ENS: an Epidemic-Inspired Node Scheduling (ENS) Protocol for Large Scaled Wireless Networks

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Abstract

Wireless sensor networks (WSNs) generally consist of densely deployed sensor nodes that depend on batteries for energy. The WSN systems have several applications, from target tracking to environment monitoring. Recently, there has been an increased interest in the design of WSN protocols for mission-critical applications, such as military surveillance, health monitoring, and infrastructure security. These applications require capability of sending data with different real time requirements. However, due to strict resource constraints of the sensor nodes, WSNs pose critical challenges in network protocol design for the mission-critical applications. In this paper, we propose an epidemic-inspired node-scheduling scheme (ENS) with aim of delay guaranteeing. The ENS controls the state of the sensor node depending on the application’s specific requirement under dynamic network environments. Simulation results indicate that the ENS achieves globally optimal behavior with reliable delay guarantees.

Keywords: Biologically-inspired networking, node scheduling, wireless networks

1. Introduction

Epidemic communications provide an effective means of transferring data in WSNs, in which the infection transmission process corresponds to the message passing among sensors. The analogy between information dissemination in WSNs and epidemics transmission in communities is evident; a sensor node can be referred to as infected when it receives a piece of information and stores it, and susceptible otherwise. A chain reaction in transmission of an infection is called the epidemic [1]-[6]. One of the prominent works of data dissemination modeled by epidemic theoretical concepts is SPIN [3]. SPIN focused on the efficient dissemination of individual sensor observations to all the sensors and proposed data descriptors to eliminate the chance of redundant transmission in WSNs. In [4], the authors proposed a TDMA-based data dissemination protocol for WSN in order to offer a degree of reliability. The Firecracker protocol [5] used a combination of routing and broadcast principles to rapidly disseminate data through WSNs. Trickle [6] was proposed for propagating and maintaining code updates as fast as possible to all nodes in the network. Trickle’s key contribution was its polite gossip that uses suppression and dynamic adjustment of the broadcast rate to limit transmissions among neighboring nodes. It only provided a mechanism for a node to decide when to propagate the code. However, these existing epidemic-inspired algorithms have some drawbacks: they do not permit control over information dissemination. Hence, it is difficult to ensure that the system can reach the desired performance of a

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specific application with fixed parameters under dynamic network conditions. To address this concern, we design an epidemic-inspired node-scheduling scheme (ENS) with adaptive information spread under dynamic WSN environments. The proposed ENS controls the node state according to the delay requirement of an application, which results in a dynamic adjustment of information spread rate.

2. Preliminaries

Epidemic theory is the study of the dynamics on how contagious diseases spread in a population, resulting in an epidemic [7]-[9]. The theory models the propagation process of an infection. Two of the simplest models describing such a propagation process are the SIR (Susceptible Infected Recovered) and the SIS (Susceptible Infected Susceptible) model. In the SIR, a susceptible individual acquires an infection and, after a duration of time called infection period, the individual recovers and becomes immune to further infections. In the SIS, the individual becomes susceptible again after being recovered. In the general SIR model, the dynamics of the infectives (I(t)), susceptibles (S(t)), and recovered individuals (Z(t)) in the total population N(t) can be described by differential equations as follows:

\[
\frac{dS(t)}{dt} = -\beta S(t)I(t) \\
\frac{dI(t)}{dt} = \beta S(t)I(t) - \gamma I(t) \\
\frac{dZ(t)}{dt} = \gamma I(t) \\
\frac{dN(t)}{dt} = S(t) + I(t) + Z(t)
\]

where \( \beta \) and \( \gamma \) denote the infection rate and the removal rate of infected individuals, respectively. The SIR model states that the decaying rate of susceptibles and the growth rate of infectives are calculated by the infectivity \( \beta \), the number of susceptibles \( S(t) \), and the number of infectives \( I(t) \). The total number of nodes is conserved over the interval of time taken into consideration. For the SIS model, it does not have the recovered \( Z(t) \) factor, and those who are infected fall back into the susceptible. In epidemiology, network topologies are used to study the spread of disease infections through a population, with nodes representing people and edges representing social contact. The network system is identical to the epidemic SIS model, in which an individual can be in only two states (susceptible or infected), and the change of state is a result of interaction between the individuals. The existing epidemic inspired networking protocols have focused on a modification of the SIS model, which is realistically closer to the behavior of WSNs.

3. ENS Model and Methods

We consider a WSN consisting of \( N \) nodes. Each sensor node can be only in one of two states, which are either “active” or “sleep” [10]. Sensor nodes turn off their radios in sleep state and turn them on in active state to exchange packets. Initially, all sensor nodes wake up periodically with period \( I_M \). If a node has received a new data during wake-up time, it sends the data to its neighbors with a calculated probability, where after it wakes up with period \( I_m \). Whenever a sensor node wakes up every \( I_m \), it determines the node state to be in active or sleep for the next time based on our proposed epidemic formula. Once activated, the sensor node remains in the active state during an interval of time \( T_a \), and then it goes to sleep. While
being in active state, if the sensor node receives a new data, it broadcasts the data. We develop a discrete-time formula of the model where the controller time is segmented into time slots with the slot duration equal to $I_m$. Also, all quantities defined are periodically measured at every $I_m$. We employ the SIS model to formulate a discrete dynamic model for the ENS as follows:

$$N_s(n + 1) = \max(\min(N_s(n) - \alpha(n)N_a(n)N_s(n) + \beta N_s(n), N_s(n) - N_{s,min}), 0)$$

$$N_a(n + 1) = \min(\max(N_a(n) + \alpha(n)N_s(n)N_a(n) - \beta N_a(n), N_{a,min}), N_a(n))$$

where

$$N_s(n) = N_s(n) + N_a(n)$$

$N_s(n)$ and $N_a(n)$ are the number of nodes in sleep state and in active state at time slot $n$, respectively. $\alpha$ is the infectivity rate, $\beta$ is a control parameter, and $N_t$ is the total number of sensor nodes. The value of $N_{a,min}$ is a minimum $N_a$ to ensure a certain level reliability and can be determined based on desired delivery ratio.

The sink node measures the maximum delay at every control period and notifies the sensor nodes of the measured delay by piggybacking in an ACK packet. With this feedback information, the dynamics of $\alpha$ is modeled by the following equation:

$$\sigma(n) = d(n) - d_s$$

$\varepsilon(<< 1)$ is a positive constant. $\eta$ is the control parameter to be chosen. The combined model of Eqs. (2)-(4) states that when the measured delay exceeds the delay requirement, the value of $\alpha$ increases, which leads to new active nodes in total nodes. On the contrary, when the measured delay is below the delay requirement, the value of $\alpha$ decreases, resulting in an increase of sleeping nodes.

Each node independently generates a random value. If the ratio of the active node to the total sensor nodes ($N_a/N_t$) is less than $\omega$, then the node goes to sleep. On the other hand, if the active node ratio is greater than $\omega$, the node will be active during the next controller time slot. If the maximum measured delay exceeds the required delay, the values of $\alpha$ and $N_a$ increases, resulting in a higher probability of being active. This leads to delay reduction with more frequent packet transmission. On the contrary, if the maximum measured delay is smaller than the required delay, the value of $\alpha$ and $N_a$ decreases, resulting in energy saving with an increase of sleep time. While being in active state, if the sensor node has not received any packet during $k$ straight time slots, the value of measured delay $d$ is written as 0, resulting in decrease of $N_a$.

4. Results

The simulations were conducted using a simulator written in C++. The simulator captures real-life events such as carrier sensing, backoff, and collisions. At the beginning of a simulation, nodes are randomly placed inside the simulation area, and the source node is placed at the center. Once nodes are deployed, nodes start duty cycling by switching between active and sleep mode. At some point, the source node starts generating packets periodically at a fixed rate. The packets are stamped with sequence numbers, so that a node does not receive or forward duplicate packets.
packets. The goal of the source node is to send the packet to all the other nodes in the network, within a given delay requirement.

Figure 1 shows the time behavior of $N_a$ for the delay requirement of 15s, 20s, and 25s, respectively. We can observe that the value of $N_a$ is controlled by delay requirement, i.e., $N_a$ converges to a higher value as the delay requirement becomes smaller, which makes the proposed ENS system adapt the node state according to the specific delay requirement. Next, we then show the averaged behavior varying the delay requirement from 0 to 60 seconds.

Figure 2 shows the averaged $N_a$ varying delay requirements. We can observe that the number of active sensor nodes is successfully controlled by the delay requirement. Specifically, as the delay requirement becomes larger, the value of $N_a$ decreases, which makes the number of sleep nodes increase. On contrary, the value of $N_a$ increases when the delay requirement becomes stricter.

Figure 3 shows the impact of the control parameter $\eta$. We use the same simulation scenario and configurations used in Figure 1 except $\eta$. In Figure 3, the time behavior of $N_a$ is illustrated in case of $\eta = 0.01$ and $\eta = 0.001$. Compared with the results of Figure 1 and Figure 3, we observe that when the values of $\eta$ are set outside the stable range, the behavior of $N_a$ oscillates excessively, resulting in an unstable system performance.
5. Conclusions

In this paper, we have presented a node-scheduling algorithm (ENS) inspired by epidemiological models for delay guarantees and energy savings in WSNs. After translating the epidemiological models into the WSN node-scheduling model, we formulate a node-scheduling model, which determines the state of each node according to the application requirement. In order to guarantee the desired performance of an
application, the proposed algorithm controls the infectivity rate, which leads to an adaptive number of active/sleep nodes depending on the specific delay requirement and dynamic network environments. The infectivity rate is determined according to the measured delay and the delay requirement of the specific application. As the measured delay is larger than the required delay, the infectivity rate increases, which leads to the increase of the number of active nodes. On the contrary, the infectivity rate decreases as the measured delay is smaller than the required delay, which results in the increase of the number of sleeping nodes. The simulation results show that the proposed ENS has a superior performance compared to the existing schemes by achieving a high delivery ratio, delay guarantees, and energy savings.

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