Wireless Pers Commun
DOI 10.1007/s11277-014-2198-9

An Adaptive Competitive Resource Control Protocol for Alleviating Congestion in Wireless Sensor Networks: An Evolutionary Game Theory Approach

Nazbanoo Farzaneh · Mohammad Hossein Yaghmaee

Abstract A wireless sensor networks (WSNs) is composed of small sensors with limited capabilities that are densely distributed in the area. WSNs are subject to more packet loss and congestion. To alleviate congestion, either the source transmission rate should be controlled or the available resources have to be increased. A precision resource control mechanism is necessary to possess an efficient and accurate congestion control. Evolutionary game theory is very useful on the design of large-scale wireless networks. Evolutionary games in large systems provide a simple framework for describing strategic interactions among large number of players. In this paper, we propose an evolutionary game theoretical resource control protocol (EGRC) for wireless sensor networks. EGRC applies evolutionary games to develop a non-cooperative game containing large number of sensors as players for alleviating and controlling congestion in wireless sensor network by utilizing the available resource and controlling radio transmission power. The proposed protocol adjusts the transmission power based on the available energy capacity and node congestion level. Simulation results show the performance of the proposed protocol that improves system throughput, and decreases packet dropping, while saving energy.

Keywords Wireless sensor network · Congestion control · Radio transmission power · Resource control · Evolutionary game theory

1 Introduction

Wireless sensor networks (WSNs) have wide applications in areas such as business, military, health and home applications. Energy conservation, congestion control, reliability in data

N. Farzaneh (✉) · M. H. Yaghmaee
Computer Department, Ferdowsi University of Mashhad, Azadi Square, Mashhad, Iran
e-mail: Farzaneh@stu-mail.um.ac.ir

M. H. Yaghmaee
e-mail: hyaghmae@um.ac.ir

Published online: 21 November 2014

dissemination, security, and management are among the factors that should be kept in mind in designing WSNs.

Congestion control is one of the main functions of transport control protocols' design. In the case of congestion, its place and time should be detected. A perfect congestion detection method should be energy-efficient and accurate. Upon the congestion is detected, there are two options to alleviate the congestion: reducing the source rate or increasing the network resource. The problem of congestion in sensor networks remains largely open yet [1,2].

Most of previous studies on congestion control in WSN control the congestion by throttling the source and intermediate node's rate. Although reducing source rate is effective in some sensor network applications [3,4], it is inappropriate for some special applications for the following reasons: firstly, usually the data during a crisis state are very important to the critical application and have great value that should be delivered to sink with higher rate, so reducing the source rate during a congested state is undesirable. Nevertheless throttling the sending rate will reduce the fidelity level (certain level of throughput) [3]. Secondly, due to elastic availability of resources in WSNs it is easier to use more resources during congestion time to increased network lifetime [3].

In general, centralized control approaches are impractical methods for large-scale networks. Due to the physical distribution of wireless sensor nodes the network systems should operate a distributed control mechanism. Classical game theory has been widely applied in wireless networking and communications. Game theory is helpful in analyzing compound decision problems among self-regarding decision makers The fundamental assumption of classical game theory is that players must be rational to determine their decisions. However, this assumption is obviously not satisfied under the real-world network environment; the evolutionary game theory (EGT) proposes a more realistic model for players with bounded rationality [5,6]. In this model, players learn how to select their strategies like as a competition play where losing strategies are removed and winning strategies remain. Therefore during the evolutionary game, players have a chance to reconsider the current strategy and react to maximize the expected payoff.

In this paper, a suitable resource control protocol under a game theoretic framework is proposed. Our goal is to answer this question: "How to improve throughput of a wireless sensor network during congestion state under some criteria?". The proposed protocol is called evolutionary game theoretical resource control protocol (EGRC). EGRC is a self organized resource control approach which is proposed to alleviate and control congestion in wireless sensor network by controlling radio transmission power. It adjusts the resource availability based on the congestion level so that it can altering radio transmission power to have more sensor nodes forwarding packets to alleviate the congestion, as well as conserve the energy consumption.

The rest of this paper is organized as follows. In Sect. 2 a brief review of related work in the WSN transport protocols is described. The background on evolutionary game theory is presented in Sect. 3. The proposed model is explained in Sect. 4. In Sect. 5 using computer simulation, the performance of the proposed model is evaluated. Finally, Sect. 6 concludes the paper.

2 Related Work

In examining related literature, we focus on accurate and efficient congestion detection which is central to WSNs. Reliability and congestion control are also of great importance. Last but not least of all is energy efficiency which is a crucial characteristic of any good protocol. There

have been a plethora of studies investigating reliable data transport in WSNs. Congestion control and fairness (CCF) was proposed in [7] as a distributed and scalable algorithm that eliminates congestion within a sensor network and ensures the fair delivery of packets to a sink node. In the CCF algorithm, each node measures the average rate r at which packets can be sent from the node, divide the rate among the number of children nodes, adjust the rate if queues are overflowing or about to overflow and propagate the rate downstream.

Priority-based congestion control protocol (PCCP) introduced in [8] an upstream congestion control protocol for WSNs. It measures the congestion degree as the ratio of packet inter-arrival time to the packet service time. Based on the introduced congestion degree and node priority index, PCCP utilizes a cross-layer optimization and imposes a hop-by-hop approach to control congestion. In [9] a new priority based rate and congestion control protocol for wireless multimedia sensor networks is presented. It consists of two major units, namely congestion control unit (CCU) and service differentiation unit (SDU). Each sensor node has two different priority indexes: traffic class priority and geographical priority. The total priority of a node is defined as the product of these two priorities. Each node measures its input rate and its maximum allowable transmission rate periodically. The CDU determines the congestion intensity by calculating the difference between the input and the output rate. CDU is responsible to notify the new rate to all network nodes. The SDU supports different QoS for different traffic classes. Separate queues are used for each traffic class. SenTcp [10] is a hop-by-hop congestion control protocol for WSNs. In every sensor node, local packet inter-arrival time, service time, and buffer occupancy ratio are used to detect congestion. Node sending rate will be adjusted by calculating the degree of congestion. RCRT [11] is a transport protocol for WSNs which consists of four major components. In the RCRT protocol, as long as end-to-end losses are repaired quickly the network is considered uncongested. The RCRT protocol uses the length of retransmission list as the indicator of congestion. In congestion case, the RCRT will use an additive increase multiplicative decrease (AIMD) rate control mechanism to adapt the transmission rate of each sensor node. Since RCRT separates rate adaptation from rate allocation, it is possible to obtain this flexibility. The sink detects packet losses and repairs them by requesting end-to-end retransmission of the packets from source nodes. In [12] a novel congestion control protocol for vital signs monitoring in wireless biomedical sensor networks is proposed. To minimize congestion in each intermediate sensor node, a separate queue is allocated to each child node to store its input packets. Based on the current congestion degree and the priority of its child nodes, the parent node dynamically computes and allocates the transmission rate for each of its children. When the central computer detects any anomaly in the received data, it sends a special message to the particular patient's sensor node and increases the patient's priority. LACAS [13] is an automata base congestion control protocol for healthcare application in WSN. In LACAS there is an automaton in every intermediate node which regulates the node's incoming rate for controlling congestion locally in that node. The learning parameter is drop packets. To be precise, the rate of flow of data into a node for which there is the least number of packets dropped is considered to be the most optimal action. In [14,15] a multi class congestion control protocol based on learning automaton in WBSNs are proposed. These protocols can adjust intermediate node arrival rate and source sending rate using learning automata. Alam and Hong [16] is a congestion control protocol that detect congestion based on two parameter queue length and the average delay to forward a packet. Sink adapts the source sending rate based on the congestion notification of the intermediate nodes. A prioritization based congestion control protocol for healthcare monitoring application in WSNs is developed in [17]. Four type of traffic is assumed in this protocol. Also the patients can have different priority based on their vital signs.

Traffic control approaches are not always effective in WSNs. So some resource control schemes are suggested in some papers. In CADA [18] when congestion occurs, a detour path is built for redirecting traffic to bypass the hotspot region. If congestion is worse, the nodes report the congestion to the sources and the sending rate is reduced according to AIMD policy. Wan et al. [19,20] increase the fidelity during periods of congestion and traffic overload by using "virtual sinks". Virtual sinks are longer range multi-radio nodes. When virtual sink find congestion is occurred, it redirects the packet using its long radio range to the physical sink. Early increase/early decrease (EIED) [3,4] is a resource increase and decrease algorithm that adjusts the effective channel capacity to the incoming traffic volume. The goal of EIED is increasing the fidelity level observed by the application during congestion in energy efficient manner. TARA [4] is a Topology-Aware Resource Adaptation to Alleviate Congestion. TARA makes off nodes active in order to change the current topology to alleviate the congestion. The overhead of TARA is high because it should know end to end topology. Another scheme is presented in [21] that distributed traffic into additional paths to bypass the congestion region. Interface-minimized multipath routing [22] balances the traffic load by discovering zone-disjoint paths. So the throughput is increased with minimal requirement of localization support. In Seon and Lee [23] an online traffic engineering algorithm is presented. The multipath routing is used to alleviate congestion. Idle and under loaded nodes are used during congestion period. A traffic aware routing algorithm is presented in [24]. Each node measure travel cost for its neighbors and selects a neighbor with minimum distance and lower queue length as a next hop. HOCA [25] is a data centric congestion management protocol using AQM is proposed for healthcare applications. HOCA avoids congestion in the routing phase using multipath and QoS aware routing. And in cases where congestion cannot be avoided, it will be mitigated via an optimized congestion control algorithm.

Evolutionary game-theoretic models have been studied in the literature. In Menasche et al. [26], the authors use game-theoretic approaches to control congestion in VOIP networks. The proposed protocol is a traffic control work that dynamically adapts the nodes data rates to maximize the media quality delivered to their respective users. An evolutionary game theoretic model of TCP for wireless networks is presented in [27]. The authors consider two populations of connections, all of which use AIMD TCP. The parameters of AIMD mechanism are defined based on the evolutionary game.

3 The Evolutionary Game Theory

In 1973 EGT is marked by biologist John Maynard Smith [28–30]. EGT studies the behavior of large populations of agents who repeatedly engage in strategic interactions [31]. While the majority of work in EGT has been studied by biologists and economists, closely related models have been applied to questions in a variety of fields, including transportation science, computer science and sociology [31]. EGT is a different approach to the classic games. Instead of directly calculating properties of a game, populations of players using different strategies are simulated and a process similar to natural selection is used to determine how the population evolves [31].

Two major mechanisms of the evolutionary process and the evolutionary game are mutation and selection. In evolutionary game, mutation is described by the evolutionary stable strategies (ESS) from static system perspective. Selection mechanism is described by the replicator dynamics from dynamic system perspective.

In a symmetric normal form game, an evolutionarily stable strategy is a (possibly mixed) strategy that cannot be invaded by another strategy [31]. ESS can serve as a refinement to the

nash equilibrium (NE). ESS is the key concept in the evolutionary process in which a group of agents choosing one strategy will not be replaced by other agents choosing a different strategy when the mutation mechanism is applied.

A strategy S^* for the symmetric game with payoff matrix A is an ESS if two conditions are met [32]:

$$\mathrm{S^T AS} \leq \mathrm{S^{*T} AS^*} \quad \text{for all strategies } \mathrm{S} \neq \mathrm{S^*}$$
$$\mathrm{S^T AS} \leq \mathrm{S^{*T} AS} \quad \text{when equality in the first condition holds}$$

Asymmetric games are more realistic in economics because economic agents play deferent roles such as residents and migrants. An ESS in the symmetric version of an asymmetric evolutionary game must be a Strict Nash equilibrium (SNE). A NE S is called strict if and only if the profile s is the unique best reply against itself. Thus SNE is stronger than ESS and the following relation is true:

$$\text{SNE} \subseteq \text{ESS} \subseteq \text{NE}$$

The natural selection process that determines how populations playing specific strategies evolve is known as the replicator dynamics. Slightly differing versions of these equations can be found in [31,33,34]. There are different replicator dynamics depending on the evolutionary model being used.

In a two-player game, the coupled replicator equations that describe the change in the frequency distribution over the pure strategies are given by [31]

$$\begin{aligned} \frac{dx_i}{dt} &= x_i \left[(Ay_i) - x^T Ay \right] \\ \frac{dy_i}{dt} &= y_i \left[(Bx_i) - y^T Bx \right] \end{aligned} \tag{1}$$

where $x(y)$ is the frequency distribution for player 1 (2), and A (B) represents its individual payoff matrix.

For N player and M strategy game the replicator dynamics are defined as:

$$\begin{aligned} \frac{dx_i(t)}{dt} &= x_i(t) K \left(U(i, x(t)) - \sum_j x_j(t) U(j, x(t)) \right) \\ &= x_i(t) K \left(\sum_j x_j(t) U(i, j) - \sum_j \sum_k x_j(t) U(j, k) x_k(t) \right) \end{aligned} \tag{2}$$

where K is a positive constant and is scaling factor of a utility function $U(\cdot)$. x is a M dimensional vector whose i_{th} element $\mathrm{x_i}$ is the population share of strategy i. Thus we have $\sum_i x_i = 1$, $x_i \geq 0$, $U(i, k)$ is the expected payoff (fitness) for a player using strategy i when it encounters a player with strategy k.

4 Proposed Protocol

In this section we explain our proposed model in details. Large scale WSNs tend to be organized in a distributed manner where nodes are locally self organized. The basic idea of the distributed algorithm is to utilize a local parameter in each node to solve a problem locally with no need to collect whole network information.

We present a model to alleviate congestion by turning on more resources as soon as the congestion is detected. Resource control scheme can reduce the congestion within the

network, but it also increases the energy consumption. Hence, it is better to halt the extra resources usage as soon as the source traffic decreases. For applications where a sensor node monitors an area and sends data packets to sink node(s) periodically, the traffic load is always low. But, when an event occurs, the sensors will generate more packets and need to transmit them to sink(s). In such cases, congestion control is of great importance. There are many resources in WSNs. When congestion occurs it is so eminent to know that which resource should be increased and how much it is to cause the best result. Increase in one resource may increase or decrease the availability of other resources. The main objective of this paper is to reduce the network congestion by selecting sundry suitable resources.

4.1 Game Model

In the proposed model we assume that $\mathrm{N} = \{1, 2, \ldots, \mathrm{n}\}$ sensor nodes are distributed in the network, uniformly. There are a set of links $\mathrm{L} = \{1, \ldots, \mathrm{l}\}$ that each one is between two nodes i and j when j is within the communication range of i. There are $\mathrm{S} = \{1, \ldots, \mathrm{s}\} \in \mathrm{N}$ source nodes and $\mathrm{D} = \{1, \ldots \mathrm{d}\}$ sinks in the network. Without loss of generality, in the simulation section we consider only one sink. Each node $i \in N$ possesses a fixed capacity $\mathrm{C_i} > 0$ and a fixed buffer size $\mathrm{b_i} > 0$. For each node $i \in N$, G_r^i is the set of node i's neighbors that are in its radio range r.

Resource allocation in wireless ad hoc networks is usually modeled in a non-cooperative game theoretic framework with the objective of maximizing individual utility. We proposed the evolutionary game framework to allow number of players that are involved in a local interaction. There are some notation and definition as follows:

- There is one population of users. The number of users in the population is large.
- We consider sensor i to be an autonomous agent, a 'player', with capability of selecting the actions. Thus there are N player in the game.
- A player's strategy is a set of available transmit power level (r_i), $r_{min} \leq r_i \leq r_{max}$, S is a non empty set of strategies. We assume that there are M pure strategies (|S|)

$$\mathrm{S} = \bigcup_{i \in N} r_i | P_i \in [r_{min}, r_{max}] \qquad |\mathrm{S}| = \mathrm{M} \tag{3}$$

- The r_{min}, r_{max} are the minimum and maximum power levels, respectively. Each player selects a single strategy from the S, and estimates the expected payoff through a utility function.
- The payoff function of all players depends on the player's own behavior and the behavior of the other players.
- The goal of each player is to maximize its own payoff by selecting a proper strategy
- The game is played many times.

Each node i for each of its transmission power $(\mathrm{r_i})$ considers all of its neighbors (G_r^i) and calculates total cost from the node to the sink. Each node has the capability to decrease or increase its transmission power. Transmission power can be defined within the power constraints. Increasing transmission power allows a node to discover more neighbors and as a result to achieve more resource. Thus, this method offers a node more available resource for transmitting the packets and detours the traffic from congested area. If higher power operation is not necessary, the radio can be reduced to a lower level to save the resources and to decrease the interference. In the proposed protocol adaptively adjusts a transmit power level in a game based online manner. Therefore by considering this trade-off, players adaptively select the most proper power level.

A utility function is a measure of the consent experienced by a player, which is as a result of a selected strategy. The utility function for player i (U_i) is defined as follows

$$U_i(\mathcal{R}) = \frac{1}{\left(\underset{r \in \mathcal{R}^i}{min} \left\{ \underset{j \in G_r^i}{min} \left\{ T_j^i(r) + P_j(r) \right\} \right\} \right)} \tag{4}$$

where $\mathcal{R}$ is the transmit power vector ($\mathrm{r_i} \ldots \mathrm{r_M}$) for all players. $T_j^i(r)$ is the cost of node i to select node j as a next hop with transmission power r and $P_j(r)$ is the estimate least cost path from node j to sink with transmission power r. Subsequently, the node with the least cost is selected as the next hop toward sink. Each node j periodically sends its local cost (I_j) and its least transmission cost to sink ($P_j(r)$) to its neighbors.

The proposed protocol uses a Bellman–Ford based algorithm to calculate the best paths (that has higher available resources and lower cost). Bellman–Ford algorithms pass periodic copies of a cost table from node to nodes and accumulate cost vectors. Regular updates between nodes communicate topology changes. Bellman–Ford algorithms are distributed route computation using only neighbor's information. When a node i receive new cost from its neighbors, it updates its own least cost path to sink (P_i) using Bellman–Ford equation. Bellman–Ford is based on dynamic programming approach as follow:

$$P_i(r) = \min_{j \in G^i} \left\{ T_j^i(r) + P_j \right\} \tag{5}$$

The total cost (T_j^i) of node i to select node j as its next hop is calculated as: $\begin{array}{l} T_j^i = F\left(I_j^i, C_{ij}\right) \\ \forall j \in G^i \end{array}$

In the proposed model, the linear function is used to calculate the total cost as follows:

$$\begin{aligned} \mathrm{T_j^i(r)} &= \alpha\, \mathrm{I_j^i(r)} + (1 - \alpha)\mathrm{C_{ij}} \\ 0 &\le \alpha \le 1 \end{aligned} \tag{6}$$

where C_{ij} is a cost of connected link between node i and its neighbor j and $I_j^i(r)$ is a cost of j_{th} neighbor of node i when node i used the transmission power r.

The parameter α controls the relative weights given to communication cost and local cost of the next hop j. A fixed value of α cannot effectively adapt to the changing conditions. Thus a value of α is adaptively modified. When the remaining energy of the node i is high, it is better to put more weight on the local cost of next node j, In this case, a higher value of α is more suitable. When the remaining energy of the node i is not enough, the energy consumption for data transmission has higher importance. In this case, a lower value of α is more suitable for the energy-consumption rate. The value of α of node i is dynamically adjusted based on the current remaining energy ratio of node i.

For a given node in the network the algorithm finds the path with lowest cost between that node and Fig. 1 shows the path cost components ($T_j^i(r)$). It can be seen that the cost consists of two main parts:

- C_{ij} : The cost of connected links between node i and its neighbor j.
- $I_j^i(r)$: The cost of j_{th} neighbor of node $i$when node i used the transmission power r.

Lets us to explain these two cost metrics in details.

$\mathrm{C_{ij}}$ is the communication energy consumption between two nodes i and j. It is calculated as follows:

$$C_{ij} = \begin{cases} e_d d_{ij}^2 + e_t & d \le d_0 \\ e_d d_{ij}^4 + e_t & d > d_0 \end{cases} \tag{7}$$

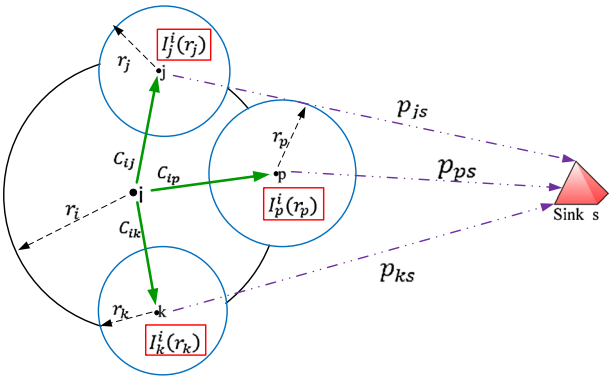


Fig. 1 Path cost components

where d_{ij} is the distance between two node i and j, e_d is the energy dissipation for transmitting unit of data over unit of distance, β is the path loss exponent and usually $2 \leq \beta \leq 4$ for the free space and short to medium range radio communication. If the distance between the transmitter and receiver is less than a threshold, the free space model is used; otherwise, the multipath model is applied. e_t is the energy dissipated for each bit in transmitter circuitry and d_0 is distance threshold.

The main part of energy cost in WSNs is the cost of sensor communication. The higher the distance between i and j (d_{ij}), the higher the C_{ij}. Thus, node's local cost worsens and j has a little chance to be selected as the next hop of node i.

The local cost ($I_j^i(r)$): indicates node's interest to be a next hop. Local cost expresses the congestion level and remaining energy ratio of the node. The higher the local cost is either the higher the congestion or the lower the remaining energy. Accordingly, node has a little chance to be elected as the next hop. Two parameters are utilized to determine the node's local cost, node drop probability ($D_p{}^i$) and node remaining energy (E_u^j).

Node drop probability includes two parts, Queue drop probability (d_q) and MAC discard probability (p_d).

The queue drop probability means that the queue possesses no free space for accepting the new packets. Based on the service rate and arrival rate per packet, the drop probability of the queue can be estimated. Due to the relationship between the drop probability and the network performance, the estimation is very prominent. Higher drop probability is associates with a higher congestion and higher packet loss. The following parameters are applied to estimate the drop probability:

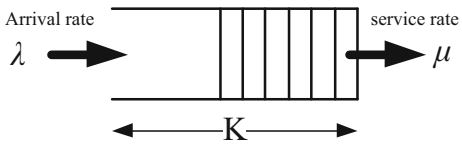
- Average arrival rate λ
- Average service time μ
- Available space in the queue (k)

Due to pay attention to channel load and queue free space, the above-mentioned parameters are effective to estimate the network congestion.

As it is shown in Fig. 2, in each node the M/M/1/K queuing system is used [35]. It means that both inter arrival time and service time have exponential distribution with rate λ and μ, respectively. The maximum capacity of the queue is K packets.

The drop probability is the probability that queue is full (there are K packets in the queue). Let P_K be the probability that there are K packets in the queue in the steady state. Using queuing theory P_K can be calculated as follows:

Fig. 2 M/M/l/K queue



$$d_q{}^i = P_K = \begin{cases} \frac{(1-\rho)\rho^K}{1-\rho^{K+1}} & \rho \neq 1 \\ \frac{1}{K+1}\rho^K & \rho = 1 \end{cases} \tag{8}$$

where $\rho = \frac{\lambda_{eff}}{\mu}$ and $d_q{}^i$ is a drop probability of node i. λ_{eff} is the effective arrival rate. When a queue is full, any arrival packet is dropped. The numbers of drop packets (L_P) is defined using the following equation:

$$\begin{aligned} \mathrm{L_P} &= \lambda \times \{\text{the probability that an arrival packet can't enter the queue} \\ &\quad \text{(there is no free space left)}\} \\ \mathrm{L_P} &= \lambda\, \mathrm{P_K} \end{aligned} \tag{9}$$

Thus, the effective arrival rate observed by server is calculated as follows:

$$\underset{\text{eff}}{\lambda} = \lambda \times \{\text{the probability that an arrival packet can enter the queue (because the queue is not full)}\}$$

Using the normalization condition $\left(\sum_{i=1}^{n} P_i = 1\right)$, the effective arrival rate, λ_{eff}, is calculated as follows:

$$\lambda_{\text{eff}} = \lambda(1 - \mathrm{P_K}) \tag{10}$$

where $(1 - \mathrm{P_K})$ is the probability that the queue is not full (the total packets in the queue is $< K$). The objective is to avoid the usage of the nodes with low buffer capacity in relaying traffic.

The MAC packet discard probability of node i, p_d^i, is the ratio of generated packets that are not successfully transmitted. p_d^i is the probability of dropping packet either in channel access failure, or because of collision. MAC packet discard probability can be computed as [36].

$$p_d = p_{dc} + p_{df} \tag{11}$$

where R is the maximum number of retransmission attempt in MAC layer and p_{dc} and p_{df} are the probabilities that a packet is discarded due to reaching the R or due to channel access failure, respectively. p_{dc} and p_{df} can be calculated as follows [36]:

$$\begin{aligned} p_{dc} &= p_c^{R+1} \\ p_{df} &= \frac{1 - p_c^{R+1}}{1 - p_c} \\ p_c &= p_{c0}(1 - p_f) \qquad p_f = (1 - y)^{R+1} \end{aligned} \tag{12}$$

where p_f and p_c are channel access failure probability and collision probability respectively. p_{c0} is the probability that at a time in which a node, is transmitting, one or more other nodes are also transmitting and y is access probability.

By substituting (12) into (11), MAC packet discard probability can be rewritten as follows [36]:

$$p_d = p_c^{R+1} + p_f \frac{1 - p_c^{R+1}}{1 - p_c} \tag{13}$$

$p_d^i(r)$ is a MAC packet discard probability of node i when it uses the transmission power r. The node drop probability is the union of the queue drop probability and MAC discard probability which shows the probability of dropping packet in a node and can be computed as follows:

$$\begin{aligned} D_p{}^i(r) &= d_q{}^i + (1 - d_q{}^i) * p_d^i(r) \\ &= \mathrm{d_q}^{\mathrm{i}} + \mathrm{p_d^i(r)} - \left(\mathrm{d_q}^{\mathrm{i}} * \mathrm{p_d^i(r)}\right) \end{aligned} \tag{14}$$

Due to pay attention to the past history of the node status, $D_p{}^i(r)$ can be computed by using a weighted average method in which each computed $D_p{}^i(r)$ over past T period of time, carries different importance.

In order to privilege the drop percentage ($D_p{}^i(r)$) of the nodes based on their past history, a new drop percentage is defined as a weighted summation of pervious drop percentage of the nodes. Consequently, the drop percentage of node i is calculated as follows:

$$\begin{aligned} D_p{}^i(t) &= \vartheta \times D_p{}^i(t) + \sum\nolimits_{j=1}^{T} (1 - \vartheta)^j \times D_p{}^i(t - j) \\ t &\geq 1, \quad 0 \leq \vartheta \leq 1 \end{aligned} \tag{15}$$

where t demonstrates the backward step to the past history. The greater the ϑ is, the more effect of current drop percentage is.

One of the characteristics of the WSNs nodes is their limited energy resources. Therefore, optimal energy consumption for WSN protocols seems essential. For increasing network life time, a node with a most energy level will be used for transmitting the packets. It is necessary to obtain fairness among nodes with considering energy consumption. Hence, the goal is to avoid sending traffic over nodes with a low remaining energy. So the nodes with higher local cost have lower chance to be selected as the next hop. The node used energy ratio (E_u) is computed as the following equation:

$$E_u = \frac{E_{ini} - E_{rem}}{E_{ini}} \qquad 0 \leq E_u \leq 1 \tag{16}$$

where E_{ini} and E_{rem} are the initial energy of node and the remaining energy of node, respectively.

Each sensor nodes has three different operation states: idle, sending and receiving. The energy consumption of each state consists of "idle mode" (E_{idle}), "Sending mode" ($E_{snd} = e_d d_{ij}^4 + e_t$) and "Receiving mode"($E_{rcv}$)

The local cost of node j ($\mathrm{I_j^i(r)}$) with transmission power r is computed as follows:

$$\begin{aligned} I_j^i(r) &= \left(\beta D_p{}^i(r) + (1 - \beta)\, E_u{}^j\right)^{Q_f{}^j} \\ 0 &\leq \mathrm{I_j^i} \leq 1 \end{aligned} \tag{17}$$

where

β : Constant coefficient that indicates the importance of each parameter $0 \leq \beta \leq 1$.

Q_f^j : the free space ratio of node $j's$queue which is calculated as follows:

$$Q_f{}^j = \frac{Q_T{}^j - Q_b{}^j}{Q_T{}^j} \qquad 0 \le Q_f^j \le 1 \tag{18}$$

Q_T^j : total queue length.
Q_b^j : number of packets in the queue.

When the queue length is high, the drop probability is high too, thus, if a node is chosen as the next hop, the number of drop packets increase, suddenly. Consequently, local cost should be increased to decrease node selection probability and reduce packet loss. As a result of this, Q_f (free queue space ratio) is utilized as a coefficient to alter the local cost.

The main interest of each player is to maximize the amount of transmitted data over a path that have lower congestion level and with the lower energy consumption. Based on above consideration, all the players try to maintain the path minimum cost and higher available resources. As a result the utility function for the player i for a given transmission power r_i is defined as follows:

$$U_i(r_i, \mathbb{R}_{-i}) = \frac{1}{\left(\underset{j \in G^i_{r_i}}{min} \left\{ T^i_j(r_i) + P_j(\mathbb{R}_{-i}) \right\} \right)} \tag{19}$$

where r_i is the transmission power of node i, $\mathbb{R}_{-i} = \{r_1, r_2, \ldots, r_{i-1}, r_{i+1}, \ldots, r_n\}$ be the transmission power of all sensors except sensor i and $P_j(\mathbb{R}_{-i})$ is the path cost from node j to sink when all the nodes along the path use the transmission power profile $\mathbb{R}_{-i}$

4.2 The Proposed Game Based Resource Control Protocol

Congestion occurs when resource demands exceeds the network capacity. Resource limitation causes packet loss. Thus, if there is sufficient bandwidth along the path to transmit all flows, the congestion will be reduced. The goal of proposed protocol is to attain the path with highest available resources. The following resources are utilized:

- Free space in node's queue
- Node's input and output rate
- Node's energy
- The energy consuming in traffic delivery
- Distance to sink
- Channel noise

As the transmission power of a node increases, the remaining energy is eliminated and the channel capacity is altered. If the channel capacity increases, the buffer length is decreased. By transmission power control, the network performance can be improved. By increasing the transmission power, the probability of successful data delivery is improved, but remaining energy maybe decreased. Therefore, there should be a trade-off between energy and cost.

The network consists of nodes which use the IEEE 802.15.4 as MAC layer. As the radio transmission power is increased, more neighboring nodes have a competition to access the shared channel to transmit their data. Hence greater packet drop ratio may be achieved and have a noticeable impact on packet discard probability, collision probability and power consumption. As a result the impact of MAC Layer on the performance of the proposed protocol should be evaluated. In [36] the behavior of the IEEE 802.15.4 is studied. Faridi et al. [36] analysis various networking metrics at many criteria such as number of neighboring

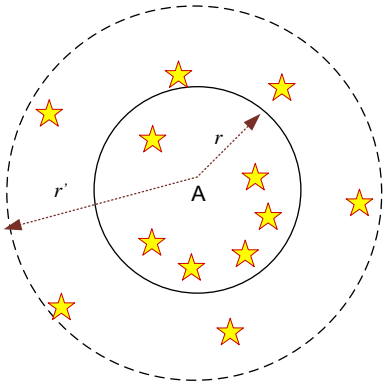


Fig. 3 Increasing of the radio range may change the number of neighbors. Node A neighbors with two different radio range r and r'. The *Stars* shows the neighbor nodes

nodes. In order to measure the impact of increasing neighboring nodes, the discard probability in MAC layer is considered as a part of nodes' local cost (Eqs. 13, 14, 17). Since radio communication among nodes might be the major source of energy consumption and packet discarding, careless increasing of radio transmission is not acceptable.

Each node has a default radio range, named r. The G_r^i is a neighbor list of node i with radio range r. if node i is unable to find a path with a reasonable cost, then it attempts to find more neighbors with a higher radio range. Higher radio range will increase the number of neighbors. Thus, a node possesses more options to obtain a path with suitable cost. In Fig. 3, for two different radio ranges, r and r', the node's neighbors are shown.

The main objective of increasing radio range is to make more resources for a node to transmit packets. In EGRC, a selection probability for each strategy is dynamically varied based on the expected payoff. During the step by-step game iteration, EGRC is adaptively tune transmit power level to alleviate congestion. The players (nodes) check their payoffs periodically in a distributed manner. The game equilibrium is defined as follows: if no player can achieve a higher advantage by changing his current strategy while the other players keep their strategies unchanged, all players do not change their strategies over a game processing time. The game consists of some iteration. Players calculate their current expected payoff based on replicator dynamics' equations at the end of each iteration. The results of the other players' strategies are used in replicator dynamics' equations to allow a player to make a proper decision for the next iteration. This interactive feedback procedure continues until the system reaches equilibrium. Therefore the game duration time is defined by the attainment of the network equilibrium. The replicator dynamics' equation in step t is defined as follows:

$$\dot{x}_i(t) = \mathbb{C} \times x_i(t-1) \times \left(\sum\nolimits_j x_j(t-1)U(i,j) - \sum\nolimits_j \sum\nolimits_k x_j(t-1)U(j,k)x_k(t-1) \right) \tag{20}$$

where $\mathbb{C}$ is some positive constant, which can control the speed of convergence.

Figure 4 shows the pseudo-code of the game procedure of the EGRC protocol.

4.3 Time to Start Game

At what time the game should be started? Each node investigates the neighbors' costs. The radio range is enhanced when the minimum cost for the current transmission power is higher than the lower bound inc_{th} as (21):

```
Algorithm EGRC
Procedure EGRC _Game()   // for node i
loop
   Initialized the selection probability of each strategy to 1/|S| (|S| is the number
of nodes' strategy)
  For each transmission power  r_i do
     For each neighbor k ∈ G^i_{r_i}
          Compute travel cost of neighbor k (T^i_k(r_i) ) according to  (6)
   end for
     Compute the U(r_{i,}, ℝ) according to (19)
  end for
  Recalculate the selection probability x according to (20)
  if changes in selection probability vector (x) is lower than thereshold (ε) then
     if  all players do not change their privous stategy then
          The equilibrium is reached and game is finished
   end if
 end if
end loop
end procedure
```

Fig. 4 Pseudo-code of the EGRC protocol

$$min_{\ j \in G^i} \left\{ T_j^i \right\} \geq inc_{th} \tag{21}$$

When the transmission power is increased, the energy per successfully transmitted packets may also be increased. As a result, each node should adapt its power so that the network remains connected while it is saving energy. To perform this, each node i evaluates its neighbors' costs, periodically. If the maximum cost is less than the threshold, dec_{th}, the node start a game to change (decrease) its transmission power to avoid energy consumption. Radio range reduction condition satisfies the following conditions:

$$\max_j \left\{ T_j^i \right\} \leq dec_{th} \tag{22}$$

The $\mathrm{dec_{th}}$ and $\mathrm{inc_{th}}$ parameters are periodically adapted based on the congestion level. Each node is able to observe periodically its neighbors' cost. When the minimum cost is increased, it informs the node about growing probability of congestion occurrence and when the minimum cost is decreased, it shows that the congestion level starts decreasing. As a result we used a EWMA based method to calculate an average of minimum cost and maximum cost over some period of time as follows:

$$Cmin_{avg}^i(t) = \delta Cmin_{avg}^i(t-1) + (1-\delta) \min_{j \in G^i} \left\{ T_j^i(t) \right\}$$

$$Cmax_{avg}^i(t) = \mu Cmax_{avg}^i(t-1) + (1-\mu) \max_{j \in G^i} \left\{ T_j^i(t) \right\}$$

$$0 \leq \mu, \quad \delta \leq 1 \tag{23}$$

$$dec_{th}(t) = dec_{th}(t-1) * \left(\frac{Cmax_{avg}^i(t-1)}{Cmax_{avg}^i(t)} \right) \tag{24}$$

$$inc_{th}(t) = inc_{th}(t-1) * \left(\frac{Cmin_{avg}^i(t-1)}{Cmin_{avg}^i(t)} \right) \tag{25}$$

where $T_j^i(t)$ is the total cost of node i to select node j at current transmission power. δ and μ are the weight and are tuned using simulation and trial approach.
The dec_{th} and inc_{th} parameters can be calculated as follows:

When the congestion level is increased, the minimum and maximum costs are increased too. As a result the radio range increment probability is grown and radio range decrement probability is reduced. The lower the inc_{th}, the higher the radio range increment probability and the lower the dec_{th}, the lower the radio range decrement probability [see the Eqs. (21) and (22)].

By using simulation and trial approach an initial value of dec_{th} and $inc_{th}$is defined based on the first cost table as follows:

$$dec_{th} = avg\left(\min_{j\in G^i}\left\{T_j^i\right\},\ \max_{k\in G^i}\left\{T_k^i\right\}\right)$$
$$inc_{th} = \max_{k\in G^i}\left\{T_k^i\right\} \tag{26}$$

where $min_{j\in G^i}\left\{T_j^i\right\}$ is the minimum cost of node i to select node j as its next hop and $max_{k\in G^i}\left\{T_k^i\right\}$ is the maximum cost of node i to select node k as its next hop in a default (initial) transmission power). After that the dec_{th} and inc_{th} parameters are periodically adapted based on the Eqs. (22) and (25), respectively.

5 Simulation Results

In this section, simulation study is applied to evaluate the performance of the proposed protocol under different scenarios. For this purpose, a wireless sensor network topology as shown in Fig. 5 is simulated using OPNET simulator [37]. To simulate a real environment, the intermediate nodes' power consumption parameters values are choose the same as 802.15.4-compliant RF transceiver CC2430 [38]. The Proposed protocol implementation was done by using the 802.15.4 protocol of the MAC layer. The proposed protocols are implemented,

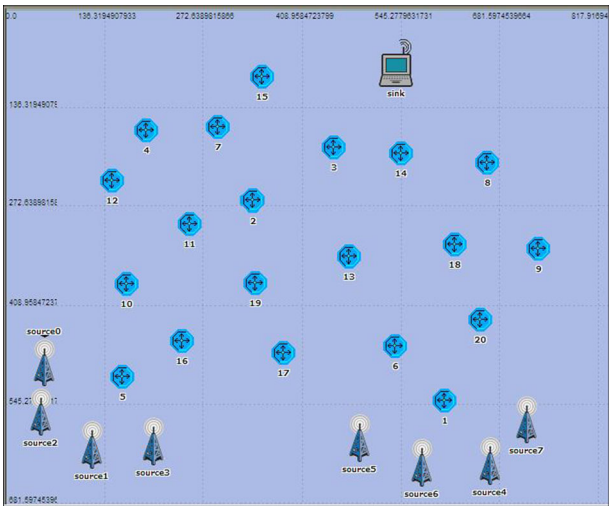


Fig. 5 The network topology used in the simulation

Table 1 Network performance

	EGRC	TADR	[26]	[27]
Average delay	0.1	0.02	0.01	1.1
Packet loss ratio	0.08	0.23	0.2	0.001 (resend packet ratio)
Network energy loss (E_L)	0.09	0.3	0.25	0.001
Total delivery ratio	88 %	77 %	80 %	100 %
Average throughput	2,000	1,500	1,500	1,000

and compared with two evolutionary game theoretical algorithms [26] and [27] and also with resource control based schema named TADR [24] protocol. Menasche et al. [26] and Altman et al. [27] are traffic control approaches that control the sending rate based on EGT. TADR [24] is not a game theoretical algorithm but it similar to our approach in that it control congestion by using resource control method but it is not a game theoretical work.

The following performance metrics are used to evaluate the protocols:

- *Packet loss ratio* = Total number of lost packets/total number of generated packets.
- *Energy loss* $\boldsymbol{E_L}$ = Total number of lost packets/total number of received packets by the sink.
- *Delivery ratio* = Total number of received packets by the sink/total number of generated packets.
- *Throughput* = Total number of received packets by the sink/time Nodes metrics:
- Energy Fairness ratio =

$$E_f{}^i = E_{rem}{}^i - \left(\sum_{j=1}^{N} E_{rem}{}^i \Big/ N \right)$$

  $E_{rem}{}^i$: Remaining energy of node i
- *Energy usage* E_u = (initial energy – remaining energy)/initial energy
- *Source delivery ratio* = number of node i packets received by sink/total number of packets generated by node i.

Table 1 shows network performance. The notable issue is that in EGRC algorithm, cost is the sum of transmitting costs of all nodes along the path, while TADR considers just the next hop cost. TADR cannot estimates the sum of queuing delays of the path. TADR just pays attention to the queue length of the next hop neighbors. Therefore, the estimation of the end-to-end delay and loss are not possible.

Altman et al. [27] and Menasche et al. [26] are both traffic control schemas so they have lower throughput than resource control based protocols (EGRC and TADR). Altman et al. [27] is a game based TCP for wireless network, although TCP guarantees delivery of data transfer, it has many drawbacks in wireless networks. For example the continuous byte streaming of the TCP protocol is considered as the main cause of consuming energy in the wireless networks. TCP is based on the ACK report from the destination node; otherwise, the packet will be retransmitted again to the destination node. Retransmission means more wasted energy will be consumed.

In this paper, we consider a realistic MAC layer model to represent the contention between nodes in the network. Thus the packet loss is occurred because of MAC layer contention and queue overflow. As it is observed in Table 1, the number of lost packets in EGRC less than

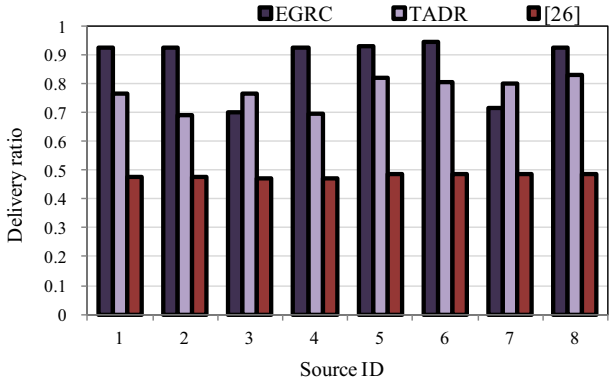


Fig. 6 Source delivery ratio

other protocols (except [27]) which is a result of using the nodes with lower drop probabilities and higher energy.

Collision is a major source of energy waste in a MAC protocol for WSNs. When a transmitted packet is corrupted it has to be discarded, and be retransmitted. The retransmission increases energy consumption. The goal of the proposed protocol is to adjust the transmission power at each node properly, in order to improve the lifetime of WSNs and alleviation congestion. Subsequently, the maximum radio range increment is determined based on node remaining energy and the increase rate of packet loss due to increasing transmission power (increasing collision). Though it seems that in the proposed protocol, a node that increases its radio transmission power, consumes more energy and has higher packet loss ratio, the total energy consumption and packet loss ratio (along the path) is decreased. In the proposed protocol, cost is the sum of transmitting costs of all nodes along the path. The consideration of path's cost makes some advantages. For instance, in the proposed protocol, a path with lower queuing delay, lower energy consumption and lower drop ratio is chosen. As mentioned before, the path cost includes some valuable metrics such as delay, drop probability (queue and MAC loss) and energy consumption. If node i is unable to find a path with a reasonable cost, then it attempts to find more neighbors with a higher radio range. Higher radio range will increase the number of neighbors. Thus, a node possesses more options to obtain a path with suitable cost. Since the nodes' local cost contains MAC packet discard probability, the nodes with higher local cost have lower chance to be selected as the next hop. The drop packets increase the network energy loss ratio and decrease the end to end successfully delivery ratio. Thus this node has a higher cost than others and has a lower chance to be selected as the next hop of the next round. Thus by increasing the transmission power, the probability of successful end to end data delivery is improved.

Figure 6 illustrates the source node delivery ratio. As it is shown in this figure, the number of lost packets in the proposed protocols are less than TADR and [26] protocols which is a result of using complete path information (in terms of loss probability). As a result, in the proposed protocols, the number of received packets will be increased.

Figure 7 displays the throughput of all protocols. Network throughput is the average rate of successful packet delivery. Our proposed protocol does not reduce sending rate while congestion. Thus, it has higher throughput than traffic control based approach.

Figure 8 plots the nodes energy consumption. As the issue of energy consumption in sensor nodes is of vital importance, so development of protocols with lower rates of energy

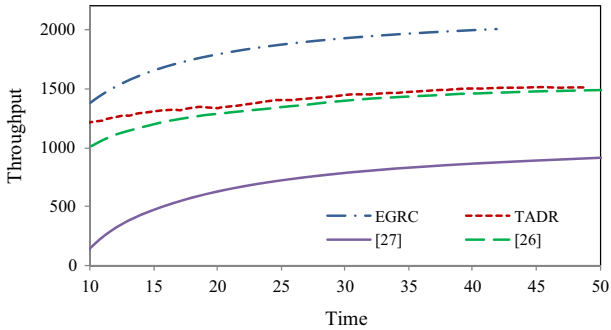


Fig. 7 Network average throughout in all algorithms

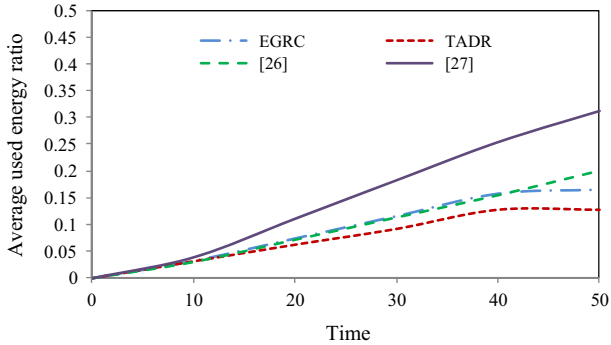


Fig. 8 Average nodes' used energy

consumption is necessitated. The proposed protocols are energy-efficient methods which avoid congestion with an acceptable rate of energy consumption. The network lifetime is the time until the first node dies. The remaining energy level is a grave parameter in the proposed protocols, thus, the traffic distribution is performed so that the network lifetime is maximized. Though it seems that EGRC protocol (in some points only) consume more energy than TADR, this protocol transmit more packets along the network than TADR. As a result, it is fairer that the ratio of energy consumption to the transmitted packets is to be considered. The reason that TCP consumes more energy than other protocols is that TCP uses ACK control message and end-to-end retransmission method thus it consumes more energy at every node. Energy efficiency is of prime importance for sensor networks.

Figure 9 reveals the percentage of the energy consumption proportion of transmitted packets. This figure indicates that EGRC protocol consume less energy than others, due to lower loss percentage. Indeed, EGRC protocol transmits packets with lower cost and lower delay, while it is increasing network throughput.

6 Conclusion

In this paper we study competitive distributed resource control mechanism in a wireless sensor network. The ultimate goal of the protocol is to utilize available resources with low energy consumption which will, in turn, lead to control congestion. To reducing congestion,

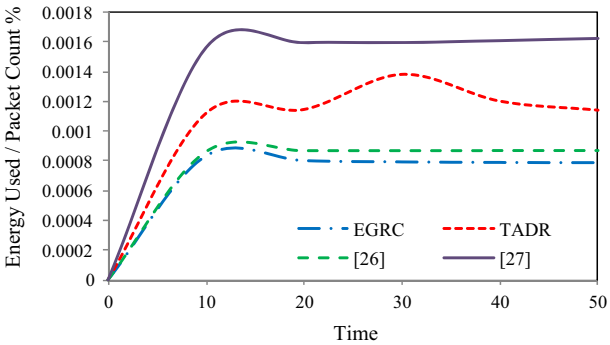


Fig. 9 Average nodes used energy versus packet transmission

the dynamic transmission-power mechanism is utilized based on the EGT, increasing the transmission power offers more neighbor nodes and a higher channel capacity. It can eliminate the delay and save remaining energy by provisioning additional resources. Several potential metrics are introduced that confirms the congestion level and available resources along the path from source to sink.

References

1. Sohraby, K., Minoli, D., & Znati, T. (2007). *Wireless sensor network: Technology, protocols, and applications*. New York: Wiley.
2. Karl, H., & Willig, A. (2005). *Protocols and architectures for wireless sensor networks*. New York: Wiley.
3. Kang, J., Zhang, Y., & Nath, B. (2006). Analysis of resource increase and decrease algorithm in wireless sensor networks. In *Proceedings of the 11th (ISCC'06)*, pp. 585–590.
4. Kang, J., Zhang, Y., & Nath, B. (2007). TARA: Topology-aware resource adaptation to alleviate congestion in sensor networks. *IEEE Transactions on Parallel and Distributed Systems*, *18*(7), 919–931.
5. Leino, J. (2003). *Applications of game theory in ad hoc networks*. Master's thesis, Helisnki University of Technology.
6. Hofbauer, J., & Sigmund, K. (2003). Evolutionary game dynamics. *Journal of Bulletin of the American Mathematical Society*, *40*(4), 479–519.
7. Wang, C., Sohraby, K., Daneshmand, M., & Hu, Y. (2007). Upstream congestion control in wireless sensor networks through cross-layer optimization. *IEEE Journal on Selected Areas in Communications*, *25*(4), 786–795.
8. Ee, C.-T., & Bajcsy, R. (2004). Congestion control and fairness for many-to one routing in sensor networks. In *Proceedings of the 2nd international conference on embedded networked sensor systems ACM*
9. Yaghmaee, M. H., & Adjeroh, D. (2009). Priority-based rate control for service differentiation and congestion control in wireless multimedia sensor networks. *Journal of Elsevier Computer Networks*, *53*, 1798–1811.
10. Wang, C., Sohraby, K., & Li, B. (2005). SenTCP: A hop-by-hopcongestion control protocol for wireless sensor networks. In *Proceedings of theIEEE INFOCOM*.
11. Paek, J., & Govindan, R. (2007). RCRT: Rate-controlled reliable transport for wireless sensor networks. In *Proceedings of the ACM conference on embedded networked sensor systems (Sensys)*.
12. Yaghmaee, M. H., & Adjeroh, D. (2010). A novel congestion control protocol for vital signs monitoring in wireless biomedical sensor networks. In *Proceedings of the WCNC conference*, pp. 1–6.
13. Misra, S., Tiwari, V., & Obaidat, M. S. (2009). LACAS: Learning automata-based congestion avoidance scheme for healthcare wireless sensor networks. *IEEE Journal on Selected Areas in Communications*, *27*(4), 466–479.
14. Farzaneh, N., & Yaghmaee, M.H. (2011). Joint active queue management and congestion control protocol for healthcare applications in wireless body sensor networks. In *Proceedings of the 9th international conference on smart homes and health telematics (ICOST)*. doi:10.1007/978-3-642-21535-3_12

15. Farzaneh, N., Yaghmaee, M. H., & Adjeroh, D. (2012). An adaptive congestion alleviating protocol for healthcare applications in wireless body sensor networks: Learning automata approach. *AmirKabir Journal of Science and Technology*, *44*(1), 31–41.
16. Alam, M., & Hong, S. (2009). CRRT: Congestion-aware and rate-controlled reliable transport in wireless sensor networks. *IEICE Transactions on Communications*, *92*(1), 184–189.
17. Farzaneh, N., & Yaghmaee, M. H. (2013). A prioritization based congestion control protocol for healthcare monitoring application in wireless sensor networks. *Wireless Personal Communications*, *72*(4), 2605–2631.
18. Fang, W., Chen, J., Shu, L., Chu, T., & Qian, D. (2010). Congestion avoidance, detection and alleviation in wireless sensor networks. *Journal of Zhejiang University*, *11*(1), 63–73.
19. Wan, A. Y., EisenmanSh, B., & Campbell, A. (2005). Siphon: Overload traffic management using multi-radio virtual sinks in sensor networks. *Sensor Systems*, *2005*, 116–129.
20. Wan, A. Y., EisenmanSh, B., Campbell, A., & Jon Crowcroft, J. (2007). Overload traffic management for sensor networks. *ACM Transactions on Sensor Networks*, *3*(4), 18.
21. Kang, J., Zhang, Y., & Nath, B. (2009). An optimal resource control scheme under fidelity and energy constraints in sensor networks. *Journal of Wireless Networks*, *15*, 497–512.
22. Teo, T., Ha, Y., & Tham, Ch. (2008). Interference-minimized multipath routing with congestion control in wireless sensor network for high-rate streaming. *Mobile Computing (IEEE Transactions)*, *7*, 1124–1137.
23. Seon, C. H., & Lee, S. (2010). Autonomous traffic engineering for boosting application fidelity. *IEICE Transactions*, *93*, 2990–3003.
24. Ren, F., He, T., Das, S. K., & Lin, C. H. (2011). Traffic-aware dynamic routing to alleviate congestion in wireless sensor networks. *Parallel and Distributed Systems*, *22*, 1585–1599.
25. Rezaee, A. A., Yaghmaee, M. H., Rahmani, A. M., & Mohajerzadeh, A. H. (2013). HOCA: Healthcare aware optimized congestion avoidance and control protocol for wireless sensor networks. *Journal of Network and Computer Applications*, *37*, 216–228.
26. Menasche, D. S., Figueiredo, D. R., & de Souza e Silva, E. (2005). An evolutionary game-theoretic approach to congestion control. *Performance Evaluation*, *62*(14), 295–312.
27. Altman, E., El-Azouzi, R., Hayel, Y., & Tembine, H. (2009). An evolution of transport protocol: An evolutionary game perspective. *Computer Networks*, *53*, 1751–1759.
28. Smith, J. M. (1972). Game theory and the evolution of fighting. In *On evolution*. Edinburgh University Press, Edinburgh, pp. 8–28.
29. Smith, J. M. (1974). The theory of games and the evolution of animal conflicts. *Journal of Theoretical Biology*, *47*, 209–221.
30. Smith, J. M., & Price, G. R. (1973). The logic of animal conflict. *Nature*, *246*, 15–18.
31. Rees, T. (2005). An introduction to evolutionary game theory. *Technical report*, UBS Department of Computer Science.
32. Cressma, R. (1992). *The stability concept of evolutionary game theory: A dynamic approach*. New York: Springer.
33. Hofbauer, J., & Sigmund, K. (1998). *Evolutionary games and replicator dynamics*. Cambridge: Cambridge University Press.
34. Weibul, J. (1995). *Evolutionary game theory*. Cambridge: MIT Press.
35. Gross, D., & Harris, C. M. (1998). *Fundamentals of queuing theory*. New York: Wiley.
36. Faridi, A., Palattella, M. R., Lozano, A., Dohler, M., Boggia, G., Grieco, L., et al. (2010). Comprehensive evaluation of the IEEE 802.15.4 MAC layer performance with retransmissions. *IEEE Transactions on Vehicular Technology*, *59*(8), 3917–3932.
37. http://www.opnet.com (2010).
38. CC2430 Preliminary Data Sheet (rev. 2.1) SWRS036F, Jun., Chipcon Products from Texas Instruments (2007).

Nazbanoo Farzaneh born in March 1980 in Tehran, Iran. She received her B.S. degree in 2002 and her M.S. degree in computer engineering from the Ferdowsi University, Mashhad, Iran in 2006. She is currently Ph.D. candidate at Department of Computer Engineering of Aforementioned University. Her main research interests include Wireless Sensor Network, Next Generation Network (NGN), Computer Networks, Congestion Control, Quality of Services, Fuzzy Logic Control, Reinforcement Learning, Game theory and Queuing Theory.

Mohammad Hossein Yaghmaee born in July 1971 in Mashhad, Iran. He received his B.S. degree in Communication Engineering from Sharif University of Technology, Tehran, Iran in 1993, and M.S. degree in communication engineering from Tehran Polytechnic (Amirkabir) University of Technology in 1995. He received his Ph.D. degree in communication engineering from Tehran Polytechnic (Amirkabir) University of Technology in 2000. He is a senior member of IEEE and has been a computer network engineer with several networking projects in Iran Telecommunication Research Center (ITRC) since 1992. November 1998 to July1999, he was with Network Technology Group (NTG), C&C Media research labs., NEC Corporation, Tokyo, Japan, as visiting research scholar. September 2007 to August 2008, he was with the Lane Department of Computer Science and Electrical Engineering, West Virginia University, Morgantown, USA as the visiting associate professor. He is author of 5 books all in Farsi language. He has published more than 80 international conference and journal papers. His research interests are in Wireless Sensor Networks (WSNs), traffic and congestion control, high speed networks including ATM and MPLS, Quality of Services (QoS) and fuzzy logic control.