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Original article

New methods of routing for the reduction of energy consumption in wireless sensor network

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A R T I C L E   I N F O

A B S T R A C T

Wireless sensor network consist of some nodes. Each node is responsible for gathering environment data and sending it to BS in order for received data to be analyzed. One of the main problems of this kind of network is the little primary energy of nodes and the little space of node memories. Each time data is sensed, node energy is reduced. Continuation of this situation results in the reduction of network lifetime or death. Suitable methods are presented for data transfer from nodes to BS. These methods have been able to optimize energy consumption in comparison with similar previous methods. One of the methods of acceptable optimization of energy consumption and network lifetime is the use of genetic algorithm in the network process of routing. Each method makes to using of different parameters that these parameters have created strengths and weaknesses. In this research, we present useful solutions for the reduction of energy consumption in network by the use of genetic algorithm. The main idea is to consider the methods proposed in recent years. The simulation results of creditable essays have been used to show the strong and weak parts of presented methods. Then, optimization solutions have been proposed by the use of simulation results and the weaknesses of existing methods.

1. Introduction

Nowadays, life without wireless communications cannot be imagined. Sensors can collect data in far areas and unsuitable places regarding human exploration. Combination lines can use these sensors to control the process of production. In strategic situations, fine sensors can be poured on energy fronts and then used in searching for the target (exp, car or human) (Czarlinska et al., 2007). Sensor is the device which distinguishes the event of a situation or the amount of a physical quantity and turns it to electrical signal. Sensors have different types like thermal, pressure, humidity, light, acceleration and magnetic… sensors (Guvensan and Yavuz, 2011).

Wireless sensor network consists of sensor nodes (Chen et al., 2008). This kind of network is used when the purpose is to collect data and examine a phenomenon (Czarlinska et al., 2007). Some features of sensor network distinguishes it's from other wireless networks. These features are as follows (Akyildiz et al., 2002): Hardware straits, consisting physical size constraints, energy resource, processing power, memory capacity. High number of nodes. High density in the distribution of nodes in operation area. The existence of ruination potential in nodes. Continuous and sometimes alternate topological changes. The use broadcast instead of point to point communication in node communications. Data centric network, this means that nodes don't have identification code (ID). The basic characteristic of this kind of network is that normal nodes collect data and send it to BS to be processed. Sensor network nodes must consume little energy. Therefore, battery lifetime determine the node lifetime (Heinzelman et al., 2000). The main problem of sensor network is the short lifetime of this kind of network (Cardei and Du, 2005). That is because of nodes, short lifetime due to the limited energy source. In addition, sometimes the special situation of a node in network intensifies the problem; for example, on the one hand, the node near to the sink soon loses its energy due to the enormous pressure of task (Hoang et al., 2010). On the other hand the communication of Sink with the whole network is interrupted due to the death of node; therefore the network stops working. Some solutions relate to the structure (Pandremmenou et all., 2011). For example, for the above – said problem, the automatic structure is an efficient solution. Sometime there are software solutions and relate to the issues such as data collection, type of routing, and proposed protocols. Although each sensor has little ability separately, but the combination of hundreds of sensor propose new facilities. In fact, the power of wireless sensor network lies in the ability to use lots of small self-organizes nodes which are capable of simultaneous routing, monitoring environmental conditions and monitoring the perfect conditions of structures or equipments of a system. There are lots of methods to optimize energy consumption in wireless sensor network. One of them is the use of genetic algorithms. In this research, methods that have used genetic algorithm to optimize energy consumption in recent years have been analyzed. The optimal solutions have been proposed to increase network lifetime by the use of weaknesses and strength of existing methods.

2. Genetic algorithm

Genetic algorithm has some basic differences with common search methods due in imitation of nature. For example genetic algorithm works with bit strings each shows the whole collection of variables. In contrast, most methods deal with the special variables individually. Genetic algorithm randomly selects for guide to search; therefore, it doesn't need derivation data. These algorithms select the best strings among organized random data (Akyildiz et al., 2002). In each generation, a new group of strings is formed by the use of best parts of previous continuations and the new random part to reach a suitable answer. However algorithms are random but they are not simple random algorithms. They effectively explore post data in searching space to head for the best answer with better answers in the new searching point. Genetic algorithms don't simply randomize .they combine past data with the thought of new search election to desirably improve (Czarlinska et al., 2007; Abbasi and Younis, 2007). Genetic algorithms does not need special information about the issue. It is therefore more flexible in comparison with most searching methods .also , genetic algorithm differs from typical searching methods which use random selection for leading their searching methods .that is because they don't walk randomly in searching space , although they use random and chance to define decision –making methods . GA optimizes by its actors .in

GA (genetic algorithm) a collection of variables are encoded with fixed length strings. In biological systems, these strings are collect chromosome or individual. The main genetic actions are selection, combination, and mutation. These actions along with other actions are implemented on chromosomes during several generations .then a new population replaces the previous population and the cycle continues. The new generation usually has more fitness; i.e. the population improves from one generation to the next. The search is profitable when the maximum generation is gained or the convergence is reached or suspension criteria are met.

2.1. Genetic actors

2.1.1. Encoding

This stage may be the most difficult stage of problem solving by the use of genetic algorithm. Instead of working on parameters or variables of the problem, genetic algorithm deals with their encoded forms. One of the methods of coding is binary coding in which the aim is to change the answer to a string of binary values (on the basis of 2) (Heinzelman et al., 2000; Cardei and Du, 2005).

2.1.2. Selection

selection stage, a pair of chromosomes is selected to combine. The selection factor is the connector between the two generations and transfers some members of present generation to the future one. After the selection, the genetic factors work on the two selected member. The criterion of member selection is their adaptation value, but the selection process id random (Bari et al., 2009). The direct and sequential selection in which the best members are chosen in pairs may seem a suitable method at first sight, but a point must be taken into consideration. In genetic algorithm, there are genes. Algorithm a member with low adaptability is not a proper member in its own generation, but may contain fine genes and if it has no chance of being selected, these fine genes cannot transfer to the next generation. Therefore, in this selection method, the members of higher adaptability are more likely to be chosen. The selection must be in a way that each generation is more adaptable compared with its previous generation as much as possible. The common selection methods are as follows: Roulette Wheel Selection, Sequential Selection, Boltzmann Selection, Selection of Steady State, Selection of Elite Democracy, Competitive Selection, Head Selection, Brindle Definitive Selection, Select to Replace Generation Modified, Competition Selection, Selection Random Match.

2.1.3. Combination

The most important factor in genetic algorithm is combination factor. Combination is a process in which the old generation of chromosomes are mixed and combined to create a new generation of chromosomes. Pairs considered as parents in selection stage, exchange their genes in this stage and create new members. In genetic algorithm, combination results in no dispersion or genetic diversity. It is because fine genes find each other (Akyildiz and Su, 2002; Aldosari and Moura, 2004). The most important methods of combination are as follows: single-point combination, two-point combination, uniform composition and account composition.

2.1.4. Mutation

Mutation is another factor which creates other possible answers. In genetic algorithm after the creation of a new member in new population, all its genes mutates with the mutation probability. In mutation, one gene of the collection of genes may be deleted, or a gene – not existing in the population – may be added. Mutation of a gene means its change. Different methods of mutation are used depending on the type of encoding (Akyildiz et al., 2002; Aldosari and Moura, 2004). The most important methods of mutation are as follow:
Binary Mutation
Real Mutation

2.1.5. Decoding

Decoding is the contrast of encoding. In this stage, when the algorithm presented the best answer for the problem, it is necessary to decode the answers to have the real clear answer (Czarlinska et al., 2007; Cardei and Du, 2005). The advantages of genetic algorithm can be summarized as follow:
It can optimize with connected and disconnected variables. It does not need derivation calculation. It can simultaneously search the whole vast searching area of expense function. It has the ability of optimizing the

problems with lots of variables. It can be implemented through parallel computers. It can optimize complex expense functions and is not trapped in local extermum. It has the ability of simultaneously obtain several answer not just one answer. Genetic algorithm are executed on a collection of solutions not just one special solution. It can encode the variables and optimize with encoded variables. Encoding accelerates the convergence speed of the algorithm.

This algorithm can work with produced numerical and experimental data as well as analysis functions. The process proposed by genetic algorithms is executed on a space of whole agents or the space of chromosomes not on the space of solutions.

2.2. Different kinds of genetic algorithms

Genetic algorithms simulate natural evolution at the level of genes and chromosomes. The common action in production of new generation is joining of chromosomes; although the mutation in genes is also used as a secondary action. Three main branches are presented in this method till now.

2.2.1. Series genetic algorithm

Series genetic algorithm is in fact the simple genetic algorithm and is an alternative to parallel genetic algorithm. Evolution is an optimization process based on gradual random changes of different samples in a population and selecting best of them. A statistical optimization technique can be obtained by modeling this process which is applicable nowadays in different complex issues specially designing (Akyildiz et al., 2002; Aldosari and Moura, 2004).

2.2.2. Parallel genetic algorithm

Two basic models have been presented in parallel genetic algorithm till now; one is the island model and the other is adjacency model. In island model, several separate demes are evolved in accordance with simple genetic algorithm. Sometimes neighboring demes exchange their best chromosomes. In adjacency model an individual model is evolved. Each chromosome of this population is located in a cell of a reticulated network and the series genetic algorithm is executed separately in a cell and its neighboring determined on the basis of neighbourhood radius. Network is considered as triode in order to prevent border effects (Meghanathan and Skelton, 2007; Salman et al., 2009).

2.3. Ending conditions of genetic algorithm execution

Different methods can be used in order to distinguish when algorithm execution stops. For example, the convergence of all population can be taken into consideration, or the distance between the fitness of the best sample of population and the fitnesses average can be considered. In the second case the distance must be smaller than a given range or the value of the fitness function must be more than a given amount or a given number of generations can be considered as a criterion for ending (Bay et al; Abbasi and Younis, 2007; Czarlinska et al., 2007). Generally, the algorithm can be stopped under these circumstances:

Obtaining the desired final answer after a few repetitions or the acceptable answer in exchange for a special error. Observing no improvement through the execution of algorithm, either the desired answer is obtained or the algorithm is stopped in a local minimum. If the value of fitness function is reach to a special amount after a few repetitions. Algorithm is reached a fixed number of generations. The maximum fitness of children is gained or no better results are obtained. manual examination, above-said combination.

3. Introducing new routing algorithm based on genetics to Reduce Energy consumption for wireless sensor network

In this section, the most important methods for the reduction of energy consumption are analyzed and in conclusion, their advantages and disadvantages will be represented. Then, using these points, solutions for the reduction of energy consumption in wireless sensor network will be presented.

3.1. The method based on genetic algorithm for routing efficient energy in two-level sensor networks.

The aid nodes of higher strength can be used as cluster heads in Two-level sensor networks to optimize network lifetime. Aid nodes may form a network between themselves to send route data to data station. In this

model, network lifetime is determined mostly by aid nodes lifetime. Energy informed communication strategy can extremely increase the lifetime of such networks (Bari et al., 2009; Ataul et al., 2009). One of these methods is a method based on GA presented by A. Bari et al. (Ataul et al., 2009). This method is effective for timing data collection from aid nodes that can considerably increase the aid node network lifetime. The main idea of aid nodes to reduce overhead is network traffic; therefore the aid node replaces nodes in areas of high density that soon lose their energy. The simulation results show an improvement in network lifetime in comparison with the previous similar methods. Figure 1 show the network lifetime in 4000 round of algorithm execution in an area of 60 Square meters in comparison with the previous methods.
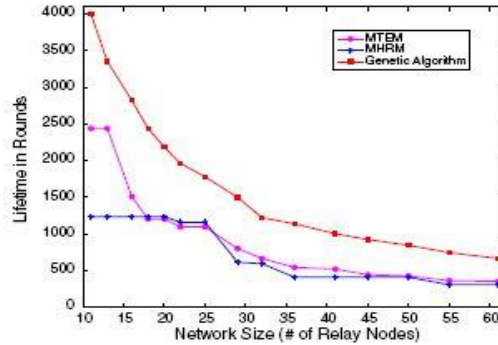

Fig. 1. Network lifetime in 4000 round of algorithm execution in an area of 60 Square meters.

As shown in figure 1, this method has been able to improve network lifetime compared with the similar previous methods. This algorithm has also been able to improve network lifetime in an area of 80 square meters after the execution of 4500 and 5000 round compared with the previous methods (Ataul et al., 2009). Also, simulation results have shown that in more rounds, this algorithm is still optimal. Figure 2 shows the execution of algorithm in an area of 21 square meters in 2000 rounds.
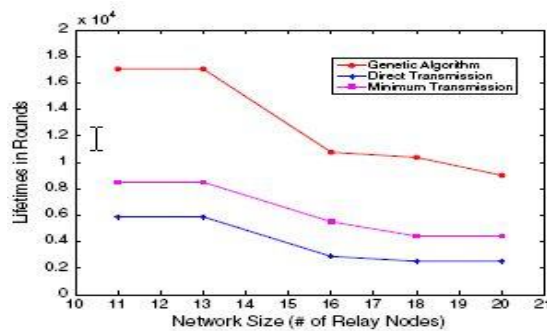

Fig. 2. Execution of algorithm in an area of 21 square meters in 2000 rounds.

As observed in above figure, network lifetime improves in higher rounds.

3.1.1. The advantages of this method

This method is suitable for smaller networks, where the overall optimum can be determined. This method is always able to final the best solution. It can also simply communicate with bigger networks and obtain considerable improvements in comparison with the traditional routing plans.

3.1.2. Weaknesses of this method

One of the important weaknesses of this method is that in the presented research, the table of parameters is not clearly mentioned. The weaknesses of this method are as follows: The primary energy of nodes is considered to be 5j which is relatively high; because in networks with lots of nodes, the total energy will not be economical. The position of base station is considered to be fixed (center of the network) and the simulation results are presented on the basis of this fixed position. This method is suitable only for small networks(networks less than 100 square meters) (Ataul et al., 2009; Jiliang et al., 2010). This method uses the single-hop or multi-hop partial

transfer. Partial transfer means the data transfer of CHs at only two levels; this means that network environment (in which nodes are distributed) is divided into four clusters. The two lower clusters send data to the two higher clusters.

3.2. Genetic algorithm for efficient energy clustering in wireless sensor networks

One of the proposed methods in wireless sensor networks is using the intelligent hierarchical clustering. This method is more efficient than several cluster-based routing protocols in energy consumption. In addition, the gradual energy download in sensor nodes is dealt with in this method (Abbasi and Younis, 2007; Sajid et al.). The advantage of energy-informed methods is that all CHs are aware of their cluster energy in every second of algorithm execution. This point can partially improve energy purpose in next rounds. One of the proposed methods in this field is HCR (hierarchical cluster based routing). It is a genetic-based method (Sajid et al.).The simulation results show that this method has been able to extend network lifetime in comparison with the previous similar methods. Figure 3 shows the execution of algorithm in an area of 200 square meters after 8000 rounds.
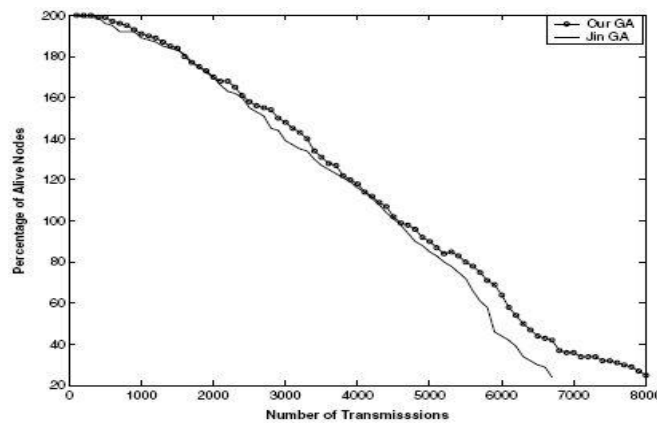

Fig. 3. Execution of algorithm in an area of 200 square meters after 8000 rounds.

As observed from the above figure, network lifetime is improved compared with the previous methods. One of the important advantages of this method is the unfixed situation of base station and size of the network.

3.2.1. The weaknesses

The primary energy of nodes is not mentioned in this method. As mentioned before , one of the most important algorithms of clustering in wireless sensor networks is LEACH algorithm .we also know that network lifetime depends on the number of alive nodes (the number of alive nodes equals lifetime) .In LEACH algorithm , alive nodes die in primary rounds . This is not fine and results in decreasing the lifetime. Simulation results show the network death in round 800. HCR method also has this problem. It means that first node death occurs in rounds lower than 1000. This range is idiomatically called FND (first node death) (Sajid et al.).

3.3. Parallel genetic algorithm for the issue of the shortest rout

Routing the shortest direction is a kind of routing which nowadays is widely use in computer networks .Even if algorithms of routing the shortest direction are well designed , alternative is using a may still have their own advantages (Salman et al., 2009). One alternative is using a routing algorithm based on parallel genetic algorithm. Using this algorithm, routing the shortest direction can be done by reducing the time of calculations (Meghanathan and Skelton, 2007). This algorithm is executed and expanded on an MPI cluster. Based on experimental results, there is a trade of between the time of calculations and the accuracy of results. However, for the same level of accuracy, the proposed algorithm can be much faster than the unparallel one (Salman et al., 2009). The shortest route means finding a direction from cluster head to base station to transfer the data of nodes of each cluster. The shortest routing can be carried out by factors like energy, distance, density of data or a combination of these factors. However, algorithm selects the best and at the same time the shortest route based on one of the above-said factors. The shortest routing can be done based on different kind of algorithms. One of these algorithms is parallel or series algorithm (Meghanathan and Skelton, 2007; Salman et al., 2009).

One of these methods is PGASPR (Parallel Genetic Algorithm for Shortest Routing) (Salman et al., 2009). This method routes the best and the shortest direction via GA. The main idea of this method is based on parallel genetic algorithm. This method has used match selection, single-point combination and binary mutation factors. The simulation results show and extend in network lifetime compared with the previous methods. Figure 4 shows the percentage of nodes of alive in different rounds. As shown in figure, this algorithm has been able to improve network lifetime.
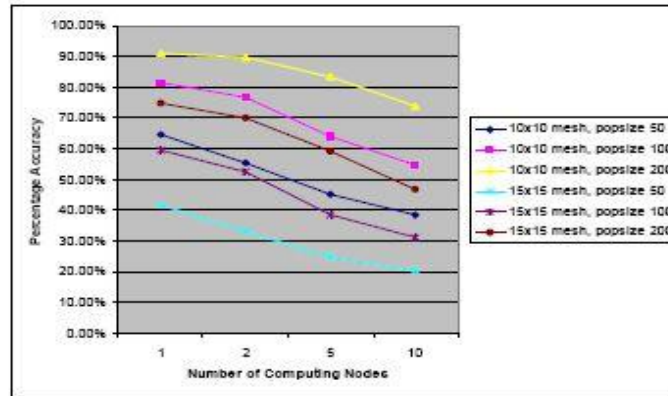

Fig. 4. Percentage of nodes of alive in different rounds.

3.3.1. Disadvantages of PGASPR method

One of the basic problems of this method is that the primary energy of nodes is not determined. Also, the number of generations, the size of primary population, the probability of combination, the probability of mutation, etc is not determined in this method because it is based on GA (Salman et al., 2009).

3.4. Adaptive decentralized re-clustering protocol

Wireless sensor networks consist of too many sensor nodes with finite energy source. A discussable issue in sensor networks is data collection via efficient energy. Clustering algorithm is a technique based on energy consumption reduction (Bajaber and Awan). One of the effective functions for routing is considering traffic conditions of the network such as crowed. The important advantages of this method are as follows:
Representing other routes in case of crowed. Little delay in high traffic loads. The increase of network operational power. In addition to the above-mentioned advantages, this algorithm has these shortcomings: The more complex logic of routing. The more complex router. More delay in low traffic loads.

One of the adaptive clustering protocols for wireless sensor networks is ADRP (Adaptive Decentralized Re-clustering Protocol). In ADRP, CHs and the next CHs are selected based on the remained energy of each node and the average energy of each cluster head in different time cycles. In this model, Hinzleman energy model is used to receive and transfer data. This method uses Graph weight strategy so that the network of nodes is pictured graphically and the weight of each node will be its remained energy in every execution of algorithm.

3.4.1. The advantages Of ADRP

The simulation results show the extension of network lifetime and a data overhead decrease by ADRP. Therefore, in lifetime, data delivery, and communication overhead periods, the function of proposed protocol is better in comparison with HEACH-C and CDC. Figure 5 shows network lifetime and the number of nodes of alive in each round of algorithm execution (Bajaber and Awan). As shown in figure 5, network lifetime has increase compared with the previous methods.
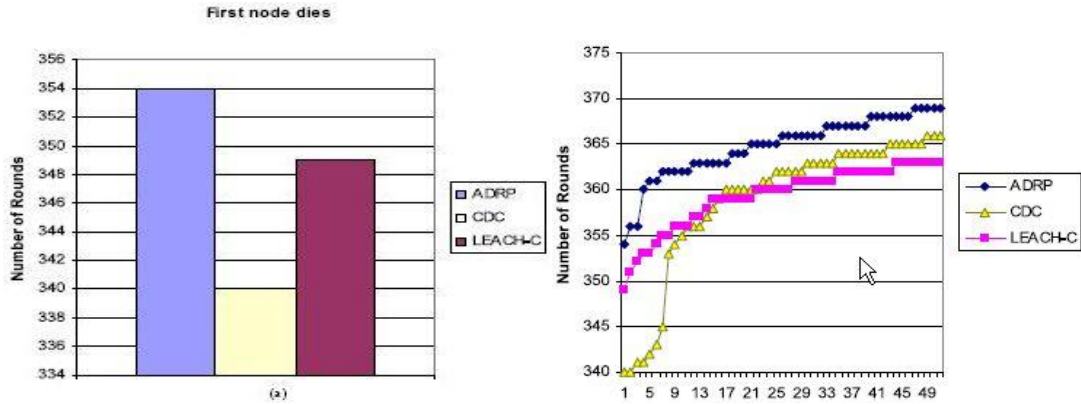
Fig. 5. Network lifetime and the number of nodes of alive in each round of algorithm execution.

3.4.2. Weaknesses of ADRP

Table 1 shows the simulation parameters in ADRP.

Table1
Simulation parameters in ADRP.

Parameter	Value
Network size	100×100
Number of nodes	100
Base station location	50×175
Data packet size	500 bytes
Initial energy	1 Joule

As shown in the above table, the number of nodes, the size of network, and the situation of base station are defined as fixed parameters. They are better to be variables. Although it is a weakness of ADRP method, but simulation parameters maybe considered variables which are not mentioned in this research. We mentioned the above-said factors as shortcomings because simulation results may answer properly only in BS 175*50 situation and improperly in 50*50 situation. This reason can also be used for the number of nodes and the size of network. Another weakness of this method is the use of affixed amount of Joule* for nodes as the primary energy. This amount is not economical for a network with lots of nodes.

3.5. Genetic algorithms in multi-dispersion routing

Multi-dispersion routing is an effective way of communication between several cluster heads in wireless sensor network (Czarlinska et al., 2007; Jiliang et al., 2010) The main issue is that how to extend network lifetime by Multi-dispersion and initial node energy. One of the presented methods in this field is GAEST (Jiliang et al., 2010). This method is based on genetic algorithm proposed for two-level sensor networks. In this method, nods follow a tree structure. This tree structure is called multi-dispersion tree. This method uses two strings of chromosomes called S and T. S chromosome keeps the vital data like children (normal nodes) and T chromosome keeps genes topology such as the position of father node compared with the normal nodes. In S chromosome, each gene consists of two parts: node identification and the number of children. Nodes Indices is done on the basis of preorder measurement (root, left, right). Figure 6 shows two states of multi-dispersion tree.
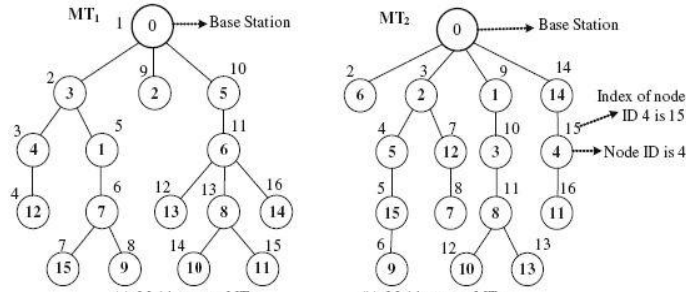
Fig. 6. Two states of multi-dispersion tree.

In GAEST method, a BS-tree-based routing algorithm is presented. In multi-dispersion tree, the shortest route to minimize energy consumption is created. This is done by GA. In this method genetic algorithm presents the ability of overall search to pass a point in the solution collection space. This is done via mutation factor. GAEST has been able to improve the mutation process and exchange the maximum remaining energy of leaf node with at least one non-leaf need considering the optimal mutation. The simulation results show the extended network lifetime by this method. Figure 7 shows the number of nodes of alive after the 8000 rounds execution of proposed method. As shown in figure 7, the proposed method has been able to improve network lifetime with 600 nodes (Jiliang et al., 2010).
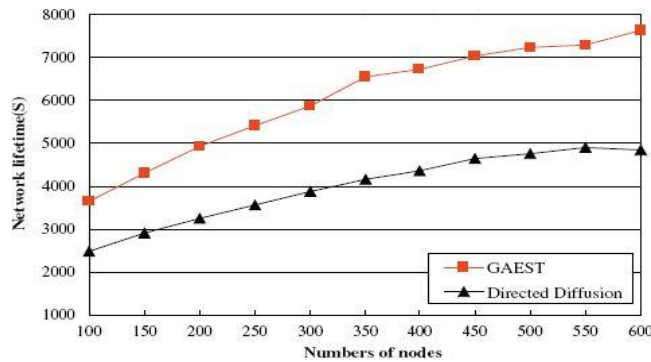

Fig. 7. Number of nodes of alive after the 8000 rounds execution of proposed method.

3.6. The application of genetic algorithms in game theory (GT)

Game Theory (GT) is a method dependent to mathematics which defines the cooperation differences between intelligent decisions. The useful application of this theory in wireless sensor network has been proved (Hai-Yan et al., 2012; Kazemeyni et al., 2011; Li et al., 2011; Koltsidas and Pavlidou, 2011). Figure 8 shows framework of the relation between wireless sensor network and GT (Hai-Yan et al., 2012).

The applications of GT in wireless sensor networks are as follows: rotting protocol designing, control topology, power control and energy consumption reduction, package transfer, data collection, spectrum allocation, band width allocation, control service quality, coverage optimization, wireless sensor network security and other duties of sensor management (Hai-Yan et al., 2012; Kazemeyni et al., 2011; Li et al., 2011; Koltsidas and Pavlidou, 2011).
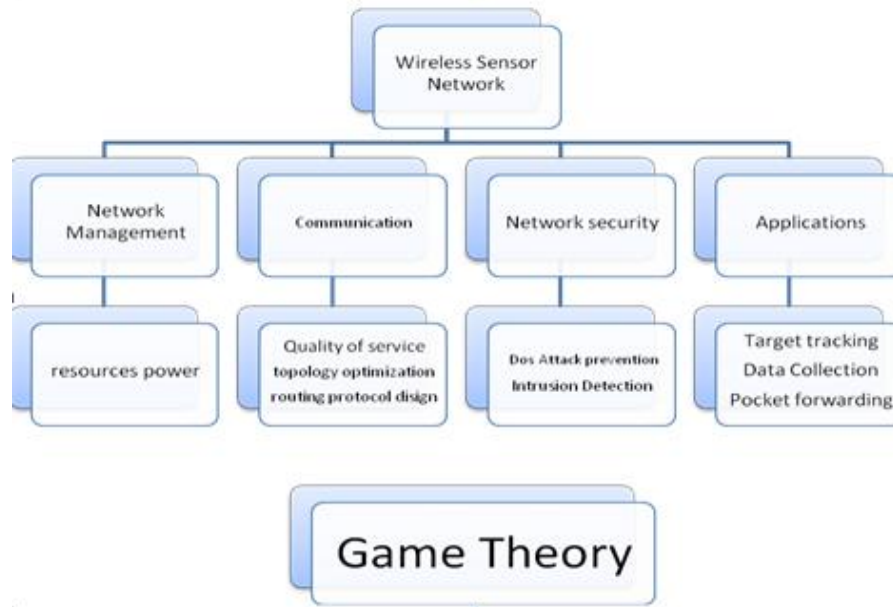
Fig. 8. Framework of the relation between wireless sensor network and GT.

3.7. The application of genetic algorithms in directional sensor networks

Directional sensor networks are networks which optimize the network coverage (Guvensan and Yavuz, 2011; Yang et al., 2010). Network coverage are mostly used in multi MAC (medium Access Control). Directional sensor nodes include ultrasonic, infra-red, and picture sensor (Guvensan and Yavuz, 2011). Picture sensors collect picture data from the physical environment (Czarlinska et al., 2008; Guvensan and Yavuz, 2011). Figure 9 shows the components of a picture network.
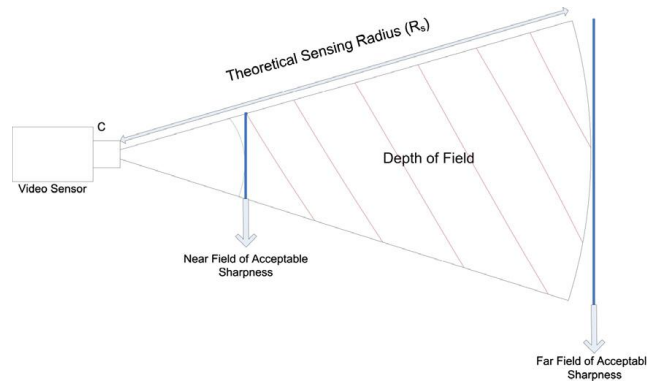

Fig. 9. Components of a picture network.

Infrared sensor is an electrical device which uses the infrared waves to collect and disperse data from and to its surrounding environment (Guvensan and Yavuz, 2011; Czarlinska et al., 2008; Liang et al., 2010).These sensors are divided into 3 range of short, average and long sensors according to their receipt radius .Generally, IR sensors are divided into two types of reflective and interrupt sensors (Guvensan and Yavuz, 2011). table 2 shows different IR sensors with different ranges.

Table 2
Different IR sensors with different ranges.

Type of IR sensor	Short-range	Mid-range	Long-range
Reflective	<4 cm	20 cm to 3 m	>3 m
Interrupter	3 mm	20 cm to 45 m	>45 m

Ultrasonic sensors produce sound waves of high frequency .Then based on these waves make special evaluations (Guvensan and Yavuz, 2011; Liang et al., 2010). The main purposes of directional sensor network are as follows: Reduction of network traffic. Extension of network lifetime. Capability of being attached in the network. Improvement of coverage. Directional sensor nodes have characteristics such as vision angle, communication radius, receipt radius, line indicator, task direction, etc (Liang et al., 2010; Czarlinska et al., 2008).

3.8. The application of genetic algorithm in ant colony and bee colony algorithm

Ant and bee colony algorithm is one of the most recent studies about routing in the networks. The most interesting behavior of ants and bees for finding food is using direction. Ants leave a chemical essence called Feromon while passing a route .This essence vaporizes soon. The route evolves by next ants following Feromon left by the previous ants. Encountering several routes, ants choose randomly the routs with more Feromon (Bay et al; Bajaber and Awan; Enan and Bara'a, 2011). -if q >q0, the position is selected based on the best state of distance-Feromon. It means: -if q> q0, the next position is obtained randomly and with this relation probability: Figure 10 shows the optimal routing of Ant algorithm.
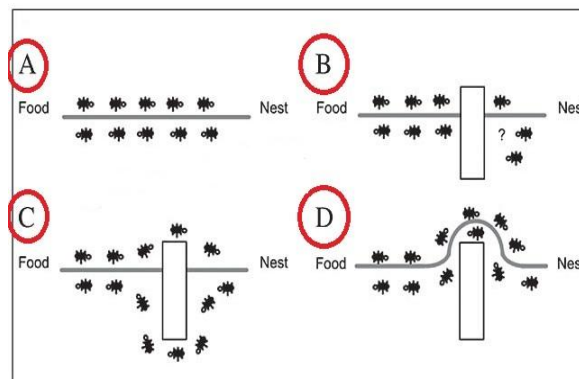

Fig. 10. Optimal routing of Ant algorithm.

Bee algorithm presented for the first time in 2005, shows the simulation of bee behavior while searching for food. This algorithm like ant, algorithm uses a random function and explain that bee stays more on a flower which is better source of food. Generally, ant colony is distance-dependant and bee colony is energy-dependant. The results of recent researches show that GA has been able to create an optimum space for ant and bee colony. Also, the most effect of GA on ant and bee colony has been the combination of these two colonies. GA has been able to present a distance and energy-based combined algorithm for the reduction of energy consumption in wireless sensor network.

3.9. The Application of Memetic Algorithms in Wireless Sensor Network Routing

Memetic algorithms are created to solve the combination optimization issues. This algorithm is nowadays one of the important discussions in the field of optimization algorithms. One of the important characteristics of this algorithm is that it uses state space to solve a problem. This state space contains all algorithm knowledge (Chen et al., 2008; Konstantinos and Theodore, 2010). The results of recent studies show that memetic algorithms execution speed is more than genetic algorithms execution speed. It means that they obtain answers of better quality in a shorter time (they converge faster). One of the methods presented in this field is MA system (Memetic Algorithm system) (Konstantinos and Theodore, 2010). This algorithm has optimized energy consumption in wireless sensor network. One of the advantages of this algorithm is fast search in the problem space. In addition, this method has improved chromosome creation speed in the form of local factor. The simulation results show that the combination of memetic and genetic algorithms and the use of a local search resulted in the improvement of first node death and therefore network lifetime.

3.10. Routing protocols informant of evolutionary energy for mechanical clustering of wireless sensor networks

Many studies have been conducted on the issue of sensor network lifetime in two dimensions of first node death and last node death (Hussain and Matin, 2006; Meghanathan and Skelton, 2007; Havet et al., 2010). If the distance between FND and LND be more, the lifetime of sensor network is been more. One of the routing protocols presented in this field is the hierarchical clustering algorithm based on GA-EAERP (Enan and Bara'a, 2011). The simulation results that this method, via GA, has been able to improve lifetime and durability of network. This method has been able to present a fitness function that adapts suitable clustering considering network conditions in which each cluster is informed of its energy level in each round. Figure 11 shows the number of nodes of alive in different rounds with 100 nodes.
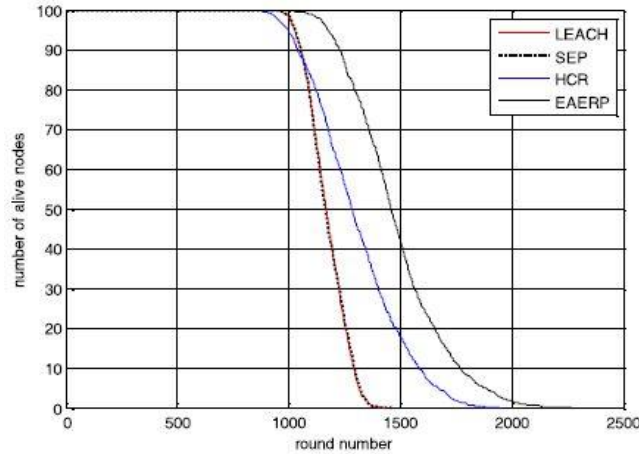

Fig. 11. Number of nodes of alive in different rounds with 100 nodes.

As shown in the above figure, this method has been able to improve network lifetime in comparison with the previous methods. Figure 12 also shows the comparison between FND and LND.
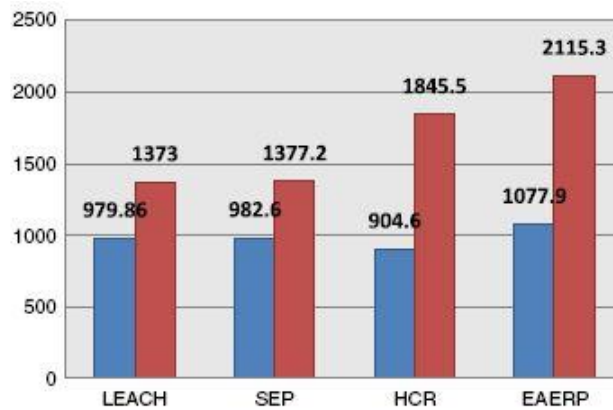

Fig. 12. Comparison between FND and LND.

4. New ideas for energy consumption optimization in wireless sensor network

In the previous section, wireless sensor networks, WSN routing algorithms, and new clustering perspectives in recent years have been presented. In this section, with regard to the weaknesses mentioned in the previous section, we intend to present new ideas for energy consumption reduction in wireless sensor networks. The main purpose of this section is to represent solutions to improve network lifetime and energy consumption.

4.1. Using a combination of genetic and memetic algorithms

As mentioned in the previous section, memetic algorithms have been successfully used in solving the problems of optimization. Genetic algorithm is a function of blind search in the state space of the problem (Konstantinos and Theodore, 2010). The difference between MA and GA is that MA is an informed, not blind perspective. Therefore MA is faster than GA (Konstantinos and Theodore, 2010; Chen et al., 2008). The main problem of MA is that it uses a local search for the optimization of on issue. It means that the whole space of the issue is not taken into consideration (Czarlinska et al., 2007). This is a big problem. Different solutions have been proposed to solve the problem of local search. These solutions can partially solve the problem of memetic algorithms (Konstantinos and Theodore, 2010). Two of the most important methods are general searcher and stochastic adaptive searcher. For example, gravity searching algorithm is a general searcher and stochastic adaptive searcher is a local searcher. Combination of these two searchers can solve the problem of locality in MA. While GA considers the whole space of the problem for optimization, the combination of MA and GA can create a method which considers the whole space of the problem together with begin a not blind, informed perspective (Konstantinos and Theodore, 2010; Czarlinska et al., 2007; Akyildiz et al., 2002). In this combined method, GA considers the whole space of the problem and MA makes the space of the problem informed, not blind.

4.2. Using parallel genetic algorithms

As mentioned before, the main problem of algorithms is the low speed of their execution. It is because GA considers the whole problem space for optimization (Meghanathan and Skelton, 2007). One method for improving GA execution speed is using parallel algorithms (Salman et al., 2009). Making GA parallel is one of the best and most basic perspectives that con provide genetic calculations and obtaining desired answers in acceptable time for problem solving. Recent researches results show that PGAs use sequential and single-population GAS.

PGA state is usually when several populations are used. PGAS using one population are called normal GA. Generally, there are four groups of PGA.

4.2.1. Master-slave gas

This kind of algorithm uses a centralized population and evaluates the individuals in a parallel way. Figure 13 shows master-slave model.
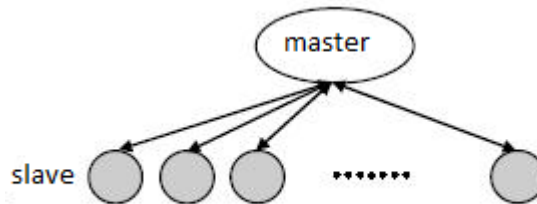

Fig. 13. Master-slave model.

4.2.2. Fine-grain parallel gas

This model consists of some demes which work not together and approximately independent of each other. All demes execute standard Gas on their own parts of the whole population. These demes exchange their individuals on a communicational topology.

4.2.3. Course-grain parallel gas

In this model all individuals are distributed in a homogeneous way on a topology of processing elements. This model can be considered as a distributed on a set of processing elements that each subset of the population is called a neighbor. Figure 14 shows fine-grain GA with two-dimensional linear topology.
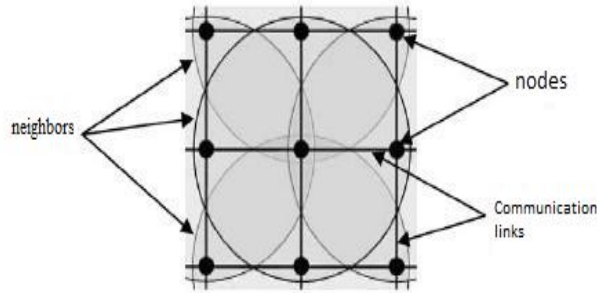
Figure14. Fine-grain GA with two-dimensional linear topology

4.2.4. Hierarchical gas

Using this kind of algorithm can be useful in optimization specially energy consumption reduction

4.3. Using in re-clustering

As mentioned in previous sections .Re-clustering can partially improve network lifetime. Re-clustering results in the reduction of executive expense of algorithm. It occurs because there is no need of re-clustering in every execution of algorithm. As observed before, in primary algorithms such as LEACH and LEACH-C, in every execution of algorithm different clusters were selected and executed. Re-clustering can eliminate these problems. Using GA in re-clustering can improve network lifetime .This improvement occurs in different number of generations. The process of generation execution is so that always best fitness occurs in last generations. The obtained measures in the last generation and the population produced by them can be used as re-clusters.

4.4. Using gas in multi-dispersion routing

When encountered to multi-dispersion routing, using tree structure is certainly desirable (GAEST method in unit 3). Using tree structure is suitable when the number of nodes are relatively law. But as mentioned before, vast sensor networks have too much nodes which results in a big tree in the problem. GAs (especially parallel Gas) can better deal with the issues of searching and optimization in vast trees.

4.5. Using optimum gas

By optimum we mean the less number of generations in GA. It means the less the number of executing generations in GA, the faster the execution of GA and the sooner the obtaining of optimization. It must also be taken into consideration that the optimum generations can be considered when no change occurs in fitness from a given round on and fitness remains constant. Figure 15 shows algorithm execution in 50 generations. Fitness has reached 0.2.

As shown in figure 4-3, the best fitness has remained constant from 40 generations on and no changes occur in it. Therefore we can execute algorithm up to 40 generations to enhance execution speed. This results to a faster algorithm execution.
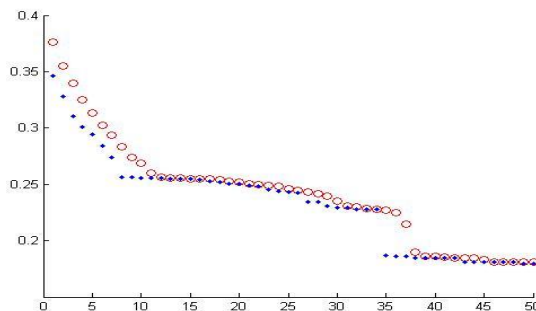

Fig. 15. Algorithm execution in 50 generations.

4.6. Using k-means and genetic algorithms one of the most famous clustering algorithms one of the most famous clustering algorithms is k-means algorithms

This algorithm divides the distance between nodes of a network to k clusters on the basis of a distance criterion. This method is idiomatically called k-adjacency method. In this method k points are first randomly selected as cluster centers. Then each node is related to one of these clusters on the basis of distance criterion like Euclid distance.

This continues up to the end of the process. One of the advantages of this algorithm is its simple execution. Also, time complexity of this method is O (N) .one of the important weaknesses of this algorithm is the probability of its stop in local minimum and no true selection occurs in initial state. It is possible that none of the initial points be in harmony with the distance criterion. It is because this algorithm works on the basis of distance criterion and initial points (cluster centers) are selected randomly. This may result in the grip of algorithm in a local point.GA can be used to solve this problem. It can be done by the selection of cluster centers via GA and clustering via k-means.

7.4. Using tree Structure and GA. By common group applications in networks, researchers tried to use multi-dispersion connections instead of point to point connections. Generally, there are two types of multi-dispersion communication: One to many and many to many connections. In both types, in case of huge data volume, finding an optimum route is difficult. Several optimum routes must be found for data transfer. The best solution of this problem is using he optimum trees. In optimum trees there are factors such as delay, transmission expense, traffic load, etc. The combination of these factors is called service quality. As mentioned in previous units, in vast wireless sensor networks finding one optimum route is not suitable, especially in area of high density of nodes. The best solution of this problem is the use of tree structure. It was also mentioned in the previous units that the more the levels of tree, the more difficult the measuring and searching process. GA can better determine the optimum points in a tree. But this can be time consuming regarding the levels of the tree. Therefore, it can be concluded that the less the levels of the tree, the sooner the finding of optimum point by GA. There are different perspectives for finding the best tree. They are as follows: rooted tree problem, minimum spanning tree problem, and Steiner tree, etc. The results of recent studies have shown that ST and GA have been able to reduce energy consumption in WSN.

The main purpose of ST is finding a tree in graph G to cover a given subset of terminals and having the least expense among similar trees. The Steiner tree is NP-complete. The problem of Steiner tree idiomatically is finding a tree with the least expense. In this tree, there is a set of special points called terminal. The tree expense equals the total of its terminals. If the produced tree only contains terminals, it is called minimum spanning tree.

This expense in wireless sensor network can be energy. Generally, in order to reduce expense (energy), nodes other than terminals, called Steiner points, are used. Steiner points connect terminals to each other. In WSN, GA can choose better Steiner points. Figure 16 shows the Steiner tree.
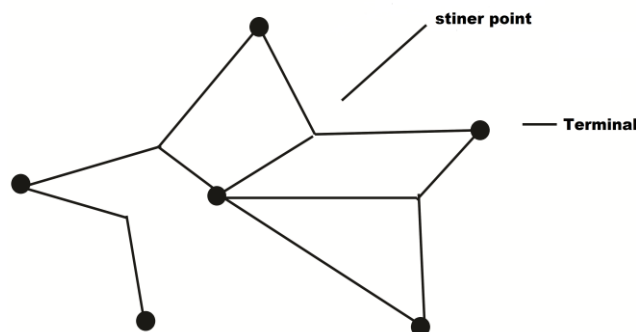

Fig. 16. Steiner tree.

4.7. Energy – based perspectives

Facing with energy problem, GA can work in two ways. – In case of high primary energy of node: In this case , although GA can select optimum nodes , but regarding the high primary energy of nodes , executing such a network is basically problematic , because too much energy is needed for the execution of such a network.

In case of low primary energy of node: Generally the low fixed energy in areas of high density is not suitable. The best solution for this problem is using a random perspective .using a random perspective has many advantages which are as follows: low minimum and maximum amount of energy.

In areas of high density, node will be distributed monotonously with high and low energy. Therefore genetic algorithm will be able to better select node or nodes with high energy.

4.8. Using fitness function or optimized expense functions in other methods

GA uses an expense function called fitness function for best routing and clustering. In general, GA finds optimal point in two stages: Finding suitable expense function. Generation execution.

Using expense function in other methods can bring algorithm execution expense to half. Generally, GA stops under one of these circumstances: Obtaining the desired final answer after a few repetitions or obtaining an acceptable answer by a special error. If no improvement occurs through the execution of algorithm, either algorithm has found the desired answer or stopped in local minimum. If the fitness function has reached a given amount after a few repetitions. Algorithm has reached a fixed number of generations. The maximum fitness of children is gained or no other better result is obtained.

Now, if fitness function is already determined, GA must only be executed in a given number of generations in order for the best generation to be obtained.

5. Conclusion

In this research we tried to study the recent methods of routing and optimizing energy consumption in wireless sensor networks in recent years, we could present new ideas for energy consumption reduction and network lifetime extension by the use of previous methods .This is done through comparison of simulation graphs in methods. As mentioned in this research, the combination of GA and new methods can considerably extend network lifetime. I this research issues such as FND , LND , lifetime , energy consumption reduction , number of generations , primary energy , size of environment , BS position , and node density were studied.

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