A Biologically-inspired Algorithm for Mission-critical Applications in Wireless Sensor Networks

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Abstract

Wireless sensor networks (WSNs) connect devices and enable collaboration on sensing and monitoring various physical phenomena for applications such as target tracking, infrastructure security, battlefield surveillance, health monitoring, and traffic control. WSNs are generally comprised of a large number of tiny sensor nodes that are battery powered. Therefore, existing medium access control (MAC) protocols for WSNs have mainly been designed for energy saving. However, existing WSN systems have considerable drawbacks, and especially limit coordination of sensor nodes for mission-critical applications, due to their large-scale nature. In this paper, we propose an energy-efficient and delay-guaranteeing algorithm inspired by biological systems, which have gained considerable attention as approaches for computing and problem solving. We introduce both a local status indicator and an active-status indicator for a sensor node to represent its local environmental conditions and its node state, respectively, in WSNs. From consideration of the analogies between cellular signaling systems and WSN systems, we formulate a new mathematical model that considers the networking challenges of WSNs. The proposed bio-inspired algorithm determines the state of the sensor node, as required by each application and as determined by the local environmental conditions, and the states of adjacent nodes. Simulation results indicate that the proposed scheme provides significant energy savings, as well as reliable delay-guarantee, by controlling the states of the sensor nodes.

Keywords: *Bio-inspired algorithm, Node coordination, Energy efficiency, Delay guarantees, Wireless sensor networks*

1. Introduction

Wireless sensor network (WSN) systems are generally comprised of a large number of tiny sensor nodes that are battery powered. The large scale of WSNs imposes limitations on the coordination of sensor nodes [1–10]. Even including distributed networking protocols in the scalability issue, the performance of a large scale WSN deteriorates as the number of nodes increases. Hence, WSNs demand such a high level of self-organization that application-specific global requirements must be achieved by having nodes react to changes in their local surroundings, particularly in the states of adjacent nodes. Recently, self-organized control inspired by biological systems has received considerable attention as an alternative for realizing robustness, scalability and adaptability in man-made (artificial) control systems [11–39]. Biological systems are versatile and adapt themselves to environmental changes. Each entity of a biological system makes decisions based on local interactions with their neighbors. For this reason, a number of methods have been proposed where the attributes of biological systems

(i.e., routing, clustering, scheduling, clock synchronization, network security, detection of misbehavior, and coordination control) were adapted for computer network systems., Among the concepts and principles derived from biological systems, those related to immune systems, sect colonies, activator-inhibitor systems, and cellular signaling systems, in particular, have been applied to WSN design [14–39].

One existing coordination protocol is based on the cellular signaling scheme of biological multicellular systems [26–38]. Delta-Notch signaling is a well-defined signaling scheme for which both Delta and Notch are transmembrane proteins [30]. During the development of certain biological tissues, Notch protein first drives multiple cells in the same area to adopt similar characteristics to form a pro-sensory patch, and then mediates hair-cell development while supporting cell differentiation within the patch. The first process is controlled by Notch-signaling lateral induction, and the second one by Notch-signaling lateral inhibition. Lateral induction is a process by which a cell heading for a particular fate induces its neighbors to adopt the same fate.

Therefore, the lateral induction mechanism generates a homogeneous spatial pattern through a feedback loop by amplifying initial similarities of membrane levels in a neighborhood of cells. In contrast to the lateral induction mechanism, lateral inhibition process inhibits the neighbors of a cell heading for a particular fate from adopting the same fate. The cells within a functional patch formed via lateral induction usually differentiate further, to a stage where some cells remain active while the rest become inactive. Theoretical biologists and mathematicians have successfully modeled the Delta-Notch signaling process by sets of coupled, ordinary differential equations (ODEs) [26–30].

These bio-inspired approaches yield systems that are highly robust and that can recover quickly without a centralized entity. However, they also have some critical drawbacks: each component in a biological system only interacts locally, and it lacks information about the global attributes of the system. In addition, most bio-inspired networking algorithms use the same component-design, derived from biological systems. There is also a conflict in scalability of performance, between biological and artificial networking systems. Moreover, existing bio-inspired systems have not yet been theoretically analyzed in terms of system stability. Due to the analytical complexity of these systems, stability issues were discovered only during simulations.

To address these concerns, we propose a biologically-inspired node-coordination scheme for WSNs. To imitate the inter-cell signaling mechanism of biological systems, we report a new mathematical formula for coordinating sensor-node states in WSNs. In Section 2, we propose a bio-inspired scheme for WSNs via a methodology motivated by the inter-cell signaling scheme. In Section 3, we evaluate the performance of the proposed scheme. Finally, we present conclusions in Section 4.

2. Bio-inspired Algorithm for Mission-critical Applications

2.1 Local Status Indicator

We introduce a local-status indicator of a sensor node in order to represent the conditions of its local environment. At every controller timeslot, node m ($\forall m \in \mathbf{M}$) evaluates the value of the congestion indicator, h_m, as follows:

$$h_m(n) = \alpha \bar{q}_m(n) + (1-\alpha)\bar{l}_m(n)$$

where

$$\bar{q}_m(n) = \frac{q_m(n)}{w_m(n) + q_m(n-1)}$$

$$\bar{l}_m(n) = \frac{r_m(n)}{r_m(n) + c_m(n)}$$

The value of r_m is the number of retransmissions. The values of q_m, w_m, c_m represent the queue length, input process, and successful outgoing packet number at node m. The parameter α $(0 \leq \alpha \leq 1)$, regulates the influence of queue loading and channel quality. As the channel gets more congested, l_m becomes one, resulting in a large number of retransmissions. On the other hand, when a larger percentage of packets are successfully transmitted, l_m is close to zero. Accordingly, the value of the congestion indicator becomes larger with the queue loading and retransmission rate. In addition to congestion, the consumed-energy level of a node is important to represent its local status. In order to consider the consumed-energy level, we modify the congestion indicator as follows:

$$\hat{h}_m(n) = e_m(n) \cdot h_m(n)$$

where $e_m(n)$ is the ratio of consumed energy to total energy. Thus, as energy consumption increases, or the current congestion level becomes high, the value of the congestion indicator becomes larger.

Using the modified congestion indicator, we set the local status indicator of node m:

$$s_m(n+1) = s_m(n) + \eta \left(g\left(\hat{h}_m(n) \right) - s_m(n) \right)$$

where η is a positive constant and $g(x)$ is defined as follows:

$$g(x) = \frac{1}{1 + bx^h}$$

2.2 Active Status Indicator and Node Coordination

Using the local status indicator, we propose a node-scheduling-control scheme inspired by the lateral inhibition method of the inter-cell signaling system. The purpose of inhibition-based, node-coordination control is to determine the state of a sensor node for the next controller timeslot. Hence, the sensor nodes compete via lateral inhibition to attain an active state, while the remaining nodes go to sleep. In order to meet application-specific requirements, we propose the use of a mathematical formula for node coordination, modified from the lateral inhibition formula. Let $a_m(n)$ denote the active-status indicator of node m. We propose the following formula for controlling a_m:

where μ and ν are positive control parameters to be chosen; δD is the delay feedback from the sink node, and is given by

$$\delta D(n) = D(n) - D_r$$

where $D(n)$ is the measured delay and D_r is the delay requirement.

According to the difference equation, a node with a higher local-status indicator than its neighbors (relative), also has an objectively high active-status level (actual). Likewise, when a sensor node has a lower local-status level than its neighbors, its actual active-status level is low. As such, any given node is more likely to have a higher value for its active-status indicator than its neighbors have. In addition, as the measured delay exceeds the delay requirement, the value of the active-status indicator increases, regardless of the level of the local-status indicator. Each sensor node decides its active/inactive status for the next controller timeslot using a uniform-distribution node-scheduling algorithm.

To specify the detailed node-scheduling algorithm, we introduce a random value ω, following the uniform distribution within [0, 1]. Each node independently generates a random value. If the active-status indicator of node m, a_m, is less than ω, then the node goes to sleep. On the other hand, if a_m is greater than ω, the node will be active during the next controller timeslot. As the relative local-status-indicator values of all the neighbors increases in relation to node m, the value of $g(\cdot)$ becomes smaller, and the active-status indicator of node m also becomes smaller. That is, the probability that node m will be selected as an active node becomes lower as its neighboring nodes gain better environmental conditions in terms of link quality, traffic loading, and consumed energy. On the other hand, when the local status of a node is better than that of its neighbors (i.e., its neighbors are not as suitable in terms of link quality, traffic loading, and energy) the node is more likely to be selected as an active node. Hence, via the competitive inhibition mechanism, only a subset of optimal sensor nodes remains active while the rest stay in sleep mode to save energy. Besides the ability to observe local quality, our proposed scheme considers global objectives, such as the application-specific-delay requirement. As the measured delay for a flow becomes greater than the delay requirement, the active-status indicator values of all the nodes involved in the flow also become higher, resulting in a higher probability of being active. Consequently, this leads to a reduction of delay, with more frequent packet transmission. In this way, the proposed controller induces the sensor nodes to estimate the overall system performance and to decide their actions by considering both global requirements and local environmental conditions.

$$a_m(n+1) = a_m(n) + \mu \left(g \left(\frac{\sum\limits_{i \in \mathbf{N}_m} s_{mi}(n)}{s_m(n)} \right) - a_m(n) \right) + \nu \delta D(n)$$

3. Results

In order to evaluate the performance of our proposed scheme, we developed a simulation environment using a MATLAB simulator. To show the effectiveness of the proposed scheme, we compared the proposed algorithm with a reference bio-inspired node activation scheme (BI-NAS) [30]. We use a simulation topology wherein 20 sensor nodes were deployed randomly in a region with a radian of 50 x 50 m. Among

the deployed sensor nodes, three nodes (nodes 1, 2, and 3) were directly connected to the sink. All sensors were static and had the same finite battery power. A node could transmit data packets to any neighbor within range. CSMA/CA was used for the transmission protocol of the MAC layer. All nodes within the carrier sensing were not able to access the medium when the channel was busy. The transmitted packets from the source node followed one of the possible paths and finally reached the sink via either node 1, 2, or 3. All source nodes generated packets in a Poisson distribution with average packet-arrival rate of one packet per second.

The size of a packet was 100 bytes, and the control period was 1 second. We set $vm = 0.6$, $Ta = 0.01$ sec, and $D = 200$ kbps. The transmitting power and sleeping power was set to 24.75 mW and 15 μW, respectively. For the proposed algorithm, we selected parameters such that conditions (40) were satisfied: $h = 1$, $a = 0.5$, $\mu = 0.1$, $v = 0.01$, $\eta = 0.01$. For BI-NAS, the active status threshold value was set to 0.5. All the nodes started with no neighbor information and thus had empty neighborhood tables.

Figure 1a represents the local-status indicators of nodes 1, 2, and 3. For Node 3, its local-status indicator was smaller than the others until 650 seconds because it started with less battery power than the other nodes. However, after 650 seconds, the local status indicators of all nodes converged to the same value. Fig. 1b shows the active-status indicator. As with the local-status-indicator result, until 650 seconds the active-status indicator of Node 3 was low compared to the others, which led to a smaller probability of achieving an active state. Since Nodes 1 and 2 had better local-status indicator values, they achieved a high active-status indicator value, compared to Node 3. In contrast, Node 3 had a lower active-status indicator value and spent more time in sleep mode to save energy. Through this iterative process, the active-status indicators of all nodes converged to the same value of 0.3 after 650 seconds. That is, the probability of becoming active was identical for all nodes.
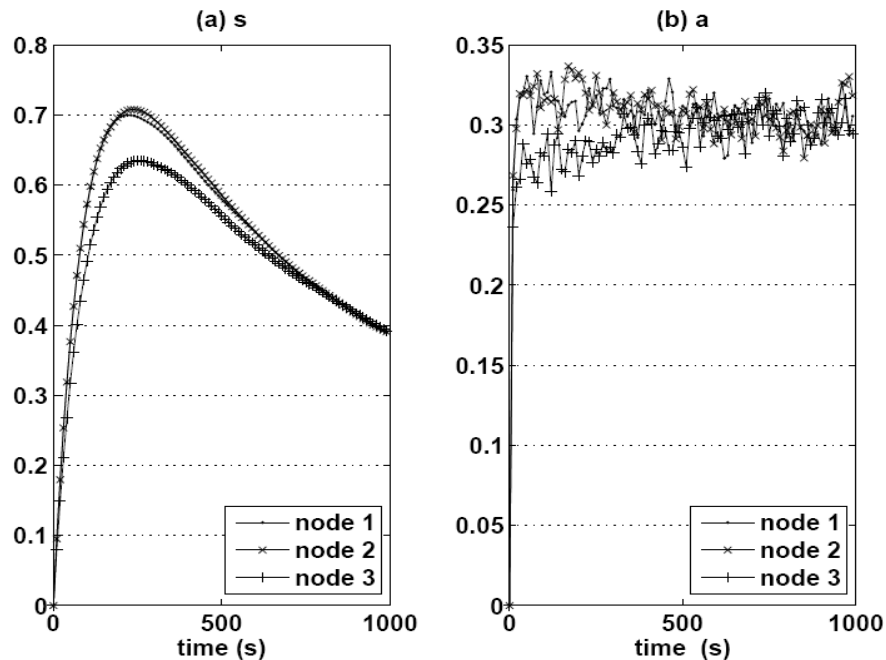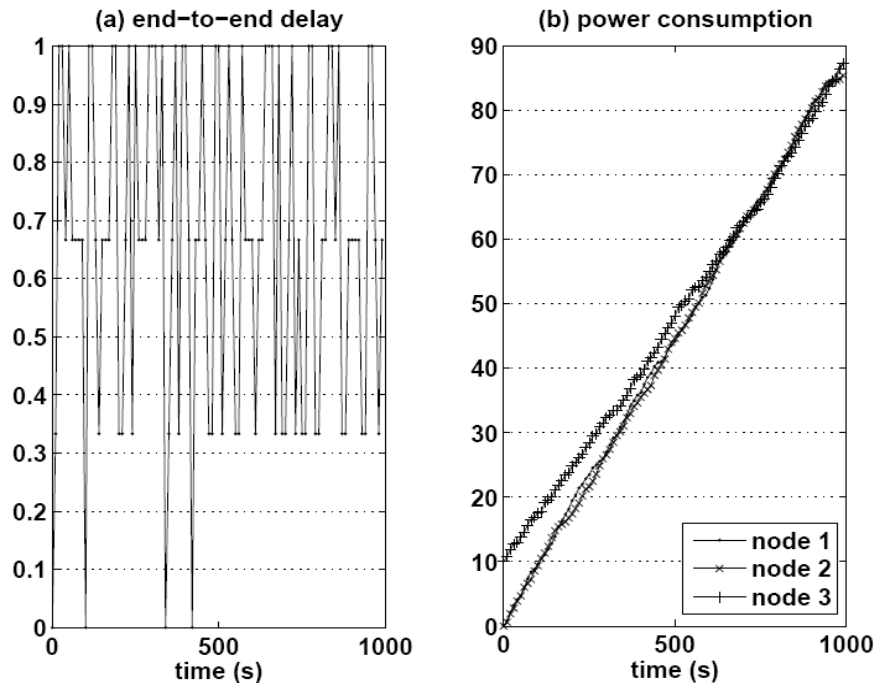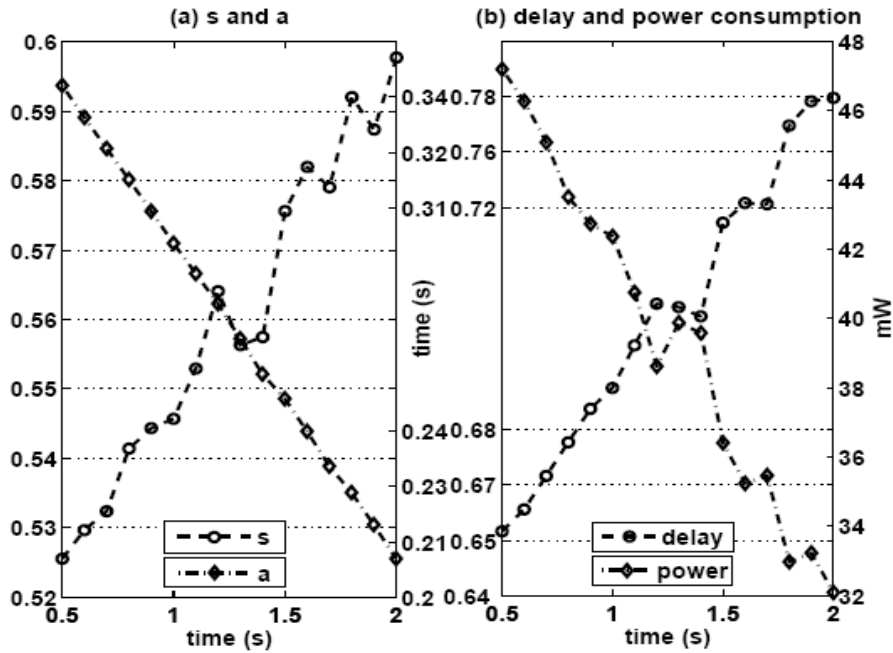

Figure 1. (a) Local-status Indicator and (b) Active-status Indicator

Figure 2a shows the average end-to-end delay for all flows. We set the delay requirement of all flows to one second. We observed that the average delay was within the range of [0, 33, 1] seconds and was always less than the delay requirement. Fig. 2b shows the power consumption of nodes 1, 2, and 3. Although the initial level of battery power was different for each node, power consumption became identical after 650 seconds, resulting in energy balancing among the nodes. This was achieved by controlling the probability of a particular node becoming active, based on its environmental quality relative to all its neighbors, as well as on the global objective of the application.

Figure 3 shows the average performance of the proposed scheme, with varying delay requirements within the range of [0.5, 2] seconds. Figure 3a shows the local-status indicator, s, and the active-status indicator, a. As the delay requirement became looser (*i.e.*, a higher value), the active-status-indicator value decreased, thereby reducing the probability of being active in the next controller timeslot. Where there was a low probability of being active, the proposed scheme increased the sleep time. Hence, as the delay requirement became looser, we attained greater power savings. On the other hand, as the delay requirement became stricter (lower value), the active-status indicator increased, leading to more frequent packet transmissions in order to meet the delay requirement. From Fig. 3b, we observe that the end-to-end delay successfully follows the varying delay requirements. In addition, as the delay requirement becomes relaxed, power consumption is reduced because of the lower probability of being active.


F igure 2. (a) End-to-end Delay and (b) Power Consumption

Figure 3. Average Performance with Varying Delay Requirements: (a) Local-Status Indicator, Active-status Indicator and (b) End-to-end delay, Power Consumption

Figure 4 shows a comparison of the performance of the proposed scheme and of BI-NAS, with varying traffic rates. We varied the packet-arrival rates within the range of [1, 5] packets per second. As shown in Fig. 4, the end-to-end delays for both schemes were kept at less than the delay requirement. In particular, BI-NAS shows a much smaller delay than the proposed scheme, but the power consumption was almost three times that of the proposed scheme. Since BI-NAS does not consider application-specific requirements to control active status, it consumes unnecessary power by transmitting packets more often than necessary. However, our proposed scheme saves more power while guaranteeing the delay requirement, in spite of changes in traffic rate.

We ran a single-hop scenario with two source nodes, to test the impact from changing the control parameters μ and h. We set the initial power consumption of Node 1 and Node 2 differently (1.5 mW and 30 mW, respectively). As shown in Fig. 5, the active-status indicator of Node 2 was much smaller than that of Node 1, due to the difference in initial power among the nodes. As the procedure iterated, the active-status indicators of all nodes converged toward the same value.
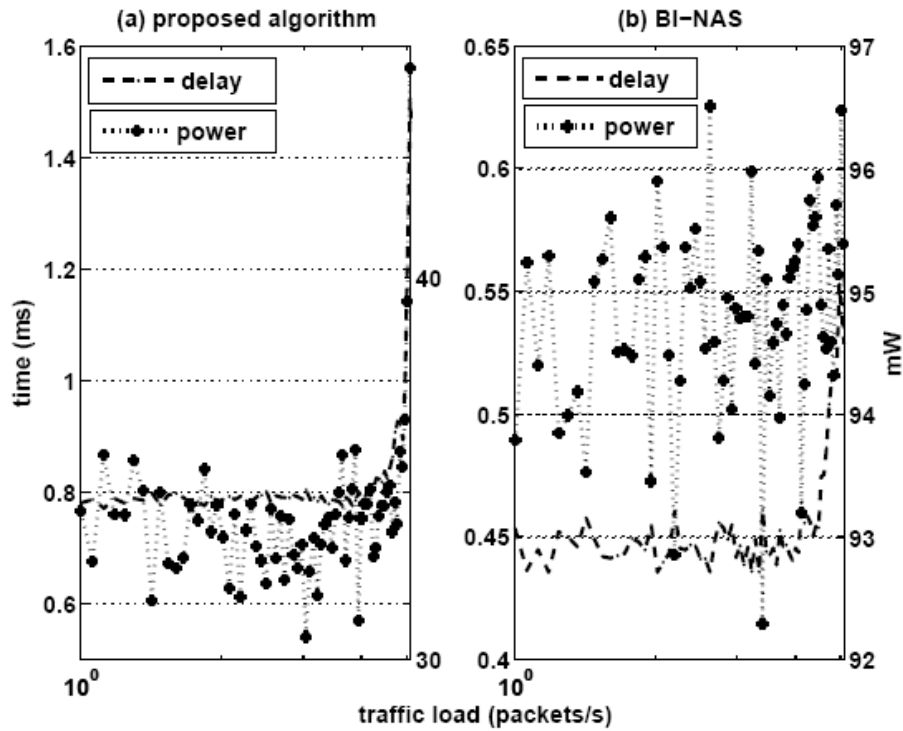
Figure 4. Average Performance with Varying Traffic Rates: (a) Proposed Scheme and (b) BI-NAS

According to Fig. 5 and Fig. 6, increasing the values of μ and h sped up the convergence time. However, large values of μ and h led to oscillatory behavior and unstable system performance. In specific, Fig. 6 shows that an active-status indicator with $h = 1$ converged more slowly than one with $h = 3$, but it showed a little oscillatory behavior. In sharp contrast, the result with $h = 3$ showed fast adaptation behavior; the active-status indicator exhibited extreme oscillatory behavior. Therefore, the choice of the control parameters can be approached as an optimization problem. In future work, we plan to extend our work to find optimal parameters.
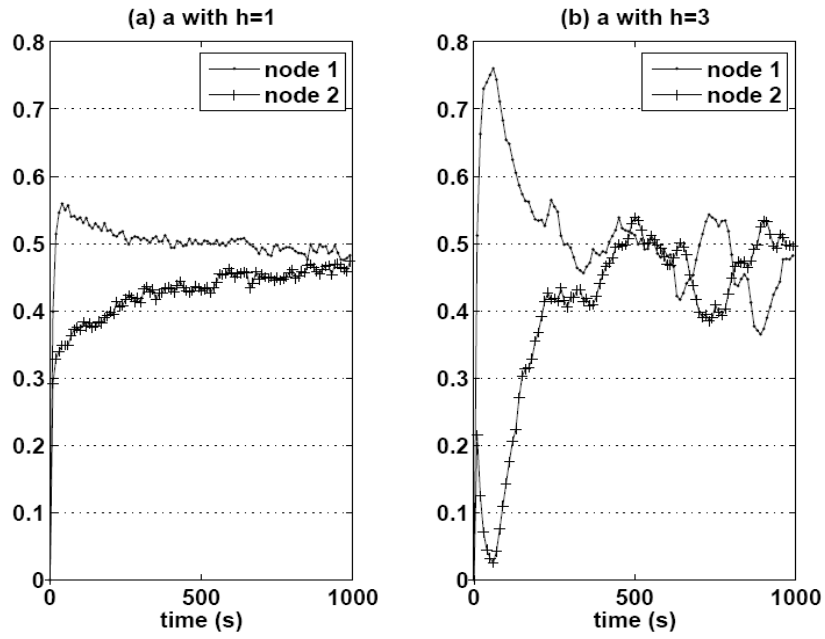
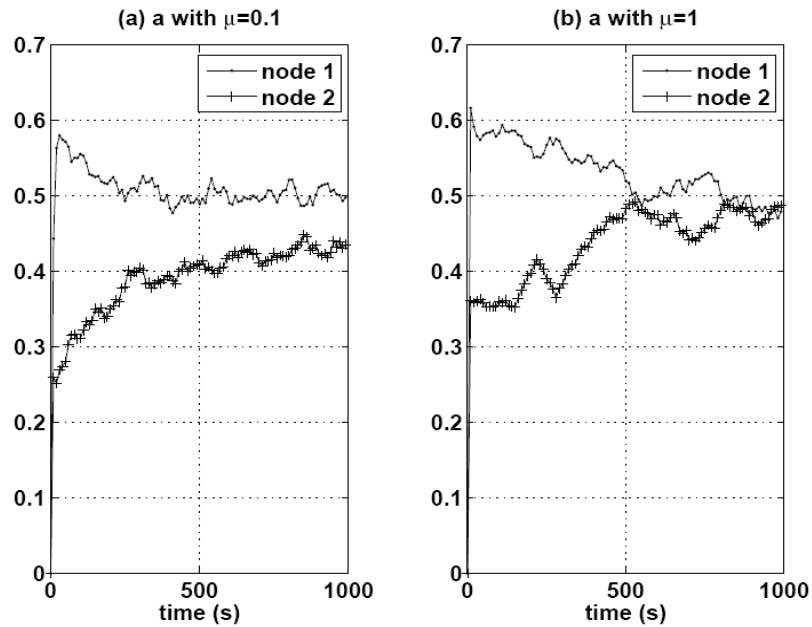**Figure 5. Active-status Indicator: (a) u = 1, and (b) u = 1**

Figure 6. Active-status Indicator: (a) h = 1, and (b) h = 3

4. Conclusions

In this paper, we proposed a bio-inspired node-scheduling-control algorithm for WSNs in order to achieve energy savings and delay guarantees. The proposed scheme introduced local-status and active-status indicators determined by the local environmental properties of the nodes, as well as by application-specific global requirements. We then developed a new mathematical formula to control the sensor-node state, based on the biological lateral-inhibition model inspired by inter-cell biological systems. Each node evaluates its local-status, and based on the proposed active-status-indicator formula only an optimal subset of sensor nodes becomes active while the rest stay in sleep mode to save energy. The simulation results indicate that our proposed scheme outperforms existing bio-inspired scheduling protocols by providing reliable delay guarantees, as well as greater energy savings.

Acknowledgements

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