DISTRIBUTED CENSORING WITH ENERGY CONSTRAINT IN WIRELESS SENSOR NETWORKS

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ABSTRACT

In wireless sensor networks (WSNs), energy is always precious for sensor nodes. To save energy, censoring is introduced to cut the total number of transmission by only transmitting informative data. This algorithm, however, ignores the energy consumption during the delivery of parameters, which can be significant comparing to the saved power. In this paper, we consider the adaptive censoring from the energy perspective. A distributed censoring algorithm with energy constraint is developed that allows sensor nodes to make autonomous decisions on whether to transmit the incoming data. We show that with the proposed algorithm, the overall energy consumption of the WSNs is reduced, while the performance loss in terms of the estimation error is negligible. Simulation results validate its effectiveness.

Index Terms— Distributed censoring, energy constraint, recursive least squares, wireless sensor networks.

1. INTRODUCTION

Wireless sensor networks (WSNs) become popular in recent years, thanks to technology advances in sensors, communications and computations. The applications of WSNs include environmental monitoring, industrial control, smart home, etc. [1], where sensor nodes are deployed over a geographical area of interest to sense the environment, and a fusion center (FC) is applied to collect data. The nature of sensor nodes determines that the energy is always a critical constraint when deploying WSNs. Reducing the data transmission can be an effective way to reduce the energy consumption [2].

There are a number of data-reduction techniques used in parameters estimation with WSNs, such as collaborative data covariance-based dimensionality reduction using convex optimization [3] [4], measurement quantization [5] and compressive sensing [6]. However, these proposed protocols either require collaboration among sensors in the data-reduction step, or require several rounds of sensor nodes to FC communication for effective data-reduction. Censoring has recently been employed to select data for estimation of parameters and dynamical processes in resource-constrained WSNs [7] [8]. Authors in [9], [10] and [11] confirmed that estimation accuracy of censored measurements can be comparable to that based on uncensored data. In [12]and [13], authors investigated distributed measurement censoring method for estimation in WSNs, which allowed sensor nodes to make autonomous decisions about whether to censor the incoming data based on the rule of having least impact on the estimator mean-square error (MSE). However, such algorithms ignore the energy cost associated with censoring. In [14], the authors focused on optimum selective transmission scheme for energy-limited WSNs, but the data censoring for distributed estimation is not explored.

In this paper, we focus on the data reduction problem with energy constraint in WSNs. We assume that the sensor nodes are battery powered thus suffer from the energy constraint. The FC has its own power supply and is free of energy limitation. We propose a distributed censoring method for parameters estimation in WSNs. The proposed algorithm takes the energy constraint of sensor nodes into account. Each node can make autonomous decisions on whether to transmit the incoming data. We show that with the proposed algorithm, the overall energy consumption of the WSNs is reduced, while the performance loss in terms of the estimation error is negligible.

The rest of this paper is organized as follows. Section II introduces the framework of distributed censoring method with energy constraint for WSNs. Performance analysis of the proposed censoring approach is presented in Section III. Section IV shows the simulation results, and Section V concludes the paper.

Notations: Lower-(upper-) case boldface letters denote column vectors (matrices). Calligraphic symbols are reserved for sets, while symbol $(\cdot)^T$ stands for transposition. $\phi(t) = (1/\sqrt{2\pi})\exp(-t^2/2)$ denotes the standardized Gaussian probability density function (PDF) and $Q(z) = \int_z^{+\infty} \phi(t)\mathrm{d}t$ denotes the associated complementary cumulative distribution function. Vector $\mathbf{I}$ denotes the identity matrix. Positive definiteness (semi-definiteness) of a symmetric matrix $\mathbf{B}$ is denoted as $\mathbf{B} \succeq \mathbf{0}$ (respectively, $\mathbf{B} \preceq \mathbf{0}$). An estimation for parameters $\boldsymbol{\theta}$ will be represented as $\hat{\boldsymbol{\theta}}$.

2. SYSTEM MODEL AND PROBLEM FORMULATION

Consider a WSN with K sensor nodes $\{\mathcal{S}_k\}_{k=1}^K$ randomly deployed over a geographical area. Unknown parameters $\boldsymbol{\theta} \in \mathbb{R}^p$, where p is the length of parameters, are related to the measurement $y_k^* \in \mathbb{R}$ at each sensor node by the linear regression model [12] [13]

$$y_k^* = \mathbf{h}_k^T \boldsymbol{\theta} + v_k, \;\; k = 1, \ldots, K, \tag{1}$$

where the regressors $\{\mathbf{h}_k\}_{k=1}^K$ are known at the FC, and v_k denotes uncorrelated, zero-mean, Gaussian distributed noise. Without loss of generality, we assume that the noise variance is σ^2 for all K sensors.

If all $\{y_k^*\}_{k=1}^K$ are available at the FC, the maximum likelihood

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estimation of $\boldsymbol{\theta}$ would be the least squares (LS) estimator [15]

$$\hat{\boldsymbol{\theta}}_{ls}(K) = \Big(\sum_{k=1}^{K} \mathbf{h}_k \mathbf{h}_k^T\Big)^{-1} \sum_{k=1}^{K} y_k^* \mathbf{h}_k. \tag{2}$$

The performance of the estimator is assessed by the covariance matrix $\mathbf{C}(K) = \sigma^2 (\sum_{k=1}^{K} \mathbf{h}_k \mathbf{h}_k^T)^{-1}$ [15].

In general, LS solution can only deal with a batch of data samples. To deal with the large datasets, we would like to reduce the overall computational complexity of the estimation task as well as the total number of utilized observations y_k^* and/or $\mathbf{h}_k$ [11].

Data censoring can be applied to reduce the number of observations adopted for estimation. With $\mathcal{R}_k$ denoting the censoring interval, a generic censoring rule to select data in (1) is given by

$$y_k = \begin{cases} \star, & \text{if } y_k^* \in \mathcal{R}_k, \\ y_k^*, & \text{otherwise.} \end{cases} \tag{3}$$

where $\star$ denotes an unspecified value. If $y_k^* \in \mathcal{R}_k$, the value of y_k^* is censored and we only know that $y_k \in \mathcal{R}_k$ for the set $\mathcal{R}_k$; otherwise, the exact measurement $y_k = y_k^*$ is obtained as the incoming data contains additional information that previous observations may not have [11].

Fig. 1 illustrates the data censoring in WSNs. In this setup, sensor nodes transmit their observations to the FC. Inter-sensor transmission is not considered. Instead of transmitting all observations, A total of $\bar{K}(< K)$ sensor nodes are selected to transmit their measurements to FC during one estimation period.

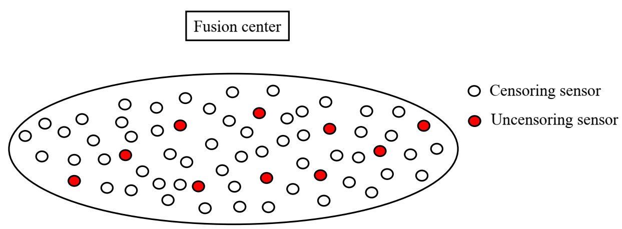

Fig. 1. Data censoring in WSNs.

The rule of selecting $\bar{K}$ is to minimize the estimation error over all possible selections. We assume that $\mathbf{h}_k$, σ^2 and $\bar{K}$ are available at the FC, since such information can be learnt from the nature of the problem or acquired during a training phase.

Now the optimization problem is to select at most $\bar{K}$ regressors from $\{\mathbf{h}_k\}_{k=1}^{K}$ for which the selected $\{\mathbf{h}_k^T \boldsymbol{\theta}\}_{k=1}^{\bar{K}}$ fit the measurements $\{y_k^*\}_{k=1}^{K}$ best in the LS sense. The distributed censoring method yields [13]

$$\boldsymbol{s}^* = \underset{\boldsymbol{s} \in \{0,1\}^K}{\arg\min} \sum_{k=1}^{K} (y_k^* - s_k \mathbf{h}_k^T \boldsymbol{\theta})^2 \tag{4a}$$

$$s.t. \sum_{k=1}^{K} s_k \leq \bar{K}, \tag{4b}$$

where $\boldsymbol{s}^*$ is a vector of binary $\{0,1\}$ selection variables. The censoring algorithm indeed minimizes the estimation error. However, this model does not consider the energy cost, and the efficiency of (4) in terms of selecting informative data depends on the initial LS estimation $\bar{\boldsymbol{\theta}} = \hat{\boldsymbol{\theta}}_{ls}(L)$ as in (2) where $p < L \ll K$ [10].

To deal with the impact of the initial estimation on estimation performance, we assume a multiple time slots scenario. Fig. 2 illustrates the data censoring with $T = 3$ time slots in WSNs. During each time slot, only $\bar{K} = 10$ sensor nodes are selected to transmit their measurements to FC. Additionally, censoring is performed independently at each sensor node during each time slot.

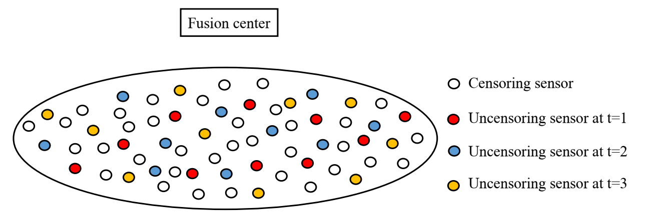

Fig. 2. Data censoring with $T = 3$ in WSNs.

The energy constraint, on the other hand, is critical to WSNs. A fair data selection method should consider the energy consumption during the data transmission. In WSNs, the energy consumed by the transceiver and the signal processing unit can be considered as a constant. The energy dissipated is approximately $\epsilon_{\text{elec}} = 400$nJ/byte to run the transmitter or receiver circuitry. The energy consumption by the power amplifier, on the other hand, greatly depends on the Euclidean distance d_k between the sensor node k and the FC. A simplified model of energy consumption per byte of the power amplifier is $\epsilon_{\text{amp}} d_k^2$, where $\epsilon_{\text{amp}} = 800$pJ/byte/m^2. As the data received and transmitted are usually short messages, we assume that the data length of the packet is m bytes for both transmitter and receiver. Thus, the total transmitting energy consumption would be $m\epsilon_{\text{elec}} + m\epsilon_{\text{amp}} d_k^2$, the total receiving energy consumption is $m\epsilon_{\text{elec}}$ [16]. To simplify notation, we normalize the energy in terms of receptions, that is to say, each reception consumes a unit of energy, while each transmission from sensor k to FC consumes [17]

$$E_k = 1 + \beta d_k^2, \tag{5}$$

where $\beta = \epsilon_{\text{amp}} / \epsilon_{\text{elec}} > 0$.

During each time slot $t = 1, \cdots, T$, $\boldsymbol{s}_t^*$ is the selection vector at time slot t which can be obtained by solving the following optimization problem

$$\boldsymbol{s}_t^* = \underset{\boldsymbol{s}_t \in \{0,1\}^K}{\arg\min} \sum_{k=1}^{K} \big[\alpha_{tk} (y_{tk}^* - s_{tk} \mathbf{h}_{tk}^T \boldsymbol{\theta})^2 + (1 - \alpha_{tk}) s_{tk} E_k\big] \tag{6a}$$

$$s.t. \sum_{k=1}^{K} s_{tk} \leq \bar{K}, \tag{6b}$$

where y_{tk}, $\mathbf{h}_{tk}$, and s_{tk} are the measurement, regressor and the selection variable of sensor node k at time slot t, respectively; α_{tk} ($0 \leq \alpha_{tk} \leq 1$) and $1 - \alpha_{tk}$ are the weights of estimation performance and transmission energy cost of sensor k at time slot t, respectively. Comparing to estimation performance, if energy cost is more important for the WSNs, a smaller α_{tk} is chosen; otherwise, a larger α_{tk} is chosen. If energy cost is not considered, i.e., $\alpha_{tk} = 1$, problem (6) reduces to the original censoring problem (4).

In the next section, we derive an adaptive censoring algorithm for (6). Its performance is also discussed analytically.

3. PROPOSED DISTRIBUTED CENSORING ALGORITHM WITH ENERGY CONSTRAINT

To deal with the optimization problem (6), we can include the constraint (6b) into the objective function with a Lagrange multiplier $\lambda_t(\lambda_t > 0)$. In addition, replacing the binary constraint $\{0,1\}$ by the interval one $[0,1]$ leads to a relaxed but convex alternative to (6). The updated quadratic optimization problem is given by

$$\boldsymbol{s}_t^*(\lambda_t) = \arg\min_{\boldsymbol{s}_t \in [0,1]^K} \sum_{k=1}^{K} \big[\alpha_{tk}(y_{tk}^* - s_{tk}\mathbf{h}_{tk}^T\hat{\boldsymbol{\theta}}_{t-1})^2 + (1-\alpha_{tk})s_{tk}E_k\big] + \lambda_t\Big(\sum_{k=1}^{K} s_{tk} - \bar{K}\Big), \quad (7)$$

where $\hat{\boldsymbol{\theta}}_t$ is initialized to $\hat{\boldsymbol{\theta}}_0 = \bar{\boldsymbol{\theta}}$, and $\hat{\boldsymbol{\theta}}_{t-1}$ is the estimated parameters after time slot $t-1$, which is available to sensor nodes through downlink broadcasting.

Problem (7) can be decomposable into K separate problems for which the k-th sub-problem attains its minimum at

$$s_{tk}^*(\lambda_t^*) = \frac{2\alpha_{tk}y_{tk}^*\mathbf{h}_{tk}^T\hat{\boldsymbol{\theta}}_{t-1} - (1-\alpha_{tk})E_k - \lambda_t^*}{2\alpha_{tk}(\mathbf{h}_{tk}^T\hat{\boldsymbol{\theta}}_{t-1})^2}, \quad (8)$$

where λ_t^* is the optimal Lagrange multiplier at time slot t. Slicing s_{tk}^* leads to the selection $s_{tk} = \mathbf{1}_{\{s_{tk}^*>0\}}$, where $\mathbf{1}_{\{\cdot\}}$ denotes the indicator function. The condition $s_{tk}^* > 0$ can be rewritten as

$$|y_{tk}^*| > \frac{(1-\alpha_{tk})E_k + \lambda_t^*}{2\alpha_{tk}|\mathbf{h}_{tk}^T\hat{\boldsymbol{\theta}}_{t-1}|} = \tau_{tk}(\lambda_t^*), \quad (9)$$

where $\tau_{tk}(\lambda_t^*)$ is the optimal threshold of sensor k at time slot t. The term y_{tk}^* and $\mathbf{h}_{tk}^T\hat{\boldsymbol{\theta}}_{t-1}$ must have the same signs; otherwise, $s_{tk} = 0$ since $s_{tk}^* < 0$.

The optimum λ_t^* should satisfy the inequality constraint (6b). Note that the number of uncensored measurements, $\sum_{k=1}^K s_{tk}$, is a random variable. Bounding $\mathbb{E}[\sum_{k=1}^K s_{tk}] = \sum_{k=1}^K \mathbb{E}[s_{tk}]$ not to exceed the desired value $\bar{K}$, yields

$$\begin{aligned}\sum_{k=1}^{K}\mathbb{E}[s_{tk}] &= \sum_{k=1}^{K}\Pr[|y_{tk}^*| > \tau_{tk}(\lambda_t)] \\ &= K - \sum_{k=1}^{K} Q\Big(\frac{-\tau_{tk}(\lambda_t) - \mathbf{h}_{tk}^T\boldsymbol{\theta}}{\sigma}\Big) - Q\Big(\frac{\tau_{tk}(\lambda_t) - \mathbf{h}_{tk}^T\boldsymbol{\theta}}{\sigma}\Big) \\ &= K - f(\lambda_t) \\ &\leq \bar{K}. \end{aligned} \quad (10)$$

It is shown that $f(\lambda_t)$ is a monotonically increasing function of λ_t. Replacing $\boldsymbol{\theta}$ by $\hat{\boldsymbol{\theta}}_{t-1}$, a one-dimensional grid search yields the desirable λ_t^* [13].

Supposing that the optimum λ_t^* and estimation $\hat{\boldsymbol{\theta}}_{t-1}$ are available at each sensor, censoring can be implemented autonomously at each sensor with the following rule

$$(y_{tk}, s_{tk}) = \begin{cases} (y_{tk}^*, 1), & \text{if } |y_{tk}^*| > \tau_{tk}(\lambda_t^*), \\ (\star, 0), & \text{otherwise.} \end{cases} \quad (11)$$

Applying recursive least squares (RLS) algorithm in FC with the censoring rule, yields [11]

$$\mathbf{C}_n = \frac{n}{n-1}\Big[\mathbf{C}_{n-1} - \frac{s_{tk}\mathbf{C}_{n-1}\mathbf{h}_{tk}\mathbf{h}_{tk}^T\mathbf{C}_{n-1}}{n-1+\mathbf{h}_{tk}^T\mathbf{C}_{n-1}\mathbf{h}_{tk}}\Big], \quad (12a)$$

$$\hat{\boldsymbol{\theta}}_n = \hat{\boldsymbol{\theta}}_{n-1} + \frac{s_{tk}}{n}\mathbf{C}_n\mathbf{h}_{tk}(y_{tk} - \mathbf{h}_{tk}^T\hat{\boldsymbol{\theta}}_{n-1}), \quad (12b)$$

where $\mathbf{C}_n$ is the sample estimation for $\mathbf{C}(K)$, and is typically initialized to $\mathbf{C}_0 = \epsilon\mathbf{I}$ for some small positive ϵ.

The computation and communication steps that constitute censoring are tabulated as Algorithm 1. During each time slot, prior to censoring, the FC calculates the optimum λ_t^* and broadcasts it and $\hat{\boldsymbol{\theta}}_{t-1}$ to all K sensors. Each sensor $\mathcal{S}_k$ autonomously decides its threshold τ_{tk}, and makes the censoring independently. Parameters estimation is performed in FC with RLS algorithm.

Algorithm 1 Distributed Censoring with Energy Constraint

Require: FC knows $\mathbf{h}_{tk}$, $\bar{K}$; $\mathcal{S}_k$ knows $\mathbf{h}_{tk}$, y_{tk}^*
1: initialize $n=1$, $\hat{\boldsymbol{\theta}}_0 = \bar{\boldsymbol{\theta}}$, $\mathbf{C}_0 = \epsilon\mathbf{I}$
2: **for** $t = 1, 2, \cdots, T$ **do**
3: FC: Finds λ_t^* from (10), broadcasts $(\lambda_t^*, \hat{\boldsymbol{\theta}}_{t-1})$
4: **for** $k = 1, 2, \cdots, K$ **do**
5: $\mathcal{S}_k$: Receives $(\lambda_t^*, \hat{\boldsymbol{\theta}}_{t-1})$, gets threshold τ_{tk}, y_{tk} and s_{tk}
6: **end for**
7: **for** $k = 1, 2, \cdots, K$ **do**
8: FC: Updates $\mathbf{C}_n$ and $\hat{\boldsymbol{\theta}}_n$ using (12), $n \leftarrow n+1$
9: **end for**
10: FC: $\hat{\boldsymbol{\theta}}_t \leftarrow \hat{\boldsymbol{\theta}}_n$
11: **end for**
12: FC: Set $\hat{\boldsymbol{\theta}} = \hat{\boldsymbol{\theta}}_T$

Next, we study the performance of the proposed method in terms of convergence.

Proposition 1: *The Cramér-Rao lower bound (CRLB) for the variance of distributed censoring method with energy constraint is given by* $\mathbb{E}[(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta})(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta})^T] - [\mathbf{I}_{TK}(\boldsymbol{\theta})]^{-1} \succeq \mathbf{0}$*, where the information matrix is given by*

$$\mathbf{I}_{TK}(\boldsymbol{\theta}) = \sum_{t=1}^{T}\sum_{k=1}^{K}\bar{\gamma}_{tk}(\boldsymbol{\theta})\mathbf{h}_{tk}\mathbf{h}_{tk}^T, \quad (13)$$

where

$$\bar{\gamma}_{tk}(\boldsymbol{\theta}) = \frac{1}{\sigma^2}\{1 - [Q(z1_{tk}) - Q(z2_{tk})]\} + \frac{1}{\sigma^2}\left\{\frac{[\phi(z1_{tk}) - \phi(z2_{tk})]^2}{Q(z1_{tk}) - Q(z2_{tk})} - [z1_{tk}\phi(z1_{tk}) - z2_{tk}\phi(z2_{tk})]\right\},$$

$$z1_{tk} = \frac{-\tau_{tk} - \mathbf{h}_{tk}^T\boldsymbol{\theta}}{\sigma}, \qquad z2_{tk} = \frac{\tau_{tk} - \mathbf{h}_{tk}^T\boldsymbol{\theta}}{\sigma}.$$

Proof of Proposition 1. Both the proposed algorithm and [13] are based on distributed censoring method. Compared to [13], the proposed method considers multiple time slots scenario and the energy cost is taken into account, which only changes the value of τ_{tk}. According to the Appendix C of [13], the CRLB of the proposed approach is obtained.

4. NUMERICAL RESULTS

In this section, we examine the proposed distributed censoring method with energy constraint. Simulations are done for the model in (1) with $K = 100$, $\bar{K} = 20$ and SNR=30 dB. The regressors $\mathbf{h}_{tk}$ and parameters vector $\boldsymbol{\theta}$ are picked uniformly over $[-1, 1]$ with dimension $p = 10$, α_{tk} is constant for each sensor node at each time slot. During all the simulations in this paper, there are K sensor

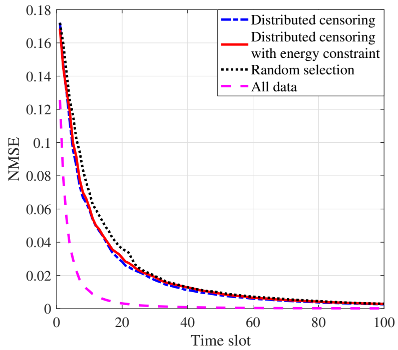

Fig. 3. Comparison of NMSE performances.

nodes randomly deployed in 1km × 1km area, the FC is located at (0.5km, 0.5km).

In the first experiment, we would like to check the algorithm performance in terms of modeling accuracy, which is defined as normalized mean-square error (NMSE $= ||\hat{\boldsymbol{\theta}}_t - \boldsymbol{\theta}||^2/||\boldsymbol{\theta}||^2$). The convergence of estimation in terms of NMSE is shown in Fig. 3, where the x-axis and y-axis represent time slot and NMSE, respectively; the black dashed line shows the NMSE of randomly selected method; the red solid line reveals the performance of the proposed algorithm with $\alpha_{tk} = 0.1$; the blue dashed line indicates the performance of distributed censoring method and the magenta dashed line represents the NMSE performance of all data method. From this figure, we observe that the NMSE of all data method benchmarks the performance of other methods, the proposed method performs slightly worse than distributed censoring method but slightly better than randomly selected method.

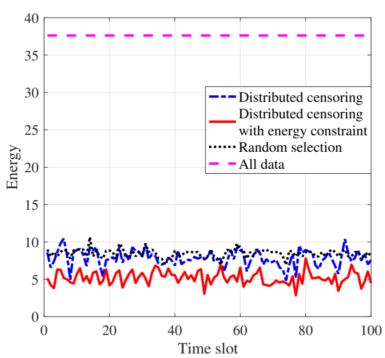

Fig. 4. Comparison of energy consumed.

Next, we study the energy efficiency of the proposed algorithm. Energy consumptions of different estimation methods at each time slot are shown in Fig. 4, where the x-axis and y-axis represent time slot and energy consumed, respectively; the legends are the same as the first simulation's. As Fig. 4 shows, the method using all data has the largest energy consumption because all data must be transmitted from sensors to FC. Energy consumptions of distributed censoring method and randomly selected method are basically the same, since the energy cost is not taken into account in both methods. The proposed method consumes the least energy than other methods. Because it not only considers the convergence performance, but also takes the energy cost into account.

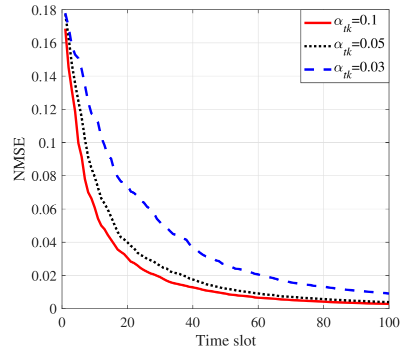

Fig. 5. Comparison of NMSE performances with different α_{tk}s.

In the third simulation, we would like to verify the convergence speed of the proposed algorithm with different α_{tk}s. In Fig. 5, the red solid line, black dashed line and blue dashed line represent the performance of the proposed method with $\alpha_{tk} = 0.1$, $\alpha_{tk} = 0.05$ and $\alpha_{tk} = 0.03$, respectively. We observe that when α_{tk} is small, the proposed algorithm converges slowly and eventually reaches a larger convergence value. When α_{tk} is large, it converges quickly and has a lower bound. Thus, the choice of α_{tk} is an important factor affecting the performance of the proposed method.

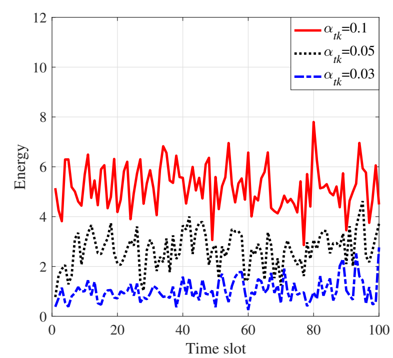

Fig. 6. Comparison of energy consumed with different α_{tk}s.

In the fourth simulation, we would like to continue our investigation of different α_{tk}s in terms of energy consumed. The legends are the same as the third simulation's. As Fig. 6 shows, the smaller the α_{tk}, the more important the energy consumption is in WSNs, the less energy is consumed. Appropriate choice of α_{tk} can achieve the trade-off between estimation performance and energy consumption.

5. CONCLUSIONS

In this paper, a distributed censoring method with energy constraint for parameters estimation in WSNs is explored. The energy cost is considered based on the distributed censoring algorithm. The overall energy consumption of WSNs is reduced, with little estimation performance loss. Simulations demonstrate that the proposed algorithm achieves a good trade-off between estimation performance and energy consumption.

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