American Academic Scientific Research Journal for Engineering, Technology, and Sciences
ISSN (Print) 2313-4410, ISSN (Online) 2313-4402
http://asrjetsjournal.org/

Optimization of Adaptive Method for Data Reduction in Wireless Sensor Networks

Abubakar Safiyan Ibrahim[a]*, Mukhtar Abubakar[b], Umar Iliyasu[c]

[a,b,c]*Federal University Dutsin-ma, Dutsin-ma, Katsina and 821101, Nigeria*
[a]*Email: abubakarsafyanibrahim@gmail.com*
[b]*Email: mabubakar2@fudutsinma.edu.ng*
[c]*Email: uiliyasu@fudutsinma.edu.ng*

Abstract

The term 'Wireless' is a cordless technology where the nodes interact or exchange information with the sink node without wired intervention to exchange or transmit any information successfully. Characteristics of the present wireless sensor networks are applied to diverse technological furtherance in minimum power communications and very large-scale integration to sustained functionalities of sensing. Tremendous number of incentive observation and algometry of data are amassed from sensors in Wireless Sensor Networks (WSNs) for the Internet of Things (IoT) applications such as environmental monitoring. However, continuous dissemination of the sensed data postulates eminent energy imbibing. Data reduction duress the sensor nodes to surcease transmitting the data when it is diffident about freshen up. One way to reduce this kind of energy imbibing is to minimize the amount of data exchanged across the sensors, therefore the research work aims to increase the communication and spatial prediction between the sensor nodes and the sink nodes.

In this research work, an **Optimization of Adaptive Method for Data Reduction in Wireless Sensor Networks** was proposed and implemented. The work adopted a bulging haplotype of two decoupled Least-Mean-Square (LMS) windowed filters with varying length for approximating the immediate metrics values both at the sink and source node such that sensor nodes have to send only their next sensed values that diverse substantially (when a pre-determine threshold) from the anticipated values. The experiment conducted on a real-world dataset of about 2,313,682, which were collected from 54 Mica2dot sensors thus, MATLAB was used as a tool for the implementation. The research work aims to increase the communication model and spatial prediction, which is the limitation of the base paper. The results show that our approach (OAM-DR) has achieved up to 98% communication reduction while retaining or carrying a high accuracy, (i.e. the anticipated values have a digression of ±0.5 from actual data values).

Keywords: Wireless Sensor Networks (WSN); Internet of Things (IoT); Least Mean Square Algorithm (LMS); Decouple Least Mean Square Algorithm.

----

* Corresponding author.

1. Introduction

Recent researches advances in sensors and actuators technologies, which offer a future prospect or potential for continuously observing of real-world consequences in administering networks. Sensors are often to distribute systematically or strategically or deployed in distributed and dynamic environments over a bombastic geographical area (i.e. sensing field). Wireless Sensor Networks rendered or enables the development of a broad range of the inherent capacity IoT apps that consist of environmental proctor example (temperature, humidity and so on). In (IOT) networks, sensory nodes necessitate a space without interruption in coverage of their next readings to humble stations. However, data transmission is an exercising influence or control factor of communication in the expense of maintenance and energy consumption in Wireless Sensor Networks [15].

To address or identify such problem, several or assorted data-driven approaches for minimizing energy consumption in Wireless Sensor Networks have been advocated or proposed in the literature such as “An Adaptive Strategy for Quality-Based Data Reduction in Wireless Sensor Networks”. In addition, data reduction strategies have gained significant great affect attention for efficaciously sullen the amount of transmissions and broaden the network lifespan. The goal and aims of data reduction strategy is that sink nodes are capable of reproducing the necessary qualities of data watercourse sensor perusal (having a sensible high accuracy) from a peculiar set of elements of data stream that are familial from sensor nodes. Data reduction comprehend dissimilar conceptualization such as in-network processing, data densification, and data prediction or anticipation. In prediction-based approaches, a model is built to depict a peculiar phenomenon such that user’s interrogation can response through conception models alternatively of accessing the sensors for fetching their existent sensed data. There are several existing works on anticipation or prediction-based methods and solutions. Some of these conceptualization or formulation adopt that sensor observations, mensuration or stargazing are highly colligated. For example, spatial and temporal correlations have been posited to selectively convey a subset of the data sensors from which the unscathed sensor readings can be reproduced based on a predictive or anticipation model and accordingly bring down the amount of data forwarded. Although such approaches are capable to bring down substantial the amount of transmissions, they endure from histrionic loss in terms of accuracy such that the predictive or anticipation models have to be updated veritably to include fined-grained modifications. To address this problem, dual prediction schemes have been proposed. Dual prediction minimizes the amount of data forwarded between sensor and sink nodes to the best level such that sensor nodes transmit only a set of their sensed values without impact in the prime of the actual measurement values. Example, [3] propose a dual prediction scheme using Kalman filters for reducing the number of transmissions. However, Kalman filters require a priori knowledge (e.g. statistical data properties on the data set).

One point to note is, data transmission is a prevailing factor of communication overhead and consumed more energy especially in wireless sensor networks. A lot of methods have been adopted to optimize data reduction in wireless sensor network but suffer from performance loss more especially in terms of accuracy and also leads to message and performance loss of the sensors. Reference [17,22,24] hence this method leads to communication and nodes failure at the same time the approach finds it challenging in reducing energy imbibing and communication overhead. To address the aforementioned challenges (OAM-DR) was proposed by introducing bulging combination of two decoupled least mean square algorithm.

In this research, an Adaptive Optimization Method for Data Reduction (AM-DR) is proposed. This approach optimized the bulging haplotype of two decoupled Least-Mean-Square algorithm in order to reduce the energy consumption of the 2,313,682 sensors collected from 54 mica2dot sensors. The research also aims to improve the performance loss and reduce the communication and nodes failures in wireless sensor networks. the method is a prediction-based data reduction that stunts Least Mean Square adaptive filters. More generally, this method is humble on a bulging accumulation of two decoupled Least Mean Square windowed filters with dissimilar sizes for computing the upcoming metrical values both at the originated and the sink node in a way that sensor nodes have to send solitary their contiguous sensed values that aberrant significantly (> e_{max}, a pre-defined threshold) from the anticipated values.

The wireless sensor network consists of specially distributed autonomous devices using the sensors e.g. temperature, pressure, humidity, home automations etc. environmental constrained has been the major problem that leads to the development of the research. Some of the environmental constrained are; energy constrained, memory limitation, limit processing capability, higher latency in communication, unreliable networks and unattended network operation. Energy consumption, message and communication loss has been the major issue that leads to this research.

Reference [15] has investigated An Adaptive Strategy for Quality-Based Data Reduction in Wireless Sensor Networks using in Network Approach. Several researchers have also investigated on how to reduce energy consumption and deal with communication loss between the sink nodes and sensor nodes.

The work of [9] proposed reliable and energy efficient dual prediction data reduction approach for WSNs based on Kalman filter. He has explained Wireless sensor networks (WSNs) as critically resource-constrained due to wireless sensor nodes' tiny memory, low processing units, power limitations, and narrow communication bandwidth. The data reduction technique is one of the most widely used techniques to reduce transmitted data over the wireless sensor networks and to minimize the sensor nodes' energy consumption, particularly, the entire network in general.

Furthermore, stated by [37,38], data transmission is seen as the main factor in energy consumption of the WSNs. Therefore, the proposed approach to energy consumption is calculated based on the number of readings transmitted from sensor nodes to the sink node.

Additionally, the work of [12] has discussed In-network based data reduction, the researchers in proposed error-aware data clustering (EDC). The approach EDC contains 3 deviated adaptive modules that allow users to choose a module that suits their required data quality.

Moreover [31], they explained Data prediction, compression, and recovery in clustered wireless sensor networks for environmental monitoring applications.

There have been diverse state-of-the art approaches dedicated to increasing WSNs longevity. The work of [9] proposed a new data transmission reduction algorithm based on the dual prediction model to decrease the amount of data transmitted to the sink node. The proposed approach aims to increase the network lifetime by bulging combination of two decoupled least mean square algorithm.

The work of [33] proposed a two-tiers data prediction framework based on dual prediction (DP) and data compression (DC) schemes. The DP proposed a method to reduce the data transmitted from the sensor nodes to their cluster heads. Simultaneously, the data compression tier is proposed to decrease the communication from cluster heads to the base station.

Likewise, a distributed data predictive model (DDPM) is proposed in [34], where the authors try to increase energy efficiency by reducing data transmissions over WSNs. The distributed data predictive model is based on a finite impulse response filter combined with a recursive least squares adaptive filter.

In the work of [10], a machine learning-based data reduction approach (MLDR) for WSNs is proposed. The proposed MLDR is mainly proposed for enhancing the environmental data reduction of agriculture applications. Same as many DP schemes, the prediction is done simultaneously in both sensor and sink nodes. Wireless sensor nodes' batteries limited in such a way that they work for a certain number of hours which rely on many features and occurrences (e.g., the number of data transmissions). Consequently, increasing the network lifespan is the trending topic in the area of research topics in WSNs [5,6].Additionally, there is deep learning-based distributed data mining (DDM) model proposed in the work of [32]. The authors in DDM aims to increase the network energy efficiency thereby reducing the data transmitted from the sensor nodes to the sink nodes. What they do is that, they divide the wireless network into several layers by combining recurrent neural network (RNN) and long short-term memory (LSTM) RNN-LSTM.Having going through the related literatures above, this research proposed a prediction-based approach which uses a bulging combination of two decoupled least mean square algorithm. The predictive model has been derived which is presented in section II of the research.

2. Modeling

Least-Mean-Square (LMS) is a de-facto adaptive filtering algorithm that has a set of filtering weights that are estimated continuously to reduce the least mean square error (i.e. the difference between the desired and the estimated data streams). Least Mean Square has a low computing overhead. It relies on a stochastic gradient descent approach in which coefficients are updated iteratively to reduce the least mean square error $e(t)$ of the filter at the current time t.

$$e(t) = x(t) - y(t) \quad (1)$$

where $x(t)$ is a data stream at time t and noise is added to it and $y(t)$ is the output of applying an adaptive filter to the input $x(t)$ and noise is also added to it such that the simulated equation of $y(t)$

$$y(t) = w(t)x(t) \quad (2)$$

$w(t)$ is the filter coefficient/weight that is altered to reduce the error $e(t)$ with a step size (α) using standard Least Mean Square rule.

$$w(t) = w\ (t - 1) + \alpha e(t)x(t) \tag{3}$$

Coalition scheme of two filters instead of using one filter has been investigated to improve the steady-state characteristics and performance of Least Mean Square Algorithm. Following the work in so many researches existing paper, a convex combination employs two filters that are decoupled and concurrent applied to the same input. Their weights are attuned to minimize the overall errors of the filters. To this point, a convex combination scheme is used to combine the weights of the decoupled filters using a parameter $\lambda(t)$. $\lambda(t)$ is a combine scalar factor ($0 \leq \lambda(t) \leq 1$) to arena the bulginess of this collection. In this case, the overall weight $w(t)$ which is the mixture filter weight is typify as follows:

$$w(t) = \lambda(t)w_1(t) + (1 - \lambda(t))\ w_2(t) \tag{4}$$

where $w_1(t)$ and $w_2(t)$ are the weights of the first filter and the second filter at a time instant t, respectively. $\lambda(t)$ is updated as a bulging combination parameter with a learning rate of α using the standard LMS adaptation rule similar to equation. 3 as follows:

$$\lambda(t + 1) = \lambda(t) + \alpha e(t)x(t) \tag{5}$$

In this project, we take a case where LMS algorithm has an invariant step size (learning rate) α. However, it must be understood that there are Least Mean Square-type algorithms with a variable learning rate such that abjurer learning rate or step size for each of the filter weights are exploited. You can dredge up to the review of Bismor and his colleagues for a minutia discussion about different Least Mean Square approaches with a variable learning rate or step size.

Note: *x(t)* and *y(t)* are measured (real) data that are derived from the identification system

3. Special Case

$$\hat{a}_1[t+1] = \hat{a}[t] + \alpha \times [t-1](y(t) - \hat{y}(t)) \tag{6}$$

$$\hat{b}_1[t+1] = \hat{b}[t] + \alpha \times [t-1](y(t) - \hat{y}(t)) \tag{7}$$

For the decoupling approach, considering the message and communication loss.

4. Result Discussion and Evaluation

4.1 Evaluation

Earlier, a lot has been discussed in the above chapters, the posit solution is constitute of two parts most notably the dual prediction strategy with a bulging or convex combination of deuce adaptive filters. A comparison of the algorithm with the state-of-the-art (Base paper) algorithm. The ethical motive of comparison between the proposed method and the selected state-of-the-art approach (baseline) is that the use a dual prediction scheme with least mean square adaptive filters and the normal least mean square approach. However, using a combination scheme of two filters instead of using one provides an enhancement of both steady-state accuracy of the convex weight parameter for a better prediction of next data observation which is the key difference here compared with the state- of-the-art and convergence.

- Dataset

The experiments is on a real-world dataset that is available at (http://db.lcs.mit.edu/labdata/labdata.html) which is same as the one used in the base paper. The dataset is for 54 Mica2Dot sensors with weather boards. Each sensor has the following parameters: temperature, humidity, light, voltage values, data and time at which a sensor reading is obtained and a sensor identifier (i.e. moteid). A clustered view for Mica2Dot sensors with weather boards is shown in Figure. 2. At the stage of the experiments, the research focus on the data reported by the temperature sensors of the same motes (1, 11, 13, 49) in ranges of March 6 to 9 to have a fair contrast and consistency or coherence with the baseline approach in the base paper.

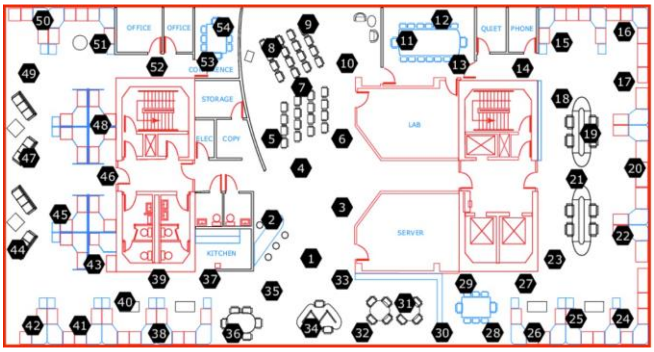

Figure 1: Clustered view for Mica2Dot sensors with weather boards

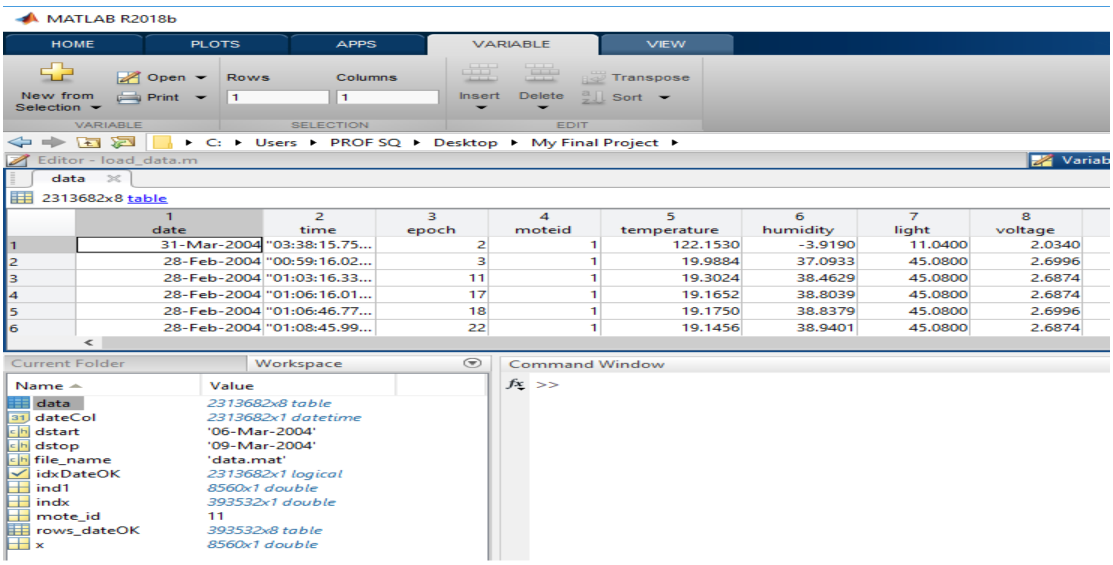

Figure 2: Data set view

The dataset in total has 18,509,456 fields which after cleansing of the data due to some errors in some fields have returned to 18,407,362 fields. The ***epoch*** determines the data in the training set when presented to the learning algorithm since the research is one of a number of prediction-based approach. The date, time moteid (you can select the moteid that you want to load its data and it should be within a data range), temperature, humidity, light and voltage fields have been captured.

- Parameter sets and reproducibility

Evaluation of the proposed approach performance against the approach in the base paper is done. The following are the specific default values that was used for each of the parameters (e_{max} = 0.5, w_f= 5, w_s = 10, α = 1.0e-007). Moreover, these parameters (N = 5, e_{max} = 0.5, μ = 10^{-5}) for the baseline approach (as reported in the previous section of this research). It is worth noting that we have selected a deviation value of 0.5 to have consistency with the baseline approach such that if the anticipated or predicted temperature sensor value is, for example, 16 and the original value for the same sensor is slightly greater than 16.5 or less than 15.5, the sensor node has to send the sensed value to the sink node.value of the baseline approach in [as stated in the section earlier] is 5, we have also use w_f = 5 and w_s= 10. Another observation during the empirical experimentation is that α *(learning rate)* should be a value of e-007 (it was verified experimentally).

4.2 Result

Evaluation of the performance of the approach (Optimization of the Adaptive Method-Data Reduction) against the baseline mentioned above. We have implemented the baseline and we have been able to reproduce similar results as in the base paper. Figures 3 and 4 demonstrate the results of adaptive method- for data reduction and baseline approaches. The red cross signal the sensor readings that have to be conveyed to sink nodes. The baseline and Adaptive Method for Data Reduction approaches achieve 92% and 95.4% communication reduction respectively with an accuracy e_{max} = ±0.5 in both approaches. Additionally, Fig. 5 and 6 show the error of both approaches of Fig. 3 and 4, respectively. The figures indicate that when the prediction error exceeds e_{max}, the sensor nodes have to transmit immediate readings to the sink, as soon as the prediction error decreases at least w_s times, the node switches to a stand-alone mode.

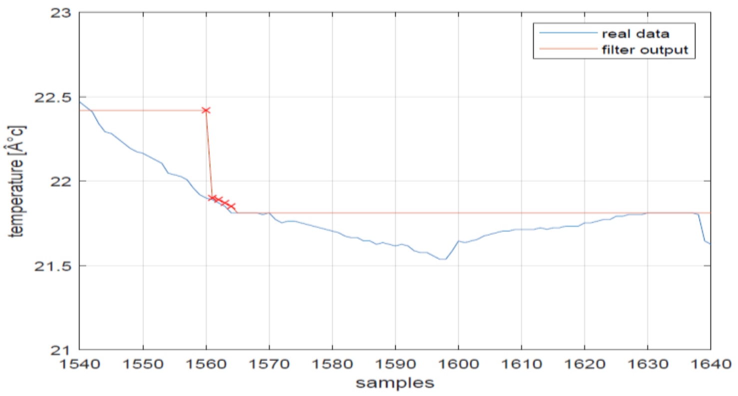

Figure 3: Dual approach: real and predicted sensor readings of mote 11

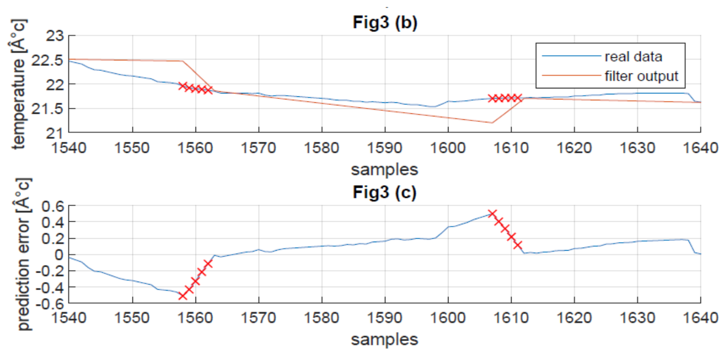

Figure 4: Baseline: real and predicted sensor readings of mote 11

We had undertaken another set of experiment and we have reported the simulation results in Figure 4.5. The figure shows the percentage of transmitted data by mote 11 with different w_s, w_f and α values (using the same values reported in (Figure 4.4) of the base paper. Figure 4.5 shows having different window sizes (i.e. filter lengths) for both of adaptive filters can guarantee up to 98% approximately communication reduction (i.e. transmitting only about 2 % of the data) with an accuracy of ±0.5. On the other hand, the baseline approach has been able to transmit about 10% of the in-hand sensor data. At this junction, we have been able to transmit a smaller number of data transmission while retaining high accuracy of ±0.5.

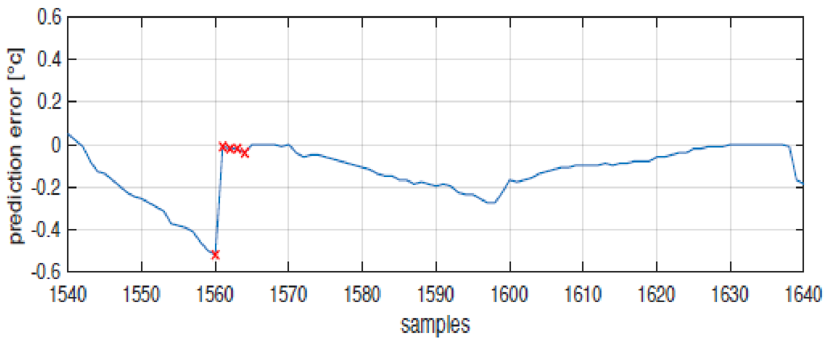

Figure 5: AM-DR: prediction error of mote 11

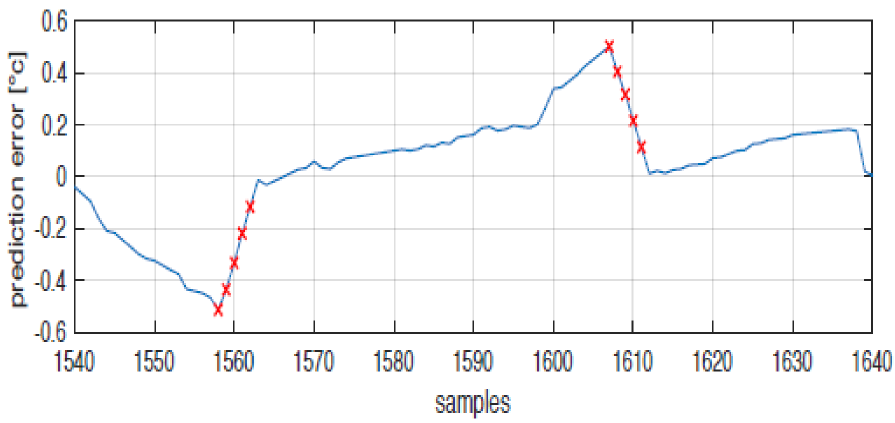

Figure 6: Baseline: prediction error of mote 11

different w_s, w_f and α values. Figure 4.6 shows having different window sizes (i.e. filter lengths) for both of adaptive filters can guarantee up to 97.5% communication reduction (i.e transmitting only about 3.5% of the data) with an accuracy of 0.5. likewise, the baseline approach has been able to transmit about 10% of the collected sensor data. It is clearly that, i have been able to transmit a lower number of data transmissions (i.e. half the number of data transmissions compared with the baseline) while retaining high accuracy.

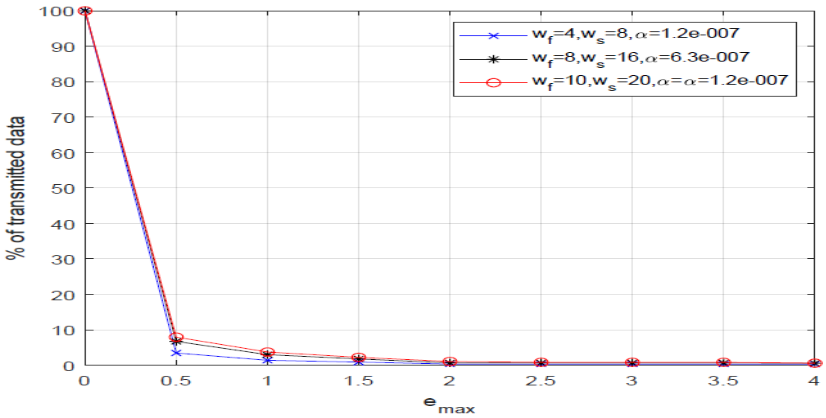

Figure 7: Percentage of transmitted data by mote 11

Note that adaptive method for data reduction have generate a more amount of data forwarded or transmitted than the one appeared in the base paper (i.e. the amount of windows size w_s measurement is dual the amount of w_f measurement such that $w_f = N$ where $N = 5$ readings in the base paper approach during the first set of simulation results). We can say that Adaptive method for data reduction have increased the algorithm performance, more especially by considering communication and message loss. In these, we can say that optimization have been achieved in terms of communication overhead and accuracy. We can check the performance of all the mote used in this experiment or trial and error (1,11,13,49) can be seen in the figure below. Looking at it visually, we can see that substantial reduction of data for all the selected motes (the motes used in the experiment). You can realize that mote 11 can only forward 5% of the measured sensors and still retain the threshold accuracy of ±0.5.

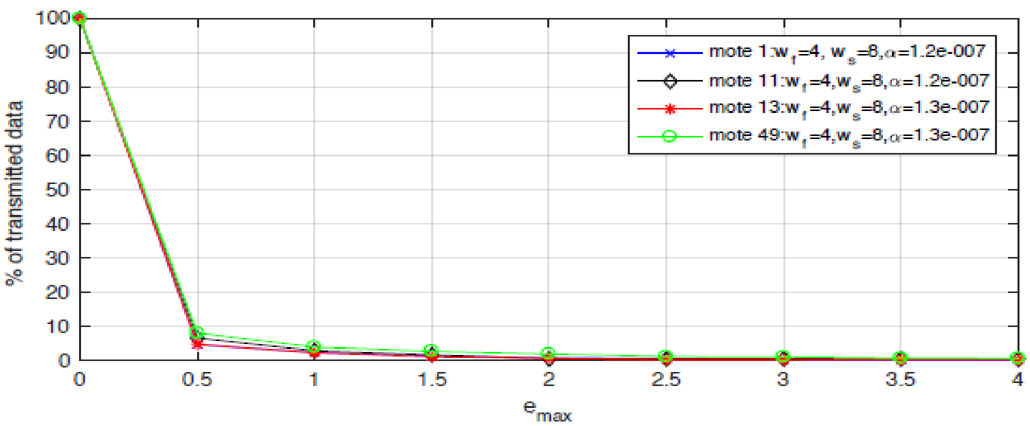

Figure 8: Mote 1,11,13,49 percentage of communication reduction

Table 1: Comparison of the base paper approach and our approach

Optimization parameters	Baseline	Our Approach
Data length	8560	8560
Transmission Length	633	364
Saving percentage	92%	98%
Transmission percentage	8%	2%

4.3 Discussion of comparison

Data length: Data length refers to the 8bit length of the data that would be loaded into the application's data buffer, contrary to the storage in the data source. From the above table, we can see that the same data length has been used to test the performance of the proposed algorithm and compare it to the base paper approach. 8560 number of data has been used for both the approach.

Transmission length: Transmission length refers to the deviation from the free-end of the beam that is compulsory to forward the fully effective prestressing-force to the surrounding concrete via a wireless as a medium of transmission.

The transmission length of the baseline approach has 633 of the data as compared to the 364 of the data transmitted using the proposed approach in this research. This is to say that there is vast difference of the data transmitted (not less than 269) for all the moteid in the training set. This reduction has shown great achievement in the proposed approach of this paper and we can say that the algorithm has been optimized using the prediction approach while retaining high accuracy of ±0.5, the same as the baseline paper.

Saving percentage: We can refer this to the percentage of disposable from the sink nodes to the sensor nodes rather than spend on consumption. The saving percentage can reflect the rate of time preference for average group or individual group of sensors. We can see that the saving percentage of the baseline approach is 92% which is great but less than the 97.75% or approximately 98% of the proposed approach in this paper. We can say that 6% increase in saving percentage can reduce a lot of energy consumption from the sensor nodes to the sink nodes. In this, the proposed approach is measured to be more optimized than the baseline for all the moteid in the training set.

Transmission percentage: Refers to the number of data transmitted to the selected moteid during the execution time of the training algorithm. In other words, we can say that it is the amount of data transmitted from the sink nodes to the sensor nodes.

Eight percent (8%) of the complete training set has been able to be transmitted in the baseline approach as compared to the 2.25% approximately just 2% of the whole training set. This means only necessary data are being transmitted reducing great number of data to be transmitted that leads to the great reduction of energy consumption which is the aim of the project and is said to be achieved using the prediction-based approach.

One of the features of this program written in MATLAB is that, each time you run the code the system automatically generates the plot results and replace it with the current one in case if some parameters value has been altered. Comments have been added to the codes so that whenever improvement on the written algorithm or the algorithm need to be optimized it will be easy to understand the needs for the optimization and can easily be manipulated.

5. Conclusion

This work has been introduced to optimized the base paper in terms of communication and message loss. The work has closed the gap of the base paper. This work named "Optimization of the Adaptive method for Data Reduction" use prediction based of data reduction. The aim of the research is to reduce the amount of data transmitted from sensor nodes to the sink nodes and also significant reduction in communication lost. Also examining the resemblances of the well-developed algorithm and a baseline approach on a collected temperature dataset. By examining the approaches, we have found out that our algorithm has been able to hit an accuracy of almost 97.75% approximately 98% and holding to the same accuracy of ±0.5 from actual observation values. Finally, we register a success in this research as almost all the areas have been covered. Even though the well-developed algorithm has given an accuracy beyond the current baseline paper, we will consider the implementation of these algorithm using deviated network models to still looks for better accuracy of the implementation. One limitation with the research work is that it may need to be reconstructed to take care of the missing data that may occur due to network failure.

Lesser nodes failure is expected to be generated even though the current algorithm has given a robust hand to this area, but still may need to be improved because some nodes can still prompt to this failure.

Acknowledgements

Our appreciation goes to the entire department which in their immense support help us achieved the objectives and aim of this research.

6. Conflict of Interests

The authors whose names are listed above certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

References

[1] Johnsen Kho, Alex Rogers, and Nicholas R. Jennings. 2009. Decentralized control of adaptive sampling in wireless sensor networks. ACM Transactions on Sensor Networks 5, 3 (May 2009), 1–35.

[2] Ankur Jain and EY Chang. 2004. Adaptive sampling for sensor networks. In 1st international workshop

on *Data management for sensor networks. 10–16.*

[3] Ankur Jain, Edward Y Chang, and Yuan-fang Wang. 2004. Adaptive Stream Resource Management Using Kalman Filters. In *ACM SIGMOD international conference on Management of data.*

[4] Hong Luo, Yonghe Liu, and Sajal K Das. 2007. Routing Correlated Data in Wireless Sensor Networks: ASurvey. December (2007), 40–47.

[5] Samuel Madden. 2004. Intel Lab Data. http://db.lcs.mit.edu/labdata/labdata.html. (June 2004).

[6] Azhar Mahmood, Ke Shi, Shaheen Khatoon, and Mi Xiao. 2013. Data mining techniques for wireless sensor networks: A survey. *International Journal of Distributed Sensor Networks* 2013 (2013).

[7] Spyros G. Makridakis, Steven C. Wheelwright, and Rob J. Hyndman. 1998. Forecasting: Methods and Applications (third edit ed.).

[8] Iftach Ragoler, Yossi Matias, and Nimrod Aviram. 2004. Adaptive probing and communication insensor networks. In Lecture Notes in Computer Science. 280–293.

[9] Wang, H., et al.: A reliable and energy efficient dual prediction data reduction approach for WSNs based on Kalman filter. *IET Commun*. 1–15 (2021)

[10] Mohanty, S.N., et al.: Deep learning with LSTM based distributed data mining model for energy efficient wireless sensor networks. *Phys. Commun*. 40, 101097 (2020)

[11] Radhika, S., Rangarajan, P.: On improving the lifespan of wireless sensor networks with fuzzy based clustering and machine learning based data reduction. *Appl. Soft Comput*. 83, 105610 (2019)

[12] Alam, M., et al.: Error-aware data clustering for in-network data reduction in *wireless sensor networks. Sensors* 20(4), 1011 (2020)

[13] Yemeni, Z., et al.: A DBN approach to predict the link in opportunistic networks. In: *Recent Developments in Intelligent Computing, Communication and Devices. Springer, Berlin, pp.* 575 587, (2019)

[14] Lu, Y., et al.: Benefits of data aggregation on energy consumption in wireless sensor networks. *IET Commun*. 11(8), 1216–1223 (2017)

[15] S. Santini and K. Romer, “An adaptive strategy for quality-based data reduction in wireless sensor networks,” in *Proceedings of the 3rd international conference on networked sensing systems (INSS 2006)*, 2006, pp. 29–36.

[16] A. Deshpande, C. Guestrin, S. R. Madden, J. M. Hellerstein, and W. Hong, “Model-driven data

acquisition in sensor networks," in *Proceedings of the Thirtieth international conference on Very large data bases-Volume 30.* VLDB Endowment, 2004, pp. 588–599.

[17] B. Stojkoska, D. Solev, and D. Davcev, "Data prediction in WSN using variable step size LMS algorithm," *in Proceedings of the 5th International Conference on Sensor Technologies and Applications*, 2011.

[18] G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella, "Energy conservation in wireless sensor networks: A survey," *Ad hoc networks, vol. 7,* no. 3, pp. 537–568, 2009.

[19] S. Goel and T. Imielinski, "Prediction-based monitoring in sensor networks: taking lessons from MPEG,"*ACM SIGCOMM Computer Communication Review,* vol. 31, no. 5, pp. 82–98, 2001.

[20] M. C. Vuran, O¨. B. Akan, and I. F. Akyildiz, "Spatio-temporal correlation: theory and applications for wireless sensor networks," *Computer Networks*, vol. 45, no. 3, pp. 245–259, 2004.

[21] A. Jain, E. Y. Chang, and Y.-F. Wang, "Adaptive stream resource management using kalman filters," *In Proceedings of the 2004 ACMSIGMOD international conference on Management of data. ACM*, 2004, pp. 11–22.

[22] J. Arenas-Garc´ıa, A. R. Figueiras-Vidal, and A. H. Sayed, "Steady state performance of convex combinations of adaptive filters," in Acoustics, Speech, and Signal Processing, 2005. Proceedings. (ICASSP'05). IEEE International Conference on, vol. 4. IEEE, 2005, pp. iv–33.

[23] M. Martinez-Ramon, J. Arenas-Garcia, A. Navia-Va´zquez, and A. R. Figueiras-Vidal, "An adaptive combination of adaptive filters for plant identification," in *Digital Signal Processing, 2002. DSP 2002. 2002 14th International Conference on,* vol. 2. IEEE, 2002, pp. 1195– 1198.

[24] Y. Zhang and J. A. Chambers, "Convex combination of adaptive filters for a variable tap-length LMS algorithm," *IEEE Signal Processing Letters,* vol. 13, no. 10, pp. 628–631, 2006.

[25] J. Arenas-Garcia, A. R. Figueiras-Vidal, and A. H. Sayed, "Mean- square performance of a convex combination of two adaptive filters," IEEE transactions on signal processing, vol. 54, no. 3, pp. 1078–1090, 2006.

[26] R. K. Martin, W. A. Sethares, R. C. Williamson, and C. R. Johnson, "Exploiting sparsity in adaptive filters," IEEE Transactions on Signal Processing, vol. 50, no. 8, pp. 1883–1894, 2002.

[27] D. Mandic, P. Vayanos, C. Boukis, B. Jelfs, S. L. Goh, T. Gautama, and T. Rutkowski, "Collaborative adaptive learning using hybrid filters," in Acoustics, Speech and Signal Processing, 2007. ICASSP 2007. IEEE International Conference on, vol. 3. IEEE, 2007, pp. III–921.

[28] D. Bismor, K. Czyz, and Z. Ogonowski, "Review and comparison of variable step-size LMS

algorithms," International Journal of Acous- tics and Vibration, vol. 21, no. 1, pp. 24–39, 2016.

[29] G. M. Dias, B. Bellalta, and S. Oechsner, "A survey about prediction- based data reduction in wireless sensor networks," ACM Computing Surveys (CSUR), vol. 49, no. 3, p. 58, 2016.

[30] D. Kalus, M. Muma, and A. M. Zoubir, "Distributed robust change point detection for autoregressive processes with an application to distributed voice activity detection," in Acoustics, Speech and Sig- nal Processing (ICASSP), 2015 IEEE International Conference on. IEEE, 2015, pp. 3906–3910.

[31] Y. Wu, R. M. Rangayyan, Y. Zhou, and S.-C. Ng, "Filtering elec- trocardiographic signals using an unbiased and normalized adaptive noise reduction system," Medical Engineering & Physics, vol.31, no. 1, pp. 17–26, 2009.

[32] Shaker, B.N., Hazar, M.J., Alzaidi, E.R.: Machine learning based for reducing energy conserving in WSN. J. Phys.: Conf. Ser. 1530, 012100 (2020)

[33] Tayeh, G.B., et al.: A spatial-temporal correlation approach for data reduction in cluster-based sensor networks. IEEE Access 7, 50669–50680 (2019)

[34] Fathy, Y., Barnaghi, P., Tafazolli, R.: An adaptivemethod for data reduction in the internet of things. In:2018 IEEE 4th World Forum on Internet of things (WF-IoT), IEEE, pp. 729–735, Singapore, 5–8 February2018

[35] Lu, Y., et al.: Benefits of data aggregation on energy consumption in wireless sensor networks. IET Commun. 11(8), 1216–1223 (2017)

[36] Jarwan, A., Sabbah, A., Ibnkahla,M.: Data transmission reduction schemes in WSNs for efficient IoT systems. IEEE J. Selected Areas Communi.37(6), 1307–1324 (2019)

[37] Elsayed, W.M., El Bakry, H.M., El Sayed, S.M.: Data reduction using integrated adaptive filters for energy- efficient in the clusters of wireless sensor networks. IEEE Embedded Sys. Lett. 11(4), 119–122 (2019)

[38] Feng, L., Kortoçi, P., Liu, Y.: A multi-tier data reduction mechanism for IoT sensors. In Proceedings of the Seventh International Conference on the Internet of Things, pp. 1–8. Linz, Austria, 22–25 October 2017