while providing reliable data messages towards the base station (BS). Moreover, DAWF CH can also suppress a large amount of spatial redundancies by utilizing the optimum DAWF parameters of the CH node.**

***Keywords*—Predictive modeling, Data aggregation, Sensor networks, Data window, Spatio-temporal, Correlations, Energy-saving.**

I. Introduction

In Wireless Sensor Networks (WSNs), if sensor nodes are used to have similar application tasks to monitor a set of physical quantities compared to the individual tasks, then the nodes may generate a large amount of redundant samples in both time and space. This is also observed in the analysis of real datasets from [1, 2] in both indoor and outdoor deployments. In [3], the authors are constructed the data models and reported parameters instead of raw sample values.

The energy-efficiency issue in WSNs can also be achieved by exploiting the both inherent temporal and spatial redundancies (SRs) in data, such as temperature, humidity, light and pressure exhibit the slight variations slowly over the period of time [4]. Moreover, this prospect may also help to balance the usage of node computational capabilities, which profitably extracts the spatio-temporal models for avoiding the unnecessary sensing. The distributed nature of data-driven approaches has been well-studied in the literature [5–9]. Since, it is necessary to use an effective data redundancy or simple prediction methods, in order to avoid the redundant data values to ensure the reliability in periodic or delay-tolerant network applications [5, 6].

The main idea of this work consists in exploiting temporal redundancies (TRs) in every node and their spatial redundancies or correlations in cluster-head (CH) nodes. This prospect emphasizes the spatio-temporal redundancies of measured physical quantities in order to compute the given spatio-temporal models, which then consecutively reduces the overall amount of required transmissions. The follow up of our A-DAWF protocol in [10], which is framed by exploiting the temporal redundancies in every node using simple and inexpensive window aggregative models based on Intel lab datasets. In order to explore the in depth research work for exploiting the spatio-temporal correlations in various physical quantities of the nodes. We then present the data-aggregative window function (DAWF) mechanism by exploiting spatial redundancies of the nodes in CHs, which we present as a preliminary study cases of the CHs model behaviors. Our proposition has been tested on real datasets obtained from one of our collaborative lab as LCIS, DREAL project data sets, and the data collected from both indoor and outdoor environments of the thermal renovations of housing estates. DAWF mechanism improves the energy efficiency in sensor nodes by showing that the overall required sensor readings can be reduced as well as their redundant data transmissions. The organization of this paper is as follows, section 2 describes the literature survey of several energy-efficient data collection and gathering protocols. System models and implementations of our work have been presented in section 3. Section 4 validates the simulation results to demonstrate that the sensor nodes can generate a huge amount of temporal redundancies (TRs) often. Final section concludes the DAWF mechanism performances through various considered metric analysis in both time and space.

II. Related Work

Energy consumption in WSNs is a widely studied issue, and a taxonomy of various categories of WSNs presented in [6, 11], and data-driven approaches are related to this work among all the categories.

The prior data collection works have suggested several data-aggregation methods under data-driven approaches, which are categorized as in-network aggregation, compression-based and prediction-based data aggregations. TiNA [12] used a clause condition for specifying the differed ranges, if the differed range is greater than the specified range between any two values, then the differed result can be reported, otherwise ignored. TiNA is more related to our work, as we also used the RV function to find TDRs between every two window stored phenomena among the individual nodes, which is presented in one of our recent research works [10]. CAG [13] proposed a cluster-based technique which reports only spatial correlations of cluster nodes by a CH to the BS, and ignores the individual nodes temporal data. The authors of [14] proposed a another cluster-based method like CAG to build a predictive model on CH nodes instead of individual sensor nodes and let the complete computational burden on header nodes itself.

In [15], the authors present a method to build predictive models for exploiting the sensed data correlations by a pair of nodes. An auto-regressive (AR) model is presented in [3]. In this regard, nodes can compute a model for the sensed data until a buffer is filled and transmits only the model parameters to the BS. Tan et al from [16], investigates the unnecessary data reduction impact of data fusion on the coverage and detection delay in WSNs.

Distributed Source Coding Using Syndromes (DISCUS) [7] used a framework for distributed data compression by using joint source and channel coding. This method reduces the inter-node communication cost for using a both quantized source and correlated side information from every individual node. In [8], the authors proposed a predictive temporal redundant model in data collection, and used it for real-time error correction. And, a source correlated model is suggested in [17] under lossy wireless sensor network with multiple sinks.

Unlike previous works, our proposal avoids the consideration of rich spatio-temporal computationally resource constrained models or predictive models, and designed a simple data redundancy algorithm based on DREAL real data-sets. In our considerations, normal nodes sense the environmental phenomena and filter through DAWF mechanism for exploiting TRs and as well as minimizing the redundant data transmissions. Furthermore, DAWF in CH nodes works with better computational memories, since CHs are assumed as super nodes for reducing the spatial redundancies (SRs) among the nodes.

III. Preliminaries

We consider a cluster-based sensor network with n normal SNs, which continuously forward the uncorrelated set of data attributes to the CH, $X(t) = (X_1, X_2, ..., X_m)$ generates the sensed physical phenomena at different time instances t, and s number of CHs as super nodes, which receive the data messages of SNs, $Y(t) = (Y_1, Y_2, ..., Y_p)$ during SNs window time intervals r and their own sensor readings $X(t)$ at different time instances of T. The attribute detection of environmental phenomena X_m, may be the attributes being sensed by nodes as temperature or humidity or may be the result of any application phenomena. If the sensor monitoring attributes are either periodic or continuous, it then consider the DAWF mechanism to monitor redundant physical phenomena. This work primarily focuses on the reduction of data redundancies at individual sensor nodes.

A. System Model

This paper considers that the network model is a single-hop cluster-based and distributed, as showin in the figure 1. The nodes can compute and process the obtained environmental data at t time instances through the DAWF mechanism. Since computation is the second highest energy consumer after the communication, even though for computing the algorithms does not require much energy compared to the communication. The preliminary use case for exploiting temporal redundancies in sensor nodes and its experimental study case are presented in [10]. Furthermore, the following implementations have been developed for reducing the spatial redundancies and correlations among the nodes.

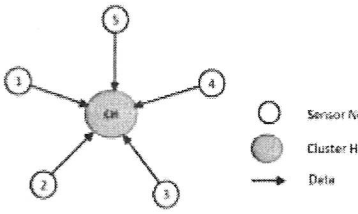

Fig. 1: A cluster-star topology, show the nature of communication between sensor nodes and CH.

In this scenario, w_Q keeps the record of nodes received data during the observed time interval R and cleared the data on the basis of FIFO approach after every successful data window transmission to the sink node or BS.

Furthermore, we implement the DAWF mechanism in CHs for finding both SRs and TRs, since CHs receive the data messages $Y(t)$ from member nodes as well as their own sensor readings and node physical quantities $X(t)$. We assume that the minimum window w_Q size of the CH is 50, which can also be varied based on CH node computational constraints for monitoring nodes data spatially and their own readings for exploiting the TRs. In this case, if sensor nodes have the same application monitoring tasks at different periods, then there will be several SRs over nodes. Hence, for reducing the SRs among nodes, CH keeps the data records of all sensor nodes during every round time interval of R at CH windows. In order to find SRs, the following expressions Eq.(1) and (2) must be satisfied in CH nodes.

$$S_{count} = \begin{cases} if \frac{|Y_{j+1} - Y_j|}{Y_j} > Th, & S_{count} = 0 \\ otherwise, & S_{count} = 1 \end{cases} \tag{1}$$

$$\mu_K = \frac{\sum_{j=1}^{Q} Y_{j+KQ}}{Q} \tag{2}$$

According to the relative variation (RV) of Eq.(1) and Eq. (3), where S_{count} represents the spatial count of RV and T_{count} states the temporal count of RV. If S_{count} is greater than the threshold Th then the S_{count} will be equal to 0 otherwise count will be reported as 1. In this scenario, we set the optimum threshold Th as 0.05 and it can also be varied as per the physical phenomena or different application physical activities. And, it can be evaluated by Eq.(2) where μ_K is the mean value of window at K times which starts from zero. And j is an index of sensor nodes delivered data property at given time instances t, and R is the round time interval of w_Q. And, Q is a window size that can either be fixed or vary based on the nodes computational resources or flash memory. During every w_Q of CH node, it can compare its member node value Y_{j+1} with the previous member node value of Y_j through the window stored readings by Eq.(1). Moreover, during every window round time interval of R after the data check based on Eq.(1), the previous sensor readings in DAWF can be flushed itself based on First-In-First-Out (FIFO) queue method. In order to exploit the temporal redundancies in both sensor nodes and CHs, and the parameters and variable considerations of TRs have the similar features as like SR expressions. But, the threshold parameters may vary since CHs has two window constraints one window function for nodes received data and another one for CH nodes sensed physical properties, as like regular sensor nodes. In this scenario, the following constraints should be satisfied in both sensor nodes and CH for exploiting the temporal redundancies, and the given expressions can be defined as

$$T_{count} = \begin{cases} if \frac{|X_{i+1} - X_i|}{X_i} > Th, & T_{count} = 0 \\ otherwise, & T_{count} = 1 \end{cases} \tag{3}$$

$$\mu_k = \frac{\sum_{i=1}^{M} X_{i+kM}}{M} \tag{4}$$

In general applications, most of the obtained environmental data are either redundant or correlated. We assume that the observed nodes data messages are highly redundant.

B. Adaptive Compression and Prediction-Based Mechanism

The iterative Algorithm 1 starts by initializing all the variables and their parameters. The core of this algorithm, consists of a data redundancy loop that predicts the node redundant or correlated data with the previous data values. If the current readings differ from the previous readings then only node can forward the data to cluster-head, otherwise the data can be flushed itself.

The entire algorithm iteratively stored the received data of nodes in an attribute window function, computed and updated in CH node. In this regard, DAWF mechanism has two time intervals; one as nodes received data time intervals t and another one as window time intervals R. Using RV function (Algorithm 1, line 4) DAWF mechanism examines the window stored data of nodes, whether they are redundant or correlated, if RV is greater than the threshold then it counts and forwards the non-correlated data towards the BS. If the window contains the redundant information then (Algorithm, line 8) DAWF uses the mean averaging function to send one appropriate data value rather than all window readings.

On the other hand, DAWF also delivers the non-correlated window data as a single packet, the authors of [18] presented that increasing a payload size (from 1 bytes to 90 bytes) to some extent does not add the additional communication costs over the nodes.

Algorithm 1 Cluster area nodes received data ($Y_j(t)$)

> **procedure** : $Initialize(s, T, r)$
> Parameters: $T \leftarrow CH\ time\ intervals.$
> $S_{count} \leftarrow Spatial\ correlations\ count$
> $T_{count} \leftarrow Temporal\ correlations\ count$
> $r \leftarrow Round\ time\ interval\ of\ the\ sensor\ nodes\ window$
> $R \leftarrow Round\ time\ interval\ of\ CH\ window$
>
>   **if** $Y_j(t)$ **then**
>   Store into the Window buffer w_Q
>   **if** $\frac{abs(Y_{j+1} - Y_j)}{Y_j} > Th$ **then**
>   Count Spatial correlations
>   **if** $S_{Count}\ mod\ 50 == 0$ **then**
>   Send mean averaging data of μ_K
>   **else**
>   Count Non-correlated Data
>   Send as a single data packet
>   **end if**
>   **end if**
>   **end if**
> **end procedure**

IV. Experimental Study Case and Results

In order to validate our models as described in the earlier section, this paper carried out a set of experiments by using real data sets, which were collected by OSAmI-FR Wired/Wireless Sensor Network (WSN) nodes, contained and supported by DREAL, LCIS research lab from [1].

Simulation results are captured among the test area of sensor nodes with the help of real sensor network data sets. According to this lab repository, the data values are captured at every one hour, and the readings (ambient temperature, relative humidity, solar temperature, light and CO_2) are collected from the indoor network deployment of several sensor nodes, between January 1 and December 30, 2011. Moreover, the sensors appear to be placed randomly in different floors in the housing project. In this experimental study case, we considered two sorts of physical phenomena as solar temperature, and humidity. However, we used in total a year measures of 6 sensor nodes with a considered CH node.

The primary study case of the simulations are presented in MATLAB. We have been further developing our propositions in COOJA/Contiki emulator for measuring the several metric analysis such as message cost and energy costs, since COOJA emulator uses its own developed software's and can be uploaded directly on any COOJA recommended real motes, for instance in our case we consider Tmote-sky for COOJA simulations and TelosB devices for network deployment.

A. Temporal Performance Analysis

This paper presents two sorts of experimental analysis. First one describes the exploitation of data redundancies over the collected data of nodes. And, second one focuses on the proposed metric of transmission cost evaluation over both time and space. Since some of the collected data dates and timings differently formatted in the data sets, thus we decided to use 11 months of data for this experimental study to validate the metric of transmission (TX) costs.

In this section, the approach in section 3, and the cluster-tree topology that we assume superimposed on the considered amount of sensor nodes. Thus allow us to investigate the outcome of the proposed algorithm in terms of suppressing required number of transmissions as well as energy saving.

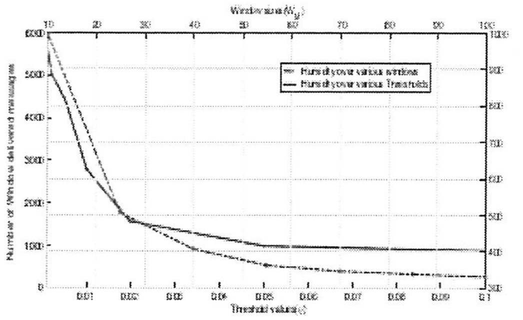

Fig. 2: DAWF different parameter performances with various thresholds Ths over different w_M sizes of temporal data.

Figure 2 illustrates the spatio-temporal DAWF mechanism of considered physical quantities by computing through various thresholds η of 0.001 to 0.1 with a fixed window size of 10, and at a different window sizes of 10 to 100 with an optimum threshold of 0.05, which was demonstrated in below subsections. In this scenario, DAWF presents a comparative analysis between nodes threshold parameters and their window constraints to validate that increasing a window size according to the nodes computational constraints would be always beneficial. Figure 2 clearly shows that node window constraints indeed plays a significant role to reduce the data bandwidth without losing any significant data. However, this is the case for temporal exploitation in nodes. But, in spatial correlations exploiting of the nodes in CH, threshold parameters are playing the major role for delivering finest data performances compared to the window sizes.

Figure 3 exploits the various window performances together with different threshold variations in time. In this scenario, we show how the window performances gradually increases while tuning the η and w_M parameters combinedly compared to the individual variations as shown in the figure 3. Which then proved that window performances of the temporal nodes are directly proportional to the optimum thresholds of the sensor nodes or their dynamicity based on the different phenomena.

Figure 4 and 5 shows the transmission (TX) cost metric performances over the considered network area. The reliability of the proposed aggregative models has been assessed by computing the transmission (TX) cost. The proposed metric of TX_{cost} is given by Eq.(5) to calculate the total amount of (percentage) of saved transmissions per node while exploiting the temporal data redundancies. As shown in figure 4, and figure 5,

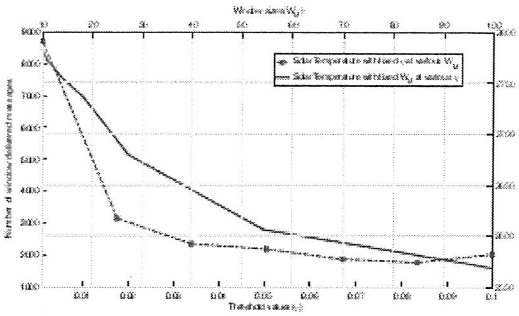

Fig. 3: CH DAWF performances of solar temperature over various window sizes

which also explored the different phenomena performances of nodes through the TX_{cost} metric. In figure 4, node can reduce a minimum of 88.62% TX_{cost} in humidity by computing through the DAWF algorithm, and the maximum of 99.62% with the consideration of higher window interval as 100 and with an optimum threshold parameter of 0.05. According to the various threshold parameters, where DAWF reduced a minimum of 39.76% redundant transmissions by a minimum window size and threshold of 10, 0.001, respectively. Thus, the maximum of 89.89% redundant transmissions was suppressed by a maximum threshold parameter of 0.1 at a constant optimum window size of 10. However, when it comes to solar temporal phenomena in figure 5, the DAWF algorithm of various window sizes shown less impact, as a minimum window size of 10 reduced 63.70% and the window size of 100 reduced 66.19% only by a constant threshold of 0.05. On the other hand, threshold parameters of solar temperatures showed better results compared to the various window sizes. With the minimum constant window size of 10 by a minimum threshold of 0.001, reduced 3.22%, and a maximum threshold parameter of 0.1 suppressed 79.94 of TX_{cost}. In this scenario, we noticed that the performances of various window sizes shown more or less like same results compared to the threshold parameters, because the nodes have less correlated data of solar temperature, since the monitored data were obtained by outdoor sensors. Therefore, the following metric is being

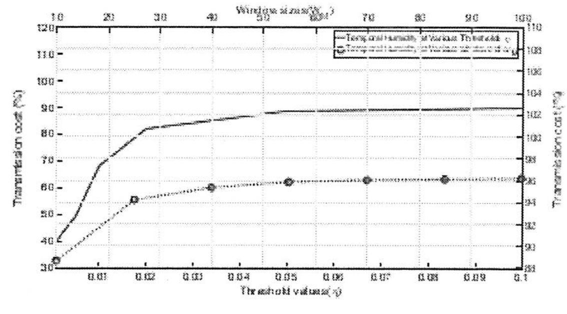

Fig. 4: CH DAWF temporal data relative humidity TX cost metric performances over various thresholds and the various window sizes.

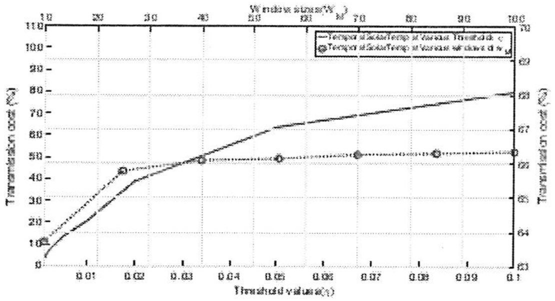

Fig. 5: Nodes TX cost metric performances Solar Temperature.

used, in order to present the nodes TX_{cost} performances after suppressing the redundant data transmissions by the window mechanism, and the TX_{cost} metric can be derived as:

$$TX_{cost} = (1 - \frac{Total\ window\ sent\ messages}{Total\ window\ read\ messages}) \times 100 \quad (5)$$

B. Spatial Performance Analysis

In order to suppress the redundant data and the required amount of transmissions spatially, we use the CH node to find the correlations among the considered sensor nodes sent data. Since we used different physical sensor quantities in nodes, in order to find and evaluate their spatial data by using pre-filtration techniques in CH node as like temporal analysis, which were also collected by both indoor and outdoor deployments.

Figure 6 exploits the nodes spatial phenomena over various window sizes and at different threshold parameters. Figure 6 is shown that the threshold parameters only delivered a varied spatial performances among different spatial phenomena of the nodes. However, in figures 6 and figure 7 window size

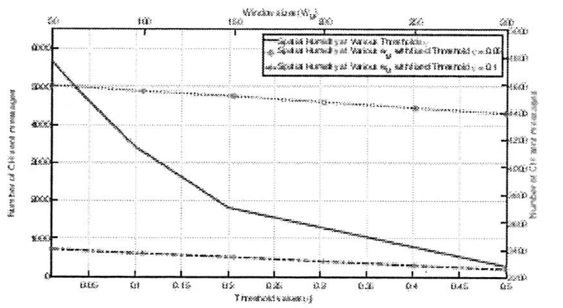

Fig. 6: CH DAWF spatial relative humidity performances over various thresholds through the window sizes.

constraints did not show any greater impacts spatially while compared to the threshold parameters in CH, like nodes, as they performed well in exploiting temporal redundancies. In this case, whatever the window size is maximized then the delivered data are showing slight variations in window performances, but many remain constant, as shown in 6(b). Because, CH collected data from the nodes are not either highly redundant nor correlated. In this scenario, we presented the window varying performances with two fixed optimum thresholds of 0.05 and 0.1. Figure 8(a) and 8(b) exploits the spatial TX_{costs} of different nodes received phenomena in CH. In this metric analysis is given by Eq.(5), we carried out the performances as threshold over window size variations. In Figure 8(a) and 8(b), where CH suppressed the amount of 5.19%, and 2.90%, respectively by computing through a minimum threshold of 0.01, and the maximum threshold of 0.5 shown the performances as 95.25%, and 78.65%, respectively. On the other hand, DAWF window sizes delivered the performances, as a minimum amount of reduced transmissions are 22.95% and 10.75% by an optimum threshold of 0.05, and with the maximum window constraints of 300 delivered the performances as 26.34% and 13.15% among the nodes. Which is clearly demonstrated that the threshold parameters always have a high impact compared to the window sizes, when it comes to spatial phenomena for delivering outperforming results. For instance, according to the data sets, nodes

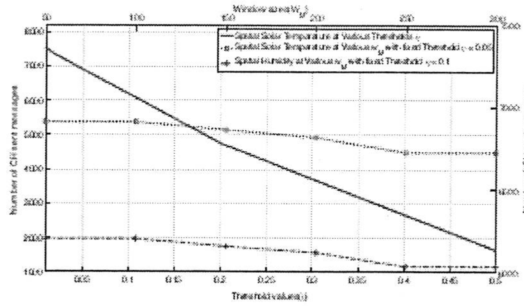

Fig. 7: CH DAWF spatial performances of solar over various thresholds through the window sizes.

follow the periodic transmission system as every hour, then it transmits total considered nodes measures of their sensed phenomena at given scheduled intervals. In the contrast, using DAWF mechanism at a minimum window size of 50 through CH where it reduces 22.95% and 10.75% amount of redundant messages out of total different received data nodes phenomena by computing through the constant threshold parameter of 0.05. Which is clearly proven by Eq.(5) that CH DAWF is necessary to have in head nodes, and it can still suppress the data correlations among the nodes spatial data.

Furthermore, temporal redundancies in CH node at various thresholds with different window sizes of w_M also performed same as sensor nodes, which presented and explained in the section 4.1. Which is also clearly stated that temporal redundancies clearly depends upon the window sizes rather than threshold values. Where it suppresses upto 90% temporal redundancies in CH received data of nodes by computing through the optimal thresholds and maximum window sizes of the CHs. Which is obvious, if the window sizes are bigger then the stored data and comparison between every two window stored readings can be drastically increased. In order to show the performance analysis of the proposed approach in terms of energy saving, as briefly illustrated in the above results. The DAWF can efficiently suppress required number of transmissions with respect to the periodic or delay-tolerant

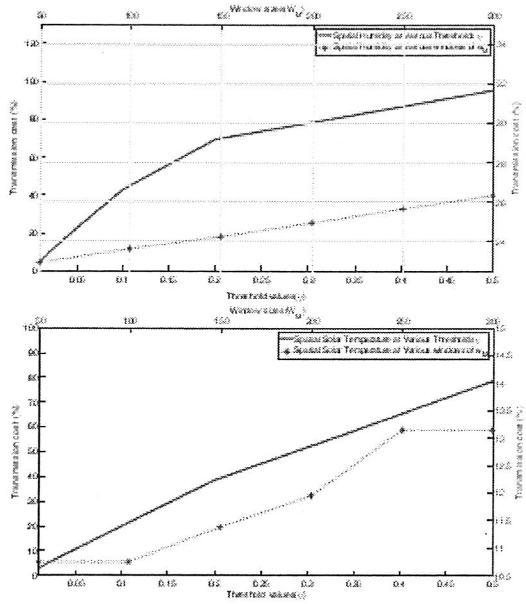

Fig. 8: (a) CH DAWF TX cost metric performances of humidity over various thresholds through the window sizes & (b) CH DAWF TX cost metric performances of solar temperature over various thresholds through the window sizes.

approach where each node forwards its obtained data whenever it detects to the collecting node or BS.

V. Conclusion and Future Works

This paper presented a fully distributed spatio-temporal novel approach in sensor nodes, which aimed to keep the Wireless Sensor Network as energy efficient as possible. The use of pre-filtration data techniques for exploiting the physical quantities allowed to reduce the communication costs over nodes, and thus maximizes the sensor nodes lifetime, by adaptively tuning their data rate. The use of simple pre-filtration techniques rather than complex computationally expensive models was the basic idea to design a window technique, which adapts the dynamicity regardless of any particularly monitored data. The experiments carried out on real data sets shown better performances, in particular when the threshold set to 5%, the overall amount of energy saving in CH node among the received nodes data phenomena are 22.9% and 10.75%, respectively. And thus, reducing the temporal redundancies in nodes, it saves upto 90% of redundant data transmissions. Furthermore, our approach requires to make a comparison between a much lower sampling rate than what chosen for the original configuration, in terms of measuring reliability.

The on-going work still need to make further improvements, in order to make the approach to have complete adaptivity, by which a node can tune the threshold parameters or window constraints based on monitored data attributes. In particular, the algorithm refinement is required, especially when the data patterns are irregularly incremented, but correlation between near by the data values. In this case, therefore non-correlated data counter should be effective in DAWF to list the all non-correlated data as single packet. Further experiments are also being examined, in order to present the comparative analysis with different metric considerations to measure the system performances, especially in terms of quality of data, latency, message costs in CH nodes if the window constraints are high, and energy cost in overall network.

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