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Energy efficient multi-hop path in wireless sensor networks using an enhanced genetic algorithm

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A B S T R A C T

Direct transmission in widespread wireless sensor networks, where the cluster heads (CHs) and the base station (BS) are far from each other, is considered a critical factor because of its influence on network efficiency in terms of power consumption and lifetime. This paper focuses on the discovery of an optimal multi-hop path between a source (CH) and a destination (BS) to reduce power consumption, which shall maximize network lifetimes, by proposing a new Optimal Multi-hop Path Finding Method (OMPFM). A genetic algorithm is utilized in the proposed method to find an optimal path by proposing a new fitness function. Moreover, two pre-processes are proposed to select the CHs and increase the efficiency of the genetic algorithm in terms of the execution time and the quality of the chromosomes. The evaluation of the proposed method is conducted in MATLAB simulator and compared with other related methods. Experimental results show that the proposed method is better than LEACH, GCA, EAERP, GAECH and HiTSeC by 35%, 34%, 26%,19% and 50%, respectively, in terms of the first node die metric, and by 100%, 99%, 87%, 78% and 50%, respectively, in terms of the last node die metric.

1. Introduction

In previous decades, wireless sensor networks (WSNs) have become regarded as an important technology in communications [1,4,5,9] due to their many critical applications, such as underwater, fire expectation and humidity monitoring [2,28]. However, the best path which can reduce power consumption and increase network lifetime shall be selected in sensing the critical data and transmitting them to the main device for analysis and decision making. Hence, routing is an important factor when designing WSNs due to its great influence on the network performance**.** In WSN, clustering routing protocols [13] have many advantages in distributing energy among nodes and maximizing the performance of a network based on its lifetime by utilizing the concept of clusters [10]. The main clustering routing protocol is the low-energy adaptive clustering hierarchy (LEACH) protocol [14].

The LEACH protocol has various advantages in terms of network lifetime due to its use of energy distribution among other sensors in a network by alternating the role of a cluster head (CH) between nodes in a cluster in order to ensure the fair energy consumption. However, this protocol suffers from many limitations, such as the direct transmission of data from

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a CH to the base station (BS) which in its turns causes a rapid drain of energy in sensors, in particular the distanced ones from the BS, in addition to the random selection of CHs, which has a significant impact on the network lifetime [20].

The transmission process is important in WSNs to achieve the goal of networks by collecting the sensed data and transmitting them to the BS for further analysis. This process helps decision makers to adopt the appropriate decisions which are compatible with the targets of the network.

The direct transmission problem in the LEACH protocol leads to a rapid power drains in CHs, especially if the distance is far between any CH that wants to send data to the BS. In this case, additional energy shall be consumed in a CH to transmit its data, which will negatively affect the overall performance in a network based on the lifetime factor.

In this paper, an enhanced method is proposed to maximize network lifetimes by finding an optimal route from a root CH to the BS, thereby reducing power consumption when compared with the direct transmission process. A genetic algorithm (GA) is utilized to discover the optimal transmission route. The proposed method maximizes the stability period of the network where all nodes remain alive. Additionally, it maximizes the lifetime of the network when all the nodes die. Such maximizations are achieved by employing the proper parameters in the fitness function and by enhancing the cluster heads selection process. The structure of this paper is as follows: Section 2 provides a background of GA; Section 6 discusses the related works; Section 4 presents the proposed method in detail; Section 5 provides a quantitative evaluation of the proposed method and other related protocols; and Section 6 concludes the paper.

2. Background

LEACH protocol and the GA are revised in this section. An overview of the LEACH protocol is provided at the beginning, then, the GA optimization technique is discussed.

2.1. The LEACH protocol

The idea of the LEACH protocol [14,21] is to improve the efficiency of WSNs by reducing power consumption. A rotation technique of CH selection using a random factor has been proposed to achieve this goal. The LEACH protocol operates in many rounds [14,20], and each of them comprises two stages, which are the set-up at the steady-state. The clusters are formed during the first stage in addition to the CHs selection. To select a CH [14], nodes from each cluster create random numbers between 0 and 1 in every round. The reference number *T(n)* is predefined for the comparison with the created numbers. When the value of the reference number is greater than the value of the randomly created number, the node that created that random number becomes the CH. Eq. (1) is used to define the value of the reference number *T(n)* [14].

$$\mathrm{T(n)} = \left\{ \begin{array}{ll} \frac{\mathrm{P}}{1-\mathrm{P}*\left(\mathrm{r} \bmod \frac{1}{\mathrm{P}}\right)} & : \text{if n} \in \mathrm{G} \\ 0 \ : \ if \ n \neg\in G & \end{array} \right\} \tag{1}$$

where P is the percentage of CHs, r is the existing round and G is a group of nodes that did not become CH in the prior $1/P$ rounds. In this manner, the energy is distributed among all nodes in the cluster. In spite of the advantage of the proposed way in the LEACH protocol, which balances the power consumption among all nodes due to the rotation of the CH role, this protocol suffers from many disadvantages. For example, LEACH does not take into account the residual energy of a node in the selection process of a CH. According to Eq. (1), the possibility of a node becoming a CH is not fixed. After several rounds, all nodes have the same probability to become CHs. Thus, nodes with high amounts of energy and nodes with low amounts of energy all have an equal chance to become a CH. Another problem is the direct transmission from a CH to the BS using single-hop communications. This situation would be a serious issue if the CH and the BS were located in distant positions because it uses more energy than when a CH is close to the BS, resulting in energy holes in which isolated nodes are unable to transmit their data. This situation considerably affects the performance of the network [14,20].

Therefore, to overcome such disadvantages of LEACH, an improvement is proposed in this paper by modifying LEACH to increase efficiency in terms of the CH selection process and data transmission, as presented in in the proposed mechanism.

2.2. The GA optimization technique

GA is an optimization algorithm that simulates nature's evolution and uses the same methods in natural selection to find optimal solutions [3,24]. GA is used in optimization and search problems to find the best global solution. The main operations in GA are selection, crossover and mutation [17]. First, the initial population is randomly generated with a set of individuals; each of them will be evaluated using the fitness function. The best individuals will then be selected from the initial population depending on the specified fitness values, and they will participate in the next generation [31]. The objective function (fitness) is important in GA and depends on the problem; it is used to evaluate the quality of individuals and select the best among them to contribute in the next generation [23]. In the crossover operator, new children are generated from the parents by combining them, and these children will have a combination of traits derived from the two parents [18]. In the mutation operator, random swaps are applied on the new children to form new solutions. The algorithm stops when a specific condition is reached [8,19,25].

Table 1
Crossover operation.

Position	1	2	3	4	5	6	7
	A	B	C	D	E	F	G
Chr1	1	0	0	1	1	0	1
Chr2	1	1	0	0	1	1	0
			Crossover point ↑				
Position	1	2	3	4	5	6	7
	A	B	C	D	E	F	G
Offs1	1	0	0	0	1	1	0
Offs2	1	1	0	1	1	0	1

Table 2
Mutation operation.

Position	1	2	3	4	5	6	7
	A	B	C	D	E	F	G
Offs1	1	0	0	1	1	1	0
Position	1	2	3	4	5	6	7
	A	B	C	D	E	F	G
Offs1	1	0	0	1	1	0	0

The crossover operator is applied on the selected parents, based on the crossover rate, to produce new offspring, thereby varying the programming of the chromosomes [18]. The parents are selected depending on the fitness value. Different forms of crossover, such as one-point and two-point crossover, can be used to exchange portions of chromosomes on the basis of the crossover point. This point is randomly selected, and the crossover operation will then be applied on two selected parents as described in the following table:

Table 1 illustrates an example of the crossover operation. The first part shows the chromosomes' presentations before the crossover, and the second part shows the chromosomes' presentations after the crossover. The crossover point is set on the third position. Following this process, the mutation operation will be applied on one of these offspring based on the mutation rate as described in the following paragraph.

Mutations only affect a single chromosome with a randomly selected gene that is called the mutation point. Several methods can be used for mutation operation. One is flipping the value of a gene, in which the value of the gene that has a position equal to the mutation point will be flipped from 0 to 1 or from 1 to 0 to obtain a new possible solution. Table 2 illustrates an example of the mutation applied on the offspring (Offs1) that is generated by the crossover in the previous example:

Based on Table 2, if the mutation point is at location 6, then the gene in the sixth position (F) is excluded from the old path ($A \to D \to E \to F$) in the first part of the table, and the new path—as shown in the second part—is:

$$A \to D \to E.$$

The same procedure will be applied on the second offspring, and the two new chromosomes will then be evaluated by finding their fitness values. Then, a greedy selection is performed between the new offspring and their parents, and the one with a higher fitness value will be kept in the population.

In the next generation selection process and after computing the fitness values of all chromosomes, some of them are selected in the current generation depending on their fitness values. The chromosomes with lower fitness values will be selected to participate in the next generation instead of those with higher values because the fitness values should be minimized to keep the population size fixed. The algorithm stops if the number of generations equals a specific number, which represents the maximum generation.

In the proposed OMPFM, the crossover and mutation operations are modified to avoid creating invalid paths by selecting the CHs—which are involved in the GA—in an efficient way while making sure that they are available in the network. Moreover, the method of finding the multi-hop path in the OMPFM will not be repeated the CH in the path because the binary representation will be used and solve this problem.

The next section describes the routing protocols that have been conducted to enhance the LEACH protocol with respect to maximizing network lifetimes based on the GA and other evolutionary algorithms.

3. Related works

Some of the related routing protocols based on LEACH are presented in this section. These protocols have been conducted to overcome the drawbacks in LEACH with regard to its limitation in considering the distance from a CH to the BS in the transmission process.

Balamurugan [7,29] presented a method to improve the efficiency of data transmission by using a GA named fitness-based routing protocol (FRP). In [29], a fitness function was proposed to find an efficient route for data transmission; the fitness function uses parameters, such as the distance from the sensor node to the BS. Optimal nodes are selected on the basis of their fitness values, and the optimized route to the Bs is then established [29]. The following equation represents the fitness function in [19]:

$$Fitness = dist(a, b) + dist(b, BS) \tag{2}$$

where the distance from node *a* to node *b* *(dist(a,b))* or from node *b* to the BS *(dist(b,BS))* is obtained by using the following equation:

$$dist(a, b) = \sqrt{(xa - xb)^2 + (ya - yb)^2} \tag{3}$$

The packet is transmitted from a sensor node to the BS through an efficient route. The relay nodes between the source node and the BS are selected depending on their fitness values, and these nodes route the packet to other nodes until they reach the BS [29]. In FRP, the energy consumption in the transmission phase is reduced, and the packet loss percentage is minimized by finding alternative nodes in case of node failure.

Another protocol is called GA for energy-entropy-based multipath routing in WSNs (GAEMW) [27]. In [27], a GA for multipath routing in WSNs was proposed on the basis of finding the node with the least residual energy in each route in the process of selecting multipath routing. To initialize a population, a routing path is presented by a set of integers. These integer numbers represent node IDs, node energy and other information [27]. The first gene represents a source node, whereas the last one represents the BS. Then, several paths (chromosomes) are created from the source to the destination. The objective function (fitness) is used to weigh the quality of each chromosome (path) by finding the minimum cost path from the source to the destination [27]. The value of each chromosome *Ci* is calculated using the following equation:

$$f(C_i) = \frac{1}{G}\sum_{k=1}^{path}\left((E_{tr} + E_{rec}) \times P_{ki} \times \left|P_{ki}^{s,d}\right| - E_{avg}\right) \tag{4}$$

where G denotes the number of paths; E_{avg} is the average load of all paths; and Etr and E_{rec} are the required energy to transmit and receive packets, respectively. From the fitness function, the preferred solution is the low variance [27]. Later, the two operators in GA—namely, crossover and mutation—are applied on the population, and the next generation is created [27]. The simulation results show that this protocol provides an effective technique to evaluate the route stability in WSNs.

In [6], a new method, which depends on GA to improve the energy efficiency, is presented by optimizing the selection of CHs and minimizing energy consumption in the communication process between a CH and the BS: specifically, a GA based on a distance-aware LEACH (GADA-LEACH). In [6], after selecting CHs on the basis of the GA, a relay node between a CH and the BS and several factors, such as the total energy of nodes, CH energy, distance between sensor nodes and CH and the distance between each CH and the BS were used to compute fitness functions, as shown in the following:

$$Fitness = [(0.3 * Fit1) + (0.35 * Fit2) + (0.35 * Fit3)] \tag{5}$$

$$Fit1 = \frac{Total\ Energy\ of\ all\ nodes}{Energy\ of\ CHs} \tag{6}$$

$$Fit2 = \frac{Eucledian\ distance\ from\ CH\ to\ its\ nodes}{Number\ of\ nodes\ in\ cluster} \tag{7}$$

$$Fit3 = \frac{Eucledian\ distance\ from\ all\ CHs\ to\ the\ BS}{Number\ of\ CHs} \tag{8}$$

On the basis of the fitness value, the top individuals are selected from the population. Then, the crossover and mutation operations are used to select the best CHs [6]. Subsequently, a relay node is introduced to minimize the distance from a CH to the BS [6]. This method performs better than the LEACH protocol on the basis of network lifetime by improving the CH selection process and introducing an intermediate node in the network.

In [12], an improved method using GA, called routing optimization strategy based on improved GA (ROS-IGA), was proposed to find a suitable route between a sensor node and the BS. This method attempts to solve the problem of generating invalid individuals, which negatively affects the efficiency of GA. For example, the route "1 → 2 → 8 → 6 → BS" is generated after the crossover and mutation operators but is not practical in accordance with the structure of the network because the neighbors of node 2 are {1, 3, 4, 5}, and no direct communication exists between nodes 2 and 8 [12].

In ROS-IGA, the node locations and other information, such as energy consumption between adjacent nodes, accumulated distance and the remaining energy of nodes, are considered in the fitness function to find the suitable and practical path [12].

Depending on the abovementioned parameters, the fitness value is obtained by using the following equations [12]:

$$f\left(p_j(id_i, s)\right) = \frac{\sum_{v_l \in p_j(id_i, s)} rene(id_l)}{\alpha f_{1+} \beta f_2 + \gamma f_3 + \delta f_4} \tag{9}$$

$$f_1 = \frac{\sum_{e \in p_j(id_i,s)} dist(e)}{\sum_{e \in E} dist(e)} \tag{10}$$

$$f_2 = \frac{\sum_{e \in p_j(id_i,s)} ene(e)}{\sum_{e \in E} ene(e)} \tag{11}$$

$$f_3 = \frac{\sum_{id_l \in p_j(id_i,s)} delay(id_l)}{\sum_{id_i \in P(id_i,s)} delay(id_i)} \tag{12}$$

$$f_4 = \frac{hop\left(p_j(id_i,s)\right)}{\sum hop(P(id_i,s))} \tag{13}$$

where *f1* is the ratio of the distance of an edge to that of all edges; *f2* is the ratio of the energy consumed by an edge to that by all edges; *f3* is the ratio of the delay of an edge to that of all edges; and *f4* is the ratio of hopes to all individuals. α, β, γ, δ are variables used to weigh the effective energy, delay and distance constrains, where $\alpha + \beta + \gamma + \delta = 1$. The fitness function in this method is the maximization function; therefore, a higher fitness value indicates more paths [12].

The crossover and mutation operations in ROS-IGA are improved. In the crossover operation, the algorithm examines whether the crossover point of an individual is the same gene as other individuals, or whether it belongs to the neighbors of the corresponding precedent in other individuals; then, the crossover will be conducted [12]. In the mutation operation, the gene belongs to both the neighbor sets of the precedent, and the succeeding gene is selected to replace the mutation gene [12]. The improved crossover and mutation operations in ROS-IGA provide suitable and practical routing in WSNs.

Another method has been proposed in [2] that is called Genetic Algorithm Based Energy Efficient Clustering Hierarchy in Wireless Sensor Networks (GAECH). In this method, the authors have enhanced the LEACH protocol by using the GA (run at the BS) with a proposed fitness function in order to form balance clusters. The chromosomes in this protocol are presented using the binary presentation, and the single point crossover is used. The parameters that are used in the fitness function are the total energy consumption, the standard deviation among clusters in the basis of energy consumption, the energy consumption in the cluster heads and the cluster head distribution. The results showed that the performance of this protocol is better than other protocols. By contrast, this protocol suffers from some drawbacks; it did not consider the distance when selecting the cluster heads, and it did not consider the routing process.

A new robust genetic algorithm for dynamic cluster formation in wireless sensor networks (GCA) has been proposed in [22] in order to increase the lifetime of the network. The authors have proposed a robust genetic clustering algorithm to balance the consumed energy within the clusters by controlling their numbers. The proposed fitness function in this method is presented in the following:

$$Fitness = \alpha * CHs + (1-\alpha) * Distance \tag{14}$$

where *CHs* is the total number of CHs; *Distance* is the total distance from cluster members to the CH in each cluster; and α is a value based on the application. The authors of this fitness function tried to minimize the consumed energy by reducing the number of CHs in the network and minimizing the total distance between the cluster members and the CH. The stability period of the network is not considered in this method.

An energy-aware evolutionary routing protocol for dynamic clustering of wireless sensor networks (EAERP) has been proposed in [16]. The idea of this method is to increase the stability period of the network and to increase the lifetime until the last node dies. Authors have used the concept of the centralized evolutionary routing protocol to optimize the CH selection process by the BS. The proposed fitness function includes the inter-cluster and the intra-cluster energies. The limitation of this method is that it only considers single-hop transmissions without taking into account multi-hop communications.

A proposed method in [15] considers the threshold that is used to select the CHs in the LEACH protocol [14]. The formula of the threshold value in the LEACH protocol is as follows:

$$T(n) = \begin{cases} \dfrac{P}{1 - P * \left(r \bmod \frac{1}{P}\right)}, & n \in G \\ 0, & n \neg \in G \end{cases} \tag{15}$$

The problem in the LEACH protocol is the randomness in selecting the CHs, which results after several rounds to select nodes with low energy as CHs; this will affect the lifetime of the network. LEACH Centralized (LEACH-C) has been proposed in [15] to enhance the process of CH selection by using a centralized clustering process that is handled by the BS by computing the average energy of the networks.

The nodes that have less energy than the average are not considered as cluster heads in the current round. The simulated annealing algorithm is used by the BS to find the efficient k cluster heads among the candidates' nodes. This protocol is good in terms of saving energy due to its centralization. On the other hand, this protocol suffers from networks becoming stuck after some rounds. Moreover, it did not take into account the transmission problem from the cluster heads to the BS.

WST-LEACH (Weighted Spanning Tree clustering routing algorithm based on LEACH) has been proposed in [30] to deal with the two problems in LEACH protocol, which are the selection of CHs and the data transmission to the BS. A modified

Table 3
The selected path.

CH_1	CH_2	CH_3	CH_4	CH_5	CH_6	CH_7
1	0	0	1	1	0	0

threshold has been proposed to select the cluster heads based on different parameters: such as the distance to the BS, the residual energy of nodes and the number of neighbors of each node. The modified threshold is computed as follows:

$$T(n)_{new} = T(n) * \left[w1 * \frac{E(n)}{Eo} + w2 * \frac{NB(n)}{N} + w3 * \frac{1}{ToBS(n)} \right] \tag{16}$$

where *T(n)* is the threshold in (14); *E(n)* is the energy of node *n; Eo* is the initial energy *NB(n)* is the number of neighbors of node *n; N* is the total number of nodes; and *ToBS(n)* is the distance from node *n* to the BS.

After selecting the CHs, this protocol constructs a weighted spanning tree to establish a communication path with the BS. This protocol increases the lifetime of the compared LEACH protocol, but it has control packets overhead.

Another method is called Hierarchical Trust-based Secure Clustering (HiTSeC), this method is proposed in [11] and uses the Bat Optimization Algorithm (BOA) to select the CHs based on some parameters: residual energy, the trust value and the number of neighbors.

Accordingly, the parameters used in the fitness function to optimize the transmission problem are not sufficient to find the best solution, which is the optimal route from the CH to the BS. In FRP and GAEMW, only the distances from the sensor node to the BS and the lasting energy of nodes are considered, respectively [27,29]. Meanwhile, GADA-LEACH, GAECH, GCA and EAERP use GA to select the best CH without considering the transmission path [5,6,16].

The related works in [15] and [30] consider a modification on the threshold value to select the CHs to balance their energy levels. Moreover, the method in [30] uses a weighted spanning tree to select a path from the CH to the BS.

The proposed method in this study uses a modified threshold value to select the CHs which is inspired from [15] and [30], in addition to using several important parameters in the fitness function to find the optimal route between the source CH and the BS. These parameters include the accumulated distance between adjacent CHs, the accumulation of consumed energy in transmitting data from one CH to the next one until it reaches the BS, the number of participants in a route and the number of participation in the transmission process for each CH. The optimal path, determined using the proposed method, is the shortest path with minimum energy consumption. The next section discusses the suggested method in detail.

4. Proposed method (OMPFM)

The proposed method named optimal multi-hop path finding method (OMPFM) is based on the GA algorithm to find the optimal path from a source CH to the BS through intermediate CHs. The GA is selected in this paper as an optimization algorithm to find the optimal solution due to its simplicity, and most of the related works have used it. The following paragraphs describe the proposed method in details.

In the proposed method, each chromosome represents a path from a source CH to the BS. The length of a chromosome varies and depends on the number of CHs in the routing path; however, it should not exceed the total number of CHs in the network in a specific round. To represent a chromosome, binary representation is used in the proposed method where each gene in a chromosome represents a CH in the path. If the value of a gene is 1, then the corresponding CH is included in the routing path, otherwise it will be 0 as described in the following example.

By assuming that seven CHs exist with IDs from 1 to 7 and the source CH is the CH with ID 1. The following chromosome in Table 3 represents a path from the source to the BS:

Based on Table 3, the first row indicates the CHs' IDs, and the second row indicates the CHs included in the path. For this example, the path from CH1 to the BS is as follows:

$$\text{CH1} \rightarrow \text{CH4} \rightarrow \text{CH5} \rightarrow \text{BS}$$

The proposed method is used to select an optimal path to send data from a source CH to the BS, which will reduce energy consumption and then increase network lifetime. The optimal path is determined by using a fitness function, which will be described later. The OMPFM improves the LEACH protocol by transmitting the data from the CH to the BS through other CHs that are selected carefully using the GA. The GA technique finds the optimal path which differs from the paths that are found in other methods by selecting the most appropriate CHs to be the candidates in the path based on their energy; it then uses important parameters in order to select the CHs to formulate the optimal path.

Before analyzing the proposed parameters that are used in the fitness function to find the optimal path from a source CH to the BS, there are two pre-processes that have been proposed to enhance the used GA optimization technique. The first one considers the selection of the CHs, and the second one considers the quality of the chromosomes in the GA, as will described in the following subsections, with the proposed fitness function.

4.1. Cluster head selection pre-process

The first modification of the CHs selection process has been inspired from [15], which used the energy average of the nodes to select the CHs, and from [30], which used many parameters to select the CHs. In this research, the residual energy and the distance to the BS are just considered in the CHs selection process.

The modified threshold in [15] is efficient during the first rounds, but after that, the network becomes stuck. For the method proposed within this paper, the threshold value used to select the CHs in the LEACH protocol (14) is modified by dividing the process of CHs selection into three levels based on the number of rounds. The modified threshold function combines the three previous methods [14,15,30]. The modified threshold function is presented in the following equation:

$$T(n)_{mod} = \begin{cases} E(n) \geq avg(E)\ and\ ToBs(n) \leq avg(D), & if\ r \leq n1 \\ T(n) * \left[\frac{E(n)}{Eo} + \frac{1}{ToBs(n)}\right], & if\ n1 < r \leq n2 \\ T(n), & if\ r > n2 \end{cases} \tag{17}$$

where $E(n)$ is the current energy of node n; $avg(n)$ is the energy average of the alive nodes; $ToBs(n)$ is the distance from node n to the BS; $avg(D)$ is the average distances between the alive nodes to the BS; Eo is the initial energy; $T(n)$ is the threshold value in (15); and $n1$ and $n2$ (boundaries) are the number of rounds to validate each case, and these numbers depend on the application.

The first level of the modified threshold value is used to start with the nodes that have energy greater than the average energy, and their distances to the BS are less than the average distance to be the CHs from the first round to the round number $n1$. However to solve the problem in the LEACH-C method [15] and avoid limitations in the network after several rounds, while taking advantage of the modified threshold value in the WST-LEACH method [30], the second level is set after n1 rounds to select nodes with maximum residual energy and minimum distance to the BS to be the CHs from round number $n1$ to the round number $n2$. Finally, in the third level, and after the round number $n2$, the threshold value is set to be the same as in the LEACH protocol [14]. The values of $n1$ and $n2$ are set based on the applications and on the parameters that are set on the networks. For example, the value of $n1$ is maximized, if it is important in the application, to increase the stable period of the network, the round where the first node dies or if the initial energy of nodes is high: i.e. 1 Joule. The value of $n2$ is always maximized because in the third level—where the threshold value $T(n)$ will be used—the number of dead nodes will increase and the selection of CHs will be done randomly.

4.2. Filtering pre-process

The second modification considers the quality of the chromosomes which will be used in generating the first generation in the GA. Before starting the GA operations, a filtering pre-process will be done to select the best CHs based on their energy levels. At first, the average energy of all CHs will be computed. Afterwards, the CHs with energy greater than the average will be participate in generating the first generation.

This modification will increase the efficiency of the GA, due to the best quality of the chromosomes, because the best CHs will be selected from the beginning. Moreover, this modification will increase the performance of the GA in terms of execution time due to minimizing the length of the chromosomes. For example, if the number of the CHs in the current round is 7, and the number of CHs with energy greater than the average is 4, then these 4 CHs will participate in the GA, and the length of the chromosome will be 3 (except the source CH) instead of 6. The following paragraphs describe the effects of energy on the quality of the chromosomes.

In the proposed transmission method, considering the number of CHs in the transmission path is required because discovering the optimal route from the source CH to the BS is an important factor. If the number of CHs in the transmission path increases, then the average consumed energy required to transmit data from one CH to another will decrease. Eq. (18) describes the average consumed energy in CHs during the transmission process.

$$Avg_{CET} = \left(\sum_{i=1}^{N} E_{Tx}(i)\right)/(N) \tag{18}$$

where $AvgCET$ is the average consumed energy, which is essential to send data from a CH to another in the path; ETx represents the energy required for sending data; and N denotes the number of CHs in the transmission path. ETx can be calculated as follows [26]:

$$E_{Tx} = E_{elec}*k + E_{amp}*k*d^n \tag{19}$$

where $Eelec$ is the electronic energy; $Eamp$ is the amplifier energy; and n is the loss exponent whose value depends on the environment. In free space, the value of n is 2, and in indoor environments, the value of n is 4 [26].

The same procedure is performed to find the average consumed energy in CHs during the receiving process, which can be described as the following:

$$Avg_{CER} = \left(\sum_{i=1}^{N} E_{Rx}(i) \right) / (N) \tag{20}$$

where *AvgCER* is the essential energy to receive data from a CH to another CH through the path; *ERx* is the energy required for receiving data; and *N* is the number of CHs in the transmission path. E_{RX} is computed as follows based on the energy model in [26]:

$$E_{Rx} = E_{elec} * k \tag{21}$$

The average energy of the CHs is calculated as:

$$Avg_{RE} = \left(\sum_{i=1}^{N} E_r(i) \right) / (N) \tag{22}$$

where Avg_{RE} is the average residual energy of all CHs in the current round; *Er* is the current energy of a CH; and *N* represents the number of CHs.

Eqs. (18), (20) and (22) show the effects of the energy in the process of transmitting data to the BS. So, the proposed pre-process in reducing the number of CHs that will participate in the GA based on (22) will increase the efficiency of the transmission process. The next subsection analyzes the proposed fitness function.

4.3. Fitness function parameters

The main goal in the proposed method is to minimize the consumed energy in the transmission process to send data from a CH to the BS. In order to achieve this goal, several parameters in the fitness function are considered.

The distance from each participated CH to the BS is one parameter in the fitness function. Moreover, the number of intermediate CHs in a path plays an important role in the fitness function. Therefore, the ratio of the suggested CHs in the path to the total number of the participated CHs is another parameter in the fitness function. The number of each cluster members is also a parameter in the fitness function due to its importance in the energy consumption of the CHs. The last parameter in the fitness function is the number of participants for each suggested CH. The shortest distance between a source and a destination in transmission results in greater energy efficiency, and the longest distance consumes more energy; but the distance itself is not enough to select the optimal path.

Therefore, a GA is used in the proposed method to determine the optimal path. It depends on the following four factors:

- The average distance from the source CH, BS and intermediate CHs is calculated as:

$$D(CH_s, BS) = \frac{\sum_{i=1}^{N-1} D(CH_i, CH_{i+1}) + D(CH_N, BS)}{N} \tag{23}$$

where *D(CHs,BS)* is the average distance from the source CH to the BS; *N* denotes the number of CHs in the path; $D(CH_i,CH_{i+1})$ represents the distance from the CH in position *i* to the CH in position *i+1*; and $D(CH_N,BS)$ is the distance between the last CH in the path and the BS. This factor is important due to its effect on the transmission process, where the distance plays an important role in calculating energy consumption as described in (19) and (21).

- The ratios of the CHs are included in the path (*Npar*) of the total number of participating CHs (*N*). This factor also has an important impact on the transmission process; if the number of CHs in the path increases, then the total energy load will decrease, and the energy in these CHs will be greatly conserved.
- The total number of participation in the transmission process of all CHs in the path (*No_of_Part*) can be calculated as:

$$No\_of\_Part = \sum_{i=1}^{N} Part_i \tag{24}$$

where $Part_i$ is the number of participation in the transmission process of the *CHi*; and *N* denotes the number of CHs in the path. This factor is important for the proposed method due to its influence on the overall consumed energy and in balancing the participation of CHs in the transmission process to reduce energy consumption. Assume there is a CH with high energy and it is close to the BS, this CH will always be selected and included in the transmission path, and this will lead to draining its energy faster. Using this factor, we will control this operation and balance the selection of the CHs that will participate in the transmission process.

- The number of members in each cluster can be calculated as:

$$members = \sum_{i=1}^{N} member_i \tag{25}$$

Table 4
Simulation parameters and values.

Symbol	Declaration	Value
A	Network size	100×100
BS(i,j)	Position of Base station	Center of the area (50×50)
N	Number of nodes	100
Etx	Transmission energy	50 nJ/bit
Eo	Initial energy	1 Joule, 0.5 Joule
Eelec	Electronic energy consumption	50 nJ/bit
Erx	Reception energy	50 nJ/bit
Eamp	Transmit amplifier	13 pJ/bit/m^2
Eda	Data aggregation energy	5 nJ/bit
Rmax	Maximum number of rounds	5000
Pack/CtrPack	Data packet size/control packet size	500 bytes/25 bytes
Indiv	Number of Individuals	40
Iter	Number of iterations	100
Cr	Crossover Rate	0.8
Mr	Mutation rate	0.04

where $member_i$ is the number of member nodes in cluster *I*; and *N* is the number of clusters for each CH in the path. This factor also is important in order to prevent the CHs that have many member nodes in their clusters to participate in the path. The increasing number of members will increase the energy consumption in the CH due to the receiving and aggregating processes.

These factors are included in the following fitness function, which is used to find the optimal path by minimizing its values:

$$F(i) = D(CH_s, BS) + \left(\frac{N_{par}}{N}\right) + No_{of_{Part}} + members \quad (26)$$

where *F(i)* represents the value of the *i*th chromosome; *D(CHs,BS)* represents the average distance from the source CH and the BS through the intermediate CHs, as presented in (23); N_{par} is the number of CHs through the path; *N* denotes the CHs in the chromosome; *No_of_Part* represents the total number of participation in the transmission process of all CHs in the path, as described in (24); and *members* denotes the total number of member nodes in all clusters that are related to the CHs in the path as described in (25).

In the first section of the fitness function, the average distance between the source CH and the BS is considered to distribute the energy consumption among all CHs. The second section represents the percentage of the participant CHs in the transmission process from the total number of the CHs in the GA, given its importance in finding the optimal path. When the percentage is low, the optimality of the path will increase considering that the proposed fitness function is the minimizing function. Optimality increases with the decrease in value. The third section represents the total number of participation in the transmission process of all CHs in the path, because if one CH participates many times in the transmission process, it will consume its energy very quickly. So, this factor will increase the value of the fitness function when its value increases, and it will give an inefficient path. The last factor is the number of member nodes in each cluster. This is also important due to its role in energy consumption.

The following algorithm summarizes the whole process of the proposed OMPFM:

1. Initialize the network in the same way used in the LEACH protocol.
2. Select the efficient CHs based on the new equation as described in Eq. (17).
3. Filter the set of the CHs by selecting the CHs with an energy level greater than the average energy of the all CHs.
4. Use the selected CHs from step 3 as an input of the GA.
5. Start the GA.
6. Find the optimal multi-hop path from each source CH in the set of CHs which is selected in step 2 to the BS using the CHs which are selected in step 3 as intermediate hops. Finding the optimal multi-hop path is based on the fitness function in Eq. (26).
7. Use the path in step 6 to send the data from the source CH to the BS.

The following section will discuss the simulation results of the proposed method, as well as a quantitative comparison between the proposed method and other related methods.

5. Simulation and experimental results

To evaluate the proposed fitness function, a simulation was conducted utilizing the MATLAB simulation tool which used the simulation parameters in Table 4 as proposed in [5]. It was performed to evaluate the fitness function in the proposed method and compare the results with the LEACH protocol [26] and other related methods [5,11,16,22]. The GA parameters, which are proposed in this paper, are also listed in Table 4; the crossover and the mutation rates are specified after applying several tuning operations.

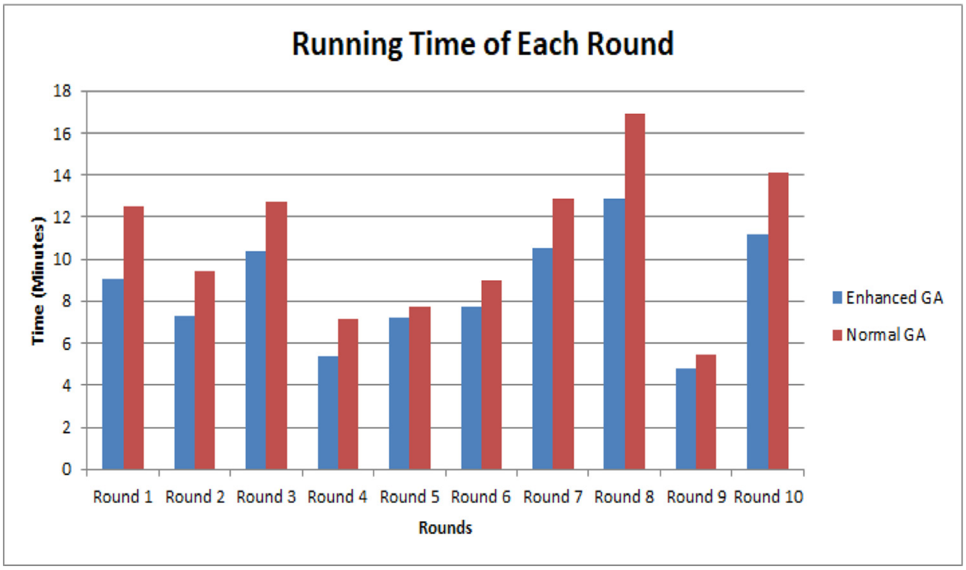

Fig. 1. Running time in the first 10 rounds.

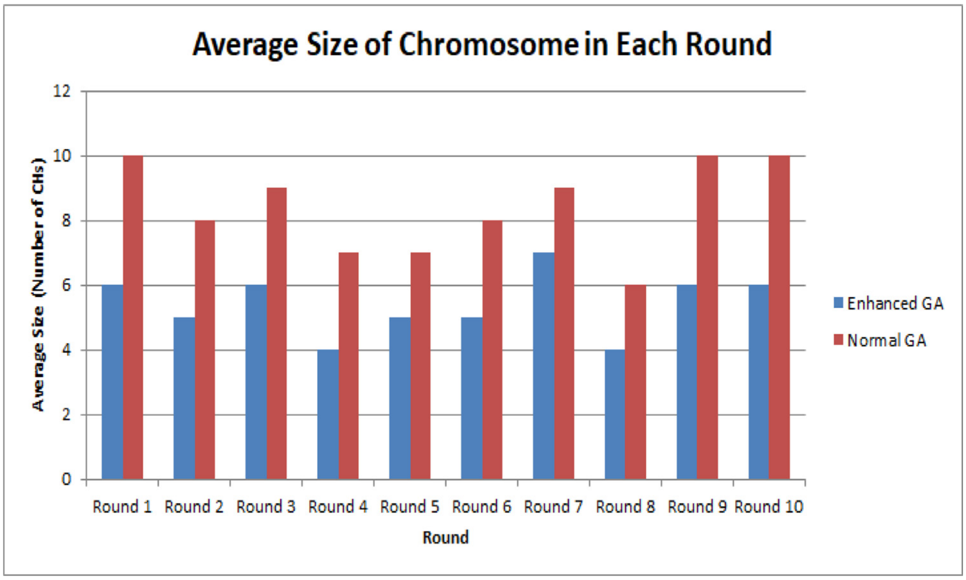

Fig. 2. Average size of chromosome in the first 10 rounds.

The LEACH protocol considers the main clustering protocol in WSN and other protocols inspire it. Therefore, it is necessary to take it as a benchmark. However, the proposed OMPFM is not only compared with the LEACH protocol, but also with many new protocols that are based on the LEACH.

Before starting the comparison of the proposed OMPFM with the related protocols, the time analysis regarding the comparison between the normal GA and the enhanced GA with the proposed preprocesses should be addressed to prove that the enhanced GA is more efficient than the normal GA in terms of chromosome sizes and the running time. The comparison is first done in one run, and the values in the initial 10 rounds are collected to show the actual difference between the normal GA and the enhanced GA, as shown in Figs. 1 and 2. The selected number of rounds is 10 to be suitable in the chart; more than 10 rounds results in an unclear chart, and less than 10 is not enough to show the values in the comparison. Additionally, the selected rounds are the first rounds because all the nodes are alive, resulting in an accurate and reliable running time, and the preferred chromosome sizes are achieved. After that, the comparison is done between the normal GA and the enhanced GA by testing them in 10 runs as shown in Figs. 3 and 4.

Fig. 1 illustrates the time required for running the normal GA and the enhanced GA in the first 10 rounds. Fig. 2 shows the average size of chromosomes in the first 10 rounds. The average chromosome sizes are calculated in each round by

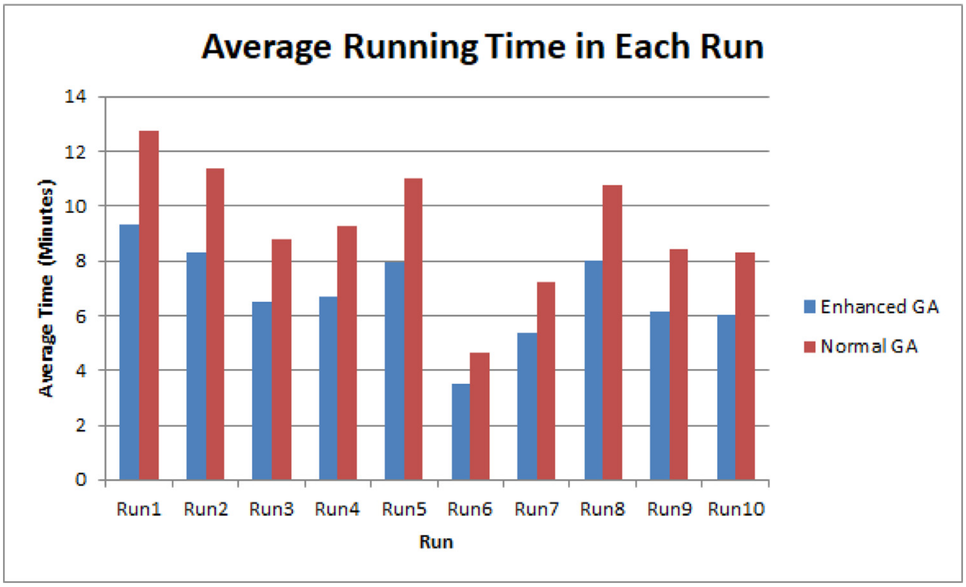

Fig. 3. Average running time in 10 runs.

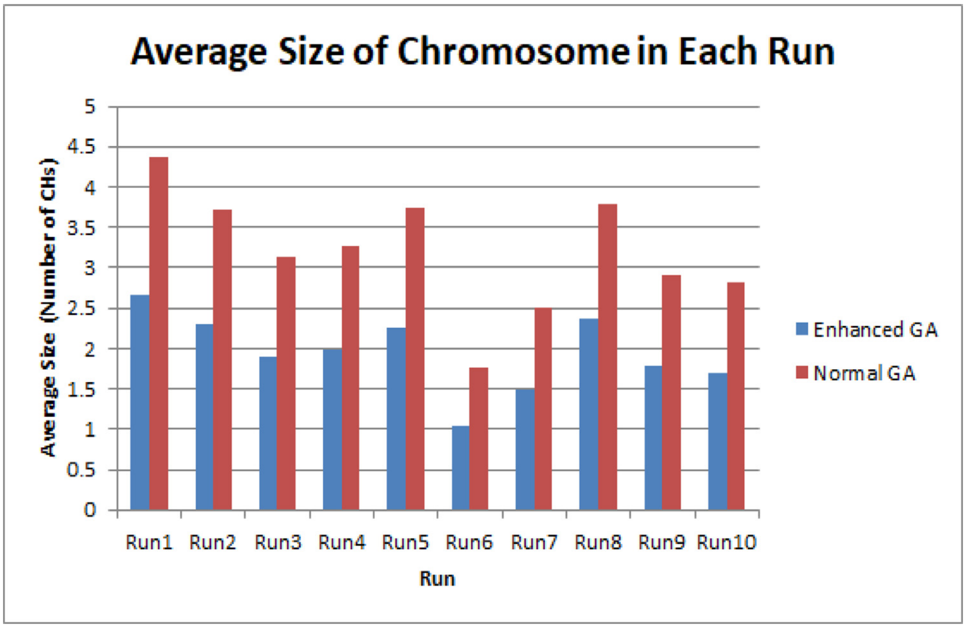

Fig. 4. Average size of chromosome in 10 runs.

finding the total size of chromosomes (total number of CHs in each path) divided by the number of CHs in each round, because there is a unique path from each CH to the BS in every round.

Based on Fig. 1, the required time for each round in the enhanced GA is less than that in the normal GA. This efficiency in the enhanced GA is due to the proposed pre-processes which reduce the running time of the GA. Moreover, the enhanced GA reduces the sizes of the chromosome when compared to the normal GA, as shown in Fig. 2. This shows the average size of chromosome in each round. The reduction in the chromosome sizes in the enhanced GA is due to the proposed pre-process that selects the optimal CHs to be involved in the GA, and this increases the efficiency of the GA by finding the optimal solution using short chromosomes as much as possible.

In the second experiment, the average running time and the average size of chromosome in 10 runs are considered in the comparison. Each run have several rounds e.g. 1200, and the average is taken to give more accurate and comprehensive view of the comparison as shown in Figs. 3 and 4.

S

1x189 struct with 18 fields

Fields	xd	yd	G	status	no_of_par	members	ToBs	type	E
1	99.8367	63.7910	0	1	26	0	140.3549	'C'	-0.0059
2	59.6141	51.5342	0	1	16	0	143.7876	'C'	-0.0037
3	66.3634	39.4811	0	1	36	0	156.3774	'C'	-0.0031
4	56.5661	69.3020	0	1	29	0	125.8694	'N'	-9.8154e-05
5	9.6247	90.9719	0	1	31	0	111.5885	'N'	-5.3343e-04
6	51.7123	19.6184	0	1	29	0	175.3899	'N'	-1.8068e-04
7	61.1383	15.5486	0	1	32	0	179.7968	'N'	-1.6328e-04
8	73.0279	72.8857	0	1	0	0	124.2666	'A'	-0.0071
9	75.3262	33.6703	0	1	29	0	163.3055	'N'	-4.1710e-04
10	85.6607	75.0740	0	1	46	0	125.1157	'N'	-5.1415e-05
11	80.8157	5.7107	0	1	31	0	191.7812	'N'	-2.8726e-04
12	44.2549	6.1709	0	1	28	0	188.9165	'N'	-2.2609e-05
13	32.2654	3.2172	0	0	0	0	192.6011	'A'	-0.0030

Fig. 5. Array data struct.

Table 5
Percentage of dead nodes and number of rounds.

Dead nodes%	Number of rounds				
	LEACH	GCA	EAERP	GAECH	OMPFM
10%	1989	2036	2155	2304	2546
20%	2031	2064	2187	2331	2612
30%	2055	2090	2201	2348	2690
40%	2075	2106	2224	2363	2755
50%	2091	2117	2247	2375	2826
60%	2102	2127	2265	2387	2895
70%	2112	2137	2278	2401	2991
80%	2126	2147	2288	2411	3133
90%	2136	2157	2298	2421	3418
100%	2144	2165	2309	2430	4316

Fig. 3 shows that the average running time in each run in the enhanced GA is less than that in the normal GA. Fig. 4 shows that the average size of chromosome (number of intermediate CHs) in the enhanced GA is less than that in the normal GA in each run. The results prove that the pre-processes in the proposed GA are efficient and increase the performance of the normal GA in terms of the running time and the size of chromosome.

Accordingly, different scenarios were designed to evaluate the proposed OMPFM. First, the simulations have been done for 20 runs in order to give a fair comparison with the related methods. In order to evaluate the proposed method, the array data structure is used with the required parameters for each sensor node in the network to compute its fitness value. The array data structure with the required fields is shown in Fig. 5.

xd and *yd* are the coordinates of each sensor; *no_of_par* is the number of participation for each CH in the routing process; *members* is the number of cluster members for each CH; *ToBs* is the distance to the BS; and *E* is the residual energy.

The main metric to evaluate the network lifetime as proposed in [5] is the number of rounds where a specific percentage of nodes die; these will be used in this comparison.

The comparative results of applying the proposed method with the related methods [5,14,16,22] are shown in Table 5 and Fig. 6 respectively.

From the above results, it is clearly noted that the proposed method shows prolonged network lifetimes when compared with the related methods based on the number of the dead nodes. The proposed method outperforms the LEACH protocol in the percent of 10% of the dead nodes by 28%, the GCA by 25%, the EAERP by 18% and the GAECH by 11%. Considering the HND (50%) of the dead nodes, the proposed is better than the LEACH protocol by 35%, the GCA by 34%, the EAERP by 26% and the GAECH by 19%. Finally, considering the LND (100%) of the dead nodes, the proposed method increased by 101%, 99%, 87% and 78% more than the LEACH, GCA, EAERP and GAECH respectively. These increments in network lifetime, using the proposed method, are due to the efficient parameters in the fitness function to select the suitable intermediate CHs in the routing path, which ultimately saves the energy of the nodes as much as possible; the LND values reflect this saving of energy.

The average of the consumed energy for all sensor nodes in each round is also considered in this comparison. The proposed method shows better performance based on the energy consumption in comparison with the related methods,

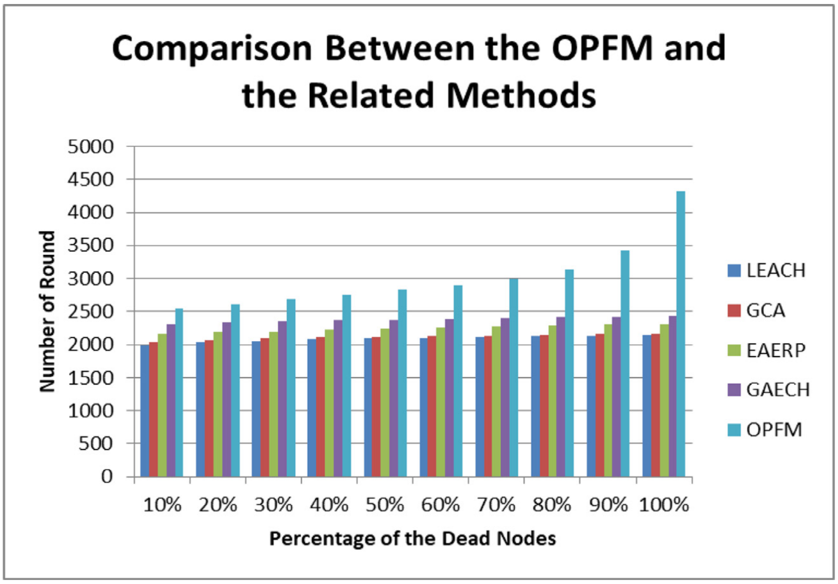

Fig. 6. Simulation results of the proposed method with the related methods.

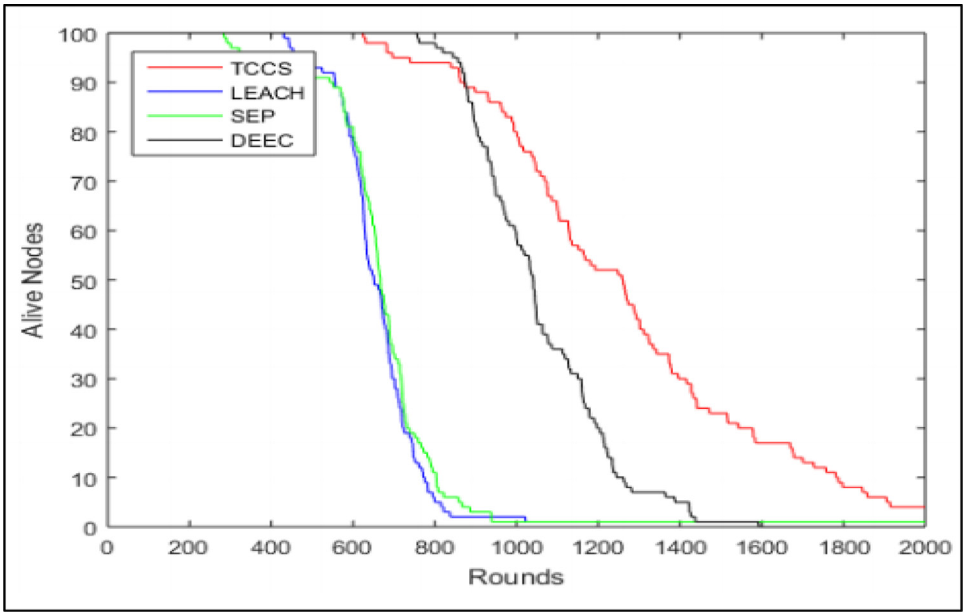

Fig. 7. FND and LND in the related method [11].

where the average of energy consumption is approximately 0.02 which is less than the GAECH method that consumed 0.04, while the LEACH protocol and the GCA method consumed approximately 0.048. On the other hand, the EAERP method consumed approximately 0.045 of energy. In general, the proposed method in this paper outperforms the related methods in terms of energy saving by approximately 50%. This result indicates that the proposed parameters in the fitness function are efficient in finding the optimal path to reduce power consumption and maximize network lifetime simultaneously. Moreover, the pre-processes are efficient and add a significant value on the proposed method.

In the second scenario, the same parameters in Table 4 were used, but the initial energy of each node in this scenario is 0.5 Joule as proposed in [11]. The FND and LND in the proposed OMPFM are presented in Table 6.

Based on Table 6, the average of the FND and LND parameters in the tenth's runs are 1695 and 3946 respectively. Fig. 5 illustrates the FND and LND in the [11] (Fig. 7).

Based on Table 6 and Fig. 5, the proposed OMPFM has greater FND and LND values than those in the related methods [11]. The average FND in the proposed OMPFM is 1695 while in the methods covered in [11] are approximately 800. More-

Table 6
FND and LND in the proposed OMPFM.

FND	LND
1725	4036
1687	4531
1671	3884
1648	3746
1705	4055
1733	3620
1737	3763
1679	4203
1659	3843
1703	3777

over, the average LND in the proposed OMPFM is 3946, while in the methods in [11] are approximately 2000. This efficient performance of the proposed OMPFM is due to the efficient selection of the parameters in the fitness function and the efficient applying of the pre-processes which increases the performance of the GA in terms of the execution time.

6. Conclusions and future works

In WSNs, data transmission has a considerable impact on the performance of a network in terms of its lifetime. Direct transmission is a problem in WSNs due to its effect on increasing energy consumption, especially if a source CH is far from the BS. Moreover, selecting proper CHs is also a problem that significantly affects the lifetime of the network. Numerous studies have been conducted to address these problems. This paper presents a method based on a modified GA to solve the direct transmission problem. Moreover, a modification on the CHs selection threshold is proposed, and the values of the boundary variables mentioned in the cluster head selection function can be changed based on the unique application to achieve better results. The simulation results proved that the proposed method is better than the LEACH protocol and other related methods on the basis of network lifetime and power consumption by approximately 50%. By contrast, the proposed method increases the running time due to the GA operations. In the future, another evolutionary algorithm should be used in order to make the execution time faster. Moreover, the multi-hop routing path in the mobile WSNs will be considered in the future.

Declaration of Competing Interest

The authors declare no conflict of interest.

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