Operational State Scheduling of Relay Nodes in Two-Tiered Wireless Sensor Networks

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2 authors:

Mohammad Fathi
University of Kurdistan

Vafa Maihami
Islamic Azad University of Sanandaj

Operational State Scheduling of Relay Nodes in Two-Tiered Wireless Sensor Networks

Mohammad Fathi and Vafa Maihami

Abstract—**Operation state scheduling of relay nodes (RNs) in two-tiered wireless sensor networks is the focus of this paper. From multiple access control (MAC) viewpoint, scheduling of transmit, receive, and sleep operation states of RNs is formulated as an optimization problem under the objective of energy cost minimization. This problem is computationally intractable to solve optimally for practical problem sizes. With the perspective of a synchronous and schedule access MAC protocol, the problem is tackled using dual decomposition, and the solution is achieved collaboratively by RNs continually over time. To make the solution practically possible, a stochastic approximation iteration is provided, which results in an energy-aware MAC protocol with linear complexity. This protocol attains statistical convergence with respect to the time-varying channel state information in the time of its scope. Numerical results demonstrate the effectiveness of this protocol in terms of consumed energy in comparison with classical protocols as a result of eliminating *idle listening* in the network.**

Index Terms—**Multiple access control (MAC), operation state scheduling, optimization, statistical convergence, wireless sensor networks (WSNs).**

I. Introduction

Wireless sensor networks (WSNs) are becoming a promising technology in environmental monitoring and distributed data processing [1]. A number of small and low-cost nodes are deployed in an area to perform data acquisition and accordingly to provide a central sink with the aggregated information. To extend the coverage area and to prolong the network lifetime, researchers have investigated typical networks, known as two-tiered WSNs [2], [3]. The idea is to decompose the functionality of the network into *coverage* and *connectivity* tiers (see Fig. 1). Sensor nodes (SNs), deployed in the sensing area, form the coverage tier and monitor the entire field of coverage. On the other hand, relay nodes (RNs), on the top of this tier, form the connectivity tier and perform link establishment and connectivity between the SNs and the sink node. Two-tiered WSNs are generally cluster-based networks, where each RN acts as a cluster head in the corresponding cluster. This node aggregates data from SNs and forwards the processed data to the sink node. The study of relay and sink node placement as a critical requirement in two-tiered WSNs have been extensively done in the literature [4]–[7].

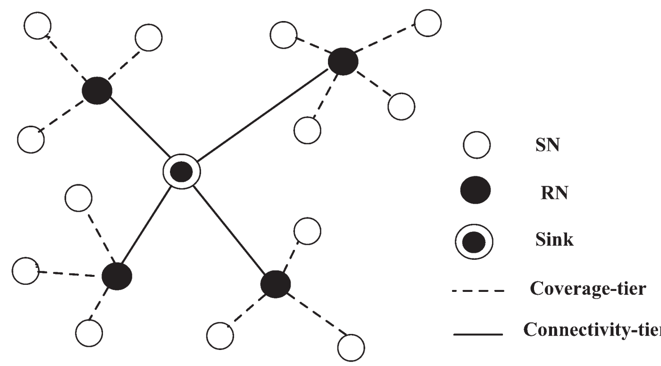

Fig. 1. Two-tiered WSN.

One key performance measure in WSNs is the network lifetime. Network nodes are battery powered and generally cannot be recharged after being deployed. Owing to the impact of nodes' radio functionality on the network energy consumption, we study here scheduling of RN operation states in the viewpoint of multiple access control (MAC) protocol. This protocol schedules RN operation states in order to avoid interference using a centralized or distributed manner. Following a MAC protocol, an RN switches its own radio on to be in active state for data aggregating and forwarding. In this state, an RN can either transmit to the sink node, receive from the sensors in the corresponding cluster, or ultimately be in idle listening, characterized with power wasting [8]. After a period of time with no activity, the node switches its radio off and enters the sleep state to save energy. Ideally, an RN should be active only during transmit and receive operations without idle listening. Therefore, an energy-aware MAC protocol is required to adaptively schedule the operation states, i.e., *transmit*, *receive,* and *sleep*, of individual RNs [9] under the objective of energy consumption minimization.

The importance of energy efficiency in WSNs motivates the design of MAC protocols in the literature. The survey in [10] investigates the similarities and differences of existing MAC protocols, and that in [11] classifies them based on problems dealt with. From these studies, MAC protocols in WSNs can be classified in two aspects: *synchronous* or *asynchronous* and *random channel access* or *schedule channel access*. In synchronous protocols, neighboring nodes wake up periodically at the same time, whereas in asynchronous protocols, each node chooses its schedule autonomously. In random channel access, nodes with a packet to send contend for the channel access

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M. Fathi is with the Department of Electrical and Computer Engineering, University of Kurdistan, Sanandaj 66177-15177, Iran (e-mail: mfathi@uok.ac.ir).

V. Maihami is with Semnan University, Semnan 35196-45399, Iran (e-mail: vafa.maihami@uok.ac.ir).

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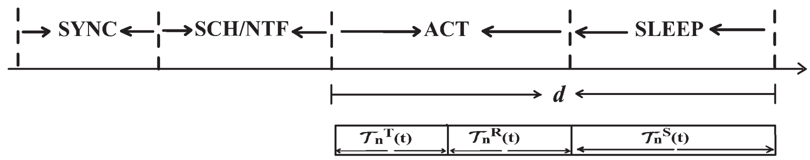

Fig. 2. Frame t of node n.

in the expense of collision, whereas in the schedule access network, resources are scheduled between transmit nodes to eliminate collision. The advantages and disadvantages of such classifications have been elaborated in the recent comprehensive review in [12].

S-MAC is a classical synchronous MAC protocol in WSNs, in which the time is divided into repeated cycles and each is further divided into active and sleep periods [13]. Nodes without activity return to the sleep mode until the start of the next cycle. The improvement of S-MAC has been investigated in [14] and [15]. In synchronous protocols, more trend is on scheduling schemes such as time-division multiple access (TDMA) that are collision free, and accordingly, there is more space for channel utilization [12], [16]. Following this approach, energy-efficient scheduling schemes are investigated in [17]–[19]. Under the objective of energy-efficient scheduling, heuristic and greedy algorithms have been proposed in the literature for establishing coverage and connectivity tiers in two-tiered WSNs [20], [21]. Genetic algorithm has been also employed to solve energy-aware scheduling and routing problems in two-tiered WSNs in [22] and [23], respectively.

The design of an energy-aware MAC protocol for *single-hop* WSNs has been investigated by the authors in [24]. The extension of this work for the case of *two-tiered* WSNs is the focus of this paper. In particular, we propose an energy-aware synchronous MAC protocol to schedule the operation states of RNs. This protocol is to schedule the *transmit*, *receive*, and *sleep* operation states at individual RNs in the connectivity tier. During the receive state of each RN, the corresponding SNs in the coverage tier are assumed to access the channel in a random or schedule manner for data delivery to the RN. The protocol is formulated as an optimization problem with the objective of minimizing the average cost of consumed energy to perform a certain task during a time horizon. The problem is computationally intractable to solve optimally for large-scale WSNs and that it requires the channel state information of the connectivity tier in the beginning of the time horizon. Alternatively, it is decomposed into a set of subproblems corresponding to individual RNs to be run over the time continually. Under the assumption of fading channels between the sink and RNs, we then propose an adaptive algorithm that makes scheduling decisions iteratively to come up with statistical convergence.

Our algorithm is different than those in [14] and [15] in that our algorithm is a schedule access scheme to mitigate the channel interference. Moreover, differently from [17]–[21] and the bulk of the literature, our problem performs state scheduling in a time horizon with time-varying channels, rather than constant-gain channels. More importantly, the problem complexity breaks down into subproblems over the time horizon so that the time complexity decreases and accordingly the need for heuristic algorithms such as those in [22] and [23] is avoided. Channel gains are taken into account progressively over the time so that the need for *a priori* channel knowledge is avoided.

This paper is organized as follows. The system model and problem formulation are given in Section II. The solution of the problem and proposed scheduling algorithm is presented in Section III. Numerical results are given in Section IV, and this paper is concluded in Section V.

II. System Model and Problem Formulation

We consider energy-efficient scheduling in a two-tiered WSN with a sink node and a set $\mathcal{N} \triangleq \{n : n = 1, \ldots, N\}$ of RNs. These nodes access the air channel in the connectivity tier using a TDMA scheme. During a time horizon $\mathcal{T}$ consisting of frames, indexed by $t \in \mathcal{T}$, each RN n aggregates data from SNs in the corresponding cluster with rate λ_n^t in frame t. The structure of frame t is shown in Fig. 2. Like all synchronized protocols, this frame starts with a SYNC period during which RNs synchronize their clock with each other. In SCH/NTF period, operation state scheduling of RNs is decided, to be followed for the rest of the frame, and is notified to these nodes. At each RN n, two periods ACT (active) and SLEEP with total length of d will be *adaptively* scheduled into the transmit state (to the sink) of power p_n^T, the receive state (from SNs) of power p_n^R, and the sleep state of power p_n^S. A typical schedule is also shown in Fig. 2 where duration periods $\tau_n^T(t)$, $\tau_n^R(t)$, and $\tau_n^S(t)$ indicate transmit, receive, and sleep states, respectively.

The focus of this paper is on scheduling three operation states to perform energy optimization in the aforementioned setup. Accordingly, energy per RN per frame can be derived in terms of given power values and the fraction of time at each operation state as

$$W_n(t) = p_n^R \tau_n^R(t) + p_n^T \tau_n^T(t) + p_n^S \tau_n^S(t). \tag{1}$$

The channel between the sink and RN n is assumed to be a flat-fading channel with channel gain γ_n^t during frame t. This gain is unvaried during a frame but absolutely can vary over the successive frames. Under the assumption of known γ_n^t and by the means of adaptive modulation [25], channel capacity c_n between RN n and the sink is obtained as

$$c_n(\gamma_n^t) = B \log_2(1 + \gamma_n^t p_n^T / \sigma^2) \text{ b/s} \tag{2}$$

where B is the channel bandwidth in hertz, p_n^T is the transmit power, and σ^2 is the additive white Gaussian noise power.

The objective of state scheduling is to minimize the average cost of energy during the time horizon. From microeconomic viewpoint, the cost value is a convex and differentiable

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function of energy. Although the following proposed framework is valid for any function with these conditions, we proceed with quadratic cost function and present the state scheduling problem as:

$$\min_{\tau=\{\tau_n^T(t),\tau_n^R(t),\tau_n^S(t)\}_{n\in\mathcal{N}}^{t\in\mathcal{T}}} \frac{1}{L}\sum_{t=1}^{L}\sum_{n=1}^{N} W_n^2(t) \tag{3}$$

$$\text{s.t.}\quad \frac{1}{L}\sum_{t=1}^{L}\sum_{n=1}^{N} c_n(\gamma_n^t)\tau_n^T(t) \geq M \tag{4a}$$

$$\sum_{n=1}^{N}\tau_n^T(t) \leq d \qquad \forall t \tag{4b}$$

$$\frac{1}{L}\sum_{t=1}^{L}\left(c_n(\gamma_n^t)\tau_n^T(t) - \lambda_n^t\tau_n^R(t)\right) = 0 \qquad \forall n \tag{4c}$$

$$\tau_n^T(t) + \tau_n^R(t) + \tau_n^S(t) = d \qquad \forall n, t \tag{4d}$$

where L is the length of the time horizon $\mathcal{T}$ in frames. The parameter M in constraint (4a) is the average number of bits required by the sink node per frame to perform a certain task. Constraints (4b) state that the total transmit time to the sink node within a frame should not exceed the maximum active length d, as a result of TDMA channel access. Constraints (4c) force a balance between inflow and outflow rates at each RN in average. This is reasonably needed to have stable queues in RNs [26]. Finally, constraints (4d) are due to the constant ACT plus SLEEP length d, as shown in Fig. 2.

Problem (3)–(4) is nonlinear with $3NL$ continuous scheduling variables $\tau = \{\tau_n^T(t), \tau_n^R(t), \tau_n^S(t)\}_{n\in\mathcal{N}}^{t\in\mathcal{T}} \in \mathbb{R}_+$. Finding the optimal solution in practical problem sizes requires an exhaustive search with the worst case exponential complexity, which is absolutely prohibitive in WSNs with limited memory and processing resources. In addition, a centralized solution requires the channel state information $\{\gamma_n^t\}_{n\in\mathcal{N}}^{t\in\mathcal{T}}$ to be fully available *a priori*. This is reasonably not possible in practice due to the time-varying fading channels in the network. Alternatively, we consider the channel gains as random variables and derive a stochastic version of (3) and (4) as

$$\min_{\mathbf{x}=\{\tau_n^T,\tau_n^R,\tau_n^S\}_{n\in\mathcal{N}}} \sum_{n=1}^{N}\mathbb{E}_{\gamma_n}[W_n^2] \tag{5}$$

$$\text{s.t.}\quad \sum_{n=1}^{N}\mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T\right] \geq M \tag{6a}$$

$$\sum_{n=1}^{N}\tau_n^T \leq d \tag{6b}$$

$$\mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T - \lambda_n\tau_n^R\right] = 0 \qquad \forall n\in\mathcal{N} \tag{6c}$$

$$\tau_n^T + \tau_n^R + \tau_n^S = d \qquad \forall n\in\mathcal{N} \tag{6d}$$

where $\mathbb{E}_{\gamma_n}$ is expectation with respect to γ_n, and $\mathbf{X}$ is the set of optimization variables. Dropping the frame index t makes it possible to propose a statistical solution to (5) and (6) in the subsequent section.

III. State Scheduling Scheme

Problem (5)–(6) is a joint optimization of scheduling decisions not only across RNs but also across the time frames. Due to the concern of complexity and scalability, *distributed* solutions are favorable, in which all RNs collaborate together to find the global solution. In this section, we use dual decomposition to decouple the joint problem into subproblems solved by different RNs. Toward this end, we incorporate constraints (6a)–(6c) into the objective function (5) and form the Lagrangian function

$$\begin{aligned} L(X,\alpha,\beta,\zeta) &= \sum_{n=1}^{N}\mathbb{E}_{\gamma_n}\left[W_n^2\right] - \alpha\left(\sum_{n=1}^{N}\mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T\right] - M\right) \\ &\quad + \beta\left(\sum_{n=1}^{N}\tau_n^T - d\right) + \sum_{n=1}^{N}\zeta n\left(\mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T - \lambda_n\tau_n^R\right]\right) \end{aligned} \tag{7}$$

where $\alpha \geq 0$, $\beta \geq 0$, and $\zeta = \{\zeta_n\}_{n\in\mathcal{N}}$ are Lagrange multipliers associated with (6a)–(6c), respectively. Optimizing with respect to the primal variables X yields the dual function

$$D(\alpha,\beta,\zeta) = \inf_{\mathbf{X}}\{L(X,\alpha,\beta,\zeta)|(6d)\} \tag{8}$$

which provides a lower bound on the optimal solution of the primal problem (5)–(6) for every feasible value of the dual variables α, β, ζ. The tightest lower bound can be obtained by the dual problem

$$\max_{\alpha\geq 0,\beta\geq 0,\zeta} D(\alpha,\beta,\zeta). \tag{9}$$

This problem is always convex and can be solved using iterative methods [27]. To evaluate the dual function in (8), we rewrite (7) as

$$\begin{aligned} L(X,\alpha,\beta,\zeta) = \sum_{n=1}^{N}\Big(&\mathbb{E}_{\gamma_n}\left[W_n^2\right] - \alpha\mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T\right] + \beta\tau_n^T \\ &+ \zeta_n\left(\mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T - \lambda_n\tau_n^R\right]\right)\Big) \\ &+ \alpha M - \beta d. \end{aligned} \tag{10}$$

Exploiting the decomposable form of this expression, we rewrite (8) as

$$D(\alpha,\beta,\zeta) = \sum_{n=1}^{N} D_n(\alpha,\beta,\zeta_n) + \alpha M - \beta d \tag{11}$$

where

$$\begin{aligned} D_n(\alpha,\beta,\zeta_n) = \inf_{\mathbf{X}_n}\Big\{&\mathbb{E}_{\gamma_n}\left[W_n^2\right] - \alpha\mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T\right] + \beta\tau_n^T \\ &+ \zeta_n\left(\mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T - \lambda_n\tau_n^R\right]\right)|(6d)\Big\} \end{aligned} \tag{12}$$

is the dual function at RN n. Moreover, $\mathbf{X}_n = \{\tau_n^T, \tau_n^R, \tau_n^S\}$ is the optimization variable at this node. Consequently, we came up with separate dual functions at individual RNs through dual decomposition. Each dual function $D_n(\alpha, \beta, \zeta_n)$ can be approximated continually over the time frames, i.e., given $\alpha(t), \beta(t), \zeta_n(t)$ and also a certain γ_n^t at frame t and node n drops $\mathbb{E}_{\gamma_n}$ and evaluates its own dual function using optimization problem

$$\begin{aligned} \min_{\mathbf{X}_n} \; & W_n^2(t) - \alpha(t) c_n\left(\gamma_n^t\right) \tau_n^T(t) + \beta(t)\tau_n^T(t) \\ & + \zeta_n(t)\left(c_n\left(\gamma_n^t\right)\tau_n^T(t) - \lambda_n^t \tau_n^R(t)\right) \\ \text{s.t.} \; & \tau_n^T(t) + \tau_n^R(t) + \tau_n^S(t) = d. \end{aligned} \tag{13}$$

Inspecting this problem, energy $W_n(t)$ is substituted by its equivalent in (1) and $c_n(\gamma_n^t)$ can be calculated from (2) with given γ_n^t. Therefore, we come up with a quadratic convex problem that can be solved efficiently using existing solvers. In particular, we use gradient-based search iterations such as interior point method [27] to find the optimal solution $\mathbf{X}_n$ at each node n per frame t.

Having obtained $\{\tau_n^T(t), \tau_n^R(t), \tau_n^S(t)\}_{n\in\mathcal{N}}$ per frame t per RN and accordingly $D(\alpha(t), \beta(t), \zeta(t))$, it is time to solve the dual problem (9) to update Lagrange multipliers. Exploiting the convexity of this problem and the decomposable form of (11), we use a subgradient method. Beginning with an initial $\{\alpha(0), \beta(0), \zeta_n(0)\}$, given $\{\alpha(t), \beta(t), \zeta_n(t)\}$ at frame t, we obtain $\{\tau_n^T(t), \tau_n^R(t), \tau_n^S(t)\}_{n\in\mathcal{N}}$ from (13). Lagrange multipliers are then updated as

$$\alpha(t+1) = \alpha(t) + \delta\left(M - \sum_{n=1}^{N} \mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T\right]\right)^+ \tag{14a}$$

$$\beta(t+1) = \beta(t) + \delta\left(\sum_{n=1}^{N} \tau_n^T - d\right)^+ \tag{14b}$$

$$\zeta_n(t+1) = \zeta_n(t) + \delta\left(\mathbb{E}_{\gamma_n}\left[c_n(\gamma_n)\tau_n^T - \lambda_n \tau_n^R\right]\right) \tag{14c}$$

where δ is a step size, and the gradient terms are derived from (11). The aforementioned approach allows RNs to contribute separately toward obtaining the global solution.

Although the gradient iteration (14) is efficient to find the optimal scheduling, a key required knowledge is the probability density function (pdf) of γ_n's. Only with this knowledge, we can evaluate the expected value $\mathbb{E}_{\gamma_n}$. Assumption of known pdf of γ_n may be reasonable for theoretic studies. However, the importance of practical scheduling schemes motivates the optimal strategy by *learning* channel state information on the fly. Interestingly, a stochastic gradient iteration can be developed to solve (9) without the pdf of γ_n *a priori*. To this end, we consider dropping $\mathbb{E}_\gamma$ from (14) to devise online iterations for *adaptive* decisions based on per-frame realization γ_n^t as

$$\hat{\alpha}(t+1) = \hat{\alpha}(t) + \delta\left(M - \sum_{n=1}^{N} c_n\left(\gamma_n^t\right)\tau_n^T(t)\right)^+ \tag{15a}$$

$$\hat{\beta}(t+1) = \hat{\beta}(t) + \delta\left(\sum_{n=1}^{N} \tau_n^T(t) - d\right)^+ \tag{15b}$$

$$\hat{\zeta}_n(t+1) = \hat{\zeta}_n(t) + \delta\left(c_n\left(\gamma_n^t\right)\tau_n^T(t) - \lambda_n(t)\tau_n^R(t)\right) \tag{15c}$$

where hats are to stress that these iterations are stochastic estimates of those in (14). Provided that the channel state information process is stationary and ergodic, the stochastic gradient iteration (15) and the ensemble gradient iterations (14) consist of a pair of primary and averaged systems [28]. Convergence of such a stochastic gradient iteration can be established *statistically* provided that δ is small enough. Such a proof is provided in the Appendix.

Given the aforementioned solution of the joint problem (5)–(6), we are now in the position to propose RN operational state scheduling (RN-OSS) MAC protocol, as stated in Algorithm 1. This protocol is based on the iterative update of Lagrange multipliers in (15). As shown in this algorithm, RN-OSS is initialized with a set of Lagrange multipliers. At each frame t, RN n derives its own scheduling decisions and then updates the corresponding $\hat{\zeta}_n(t)$. This node also lets the sink node to know about $\tau_n^T(t)$ through a control and error-free channel. With this knowledge, the sink node updates $\hat{\alpha}(t)$ and $\hat{\beta}(t)$ as the system-wide Lagrange multipliers and then forwards this renew information to the RNs through a signaling channel.

Algorithm 1 RN-OSS MAC protocol

Initialization: $t = 0$, $\hat{\alpha}(0) = \alpha_{\text{init}}$, $\hat{\beta}(0) = \beta_{\text{init}}$, $\hat{\zeta}_n(0) = \zeta_{\text{init}} \quad \forall n \in \mathcal{N}$.
while $t \in \mathcal{T}$ **do**
  for $n \in \mathcal{N}$ **do**
    RN n obtains $\{\tau_n^T(t), \tau_n^R(t), \tau_n^S(t)\}$ from (13).
    RN n updates $\hat{\zeta}_n(t)$ using (15c).
  end for
  Sink node updates $\hat{\alpha}(t)$ and $\hat{\beta}(t)$ using (15a) and (15b) and then broadcasts to the RNs.
  $t = t + 1$.
end while

RN-OSS is partially distributed in the sense that each RN solves its version of problem (13) separately and updates its own Lagrange multiplier in (15c). The sink node as a central only updates Lagrange multiplier in (15a) and (15b) and finally notifies RNs of this information.

As in any distributed protocol, a concern is raised on the computational complexity and signaling overhead of RN-OSS. This protocol takes advantage of two decomposition levels over the time frames and RNs. First, rather than a whole scheduling decision for the time horizon *a priori*, scheduling decisions are made frame by frame. Second, each RN contributes to its own scheduling decisions separately. As a consequence of these decomposition levels, the exponential complexity of (3)–(4) is reduced to $O(LN)$ in RN-OSS, which is linear in the length of time horizon $\mathcal{T}$ and the number of RNs. With this significant achievement on complexity reduction, signaling overhead of RN-OSS is relatively low. Each node n sends transmit time $\tau_n^T(t)$ to the sink at each frame. The sink node, in return, broadcasts $\hat{\alpha}(t)$ and $\hat{\beta}(t)$ in the network. This is the only information required to be exchanged on the air per frame, which is worth the complexity reduction. Moreover, it is noteworthy that the statistical convergence of RN-OSS has been also proved in the Appendix.

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TABLE I
SIMULATION PARAMETERS

Parameter	notation	value
Transmit power	p_n^T	75 mW
Receive power	p_n^R	50 mW
Sleep power	p_n^S	25 mW
Noise power	σ^2	-60 dBm
Frame length	d	10 ms
Channel bandwidth	B	1 kHz
Minimum data per frame	M	50 bits
Step size	δ	0.0001

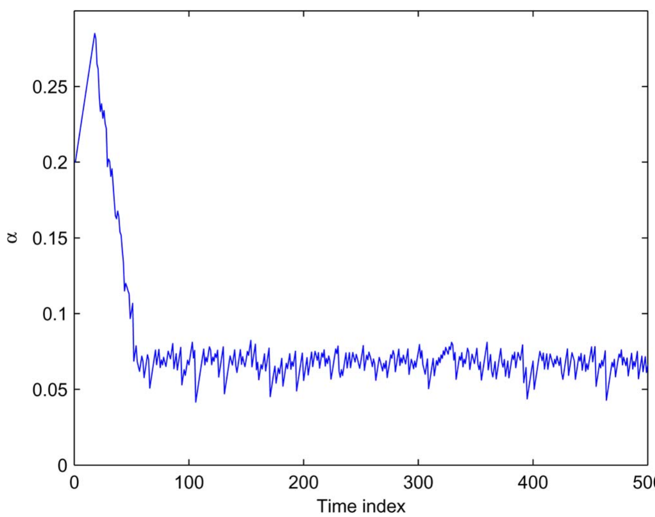

Fig. 3. Lagrange multiplier $\hat{\alpha}$.

IV. PERFORMANCE EVALUATION

Simulation results of RN-OSS are provided in this section. First, we consider a two-tiered network with $N = 10$ RNs located at the same distance from the sink node. The channel between each node and the sink is assumed to be a Rayleigh fading channel with average gain of 0 dB. Simulation parameters are provided in Table I. Aggregation rate in all RNs follows a Poisson process with mean 50 b/frame, i.e., 5 kb/s.

RN-OSS is run for 500 realizations of the fading channel. The Lagrange multiplier $\hat{\alpha}$ and instantaneous total energy over the simulation time are shown in Figs. 3 and 4, respectively. The resulting curves demonstrate the statistical convergence of RN-OSS. Variations in steady state are due to the variable channel state information in the network.

The average transmit, receive, and sleep times per RN per frame are shown in Fig. 5. Because of the same average channel gains, all the RNs mostly demonstrate the same behavior, i.e., the length of each operation state (τ_n^T, τ_n^R, τ_n^S) is approximately the same for all nodes. In particular, the frame of length 10 ms is uniformly distributed among RNs to transmit to the sink node.

As introduced in Section I, one fundamental MAC protocol designed for WSNs is S-MAC [13]. This scheme treats all the nodes similarly and divides each frame into two subframes. One node can be either in transmit state or in receive state in the first subframe, and it switches into sleep state in the second subframe. The performance of S-MAC is compared with RN-OSS in the following. For this purpose, we adopt a customized version of S-MAC for this comparison. During a frame, one-half of RNs transmit and one-half receive. Each RN alternates

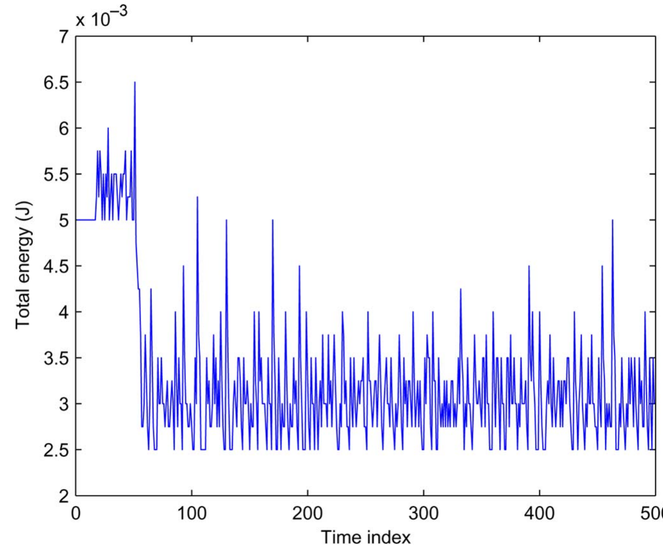

Fig. 4. Instantaneous total energy.

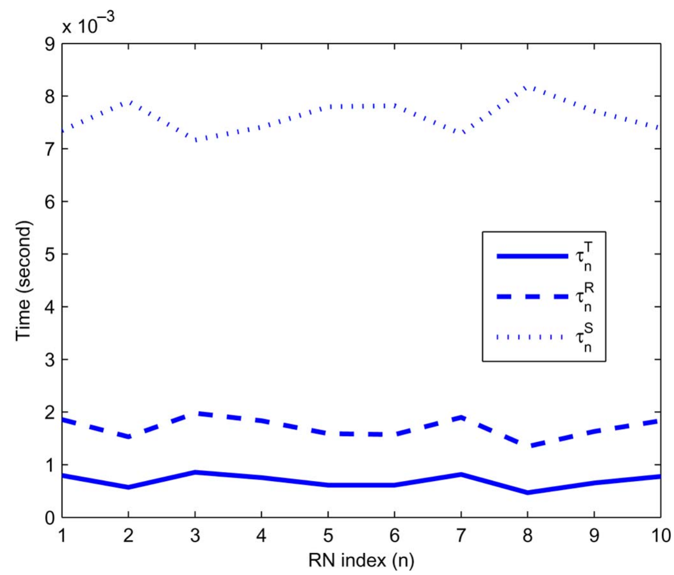

Fig. 5. Average scheduling times.

between transmit and receive states in two successive frames. Transmitting RNs in each frame use the frame length equally for transmitting to the sink node, i.e., $\tau_n^T(t) = (d)/(N/2) \forall t$. For more reasonable comparison, the receive time of every receiving RN n at frame t is obtained by

$$\tau_n^R(t) = \frac{c_n\left(\gamma_n^t\right)}{\lambda_n^t} \tau_n^T(t) \tag{16}$$

to satisfy constraint (6c), where $c_n(\gamma_n^t)$ is the channel capacity, as defined in (2). The rest of the frame at each transmitting or receiving RN is considered as sleep time. The adopted receive time in (16) is indeed a conservative view of S-MAC since this scheme originally does not include any relation between receive and transmit duration periods and accordingly results in an upper bound performance.

In the aforementioned network with ten nodes, the consumed energy per node during the simulation is shown in Fig. 6 for both RN-OSS and S-MAC. We also include results from

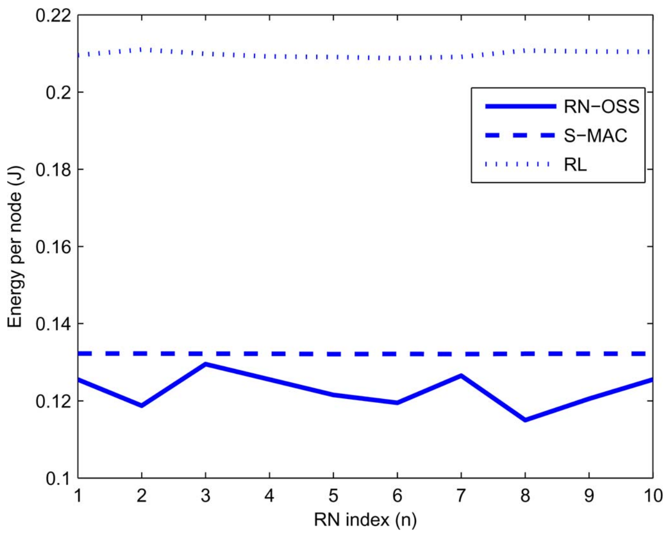

Fig. 6. Energy per RN.

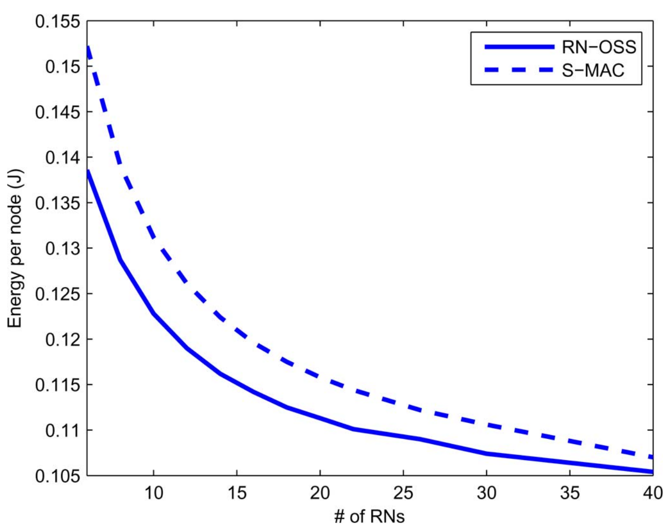

Fig. 7. Average energy per RN.

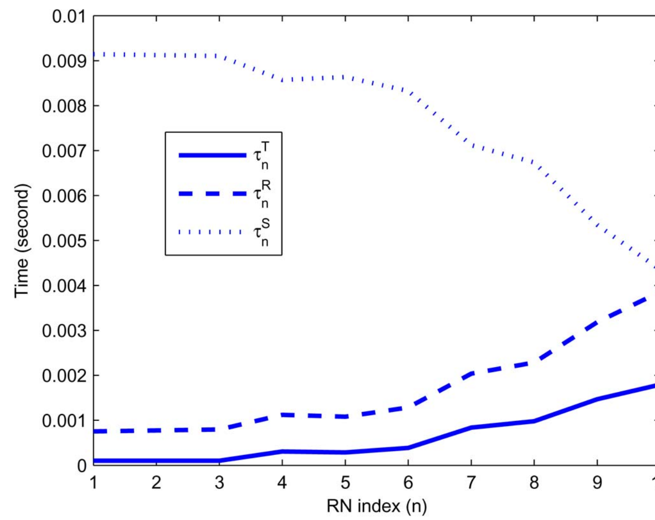

Fig. 8. Average scheduling times.

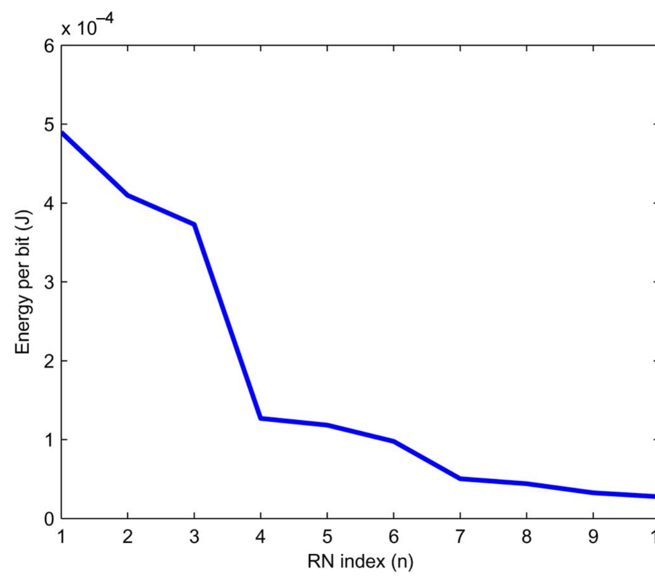

Fig. 9. Average energy per bit.

a distributed self-learning approach based on reinforcement learning (RL), such as [29]. As shown, RN-OSS results in the lowest energy for all nodes. The reason for this observation results from the capability of RN-OSS that allows all the RNs to have dynamic transmit and receive opportunities in accordance with their channel gains during each frame, resulting in no idle listening. This is in contrast to unintelligent S-MAC that contains either transmitted or received opportunity per frame per RN, probably with idle listening.

The average energy per RN is shown in Fig. 7, when the number of RNs varies between 6 and 40. RL scheme, due to its low performance, has been excluded to have a reasonable comparison between RL-OSS and S-MAC. Again, RN-OSS outperforms S-MAC for all instances. With the increase in the number of RNs, constraint (6a) has the possibility to be satisfied with a smaller number of bits handled by each RN. In other words, transmit and receive duration periods of RNs per frame tend to decrease, which in turn result in lower energy consumption and accordingly longer network life, as observed in Fig. 7. With further increase in the number of RNs, in the limit, we can say that these nodes get slept entirely during each frame in both RN-OSS and S-MAC schemes. Consequently, consumed energy during 400 accounted frames approaches 400 frames $\times$ $p_n^S d = 400 \times 25$ mW $\times$ 10 ms $= 0.1$ J. These results can be also observed in Fig. 7, where the performance gap between RN-OSS and S-MAC decreases and both converge to 0.1 J.

In the following, ten RNs are assumed to be located in different distances from the sink node with average channel gains $-4:1:5$ dB from node 1 to node 10, respectively. The average transmit, receive, and sleep duration periods of all nodes are shown in Fig. 8. Unlike the previous case, as the channel gain increases transmit time and as a result of constraint (6c), receive time also increases. Reasonably, sleep time decreases due to constraint (6d). As shown, low channel gain nodes are mostly slept. This observation means that it would be more energy efficient if the sink node gathers its required data (M bits per frame in average) from high channel gain RNs. To justify this statement, the average energy per bit during the simulation is shown in Fig. 9 for RNs. With the increase in the channel gain,

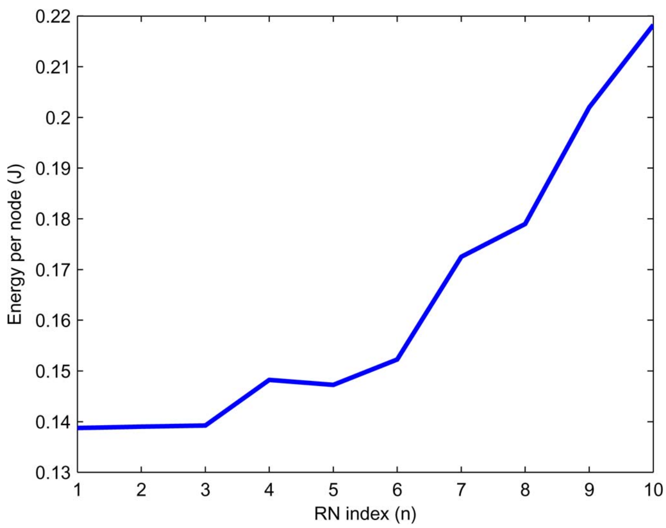

Fig. 10. Average energy per RN.

the required power in (2) to satisfy constraint (6a) is decreased, which results in smaller required energy for these nodes, as shown in this figure. This observation reveals the reason of allocating higher transmit times to higher channel gain RNs by RN-OSS in Fig. 8. Moreover, consumed energy per node is shown in Fig. 10. Higher energy for high channel gain nodes is intuitively expected due to the underlying convex cost function of energy and resulting high activity (transmit and receive time) of these nodes in Fig. 8.

V. Conclusion

A synchronized energy-aware MAC protocol, i.e., RN-OSS, has been proposed for RNs in WSNs. With the objective of increasing the network lifetime, the protocol schedules transmit, receive, and sleep operation states through a stochastic approximation iteration in a linear-complexity and low-signaling overhead. Numerical results demonstrated the statistical convergence of RN-OSS performance in spite of time-varying fading channels. Moreover, this protocol outperforms classical synchronized protocols as a result of eliminating idle listening. As shown by RN-OSS, in a network with divers channel gain nodes, it would be more energy efficient to gather required data from high channel gain RNs.

Appendix
Convergence of the Stochastic Iteration

As obtained in Section III, the solution of dual problem (9) is obtained by stochastic iteration

$$x(t+1) = x(t) + \delta\,(g(t))^{+} \tag{17}$$

where $x(t) \equiv \hat{\alpha}(t)$, and $g(t) \equiv M - \sum_{n=1}^{N} c_n(\gamma_n^t)\tau_n^T(t)$. Let x^* be the optimal solution of x. Taking *norm-2* of $(x(t+1) - x^*)$, we get

$$\begin{aligned}\|x(t+1) - x^*\|^2 &\leq \|x(t) + \delta g(t) - x^*\|^2 \\ &= \|x(t) - x^*\|^2 + 2\delta g(t)\,(x(t) - x^*) + \delta^2\,\|g(t)\|^2 . \end{aligned} \tag{18}$$

Considering the concavity of $D(x^*)$, we have $D(x^*) \leq D(x(t)) + \delta g(t)(x^* - x(t)))$ [30]. This implies

$$\begin{aligned}\|x(t+1) - x^*\|^2 \leq \|x(t) - x^*\|^2 \\ - 2\,(D^* - D(t)) + \delta^2\,\|g(t)\|^2\end{aligned} \tag{19}$$

where $D(t) \equiv D(x(t))$ and $D^* \equiv D(x^*)$. Taking a similar recursive approach from $x(t)$ to $x(0)$ as an initial value, we derive

$$\begin{aligned}\|x(t+1) - x^*\|^2 \leq \|x(0) - x^*\|^2 \\ - 2\sum_{i=0}^{t}(D^* - D(t)) + \delta^2 \sum_{i=0}^{t}\|g(i)\|^2 .\end{aligned} \tag{20}$$

Since the left-hand side is always nonnegative, we derive

$$2\sum_{i=0}^{t}(D^* - D(t)) \leq \|x(0) - x^*\|^2 + \delta^2 \sum_{i=0}^{t}\|g(i)\|^2 . \tag{21}$$

We take the following two assumptions.

1) $\|g(i)\| \leq G$, for all i.
2) $\|x(0) - x^*\|^2 \leq R^2$.

With reference to the system model in Section II, these assumptions are reasonable and can be provided in our case. Dividing both sides of (21) by $2t$, we derive

$$\frac{\sum_{i=0}^{t}(D^* - D(t))}{t} \leq \frac{R^2}{2t} + \frac{1}{2}\delta^2 G^2. \tag{22}$$

If $t \to \infty$, by the law of large numbers, we have

$$D^* - \bar{D} \leq \frac{1}{2}\delta^2 G^2 \tag{23}$$

where $\bar{D} = E[D(t)]$. Since D is a concave function, by Jensen's inequality [27], we have $\bar{D} \leq D(\bar{x})$, and accordingly

$$D^* - D(\bar{x}) \leq \frac{1}{2}\delta^2 G^2. \tag{24}$$

Finally, choosing step size δ small enough, we conclude that the stochastic iteration (17) converges statistically.

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Mohammad Fathi (M'10) received the M.Sc. and Ph.D. degrees in electrical engineering from Amirkabir University of Technology, Tehran, Iran, in 2003 and 2010, respectively. He conducted part of his Ph.D. research work in the Communications and Networking Theory Laboratory, Royal Institute of Technology, Stockholm, Sweden, in 2010.

From 2003 to 2006, he was a Lecturer with the Department of Electrical and Computer Engineering, University of Kurdistan, Sanandaj, Iran, where he is currently an Assistant Professor. His current research interests include network resource allocation and optimization, power scheduling, and smart grid control.

Vafa Maihami received the M.S. degree in computer engineering from the University of Kurdistan, Sanandaj, Iran, in 2012. He is currently working toward the Ph.D. degree in computer engineering at Semnan University, Semnan, Iran, working on artificial intelligence algorithms.

His research interests include wireless sensor networks, machine learning, machine vision, and image processing.