IJICTR International Journal of Information & Communication Technology Research CSRI

Volume 5- Number 2- Spring 2013 (55-62)

Optimized Task Scheduling for Estimation in Wireless Sensor Networks

Amir Hossein Mohajerzadeh
Ferdowsi University of Mashhad
Mashhad, Iran
ah.mohajerzadeh@stu-mail.um.ac.ir

Mohammad Hossein Yaghmaee
Ferdowsi University of Mashhad
Mashhad, Iran
hyaghmae@um.ac.ir

Vahid Fakoor
Ferdowsi University of Mashhad
Mashhad, Iran
fakoor@math.um.ac.ir

Received: September 1, 2012- Accepted: February 25, 2013

***Abstract* — In this paper, the distributed estimation in Wireless Sensor Network (WSN) using optimal task scheduling is looked upon. The main goal is to prolong network lifetime while the target parameter is estimated with desirable precision. The lifetime is defined as the number of rounds accomplished before network becomes nonfunctional. In order to prolong network lifetime, we determine the optimal number of active sensor nodes and the number of samples provided by each of them based on the degree of certainty (utilizing linear programming). Sensor observations from environment are quantized into messages and then directly forwarded to a fusion center where a final estimation is performed. Simulation results confirm that our optimal proposed algorithm has achieved significant efficiency when compared with other heuristic methods.**

Keywords- Degree of Certainty; Estimation; Task scheduling; Wireless sensor networks; Network lifetime.

I. INTRODUCTION

Wireless Sensor Networks (WSN) consists of a set of geographically distributed sensor nodes which perform their tasks as an integrated system. Sensor nodes have constraints such energy sources, computational power, storage capacity, etc [1]. WSN have current applications such as environment monitoring, healthcare, battlefield surveillance, home automation, etc [2] and growing future applications such as distributed estimation, distributed detection and tracking.

In this work, the distributed estimation of unknown deterministic target parameter has been performed using set of observations that provided by distributed sensor nodes. In distributed estimation each node provides a set of observations from environment to a central node called *Fusion Center* (FC). The main goal of the FC is to reconstruct the underlying physical phenomenon based on input data gathered from sensor measurements. Estimation literature attracts a great deal of attention in computer networks [3, 4], also nowadays, it becomes an attractive topic in signal processing in wireless sensor networks [5, 6]. The problem of decentralized estimation has been studied in distributed control [7], in tracking [8] and in data fusion [9]. With respect to the WSN's characteristics, various distributed estimation algorithms have been proposed [10, 11]. [12] proposes an optimal power scheduling for the decentralized estimation of a noise-corrupted deterministic signal in an inhomogeneous sensor network. They determine the optimal quantization and transmit power level at local sensors so that minimizing the total transmission power while ensuring a given Mean Square Error (MSE) performance. [13] studies the optimal tradeoff between the number of active sensors and the quantization bit rate for each active sensor to minimize the estimation MSE. In [14] the estimation of a scalar field over a bidimensional scenario through a WSN with energy constraint is investigated. The paper provides a mathematical framework to analyze the independent aspects of WSN communication protocols and signal processing design. [15] has studied the performance-energy tradeoff for distributed estimation in a WSN. It has applied Best Linear Unbiased Estimation (BLUE) to estimate observed phenomena. Like so many other works, [15] and [16] use optimization problem to attain the best possible functionality. Except [16, 17], to the best of our knowledge, most of studies on estimation (using WSN infrastructure), do not explicitly consider network lifetime as a goal. In this paper, we try to maximize network lifetime (using scheduling technique which is discussed later) while estimation precision is desirable. Furthermore, we have employed confidence interval method to participate application's required precision in estimation process.

Generally, one of the most efficient ways to deploy a WSN over a target area is to cover the whole terrain using minimum possible number of sensor nodes. One of the easiest ways is to schedule node's activity. WSN nodes can be active or inactive. Active nodes are able to perform their tasks, but, they consume energy more than inactive nodes. Inactive nodes shut down most of their equipments in order to preserve energy. Basically, scheduling is classified into four main categories [18]; "*always alive*", "*random on-off*", "*adaptive on-off*" and "*periodic on-off*". The proposed scheme acts as an adaptive on-off scheduling scheme in which the FC creates a total scheduling program and other sensors only follow that. Some of the prior studies schedule nodes' tasks depended on MAC layer protocol [19, 20]. [21] explores numbers of different techniques utilizing realistic simulation models under the many-to-one communication paradigm known as convergecast. It considers time scheduling on a single frequency channel with the aim of minimizing the number of time slots required to complete a convergecast. They combine scheduling with transmission power control to mitigate the effects of interference. In this article, we have proposed a scheduling algorithm using a linear optimization problem to schedule node's activity during their lifetime. The algorithm is fully adjusted to the requirements of estimation process and hierarchical wireless sensor network.

As discussed earlier, estimating target parameter in wireless sensor network is studied in various aspects. However, in this paper by utilizing "degree of certainty" (confidence interval [22]) technique and sample size parameter, we have modeled estimation process according to required precision which is determined by the user. Moreover, by controlling data collection and transmission using proposed scheduling technique and guaranteeing estimation with user defined precision, the objective of the paper is to prolong network lifetime as much as possible. With respect to the application (estimating target parameter) we have considered hierarchical sensor network. Each cluster consists of a fusion center and set of observer nodes which are in charge of observing the environments and collecting data.

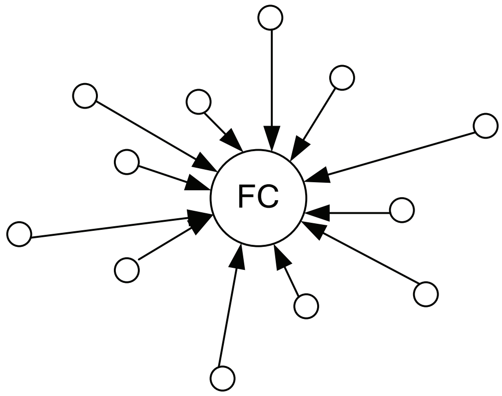

Figure 1. N sensor nodes make a cluster

The paper is organized as follows. Section II introduces the system model of estimation in single hop WSN (inside the cluster). Section III presents the scheduling algorithm which is the output of the network lifetime maximization problem for the estimation in WSN (formulated as a linear programming). In order to demonstrate the performance of the proposed algorithm, simulation results have been illustrated in section IV. Finally, section V concludes the paper.

II. PROBLEM FORMULATION

Figure 1 presents an example of a cluster of a wireless sensor network. As mentioned before, we have considered hierarchical WSN, where each cluster consists of a set of N distributed cluster member sensor nodes and a FC (cluster head acts as fusion center), designed to cooperate to estimate an unknown target parameter. Each cluster member observes the event, quantizes and transmits its collected information to the fusion center. The FC makes the final estimation based on all the received messages from cluster members. The observations are corrupted by additive noise as described in equation 1:

$$x_{ki} = \theta + \varepsilon_{ki} \qquad (1)$$

$$k = 1,2,\dots,N \;\; ; \;\; i = 1,2,\dots,n_k$$

x_{ki} refers to the i^{th} observation of sensor node k. Each sensor node can send many samples (observations). n_k is the samples which should be provided by node k. Sensor noise variables ,ε_{ki}, are considered to be independent, mean zero Gaussian random variables with $var(\varepsilon_k) = \sigma_k^2$ ($k = 1,2,\dots,N$). θ is the parameter to be estimated. At the first step of estimation process, due to severe bandwidth and energy limitation of WSN, each sensor locally quantizes the real valued analog observation y_k into an unbiased discrete message $m_k = Q_k(y_k)$ of length L_k bits as in [23]. $Q_k(y_k)$ is quantization function, and final message m_k is transmitted to the FC via direct wireless channel.

Network lifetime is divided into the sundry rounds. In each round based on the scheduling program which is advertised by the FC, cluster member nodes deliver their observations $(x_{11}, x_{12}, \dots, x_{Nn_k})$ to the FC (the scheduling program will be explained in details in section III). Then, the FC makes final estimation of collected observation using a fusion function $f{:}\,\bar{\theta} =$

$f(x_{11}, x_{12}, \dots, x_{Nn_k})$. The precision of the estimation of unknown parameter θ is a crucial parameter for proposed algorithm efficiency. In this paper, using interval estimation, we wish the error of the estimation to be under control. The estimation process is done independently in each cluster.

For each round, the FC determines the number of sent messages, the time which they sent and "*On-Off*" mode for every node, using scheduling program. The main goal of this paper is to maximize network lifetime and keep error in desired bound by designing a scheduling program (in compliance with estimation model) to manage cluster member activities.

Different methods have been proposed for transmitting data inside the clusters [24]. Due to limited geographical area of clusters, in most of WSNs, direct forwarding is still one of the most applicable solutions. Finally, cluster head sends estimation results to the sink.

Following, section 2-A presents the proposed method to find the required sample size using "degree of certainty" method and based on estimation model discussed earlier. Sample size is the output of estimation model. It is the number of samples which should be provided by the observers for the FC, so that it will be able to estimate target parameter with desired precision. Therefore, FC first determines the required sample size based on the estimation model easily and then according the proposed scheduling algorithm which is explained in section 3, it determines the activity of the sensor nodes (observers) during their lifetime. FC uses linear optimization problem to determine the best scheduling program for its cluster member nodes. The outputs of the optimization problem are scheduling program and the number of rounds (the estimation will be performed in each round). FC can predict the estimation rounds, because it knows key information about the task (such as required sample size, energy model, primary energy of the nodes etc). Figure 2 briefly presents the proposed algorithm.

A. Estimation with degree of certainty

In this section, the proposed estimation model (which uses the degree of certainty) will be explained in details. If the FC node knows environmental distortion and cluster member nodes deliver their observations to the FC on time using BLUE [25] estimator for (point) estimating parameter θ, equation (2) will be considered.

$$\bar{\theta} = \sum_{k=1}^{N}\sum_{i=1}^{n_k} x_{ki} \Big/ (n_1 + \cdots + n_N) \tag{2}$$

where N is the number of cluster member nodes (observers), n_k is the number of samples which should be provided by k^{th} node, and x_{ki} is the i^{th} observation of k^{th} sensor node. Clearly, linear combination of normal random variables is normal, $\bar{\theta} \sim N(\theta, var(\bar{\theta}))$; where $var(\bar{\theta})$ is presented in equation (3).

$$V(\bar{\theta}) = \sum_{i=1}^{N} n_i\sigma_i^2 \Big/ \left(\sum_{i=1}^{N} n_i\right)^2 \tag{3}$$

where σ_i^2 is the variance of the distribution function of the error of i^{th} node's observations. In the execution of estimation process for parameter θ in each round, each cluster member node delivers its observations to the FC, based on scheduling program. Each sample consists of the last observation of the node. BLUE scheme is not efficient for wireless sensor networks because of high communication cost. Therefore, instead of sending real-valued observations, data volume will be decreased by using quantization procedure. Different methods of quantization have been proposed [26]; one of them is *uniform randomized quantizer* [27]. Quantizers are applicable for noises with various Probability Density Functions (*pdf*). They finally generate unbiased message function. It is worth mentioning that, we assume that environmental noises corrupt data only in observation phase.

Considering the observation error, wireless sensor network applications have various limitations. In other words, depending on the application requirements, different level of error is acceptable. The proposed algorithm uses *Error Bound of Estimation (EBE)* to determine the best value for sample size. EBE is the required precision of the estimation process. It is determined by the user based on the application. So, experimenter must specify a desired bound on the error of estimation, called γ, and associated confidence level, $(1-\alpha)$. With respect to the EBE, sample size required to estimate parameter θ is determined. Equation (4) uses BLUE estimator, $\bar{\theta}$, to estimate unknown parameter θ based on interval estimation.

$$P\left(\left|\bar{\theta} - \theta\right| < \gamma\right) \geq (1-\alpha) \tag{4}$$

γ and $(1-\alpha)$ (the confidence level) are determined based on EBE. If $\gamma = 0.01$ and $\alpha = 0.01$ the concept of the equation (4) is "*the error of estimation for parameter θ must be less than 0.01 with at least probability of 0.99*".

The goal in this section is to determine sample size, $n_1, n_2, \dots, n_N$ (provided by the cluster members in each round), which are required to estimate parameter θ based on input parameters γ and α with respect to equation (4). The FC node needs many samples which are provided by the cluster members to estimate the real value of parameter θ. The number of samples influences the estimation error. The more the samples are provided, the more precise estimation will be performed (lower error will be achieved).

Using equation (4), we have the following equation (5):

$$(1-\alpha) \geq P\left(\frac{\left|\bar{\theta}-\theta\right|}{\sqrt{V(\bar{\theta})}} < \frac{\gamma}{\sqrt{V(\bar{\theta})}}\right) = P\left(|Z| < \frac{\gamma}{\sqrt{V(\bar{\theta})}}\right) \tag{5}$$

where $Z \sim N(0,1)$. By selecting two tail-end values of standard normal distribution, $z_{\frac{\alpha}{2}}$ and $-z_{\frac{\alpha}{2}}$, we

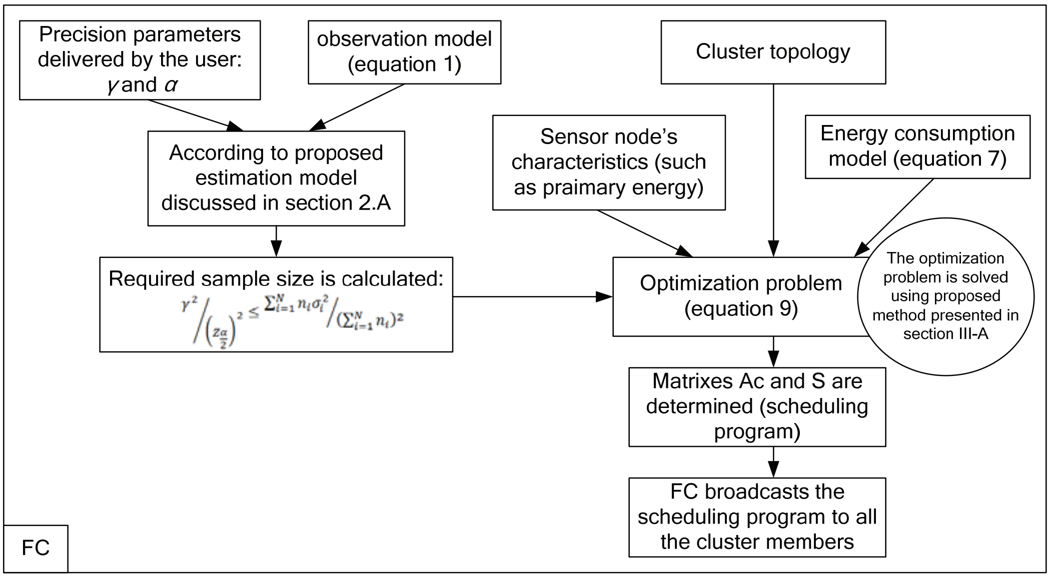

Figure 2. Flow chart of proposed algorithm

have $\gamma \le \sqrt{V(\bar{\theta})} \times z_{\frac{\alpha}{2}}$. Therefore, using equation (3) we can easily conclude equation (6),

$$\gamma^2 \Big/ \left(z_{\frac{\alpha}{2}}\right)^2 \le \sum_{i=1}^{N} n_i\sigma_i^2 \Big/ \left(\sum_{i=1}^{N} n_i\right)^2 \tag{6}$$

In equation (6) parameters γ^2 and $z_{\frac{\alpha}{2}}^2$ are known and the goal is to find desirable values for variables $n_1, n_2, \dots, n_N$. In other words, equation (6) determines the number of samples required to perform estimation process based on parameters γ and α. Different values of variables $n_1, n_2, \dots, n_N$ are eligible in equation (6). In section 3, the best values will be selected using an optimization problem

III. Proposed Scheduling Algorithm

One of the most important challenges of the wireless sensor networks is to decrease energy consumption while nodes perform their tasks, effectively. In this paper, WSN's nodes are divided into different independent clusters. Cluster member nodes deliver their observation to the FC using direct link based on the scheduling program provided by the FC. In this section, the proposed scheduling algorithm is explained.

Sensor nodes can change their radio range by adjusting transmission power; energy consumption of node i for transmitting one message (with fixed length) to the FC is calculated based on equation (7). Proposed algorithm requires the energy consumption of all nodes; therefore, we have collected all of them in a vector called E. The vector E is presented in equation (8).

$$e_i = \omega(b).d_i^{\partial} \tag{7}$$

$$E = (e_1, e_2, \dots, e_N) \tag{8}$$

In equation (7), ∂ is path loss exponent depending on the channel characteristics. Parameter ∂ is usually set 2. $\omega(b)$ is a function determining the required energy to transmit a b-bit message one meter (using energy model presented in [28]).

In scheduling program two following concepts should be determined for each round. 1) The nodes mode in round, "*on-off*", and 2) number of samples provided for the FC (only active nodes). With respect to the points mentioned before, matrixes S and AC have been considered. S is a $N \times R$ matrix. N is number of cluster member nodes and R is the number of performed rounds during network lifetime. All the rounds have the same length, T time units. $S(i,j)$ element of matrix S determines the number of samples provided by j^{th} node in i^{th}round for the FC. Elements of AC matrix determine whether nodes are active or not in a round. If $AC(i,j) = 1$, it means that j^{th} node is active in i^{th}round and if $AC(i,j) = 0$, it means that j^{th} node is inactive in i^{th}round. In fact, the collection of AC and S matrixes is the scheduling program. These two matrixes determine the activity of each node during its lifetime.

In equations (9)-(12), optimization function that finds the best values for elements of the AC and S matrixes are presented.

The objective of the optimization problem is to minimize function F. First component of function F is " $\sum_{i=1}^{R}\sum_{j=1}^{N} S(i,j).E(j)$ ", it is the total energy consumption of all network nodes in all rounds. It has positive coefficient, therefore, it should be minimized. Second component of function F is R, it is the number of estimation rounds accomplished before the network becomes non functional. It has negative coefficient, hence, it should be maximized. Network lifetime is equal to "$R \times T$" (as mentioned before, parameter T is the length of each round and it is considered constant and predefined).

Equation (10), determines that each node can consume energy at most E_{pri} units. E_{pri} is initial energy of the node. Node energy consumption consists of two parts. First part discusses that each node consumes energy proportional to number of sent

$$Min\ F = \sum_{i=1}^{R}\sum_{j=1}^{N} S(i,j).E(j) - R \tag{9}$$

$$S.T: \forall j \in N, \sum_{i=1}^{R}\left(S(i,j).E(j)\right) + \left(E_{ac}.AC(i,j)\right) < E_{pri} \tag{10}$$

$$S.T: \forall i \in R, \forall j \in N, AC(i,j) = \left\lceil {S(i,j)}\Big/{\sum_{k=1}^{N} S(i,m)} \right\rceil \tag{11}$$

$$S.T: \forall i \in R, \left({\gamma^2}\Big/{\left(z_{\frac{\alpha}{2}}\right)^2} \right) \leq \left({\sum_{j=1}^{N} S(i,j).\sigma_i^2}\Big/{\left(\sum_{j=1}^{N} S(i,j)\right)^2} \right) \tag{12}$$

messages and its relative distance to the FC. Second part is relevant to the node's energy consumption due to being active in the rounds. E_{ac} is amount of energy consumed by the node in each round when it is active (without considering sent messages). With respect to the equation (10), optimization problem tries to determine nodes mode ("on-off") in order to maximize network lifetime. In inactive "off" mode node's energy consumption is very low, and as a result, it is negligible. Equation (11) presents relation between S and AC matrixes. If $\mathrm{S(i,j)}$ has non zero value, $\mathrm{AC(i,j)}$ will be 1, otherwise, $\mathrm{AC(i,j)}$ will be 0.

Equation (12) is derived from equation (6) by only changing variables. It is essential condition about EBE. As discussed before, the least number of samples in each round is calculated based on EBE. Also equation (12) is essential about determining network lifetime. In a round, if cluster member nodes have no sufficient residual energy in order to satisfy EBE, practically network lifetime is over

A. Calculating matrixes S and AC (solving the optimization problem)

Using equations (9)-(12), the best values for matrix *S* elements are calculated. Equations (9) and (12) are nonlinear because of variable *R* and the term "$\left(\sum_{j=1}^{N} S(i,j)\right)^2$", respectively. Solving optimization problem presented in equation(9) using available methods is so hard. In most of situations, solving nonlinear optimization problems is complicated. Therefore, we have used our proposed method to solve the optimization problem. At the rest of this section, the proposed method is explained in details.

If we disjoin parameter *R* from equation (9), remained objective function is linear. It is presented in equation (10).

$$Min\ F = R \times \left(\sum_{j=1}^{N} S(i,j).E(j) - 1\right) \tag{13}$$

The new optimization problem is fully the same by equation (9) with only one difference. Variable R in equation (9) is unknown, but in new optimization problem (equation (13)), variable R is considered known.

In most of WSN's applications, sensor nodes are homogeneous and the target terrain has almost the same characteristics. Therefore, it is reasonable to assume that, "$\forall_{i,j}\ \sigma_i = \sigma_j$". This means that the different observations have sundry errors, although all have the same *pdf*. Based on what mentioned here, equation (12) will be linear and rewritten as following equation (14). We can solve proposed linear optimization problem easily using available methods (some of them have been presented in [29]), and the answer will be unique and qualified.

$$\forall i \in R, \left({\gamma^2}\Big/{\left(z_{\frac{\alpha}{2}}\right)^2} \right) \leq \left({\sigma_i^2}\Big/{\sum_{j=1}^{N} S(i,j)} \right) \tag{14}$$

Parameter *R* is actually one of the unknown parameters while we consider it as known. We have used the following proposed particular method to solve the optimization problem.

In first step, a bound is considered for variable *R*. Using known parameters of the problem, we can determine a bound for variable *R*. The main goal of optimization problem is to find the maximum value of parameter *R*, by selecting appropriate values for matrixes *S* and *AC* elements. The value of parameter *R* determines network lifetime. By multiplying *R* and *T* (each round longevity), lifetime is calculated. Here, network lifetime is considered function based. For the estimation application, the wireless sensor network is considered functional if it can estimate the unknown target parameter θ with admissible error (refer to section 2-A). As mentioned earlier, the network lifetime L ($L = T \times R$) is defined as the number of estimation rounds accomplished before the network becomes non functional.

Two main conditions of optimization problem are presented in equations (10) and (12). Equation (10) is called vertical condition. It considers node's energy consumption. i^{th} column elements of matrix *S* represent the sent packets from node *i* to the *FC* in different rounds. Absolutely, sum of them is total number of sent packets from node *i*. Node *i* consumes energy due to sending each of packets.

Equation (12) is essential condition about network performance precision (called horizontal condition).

With respect to desirable precision defined by user and by considering condition (12), based on what mentioned in section 2-A, number of required samples in each round is determined. In other words, the *FC* should receive at least some messages (determined based on equation (12)) to be able to estimate parameter θ with desirable EBE.

Pseudo code used for solving optimization problem is presented in figure 3.

In first line of figure 3, the bound of parameter R is determined. The lower bound of R is zero and the upper bound is R_M. The method of finding R_M value will be discussed in section 3-B. As discussed before, parameter R determines the network lifetime. When $R = 0$, it means that the network has not enough energy to perform even one round. Theoretically, R_M can be the maximal value for parameter R; but with respect to the conditions considered for the network (will be discussed in section (3-B)), practically, lifetime equal to or bigger than R_M is not possible.

In line 4, it is pointed out that the problem is solved, successfully. We should emphasize two following points, 1) if current value of parameter R be larger than the optimal value of R (of course in this step, the optimal value is still unknown) optimization problem (equation (9)) is not solvable. This happens because of contradiction between equations (10) and (12). If R be considered larger than optimal R, for some rows of matrix S equation (12) cannot be satisfied (the rounds bigger than optimal R); therefore optimization problem has not solution. 2) In other side, if optimization problem is solved for current value of R, the solution is acceptable; but by continuing algorithm it is evaluated that whether a bigger value for R is available or not.

B. Calculating R_M

In order to calculate R_M, we have considered the over optimal situation which is not practical in real. Consequently, a network with following conditions has been considered: 1) it consists of only one node (called selected node), 2) initial energy of selected node is E_T, 3) selected node consumes E_L unit energy due to send each message to the FC. Considering that only one node exists in the network, equation (12) is rewritten as equation (15). Parameters E_L and E_T are calculated using equations (16) and (17) respectively.

$$\forall i \in R, \left(\gamma^2 \Big/ \left(z_{\frac{\alpha}{2}}\right)^2 \right) \leq \left(\sigma^2 / N.n_q \right) \tag{15}$$

$$E_L = min\,(E_{i\in(1:N)}) \tag{16}$$

$$E_T = N \times E_{pri} \tag{17}$$

Equation (16) describes that E_L is the least energy consumption for forwarding message to the FC, considering energy consumption of all the cluster member nodes. Practically, selected node energy consumption has been considered the same by the least cluster member's energy consumption. Equation (17) describes that parameter E_T is sum of initial energy of all the cluster members. Practically, initial energy of selected node is sum of initial energy of all the cluster members.

```
0. R ∈ (0-R_M)
1. R=R_M , LB=0 , UB=R_M
2. for i=1 : log2 R_M
3.      Solve Equ(9) using R
4.      if Equ(9) is solved successfully
5.           then: LB=R
6.           else: UB=R
7.      R=(LB+UB)/2
8. result is R
```

Figure 3. Proposed method to find optimal R

With respect to the values obtained for parameters n_q (using equation (15)), E_L and E_T, target parameter R_M is computed using equation (18). Figure 4 briefly presents steps of solving the optimization problem.

$$R_M = \left\lfloor E_L \big/ (n_q . E_T) \right\rfloor \tag{18}$$

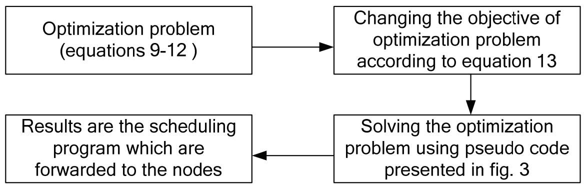

Figure 4. The procedure of solving the optimization problem

IV. PERFORMANCE EVALUATION OF PROPOSED ALGORITHM

In this section, we present some simulation results to compare efficiency of the proposed algorithm and following heuristic methods:

1) Heuristic 1: in each round, nodes send samples to the sink depending on their remaining energy. Assume that, node i has e_i unit remaining energy, then the number of samples provided by node i is "$\left(e_i \big/ \sum_{k=1}^{N} e_k \right) \times N_b$". N_b is the number of samples determined using BLUE estimator, besides degree of certainty.

2) Heuristic 2: in each round, nodes provide samples equally, in other words all the nodes participate in estimation process with uniform energy scheduling.

In considered scenarios, different numbers of network nodes have been deployed. The noise variance σ_k^2 and the initial energy source E for all the nodes are the same. We consider all the variances the same, but this means the observation error is not the same in all nodes. It means that average observation error in all the nodes is alike, but in each individual sample different amount of error exists.

Figure 5 illustrates the network lifetime achieved by proposed algorithm under different values of γ. As discussed in section 2-A, γ is determined based on

EBE. This means that user can determine desirable error bound by determining γ. The bigger values of γ causes more flexible estimation process with respect to EBE. As noted before, we have estimated unknown parameter θ, using degree of certainty. Thus, when estimation process precision is more flexible (bigger values for parameter γ is acceptable), by collecting lower number of samples, desirable precision is achievable. Lower number of samples leads to average network lifetime extension.

Horizontal axis in figure 5 presents parameter W which is calculated based on parameters $z_{\alpha/2}$ and γ. Based on equation (12), we can easily define relationship between W and the two $z_{\alpha/2}$ and γ parameters (see equation (19)).

$$W = \gamma^2 \Big/ \left(z_{\frac{\alpha}{2}}\right)^2 \qquad (19)$$

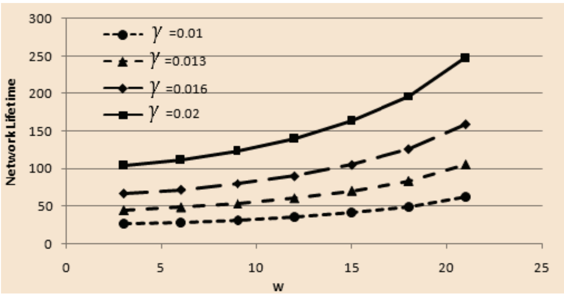

Figure 5. Network lifetime versus Parameter W for different values of γ

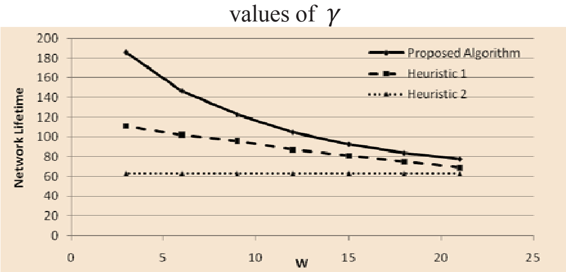

Figure 6. Network lifetime versus parameter W for all the algorithms

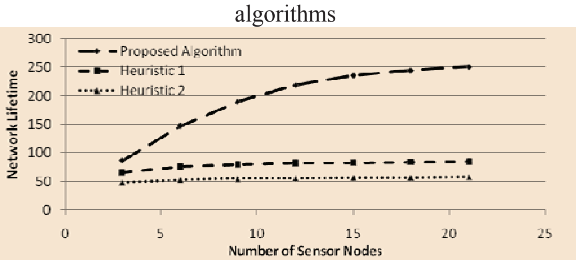

Figure 7. Network lifetime versus number of sensor nodes, for all the algorithms

As you can observe in figure 5, network lifetime becomes larger for bigger values of γ. This is because of lower number of samples. It is worth mentioning that the main goal of proposed algorithm is to prolong network lifetime by scheduling nodes activity with respect to desirable estimation precision.

Figure 6 illustrates network lifetime achieved by proposed algorithm, heuristic 1 and heuristic 2 methods versus parameter W. In figure 6, results have been gained by a network with $N=10$ sensor nodes. Parameters W is described in details before in this section. As clear in figure 6, proposed algorithm is more efficient rather than the two other methods. The lower values of parameter W, the more difference between proposed algorithm and heuristic 1 is. But for higher values of parameter W, efficiency of algorithms is closer. In real world, big value for W is not applicable.

In figure 7, we have evaluated the influence of the number of sensor nodes on proposed algorithm efficiency. Horizontal axis is the number of sensor nodes and vertical axis shows network lifetime. It manifests network lifetime achieved by proposed algorithm in comparison with Heuristic 1 and Heuristic 2 methods under different total number of sensor nodes, respectively. It is easily possible to see that proposed algorithm improves network lifetime significantly compared with Heuristic 1 and Heuristic 2. When sensor network becomes denser, proposed algorithm acts more efficient than the two other methods. Proposed algorithm manages its available sources (sensor nodes remained energy) better than two other methods. Heuristic 1 methods uses BLUE estimator, therefore it is more efficient that the simple methods Heuristic 2. We should note that, all 3 methods use single hop routing. The main reason behind significant improvement of proposed algorithm is the scheduling process which is discussed in section 3. Optimization process provides the best possible scheduling program for the sensor nodes. Based on the results shown in this section proposed algorithm achieved its goal.

V. Conclusion

In this paper, we have proposed a task scheduling method for estimation in wireless sensor networks, which is rarely addressed in the literature. We consider the distributed estimation in energy-limited wireless sensor networks while our main goal is to maximize network lifetime. From the application perspective, the estimation rounds which accomplished before the time network becomes nonfunctional are considered as network lifetime. We have applied linear programming to find the best possible scheduling program, which can be easily solved by any LP solver. Task scheduling program determines the number of samples which should be provided by each sensor node in each round. In this work, we have assumed that the observation noises among different sensors are independent and mean zero Gaussian random variables and the channels from the local sensors to the fusion center are error free. For the future work, we have planned to extend the optimization problem for multihop wireless sensor networks. We have simulated proposed protocol using Opnet simulator; results confirm that proposed protocol manages to attain its goals.

References

[1] M. Tubaishat, S. Madria, "Sensor Networks: An Overview." IEEE Potential April/ May, pp 23, 2003

[2] J. Yick, B. Mukherjee, D. Ghosal, "Wireless sensor network survey", Computer Networks, vol. 52, pp. 2292–2330, 2008

[3] D. Sierociuk, I. Tejado, B. M. Vinagre, "Improved fractional Kalman filter and its application to estimation over lossy networks", Signal Processing, vol 91, pp. 542-552, 2011

[4] M. R. M. Castillo, et al, "Offline Detection, Identification, and Correction of Branch Parameter Errors Based on Several Measurement Snapshots", IEEE Transactions on Power Systems, vol. 26, pp. 870-877, 2011

[5] T. C. Aysal, K. E. Barner, "Constrained Decentralized Estimation Over Noisy Channels for Sensor Networks". IEEE Transactions on Signal Proceeing, vol. 56, no. 4, pp. 1398-1410, 2008

[6] Y. Huang, Y. Hua, "On Energy for Progressive and Consensus Estimation in Multihop Sensor Networks" IEEE Signal Processing Magazine, vol. 59, no. 8, pp. 3863 - 3875, 2012

[7] S. Cui, A. Goldsmith, A. Bahai, "Joint modulation and multiple access optimization under energy constraints," Proc. IEEE Global Telecommunication Conference, Dallas, Texas, pp. 151–155, 2004

[8] N. Roseveare, B. Natarajan, "Distributed Tracking with Energy Management in Wireless Sensor Networks". IEEE Transactions on Aerospace and Electronic Systems, vol. 48 , pp. 3494 - 3511, 2012

[9] A. S. Behbahani, A. M. Eltawil, H. Jafarkhani, "Linear Estimation of Correlated Vector Sources for Wireless Sensor Networks with Fusion Center". IEEE Wireless Communications Letters, vol. 1, pp. 400 - 403, 2012

[10] M. Chaudhary, L. Vandendorpe, "Power Constrained Linear Estimation in Wireless Sensor Networks With Correlated Data and Digital Modulation". IEEE Transactions on Signal Processing, vol. 60, no. 2, 2012

[11] A. Bertrand, M. L. Moonen, "Distributed Adaptive Estimation of Node-Specific Signals in Wireless Sensor Networks With a Tree Topology", IEEE Transactions on Signal Processing, vol. 59, no. 5, 2011

[12] J. J. Xiao, S. Cui, Z. Q. Luo, A. J. Goldsmith, "Power Scheduling of Universal Decentralized Estimation in Sensor Networks". IEEE Transactions on Signal Proceeing, vol. 54, no. 2., 2006

[13] J. J. Xiao, A. Ribeiro, Z.-Q. Luo, and G. B. Giannakis, "Distributed compression-estimation using wireless sensor networks," IEEE Signal Process. Mag., vol. 23, no. 4, pp. 27–41, Jul. 2006

[14] D. Dardari, A. Conti, C. Burrati, R. Verdone, "Mathematical Evaluation of Environmental Monitoring Estimation Error through Energy-Efficient Wireless Sensor Networks", IEEE Transactions on Mobile Computing, vol. 6, no. 7, 2007

[15] H. Chen, "Performance-Energy Tradeoffs for Decentralized Estimation in a Multihop Sensor Network". IEEE Sensors Journal, vol. 10, no. 8, 2010

[16] J. Li, G. AlRegib, "Network Lifetime Maximization for Estimation in Multihop Wireless Sensor Networks". IEEE Transactions on Signal Processing, vol. 57, no. 7, 2009

[17] S. Narieda, "Lifetime Extension of Wireless Sensor Networks Using Probabilistic Transmission Control for Distributed Estimation", IEEE Transactions on Vehicular Technology, vol. 61, 2012

[18] C. T. Cheng, C. K. Tse, F. C. M. Lao, "An Energy-Aware Scheduling Scheme for Wireless Sensor Networks", IEEE Transactions on Vehicular Technology, vol. 59, no. 7, 2010

[19] F. Liu, C. Y Tsui, Y. J. Zhang, "Joint Routing and Sleep Scheduling for Lifetime Maximization of Wireless Sensor Networks", IEEE Transactions on Wireless Communications, vol. 9, no. 7, 2010

[20] Y. Wu, X. Y. Li, Y. Liu, W. Lou, "Energy-Efficient Wake-Up Scheduling for Data Collection and Aggregation", IEEE Transactions on Parallel and Distributed systems, vol. 21, no. 2, 2010

[21] Z. D. Incel, A. Ghosh, B. Krishnamachari, K. Chintalapudi, "Fast Data Collection in Tree-Based Wireless Sensor Networks", IEEE Transactions on Mobile Computing, vol. 11, no. 1, 2012

[22] W. Mendenhall, D. D. Wackerly, R. L. Scheaffer, "Mathematical statistics with appications", PWS-KENT, 1989.

[23] E. Ayanoglu, "On optimal quantization of noisy sources". IEEE Transactions on Information Theory, vol. 36, no. 6, pp. 1450–1452, 1990

[24] I. F. Akyildiz, W. Su, Y. Sankarsubramaniam, E. Cayirci, "Wireless sensor networks:A survey," Computer Netw., vol. 38, pp. 393–422, Mar. 2002.

[25] Z. Q. Luo, "Universal Decentralized Estimation in a Bandwidth Constrained Sensor Network", IEEE Transactions on Information Theory, vol. 51, no. 6, 2005

[26] H. Papadopoulos, G. Wornell, A. Oppenheim, "Sequential signal encoding from noisy measurements using quantizers with dynamic bias control," IEEE Transactions Inf. Theory, vol. 47, pp. 978–1002, Mar. 2001.

[27] J. J. Xiao, Z. Q. Luo, "Universal decentralized estimation in an inhomogeneous sensing environment," IEEE Transactions Inf. Theory, vol. 51, no. 10, pp. 3564–3575, Oct. 2005.

[28] R. Verdone, et al., "enabling technologies, information processing and protocol design", Wireless Sensor and Actuator Networks, Elsevier, 2008

[29] J. E. Beasley, "Advances in Linear and Integer Programming", Oxford Science press, 1996.

Amir Hossein Mohajerzadeh was born on July 1984 in Tehran, Iran. He received the B.Sc. and M.Sc. degrees in computer engineering from the computer department, Ferdowsi University of Mashhad, Mashhad, Iran, in 2006 and 2008, respectively. He is a Ph.D. candidate in computer engineering at computer department, Ferdowsi University of Mashhad. His research interests are in QoS in networks, Wireless Sensor Networks and Next Generation Networks.

Mohammad Hossein Yaghmaee was born on July 1971 in Mashhad, Iran. He received his B.Sc. degree in Communication Engineering from Sharif University of Technology, Tehran, Iran in 1993, and M.Sc. degree in communication engineering from Tehran Polytechnic (Amirkabir) University of Technology in 1995. He received his Ph.D. degree in communication engineering from Tehran Polytechnic (Amirkabir) University of Technology in 2000. He has been a computer network engineer with several networking projects in Iran Telecommunication Research Center (ITRC) since 1992. From November 1998 to July1999, he was with Network Technology Group (NTG), C&C Media research labs., NEC corporation, Tokyo, Japan, as visiting research scholar. September 2007 to August 2008, he was with the Lane Department of Computer Science and Electrical Engineering, West Virginia University, Morgantown, USA as the visiting associate professor. He is author of 3 books all in Farsi language. He has published more than 60 international conference and journal papers. His research interests are in Wireless Sensor Networks (WSNs), Traffic and Congestion Control, High Speed Networks including ATM and MPLS, Quality of Services (QoS) and Fuzzy Logic Control.

Vahid Fakoor received his B.Sc. degree in Statistics from Islamic Azad university of Mashhad, 1996, and his M.Sc. degree in Pure Statistics from Ferdowsi University of Mashhad, in 1999. He received his Ph.D. degree in Statistics from Ferdowsi University of Mashhad in 2005. He is a member of the Iranian Statistical Society. His research interests are Probability Theory, Stochastic Processes, and Survival Analysis.