# A Cooperative Game Theoretic Solution for Lifetime Maximization of WSNs in Sequential Estimation

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***Abstract*—In this paper, the problem of sequential estimation and lifetime maximization of a wireless sensor network (WSN) is formulated in a cooperative game theoretic framework. This framework allows addressing problems of fair resource allocation for sequential estimation at the Fusion center (FC) of a wireless sensor network as a solution of a cooperative game. We propose a simple game theoretic solution to power allocation problem for sensor nodes such that the obtained solution leads to increased lifetime of the WSN. Simulation results show that the proposed solution achieves target estimation quality at the FC, and at the same time lifetime of the overall sensor network is increased.**

***Keywords*—Cooperative game theory, wireless sensor network, sequential estimation, collaborative information processing, resource allocation, Shapley function, network lifetime.**

## I. Introduction

Wireless sensor networks (WSNs) are spatially distributed data acquisition systems consisting of many sensing nodes tasked with cooperatively monitor a Phenomenon of Interest (PoI). Wireless sensor networks are gaining popularity due to their potential to be useful for a wide range of applications including environmental monitoring, intrusion detection, and various military and civilian applications [1]. Sensor networks are prone to premature failure since some nodes might run out of their batteries rapidly due to work load variations (i.e. relay nodes or nodes that are in close proximity to certain PoI are triggered frequently), different communication environments or hardware setup. It is undesirable for a sensor node to waste power as excessive use of battery power can shorten the lifetime of a node. Hence, a common performance criteria for many wireless sensor networks is the network lifetime while satisfying required coverage and connectivity over the deployment region.

Resource-constrained WSNs rely on collaborative signal and information processing for efficient handling of large volumes of data collected by distributed sensor nodes. Node collaboration, however, requires inter sensor communication. Payoff and cost of collaboration can be modeled, respectively, as the improved quality of processed outputs and the required power or bandwidth for communication. Thus there needs to be a trade-off between performance and cost of collaborative information processing. This situation can be interpreted as a collection of interacting nodes competing with each other to make decisions on collaboration with the individual objectives of not wasting node resources or paying excessive penalties.

Cooperative game theoretic concepts can be a useful tool in approaching such collaborative signal processing problems in distributed sensor networks. Unlike non-cooperative game theory, where individual players compete with each other to achieve their goals of maximizing individual payoffs, cooperative game theory allows competing players (or nodes) to form coalitions so as to efficiently achieve their individual goals. Although collaborative signal and information processing for sensor networks have been extensively studied in the literature [2]–[7], there is still ample room for research aimed at developing a formal analytical framework for collaborative information processing in resource-constrained sensor networks, especially when maximizing the sensor network lifetime is the most important objective. The fact that nodes act to optimize their own payoffs has triggered research on using non-cooperative game theory to manage powers in wireless sensor networks [8]–[10]. On the other hand, for a resource constrained WSN, cooperative game theory can be a natural choice and comes in handy when estimating a parameter with desired estimator quality is the ultimate goal. In current literature, very few attempts have been made to exploit the rich collection of cooperative game theory in power/energy-constrained WSNs tasked with estimating a parameter. For example, in [11], a novel concept of incompletely cooperative game theory was used to simultaneously achieve energy conservation and throughput for WSNs. On the other hand, [12], [13] used cooperative game theory for channel/bandwidth allocation problem. In this paper, we use tools from cooperative game theory to develop a formal analytical framework for fair allocation of power among participating sensor nodes to achieve a sequential estimation task while at the same time maximizing overall network lifetime. In particular, we use the concept of the Shapley value [14] to achieve power allocation among distributed nodes with power constraints.

The remainder of this paper is organized as follows: Section II presents the sensor network model for the sequential estimation problem. Section III discusses about the basic concepts and theorems for the Shapley value based solution method. The proposed power allocation algorithm is discussed in Section IV. Section V evaluates the performance of the proposed solution via simulations. Finally Section VI concludes the paper by summarizing our results.

## II. Sensor Network Model for Sequential Estimation

We consider a sensor network consisting of a Fusion Center (FC) and $N$ nodes tasked with estimating a non-random parameter $\theta$ sequentially as shown in Fig. 1. We consider the FC itself as a node with its own estimate of the parameter $\theta$ and is denoted as node-0. The set of distributed nodes are denoted as $\mathcal{N} = \{1, 2, \cdots, N\}$. Objective of each node, or a set of nodes, is to obtain a reliable estimation of $\theta$. Sensor network may consists of mobile nodes or a hybrid of fixed and mobile nodes and the wireless channel can be time-varying. However, only a *quasi-static network* is considered here, in which node locations as well as fading coefficients can be assumed fixed for a certain period of time, whereas from block to block they could be varying.

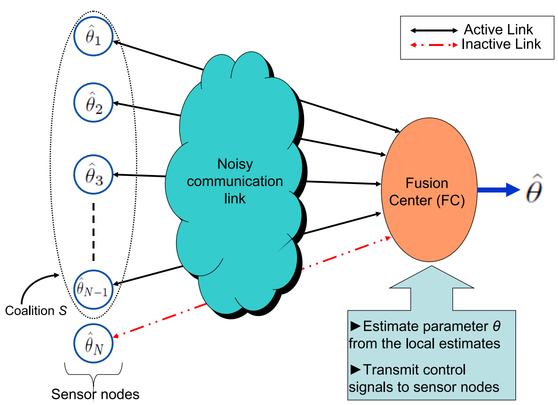


Fig. 1. A typical wireless sensor network (WSN) architecture with a Fusion center (FC).

Local estimator at node $i$ is denoted by $\hat{\theta}_i$, for $i = 0, 1, 2, \cdots, N$. All local estimators are assumed to be unbiased and their respective variances denoted by $V_i$. Under the quasi-static assumption, we may assume that at the beginning of each block, the FC (node-0) has access to the quality of estimates at the distributed nodes as given by $V_i$'s for $i \in \mathcal{N}$. It is assumed that the FC forms its updated estimator sequentially (in a predetermined order or randomly) by combining its own observation with the noise-corrupted estimates of the selected distributed nodes received over noisy communication links. The FC keeps on sequentially updating its estimator until it achieves a certain predetermined estimation quality denoted by $V_t$. We consider the case when the distributed nodes are not supposed to transmit at their maximum powers, while the goal is to achieve a desired quality of estimate at the FC using as fewer a number of nodes as possible, and at faster a rate as possible. The objective is to define a fair allocation of network resources for collaborating nodes in terms of their transmit powers. The sensor nodes in the assumed WSN are powered by batteries with limited lifetime, which is dissipated during the data transmission/reception. Note that, we define the lifetime of a sensor network as the time after which at least one or a certain fraction of sensor nodes run out of their batteries, resulting in a hole within the network. We assume that the FC is equipped with sufficient energy, hence we are only concerned about the distributed nodes in the set $\mathcal{N}$.

For simplicity, AWGN channel with quasi-static fading is considered. Signal received at the FC from node $j \epsilon \mathcal{N}$ can be expressed as

$$x_j = \hat{\theta}_j + w_j, \tag{1}$$

where $w_j$ is the zero-mean receiver noise with variance $\frac{1}{P_j |h_j|^2}$, $P_j$ and $h_j$ are the transmit power of node $j$ and the quasi-static fading coefficient from node $j$ to the FC, respectively. For $N$ nodes, the data vector available at the FC can be written as

$$\mathbf{X}_0 = \begin{pmatrix} \hat{\theta}_0 \\ x_1 \\ \vdots \\ x_N \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} \theta + \begin{pmatrix} \tilde{\theta}_0 \\ \tilde{\theta}_1 \\ \vdots \\ \tilde{\theta}_N \end{pmatrix} + \begin{pmatrix} 0 \\ w_1 \\ \vdots \\ w_N \end{pmatrix},$$

so that

$$\mathbf{X}_0 = \mathbf{1}\theta + \tilde{\mathbf{\Theta}}_0 + \mathbf{w}_0. \tag{2}$$

where $\tilde{\theta}_i = \hat{\theta}_i - \theta$ is zero-mean with variance $V_i$ for all $i$, $\mathbf{1}$ is the vector of all ones, $\tilde{\mathbf{\Theta}}_0 = [\tilde{\theta}_0, \tilde{\theta}_1, ..., \tilde{\theta}_N]^T$ and $\mathbf{w}_0 = [0, w_1, ..., w_N]^T$. Let us denote by $\Sigma^0 = \Sigma^0_\theta + \Sigma^0_w$ the covariance matrix of $\mathbf{X}_0$, where $\Sigma^0_\theta$ and $\Sigma^0_w$ are the covariance matrices of $\tilde{\mathbf{\Theta}}_0$ and $\mathbf{w}_0$ respectively. The optimal BLUE estimator formed at the FC is given by $\hat{\theta}_{0,n} = \frac{\mathbf{1}^T [\Sigma^0]^{-1} \mathbf{X}_0}{\mathbf{1}^T [\Sigma^0]^{-1} \mathbf{1}}$ with the updated estimator variance $V^{up}_0 = \left( \mathbf{1}^T \left[ \Sigma^0 \right]^{-1} \mathbf{1} \right)^{-1}$. The covariance matrix of the observation vector $\mathbf{X}_0$ at the FC is given by (3), where $C_{ij} = Cov\{\hat{\theta}_i, \hat{\theta}_j\}$ is the covariance between the random variables $\hat{\theta}_i$ and $\hat{\theta}_j$.

## III. Basics of Shapley Value Based Solution

For game theoretic formulation of our sequential estimation problem, we consider a game in which the players (sensor nodes) may choose to cooperate by forming coalitions. Cooperative game theory allows competing agents to form coalitions so as to further their individual objectives. In this section, we use the concept of Shapley function [14] as an average measure of fairness for each node.

*Definition 1:* A *Shapley function* $\phi(v)$ is a function that assigns to each possible characteristic function $v$ a real number, i.e.,

$$\phi(v) = [\phi_1(v), \phi_2(v), \cdots, \phi_N(v)], \tag{4}$$

where $\phi_i(v)$ represents the worth or value of player $i$ in the game. Note that, the characteristic function of a coalition $S \subset N$ is the *largest* guaranteed payoff to the coalition and is defined as follows:

$$\Sigma^0 = \begin{pmatrix} V_0 & C_{01} & \dots & C_{0N} \\ C_{10} & V_1 + \left(P_1|h_1|^2\right)^{-1} & \dots & C_{1N} \\ \vdots & \vdots & \ddots & \vdots \\ C_{N0} & C_{N1} & \dots & V_N + \left(P_N|h_N|^2\right)^{-1} \end{pmatrix} \tag{3}$$

*Definition 2:* Let $2^N$ denote the set of all possible coalitions for the players $N$. Any function $\upsilon : 2^N \to \mathcal{R}$ satisfying

$$\upsilon(\phi) = 0 \qquad \text{and} \qquad \upsilon(N) \geq \sum_{i=1}^{n} \upsilon(i) \tag{5}$$

is a characteristic function of an n-person cooperative game.

The Shapley axioms for $\phi(\upsilon)$ are [15]:

1. ***Efficiency:*** $\sum_{i\in N} \phi_i(\upsilon) = \upsilon(N)$.
2. ***Symmetry:*** If $i$ and $j$ are such that $\upsilon(S \cup \{i\}) = \upsilon(S \cup \{j\})$ for every condition $S$ not containing $i$ and $j$, then $\phi_i(\upsilon) = \phi_j(\upsilon)$.
3. ***Dummy axiom:*** If $i$ is such that $\upsilon(S) = \upsilon(S \cup \{i\})$ for every coalition $S$ not containing $i$, then $\phi_i(\upsilon) = 0$.
4. ***Additivity:*** If $u$ and $\upsilon$ are characteristic functions, then $\phi(u + \upsilon) = \phi(\upsilon + u) = \phi(u) + \phi(\upsilon)$.

It can be proved that there exists a unique function $\phi$ satisfying the above axioms, and this Shapley function can be written as [14]

$$\phi_i = \sum_{S \subseteq \mathcal{N} - i} \frac{(|S|)!\,(N-1-|S|)!}{N!} \left[\upsilon(S \cup \{i\}) - \upsilon(S)\right]. \tag{6}$$

The physical meaning of the Shapely function can be interpreted as follows: suppose that $N$ sensor nodes form a coalition, in which each node joins the coalition in random order. There are $N!$ different ways that the nodes might be ordered in joining the coalition, For any coalition $S$ that does not include node $i$, there are $|S|!\,(N-1-|S|)!$ different ways to order the nodes so that $S$ is the set of nodes who enter the coalition before node $i$. If various orderings are equally likely, $\frac{(|S|)!(N-1-|S|)!}{N!}$ is the probability that, when node $i$ enters the coalition, the coalition $S$ of size $|S|$ is already formed. When node $i$ finds $S$ ahead of it as it joins the coalition, then its marginal contribution to the worth of the coalition is $\upsilon(S \cup \{i\}) - \upsilon(S)$. Thus under the assumption of randomly-ordered joinings, the Shapley value of each node is its expected marginal contribution when it joins the coalition.

## IV. Shapley Value Based Solution

For simplicity of exposition, in this section, we consider the case when all local estimators are uncorrelated and communication is over orthogonal channels. In this paper, our goal is to estimate a non-random parameter sequentially and at the same time allocate powers among the transmitting/participating nodes in a way that the overall lifetime of the sensor network is maximized. Let $\bar{P}_n$ be the maximum possible transmit power of node $n$ and $P_n$ be the actual transmit power to be obtained from game-theoretic solution. Let us define the lifetime of node $n$ at $\bar{P}_n$ transmit power as $T_n$. Hence according to the definition of lifetime given before, network lifetime, $T_{net} = T_{min} = \min_n T_n$. Then the available power of $n$-th node if all nodes are to have the same $T_{min}$ lifetime is $\psi_n = \frac{\bar{P}_n T_n}{T_{min}}$. We define the coalitional gain of a coalition $S = \{i, j, k\}$ of nodes as:

$$\upsilon(S) \;=\; \left\{ \begin{array}{ll} \sum_{n=i,j,k} \lambda_n \psi_n & \text{if} \quad T_i = T_j = T_k \\ \sum_{n=i,j,k} \left(\psi_n - \bar{P}_n\right) & \quad\text{otherwise} \end{array} \right\} \tag{7}$$

where $\lambda_n$ is a suitably chosen weighting parameter which is proportional to the inverse of the variance $V_n$ of the local estimate at node $n$. According to the definition of $\upsilon(S)$ given above, $\upsilon(\emptyset) = 0$. The Shapley value for any node $n$ in the coalition $S$ can be found to be

$$\phi_n = \frac{1}{6} \sum_{\substack{m \neq n \\ m \in S}} \upsilon(\{n, m\}) + \frac{1}{3}\left[\upsilon(S) - \upsilon(S \backslash \{n\})\right]. \tag{8}$$

A possible fair allocation of node transmit power can be based on the Shapley value of each node as defined below:

$$\frac{P_j}{P_i} = \frac{\phi_j}{\phi_i} \quad \text{and} \quad \frac{P_k}{P_i} = \frac{\phi_k}{\phi_i}, \tag{9}$$

where $P_i$, $P_j$ and $P_k$ are the powers to be committed by the sensor nodes $i$, $j$ and $k$ respectively. The rationale is that a node with higher Shapley value corresponds to having higher available battery life and better local estimate because of the way the characteristic function $\upsilon(S)$ is formulated. Hence, a node with longer remaining battery life or a better local estimate is allowed to transmit at a higher power than a node with shorter residual battery life, thereby extending the overall lifetime of the sensor network and at the same time achieving the estimation goal.

For the monotonic decrease in the updated variance at the FC, we need $V_0^{up} < V_0$, where $V_0^{up} = \left(\frac{1}{V_0} + \sum_{n=i,j,k} \frac{1}{V_n + (P_n h_n^2)^{-1}}\right)^{-1}$. Let us define $V_0^{up} = \epsilon V_0$ where $0 < \epsilon < 1$. The parameter $\epsilon$ can be used to control the rate at which the updated estimator variance at the FC improves. It also determines the existence of valid solutions for $P_n$'s. The criterion for monotonic decrease of $V_0^{up}$ as more nodes are included in the sequential estimation can be written as

$$\sum_{n=i,j,k} \frac{1}{V_n + (P_n h_n^2)^{-1}} + \frac{1}{V_0}\left(1 - \frac{1}{\epsilon}\right) = 0. \tag{10}$$

If $\epsilon$ is too low, the required rate of monotonic decrease in $V_0^{up}$ is too high, and in that case there might not be a feasible solution. On the other hand, if $\epsilon$ is too high, rate of sequential estimation quality at the FC may not be satisfactory. $P_i$, $P_j$

and $P_k$ can easily be solved from (9) and (10) for the nodes $i$, $j$ and $k$.

We propose the Shapley value based algorithm below to solve for the sequential estimation problem. The details of the algorithm is described in Fig. 2. The proposed algorithm is particularly suitable for sensor networks in which it is necessary to control the rate at which FC reaches the target quality of estimation, while at the same time achieving increased network lifetime.

**Algorithm 1** Shapley value based Power Allocation

1. FC (node-0) picks any three nodes $i, j, k \in \mathcal{N}$, $i \neq j \neq k$ randomly or in a predetermined order. Calculate $P_i$, $P_j$ and $P_k$ from (9) and (10).
2. FC sends control signals to nodes $i$, $j$, $k$, and ask them to transmit their signals with the allocated powers. Rest of the nodes are in sleep mode. Update the estimator variance $V_0^{UP}$ at the FC and remove $i$, $j$ and $k$ from the set $\mathcal{N}$.
3. Repeat the same procedures until $V_o^{UP} \leq V_t$ or $\mathcal{N} = \emptyset$ where $V_t$ is the desired quality of estimate at the FC.

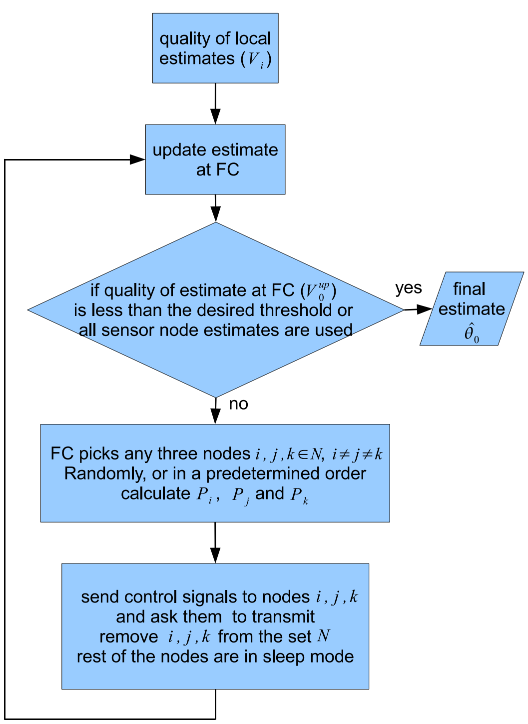


Fig. 2. Sequential estimation process using the proposed algorithm.

Our proposed algorithm guarantees that when the three nodes satisfy the criteria $V_0^{up} < V_0$, the nodes with longer battery lives transmit at higher power levels. Since FC has the knowledge of the quality of estimates at nodes $i$, $j$ and $k$, all the calculations can be done at the FC. Then it sends control signals to selected nodes informing them the allocated power levels.

## V. Simulation Results

In this section, we investigate the performance obtained by our proposed algorithm. We will compare the performance with the case when all nodes transmit at their maximum powers. Parameters used for simulations are: number of distributed nodes $N = 51$, estimator variances $V_i \sim \mathcal{U}[1, 20]$. We assume that all channel gains follow Rayleigh distributions with all channel coefficients normalized so that $\mathbb{E}\left\{h^2\right\} = 1$. For our simulation, we have chosen $\lambda_n = \frac{V_{max}}{V_n}$, where $V_{max} = \max_n V_n$.

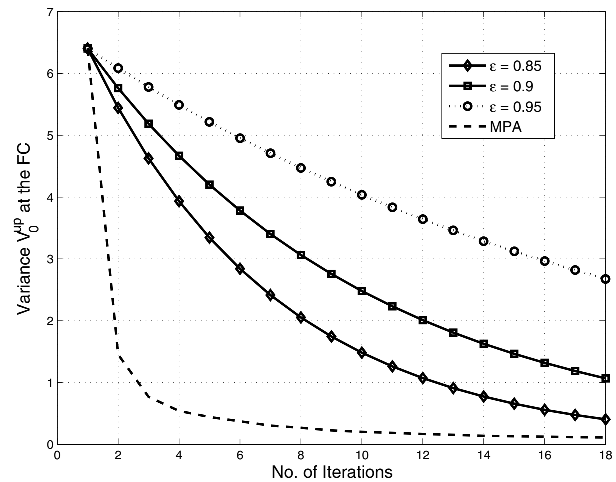


Fig. 3. Updated variance at the FC using Shapley value-based algorithm for different values of $\epsilon$.

Figure 3 shows the performance of the proposed algorithm as local estimates from the distributed nodes are used by the FC to sequentially update its own estimates. For each iteration in Fig. 3, local estimates from 3 different nodes are considered. As it can be seen, the quality of estimate at the FC improves as more nodes are incorporated into estimation process. Algorithm 1 provides the system manager with the flexibility to control the rate at which the variance of estimate at the FC decreases. In Fig. 3, we have shown how the values of $\epsilon$ can affect the rate of improvement of the quality of estimate at the FC. The monotonic decrease in variance at the FC center is also shown for the case when all nodes transmit at their maximum powers (MPA) with the proposed algorithm. By MPA (Maximum Power Allocation), we mean to follow all the steps in the proposed algorithm except for setting $P_i = \bar{P}$.

Figure 4 shows network lifetime improvement at the end of each time period or estimation block using the proposed algorithms. By each time period or estimation block, we mean that all distributed sensor nodes monitor/sense a PoI and the data collected by the sensor nodes are sent to the FC for estimation purpose. Since FC is equipped with sufficient energy, we are only concerned about the distributed nodes. We assume that each distributed node is provided with fixed limited energy at the beginning of the estimation process. After each estimation block, some amount of node energy is dissipated due to data communication and processing, and new lifetime of the sensor network is updated by the FC. At the end of the $j$-th time block, the network lifetime can be defined as $T^j_{net} = \min_i \left( \frac{E_i^{j-1} - P_i^j t_p}{\bar{P}} \right)$, where $E_i^{j-1}$ is the energy available at the sensor node $i$ at the end of $(j-1)$-th time period, $P_i^j$ is the power to be spent by the node $i$ during the $j$-th estimation block and $t_p$ is the time each node spends transmitting to the FC. For our simulation, we have used $t_p = 1$ sec, $\bar{P} = 1$ watt and initial node energy $E_i^0 = 10$ joule for $i \in \mathcal{N}$. It can be seen that there is considerable increase in the overall network lifetime using the proposed algorithm. This is because: Algorithm 1 ensures that node with comparatively higher battery life is allowed to transmit at a higher power than that with less battery life, which leads to an overall increase of the network lifetime.

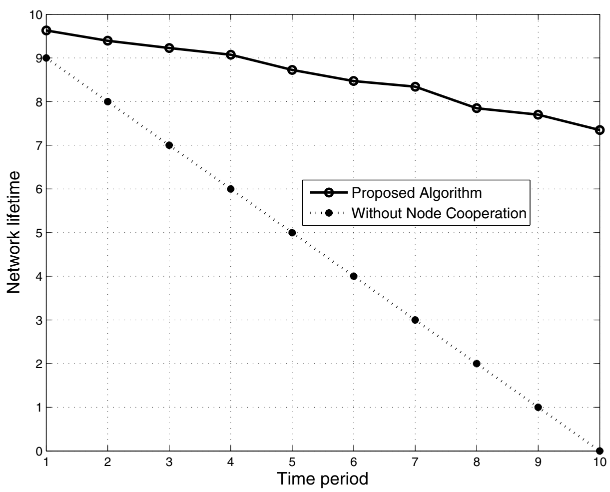


Fig. 4. Network lifetime improvement using the proposed algorithm for equal initial node energy with $\epsilon = 0.85$.

In Fig. 5, we assume that sensor nodes' lifetimes are uniformly distributed as $\mathcal{U} \sim [0, 10]$. Network lifetime using our proposed algorithm and MPA are obtained by averaging over 100 initial lifetime realizations. Figure 5 shows the average lifetime performance and improvement in the updated variance at the FC as a function of the time period/estimation block. We have used $t_p = 0.1$ sec and $\bar{P} = 1$ watt. It can be seen that although MPA reaches the desired quality of estimate at the FC faster than that with the proposed algorithm, our proposed algorithm outperforms MPA as far as network lifetime improvement is the objective.

Figure 6 shows network lifetime as a function of processing time $t_p$. Network lifetime is represented in terms of the number of estimation tasks the sensor network can perform before at least one node runs out of energy. In obtaining Fig. 6, we have fixed the rate controlling parameter $\epsilon = 0.85$ and target final variance at the FC $V_t = 0.15\times$(*initial variance at the FC*). At the end of each estimation task node lifetimes are updated by subtracting the energy spent. It can be seen from Fig. 6 that the proposed algorithm performs better than the MPA in terms of network lifetime improvement. As one would expect while the processing time $t_p$ increases, network lifetime in both cases decreases. Note that, MPA might achieve the target quality of estimate at the FC with a few nodes transmitting at a higher power while the proposed algorithm might use a large number of nodes transmitting at a lower power levels.

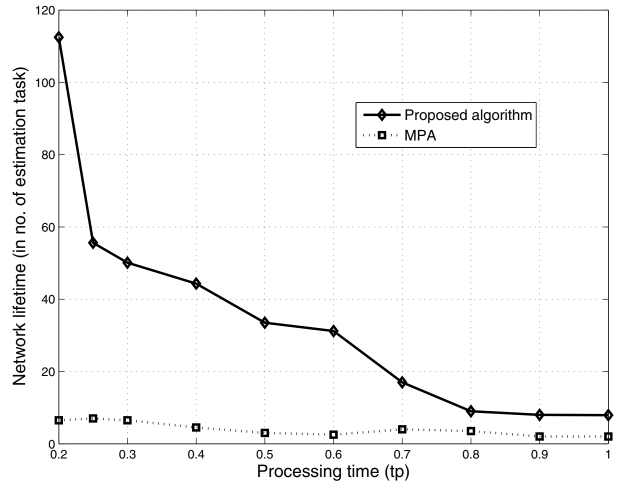


Fig. 6. Network lifetime in number of estimation task as a function of processing time ($t_p$) for random initial node energy.

Let us also define the lifetime of the sensor network as the time at which a certain fraction $\alpha \in [0, 1]$ of the distributed nodes have the remaining energy/lifetime below a certain threshold value. For our simulation we assume that the initial lifetimes are distributed as $\mathcal{U} \sim [5, 10]$, processing time $t_p = 2$ sec and lifetime threshold to be 4.8 sec. We have fixed the rate controlling parameter $\epsilon = 0.85$ and target final variance at the FC $V_t = 0.75\times$(*initial variance at the FC*). Node lifetimes are updated at the end of each estimation task. It can be seen from Fig. 7 that the proposed algorithm performs better than the MPA in terms of network lifetime improvement. Figure 7 shows that for both of the cases, network lifetime increases with the increase of $\alpha$ which is expected. Note that the improvement in network lifetime is more with the proposed algorithm because of the power allocation strategy used in the proposed Algorithm 1.

## VI. Conclusion

In this paper, a cooperative game-theoretic framework has been proposed to achieve a fair allocation of transmit power for collaborating nodes in a Fusion center (FC) based wireless sensor network tasked with sequential estimation of a non-random parameter. In particular, we proposed an algorithm based on the concept of the Shapley function to arrive at a fair allocation of power for the nodes. Through simulation results, we have shown that the proposed algorithm achieves target quality of estimate at the FC while improving the overall network lifetime.

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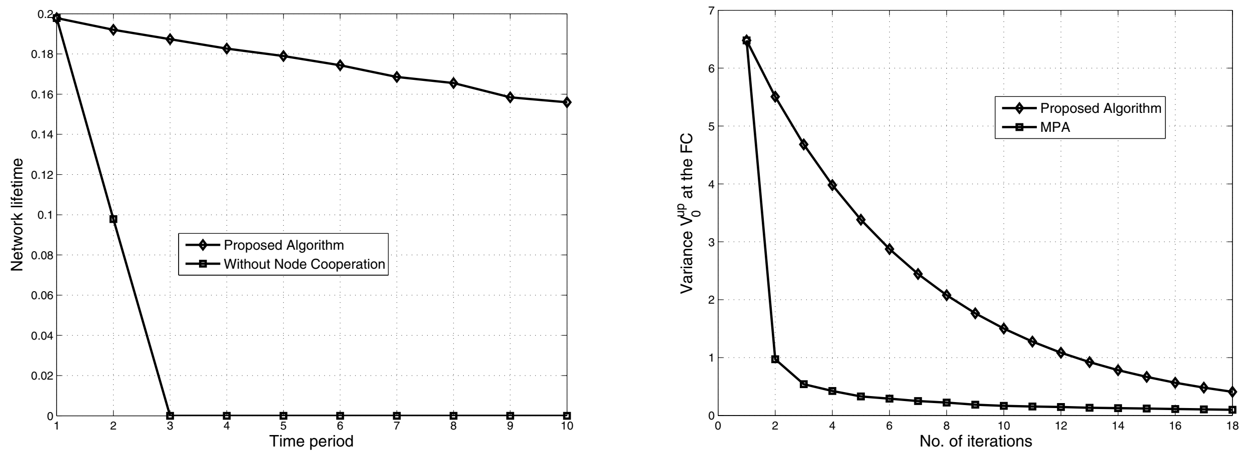


(a) (b)

Fig. 5. Improvement in the (a) Network lifetime, (b) Variance of estimation at the FC for random initial node energy with $\epsilon = 0.85$.

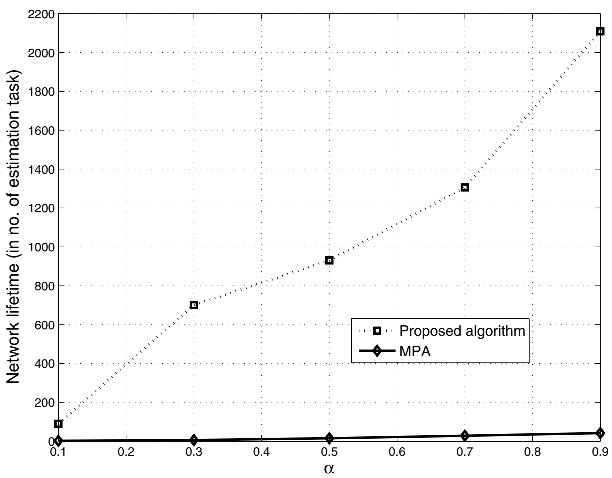


Fig. 7. Network lifetime in number of estimation task as a function of $\alpha$ for random initial node energy.

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