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REGULAR PAPER

A new evolutionary based application specific routing protocol for clustered wireless sensor networks

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ABSTRACT

Energy consumption is a major issue in designing wireless sensor networks. To achieve the energy efficiency, many routing protocols have been proposed and LEACH is the representative one. LEACH utilizes randomize rotation of the cluster heads to evenly distribute energy load among all nodes. However, it depends only on a probability model and energy efficiency could not be maximized. In this paper, a new application specific low power routing protocol named ASLPR is introduced that takes into account some concepts from sensor nodes (e.g., distance from base station, residual energy, distance between cluster heads) to elect the optimal cluster heads. As the proposed routing protocol is complex and has some controllable parameters, tuning of its parameters is an important problem to achieve the best performance based on the application. In this work, a hybrid algorithm based on genetic algorithm and simulated annealing is applied to optimize ASLPR in order to prolong the network lifetime, based on the application specifications. Simulation results demonstrate the efficiency of the proposed methodology to balance the energy consumption of nodes and maximize network lifetime. The gain (on average) in stable region of ASLPR until first node dies is 78%, as compared with three LEACH-based protocols.

1. Introduction

The combination of a number of wireless sensors makes a wireless sensor network (WSN) which provides unprecedented opportunities in several domains ranging from military to agriculture, and has applications in civil as well as construction structural monitoring, industrial control, health monitoring, and home networks [1]. In the past few years, an intensive research was conducted that addresses the potential of collaboration among wireless sensors in data gathering and processing. However, wireless sensor nodes are constrained in the energy supply, processing power, bandwidth and memory. Since the network lifetime depends on energy consumption of the nodes within the network, the power supply component in the nodes is very important. Thus, innovative techniques that minimize the energy consumption and maximize the lifetime of the network are highly required. A routing protocol should takes into account the energy-awareness at all layers of the networking protocol stack (e.g., routing at the network layer), in such a way that the network lifetime is maximized [2].

In WSNs, a routing protocol is required when a node cannot send its data packet directly to its destination node, and has to rely on the assistance of intermediate nodes to forward its packet. Routing in WSNs is very challenging, due to several natural characteristics that distinguish them from typical communication networks such as wireless ad-hoc networks [3]. First, classical IP-based protocols cannot be used for WSNs, due to its inability to build a global addressing scheme for the deployment of wireless sensor nodes. Second, in contrast to the typical communication networks almost all applications of WSNs require that the sensed data from multiple sensor sources are flow to a particular base-station. Third, the generated data traffic has substantial redundancy, since the multiple wireless sensor nodes may sense the same data in the case of homogeneous WSNs. Such redundancy needs to be exploited via the routing protocol to improve the energy and bandwidth utilization. Fourth, wireless sensor nodes are tightly constrained in terms of transmission power, energy, and storage. Therefore, they require careful resource management [4]. In the last few years, many protocols have been proposed for the routing problem in WSNs [4]. In general, routing protocols for WSNs can be categorized into *flat*, *hierarchical*, and *location-based* [5]. In flat routing, all nodes have the same functionality and they work together to sense and route [6]. Hierarchical routing techniques divide the network into distinguished clusters. The most famous and attractive hierarchical protocol is Low Energy

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Adaptive Clustering Hierarchy (LEACH), which has been widely accepted for its energy efficiency and simplicity [7]. In location-based routing approaches, the information about the location of sensor nodes is used to generate the routing path [8].

An intermittently connected mobile ad hoc network is a special type of wireless mobile network, in which, disconnection occurs frequently. Therefore, these networks cannot guarantee a completed path between the source and destination most of the time. To overcome such a drawback, Sun et al. [9] have proposed a routing scheme called primate-inspired adaptive routing protocol (PARP), which can utilize the features of the primate mobility to assist routing. For intermittently connected mobile networks, the number of message copies is another significant factor that affects the performance of the networks. Since the connection is hard to establish in these networks, the nodes need more strict mechanism on energy savings to guarantee future communications. The most efficient way for energy saving is to control the number of message copies. PARP determines the number of message copies and the routing strategy based on the walking length of the mobility model. Distinct from the conventional routing protocols for mobile ad hoc networks, PARP combines the mobility model and routing together [9]. Recently, cross-layer routing design for cognitive radio networks has been widely studied. A large queuing and back-off delay will reduce the transmission efficiency of a link and increase the cumulative end-to-end delay. In Ref. [10], a source routing protocol based on on-demand routing and dynamic channel assignment has been proposed to improve the transmission efficiency under multi-link interference situation. The channel assignment tries to maximize the transmission efficiency of links along the selected path, to reduce the average cumulative end-to-end delay of all flows and increase the packet delivery ratio [10].

There are some popular criteria for definition of network lifetime in WSNs, including First Node Dies (FND), Half Node Die (HND), Last Node Dies (LND), etc. [3]. It is remarkable that the network lifetime is defined based on the application, and there is no an specific definition that covers all of the applications. For example, in a hospital health monitoring network, lifetime should be defined as FND, due to the information of sensor nodes is distinguished, and it is different from a node to another. In these networks perishing of a sensor node may generate irreparable damages. Therefore, lifetime in these kind of applications with distinguished nodes should be define as FND. On the other hand, there are a large number of applications with homogeneous nodes, such as construction structural monitoring in Buildings, Tunnels, Bridges, etc. Perishing of some of sensor nodes is not critical in these applications, and network is trustable as long as at least the determined number of nodes will be remained alive. Therefore, lifetime may be defined in different criteria based on node density, application specifications, and distribution of nodes in the network.

In the clustering-based routing protocols, data gathered by the sensor nodes is transmitted to the sink through the cluster heads (CHs). As the nodes communicate data over shorter distances in these protocols, the energy spent in the network is likely to be substantially lower compared to when each node communicates directly to the Base Station (BS). It is notable that as distance increased, energy consumption grows exponentially for the transmitter node. To this end, various clustering-based protocols have been proposed aim at generating the minimum number of clusters and minimum transmission distances. These algorithms are distinguished by how the CHs would be elected. Recently, Swarm Intelligence (SI) algorithms have begun to attract attention from researchers to develop clustering-based routing protocols in WSNs [3,11–16]. The main goal of these SI-based protocols is to dynamically cluster sensor nodes such that the energy consumption of the network is minimized. They have proved that their protocols outperform other attractive routing protocols such as LEACH in prolonging the network lifetime. However, making a precise inspection of their results, one can see that one common drawback emerges. While these SI-based routing protocols prolong the network lifetime (e.g., HND or LND), they decrease the stability period of the system (e.g., FND) which is crucial for many applications like health monitoring networks.

In this paper, a hybrid clustering-based Application-Specific Low Power Routing (ASLPR) protocol is introduced, that takes into account some concepts from the current situation of sensor nodes in the network (e.g., the distances from sensors to the base station, the remained energy of sensors, distance of nodes from other cluster heads etc.), and can optimally balance the energy consumption among the sensors. As the proposed routing protocol is complex with some controllable parameters, a hybrid algorithm based on genetic algorithm and simulated annealing is used to optimize the proposed protocol. The main advantage of the proposed protocol is that ASLPR can adaptively tune its parameters in order to generate the maximum lifetime in each specific application. Therefore, we are motivated by the fact that there are many applications that would benefit highly from maintaining the stability as well as the network lifetime, thus maintaining better tradeoff between reliability and lifetime of the system. On the other hand, the proposed ASLPR protocol can maximize the defined lifetime scheme (e.g., FND, HND, etc.), based on the application.

The rest of the paper is organized as follows: Section 2 briefly reviews some hierarchical clustering-based routing protocols in WSNs. In Section 3, the drawbacks of the current hierarchical clustering-based routing protocols are addressed and the ASLPR algorithm is proposed as an effective solution to their problems. The optimization procedure of ASLPR protocol using hybrid genetic algorithm and simulated annealing is described in Section 4. Also, Section 5 presents simulation results and comparison with other LEACH-based routing protocols. Finally, Section 6 concludes this paper with possible future directions.

2. Related works

In this section, three clustering-based routing protocols, including LEACH [7], energy-aware LEACH-EP [17], and distance-aware LEACH-DT [18] are discussed in details. Generally, clustering-based protocols segment a network into non-overlapping clusters, each of them contains a CH. Non-CH nodes transmit their data packet to CH nodes, where the sensed data can be aggregated as these signals can be sufficiently correlated, and transmitted to sink. The LEACH protocol [7] uses stochastic self-election, where each node has a probability P of becoming a CH in each round. On the other hand, LEACH forms clusters via a distributed algorithm, where nodes make autonomous decisions to be CHs without any centralized control. It guarantees that each node would be a CH only once in consecutive $1/P$ rounds. Initially, each node decides to be a CH with a probability P. The role of being a CH is rotated periodically among the nodes of the cluster aims to balance the load and distribute the energy consumption. The operation of LEACH in the every round can be separated into two phases: the setup phase and the steady phase. During the setup phase, each sensor node n chooses a random number between 0 and 1. The node n becomes a CH for the current round, if its random number is less than the threshold $T(n)$. The threshold $T(n)$ is calculated according to Eq. (1), where P is the desired percentage of nodes to become CHs, r is the current round number, and G is the set of all nodes that have not being selected as CH in the last $1/P$ rounds.

$$T(n) = \begin{cases} \dfrac{P}{1 - P \times \left[r \bmod (1/P) \right]} & \textit{if} \quad n \in G \\ 0 & \textit{otherwise} \end{cases} \qquad (1)$$

After CHs have been selected, they advertise to all sensor nodes in the network that they are the new CHs. Once each non-CH node receives the advertisement from CHs, it determines its CH with the minimum communication distance. Once the clusters are created and the TDMA schedule is fixed, data transmission can begin. After a given time spent on the steady phase, the network goes into the setup phase again and enters another roundf selecting CHs. As proved in Ref. [7], the optimal number for CHs can be calculated according to Eq. (2). Note that the optimal percentage of nodes to become CHs, $P_{optimum}$ is equal to $K_{optimum}/N$.

$$K_{optimum} = \frac{\sqrt{N}}{\sqrt{2\pi}} \times \frac{\sqrt{\varepsilon_{fs}}}{\sqrt{\varepsilon_{mp}}} \times \frac{M}{d_{\sin k}^2} \tag{2}$$

where N is the total number of alive sensor nodes, M is the maximum length of the side of square region, d_{sink} is the distance between nodes and the BS. Also ε_{fs} and ε_{mp} are the amplification coefficients of the power-amplifier in the free space and the multipath fading channel models, respectively.

Compared with flat protocols, LEACH has good performance in extending the network lifetime. However, residual energy of nodes is not taken into account for CH-election in LEACH protocol. On the other hand, if the node with lower residual energy decides to become a CH, it will be rapidly dead. Considering the fact that more energy consumption is involved in collecting the average residual energy of all nodes compared with all CHs, LEACH-EP [17], an extension of LEACH has been proposed, in which, an energy factor is also takes into account. In LEACH-EP protocol, the nodes with more energy have more opportunities to serve as CH. Energy-based threshold $T_{ep}(n)$ for node n in LEACH-EP is calculated via Eq. (3), where P is the desired percentage of nodes to be CHs, $E(n)$ is the current residual energy of node n, and $E_{ch\_av}(r-1)$ is the average residual energy of all CHs in the previous round. Authors in [17] show that LEACH-EP improves the FND lifetime over 33% in contrast to the LEACH.

$$T_{ep}(n) = \begin{cases} P \times \dfrac{E(n)}{E_{ch\_av}(r-1)} & \text{if} \quad E(n) \geq 0.5 \times E_{ch\_av}(r-1) \\ 0 & \text{if} \quad E(n) < 0.5 \times E_{ch\_av}(r-1) \end{cases} \tag{3}$$

Recently, several distance-based routing protocols have been proposed. In [19], a CH election algorithm was proposed using the minimum and maximum of the distance to the sink. In [18], the authors investigated a distributed LEACH-based CH election algorithm called LEACH with Distance-based Threshold (LEACH-DT), aims to balance the energy consumption among all nodes. In LEACH-DT, nodes are self-selected to become CH with different probabilities based on their distances to the sink. LEACH-DT uses the same formula as the original LEACH (see Eq. (1)). However, unlike LEACH, P_n in LEACH-DT is not a constant parameter and can be calculated according to Eq. (4), as a function of distance from node n to sink. let $\xi_n = 1/(\bar{E}_{CH} \times d_n - \bar{E}_{non-CH})$, where d_n is the distance from node n to sink, and $\bar{E}_{CH}$ and $\bar{E}_{non-CH}$ are the average residual energy of CHs and non-CH nodes, respectively. Authors in [18] show that their protocol outperforms the original LEACH with improved lifetime over 10%.

$$P_n = K \times \frac{\xi_n}{\sum_{j=1}^{N} \xi_j} \quad (0 < P_n < 1) \tag{4}$$

3. ASLPR routing protocol

3.1. Communication model

In order to calculate energy consumptions, the first order radio communication model [7] is used. In this model, a radio dissipates E_{elec} (per a bit) to run either the transmitter or the receiver circuitry. Also, depending on the transmission distance the free space and the multi-path fading channel models are used for the transmitter amplifier [20]. To transmit an l-bit data packet from the transmitter node to the receiver node with a distance d between them, the energy consumption for the transmitter node and receiver node, respectively can be calculated as follows:

$$\begin{aligned} E_{TX}(l,d) &= E_{TX\_elec}(l) + E_{TX\_amp}(l,d) \\ &= \begin{cases} l \times E_{elec} + l \times E_{fs} \times d^2 & \text{if } d \leq d_0 \\ l \times E_{elec} + l \times E_{mp} \times d^4 & \text{if } d > d_0 \end{cases} \end{aligned} \tag{5}$$

$$E_{RX}(l) = E_{RX\_elec}(l) = l \times E_{elec} \tag{6}$$

where, the threshold distance d_0 is defined as $d_0 = \sqrt{E_{fs}/E_{mp}}$. The electronic energy E_{elec} depends on such electronic factors as digital coding, modulation, filtering, and spreading ofhe signal, whereas the amplifier energy in free space E_{fs} or in multipath environment E_{mp} depends on the distance from the transmitter to the receiver.

3.2. CH-election via ASLPR routing protocol

As mentioned above, residual energy of nodes, their location in the network, etc. are not taken into account for CH-election in LEACH protocol. On the other hand, if the node with lower residual energy and large distance from sink decides to become a CH, it will be rapidly dead. According to Eq. (1), each qualified node in set G has an identical opportunity to become CH per round, in LEACH protocol. It is obviously that this mechanism leads to unbalanced energy consumption. On the other hand, this incurs more energy consumption for those nodes that are farther from the sink. In this paper, an application-specific clustering-based routing protocol named ASLPR is introduced, that takes into account some concepts from the current situation of sensor nodes in the network (e.g., the distance from the sink, the residual energy, the number of previously became CH, the distance from the other CHs, etc.). By considering the sensor node situation in the network, ASLPR, an extension of LEACH is introduced here. The adaptive threshold $T_{ASLPR}(n)$ for node n in ASLPR is calculated as follows:

$$T_{ASLPR}(n) = \begin{cases} Z(N) & \text{if} \quad E(n) \geq t_1 \times \dfrac{1}{N}\sum_{i=1}^{N} E(i) \\ 0 & \text{if} \quad E(n) < t_1 \times \dfrac{1}{N}\sum_{i=1}^{N} E(i) \end{cases} \tag{7}$$

where Z(n)=α_1T$_1$(n)+α_2T$_2$(n)+α_3T$_3$(n)+α_4T$_4$(n), in which, α_1, α_2, α_3, and α_4 are four weighting constant parameters applied to adjust the relative influence of the sub-threshold terms within the multi-threshold $T_{ASLPR}(n)$. Note that it must be $\sum_{i=1}^{4} \alpha_i = 1$, in order to normalize the threshold value in contrast to the traditional LEACH protocol. The four sub-threshold rms from $T_1(n)$ to $T_4(n)$ can be formulated as follows:

$$T_1(n) = \begin{cases} P \times \dfrac{E(n)}{\frac{1}{N}\sum_{i=1}^{N} E(i)} & \text{if} \quad E(n) \geq t_2 \times \dfrac{1}{N}\sum_{i=1}^{N} E(i) \\ 0 & \text{if} \quad E(n) < t_2 \times \dfrac{1}{N}\sum_{i=1}^{N} E(i) \end{cases} \tag{8}$$

$$T_2(n) = \begin{cases} P \times \dfrac{\frac{1}{N}\sum_{i=1}^{N} d_{\sin k}(i)}{d_{\sin k}(n)} & \text{if} \quad d_{\sin k}(n) \leq t_3 \times \dfrac{1}{N}\sum_{i=1}^{N} d_{\sin k}(i) \\ 0 & \text{if} \quad d_{\sin k}(n) > t_3 \times \dfrac{1}{N}\sum_{i=1}^{N} d_{\sin k}(i) \end{cases} \tag{9}$$

$$T_3(n)=\begin{cases} P\times\dfrac{\dfrac{1}{Q}\sum_{i=1}^{Q}d_{ch}(n,i)}{\dfrac{1}{Q\times(Q-1)}\sum_{i=1}^{Q}\sum_{j=1}^{Q}d_{ch}(j,i)} & if \quad Q>1\\ P\times\dfrac{2\times d_{ch}(n,Q)}{M} & if \quad Q=1\\ P & if \quad Q=0\end{cases} \tag{10}$$

$$T_4(n)=\begin{cases} P\times\dfrac{\dfrac{1}{N}\sum_{i=1}^{N}N_{ch}(i)}{N_{ch}(n)} & if \quad round>1\\ P & if \quad round=1\end{cases} \tag{11}$$

where N is the number of alive sensor nodes in t network, P is the desired percentage of nodes to be CHs, $E(n)$ is the current residual energy of node n, $d_{\mathrm{sink}}(n)$ is the distance from node n to the sink, $d_{ch}(j,i)$ is the distance between node i and the CH node j, and $N_{ch}(n)$ is the total number of rounds that the node n was selected as CH node, so far, and M is the number of nodes which have been selected as CHs in the current round, so far. Also, t_1 and t_2 are two threshold constant parameters.

3.3. Overall operation of ASLPR protocol

Like original LEACH protocol, the operation of ASLPR in the every round can be separated into the setup phase and the steady phase. During the setup phase, each sensor node n chooses a random number between 0 and 1. The node n becomes a CH for the current round, if its random number is less than thproposed adaptive threshold $T_{alprp}(n)$ as seen in Eq. (7). After selection of the CHs, they advertise to all sensor nodes in the network that they are the CHs in the current round. Once each non-CH node receives the advertisement from the CHs, it determines its cluster by choosing one of the CHs with the minimum communication distance (based on the signal strength of the advertisement from the CHs). Then, each non-CH node informs the appropriate CH that it is a member of the corresponding cluster. During the steady phase, the nodes can begin sensing and transmitting data to the CHs. Then, each CH can aggregate data packets from the nodes in its cluster before sending these data to the sink. Based on the member count, each CH creates a TDMA schedule telling each member node when it can transmit its data packet. After that the TDMA scheduling has been constructed, it is broadcast back to the non-CH nodes in the cluster. Once the clusters are created and the TDMA schedule is fixed, data transmission can begin. After a given time spent on the steady phase, the network goes into the setup phase again and enters another round of selecting CHs.

4. Optimization of the ASLPR protocol via GA-SA algorithm

4.1. Problem representation

In this paper, a new application-specific routing protocol is presented which utilizes some concepts from the sensor nodes details in order to elect optimized CHs. There are seven controllable parameters in the proposed ASLPR protocol including α_1, α_2, α_3, α_4, t_1, t_2, and t_3. Changing in these parameters leads to have many different operations of ASLPR. Therefore, the proposed routing protocol is an adaptive protocol which can operate in different models based on the application. For example, if we set $\alpha_1=1$, $t_2=0.5$, and $\alpha_2=\alpha_3=\alpha_4=t_1=t_3=0$, the proposed ASLPR is operated similar to the LEACH-EP in [17] (compare Eq. (7) with Eq. (3)). The each α_1 must be optimized in the range of [0.1], and each t_j should be optimized in the range of [0.2]. In this paper, binary encoding is used, in which every optimization parameter is discretized with the resolution of 0.01. Therefore, seven digits are required for encoding of each α_k and eight digits are required for each t_s. Here, a feasible solution can be represented as a binary string of length L, where $L=52$. An example for a feasible solution can be seen in Fig. 1. The size of whole search space containing all possible solutions can be calculated as 2^L. Thus, the optimization problem here is an NP-hard problem, and evolutionary algorithms are the best choice to optimize it. In this paper, a hybrid GA-SA algorithm is applied in order to optimize the controllable parameters of ASLPR protocol.

4.2. Proposed fitness function

As mentioned above, the fitness function in ASLPR should be defined based on the application specifications. However, for evaluation of the proposed routing protocol, here we consider the global situation, in which the proposed multi-objective fitness function and its constraints can be formulated as follows:

Maximize:

$$fitness = w_1\times FND + w_2\times HND + w_3\times LND \tag{12}$$

Subject to:

$$0\le\alpha_k\le 1 \quad (k=1,2,3,4),\quad \sum_{k=1}^{4}\alpha_k=1 \tag{13}$$

$$0\le t_s\le 2 \quad (s=1,2,3),\quad t_1\le t_2 \tag{14}$$

$$0\le w_u\le 1 \quad (u=1,2,3),\quad \sum_{u=1}^{3}w_u=1 \tag{15}$$

where w_1 to w_3 are three constant weights to adjust the relative importance of the three objective terms within the proposed cost function, based on the application. For example, in healthcare-monitoring networks which only *FND* is important, we set $w_1=1$ and $w_2=w_3=0$. In the above equations, the indices and notations can be defined as follows:

N	total number of alive nodes in current round
M	length of the square workspace (meter)
Q	number of elected CHs in current round, so far
L	length of a feasible solution
K	desired number of nodes to be CHs
P	desired percentage of nodes to be CHs
l	data packet size (bit)
d	distance from transmitter node to receiver node (meter)
n	node index, $n=1, 2, \ldots, N$
i	node index, $i=1, 2, \ldots, N$
j	CH index, $j=1, 2, \ldots, M$
α_k	kth ASLPR sub-threshold weight, $k=1, 2, 3, 4$
t_s	s^{th} ASLPR threshold parameter, $s=1, 2, 3$
w_u	u^{th} weight within fitness function, $u=1, 2, 3$
E(n)	residual energy of node n (joule)
$d_{\mathrm{sink}}(n)$	distance from node n to the sink (meter)
$d_{ch}(j,i)$	distance between node i and CH j (meter)
$N_{ch}(n)$	number of rounds that node n was CH, so far
$E_{TX}(l,d)$	energy consumption (joule) in transmitter node
$E_{RX}(l)$	energy consumption (joule) in receiver node
E_{elec}	electronic energy consumption
E_{fs}	amplifier energy consumption in free space
E_{mp}	amplifier energy consumption in multipath environment
FND	the round in which the first node dies
HND	the round in which half of nodes die
LND	the round in which the last node dies

4.3. ASLPR optimization procedure

As mentioned above, the main advantage of the proposed routing protocol is that it can adaptively tune its parameters in order

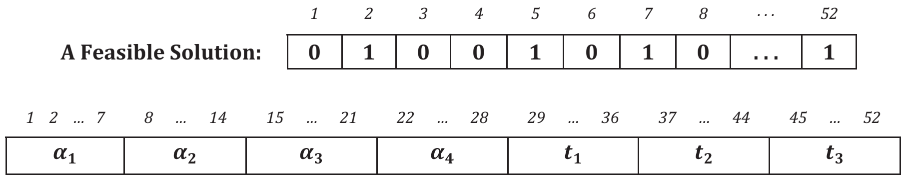

Fig. 1. A feasible solution to optimize the controllable parameters of the proposed ASLPR protocol.

to achieve the best performance. The ASLPR protocol should be optimized based on the application specifications and lifetime definition, once before it operates. In this paper, a hybrid algorithm based on Genetic Algorithm (GA) and Simulated Annealing (SA) is used to optimize the controllable parameters of ASLPR. GA [21] is a population-based evolutionary algorithm, which generates solutions for the optimization problems using techniques inspired by natural evolution, such as selection, crossover, and mutation. Also, SA [22] is a meta-heuristic optimization algorithm, inspired from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects. The notion of slow cooling in SA means slow decrease in the probability of accepting worse solutions as it explores the solution space. Accepting worse solutions allows for a more extensive search for the optimal solution [22].

Since GA is a population-based algorithm, it has a good global-based exploration among the search space. On the other hand, SA has very good local-based exploration in the search space, due to its local search mechanism and single-solution evolution. So, in this paper, a hybrid strategy based on GA and SA is used to optimize the proposed ASLPR protocol. At first, GA is performed for global searching among the search space. Then, SA is applied to search locally around the final solution found via GA, in order to improve it. In this way, the final solution found via GA is used as the initial solution of SA. The overall flowchart of the hybrid GA-SA algorithm for optimization of the ASLPR can be seen in Fig. 2.

4.3.1. GA phase

At the first step in GA, the initial population is randomly generated. Then, two overall steps are consequently done, until the maximum number of iterations of GA has been reached: *fitness evaluation* and *population updating*. After fitness evaluation of the current population, some of the best chromosomes are selected as the parents for updating the population. Then, offspring are constructed from the parents via crossover operator. After that all offspring have been generated, the mutation operator is applied to change randomly in the value of some genes within the generated offspring, aim at avoid trapping in local minima points.

4.3.1.1. Generation of the initial population. As mentioned above, binary encoding is used to represent a feasible solution (see Fig. 1). Each chromosome can be represented as a binary string with L genes, where L is 52. At first, the initial population of GA is generated randomly, in such a way that each gene within the each chromosome has equal probability to be “0” or “1”.

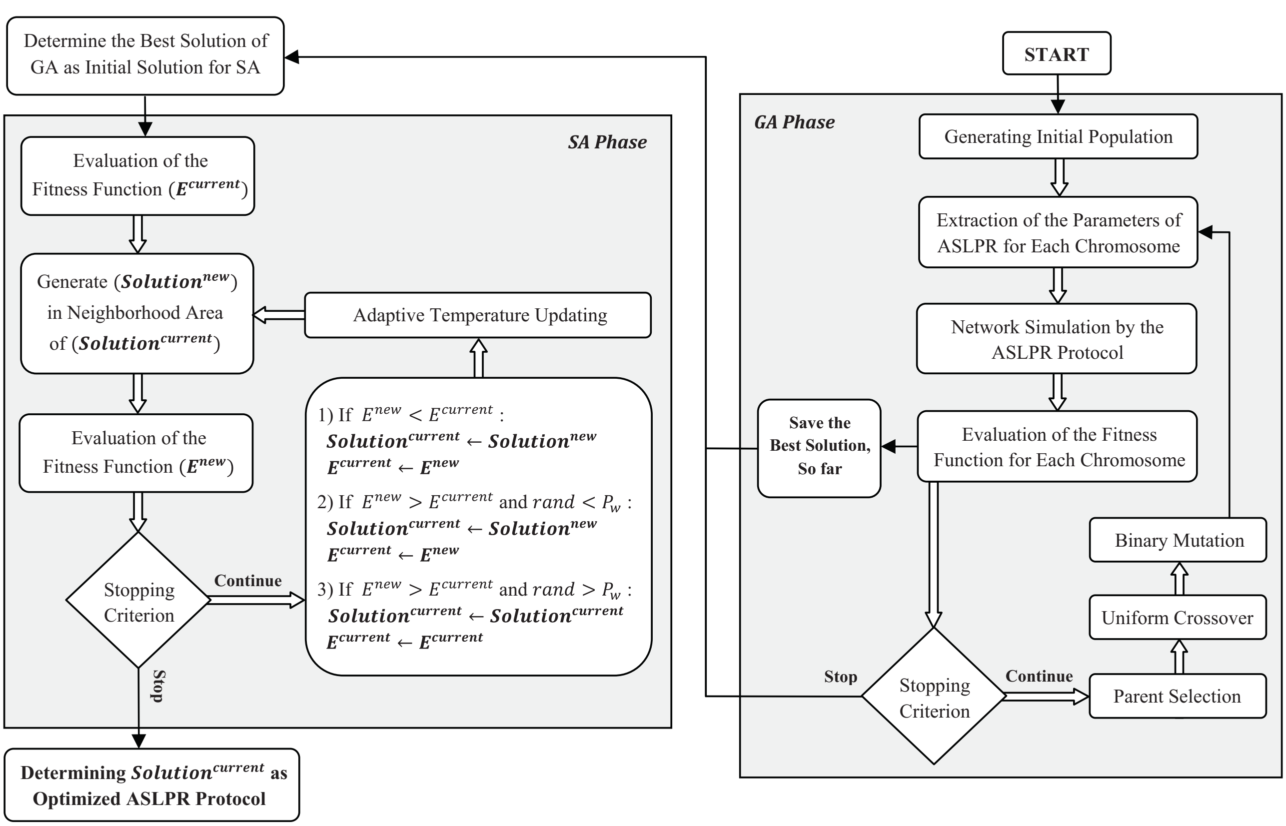

Fig. 2. Overall flowchart of the proposed hybrid GA-SA algorithm for optimization of the ASLPR routing protocol.

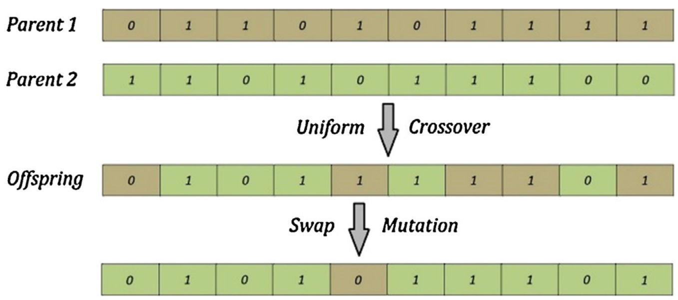

Fig. 3. Population updating in GA: uniform crossover operator and binary swap mutation operator.

4.3.1.2. Fitness evaluation. After updating the population in the every iteration, the fitness value of the each chromosome is evaluated according to the proposed fitness function. In this way, firstly, each chromosome should be decoded to extract its corresponding parameters (α_1, α_2, α_3, α_4, t_1, t_2, and t_3). Then, the WSN is simulated using ASLPR protocol with the same parameters, for the each chromosome. Finally, network lifetime is calculated for the each chromosome, and the fitness value is evaluated according to Eq. (12). After evaluation of the fitness values for all chromosomes, they are sorted from the best to the worst. Then, some of the best chromosomes are selected based on a selection strategy (e.g. roulette wheel election, rank selection, or elitism selection), as the parents for updating the population. In this paper, the elitism selection strategy was used. Also, in the every iteration of GA, the global best solution is updated (by comparing the best solution among the current population with the best solution found so far).

4.3.1.3. Population updating. In order to generate an offspring, two parents are randomly chosen among the best individuals (parents) of the population, and crossover operator is performed on them. In this paper, uniform crossover operator is used (see Fig. 3). In uniform crossover, each gene in the offspring is copied from the same gene from one of the two parents, with the same probability. After generation of each offspring, each gene can be mutated with the probability of P_m. As seen in Fig. 3, binary swap mutation was used, in which, the value of the selected gene is complemented. We used an adaptive mutation strategy in order to improve the investigation of the search space. In this way, the mutation probability P_m is considered to be decreased linearly from $P_m^{\max}$ to $P_m^{\min}$ during execute algorithm (see Eq. (16)), where t_{GA} and max_iter_{GA} are the current iteration, and the defined maximum number of iterations for GA, respectively. The larger P_m, the more genes would be complemented via mutation operator.

$$P_m = P_m^{\max} + \frac{t_{GA}}{\max\_iter_{GA}} \times (P_m^{\min} - P_m^{\max}) \tag{16}$$

4.3.2. SA phase

Generally, SA starts with a random initial solution. However, in the proposed hybrid GA-SA algorithm, the final global solution of GA is used as the initial solution for SA. On the other hand, SA is performed in order to improve the solution of GA via a local search strategy. At the every iteration of SA, a new solution ($Solution^{new}$) is generated in the neighborhood area of the current solution ($Solution^{current}$). If $E^{new} < E^{current}$, then the current solution is replaced with the new one. On the other hand, if $E^{new} > E^{current}$, the new solution may be accepted with the probability of $P_w = \exp(-(\Delta E)/T)$, where, $\Delta E = E^{new} - E^{current}$. Note that $E^{current}$ and E^{new} are the cost values of the $Solution^{current}$ and the $Solution^{new}$, respectively, in which $E = 1/fitness$. As seen in Eq. (17), the temperature T is considered to be decreased linearly from $T_{initial}$ (initial temperature) to T_{final} (final temperature), during execute algorithm. t_{SA} and max_iter_{SA} are the current iteration, and the defined maximum number of iterations of SA, respectively. If $T = 0$, it means that the new solution never could be accepted, when $E^{new} > E^{current}$. On the other hand, the larger T, the more probability for accepting worse solutions. Binary swap operator (as in GA) is used for local-search in SA, where, the probability of changing in a gene is set to P_{change}. Like GA, an adaptive local-search strategy is used to improve the convergence of SA. In this way, as seen in Eq. (18), P_{change} is considered to be decreased linearly from $P_{change}^{\max}$ to $P_{change}^{\min}$ during execute algorithm. The larr P_{change}, the more changes would be done in $Solution^{new}$ as compared with $Solution^{current}$.

$$T = T_{initial} + \frac{t_{SA}}{\max\_iter_{SA}} \times (T_{final} - T_{initial}) \tag{17}$$

$$P_{change} = P_{change}^{\max} + \frac{t_{SA}}{\max\_iter_{SA}} \times (P_{change}^{\min} - P_{change}^{\max}) \tag{18}$$

Table 1
Setting the controllable parameters of GA.

GA parameter	Value/Description
max_iter_{GA}	30
Population size	15
Number of parents	3
Selection strategy	Elitism selection
Crossover operator	Uniform
Crossover probability (P_c)	0.9
Mutation operator	Binary swap
$P_m^{\max}$ in Eq. (16)	0.05
$P_m^{\min}$ in Eq. (16)	0.005

5. Performance evaluation

All experiments were carried out in MATLAB R2012b. We compare the performance of our ASLPR protocol against the well known LEACH protocol [7], the energy-aware LEACH-EP protocol [17], and the distance-aware LEACH-DT protocol [18], in terms of the first node dies (FND), the half nodes die (HND), the last node dies (LND), and the total number of data packets received in sink from start of operation until arrival the network lifetime.

5.1. Simulation settings

In order to tune the controllable parameters of GA and SA, different values were evaluated for the each parameter, and the best values were selected for simulations. In our experiments, the population size of chromosomes was set to 15, and the maximum number of iterations in GA was set to 30. As SA is not population-based and is a single-solution-based algorithm, the maximum number of iterations in SA is set to 150, five times larger than the GA. Parameter settings for GA and SA can be summarized in Table 1 and Table 2, respectively. In order to demonstrate the effectiveness of the ASLPR protocol in term of prolonging network lifetime, simulation results of the proposed are compared with those of LEACH, with those of LEACH-EP, and with those of LEACH-DT for 15 different heterogeneous topographical areas. The first five WSNs composed of 100 sensor nodes randomly deployed in topological areas of dimension 100 m × 100 m. The second five WSNs each

Table 2
Setting the controllable parameters of SA.

SA parameter	Value/Description
$\max\_iter_{SA}$	150
$T_{initial}$ in Eq. (17)	0.1
T_{final} in Eq. (17)	0
$P_{change}^{\max}$ in Eq. (18)	0.05
$P_{change}^{\min}$ in Eq. (18)	0.02

Table 3
Network parameters.

Parameter	Value
Initial energy of nodes	1 J
E_{elec}	50 nJ/bit
E_{fs}	100 pJ/bit/m^2
E_{mp}	0.013 pJ/bit/m^4
Data packet size	5000 bit
Control packet size	50 bit

composed of 200 nodes randomly located in a topographical area of dimension 150 m × 150 m. Finally, the last five WSNs composed of 500 nodes randomly deployed in topographical areas of dimension 200 m × 200 m. The performance of the mentioned routing protocols is tested in these 15 WSNs. There is only one sink which located at the center of each network. All sensor nodes have the same initial energy of 1 Joule. All WSNs use the first order radio communication model, which is largely used in the area of routing protocol evaluation in WSNs. Table 3 presents the network parameters in details.

5.2. Simulation results

The weighting parameters within the proposed fitness function of Eq. (12) should be set based on the application specifications and lifetime definition. Here, the weighting parameters within Eq. (12) were set to $w_1 = 0.7$, $w_2 = 0.3$ and $w_3 = 0$, that means FND is the major factor, HND is the minor factor, and LND is not important (almost in all applications after HND is not important). As mentioned above, we should adaptively tune the ASLPR controllable parameters via the hybrid GA-SA algorithm in such a way that it is optimized, once before it operates, to prolong the application-specific defined network lifetime. So, the hybrid GA-SA algorithm was applied 15 times for different 15 WSNs. The optimized ASLPR controllable parameters can be summarized in Table 4. As seen, there is no major variance for the each parameter optimized in different WSNs.

In order to capture the performance of the proposed ASLPR routing protocol in several network test instances and to study its behavior against LEACH, LEACH-DT, and LEACH-EP protocols, Figs. 4–6 statistically qualify them for the WSN #1 (with 100 nodes), WSN #6 (with 200 nodes) and WSN #11 (with 500 nodes), respectively. The figures depict the total number of alive sensor nodes versus rounds. Figs. 4–6 clearly show that ASLPR is more stable than the other protocols, because node deaths begin later and continue linearly until all sensor nodes die. Additionally, to give a detailed insight into the performance of these protocols, quantitative results

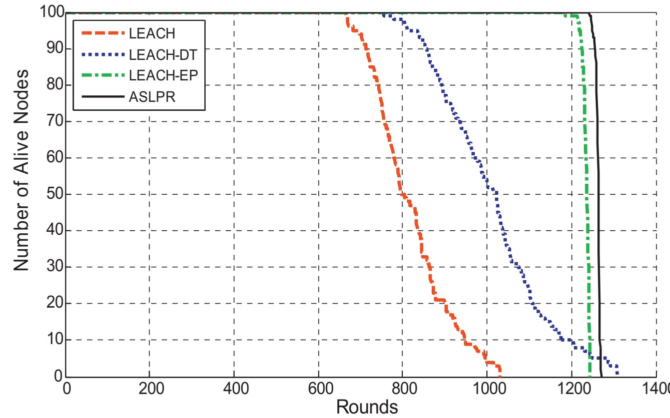

Fig. 4. Total number of alive nodes versus rounds, for WSN #1 with 100 nodes.

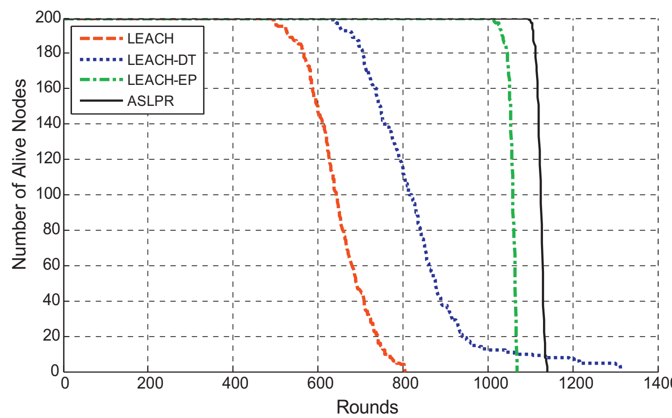

Fig. 5. Total number of alive nodes versus rounds, for WSN #6 with 200 nodes.

are also included summarizing network lifetimes in FND, HND, and LND (Tables 5–7), round history of dead nodes (Tables 8–10), and total data packets received in the base station (Tables 11–13). In these tables, the best performance values are given in bold. Also, comparison of the average CPU time consumption (running time complexity) in each round for the different routing protocols can be seen in Table 14.

The results in Tables 5–7 record different lifetime criteria for the compared protocols. Results in the tables clearly illustrate the positive impact of the proposed ASLPR for decreasing the number of dead nodes while the rounds proceed, and hence, increasing

Table 4
Optimized values for the controllable parameters of ASLPR, achieved by hybrid GA-SA algorithm.

WSN #	α_1	α_2	α_3	α_4	t_1	t_2	t_3
1	0.65	0.09	0.22	0.04	0.77	0.91	1.91
2	0.67	0.08	0.20	0.05	0.73	0.92	1.83
3	0.66	0.11	0.19	0.04	0.80	0.92	1.75
4	0.71	0.06	0.18	0.05	0.78	0.88	1.82
5	0.62	0.09	0.23	0.06	0.73	0.93	1.75
6	0.63	0.12	0.21	0.04	0.81	0.89	1.78
7	0.67	0.09	0.18	0.06	0.77	0.90	1.69
8	0.72	0.07	0.18	0.03	0.75	0.88	1.76
9	0.66	0.10	0.19	0.05	0.80	0.94	1.93
10	0.64	0.11	0.21	0.04	0.74	0.90	1.72
11	0.63	0.08	0.22	0.07	0.82	0.89	1.90
12	0.70	0.08	0.19	0.03	0.86	0.92	1.77
13	0.68	0.06	0.20	0.06	0.81	0.87	1.68
14	0.73	0.05	0.18	0.04	0.78	0.90	1.75
15	0.67	0.06	0.22	0.05	0.85	0.88	1.80
Average	**0.669**	**0.083**	**0.2**	**0.047**	**0.787**	**0.902**	**1.789**
Standard deviation	**0.034**	**0.021**	**0.017**	**0.012**	**0.04**	**0.021**	**0.076**

Table 5
Network lifetime over simulations of 5 WSNs (with 100 nodes).

WSN #	LEACH			LEACH-DT			LEACH-EP			ASLPR		
	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND
1	667	804	1031	756	1022	**1309**	1187	1236	1245	**1244**	**1263**	1271
2	685	833	1065	770	1051	**1341**	1202	1258	1266	**1268**	**1285**	1294
3	644	772	985	729	991	**1277**	1135	1187	1195	**1210**	**1230**	1239
4	650	782	1008	744	1011	**1307**	1145	1202	1211	**1227**	**1251**	1258
5	696	847	1082	785	1070	**1363**	1231	1291	1300	**1295**	**1329**	1341
Average	668.4	807.6	1034.2	756.8	1029	**1319.4**	1180	1234.8	1243.4	**1248.8**	**1271.6**	1280.6

Table 6
Network lifetime over simulations of 5 WSNs (with 200 nodes).

WSN #	LEACH			LEACH-DT			LEACH-EP			ASLPR		
	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND
6	494	643	804	631	820	**1313**	1051	1059	1069	**1099**	**1125**	1140
7	512	662	820	662	844	**1355**	1093	1105	1115	**1151**	**1170**	1184
8	485	628	787	616	799	**1285**	1022	1033	1045	**1075**	**1093**	1108
9	523	677	836	671	849	**1359**	1111	1123	1132	**1167**	**1188**	1205
10	504	656	854	645	838	**1328**	1067	1079	1092	**1131**	**1155**	1176
Average	503.6	653.2	820.2	645	830	**1328**	1068.8	1079.8	1090.6	**1124.6**	**1146.2**	1162.2

Table 7
Network lifetime over simulations of 5 WSNs (with 500 nodes).

WSN #	LEACH			LEACH-DT			LEACH-EP			ASLPR		
	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND
11	297	585	802	419	714	**1196**	784	901	920	**935**	**1039**	1054
12	334	598	813	433	720	**1243**	788	905	922	**942**	**1040**	1056
13	310	591	806	425	717	**1250**	792	896	917	**947**	**1042**	1055
14	292	604	824	441	704	**1225**	770	887	905	**928**	**1030**	1044
15	312	599	827	437	732	**1265**	804	914	930	**951**	**1049**	1061
Average	309	595.4	814.4	431	717.4	**1235.8**	787.6	900.6	918.8	**940.6**	**1040**	1054

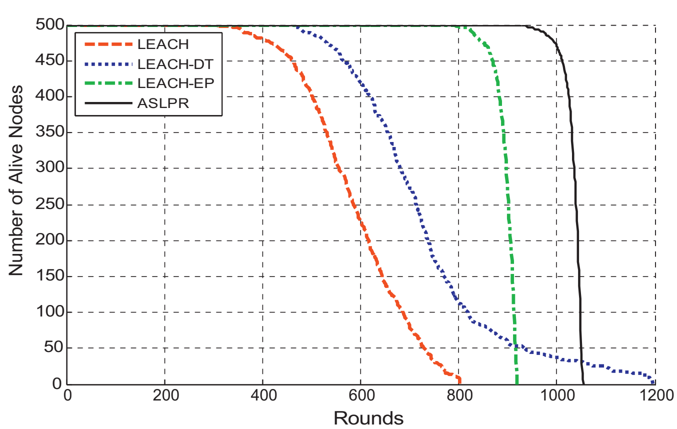

Fig. 6. Total number of alive nodes versus rounds, for WSN #11 with 500 nodes.

Table 8
Round history of dead nodes over simulations of 5 WSNs (with 100 nodes).

% dead nodes	LEACH	LEACH-DT	LEACH-EP	ASLPR
1 (FND)	668.4	756.8	1180	**1248.8**
10	715.2	857	1219.2	**1255.8**
20	740.6	889.2	1226	**1262.2**
30	756.4	931.2	1230.2	**1264**
40	782	971.4	1232.8	**1267.8**
50 (HND)	807.6	1029	1234.8	**1271.6**
60	836.2	1042.4	1237.2	**1273**
70	857	1077.8	1240.2	**1274.8**
80	903.6	1106.2	1241.6	**1276.4**
90	943	1192.4	1242.6	**1278.2**
100 (LND)	1034.2	**1319.4**	1243.4	1280.6

Table 9
Round history of dead nodes over simulations of 5 WSNs (with 200 nodes).

% dead nodes	LEACH	LEACH-DT	LEACH-EP	ASLPR
1 (FND)	503.6	645	1068.8	**1124.6**
10	576.2	714.4	1072	**1134.4**
20	591.4	744.8	1074.4	**1137.2**
30	622.2	768.2	1076.2	**1140**
40	636.8	802.4	1078.2	**1143.4**
50 (HND)	653.2	830	1079.8	**1146.2**
60	673	852.4	1082.2	**1148.2**
70	688.8	871.4	1084	**1150**
80	717.6	906.2	1085.8	**1152.4**
90	759	956.4	1088	**1155.4**
100 (LND)	820.2	**1328**	1090.6	1162.2

Table 10
Round history of dead nodes over simulations of 5 WSNs (with 500 nodes).

% dead nodes	LEACH	LEACH-DT	LEACH-EP	ASLPR
1 (FND)	309	431	787.6	**940.6**
10	475.4	543.8	850.4	**994.2**
20	511.2	617.8	871.6	**1012**
30	536.8	645	886	**1026.4**
40	568	676.6	894.2	**1033.2**
50 (HND)	595.4	717.4	900.6	**1040**
60	632.8	736	905	**1042.6**
70	650.4	773.8	909.2	**1045.8**
80	692.6	825.6	913.6	**1049.6**
90	745.6	917.4	916	**1051.2**
100 (LND)	818.4	**1235.8**	918.8	1054

Table 11
Total number of data packets received in base station over simulations of 5 WSNs (with 100 nodes).

WSN #	LEACH			LEACH-DT			LEACH-EP			ASLPR		
	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND
1	66,700	77,405	81,890	75,600	96,577	101,259	118,700	123,210	123,413	**124,400**	**126,058**	**126,183**
2	68,500	79,522	84,104	77,000	97,885	102,552	120,200	125,017	125,250	**126,800**	**128,380**	**128,518**
3	64,400	74,890	79,182	72,900	94,162	98,960	113,500	118,158	118,381	**121,000**	**122,715**	**122,851**
4	65,000	75,618	79,890	74,400	95,990	100,683	114,500	119,230	119,447	**122,700**	**124,285**	**124,304**
5	69,600	80,873	85,238	78,500	99,952	104,940	123,100	127,899	128,113	**129,500**	**131,108**	**131,235**
Average	66,840	77,661.6	82,060.8	75,680	96,913.2	101,678.8	118,000	122,702.8	122,920.8	**124,880**	**126,509.2**	**126,618.2**

Table 12
Total number of data packets received in base station over simulations of 5 WSNs (with 200 nodes).

WSN #	LEACH			LEACH-DT			LEACH-EP			ASLPR		
	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND
6	98,800	123,554	129,243	126,200	156,370	166,086	203,000	210,820	211,291	**219,800**	**224,162**	**224,654**
7	102,400	127,502	133,002	132,400	163,257	172,364	218,600	225,939	226,450	**230,200**	**234,511**	**235,022**
8	97,000	121,690	127,459	123,200	152,302	161,558	204,400	211,785	212,302	**215,000**	**219,440**	**219,966**
9	104,600	129,192	134,785	134,200	163,890	174,268	222,200	228,900	229,255	**233,400**	**238,109**	**238,677**
10	100,800	126,100	131,777	129,000	158,458	167,876	213,400	220,998	221,405	**226,200**	**231,004**	**231,496**
Average	100,720	125,607.6	131,253.2	129,000	158,855.4	168,430.4	212,320	219,688.4	220,140.6	**224,920**	**229,445.2**	**229,963**

Table 13
Total number of data packets received in base station over simulations of 5 WSNs (with 500 nodes).

WSN #	LEACH			LEACH-DT			LEACH-EP			ASLPR		
	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND
11	148,500	272,247	294,245	209,500	334,563	367,204	392,000	445,282	447,597	**467,500**	**514,877**	**516,600**
12	167,000	301,455	324,308	216,500	348,902	381,058	394,000	447,980	450,644	**471,000**	**518,118**	**519,306**
13	155,000	283,890	306,555	212,500	339,004	374,925	396,000	450,049	452,309	**473,500**	**521,387**	**522,491**
14	146,000	269,838	293,423	220,500	352,093	386,110	385,000	439,745	442,490	**464,000**	**512,380**	**513,397**
15	156,000	285,110	308,885	218,500	350,018	383,180	402,000	457,193	460,008	**475,500**	**523,379**	**524,631**
Average	154,500	282,508	305,483.2	215,500	344,916	378,495.4	393,800	448,049.8	450,609.6	**470,300**	**518,028.2**	**519,285**

the network lifetime. In Table 5, the gain in stable region of ASLPR until FND is 86%, 65%, and 6%, as compared with LEACH, LEACH-DT, and LEACH-EP, respectively. Also, in Table 6, the gain in stable region of ASLPR until FND is 123%, 74%, and 5%, as compared with LEACH, LEACH-DT, and LEACH-EP, respectively. Finally, in Table 7, the gain in FND of ASLPR is 204%, 118%, and 19%, as compared with LEACH, LEACH-DT, and LEACH-EP, respectively. Additional remark can be drawn from these tables, which reflect the behavior of ASLPR against LEACH-DT, when there is 10–0% of alive nodes (see Figs. 4–6 and Tables 8–10). In this case, we see that LEACH-DT slightly outperforms ASLPR in the case of prolonging LND larger than that of ASLPR. However, the total number of data packets received in base station until LND in ASLPR is larger than that of LEACH-DT (see Tables 11–13). Similar to LEACH-DT behavior occurs for LEACH protocol but for shorter lifetime. Clearly, there is a tradeoff between FND and LND, but ASLPR (on average) achieves better tradeoff than that of the others. In spite of the mentioned advantages of the proposed routing protocol to prolong the network lifetime, ASLPR encounters higher computational complexity, and thus consumes higher running time than the three compared protocols (see Table 14). However, it can be ignored, due to the power of ASLPR to prolong the network lifetime.

Table 14
Comparison of the average running time (micro second) in each round.

WSN #	LEACH	LEACH-DT	LEACH-EP	ASLPR
1 to 5 (with 100 nodes)	315	358	465	1040
6 to 10 (with 200 nodes)	473	538	643	1567
11 to 15 (with 500 nodes)	870	967	1135	2055
Average	**552**	**621**	**747**	**1554**

6. Conclusion

To achieve the energy efficiency in WSNs, many routing protocols have been proposed and LEACH is the representative one. LEACH utilizes randomized rotation of the cluster heads. However, it depends on a probability model and the network lifetime is not maximized. In this paper, an application specific low power routing protocol (named ASLPR) based on LEACH architecture with an extension to the energy predication has been proposed. The main advantage of the ASLPR is to prolong the lifetime of the WSN according to the application. As the proposed protocol is complex with some controllable parameters, tuning these parameters is an important problem to achieve the best performance. To achieve this goal, the paper focused on optimization of the ASLPR parameters according to the application specifications via a hybrid optimization algorithm based on genetic algorithm and simulated annealing. Simulation results show that the proposed hybrid optimization algorithm can efficiently balance the energy consumption of nodes and maximize the network lifetime. The ASLPR outperforms three other LEACH-based routing protocols with improved network lifetime and received data packets in base station. In spite of the mentioned advantages, ASLPR needs extra computations in centralized processor within the base station, to elect optimal cluster heads. The proposed protocol was designed for the WSNs that have stationary sensor nodes. As a future work, it can be extended for handling mobile sensor nodes. Also, we plan to extend the proposed routing methodology with multi-hop routing in order to cope our protocol for routing in large topological areas.

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