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Distributed Data Aggregation protocol for improving lifetime of Wireless Sensor Networks

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ABSTRACT

In Wireless Sensor Networks (WSN), the deployed sensor nodes can sense the same measures from the monitored area and forward these redundant measures to the sink node. Although redundant measures provide better accuracy but consume a lot of energy during the communication and the processing at the node and the sink, and thus decrease the lifetime of the WSN. Therefore, the elimination of redundant measures and reducing the communication cost are considered as essential characteristics during design the WSNs. In this article, a Distributed Data Aggregation (DiDA) protocol for prolonging the lifetime of WSNs is suggested. DiDA protocol is an energy efficient approach for a clustered network. DiDA works into cycles and each cycle aggregates and reduces data dimensionality by using an Adaptive Piecewise Constant Approximation (APCA) method. DiDA was successfully evaluated using OMNeT++ network simulator and based on sensed data of a real sensor network. Percentage of Sent data to the Cluster Head (CH), data accuracy, and energy consumption are the performance metrics applied to assess the effectiveness of the DiDA protocol. The conducted simulation results show that the proposed DiDA protocol decreases the consumed energy and extending the network lifetime, in comparison with a method without using data aggregation technique, whilst keeping the sensed data quality at the sink node.

1. INTRODUCTION

In the last years, a novel type of networks is emerged called Wireless Sensor Networks (WSNs) due to the fast development in the wireless devices, electronics, and the technology of embedded computing. A WSN consists of a large number of tiny low-cost limited-energy devices that can sense, process, store, and transmit data of surrounding environment with limited capabilities across the network to the sink

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node. The most significant resource in the sensor node that impacts on the lifetime of WSN is the energy provided by the battery which is difficult or impossible to replace (or recharge) it especially in the remote or hostile environment. One of the biggest challenges in WSN is the lifetime maximization of the battery [1, 2, 33, 34]. Therefore, it is important to transmit as less volume of data as possible to the base station (sink).

The sensed data received by the sink node may be similar because there is more than one sensor monitors the same region. In addition, the large volume of sensed data generated by dense WSN leads to high processing load on the sink node. Therefore, it is necessary to improve the energy efficiency of the sensor network to operate over a long period of time. This can be done by using an energy efficient ways such as Data aggregation methods [3]. The main objective of data aggregation algorithms is to collect and accumulate sensed data with removing redundancy from sensed correlated data generated by closely located neighboring sensors so as to save the energy thus extend the network lifetime [3, 4].

Data gathering can be either triggered events (such as forest fire and gas or oil leaks detection [5, 6]) or periodic triggering (such as habitat monitoring [7]). This paper focuses on the periodic data gathering and aggregation in WSNs. In some specific WSN applications, the accuracy of the observations is very critical for understanding the underlying processes. Therefore, in order to design data aggregation algorithms for such applications, it is very important to ensure the accuracy of the received sensed data by the sink node.

This article provides the following contributions:

1- A new protocol named DiDA (Distributed Data Aggregation) is proposed to aggregate the sensed data and prolong the network lifetime in WSNs. It uses an energy efficient method for data aggregation for a clustered network. DiDA protocol uses the Adaptive Piecewise Constant Approximation (APCA) method to aggregate, and reduce the sensed data dimensionality.

2- DiDA protocol is evaluated by OMNeT++ network simulator using extensive simulation experiments. DiDA has been compared to the results of the method without using data aggregation technique.

The rest of this paper is organized as follows. Next section exhibits literature review. Section 3 explains the description of (DiDA) protocol. Protocol evaluation is shown in Section 4. Finally, we present the conclusion and future works in Section 5.

2. LITERATURE REVIEW

This section investigates some existing related works to data aggregation in WSNs. In recent years, several proposed data management works focused on the data aggregation in WSNs [8, 9, 10, 35, 36]. The principle objective of aggregating the sensed data is to eliminate the redundancy in the sensed data and minimize the consumed energy thus extending the lifetime of the network [11].

However, in order to reduce the data transferring, the works in [12]-[15] used simple aggregation functions (such as max, min, avg, and sum) for aggregation. These methods do not consider the correlation among the sensed data. Although they provide a high aggregation performance but the accuracy of recovered data is badly poor. Therefore, these methods are

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inappropriate for those applications that require a high data accuracy [16]. For example, LEACH [17] protocol divides the network into several clusters. The cluster heads are chosen during the setup phase whilst the data are aggregated using AVG method at each cluster head in the steady phase so as to reduce the network data traffic [18].

HEED protocol [19] is the extended version of LEACH protocol. The cost of the intra-cluster communication and the limits of communication range are included in original LEACH. It elects the cluster head in a periodic way and based on two parameters: remaining energy and the degree of the node. The authors in [12] presented EAST method for data gathering based on spatial-temporal correlations. The nodes are spatially clustered by this method into groups according to their positions in the region. The temporal correlation is achieved by the cluster head to aggregate and transmit the sensed data to the sink only in the case when they exceed a particular threshold. This method is suitable for event-driven data aggregation [31]. It is not relevant for periodic data sending due to the processing and communication overhead caused by the dynamic selection of the cluster head [18].

The works in [20]-[23] divided the sensor nodes into different clusters. One or several nodes in each cluster are chosen as a representative set of nodes for data collecting and sending whilst deactivating the other nodes in the same cluster. The node's energy can be saved significantly with these methods, but this can lead to important data loss due to a large number of deactivated nodes.

The authors in [24] proposed a round-based clustering scheme that resolves the transmission of redundant data in the network so as to improve network lifetime. Proposed scheme works in four phases rounds: initialization, cluster-head selection, clustering, and data aggregation. Proposed clustering scheme reduces energy consumption, thus increasing network throughput by dealing with most of the redundant data. Several data aggregation methods are proposed in [32].

This paper proposes a Distributed Data Aggregation (DiDA) protocol for lifetime enhancement in WSNs. DiDA aggregates and decreases the data dimensionality using an Adaptive Piecewise Constant Approximation (APCA) method. DiDA is assessed using OMNet++ network simulator and based on real sensed data from a sensor network. The results explain that the suggested DiDA protocol reduces the energy consumption and prolonging the WSN lifetime compared to the results of the method without using data aggregation technique while maintaining the quality of sensed data at the sink node.

3. DATA AGGREGATION STAGE USING APCA

The proposed protocol in this article is distributed on the sensor nodes. These nodes are considered grouped into clusters so as to achieve energy efficient data aggregation with reduced cost of communication. In this paper, DiDA protocol achieves the data aggregation at the level of the sensor node periodically and then transmits the sensed data to the cluster head. After that, the cluster head sends the data directly to the sink. Figure 1 illustrates the flowchart of the proposed DiDA protocol. Table 1 explains some parameters used in this paper.

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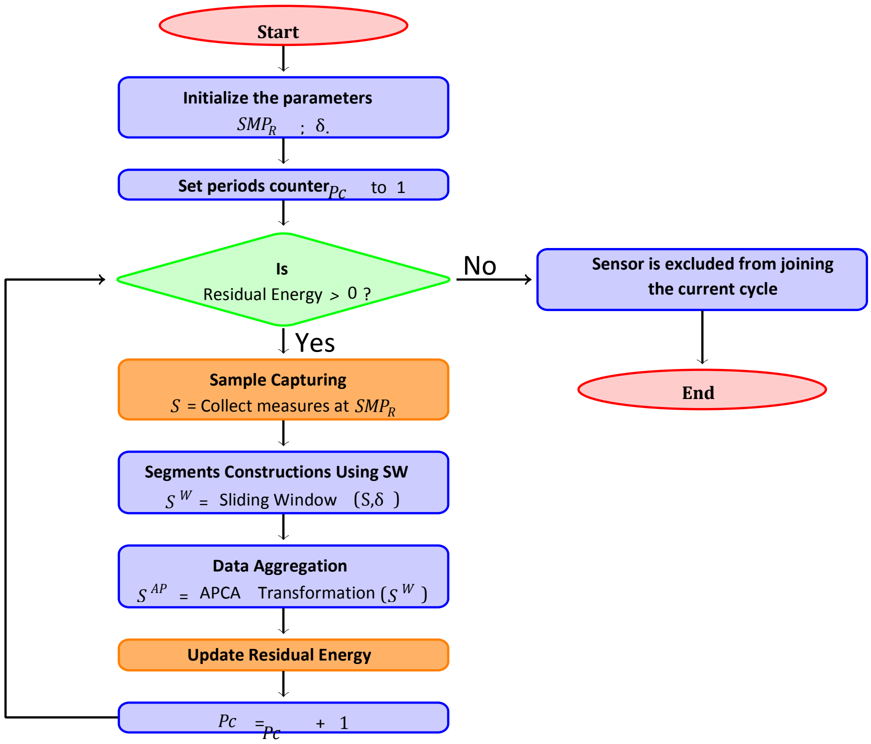

Figure 1. Flowchart of proposed DiDA protocol.

Table 1: Some parameters used in this paper.

SMP_R	Sampling rate = ρ
S	Temperature readings series $S = s_1, \dots, s_n$
S^W	Segment construction using SW(S, ε), $S^W = s_1^w, \dots, s_m^w$
S^{AP}	APCA of S^W, $S^{AP} = c_1^{ap}, \dots, c_w^{ap}$
ε	Reconstruction error bound
n	Sensor id
n_e	Remaining energy of sensor n

The PSN consists of N nodes$(n_1, n_2, \dots, n_N)$, each node is responsible for sensing the data measures of the dynamic physical environment such as humidity, temperature, or pressure etc. In PSN, the periods are partitioned into time slots. Therefore, each sensor node n captures the data reading periodically. Consequently, the time-ordered sequence of sensed data constitutes a time series, $S_i = \{s_1, s_2, \dots, s_{p-1}, s_p\}$, where ρ is the total number of temperature readings generated by sensor node n_i every T seconds. The redundant temperature readings captured by the sensor node increase in two states: short time slot and slowly variation of a monitored area of interest.

Often, the volume of temperature readings series is very huge. Therefore, it is not practical to send all the collected raw readings from every sensor node back to the base station due to the constrained bandwidth and energy consumption on data sending (radio transmission). The dimensionality ρ of temperature readings series (which is the number of observed measures) have a direct proportionality relation with the communication cost. Thus, a smaller ρ can result in a significant reduction in the communication cost and hence, it will prolong the lifetime of the sensor network [25]. In this stage, the DiDA protocol aims to perform

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dimensionality reduction by removing the redundant data. It exploits the correlation nature which is temporal among the sensed data of the sensor node efficiently by applying an Adaptive Piecewise Constant Approximation (APCA) technique. DiDA protocol transforms the temperature readings series $S_i = \{s_1, s_2, \dots, s_{p-1}, s_p\}$ that collected during the period to an APCA representation in order to decrease the dimensionality of series. The APCA divides the sorted temperature readings series S into a set of constant value segments (with a bounded reconstruction error δ) of varying lengths based on data such that their individual reconstruction errors are minimal. More formally, $| R(S^{AP}) - S | < \delta$, $R(S^{AP})$ is the reconstruction function, and δ is an error threshold. Long segments are used to represent data regions of low activity, and short segments are used to represent regions of high activity [26]. The APCA representation of S is given as follow:

$$S^{AP} = \{(dm_1, dr_1), \dots, (dm_m, dr_m)\}, dr_0 = 0. \quad (1)$$

The APCA approximates each segment S_j^{AP} by a pair (dm_j, dr_j) of two numbers, where dm_j is the mean value of temperature readings in the j^{th} segment which is defined as

$$dm_j = \frac{\sum_{k=dr_{j-1}+1}^{dr_j} Sk}{dr_j - dr_{j-1}} \quad (2)$$

Whilst dr_j is the right endpoint of the j^{th} segment [27].

By using the standard form of APCA with a constant number of segments of varying lengths can influence on the accuracy of temperature readings. Hence, the problem addressed here is: for a given temperature readings series S and a given reconstruction error bound δ, find the number of segments to approximate the time series, such that the difference between any approximation value and its actual value is less than δ. In our method, we make some slight modifications on APCA. First, the number of segments m will not be constant and predetermined, but it will be adaptive based on the user specified reconstruction error δ. In order to achieve this goal (i.e. making the number of segments adaptive), the sliding window algorithm is utilized. The reason for making the number of segments adaptive is to increase the accuracy of approximated measures by using a user-specified reconstruction error. Second, we modified d_r to represent the length of the segments rather than record the locations of their right endpoints.

At the end of each period, DiDA protocol will apply the sliding window algorithm on the collected readings to produce a different number of segments with varying lengths. The Sliding Window approach is used because it is simple, online, and intuitive [28]. Algorithm 1 represents the process of segment construction using sliding window algorithm.

Algorithm 1. Segments Construction using Sliding Window
Input: $S(\rho - dimensional\ temperature\ readings\ series)$;
$\delta: Reconstruction\ Error\ bound$
Output: S^W $the\ set\ of\ segments\ with\ m\ subsets$
Process:
1: $S \leftarrow Sorting\ (S)$ **//Sorting temperature readings in descending order.**
2: $Flag \leftarrow 1$ **// Starting point.**
3: $SEG_{No} \leftarrow 1$ **// Number of Segments.**
4: $\boldsymbol{while}\ (x < \rho)\ \boldsymbol{do}$
5: $x \leftarrow 2$
6: $\boldsymbol{while}\ (Calculate\_Error(S[Flag: Flag + x]) < \delta)\ \boldsymbol{do}$
7: $x \leftarrow x + 1$
8: $\boldsymbol{end\ while}$
9: $S^W[SEG] \leftarrow Create\_Segment\ (S[[Flag: Flag + x - 1]$

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$Flag \leftarrow Flag + x$
$SEG_{No} \leftarrow SEG_{No} + 1$
end while
return S^W

After segmenting the temperature readings series using sliding window algorithm, the produced set of segments $S^W = (S_1^W, S_2^W, \ldots, S_m^W)$ is used by algorithm 2 to produce the APCA representation for temperature readings series S. Algorithm 2 illustrates the process of dimensionality reduction using APCA.

Algorithm 2. Aggregation Stage using APCA.
Input: S^W *the set of segments with m subsets.*
Output: S^{AP} *the set of segments with m subsets and two numbers per segment.*
Process:
for $i \leftarrow 1$ *to* m ***do***
  $SG \leftarrow S_i^W$
  $Sum \leftarrow 0$
  $Count \leftarrow 0$
  for $j \leftarrow 1$ *to* $Len(SG)$ ***do***
    $Sum \leftarrow Sum + SG[j]$
    $Count \leftarrow Count + 1$
  end for
  $SEG_{len} \leftarrow Count$
  $SEG_{\mu} \leftarrow \frac{Sum}{Count}$
  $S_i^{AP} \leftarrow Create\_segment(SEG_{\mu}, SEG_{len})$
end for
return S^{AP}

In the aggregation stage and at the end of every period, each sensor n_i will have a set of segments S^{AP} with m subsets$(S_1^{AP}, S_2^{AP}, \ldots, S_m^{AP})$, and two numbers per segment $(SEG_{\mu i}, SEG_{leni})$ that meet the reconstruction error bound δ, with no redundant measures. The problem mentioned above is solved by constructing a set of segments S^{AP} with m subsets that meet the reconstruction error bound δ.

4. PROTOCOL EVALUATION

In this section, we provided the framework of simulation and conducted a series of simulations to assess the effectiveness and the relevance of the proposed protocol.

4.1. Simulation framework

In order to evaluate DiDA protocol, extensive simulations experiments are performed with discrete event simulator OMNeT++ [29] and based on real sensor data. In these simulations, we consider *N* sensors deployed in the lab. Sensors periodically capture local readings (e.g., temperature) at a specified rate. We assume there is a single cluster head located at the center of the lab. The cluster head receives sensed data readings from each sensor node in the lab periodically via a single hop. DiDA protocol is distributed at each sensor node and it is based on the dataset of Intel Berkeley Research Lab [30]. PSN in this Lab includes 54 Mica2Dot sensors.

The sensed data of the weather (such as temperature, humidity, and light) are periodically collected by these sensors once each 31 seconds. In our simulation, the sensor nodes use a log file contains about 2.3 million readings collected previously by Mica2Dot sensor nodes

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in the Lab. This article uses only one measure of sensor node measurements: temperature[4]. There are 7 sensor nodes didn't used in our simulation because its data may be missed or truncated. Therefore, the results are the average of 47 sensor nodes. Table 2 gives the selected parameters settings.

Table 2: Simulation Parameters for PSN initialization.

Parameter	Value
PSN size	47 nodes
ρ	20, 50 and 100 readings
δ	0.03, 0.05, 0.07 Reconstruction error bound
E_{elec}	50 nJ/bit
β_{amp}	100 pJ/bit/ m^2

In the experimental simulations, some performance metrics are applied to assess the effectiveness of the DiDA protocol such as Percentage of Sent data to the CH, data accuracy, and energy consumption. DiDA protocol uses the same energy consumption model discussed in [30]. Energy consumed by the sensor node is caused by the communication unit (data transmission and reception). Therefore, the cost of transmission is calculated for a $m-$ bits message and for a distance d as follow

$$E_{TX}(m,d) = E_{elec} * m + \beta_{amp} * m * d^2. \tag{7}$$

The energy consumption required for reception $m-$ bits is calculated as follow

$$E_{RX}(m,d) = E_{elec} * m. \tag{8}$$

These experiment simulations consider the length of data reading m equal to 64. In fact, we set the value of m to 64 bits because we consider each data reading as a double data type that takes 8 bytes. In the case of transmission, 64 bits are added to $m-$ bits message which corresponds to the frequency of data reading m. The length of the transmitted data packet is calculated as follow DataPacket length = (Number of readings in the data set ×2) ×64 bits. Hence, the packet length is the number of reading in the sensed data set with their frequencies multiplying by 64 bits.

4.2. Performance comparison and analysis

Several experiments are achieved in this section to show the performance of DiDA protocol. DiDA is distributed at each sensor node in the PSN. Every node reads real temperature readings periodically and aggregate them using APCA. Furthermore, DiDA protocol is compared to the results of the method without using data aggregation technique.

1) **Percentage of Sent data to CH after applying aggregation stage**: The result of the aggregation in this stage depends on the chosen reconstruction error bound δ, the number of the collected measures ρ in the period, and the changes in the monitored region. Figure 2 illustrates the Percentage of Sent data to the CH without and with applying aggregation stage at the end of simulation by every sensor node using DiDA protocol compared with the results of the method without using data aggregation technique. The results show a maximum of 25% of the data sent to CH after applying the aggregation stage by DiDA protocol at each period, whilst the rate is equal to 100% without applying the aggregation step. Therefore, DiDA protocol decreases the volume of sensed data transmitted to the CH by removing the

[4] The other is done by the same manner.

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duplicated measures at every period successfully. It can be seen at the step of aggregation, when the ρ or δ increases, the sent data are decreases. The reason behind this is remove a larger amount of similar data by using APCA method.

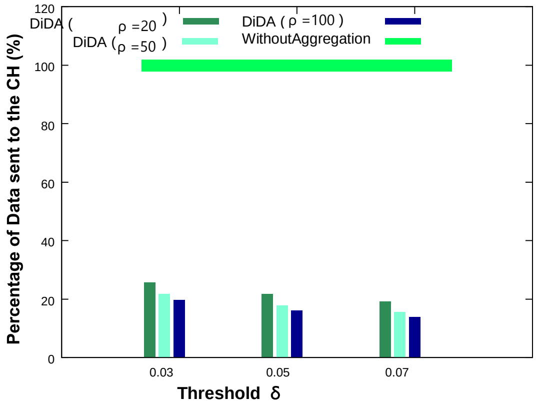

Figure 2. Percentage of Sent data to the CH.

2) **Data Accuracy:** In this experiment, the data accuracy is considered as an essential performance factor in WSNs. In this paper, it represents the percentage of data loss after applying the aggregation inside the sensor node. It has a significant impact on the final decision that will be taken by the end user. It can be considered as the error of aggregation. In this section, the proposed DiDA protocol is compared with the results of the method without using data aggregation technique. Table 3 shows the results of data accuracy without and with using our technique DiDA. It can be seen that our protocol provides good results from the data accuracy point of view. In the worst case, the percentage of data which are not received by the sink are almost 0.298 % (i.e. ρ =100). This percentage is not important in comparison with the received data by the base station. Therefore, it can be noted that our protocol is able to get rid of the redundant data while maintaining the accuracy of received data by the end user. Furthermore, the data loss percentage minimizes when ρ and δ decreases because of using efficient method for data reduction.

Table 3: Data Accuracy (percentage of data loss after applying the aggregation inside the sensor).

Threshold δ	Percentage of Lost Measures (%) DiDA (p=20)	DiDA (p=50)	DiDA (p=100)	Without Aggregation
0.03	0.0013	0.004442553	0.298617021	0
0.05	0.0013	0.004442553	0.298617021	0
0.07	0.0013	0.004442553	0.298617021	0

3) **Energy consumption:** The energy consumption is another performance factor for evaluating our protocol in comparison with the results of the method without using data aggregation technique. Figure 3 shows the energy consumption at each sensor node. The

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energy consumption minimized when the transmitted data to the cluster head minimized. DiDA protocol decreases the consumed energy while maintaining the integrity of information by applying an energy efficient data aggregation approach. Figure 6 display the energy consumption without and with using our technique DiDA for various δ and ρ values. The conducted simulation results explain that DiDA is the better from the energy consumption point of view. DiDA saves more energy when both ρ or δ increase.

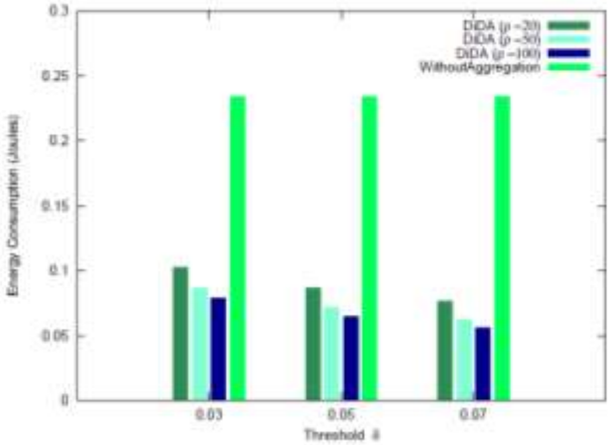

Figure 3. Energy consumption at each sensor node.

5. CONCLUSION AND FUTURE WORKS

The increased use of the sensor networks in several applications led to provide a huge amount of data which are transmitted across the network. This is greatly contributed in decreasing the network lifetime due to the high communication cost. Therefore, the energy efficient data aggregation approaches are very necessary for eliminating the replicated data in the network. In this article, we propose a protocol named DiDA (Distributed Data Aggregation) to extend the lifetime of the WSNs. This protocol uses Adaptive Piecewise Constant Approximation (APCA) as an energy efficient data aggregation, thus improving the network lifetime. The simulation results that based on real data of the sensor network using OMNet++ network simulator show that DiDA protocol outperforms the method without using data aggregation technique in terms of data reduction percentage that will be transmitted to the cluster head, energy consumption, and acceptable data accuracy. In future, we plan to apply the data aggregation into two levels: sensor node level and aggregator node level (cluster heads). The first level is responsible for temporal correlation among the data inside the sensor node whilst the second level deals with data correlation among neighboring nodes. In addition, we plan to compare our proposed method with two existing methods in the literature [35] and [36].

REFERENCES

[1] S. Misra, I. Zhang, and S. C. Misra, *Guide to wireless sensor networks*. Springer Science & Business Media, 2009.

[2] A. K. Idrees, K. Deschinkel, M. Salomon, and R. Couturier, “Distributed lifetime coverage optimization protocol in wireless sensor networks,” *The Journal of Supercomputing*, vol. 71, no. 12, pp. 4578 – 4593, 2015.

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[3] X. Zhai and T. Vladimirova, “Data aggregation in wireless sensor networks for lunar exploration,” in *2015 Sixth International Conference on Emerging Security Technologies (EST)*. IEEE, 2015, pp. 30–37.

[4] S. Pino-Povedano, R. Arroyo-Valles, and J. Cid-Sueiro, “Selective forwarding for energy-efficient target tracking in sensor networks,” *Signal Processing*, vol. 94, pp. 557–569, 2014.

[5] L. Yu, N. Wang, and X. Meng, “Real-time forest fire detection with wireless sensor networks,” in *Proceedings. 2005 International Conference on Wireless Communications, Networking and Mobile Computing, 2005.*, vol. 2. IEEE, 2005, pp. 1214–1217.

[6] M. Dalbro, E. Eikeland, A. J. in’t Veld, S. Gjessing, T. S. Lande, H. K. Riis, and O. Sørasen,˚ “Wireless sensor networks for off-shore oil and gas installations,” in *Sensor Technologies and Applications, 2008. SENSORCOMM’08. Second International Conference on*. IEEE, 2008, pp. 258–263.

[7] A. Mainwaring, D. Culler, J. Polastre, R. Szewczyk, and J. Anderson, “Wireless sensor networks for habitat monitoring,” in *Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications*. ACM, 2002, pp. 88–97.

[8] B. Yu, J. Li, and Y. Li, “Distributed data aggregation scheduling in wireless sensor networks,” in *INFOCOM 2009, IEEE*. IEEE, 2009 , pp. 2159–2167.

[9] Y. Zheng, K. Chen, and W. Qiu, “Building representative-based data aggregation tree in wireless sensor networks,” *Mathematical Problems in Engineering*, vol. 2010, 2010.

[10] J. M. Bahi, A. Makhoul, and M. Medlej, “Data aggregation for periodic sensor networks using sets similarity functions,” in *2011 7th International Wireless Communications and Mobile Computing Conference*. IEEE, 2011, pp. 559–564.

[11] M. A. Sharaf, J. Beaver, A. Labrinidis, and P. K. Chrysanthis, “Tina: a scheme for temporal coherency-aware in-network aggregation,” in *Proceedings of the 3rd ACM international workshop on Data engineering for wireless and mobile access*. ACM, 2003, pp. 69–76.

[12] F. Ren, J. Zhang, Y. Wu, T. He, C. Chen, and C. Lin, “Attribute-aware data aggregation using potential-based dynamic routing in wireless sensor networks,” *IEEE transactions on parallel and distributed systems*, vol. 24, no. 5, pp. 881–892, 2013.

[13] H. Luo, H. Tao, H. Ma, and S. K. Das, “Data fusion with desired reliability in wireless sensor networks,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 22, no. 3, pp. 501–513, 2011.

[14] X. Xu, X.-Y. Li, P.-J. Wan, and S. Tang, “Efficient scheduling for periodic aggregation queries in multihop sensor networks,” *IEEE/ACM Transactions on Networking (TON)*, vol. 20, no. 3, pp. 690–698, 2012.

[15] W. B. Heinzelman, “Application-specific protocol architectures for wireless networks,” Ph.D. dissertation, Massachusetts Institute of Technology, 2000.

[16] C. Liu, J. Luo, and Y. Song, “Correlation-model-based data aggregation in wireless sensor networks,” in *Fuzzy Systems and Knowledge Discovery (FSKD), 2015 12th International Conference on*. IEEE, 2015, pp. 822–827.

[17] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, “Energyefficient communication protocol for wireless microsensor networks,” in *System sciences, 2000. Proceedings of the 33rd annual Hawaii international conference on*. IEEE, 2000, pp. 10 –pp.

[18] I. H. Brahmi, S. Djahel, D. Magoni, and J. Murphy, “A spatial correlation aware scheme for efficient data aggregation in wireless sensor networks,” in *Local Computer Networks Conference Workshops (LCN Workshops), 2015 IEEE 40th*. IEEE, 2015, pp. 847–854.

[19] O. Younis and S. Fahmy, “Heed: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks,” *IEEE Transactions on mobile computing*, vol. 3, no. 4, pp. 366–379, 2004.

[20] J. Yuan and H. Chen, “The optimized clustering technique based on spatial-correlation in wireless sensor networks,” in *Information, Computing and Telecommunication, 2009. YC-ICT’09. IEEE Youth Conference on*. IEEE, 2009, pp. 411–414.

[21] Z. Liu, W. Xing, Y. Wang, and D. Lu, “An energy-efficient data collection scheme for wireless sensor networks,” in *Advanced Communication Technology (ICACT), 2013 15th International Conference on*. IEEE, 2013, pp. 60–65.

[22] L. A. Villas, A. Boukerche, H. A. De Oliveira, R. B. De Araujo, and A. A. Loureiro, “A spatial correlation aware algorithm to perform efficient data collection in wireless sensor networks,” *Ad Hoc Networks*, vol. 12, pp. 69–85, 2014.

[23] T. D. Le, N. D. Pham, and H. Choo, “Towards a distributed clustering scheme based on spatial correlation in wsns,” in *2008 International Wireless Communications and Mobile Computing Conference*. IEEE, 2008, pp. 529–534.

[24] K. T.-M. Tran and S.-H. Oh, “Uwsns: A round-based clustering scheme for data redundancy resolve,” *International Journal of Distributed Sensor Networks*, vol. 2014, 2014.

[25] C. Liu, K. Wu, and J. Pei, “An energy-efficient data collection framework for wireless sensor networks by exploiting spatiotemporal correlation,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 18, no. 7, pp. 1010–1023, 2007.

[26] A. Zifan, M. H. Moradi, S. Saberi, and F. Towhidkhah, “Automated segmentation of ecg signals using piecewise derivative dynamic time warping,” *International Journal of Biological and Life Sciences*, vol. 1 , pp. 181–185, 2007.

[27] Y. Wang, P. Wang, J. Pei, W. Wang, and S. Huang, “A data-adaptive and dynamic segmentation index for whole matching on time series,” *Proceedings of the VLDB Endowment*, vol. 6, no. 10, pp. 793–804 , 2013.

[28] Y. B. Yahmed, A. A. Bakar, A. R. Hamdan, A. Ahmed, and S. M. S. Abdullah, “Adaptive sliding window algorithm for weather data segmentation,” *Journal of Theoretical and Applied Information Technology*, vol. 80, no. 2, p. 322, 2015.

[29] “Omnet++ discrete event simulator.” 2016, [Online; accessed 23August-2016].

[30] S. Madden, “Intel berkeley research lab,” 2004, [Online; accessed 25-August-2016]. [Online]. Available: http://db.csail.mit.edu/labdata/ labdata.html.

[31] M. Kamarei, M. Hajimohammadi, A. Patooghy, and M. Fazeli, “An Efficient Data Aggregation Method for Event-Driven WSNs: A Modeling and Evaluation Approach,” Wireless Personal Communications, vol. 84, no. 1, pp. 745–764, 2015.

[32] Jesus, P., Baquero, C. and Almeida, P.S., “A survey of distributed data aggregation algorithms,” IEEE Communications Surveys & Tutorials, vol. 17, no. 1, pp. 381-404, 2015.

[33] Idrees AK, Deschinkel K, Salomon M, Couturier R. Coverage and lifetime optimization in heterogeneous energy wireless sensor networks. ICN 2014. 2014 Feb 23:60.

[34] Idrees AK, Deschinkel K, Salomon M, Couturier R., "Perimeter-based coverage optimization to improve lifetime in wireless sensor networks," Engineering Optimization, vol. 48, no. 11, pp. 1951-72, 2016.

[35] Bahi, J.M., Makhoul, A., Medlej, M.: A two tiers data aggregation scheme for periodic sensor networks. Adhoc & Sensor Wireless Networks, vol. 21, no. 1, 2014.

[36] Harb, H., Makhoul, A., Couturier, R. and Medlej, M., "ATP: An Aggregation and Transmission Protocol for Conserving Energy in Periodic Sensor Networks," In IEEE 24th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE), pp. 134-139, 2015.