Analysis of Processing Architectures for Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSN) are networks of low-cost communication devices with sensing and computational capabilities enabling remote, real-time measurement, monitoring and control of divers physical and environmental parameters. As WSNs are typically battery powered, energy-aware techniques are critical for extending its lifetime. Aside from energy-efficient communication protocols, distributed processing strategies are being explored whereby,computational capabilities of sensor nodes are utilised to locally process sensed data in order to reduce communication cost. However, as local processing increases, the impact of processing energy cost becomes significant creating a need to analyse WSNs under this emergent scenario as previous work have focused mostly on communication cost. We analysed the energy cost for WSN under different processing architectures. We used a fairness metric to quantify the fairness of energy cost distribution in the network. Our results showed a positive correlation between fairness and network lifetime. Hence, we argue that local processing can be exploited to reduce transmission and improve system performance without adversely reducing network lifetime. We conclude that although local processing marginally increases node energy consumption, it improves overall network life time as energy cost is evenly distributed in the network. Moreover, it enhances network maintenance as nodes have similar lifetimes.

1 INTRODUCTION

Wireless Sensor Networks (WSN) have been applied in a variety of application areas especially where wired technologies are impracticable such as agriculture (Baggio, 2005), health (Jafari et al., 2005), environmental monitoring (Othman and Shazali, 2012) and infrastructural monitoring (Wang et al., 2007). Although the success of WSN have been demonstrated in these varied areas, a major challenge limiting its widespread adoption is energy-efficiency. Early WSN applications were mainly used for remote data harvesting therefore, existing work focused mainly on developing energy-efficient communication protocols (Pantazis et al., 2013) due to the high energy cost associated with radio communication on sensor nodes. Recently, WSNs are being used beyond simple monitoring and data harvesting applications. For instance, on-chip processing capabilities of sensors are being exploited for energy-aware distributed processing (Chong et al., 2011). Distributed processing improves the latency of system response in wireless sensor and actuator networks because event detection and control decisions can be performed faster, locally. It also reduces transmission of large sized raw-data thereby reducing communication cost. Existing work have focused mostly on the energy cost of communication activities in WSN but less attention have been given to analysing the cost of distributed processing as we have done in this work. We analyse local and global energy costs for our models and quantify energy efficiency in terms of a fairness metric. We discuss our results and show that the advantages of distributed processing in WSN can be explored without significantly affecting network lifetime.

2 PROCESSING ARCHITECTURE

2.1 Centralised Architecture

A centralised processing architecture is shown in figure 1. In this case, processing actions such as filtering and classification are performed on a single central node called the sink. The leaf nodes only sense and transmit raw data to the central node for use in processing as shown. For all the network diagrams in this paper, the nodes with reduced functionality are

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represented by a circle while nodes with processing function are denoted by a square.

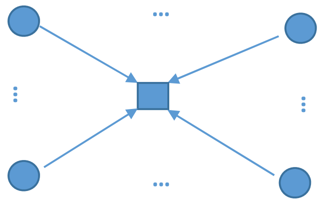

Figure 1: Centralised Processing.

2.2 Distributed Architecture

2.2.1 Node Level

Node level distributed architecture is represented as shown in figure 2.

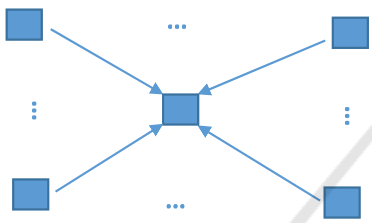

Figure 2: Node Level Distributed Processing.

In this case, processing is purely distributed with every sensor node performing localised processing before transmitting to the sink.

2.2.2 Network Level

In the network level architecture, processing activities are performed locally on a subset of nodes (sometimes called cluster heads) which cooperatively achieve the network's objective as shown in figure 3.

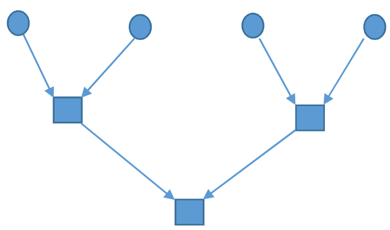

Figure 3: Network Level Distributed Processing.

Typical monitoring and control objectives require sensors to cooperate to achieve results. Hence, the need to investigate the prospects of using energy-constrained sensor nodes as a distributed processing resource.

3 ENERGY COST MODELS

The energy cost of sensing is usually the same for every node irrespective of it's role in the network. However, communication cost depends on the communication distance between the source node and the sink node as well as on the size of data packets. Similarly, processing cost is dependent on the energy costs associated with switching and leakage currents in the processor circuit.

The consensus of existing literature on energy consumption models for WSNs is that radio communication is the most energy consuming activity for wireless sensors due to high energy dissipation by the wireless radio. Therefore, several communication protocols have been proposed for energy-efficient communication in WSN. However, most of these protocols are very small incremental improvements of an existing protocol based on the radio energy model proposed in (Heinzelman et al., 2002; Heinzelman et al., 2000).

Recently, a more comprehensive energy model presented by (Halgamuge et al., 2009) which accounted for *seven* different aspects of sensor energy consumption activities showed that the results obtained using the former model were over-estimated as the model focused mainly on the communication energy cost. Thus, instead of assuming a fixed value for processing energy as most previous work did, processing energy, was expressed in terms of switching and leakage current losses thereby accounting for other factors which were unaccounted for in pre-existing models. These two models provided the basis for further investigation into the effect of increased distributed in-network processing on the lifetime of WSNs.

3.1 Communication Energy Cost Model

The communication energy cost E_{comm}, is defined as the energy required to communicate n bits of data over a communication distance d as follows:

$$E_{comm} = E_T + E_R \tag{1}$$

where, E_T and E_R is the cost of transmitting and receiving data respectively. E_T and E_R is computed from equations 2 and 3 as follow:

$$\begin{aligned} E_T &= E_{T_e}(n) + E_{T_a}(n,d) \\ &= n * (E_{elect} + \varepsilon_{mp} * d^4) \end{aligned} \tag{2}$$

and

$$E_R = n * E_{elect} \tag{3}$$

where, E_{T_e} is energy consumed by transmission electronics, E_{T_a} is energy consumed by amplifier electronics; E_{elect} is energy consumed by device electronics; ε_{mp} is the distance based energy loss constant.

3.2 Processing Energy Cost Model

The energy cost of processing, $E_{process}$, is defined as the energy cost of processing n bits of data and is given by equation 4.

$$E_{process}(n, N_{clock}) = \underbrace{nN_{clock}C_{avg}V_s^2}_{\text{switching current}} + \underbrace{nV_s\left(\frac{N_{clock}}{f}\right)\left(I_{leak}e^{\frac{V_s}{pV_t}}\right)}_{\text{leakage current}} \quad (4)$$

where, n remains the data size in bits; N_{clock} is the number of clock cycles required to complete a single processing task; C_{avg} is the average capacitance switched per cycle; V_s is the supply voltage; f is the processor frequency; I_{leak} is the leakage current; p is a constant depending on the processor and V_t is the thermal voltage of the processing circuit.

3.3 Sensor Life Time

We define network lifetime as the time taken for the first node to die (i.e. run out of battery power) (Chang and Tassiulas, 2004). A node's role within the network determines how much energy it expends thereby affecting its lifetime.

Given that a sensor node has an initial energy in Joules; the lifetime of the sensor (L_t) can be estimated using equation 5.

$$L_t = \frac{E_{init}}{E_{rmax}} * T \quad (5)$$

where E_{init} is the initial energy associated with the node, E_{rmax} is the maximum node energy cost for one event cycle and T is the time in seconds taken to complete one event cycle.

Equation 5 can be used to estimate network lifetime prior to deployment providing useful information for planning network maintenance.

3.4 The Fairness Metric

Jain's fairness index (Jain et al., 1998) is a performance criteria used in resource allocation schemes for shared resources however, in this context, we define it as a global metric which is a measure of the equity of energy cost distribution among nodes in a sensor network. The fairness value lies between 0 & 1 with higher values corresponding to fairer distributions. The fairness index, F is given by equation 6.

$$F(x_1, x_2, \ldots, x_s) = \frac{(\sum_{i=1}^{s} x_i)^2}{s.\sum_{i=1}^{s} x_i^2} \quad (6)$$

where x_i is computed as

$$x_i = \frac{E_{round_i}}{E_{global}} \quad (7)$$

s represents the number of nodes in the network; E_{round_i} is the local energy cost for node i and E_{global} the network energy cost for one event cycle respectively. A high fairness index implies that energy cost is evenly spread among the nodes with a more uniform lifetime while a low index value shows that only a few nodes are overburdened by the energy cost of the system.

4 ENERGY COST ANALYSIS

In this section, we present the energy cost analysis using our energy cost models. Five scenarios denoted as S1-S5 representing the main processing architectures used in literature were defined. For simplicity, we focused only on communication and processing costs as we assumed other node energy costs to be fairly constant for all network nodes.

We provide analytical expressions for the local and global energy cost functions for the different network architectures. The local energy cost captures the energy expended by a single node in the network and is a function of the node's role within the network and the communication model used while the global energy cost captures the total energy expended by all nodes in the network after each complete event cycle.

We classify node functions into : basic roles (common to all nodes e.g. sensing, logging, communication) and non-basic roles (nodes can posses either or none e.g. processing, control, actuation). Sensor nodes can operate either in the full-function (FF) mode or the reduced-function (RF) mode. RF nodes perform only basic roles and are represented by a circle shape while FF nodes perform one or more non-basic roles in addition to basic roles and are represented by a square shape.

We carry out analysis and simulation using MATLAB for the different architectures to identify the best network architecture for distributed processing in terms of energy-efficiency. Our analysis was based on the following assumptions:

1. Every data processing activity takes equal number of clock cycles so that N_{clock} is equal to a constant value (Halgamuge et al., 2009).

2. Carrier access is by TDMA and all node functions are completed within a full cycle.
3. The packet size n, is equal to a maximum of 133 bytes (1064 bits); 114 bytes for data, 19 bytes for control over head (Wang et al., 2006).
4. The communication distance between nodes d_{comm} is the same across scenarios.
5. The energy cost of device electronics E_{elect} = $50nJ/bit$ while $\in_{mp}$ = $0.0013pJ/bit/m4$ (Heinzelman et al., 2000).
6. Other parameters were substituted for using the values obtained from data sheets as shown in table 1 (Halgamuge et al., 2009).

Table 1: Table of Parameters for Energy Cost Analysis.

Symbol	Description	Value
N_{clock}	clock cycles per task	$0.97 * 10^6$
C_{avg}	average capacitance	22pF
V_s	supply voltage	2.7V
f	sensor frequency	191.42 MHz
I_{leak}	leakage current	1.196mA
V_t	thermal voltage	$0.2V$
p	processor constant	21.26
n	size of data packet	1064 bits
d_{comm}	communication distance	100m

4.1 S1: Centralised Processing with Direct Communication

The S1 scenario represents the simple sense and send network design with only direct data communication allowed between the source and sink. Data processing occurs centrally at the sink node as illustrated in figure 4. All nodes are assumed to be equally spaced from the sink hence the communication distance d_{comm} is equal for all the nodes in the network. The local energy costs for S1 is given in equations (8) and (9).

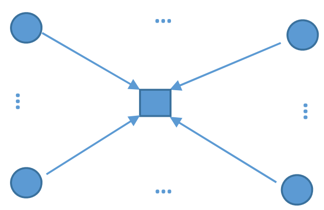

Figure 4: S1 Network Diagram.

(i) *sink node*

$$E_{Snode} = \sum_{i=1}^{s-1} E_{R_i} + E_{process} \tag{8}$$

(ii) *other nodes (s-1)*

$$E_{node} = E_T \tag{9}$$

where E_{node} and E_{Snode} are source node and sink node local energy costs respectively.

The global energy costs for S1 is also given by equations (10)-(12).

$$E_{commT} = \sum_{i=1}^{s-1} E_{R_i} + \sum_{i=1}^{s-1} E_{T_i} \tag{10}$$

$$E_{processT} = E_{process} \tag{11}$$

$$E_{global} = \sum_{i=1}^{s-1} E_{R_i} + \sum_{i=1}^{s-1} E_{T_i} + E_{process} \tag{12}$$

where E_{global} is the total energy cost for the network and E_{comm_T}, $E_{process_T}$ are global communication and processing energy costs respectively. The same nomenclature is assumed for all scenarios.

4.2 S2: Centralised Processing with Multi-hop Communication

The S2 scenario is similar to S1 but with multi-hop communication. This represents network architectures used for monitoring long horizontal structures such as water or oil pipelines and bridges with only 1-D, multi-hop communication possible between source and sink nodes. Processing activity such as aggregation or filtering takes place only at the sink node as shown in figure 5.

Figure 5: S2 Network Diagram.

Equal spacing is assumed between adjacent nodes so that the communication distance d_{comm} is equal for all nodes. Thus, the local energy costs for S2 is given by equations (13) - (15) where E_{fnode}, is local energy cost for the first node.

(i) *sink node*

$$E_{Snode} = E_R + E_{process} \tag{13}$$

(ii) *first node*

$$E_{fnode} = E_T \tag{14}$$

(iii) *other nodes (s-2)*

$$E_{node} = E_T + E_R \tag{15}$$

Similarly, the global energy costs for S2 is given by equations (16) - (18).

$$E_{commT} = \sum_{i=1}^{s-1} E_{R_i} + \sum_{i=1}^{s-1} E_{T_i} \tag{16}$$

$$E_{processT} = E_{process} \tag{17}$$

$$E_{global} = \sum_{i=1}^{s-1} E_{R_i} + \sum_{i=1}^{s-1} E_{T_i} + E_{process} \tag{18}$$

4.3 S3: Decentralised Processing with Direct Communication

In S3 scenario, processing occurs in a distributed manner at individual nodes. Additionally, every node communicates directly with the sink node by a single hop as shown in figure 6.

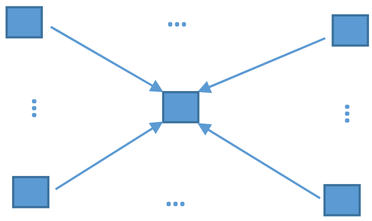

Figure 6: S3 Network Diagram.

In this case, a single network objective function maybe divided into smaller tasks which could be performed in a distributed or cooperative manner within the network. The sink node is then responsible for aggregating the final results as shown in the network diagram. Again, the communication distance d_{comm}, is constant as each node is assumed equally spaced from the sink node for direct communication.

The local energy costs for S3 is given by equations (19) and (20).

(i) *sink node*

$$E_{Snode} = \sum_{i=1}^{s-1} E_{R_i} + E_{process} \tag{19}$$

(ii) *other nodes (s-1)*

$$E_{node} = E_T + E_{process} \tag{20}$$

Similarly, the global energy costs for S3 is given by equations (21) - (23).

$$E_{commT} = \sum_{i=1}^{s-1} E_{R_i} + \sum_{i=1}^{s-1} E_{T_i} \tag{21}$$

$$E_{processT} = \sum_{i=1}^{s} E_{process_i} \tag{22}$$

$$E_{global} = \sum_{i=1}^{s-1} E_{R_i} + \sum_{i=1}^{s-1} E_{T_i} + \sum_{i=1}^{s} E_{process_i} \tag{23}$$

4.4 S4: Decentralised Processing with Multi-hop Communication

Scenario S4 is similar to the distributed architecture in S3 but with 1D-multi-hop communication as shown in figure 7.

Figure 7: S4 Network Diagram.

The nodes are equally spaced apart so that communication distance between adjacent nodes is equal to d_{comm}. Therefore, the local energy costs for S4 is given by equations (24) - (26).

(i) *sink node*

$$E_{Snode} = E_R + E_{process} \tag{24}$$

(ii) *first node*

$$E_{fnode} = E_{process} + E_T \tag{25}$$

(iii) *other nodes (s-2)*

$$E_{node} = E_R + E_T + E_{process} \tag{26}$$

Similarly, the global energy costs for S4 is given by equations (27) - (29).

$$E_{commT} = \sum_{i=1}^{s-1} E_{R_i} + \sum_{i=1}^{s-1} E_{T_i} \tag{27}$$

$$E_{processT} = \sum_{i=1}^{s} E_{process_i} \tag{28}$$

$$E_{global} = \sum_{i=1}^{s-1} E_{R_i} + \sum_{i=1}^{s-1} E_{T_i} + \sum_{i=1}^{s} E_{process_i} \tag{29}$$

4.5 S5: Decentralised Processing with Cluster Heads

Scenario S5 represents the processing architecture obtained in dense WSNs. A dense network is divided into smaller sub-networks called clusters with a coordinating node in each cluster called a cluster-head(CH). The end nodes operate in the RF mode and communicates with the CH by a single hop. The CHs operate in the FF mode with a single hop communication to the sink as illustrated in figure 8.

The communication distance within clusters, d_{sc}, is the distance between a leaf node and its CH and is assumed equal for all leaf nodes. The cluster heads are also assumed to be equally spaced within the network from the sink node with a communication distance equal to d_{comm}. The number of nodes within

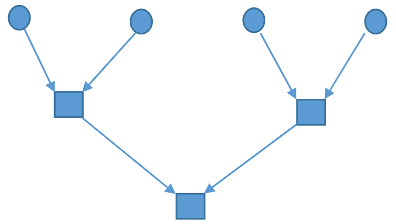

Figure 8: S5 Network Diagram.

a cluster S_{npc}, is given by $\frac{s}{S_{clust}}$; where S_{clust} is the number of desired clusters within the network and s remains the network size. Similarly, the number of clusters can be obtained as $S_{clust} = \frac{s}{S_{npc}}$. Hence, the values of S_{npc} and S_{clust} can be easily adjusted depending on the desired network parameters.

The local energy costs for S5 is given by equations (30) - (32).

(i) *cluster head nodes* (S_{clust})

$$E_{CH} = \sum_{i=1}^{S_{npc}-1} E_{R_i} + E_T + E_{process} \tag{30}$$

(ii) *other nodes* $[s - S_{clust} - 1]$

$$E_{node} = E_T \tag{31}$$

(iii) *sink node*

$$E_{Snode} = \sum_{i=1}^{S_{clust}} E_{R_i} + E_{process} \tag{32}$$

where E_{CH}, E_{Snode} and E_{node} corresponds to local energy cost for cluster heads, sink node and leaf nodes respectively. The global energy costs for S5 are given by equations (33) - (35).

$$\begin{aligned} E_{commT} &= S_{clust}\left[\sum_{i=1}^{S_{npc}-1} E_{R_i} + E_T\right] \\ &+ \left[\sum_{i=1}^{s-S_{clust}-1} E_{T_i}\right] + \sum_{i=1}^{S_{clust}} E_{R_i} \end{aligned} \tag{33}$$

$$E_{processT} = \sum_{i=1}^{S_{clust}+1} E_{process_i} \tag{34}$$

$$\begin{aligned} E_{global} &= S_{clust}\left[\sum_{i=1}^{S_{npc}-1} E_{R_i} + E_T\right] + \sum_{i=1}^{S_{clust}} E_{R_i} \\ &+ \left[\sum_{i=1}^{s-S_{clust}-1} E_{T_i}\right] + \sum_{i=1}^{S_{clust}+1} E_{process_i} \end{aligned} \tag{35}$$

5 RESULTS AND DISCUSSION

In this section, we present the results of our energy cost analysis for the different processing architectures S1-S5. The local and global energy costs were computed separately for the five scenarios in MATLAB. A network size of $s = 100$ and communication distance $d_{comm} = 100m$ was used. The fairness metric for each scenario was computed as a function of the local and global energy costs. The results section which follows next, presents and discusses the results of our analysis in terms of network lifetime and fairness for distributed processing architectures in WSNs.

5.1 Local Analysis

The local analysis results are shown in table 2. In the central processing architectures (S1 & S2), the maximum energy cost corresponds to the energy cost of the sink node which operates in FF mode. For the distributed architectures (S3 & S4), the maximum local energy cost is nearly the same for all nodes in the network because all the nodes operate in FF mode thereby resulting in a higher local energy cost per node. In the cluster scenario S5, the maximum local energy is expended by CHs which run in FF mode.

Table 2: Local analysis for S1-S5, $s = 100$ nodes.

Metric	S1	S2	S3	S4	S5
Max. Energy (J)	0.204	0.198	0.204	0.199	0.199
Min. Energy (J)	0.000192	0.000192	0.199	0.198	0.000192

The maximum local energy expended by a single node is $\sim$ 0.2J for all scenarios while the minimum varies depending on the degree of distributed processing performed in the network as shown in table 2. The communication and processing costs is dependent on packet size n. Thus, a sensor node operating in FF mode expends 99.91% more energy than a node operating in RF mode for a given n as shown by the minimum and maximum local energy costs. This implies that n has a high impact on processing energy cost which is not negligible and so, must be accounted for in robust energy models.

5.2 Global Analysis

The global communication cost E_{comm_T}, remained fairly constant while global processing cost $E_{process_T}$, varied across the scenarios as shown in table 3.

This is because our network model restricts communication between source and sink to a single hop in the first four scenarios S1- S4, irrespective of the position and role of the node in the network. However,

Table 3: Global analysis for S1-S5, $s = 100$ nodes.

E_{comm_T} (J)	0.0242	0.0242	0.0242	0.0242	0.0243
$E_{process_T}$ (J)	0.198	0.198	19.838	19.838	4.166
E_{global} (J)	0.223	0.223	19.862	19.862	4.19
Fairness Index	0.0119	0.0126	0.999	0.999	0.212

we observe an increase in communication cost for the cluster model S5 where the sink node is 2 hops away from the source. The purely distributed processing architectures gave the highest global energy cost across the scenarios. However, restricting processing to only a subset of nodes reduced the global energy cost by $\sim 75\%$ in the S5 scenario. This is because distributed processing increases local energy cost resulting in a higher global cost.

5.3 Fairness Analysis

The fairness metric gives an indication of the degree of uniformity of energy cost distribution among the network nodes. From table 3, we show that central processing architectures results in an unfair distribution of energy cost among network nodes as only a small fraction of the nodes operate in the FF mode while the rest operate in the RF mode. On the other hand, distributed processing architectures result in a fairer distribution of energy cost as most of the nodes are operating in FF mode. Our results so far show that although increased processing activity marginally increases the global energy cost, it does not affect the maximum local cost. However, the cluster model S5, is a preferred architecture as it combines the advantages of a lower global energy cost and higher fairness index associated with the centralised and purely distributed architectures respectively.

5.4 Network Lifetime

If we assume a fixed initial amount of energy, E_{init}, to be available to every node in the network, the overall network lifetime which is determined by the maximum local cost is not significantly affected by distributed processing since the maximum cost is same across scenarios ($\sim$ 0.2J). This provides a basis for exploiting on-node processing capabilities of wireless sensor nodes for distributed and localised processing in relevant application areas where they provide the advantage of improved network performance. Based on our results, we also argue that the global energy cost is not a good indication of the lifetime of the network because it does not provide adequate information on the energy cost associated with individual nodes. As WSNs are made up of individual nodes, local energy cost provides a better metric for analysis as it provides information on the energy costs associated with every nodes in the network which is critical for estimating network life time.

5.5 Effect of Network Density on Energy Cost and Fairness

The effect of network density on energy costs and fairness for S1-S5 is shown in table 4.

Table 4: Effect of Network Size on Global Energy Cost and Fairness.

S	Model	Proc. cost	Comm. cost	Total cost	Fairness
100	S1	0.198379572	0.02422728	0.22260685	0.011947738
	S2	0.198379572	0.02422728	0.22260685	0.012583027
	S3	19.83795725	0.02422728	19.8621845	0.999993536
	S4	19.83795725	0.02422728	19.8621845	0.99999999
	S5	4.165971022	0.02428048	4.1902515	0.211523937
500	S1	0.198379572	0.12211528	0.32049485	0.004059142
	S2	0.198379572	0.12211528	0.32049485	0.00521334
	S3	99.18978625	0.12211528	99.3119015	0.999964859
	S4	99.18978625	0.12211528	99.3119015	0.999999998
	S5	20.03633682	0.12216848	20.1585053	0.203538262
1000	S1	0.198379572	0.24447528	0.44285485	0.003098163
	S2	0.198379572	0.24447528	0.44285485	0.004973211
	S3	198.3795725	0.24447528	198.624048	0.999928995
	S4	198.3795725	0.24447528	198.624048	0.999999999
	S5	39.87429407	0.24452848	40.1188226	0.202538755

In general, our results show a marginal increase in global energy cost as the network size increases with the distributed processing scenarios showing the highest values as before due to higher processing cost associated with each node. This is not surprising as higher number of nodes means more energy cost per node. However, we note that local energy cost was unaffected by network size because although the network size increased, individual node roles did not change hence local energy cost remained unchanged. Processing cost remained constant for scenarios S1 and S2 as the network size increased because the number of nodes in FF mode remained unchanged however, scenarios S3-S5 experienced significant increase because the number of nodes in FF mode increased with network size. Communication cost remained unchanged for scenarios S1-S4 due to the single-hop communication maintained as the network size increased. However, for the S5 scenario, the multi-hop communication resulted in higher communication energy cost at CHs for higher network sizes. The fairness of centralised processing decreased as the network size increased but increased for distributed processing. This was because of the widening gap between the minimum and maximum local energy costs as the network size increased.

6 CONCLUSION

In this work, we studied the effect of processing architectures on energy cost in WSNs. We performed local and global cost analysis for 5 configurations and compared results across scenarios. We showed that a higher number of FF nodes results in higher global cost but the maximum local cost remains unaffected. We identified a positive correlation between network lifetime and fairness and argue that a marginal increase in global cost does not automatically correspond to a lower network lifetime. Rather, due to the higher fairness associated with distributed processing, network designers could exploit the on-node processing capabilities of sensors for performance improvement during the fixed lifetime of the network. Uniform energy cost distribution aids the planning of scheduled network maintenance as every node in the network has a similar lifetime. Thus, our results support the continued exploration of energy-efficient strategies for in-network processing in WSNs with energy constraints.

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REFERENCES

Baggio, A. (2005). Wireless sensor networks in precision agriculture. In *ACM Workshop on Real-World Wireless Sensor Networks (REALWSN 2005), Stockholm, Sweden*.

Chang, J.-H. and Tassiulas, L. (2004). Maximum lifetime routing in wireless sensor networks. *Networking, IEEE/ACM Transactions on*, 12(4):609–619. ID: 16.

Chong, S. K., Gaber, M. M., Krishnaswamy, S., and Loke, S. W. (2011). *Energy-aware data processing techniques for wireless sensor networks: a review*, pages 117–137. Transactions on large-scale data-and knowledge-centered systems III. Springer.

Halgamuge, M. N., Zukerman, M., Ramamohanarao, K., and Vu, H. L. (2009). An estimation of sensor energy consumption. *Progress In Electromagnetics Research B*, (12):259–295. Cited By :34.

Heinzelman, W. B., Chandrakasan, P., and Balakrishnan, H. (2002). An application-specific protocol architecture for wireless microsensor networks. *IEEE Trans Wirel Commun*, 1(4):660–670.

Heinzelman, W. R., Chandrakasan, A., and Balakrishnan, H. (2000). Energy-efficient communication protocol for wireless microsensor networks. In *System Sciences, 2000. Proceedings of the 33rd Annual Hawaii International Conference on*, page 10 pp. vol.2. ID: 1.

Jafari, R., Encarnacao, A., Zahoory, A., Dabiri, F., Noshadi, H., and Sarrafzadeh, M. (2005). Wireless sensor networks for health monitoring. In *Mobile and Ubiquitous Systems: Networking and Services, 2005. MobiQuitous 2005. The Second Annual International Conference on*, pages 479–481. IEEE.

Jain, R., Chiu, D.-M., and Hawe, W. (1998). A quantitative measure of fairness and discrimination for resource allocation in shared computer systems.

Othman, M. F. and Shazali, K. (2012). Wireless sensor network applications: A study in environment monitoring system. In *Procedia Engineering*, volume 41, pages 1204–1210. Cited By :21.

Pantazis, N. A., Nikolidakis, S. A., and Vergados, D. D. (2013). Energy-efficient routing protocols in wireless sensor networks: A survey. *IEEE Communications Surveys and Tutorials*, 15(2):551–591. Cited By :34.

Wang, M., Cao, J., Chen, B., Xu, Y., and Li, J. (2007). *Distributed processing in wireless sensor networks for structural health monitoring*, volume 4611 LNCS of *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Cited By :5.

Wang, Q., Hempstead, M., and Yang, W. (2006). A realistic power consumption model for wireless sensor network devices. In *Sensor and Ad Hoc Communications and Networks, 2006. SECON '06. 2006 3rd Annual IEEE Communications Society on*, volume 1, pages 286–295. ID: 10.