A Forecasting-Based Monitoring and Tomography Framework for Wireless Sensor Networks

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***Abstract*— The lifetime of a wireless sensor network (WSN) is generally limited by the battery lifetime of the sensor nodes. In this respect, efficient monitoring of the entire network's available energy is of great importance to take appropriate preventive actions. However, the physical limitations of WSNs, such as limited memory and energy resources, mandate such a monitoring mechanism to have low complexity and minimum energy dissipation. In this paper, a forecasting-based monitoring and tomography (FMT) framework is presented for WSNs. The objective of the FMT framework is to achieve overall monitoring and to capture the tomography of the available energy in WSNs with minimum energy expenditure. To reduce the amount of energy consumed for monitoring purposes, the FMT framework incorporates available energy forecasting and network aggregation mechanisms. Comparative performance evaluations show that the FMT framework achieves accurate energy monitoring and obtains the network energy tomography of large scale WSNs with minimum energy consumption.**

***Index Terms*— Wireless Sensor Networks, Network Management, Available Energy Monitoring, Network Energy Tomography.**

I. Introduction

Wireless Sensor Networks (WSNs) have significant resource constraints, such as limited memory and energy sources. Due to the large scale of the network, it is impractical, or even impossible, to replace or recharge the batteries of the individual sensor nodes. The limited resources in WSNs should be efficiently utilized to increase the lifetime of the network. In this regard, the main objective of all communication protocols proposed for WSNs is to minimize energy consumption while performing their specific tasks [2]. Although these protocols prolong network lifetime to a certain extent, it is inevitable that the sensor network will be nonfunctional because of several problems originated by energy depletion of the sensor nodes. Hence, the overall energy resources in WSNs must be effectively monitored and managed to further prolong the network lifetime and to enable the realization of possible precautions such as reconfiguration of the network and incremental sensor node deployment.

However, the management of sensor networks is a challenging task due to their unique characteristics. First, unlike other distributed systems, sensor networks are typically limited by energy sources, communication bandwidth and computational power. Second, the large number of sensor nodes makes it infeasible to collect detailed status information from individual sensor nodes. Third, the working environment of the sensor nodes can be inaccessible for humans, e.g., consider the scenarios where sensors scattered in a battlefield or over a very high altitude region. All these challenges in WSNs make the *use and throw* approach very attractive [6]. In this approach, the sensors that either have run out of battery or have failed are simply discarded and more sensors are thrown to compensate for the weak sensor nodes. Another solution to the problem of failed regions in WSNs is that the network can reconfigure and adapt itself dynamically in such a way that a new routing topology around the failed regions is constructed to maintain the network connectivity throughout the sensor field. On the other hand, such a compensation method or reconfiguration algorithm require an energy efficient monitoring mechanism for WSNs.

Therefore, given their specific characteristics and unattended nature, it is essential that the sensor nodes have to be closely monitored by some remote controller, e.g., the sink or the monitoring node, which should be informed about the current state of the sensor nodes in terms of available energy resources. In other words, even when no anomalies in WSNs exist, the monitoring node must be sure whether the sensor nodes are alive and functional. This is because if a region of the sensor network fails, then the sensor network cannot perform its collaborative sensing task. For example, in a battlefield application, a perimeter defense system may no longer be able to detect breaches of the perimeter in case a part of the network fails. In addition, if the monitoring node is not aware of this network partition, then a security breach might have occurred. Especially for military applications, unexpected and unpredictable failures in WSNs are unacceptable, since these failures make the sensor network unreliable. It is therefore critical for the monitoring node to control whether the network connectivity is maintained or not.

This monitoring and control process can also be useful for forecasting network failures so that preventive action is taken in a timely manner. In this respect, monitoring of available energy or activity in the sensor field is required to determine the failed areas in the network. The available energy distribution at different parts of the network can be represented properly by *network energy tomography maps*, which is an analogy to the medical tomography method of imaging the internals of the human body. These energy tomography maps depict a complete picture of the remaining energy levels in the sensor network. We can illustrate the energy map of a sensor network as a shaded color surface image, in which the cavities in the surface represent critical regions with scarce energy. Using the simulation environment described in Section IV, the energy distribution of a typical sensor network is obtained and its associated available energy map is depicted in Fig. 1. This case study clearly illustrates that

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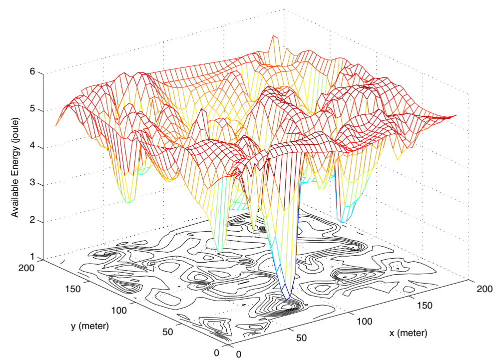

Fig. 1. Available energy distribution where 200 sensor nodes are randomly distributed on a 200m by 200m square plane. The monitoring node is randomly selected and located at position (X, Y)=(69.47, 43.25).

the sensor nodes around the monitoring node and the source nodes that detect event features consume much higher energy than the other nodes in the network. Especially, the residual energy of sensor nodes around the monitoring node decreases rapidly, since they are used more frequently to relay the packets to the monitoring node.

The nonuniform energy distribution within the entire sensor network may lead to network partitioning. The available energy maps can be used to identify whether any region of the network is about to lose the network connectivity in the near future due to depleted energy. The information of low-energy regions can also aid in incremental deployment of sensor nodes to those energy scarce regions [2]. Moreover, the optimal place for the monitoring node can be found by means of the available energy maps. In other words, if the monitoring node is moved to the network regions with more remaining energy, the lifetime of the network can be further increased.

In summary, the potential gains of deploying energy management and forecasting scheme in WSNs can be outlined as follows:

- *Network management and load balancing:* The energy management and forecasting scheme can provide guidance to prolong network lifetime by early warnings of system failure, hence such an energy management forecasting scheme may work in harmony with energy efficient congestion control protocols such as [1]. For example, the reporting rate of sensor nodes can be decreased in energy scarce regions identified by the energy management and forecasting scheme.
- *Network reliability and forecasting network behavior:* The dynamic network behavior can be captured effectively by the energy management and forecasting scheme. This can be useful for predicting network failures and taking preventive actions accordingly. This way, the reliability of the network can be maintained within dynamic sensor network environment.
- *Future deployment:* In WSNs, sensors are typically deployed in a random fashion with no prior knowledge of the target area. The forecasting model can identify energy constrained regions and future deployment of sensor nodes can be performed properly to provide network connectivity.
- *Optimal placement of the monitoring node:* The sensor nodes around the monitoring node are likely to consume more energy, since they are used more frequently to relay the packets to the monitoring node. Thus, the monitoring node can be moved to the network parts with more remaining energy, so that the lifetime of the network is increased.

All these potential gains imply that the available energy map of the sensor network is of great importance for the optimal organization and management of the network. However, continuous monitoring process in such energy constrained networks is challenging. Especially if the monitoring is done frequently, the status updates can cause high communication costs resulting in an extra energy burden. On the other hand, without updated data, inaccurate network management decisions can be made. Therefore, there is a tradeoff between accuracy and energy efficiency in the monitoring process.

In this paper, to address the issues introduced above, we present the forecasting-based monitoring and tomography (FMT) framework for WSNs. The objective of the FMT framework is to achieve overall monitoring and to capture the tomography of the available energy in WSN with minimum energy expenditure. To reduce the amount of energy consumed for monitoring purposes, the FMT framework incorporates available energy forecasting and network aggregation mechanisms. The comparative performance evaluations show that the FMT framework achieves accurate energy monitoring and obtains network energy tomography of large scale WSNs with minimum energy consumption.

The remainder of the paper is organized as follows. In Section II, we explore the existing work on the monitoring mechanisms of the available energy in WSNs. In Section III, we describe the forecasting-based monitoring and tomography (FMT) framework for WSNs in detail. In Section IV, the comparative performance evaluations and simulation results of the FMT framework are presented. Finally, the paper is concluded in Section V.

II. Related Work

The problem of monitoring sensor networks is of great significance to prolong the network lifetime and to maintain the network connectivity [20]. Recently, different algorithms are proposed to discover failed sensor nodes [3],[21], to compute the coverage and exposure bounds of sensor networks [12],[13] and to provide topological mapping of the network [4]. These approaches detect one or more specific network failures in resource constrained WSNs. Our work is complimentary, enabling early system failure warnings to invoke these other monitoring and diagnostics tools.

As far as energy monitoring in WSNs is concerned, in [24], the authors propose to obtain approximate residual energy variation of the network by using an aggregation based approach, called Residual Scan. In Residual Scan, the significant energy savings are achieved utilizing network aggregation. However, the aggregated data in the monitoring node is actually a delayed view of the sensor network [24]. In order to obtain an updated energy information in the monitoring node, the status update frequency must be high, which may cause congestion and extra energy burden in the network. In [17], the authors present a model, in which each sensor node tries to predict its energy consumption by using discrete time Markov chains. Although the predicted

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energy consumption of each sensor node decreases the number of energy packets sent in the network, the transmission of predicted energy packets from all sensor nodes to the monitoring node results in significant energy consumption and congestion in energy and bandwidth scarce WSNs.

In our work, to continuously update the energy information with minimum energy expenditure, each sensor node sends not only its available energy, but also its forecasted energy dissipation rate to the monitoring node. This way, energy information is transmitted to the monitoring node only when there is a variation in the network behavior, which significantly decreases the amount of energy consumed for monitoring purposes. In addition, instead of collecting the raw energy information from individual nodes, we apply energy forecasting and network aggregation mechanisms together in order to further reduce the monitoring costs in the network. This combined forecasting and network aggregation mechanism distinguishes our work from existing energy monitoring solutions.

III. FMT: The Forecasting-based Monitoring and Tomography Framework

A. Network Model

In the FMT framework, N sensor nodes are randomly distributed on a 2-D plane and the monitoring node, where all source data is gathered, is randomly located. In our study, each sensor node is static and can communicate with other nodes within its communication range. In addition, we assume that each sensor node is aware of its position on a 2-D plane through GPS (Global Positioning System) or other location determination techniques [8],[10]. Sensor nodes are powered by batteries with normalized capacity of 100% and they can measure its available energy using smart battery monitor components [5]. Each sensor can perform one or more sensing tasks in the deployment field.

Moreover, we ignore the processing cost in our model, since the processing cost is much lower than the communication cost. This is justified by experimental results on sensor network prototypes such as [19], where the energy necessary to transmit 1 kbit is shown to be equivalent to the energy necessary to execute 300,000 processor instructions. This energy tradeoff between communication and data processing implies that data processing inside the network, instead of simply transmitting the raw sensor data to the monitoring node, can efficiently be exploited to reduce the amount of energy consumed for monitoring purposes.

B. Available Energy Forecasting

The available energy forecasting method allows energy information to be communicated to the monitoring node only when there is a variation in the network behavior. This significantly reduces the amount of energy consumed for monitoring purposes. The key feature of the proposed forecasting method is its mathematical simplicity and thus, it is easily applicable in computational power constrained sensor nodes. Furthermore, this method imposes small memory requirements to the network, which is also extremely crucial for WSNs, since the memory is another limited resource in WSNs.

The motivation of forecasting available energy is that if the sensor node can forecast its energy dissipation rate and send this information to the monitoring node, then there is no need to send its energy information to the monitoring node, while the forecast of its available energy approximately represents the current energy of the sensor node. Hence, using the forecasted energy dissipation rate and received available energy value, the monitoring node can continuously make an estimation of the residual energy of the sensor node with low energy consumption.

To make accurate forecasting of the available energy distribution within the sensor network, it is necessary to remove the effects of obsolete data in some manner. The proper approach is to make an estimation by using only the last portion of the data, e.g., the last τ samples, and to give relatively more weights to the recent observations than the older observations [23]. In this regard, what we would like to accomplish is an efficient forecasting method that would apply the most weight to the most recent observed available energy values and accurately forecast the available energy in WSNs.

The proposed available energy forecasting method, i.e., Single Parameter Double Exponential Smoothing, of the FMT framework is an appropriate forecasting technique that satisfies all these requirements mentioned above [9],[15]. The details of Single Parameter Double Exponential Smoothing are presented in the following section.

1) Single Parameter Double Exponential Smoothing: This method is an efficient forecasting technique for the observed data exhibiting a trend pattern, e.g., a consistent decrease. Hence, it is an appropriate method so as to forecast the WSN's available energy, which continuously decreases after the deployment of the sensors to the field. In addition to its appropriateness for the observed data exhibiting a trend pattern, this technique requires little storage and few computations, which is extremely important for resource constrained WSNs [15].

In this study, our objective is to obtain the available energy forecast of the sensor node by utilizing its observed available energy value, E_t. The general equations used in implementing Single Parameter Double Exponential Smoothing are as follows:

$$S_t = \alpha E_t + (1-\alpha) S_{t-1} \tag{1}$$

$$S'_t = \alpha S_t + (1-\alpha) S'_{t-1} \tag{2}$$

where $\alpha \in (0, 1]$ is the smoothing constant and E_t, S_t, S'_t represent the available energy, single smoothed and double smoothed values at time $t \in \{0, 1, 2, ...\}$, respectively.

In this technique, the initial values of S_t and S'_t are set to the value of the first observed energy value, E_0, [15]. Moreover, this technique makes additional adjustments to accordingly forecast the trend pattern in the observed data. In order to make these adjustments, we define the following auxiliary terms:

$$a_t = S_t + (S_t - S'_t) = 2S_t - S'_t \tag{3}$$

$$b_t = \frac{\alpha}{(1-\alpha)}(S_t - S'_t) \tag{4}$$

Using the auxiliary terms a_t and b_t, we can express the

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Algorithm 1 Available Energy Forecasting

Pseudocode of Available Energy Forecasting
begin
// Sensor node
$D_t = \frac{F_{t+\tau} - E_t}{\tau}$
if $(\left|\frac{D_t - D_{t-\tau}}{D_{t-\tau}}\right| \geq \Delta)$ **then**
    $send\,(E_t, D_t)$
end if
// Monitoring node
$UpdateEnergyMap()$
end

available energy forecast as follows:

$$F_{t+\tau} = a_t + b_t\tau \tag{5}$$

where $F_{t+\tau}$ represents the available energy forecast value for time $t + \tau$, which is calculated by the sensor at time t, and τ stands for the length of the forecast interval, which is specific to the application requirements.

After calculating its available energy forecast using eqn. (5), each sensor node computes its forecasted energy dissipation rate, $D_t = \frac{F_{t+\tau} - E_t}{\tau}$, and sends it to the monitoring node. Note that before sending its dissipation rate to the monitoring node, each sensor compares its previous forecasted dissipation rate, $D_{t-\tau}$, with the newly calculated one, D_t. If the normalized difference, $\left|\frac{D_t - D_{t-\tau}}{D_{t-\tau}}\right|$, is not higher than a certain threshold, Δ, it does not send the newly calculated dissipation rate to the monitoring node in order to save limited energy in the network.

Then, using the energy dissipation rate, D_t, and the received available energy value, E_t, the monitoring node continuously updates residual energy of the sensor nodes. The pseudocode of available energy forecasting is given in Algorithm 1.

C. Network Aggregation Mechanism

Although available energy forecasting method achieves significant reduction in the monitoring costs, the large number of sensor nodes and limited energy resources make it infeasible to collect energy information from each individual sensor node. For this reason, the FMT framework constructs aggregated views of the remaining energy levels in the deployment field. This way, the communication costs are further reduced, while achieving acceptable levels of accuracy in estimating residual energy of the sensors. In Section IV, we show the trade-offs between reduced accuracy and energy savings.

In fact, the network aggregation mechanism exploits the fact that the energy dissipation of the sensors in WSNs is spatially correlated. In other words, the nodes within a certain neighborhood detect the similar events and thus, dissipating similar energy to perform the sensing task [22]. Hence, due to spatial correlation, available energy knowledge from spatially separated sensors is more useful for the monitoring node than highly correlated information from the nodes in close proximity.

In this respect, the sensor nodes that receive two or more available energy information can aggregate the received information, if the received available energy levels are similar and the locations of the sensors are topologically adjacent within a certain resolution. More specifically, we can define aggregated view of the remaining energy level as a collection of $(RECORD, GROUP)$ tuples:

Definition 1: $RECORD$ is the quantitative representation of the energy information. It may have a more complex form than a single scalar value [14]. In the FMT framework, we use $RECORD = (E_{avg}, D_{avg}, N_{node})$, where $E_{avg}, D_{avg}, N_{node}$ are the average available energy, the average forecasted energy dissipation rate, and the number of nodes, respectively.

Definition 2: $GROUP$ denotes the set of nodes in the sensor field that has similar energy information. In the FMT framework, the sensor nodes are represented by their locations and the $GROUP$ describes the region, which covers adjacent nodes with similar energy levels. Note that the $GROUP$ region can also be represented by a polygon [24], whose vertices are the locations of the boundary nodes.

Initially, each sensor calculates its forecasted energy dissipation rate (see Section III-B) and sends it to its forwarding node towards the monitoring node. Along the aggregation path, if a node receives two or more energy information, it will try to aggregate those into a composite one. For example, energy information X and Y can be aggregated, if $X.RECORD$ and $Y.RECORD$ are similar and $X.GROUP$ and $Y.GROUP$ are adjacent. These conditions can be defined as follows:

i. $X.RECORD$ and $Y.RECORD$ are similar if:

   $\frac{|X.E_{avg} - Y.E_{avg}|}{min(X.E_{avg}, Y.E_{avg})} \leq \Delta$ and $\frac{|X.D_{avg} - Y.D_{avg}|}{min(X.D_{avg}, Y.D_{avg})} \leq \Delta$

   where Δ denotes the maximum relative error of remaining energy information allowed by aggregation.

ii. $X.GROUP$ and $Y.GROUP$ are adjacent if:

   $Dist((\text{X.GROUP})_{CM}, (\text{Y.GROUP})_{CM}) \leq \beta$

   where β represents the resolution used in determining whether two groups are adjacent and $Dist((X.GROUP)_{CM}, (\text{Y.GROUP})_{CM})$ gives the distance between the center of masses [7] of $X.GROUP$ and $Y.GROUP$, respectively.

If both conditions are met, the aggregated energy information Z will be in the form of:

$$Z.E_{avg} = \frac{X.E_{avg} * X.N_{node} + Y.E_{avg} * Y.N_{node}}{X.N_{node} + Y.N_{node}}$$

$$Z.D_{avg} = \frac{X.D_{avg} * X.N_{node} + Y.D_{avg} * Y.N_{node}}{X.N_{node} + Y.N_{node}}$$

$$Z.N_{node} = X.N_{node} + Y.N_{node}$$

$$Z.GROUP = merge(X.GROUP,\ Y.GROUP)$$

where $merge(X.GROUP, Y.GROUP)$ combines two GROUPS, if they are adjacent according to condition (ii). Note that Δ and β controls the aggregation level in the network and thus, determines the accuracy of the aggregated view of the energy information. In the FMT framework, we select β as radio communication range and compare the performance

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of the FMT framework with various values of Δ (see Section IV-B).

IV. Performance Evaluation

In this section, the performance of FMT framework for WSNs is evaluated. In order to investigate the performance of the FMT framework, extensive simulation experiments are conducted under varying number of sensor nodes. We also compare the performance of the FMT framework with Residual Scan [24] using the following performance metrics:

- *Energy Cost Ratio ($R = \frac{E_0}{E_c}$):* is the ratio of total energy consumption without any in-network processing (E_0) over that of with in-network processing (E_c). Energy cost ratio represents the energy savings achieved by in-network processing. The larger the energy cost ratio, the higher the energy saving is.
- *Distortion (D):* is the average distortion achieved at the monitoring node according to the received energy information. The distortion is calculated by the relative mean square error between received energy information and the actual values:

$$D = \sqrt{\frac{\sum_{i=1}^{N}(\frac{E_i - \hat{E}_i}{\hat{E}_i})^2}{N}}$$

where E_i, $\hat{E}_i$, N are the estimated remaining energy of node i, the actual available energy of node i and the number of nodes in the network, respectively.

A. Simulation Environment

To evaluate the performance of the FMT framework, we developed an evaluation environment using ns-2 [18]. In the simulations, we used CSMA/CA based MAC layer protocol and directed-diffusion [11] as a routing protocol. In addition, sensor nodes were randomly distributed on a 200m by 200m square plane and the monitoring node, where all energy data was gathered, was located on the bottom-left corner of the deployment field. Sensor node parameters such as energy consumption rates and radio range were carefully chosen to mirror typical sensor mote values [16]. Event centers (X_{ev}, Y_{ev}) were randomly chosen and all sensor nodes within the event radius behave as source nodes for that event. Event radius was randomly selected between event radius minimum and event radius maximum values throughout the simulations. Event duration was also randomly chosen between event duration minimum and event duration maximum values. The duration of each simulation is 1000 sec. In Table I, the default parameters of the simulations are shown. Unless specified otherwise, these values were used as the parameters in the simulations. For each simulation, we run 20 experiments and take the average of the measured values.

TABLE I
NS-2 SIMULATION PARAMETERS

Area of sensor field	200x200 m^2
Radio range of a sensor node	30 m
Packet length	30 bytes
IFQ length	65 packets
Transmit Power	95 mW
Receive Power	55 mW
Idle Power	25 mW
Event radius (min, max)	(20 m, 60 m)
Event duration (min, max)	(10 sec, 60 sec)
Smoothing constant (α)	0.05
Forecast interval (τ)	10 sec

B. Results

In Fig. 2 (a), the energy savings achieved by the FMT framework is compared with Residual Scan scheme [24] under varying number of sensor nodes. Recall that the Residual Scan scheme obtains approximate energy variation of the network by using an aggregation based approach. On the other hand, the FMT framework exploits the idea of both energy forecasting and network aggregation to find an updated energy information in the network. As shown in Fig. 2 (a), the FMT framework outperforms the Residual Scan scheme for varying number of sensor nodes. This is because in addition to network aggregation, available energy forecasting mechanism of the FMT framework allows energy information to be communicated to the monitoring node only when there is a variation in the network behavior. This significantly reduces the amount of energy consumed for monitoring purposes. For example, for a threshold percentage value equal to 5% and 400 sensor nodes, the energy savings achieved by the FMT framework is approximately 20% and 14 times higher than that of Residual Scan scheme and centralized scheme with no in-network processing, respectively. Note that given a fixed threshold value, the energy cost ratio for the FMT framework increases with increasing number of sensor nodes. This indicates that collection of energy information with energy forecasting and network aggregation has better scalability than centralized energy information collection with no in-network processing. This result confirms our main design principle that given limited network resources, one can efficiently exploit in-network processing instead of simply transmitting the raw sensor data to the monitoring node. This way, the amount of energy consumed for monitoring purposes is significantly reduced.

In Fig. 2 (b), we also show the distortion experienced by the FMT framework and the Residual Scan scheme under varying sensor nodes. As shown in Fig. 2 (b), the distortion level introduced by the FMT framework is always lower than that of the Residual Scan Scheme. For example, for a threshold percentage value equal to 25% and 300 sensor nodes, the distortion introduced by the FMT framework is approximately 25% lower than that of Residual Scan scheme. Moreover, we can clearly observe the tradeoffs between energy savings and the accuracy levels using Figs. 2 (a) and (b). For example, for a threshold percentage value equal to 25% and 500 sensor nodes, the FMT framework can save energy costs by a factor of 22, but only introduces 10% distortion.

In Fig. 2 (c) and (d), we compare the FMT framework with the Residual Scan scheme [24] under varying aggregation threshold values. As shown in Fig. 2 (c), the energy savings achieved by the FMT framework and the Residual Scan scheme increases sharply for increasing threshold values. However, as

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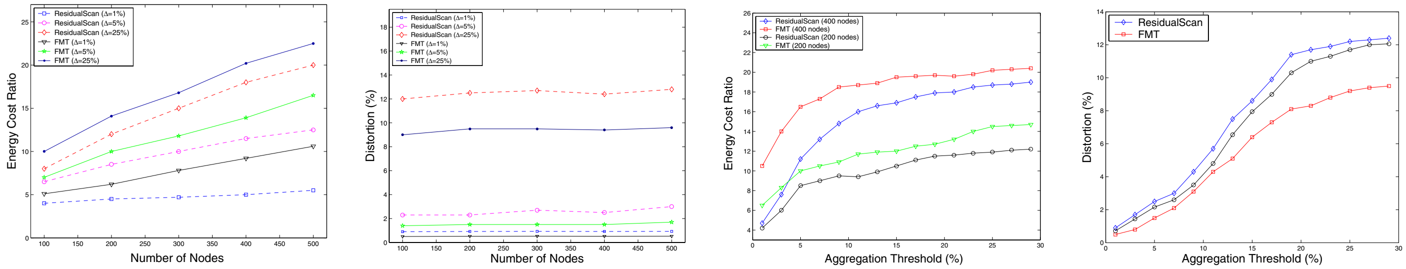

(a) (b) (c) (d)

Fig. 2. (a) Energy savings achieved under varying number of nodes, (b) Distortion values for varying number of nodes, (c) Energy savings achieved under varying threshold values, (d) Distortion values for varying threshold values.

the aggregation threshold values increase, the energy cost ratio of the FMT framework and the Residual Scan scheme converge to 21 and 19, respectively. Note that the energy savings achieved by the FMT framework is always higher than those of the Residual Scan scheme. Fig. 2 (d) shows the distortion experienced by the FMT framework and the Residual Scan scheme under varying threshold values. As shown in Fig. 2 (d), the distortion level introduced by the FMT framework is always lower than that of the Residual Scan Scheme. For example, for a threshold percentage value equal to 15% and 400 sensor nodes, the distortion introduced by the FMT framework is approximately 30% lower than that of Residual Scan scheme.

V. Conclusion

Effective operation of wireless sensor networks requires knowledge of the current status of sensor nodes, since the lifetime of a sensor network is generally limited by the battery lifetime of the sensor nodes. Therefore, efficient monitoring of the entire network's available energy is important so that appropriate preventive actions can be taken. The key constraints of monitoring mechanisms for energy scarce WSNs include low complexity and minimum energy dissipation. In this paper, a new forecasting-based monitoring and tomography (FMT) framework is proposed to address the need for an energy efficient monitoring mechanism for WSNs. To reduce the amount of energy consumed for monitoring purposes, the FMT framework incorporates available energy forecasting and network aggregation mechanisms. Instead of collecting the available energy data from individual nodes periodically, the FMT framework enables energy information to be communicated to the monitoring node only when there is a variation in the network behavior, which significantly reduces the amount of energy consumed for monitoring purposes. The comparative simulation results show that the FMT framework achieves accurate energy monitoring and obtains network energy tomography of large scale wireless sensor networks with minimum energy expenditure. Future work includes extending the FMT framework to different application scenarios, e.g., multiple and mobile sink nodes, and investigating the impact of different network parameters and performance metrics on the design of monitoring mechanisms of WSNs.

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