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A Novel Fault Tolerance Energy-Aware Clustering Method via Social Spider Optimization (SSO) and Fuzzy Logic and Mobile Sink in Wireless Sensor Networks (WSNs)

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In recent years, the application of WSNs has been remarkably increased and notable developments and advances have been achieved in this regard. In particular, thanks to smart, cheaper and smaller nodes, different types of information can be detected and gathered in different environments and under different conditions. As the popularity of WSNs has increased, the problems and issues related to networks are examined and investigated. As a case in point, routing issue is one of the main challenges in this regard which has a direct impact on the performance of sensor networks. In WSN routing, sensor nodes send and receive great amounts of information. As a result, such a system may use lots of energy which may reduce network lifetime. Given the limited power of a battery, certain method and approaches are needed for optimizing power consumption. One such approach is to cluster sensor nodes; however, improper clustering increases the load imposed on the clusters around the sink. Hence, for proper clustering, smart algorithms need to be used. Accordingly, in this paper, a novel algorithm, namely *social spider optimization* (SSO) algorithm is proposed for clustering sensor network. It is based on the simulation of the social cooperative behavior of spiders. In the proposed algorithm, nodes imitate a group of spiders who interact with each other according to biological rules of colony. Furthermore, fuzzy logic based on the two criteria of battery level and distance to sink is used for determining the fitness of nodes. On the other hand in WSNs with a fixed sink, since the nodes near the sink share multi-hop routes and data and integrated towards the sink, these nodes are more likely to deplete their battery energy than other nodes of the network. Also In this paper, mobile sink was suggested for dealing with this problem. For investigating and demonstrating the performance of the proposed method, we compared it with DCRRP and NODIC protocol. The results of simulation indicated better performance of the proposed method in terms of power consumption, throughput rate, end-to-end delay and signal to noise ratio and has higher failure tolerance especially in terms of sensor nodes' failure.

Keywords: WSN (wireless sensor network); swarm intelligence; SSO (social spider optimization), clustering; DCRRP; NODIC protocol; Fuzzy Logic.

1. INTRODUCTION

WSNs include sets of sensor nodes which communicate with each other through wireless links so that they can gather data

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efficiently and carry out routing. In such networks, sensor nodes are densely organized in a geographical region and they are used for sensing environment and gathering data. Moreover, collected data is navigated by sensor nodes via intermediate nodes so that data is transmitted to a base node called sink where the transmitted data is stored for further investigation and analysis. In such a scenario, sensor nodes consume more energy for transmitting data to the sink node. Hence, more energy than that is required for data processing in the sink is consumed for data transmission. Thus, the optimization of the available power in sensor nodes is a notable issue in WSN which can enhance network lifetime. This purpose may be fulfilled by developing an energy-efficient routing algorithm. Clustering is regarded as one of the existing methods for optimizing power consumption in data routing. In cluster-based routing, nodes are divided into small groups called clusters. By sending information through cluster-heads (CHs), power consumption is reduced. In this scenario, in case coordinators or CHs are close to the base node, they can directly send data to the base node. On the other hand, if coordinators are not close to the sink node, they should indirectly send data to the sink node via a multi-stage communication with other CHs. If a node remains as a coordinator for a long time, its power will be quickly depleted; as a result, network lifetime will be reduced.

Clustering is a method which is aimed at optimizing power consumption and enhancing network lifetime. In fact, clustering operation determines how to classify sensor nodes [1]. In practice, as a result of clustering, different responsibilities of information reception from the surrounding environment are assigned to sensor nodes. Since CH manages communication among nodes, information gathering, information transmission to the sink and its processing, it is known as the leader and navigator of the cluster. The remaining nodes which sense and send information are known as member nodes [2]. In developing clustering algorithms, factors such as service quality, storage capacity, power consumption, network lifetime and the security of communication channels should be taken into consideration [3].

In this paper, a clustering-based hierarchical routing algorithm is proposed which is aimed at balancing power consumption with the help of SSO algorithm and fuzzy logic in WSNs. Fuzzy logic is a mathematical theory, which encompasses the idea of vagueness when defining a concept or a meaning. In the proposed method, power consumption in clusters is divided into two parts: intra-cluster power consumption and inter-cluster power consumption. In this protocol, based on the remaining power level and shorter distance from the sink, nodes compete with each other for becoming CH; in this way, the node with further power level and shorter distance from the sink is selected as the CH and those nodes which were not selected as CH will join the closest CH. This method guarantees that there is, at least, one CH within the covered radio range R_C. It is assumed that nodes are distributed non-uniformly. Accordingly, in dense regions, clusters have more members; in a similar vein, in low coverage areas, there are fewer cluster members. This condition leads to imbalanced power consumption among clusters. Hence, for balancing power consumption among different clusters, a routing tree based on CHs is created. Multi-hop communications from CH to the base station reduces power consumption. In this routing tree, each CH selects a neighbor with greater remaining energy and shorter distance from the sink as the next hop. Also in a WSN, the sensor nodes close to the sink are overburdened as they act as a bridge between the sink and the rest of the network for forwarding data to the sink. This results in rapid energy depletion of these sensor nodes and leads to network partitioning. Such adverse circumstance is termed as hot spot problem in a large WSN, while the sensor nodes nearby the sink exhaust their energy, the far away sensor nodes. Using mobile sinks has been suggested as a possible solution for sorting out this problem. The hot spot area around the sink changes as a result of sink mobility and the excessive energy consumption around the sink is distributed throughout the network then In this paper, mobile sink was suggested for dealing with this problem. The proposed method is simulated with OPNET 11.5 and compared with NODIC (novel distributed clustering) algorithm [4] and DCRRP [12] in terms of end-to-end delay, power consumption, throughput and media access delay (MAC).

2. RELATED WORKS

Clustering sensor nodes in WSN is regarded as an effective method for optimizing power consumption. Given different clustering techniques presented in related works for cluster-based routing, network-based clustering has better performance due to its direct transmission. Also, uniform structure control leads to reduced routing overhead. That is to say, in network-based clustering, a data collection and measurement field is divided into smaller networks with specific length. A sensor node from each network is selected as a GC (grid coordinator) which condenses and navigates data gathered from other sensor nodes in the network towards the base station. Network nodes closer to the end node are loaded by entering sequential data from other participating nodes. Hence, the energy of these nodes is rapidly decreasing which leads to the separation of network system from these nodes; this phenomenon is referred to as hot spot.

For effectively handling the issues and problems regarding power consumption, Logambigai et al [5]. proposed energy-efficient clustering-based routing algorithm which uses nodes' energy efficiently. GC is selected for each network by means of using fuzzy logic; fuzzy variables are used for selecting GC based on nodes' remaining energy, their movement pattern and distance from the end node. Since transmission consumes energy according to distance, distance from the end node is considered to be a significant parameter for selecting CG. Hence, energy use is completely supervised. Sabet and Naji [6] proposed a WSN decentralized hierarchical algorithm for clustering. They also suggested multi-hop clustering for transmitting fewer control packets. The reduction of the number of transmitted messages may also lead to reduced power consumption. In this clustering method, information transmission by CHs to other clusters and within the related cluster is maximized. This algorithm uses three main correction parameters for selecting CH which includes using consumed power, energy change flow and precise distance. The simulation of these parameters indicates minimized power consumption and improved network lifetime. Yuvaraju et al [7] proposed a new multi-route protocol, called *secure energy efficient load balancing multipath routing protocol with power management for WSNs (tSEL)*. This protocol uses multi-path routing for achieving a better load balance in comparison with single-path route. It also provides security. tSEL protocol selects numerous separate paths and effectively distributes workload among them. Simulation results indicated that network lifetime is enhanced accordingly. Abasıkeleş and Hafif [4] developed a WSN clustering method for selecting CH within each cluster. In this method, CHs are selected randomly. By sending a connection message, normal nodes inform the CH of their membership request as well as the amount of their remaining energy. Then, the temporary CH obtains information about the total remaining energy of the nodes in the network. If the remaining energy of the network is higher than 50%, the node with greater energy will be selected as the CH. Otherwise, the node with more neighbors will be selected as the new CH. In this way, in their paper, the criteria of energy, location and communication were used in selecting CH which led to enhanced network lifetime.

Mohammed et al [8] proposed two distributed routing protocols, namely energy-efficient and connection-aware protocols for solving the problem of routing gap. These protocols are On-Hole Children Reconnection (OHCR) with local nature and On-Hole Alert (OHA) with global nature.

In [8], the exchange between connection and network overhead was investigated with regard to power consumption. The researchers focused on monitoring programs in which it is essential to gather periodic information. The termination of network lifetime is more likely in such monitoring programs; especially when BS is far from the region of interest (ROI). Network structure consists of a single route between source and destination with a single adjustment step. Hence, they proposed two solutions for this type of network for protecting connection and avoiding increased overhead by the dynamic routing protocols. The two solutions are OHCR and OHA which are specified thanks to their high compatibility and with the application specifications with local and global nature.

For saving nodes' power consumption and enhancing their network lifetime, Su and Zhao [9] proposed a clustering algorithm for WSNs according to average C fuzzy. Given the imbalanced distribution of sensor nodes and the uncertainty of radio channel, nodes' cluster formation process was modeled in this study as a sample fuzzy space in [9]. The total power consumption of the network was firstly analyzed and the desirable number of CHs was estimated according to nodes' density. In designing target function, the distance between node and CH and the weight of membership values are taken into consideration. Then, the optimized average C fuzzy clustering algorithm was put forth for dividing sensor nodes into certain number of clusters. Simulation results indicated that this algorithm was able to achieve uniform distribution of clusters and effectively balance network power consumption. Xu et al [10] proposed a method based on game theory for efficient clustering in WSNs. The main rationale behind this method is that CH is selected based on game theory. Sub-CH is also created in the clustering process for preventing the failure impact of CH project. Round method is not used. When a CH does not function properly, candidate CHs should be reset which leads to excessive power consumption of the clusters participating in re-expansion.

Zahedi et al [11] proposed a fuzzy routing protocol based on hybrid swarm intelligence, firefly algorithm and simulated annealing. In this protocol, fuzzy C-means algorithm was used for clustering all the nodes within balanced clusters which applied Mamdani fuzzy inference system for selecting CHs. This method not only guarantees balanced clusters but also determines the precise number of clusters. The main objective of this protocol was to enhance network lifetime according to different applications.

In WSNs with a fixed sink, since the nodes near the sink share multi-hop routes and data and integrated towards the sink, these nodes are more likely to deplete their battery energy than other nodes of the network. Nodes' shutdown leads to topology failure and the reduction of the sensing coverage which interrupts sensors' data reporting tasks. Tabatabaei et al [12] proposed, mobile sink for dealing with this problem so that load balance and uniform energy consumption can be achieved throughout the network. The proposed method, referred to as DCRRP (distributed clustering reliable routing protocol), operates in the distributed form and is able to minimize the reported delay. Simulation results and the comparison of the proposed protocol with NODIC protocol indicated that the proposed protocol performs better and has higher failure tolerance especially in terms of sensor nodes' failure. Sharma et al [13] proposed a clustering-based evolutionary method by using IWO (invasive weed optimization algorithm) based on fuzzy modeling for WSNs. It was able to select the most appropriate node as the CH for enhancing network lifetime and handling the challenge of power preservation in WSNs. Simulation results indicated significant reduction in the number of dead nodes in each execution round and power consumption reduction in sensors. The merit of this method is related to using IWO algorithm which has the capabilities of randomness and adjustability. Furthermore, thanks to using fuzzy inference model, it has high precision. High processing cost is regarded as the drawback of this method which is attributed to using fuzzy logic as well as the IWO algorithm. Qureshi et al [14] proposed an Energy Aware Routing (EAR) protocol to minimize energy consumption and select the next step by evaluating the quality of the sensor nodes link. This protocol has adopted residual energy and link quality as routing criteria for routing decisions. Through the weight function, the node selects the next distribution to route the data in WBAN. The proposed protocol evaluates the primary energy level, the quality of the connection, and the remaining energy level to balance the load, minimize energy consumption, and increase data transfer. Experimental results showed that the proposed protocol has a better mechanism for routing and a better solution to minimize the energy of the sensor nodes in WBANs. Amini et al [15] proposed an energy efficient routing algorithm with Sinks Mobile. In this study, author considered hexagons beehives feature where sensor nodes are distributed across a hexagon randomly. This hexagonal is divided into equal clusters based on the radius of hexagonal. Also, the need for cluster heads to be close to their center of clusters is solved by adding mobility to the sinks. The results of simulating this algorithm indicated that this method can increase in the average of residual energy between sensor nodes, reducing total energy consumption, increasing the lifetime of wireless sensor networks. Jyothi et al [16] proposed a novel clustering technique using multi-scale optimization in order to leverage the energy conservation among the sensor nodes for increased network operation in WSN. In this technique clustering technique is shown with an aid of single and multi-level clustering approximation method. The technique can solve the energy problems in data aggregation for large scale WSN. The result acquired from the study exhibits to better performance with respect to energy conservation. Moridi et al [17] proposed a fault tolerant clustering based multipath algorithm. In the proposed method, sensor nodes are clustered through HEED (hybrid energy efficient distributed clustering approach) algorithm and a main CH is selected for nodes. Then due to the importance of CH and increase of its fault tolerance, a backup node is selected for current CH. Backup CH monitors the performance of CH and stores a copy of its data. In collecting data phase, CH detects and isolates the majority of faulty nodes through hypothesis testing and majority voting to avoid propagating fault to higher levels. The results of simulation of this method reveal improving energy consumption, increasing correct data rate, and decreasing data loss rate.

Aziz et al [18] proposed a new approach based on a genetic algorithm and an agent cluster head to solve a WSN optimization problem. In the proposed method, the genetic algorithms have been successfully applied to many hard problems. In the proposed method used genetic algorithm to the problem of finding optimum number of CHs based on minimizing the communication consumption energy of sensor nodes to efficiently maximize the network lifetime and to improve the stability period. The proposed method also determine both the number and location of the cluster heads The results of simulation of this method reveal improving energy consumption than LEACH protocol. A genetic algorithm is a search technique used in computing to estimate approximate solutions for optimization and search problems. In the proposed algorithm, we used fuzzy logic based on the two criteria of battery level and distance to sink for determining the fitness of nodes. Fuzzy logic is applied to several fields like control theory or artificial intelligence. The use of Fuzzy Logic Controllers is considered for solving two problems to which a standard Genetic Algorithm could expose limited search speed and premature convergence. This due to the fact that 1) control parameters are not well chosen initially for a given task. 2) Parameters always being fixed even though the environment in which the GA operates could be variable and 3) problems resulting from the selection of several parameters like population size and in perceiving their influence [19]. Therefore in this paper we use fuzzy logic for determining the fitness of nodes.

3. THE PROPOSED METHOD

Social spider optimization algorithm is discussed here. Then, how to use social spider optimization algorithm for clustering sensor networks is described. Social spider is an example of social insects. It is a sort of spider that maintains complicated interactive behaviors. Although most spiders are regarded as individually behaving members and even aggressive insects in comparison to other members of their species, social spiders have demonstrated that they tend to live in groups and establish long-lasting groups which are referred to as colonies. In a social spider colony, each member, depending on its type, has various responsibilities such as hunting, mating, designing network and social interaction [20]. Network is a significant part of colony because it is not only a common environment for all the members but it is also a communication channel among them [21]. Thus, significant information (including trapping probability and mating probability) is transferred through network by small vibrations. Such information, which is known as local knowledge, is applied by each of the members for doing cooperative behavior under the simultaneous effect of social colonial regulations.

In this paper, an algorithm, namely *social spider optimization* (SSO), is proposed for clustering sensor networks. SSO algorithm is based on simulating the cooperative behavior of social spider. SSO is a population-based algorithm which was firstly proposed by Gauss in 2013. Social spider colony has two main components including social members and public network. Social members are divided into male and female groups. 70% of the total members are females and 30% of them are males. Female spider indicates appeal or distaste towards other spiders with regard to weight and distance from other members. Moreover, male spiders are divided into two groups, i.e. dominant male spiders and non-dominant male spiders. Dominant male spiders have better fitness than non-dominant male spiders. In the proposed algorithm, individuals imitate a group of spiders that interact with each other based on biological rules of colony. This algorithm includes two different (spider) search factors: male and female. Depending on the type, each individual takes tasks and responsibilities according to different evolutionary factors that imitate normal cooperative behaviors in the colony. Since each individual in the proposed method is modeled based on two types, this condition not only simulates a better and more realistic way of the colonial cooperation but also applies better computational mechanisms for preventing critical faults and drawbacks such as early convergence and false discovery. Spider, as a social insect, interacts and cooperates with other members of colony. The manner of this behavior depends of the type of spider. Female spiders that are keen to socialize with other spiders demonstrate attractiveness or incompatibility towards other spiders regardless of the type. Given a specific female spider, such attraction or incompatibility is usually expanded in relation to other spiders according to the vibrations they emit over the network which indicates that it is a strong member of the colony [22]. Since vibrations depend on weight and the distances of the members, stronger vibrations are generated by big spiders or the members of the neighbor. The larger the spider, the better it is to be considered as a member of the colony. The final decision regarding the admission or rejection of a specific member is based on the internal state which is affected by several factors such as reproduction, curiosity and other random phenomena. Unlike female spiders, the behaviors of a male spider are determined according to fertility. The male spider considers itself as a subgroup of men who dominate the colonial resources. Hence, male population is divided into two categories: dominant male spider and non-dominant male spider of the network. Unlike non-dominant spider, dominant male spider has better physical fitness (usually size). Regarding normal behavior, dominant men are attracted to the nearest female spider. In contrast, non-dominant male spiders focus on a strategy for exploiting the resources destroyed by dominant men [23]. Mating is a significant operation which not only guarantees

Spider 1	**40**	**35**	**10**	**16**	**20**

Figure 1 A sample solution in the proposed method.

$$for(i = 1; i < N_f + 1; i++)$$
$$for(i = 1; i < n + 1; i++)$$
$$f_{i,j}^{0} = p_j^{low} + rand(0,1).(p_j^{high} - p_j^{low})$$

End for

End for

$$for(k = 1; k < N_m + 1; k++)$$
$$for(j = 1; j < n + 1; j++)$$
$$m_{i,j}^{0} = p_j^{low} + rand.(p_j^{high} - p_j^{low})$$

End for

End for

Figure 2 The implemented pseudo-code of stage 2 in the proposed method.

the survival of the colony but also allows members to exchange information among each other. Mating in the colony of social spiders is carried out by dominant men and female members. Under such conditions, when a dominant male spider finds some female members within a specific range, it mates with all the female spiders for producing children [24].

3.1 Stage One: Cluster Production Phase

In the proposed method, clustering algorithm is executed within the sink in the centralized way for saving nodes' energy. Hence, before the execution of the clustering algorithm, each node encloses information such as its ID, neighbor's ID, power level of the battery and its distance from the sink within a packet and sends it towards the sink. After the sink receives all the packets from sensor nodes, it executes the clustering algorithm. After CHs are determined by SSO algorithm, all the network nodes are informed of the ID of the CHs. In the proposed method, it was assumed that sensor nodes are fixed; they were not regarded as mobile. Furthermore, simulation space was three-dimensional. Clustering in the proposed method is done based on two criteria: battery energy level and distance from the sink. Thus, a sensor with the shorter distance from the sink and the highest energy level is given the top priority. The procedure is as follows:

1. *Formation of initial population*: algorithm starts with the initial valuation of the S set out of N spider positions. Each spider position fi or mi is an n-dimensional vector which includes parameter values for optimization. Such values are restricted randomly and uniformly between the low initial parameter $\mathrm{Pj}^{\mathrm{low}}$ and the high elementary parameter $\mathrm{Pj}^{\mathrm{high}}$. In fact, each solution is considered to be a set of sensor nodes which are candidates for becoming CHs. Thus, 10 random solutions are produced. Since the number of clusters to be formed for 50 sensor nodes is 5, each solution is regarded as a 5-string array. The elements of the array are the same as the IDs of the candidate sensor nodes for becoming Ch. Figure 1 depicts a solution which has randomly selected sensor nodes with the IDs 40, 35, 10, 16 and 20. It should be noted that female spiders form 70% of the spider population and male spiders form 30% of the population.

   In this stage, by considering N as the total number of the n-dimensional colony members, N_m defines the number of male spiders and N_f defines the number of female spiders in the total population S.

$$N_f = \mathrm{floor}[(0.9 - rand * 0.25) * N] \tag{1}$$
$$N_m = N - N_f \tag{2}$$

   where rand denotes a random number within the range [0, 1]. Floor indicates a real number in relation to an integer number.

2. ($\mathrm{F} = \{\mathrm{f1}, \mathrm{f2}, \ldots, \mathrm{fn}f\}$) are female members and ($\mathrm{M} = \{\mathrm{m1}, \mathrm{m2}, \ldots, \mathrm{mN}m\}$) are male members in which $\mathrm{S} = \{\mathrm{s1} = \mathrm{f1}, \mathrm{s2} = \mathrm{f2}, \ldots, \mathrm{sN}f = \mathrm{fN}f, \mathrm{sN}f + 1 = \mathrm{m1}, \mathrm{sN}f + 2 = \mathrm{m2}, \ldots, \mathrm{sN}m = \mathrm{mN}m$ is randomly started and mating radius is computed according to equation 3.

$$r = \frac{\sum_{j=1}^{n}(p_j^{\mathrm{high}} - p_j^{\mathrm{low}})}{2 * n} \tag{3}$$

   The implemented pseudo-code is depicted in figure 2.

$$for(i = 1; i < N + 1; i++)$$
$$W_i = \frac{J(s_i) - Worst_s}{best_s - worst_s}$$
$$Where\ best_s = max_{k\varepsilon\{1,2,\ldots,N\}}\big(j(s_k)\big)\ and$$
$$Worst_s = min_{k\varepsilon\{1,2,\ldots,N\}}\ (j(s_k))$$
$$End\ for$$

Figure 3 The implemented pseudo-code of stage 3 in the proposed method.

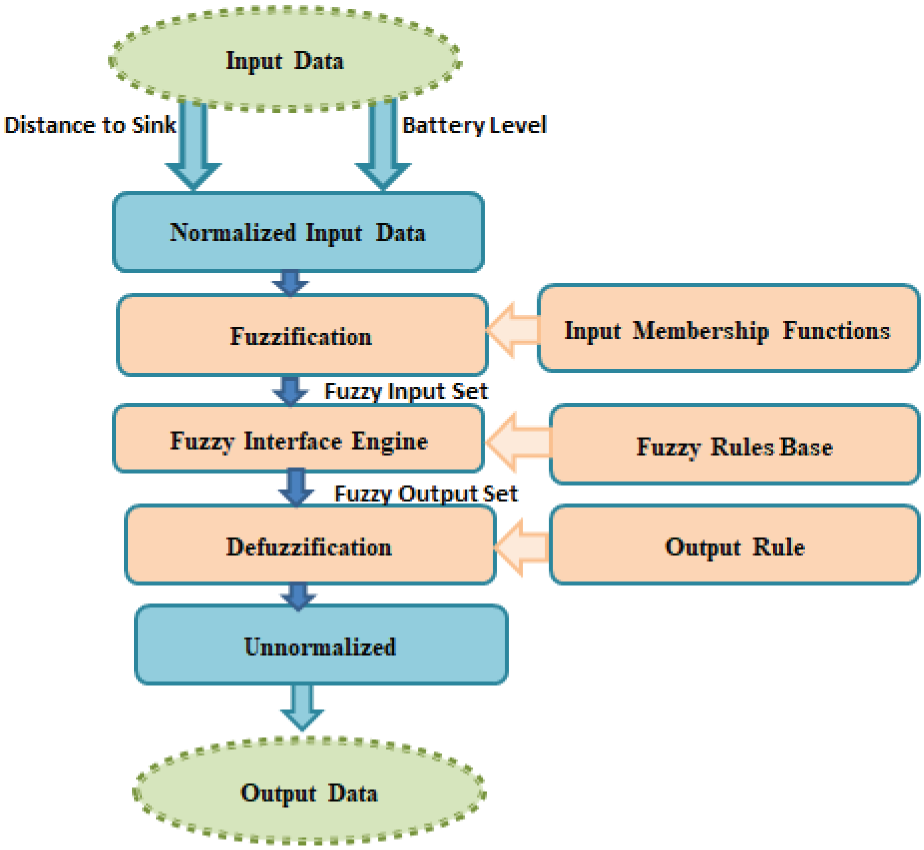


Figure 4 Block diagram of fuzzy logic system [25].

3. The weight of each spider S is computed according to equation 4.

$$W_i = \frac{J(s_i - \text{Worst}_s)}{\text{best}_s - \text{worst}_s} \tag{4}$$

Where $J(si)$ indicates the degree of position fitness of the obtained si spider. The best_s and the worst_s positions refer to maximum and minimum fitness in the population which are measured by fuzzy logic. The implemented pseudo-code is given in figure 3.

For determining the fitness value of nodes, we used fuzzy logic which is described below.

Fuzzy logic provides a meaningful and powerful representation for measurement of uncertainties. For example, there is uncertainty in expressions like "low" or "high," for battery level since these expressions are relative. Thus, the variables considered are termed "fuzzy" as opposed to "crisp."

The two criteria of battery level and the distance to sink were used for specifying clusterheads. These two criteria are fed into the fuzzy system as the fuzzy input. The fuzzy logic mechanism was used in this study for determining the degree of fitness of nodes so as to select clusterheads in the sensor network. This mechanism operates as an adaptive fuzzy controller based on fuzzy logic which is illustrated in Figure 4.

As illustrated in Figure 4, it can be observed that there are three main stages for applying fuzzy control to the above system. These three stages are discussed below.

- *Fuzzification stage*: in this stage, fuzzy sets are defined for the input and output variables. The conversion of real inputs into appropriate fuzzy sets for applying into the inference engine is referred to as fuzzification. In other words, fuzzification is an interface between real inputs and the inference engine [16].

  In the proposed method, two parameters are regarded as the fuzzy system input, i.e. the battery level and the distance to sink. For each of the input variables,

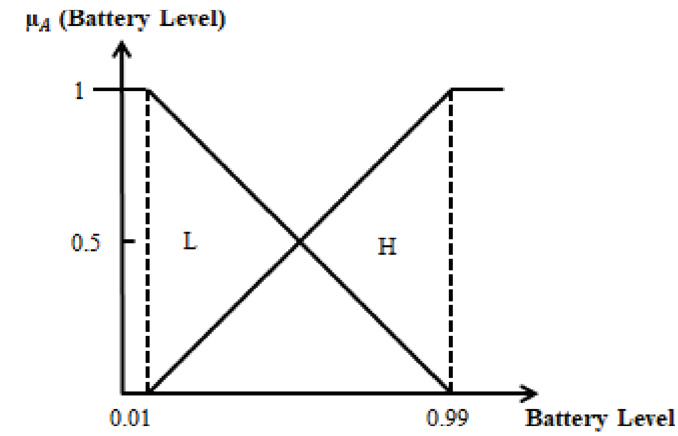


Figure 5 Membership functions for the input variable of battery level.

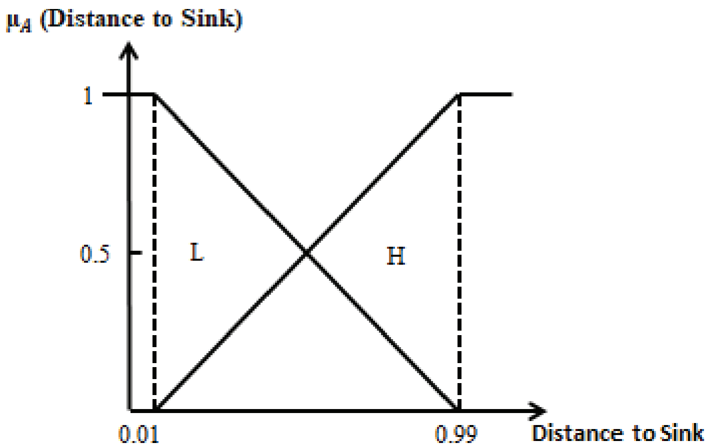


Figure 6 Membership functions for the input variable of the distance to sink.

three fuzzy sets are defined (H denotes the high limit and L indicates the low limit) which are depicted in Figure 5 and 6. The justification for using trapezodial membership functions is that they are precise and accurate. Regarding the output, namely the degree of the fitness of the node, three fuzzy sets with triangular membership functions were used (L denotes low limit, M denotes middle limit, and H refers to high limit).

- *Fuzzy inference engine*: in the inference stage, fuzzy rules are used for measuring the fitness value of node with respect to the considered parameters, i.e. battery level and the distance to sink. Each fuzzy rule has two parts: one introduction part, i.e "if distance to sink is low and the battery level is high" and one conclusion part, i.e. "then, the degree of fitness allocated to the node will be high". In the proposed method, the fuzzy inference engine was regarded as Mamdani minimum.

  For each of the two input parameters, three fuzzy sets are defined; as a result, 4 fuzzy rules are obtained. These fuzzy rules are given and defined in Table 1:

- *Defuzzification:* this stage is used for translating fuzzy output into a numerical value from defuzzificator of the mean of the centers. This is measured through equation 5.

$$\text{Fitness} = \frac{\sum_{l=1}^{m} y^{-1} \prod_{i=1}^{n} \mu A_t^l(X_i)}{\sum_{l=1}^{m} \prod_{i=1}^{n} \mu A_t^l(X_i)} \tag{5}$$

The parameters of equation 5 are the followings: indicates the index of route; m denotes the number of fuzzy rules (here, it is 4); n refers to the number of membership functions of the input variables (here, it is 2). $\mu A_i^l(X_i)$ indicates the fuzzy value of membership functions and y^{-1} refers to the output centers.

4. Female spider moves with respect to female cooperation factor according to equation 6.

   Social spiders interact and cooperate with other colony members. The type of behavior depends on the gender of the spider. Female spiders show attraction or incompatibility in relation to others regardless of their gender. For a specific female spider, the attraction or incompatibility towards other spiders is expanded according to vibrations distributed in the public network. Inasmuch as vibrations depend on the weight and distance of the members which generate them, strong vibrations are produced by large spiders or other neighbor members who perceive it. The final decision regarding attraction or incompatibility towards a specified member depends on the internal state which is affected by numerous factors such as reproduction, curiosity or other random phenomena. A new factor was defined for imitating the cooperative behavior of the female

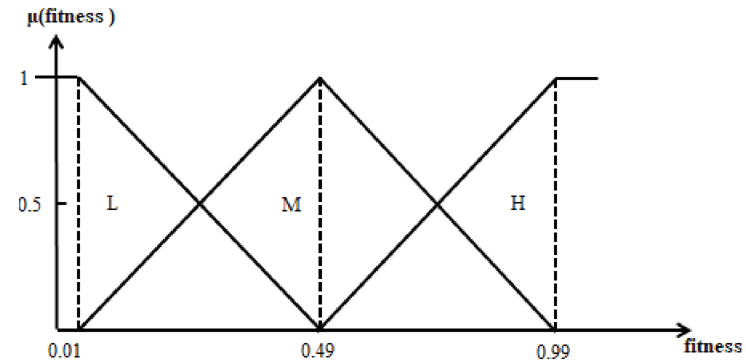


Figure 7 Membership functions for the output variable of fitness.

Table 1 Database of fuzzy rules.

Number	Inputs		Outputs
	Distance to Sink	Battery Level	Fitness
1	Low	Low	Medium
2	Low	Medium	Low
3	Low	High	Very high
4	Medium	Low	Low

spider. This factor considers the changing position of the female spider i in each iteration. Such a position change which may be attraction or stimulation is computed as a combination of three different elements. The first case includes the change in relation to the nearest member to i which has higher weight; it produces Vibci vibration. The second case is related to the change of the best individual of the total population S which produces Vibbi vibration. Finally, the third case includes random movement. Since the final movement of attraction or incompatibility depends on some random phenomena, the selection is modeled as a random decision. For this operation, a uniform random number is produced within the range [0, 1]. If r_m is smaller than the threshold PF, the attraction movement is generated. Otherwise, an invasive movement is produced. Thus, such factor can be defined according to equation 6.

$$f_i^{k+1} = \begin{cases} f_i^k + \alpha Vibc_i.(s_c - f_i^k) + \beta.Vibb_i(s_b - f_i^k) \\ \quad + \delta \left(rand - \frac{1}{2}\right) \\ f_i^k - \alpha.Vibc_i(s_c - f_i^k) - \beta.Vibb_i(s_b - f_i^k) \\ \quad + \delta.\left(rand - \frac{1}{2}\right) with\, probabilitu1 = PF \end{cases} \tag{6}$$

Where α, β, δ and rand are random numbers within [0, 1]. K refers to the number of iteration. S_c and s_b indicate the closest member to i which has higher weight; it is the best member of the population S. Under these operations, each particle indicates a motion which combines a past position including attraction or incompatibility vector in relation to the best element s_c and the best member s_b of the world which has been ever seen. This specific type of interaction prevents rapid condensation of particles in a point. It supports each particle for search around the selected local area within the range (s_c) instead of interacting with the particle (s_b) in a remote area of the range. It should be noted that, in equation 6, Vibbi and Vibci denote the spider's vibrations. Vibrations depend on weight and distance of the spider which produces them. Distance depends on the individual which leads to the stimulation of the vibrations and the member which determines it. Hence, the members closer to the individual which cause the stimulation of the vibrations perceive stronger vibrations in comparison with the members located in remote positions. For reproducing this process, the vibrations perceived by the individual i are modeled as a result of the information transmitted by member j according to equation 7.

$$Vib_{ij} = W_j * e^{-d_{ij}^2} \tag{7}$$

Where d_{ij} refers to the Euclidean distance between spider i and j. Although the perceived vibrations can be approximately computed by considering each pair of the individuals, three specific equations have been considered in SSO algorithm:

- Vibci vibrations by person i (si) as a result of information transmitted by member c (s_c) that is a person who has two important characteristics: it is the nearest member to i and has higher weight in comparison to i $(wc \geq wi)$.
- Vibbi vibrations by person i as a result of information transmitted by member b (sb) in which b has the best weight (best fit value) out of the entire population S in such a way that $wb = \max k2\{1, 2, \ldots, N\}(wk)$ is true.
- Vibfi vibrations by person $i(si)$ are considered as a result of the information transmitted by member $f(sf)$ in which f is the closest female to person $i(si)$.

Figure 8 shows the implemented pseudo-code for this stage.

$$for\left(i=1;i<N_f+1;i++\right)$$
$$(equation6)CalculateVibc_i andVibb_i$$
$$f_i^{k+1}=f_i^k-\propto.Vibc_i.\left(s_c-f_i^k\right)-\beta.Vibb_i\left(s_b-f_i^k\right)+\delta.\left(rand-\frac{1}{2}\right)$$
$$else\ if$$
$$f_i^{k+1}=f_i^k-\propto.Vibc_i.\left(s_c-f_i^k\right)-\beta.Vibb_i\left(s_b-f_i^k\right)+\delta.\left(rand-\frac{1}{2}\right)$$
$$End\ if$$
$$End\ if$$

Figure 8 The implemented pseudo-code in the proposed method.

$$for(i=1;i<N_m+1;i++)$$
$$Calculate\ Vibf_i(equation\ 6)$$
$$if(W_{N_f+1}>W_{N_f+m})$$
$$m_i^{k=1}=m_i^k+\propto.vibf_i.(s_f-m_i^k)+\delta.\left(rand-\frac{1}{2}\right)$$
$$Else\ if$$
$$m_i^{k+1}=m_i^k+\propto.\left(\frac{\sum_{h=1}^{N_m}m_h^k\cdot W_{N_f+h}}{\sum_{h-1}^{N_m}W_{N_f+h}}\right)-m_i^k$$
$$End\ if$$
$$End\ for$$

Figure 9 The implemented pseudo-code of stage 5 in the proposed method.

5. Male spider moves with respect to male cooperation factor according to equation 7. Given the biological behavior of the social spider, male population is divided into two elements: dominant and non-dominant elements. When compared with non-dominant spider, the dominant spider has better physical fitness (usually with regard to the size). Dominant males are attracted to the nearest female spider in the social network. In contrast, the non-dominant male spider, in the center of male population, focuses on exploiting the resources which have been wasted by the dominant male spiders.

   For imitating cooperative behavior, male members are split into two different categories, namely dominant members (DM) and non-dominant members (ND) with regard to position in relation to average members. Thanks to their higher weight value in comparison to the average value among the male population, male members are regarded as the dominant individuals. On the other hand, members with lower than the average values are called non-dominant males. For executing such computations, male population, M ($M=\{m1,m2,\ldots,mN_n\}$), is sorted in order of weight reduction. Hence, the individual with the weight wN_f+m is placed at the center as the male member. Since male population indexes increase in relation to the total population S by the number of female members NF, the average weight is denoted by $Nf+m$. As a result, the position change for the male spider can be modeled according to equation 8.

$$m_i^{k+1}=\begin{cases}m_i^k+\propto.Vibf_i.(s_f-m_i^k)+\delta\left(rand-\frac{1}{2}\right)\\ \quad if\ W_{N_f+i}>W_{N_f+m}\\ m_i^k+\propto.\left(\frac{\sum_{h=1}^{N_m}m_h^k\cdot W_{N_f+h}}{\sum_{h=1}^{N_m}W_{N_f+h}}-m_i^k\right)\\ \quad if\ W_{N_f+i}\leq W_{N_f+m}\end{cases}\tag{8}$$

   where S_f individual indicates the nearest female to male member. By using this factor, two different behaviors are created. Firstly, D set of particles is attracted to others for stimulating mating. Such behavior leads to variety in the population. Secondly, ND out of the particle set is attracted to the average weight population of males. This condition partially controls the search process with respect to the average performance subgroup. Such mechanism operates as a filter which prevents the impact of extremely good or extremely bad individuals on the search process. The pseudo-code of the this stage is shown in figure 9.

6. Mating operation is executed according to equation 9. Mating operation in the social spider colony is done by dominant males and female members. Under these circumstances, when the dominant male spider mg ($g\in D$) is placed in the E^g set of the female members within a

$$for\,(i = 1; i < N_m + 1; i++)$$
$$If\,(m_i \varepsilon D)$$
$$Find\ E^i$$
$$If\,(E^i) is\ not\ empty$$
$$From\ S_{new}\ using\ the\ rouletted\ method$$
$$If\,(W_{new > W_{wo}})$$
$$S_{wo} = S_{new}$$
$$End\ if$$
$$End\ if$$
$$End\ if$$
$$End\,for$$

Figure 10 Pseudo-code implemented in stage 6 of the proposed method.

specific range r (mating range), it mates with the females and new children (snew) are generated by considering all the elements in Tg set which was produced by $Eg \cup mg$. it should be highlighted that in case the set of numbers E^g is empty, mating operatin will be cancelled. The range r is defined as a radius which depends on the search space. r radius is computed according to equation 3.

In the mating process, the weight of each involved spider (Tg elements) determines impact probability for each individual on the new children. Spiders with more weight are more probable to impact on the new product and elements with less weight are less probable to impact on the new product. The penetration probability Psi of each element is determined by Roulette wheel which is defined as equation 9.

$$P_{si} = \frac{w_i}{\sum_{j \epsilon T}^{K} W_j} \tag{9}$$

Where $i \in Tg$. When the new spider is formed, it is compared with the new candidate spider snew which includes the worst spider s_{wo} from the colony with regard to the values of its weight (in which wwo = minl2{1, 2, ..., N} (wl)). If the new spider is better than the worst spider, the new worst spider will be replaced. Otherwise, the new spider will be destroyed and the population does not suffer from the changes. In case the replacement occurs, the new spider will assume the gender and index of the replaced spider. Pseudo-code of this stage is given in figure 10.

7. If stop criterion, which is reaching the hundredth round, is executed, the process is terminated and appropriate nodes (10% of network nodes) with the highest energy level and the shortest distance with high fitness is selected as CH. Hence, the sink sends the message of becoming CH to CH nodes. Then, other nodes which are not CHs send the connection message to the nearest CH based on distance. In this way, clusters are formed. Otherwise, t goes back to stage 3.

8. The clusterheads collects data form clustermember when data collection task by the clusterheads is finished, clusterheads send a message to the sink and inform it about their remaining energy after they have exchanged a message. They announce that they have data to be transmitted. Now, it is the sink's turn to begin to receive data. One of the proposed solutions is to use a mobile sink and make decisions about selecting the replacemnet location. the sink will make decisions according to the clusterheads' remaining energy which is included in the table. If the remaining energy of the clusterheads is more than 50% of their total initial energy, the sink will move to the location which was randomly embedded for it. However, in case the remaining energy of the clusterheads is less than 50% of their total initial energy, the sink will move towards a dense area. It should be noted that the sink will place a node as its representative in the embedded location which is responsible for collecting data from clusterhead. Now, the clusterheads will be informed of the two coordinates which were specified for receiving data. Hence, they will send data to the closest coordinate through a single-hop or multi-hops. At the end, the sink returns to its main position and receives data via the representative node. After that, clusters' activities start again. The next round will be carried out in the same way.

3.2 Stage Two: Establishing Reliability

Since failure can result in the degradation of the overall performance of the network, a clusterhead's failure can be regarded as a limitation for those sensor nodes' which are observed by that clusterhead. Indeed, it prevents data collection and data dissemination. Hence, routing algorithms in clustering should be tolerant of errors, especially with respect to errors occuring in clusterheads. Consequently, the objective of this stage is to select the best alternative clusterhead when the previous clusterhead fails. In this way, reliability is enhanced. According to the previous stage, in establishing DVB, each

Table 2 Simulation parameters.

Parameter	Value
Nodes' distribution in the area	Random
Size of simulation environment	1000m*1000m*1000m
Transmission type	CBR
Packet size	1024 byte
Battery model	Constant
Simulation time	200 s
Initial energy level	200 to 400 joules
Number of sinks	1
Number of nodes	50
Radio transmission range	100 m
Packet inter-arrival time	Constant
Dimensions of simulation environment	3-D

n-1-level clusterhead has several parents and the clusterhead itself might operate as a parent for the n-level clusterheads. On the other hand, the clusterhead of a cluster might have k sensor nodes.

When a clusterhead is in error due to battery depletion or another hardware issue, its communication with other cluster members is disconnected. Also, it cannot operate as the father for the nodes of the next level. Moreover, its communication with its parents is also disconnected. In the previous stage, while establishing routing tree, each node which is selected as the clusterhead transmits a list, i.e. list of parents, to the cluster member nodes while transmitting TDMA pack. This list indicates father clusterheads. In this way, nodes become aware of the information of their clusterhead's parent node so that they can quickly restore the tree when a problem occurs for the current clusterhead. As a result, nodes can keep doing their activities. In case a clusterhead has a problem within the cluster, member nodes of that cluster can easily notice the clusterhead error because they do not receive any ACKs for the data packets they have transmitted. At this time, cluster member nodes whose clusterhead is in error broadcast a HELP message within their radio range. This message includes information about nodes' energy level, their IDs, previous clusterhead's ID and their distances from BS. If a node is the member of another clusterhead, when it receives the HELP message, it will destroy it. Otherwise, it competes for being selected as the clusterhead. After each sensor node receives HELP message, it sets its timer according to (2). It carries out the stages of clustering phase so that one of the cluster members whose clusterhead is in error is selected as the clusterhead. Until now, cluster and cluster members' communication was maintained by selecting a new clusterhead from the parent nodes of the previous clusterhead. That is, the communication of the cluster and new clusterhead with the sink or BS is maintained via parent nodes. As mentioned above, while n-1 level clusterhead operates as the parent of n-level clusterhead, in case it commits an error, n-level clusterhead will easily detect it. That is to say, when it sends each data packet, it does not receive any ACKs from it. Hence, for identifying new n-1 level clusterhead as its parent, the new n-1 level clusterhead broadcasts a message within its 2R range while it transmits the declaration message (advertisement) about becoming the clusterhead. With respect to the ID of the available previous clusterhead in this message, the clusterheads can compare the ID with the IDs that they have in their parent list. If the ID is available in the list of the existing parent nodes, they remove the characteristics of the previous clusterhead from the parent list and replace it with the new clusterhead. Next, they measure the average remaining energy of the available clusterheads in the list and establish the new parent list; this list includes clusterheads with higher average remaining energy or equal average remaining energy. The members of this set operate as the parent nodes of the clusterheads. The new clusterhead may or may not a member of the list of new parents. Thus, using the method proposed in this paper, in case a problem occurs for the clusterhead, we were able to restore the availabe routing tree and prevented the creation of a new routing tree [12].

4. SIMULATION OF THE PROPOSED METHOD

4.1 Simulation Setting

In this paper, we used OPNET 11.5 for simulating the proposed method and comparing it with the DCRRP and NODIC. This simulator is a 3-layer hierarchical model including network, node and process. It can be used for graphically modeling WSN topology; various network parameters can be modified in the simulation and the results obtained from simulation may be used for comparison. Simulation parameters are given in table 2. As shown in figure 11, network topology consisted of 50 nodes in the proposed method in which three scenarios were taken into consideration. In the first scenario, sensor nodes are randomly distributed in the area based on DCRRP protocol. In the second scenario, nodes are randomly distributed in the area where SSO algorithm and fuzzy logic carry out the clustering operation. The proposed protocol was referred to as SSFBCA (Social Spider Fuzzy Based Clustering Algorithm). In the third scenario, sensor nodes were clustered by NODIC protocol where information is transmitted to the target by means of CH to the sink node. Identical topology was considered for all the three scenarios. Figure 12 illustrates network topology where a number of nodes are in error.

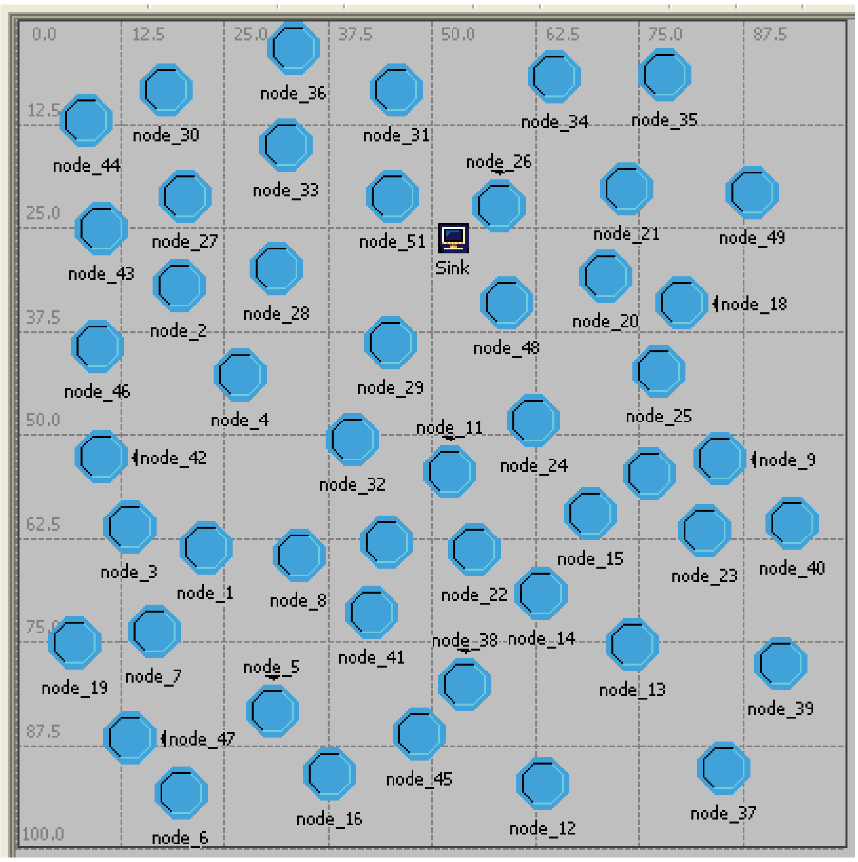


Figure 11 Network topology with 50 sensor nodes.

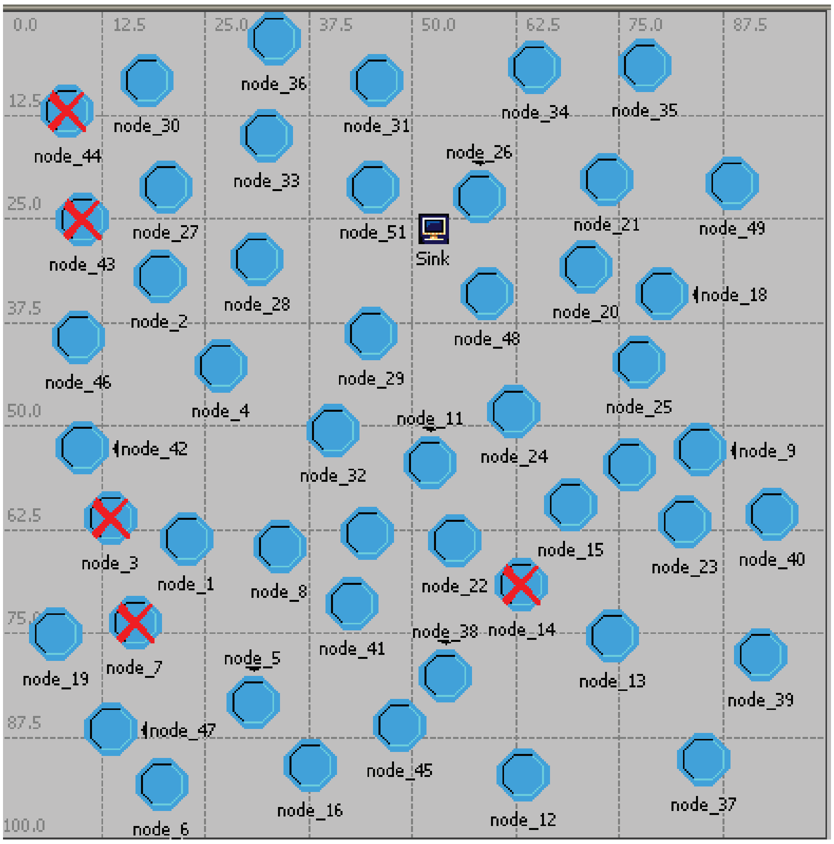
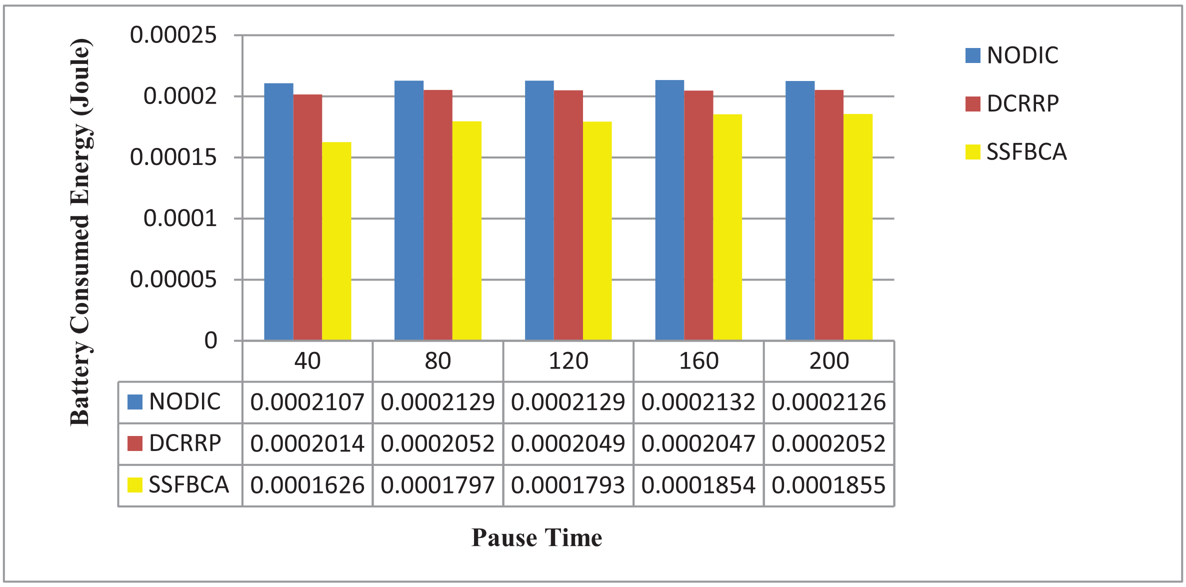
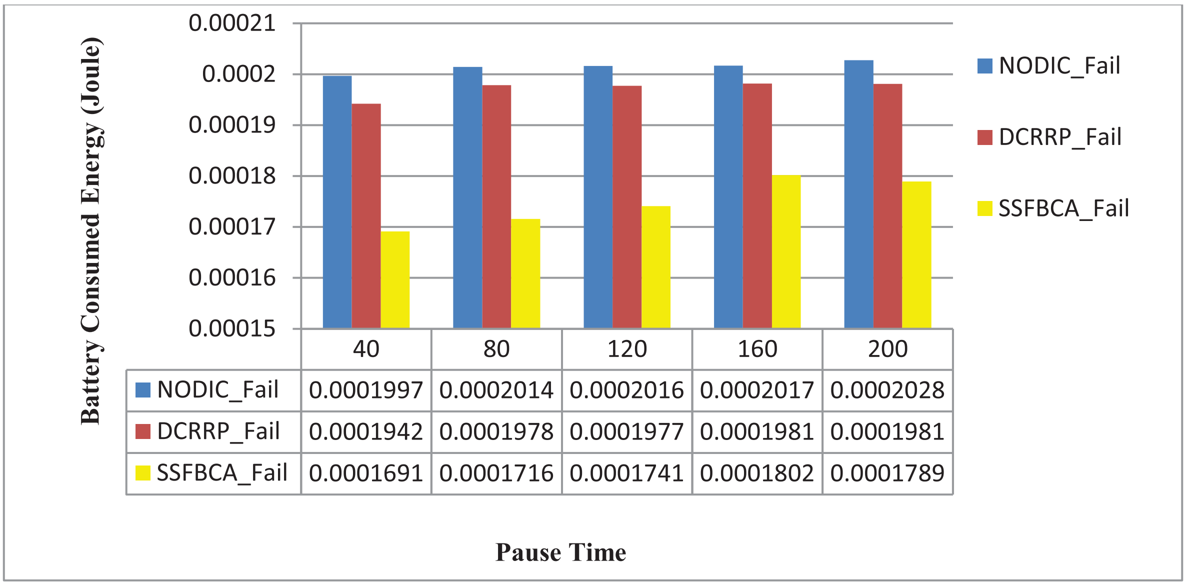


Figure 12 Network topology with 50 sensor nodes for the mode with errors.



	40	80	120	160	200
NODIC	0.0002107	0.0002129	0.0002129	0.0002132	0.0002126
DCRRP	0.0002014	0.0002052	0.0002049	0.0002047	0.0002052
SSFBCA	0.0001626	0.0001797	0.0001793	0.0001854	0.0001855

Figure 13 Average power consumption of the network without errors.



	40	80	120	160	200
NODIC_Fail	0.0001997	0.0002014	0.0002016	0.0002017	0.0002028
DCRRP_Fail	0.0001942	0.0001978	0.0001977	0.0001981	0.0001981
SSFBCA_Fail	0.0001691	0.0001716	0.0001741	0.0001802	0.0001789

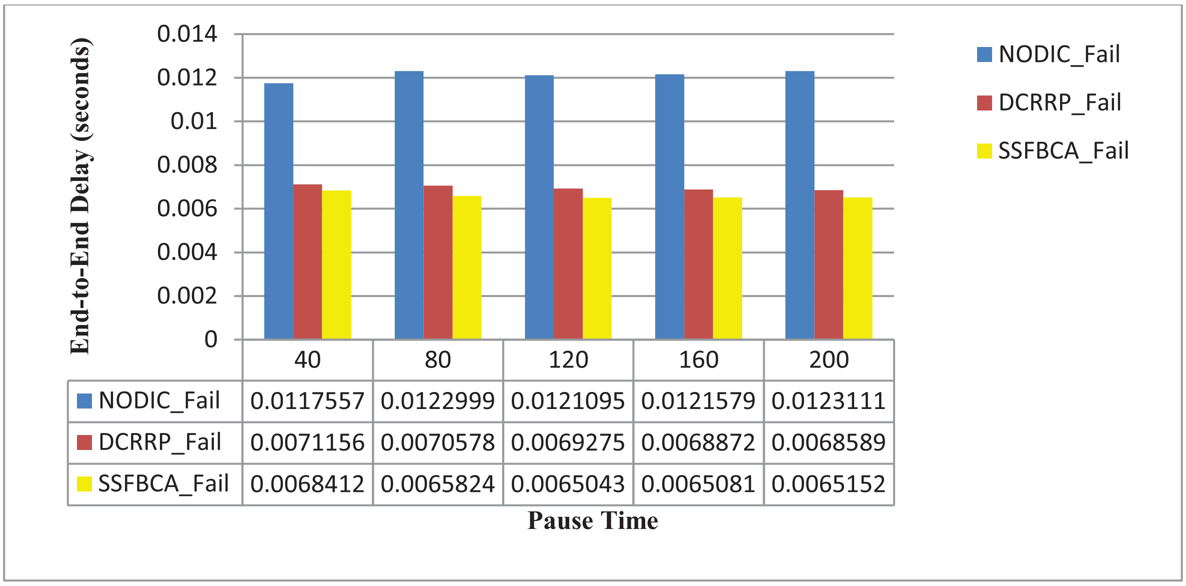
Figure 14 Average power consumption of network in the scenarios with errors.

4.2 Simulation Results

As depicted in figure 13, average power consumption of network was investigated for SSFBCA scenario, DCRRP scenario and NODIC scenario. The vertical axis denotes power consumption and the horizontal axis indicates simulation time. Power consumption is equal to the total energy used by the nodes within the network for communicating including data transmission, data reception and the expected power consumption. It was observed that NODIC protocol had the highest power consumption. Network subgroups did not operate consciously. That is, they directly send the gathered data to the sink regardless of the node' degree of power consumption. Also, in DCRRP protocol, given the fact that the network has focused on selecting CH based on node's location, the node with more neighbors and power level more than the threshold is selected as the CH. Otherwise, if a node with these characteristics is not available, the algorithm will not perform clustering again. The selected CHs in the next rounds may have less energy and fewer neighbors. In case large amounts of power are consumed in CHs, they will quickly lose their energy; as a result, network topology collapses.

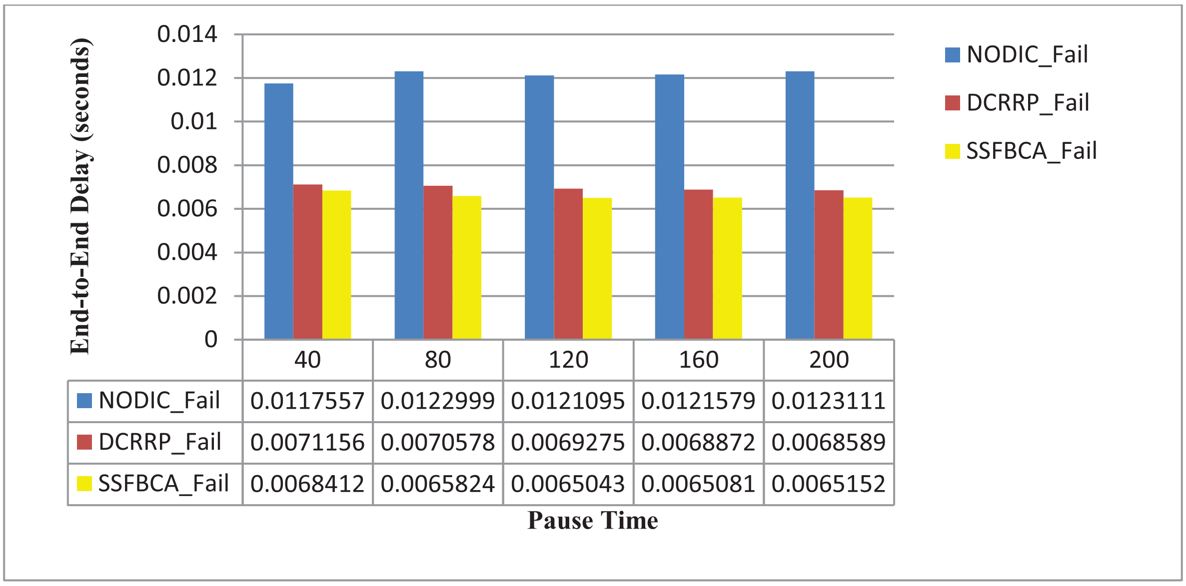
In case clustering is done in SSFBCA by SSO algorithm and fuzzy logic, a node will be used as CH for data transmission which has more power and shorter distance from the sink. On the other hand, since member nodes join CH based on their distance from it, not much energy is consumed for transmitting data from member node to CH. On the other hand, inasmuch as the proposed algorithm is based on local and global search, it usually finds acceptable responses for becoming CH due to its focus on local search. Suitable nodes with high energy and shorter distance from the sink become CHs. Hence, less energy is required for communicating with the sink.

Figure 14 shows the comparison of the proposed algorithm with NODIC protocol and DCRRP in terms of average energy



	40	80	120	160	200
NODIC_Fail	0.0117557	0.0122999	0.0121095	0.0121579	0.0123111
DCRRP_Fail	0.0071156	0.0070578	0.0069275	0.0068872	0.0068589
SSFBCA_Fail	0.0068412	0.0065824	0.0065043	0.0065081	0.0065152

Figure 15 End-to-End delay for the scenarios without errors.



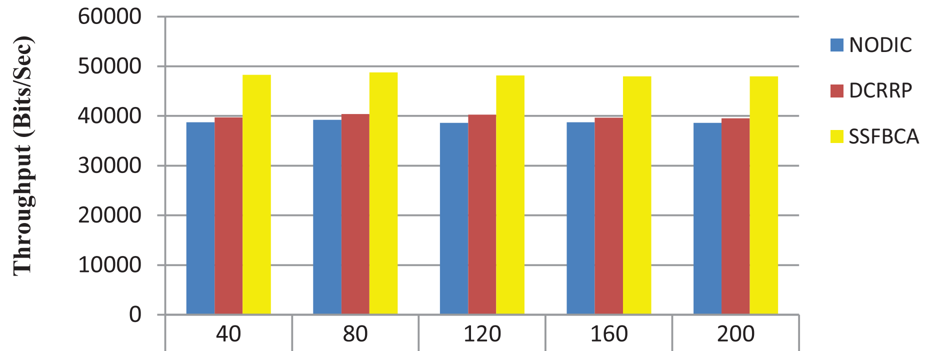
	40	80	120	160	200
NODIC_Fail	0.0117557	0.0122999	0.0121095	0.0121579	0.0123111
DCRRP_Fail	0.0071156	0.0070578	0.0069275	0.0068872	0.0068589
SSFBCA_Fail	0.0068412	0.0065824	0.0065043	0.0065081	0.0065152

Figure 16 End-to-End delay for the scenarios with errors.

consumption. The vertical axis denotes power consumption and the horizontal axis indicates simulation time. As it is expected, with regard to the scenarios with errors, NODIC and DCRRP protocol had higher power consumption than the proposed protocol. In the proposed method, when some of the clusterheads have errors, thanks to local selection, the best clusterheads from the cluster members replace the erroneous clusterheads which enhances network reliability. Accordingly, data is transmitted through the alternative clusterhead.

Figure 15 depicts the comparison of SSFBCA, DCRRP and NODIC protocols with regard to end-to-end delay. The vertical axis denotes end-to-end delay and the horizontal axis refers to simulation time. End-to-end delay indicates the time length during which a data packet is transmitted from sender to the receiver. For computing mean end-to-end delay, end-to-end delays of all the packets received by the receivers are measured and its mean value is calculated. It was observed that, in DCRRP protocol, CHs' power level decreases from the very initial rounds. Hence, it may not be able to transmit the sensed data. Hence, delay increases. In a similar vein, delay increases in NODIC protocol because some network nodes might send a part of the data but fail to complete the data transmission due to power shortage. However, in SSFBCA, since nodes with more power level are selected as CHs in the clustering process and cluster members joint the CH based on their distances from the CH, end-to-end delay is reduced.

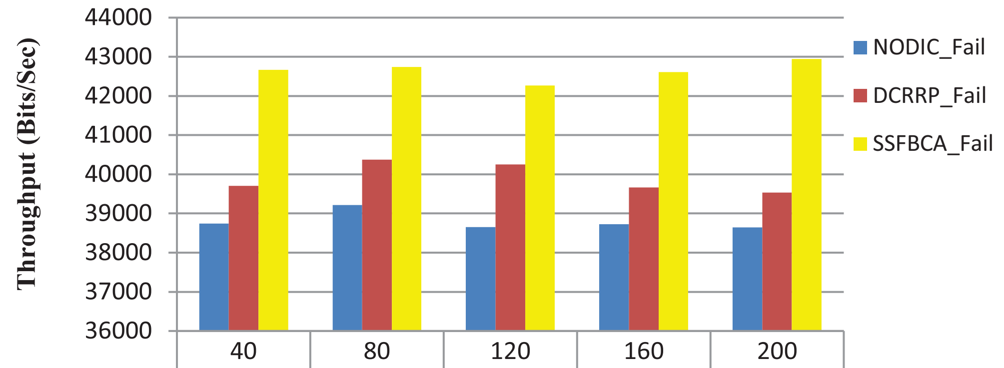
Also, the following figure illustrates the comparison of the two algorithms with repect to end-to-end delay in the scenarios with errors. The vertical axid denotes end-to-end delay and the horizontal axis refers to simulation time. In a similar vein, it was found that, in the scenarios with errors, NODIC and DCRRP protocol increased end-to-end delay. That is, in case an error occurs, the clusterheads in NODIC and DCRRP have no pre-planned solutions. Thus, nodes might use loger routes



	40	80	120	160	200
NODIC	38741.429	39212.683	38650.361	38724.469	38643.92
DCRRP	39708.286	40377.659	40253.607	39664.765	39530.72
SSFBCA	48308.571	48777.756	48183.803	47997.704	47953.96

Pause Time

Figure 17 Throughput rate for the scenarios without errors.



	40	80	120	160	200
NODIC_Fail	38741.429	39212.683	38650.361	38724.469	38643.92
DCRRP_Fail	39708.286	40377.659	40253.607	39664.765	39530.72
SSFBCA_Fail	42667.048	42741.512	42264.164	42612.049	42944

Pause Time

Figure 18 Throughput in the proposed, DCRRP and NODIC protocols in the scenarios with errors.

for transmitting data which leads to increased end-to-end delay. In contrast, in the proposed protocol, in the case of an error occurrence, by selecting the best alternative node from the cluster member nodes, direct virtual backbone (DVB) to the sink node is quickly created. As a result, end-to-end delay is reduced.

Also, throughput rates for the three scenarios ae shown in figure 17. The horizontal axis denotes simultion time and the vertical axis indicates the numbe of delivered data bits at a time which is referred to as throughput rate. Throughput is equal to the total of packets received by the receviers divided by the time between the reception of the first packet and the last packet. In fact, it is tantamount to the division of file size at that time in units of megabits per second. As shown in figure 17, whne compared with DCRRP and SSFBCA protocols, NODIC protocol has delivered fewer packets to the sink in relation to the total transmitted packets by the sensor nodes which is attributed to nodes' possible shutdown due to battery depletion. However, in SSFBCA protocl, after clustering is done, nodes with highest route power are selected. After a route is discovered, due to discovering stable routes, we are sure that data transmission is maintained at leat until the end of phase. Hence, nodes' energy is not depleted early at the selected route. Stable routes do not change until the end of data transmission phase. Consequently, the number of delivered packets to the sink node will be more in the SSFBCA.

Figure 18 shows the comparison of the proposed algorithm with NODIC protocol and DCRRP protocol in terms of throughput. The horizontal axis denotes simulation time and the vertical axis refers to the number of delivered packets at the time, i.e. throughput. It was found that, in NODIC protocol in the scenarios with errors, throughput is poor which is attributed to the probable shutdown of the clusterheads due to error or the depletion of the energy of the batteries. However, in the proposed protocol, inasmuch as the sink moves towards the data transmission requesting node and it is placed in the vicinity of

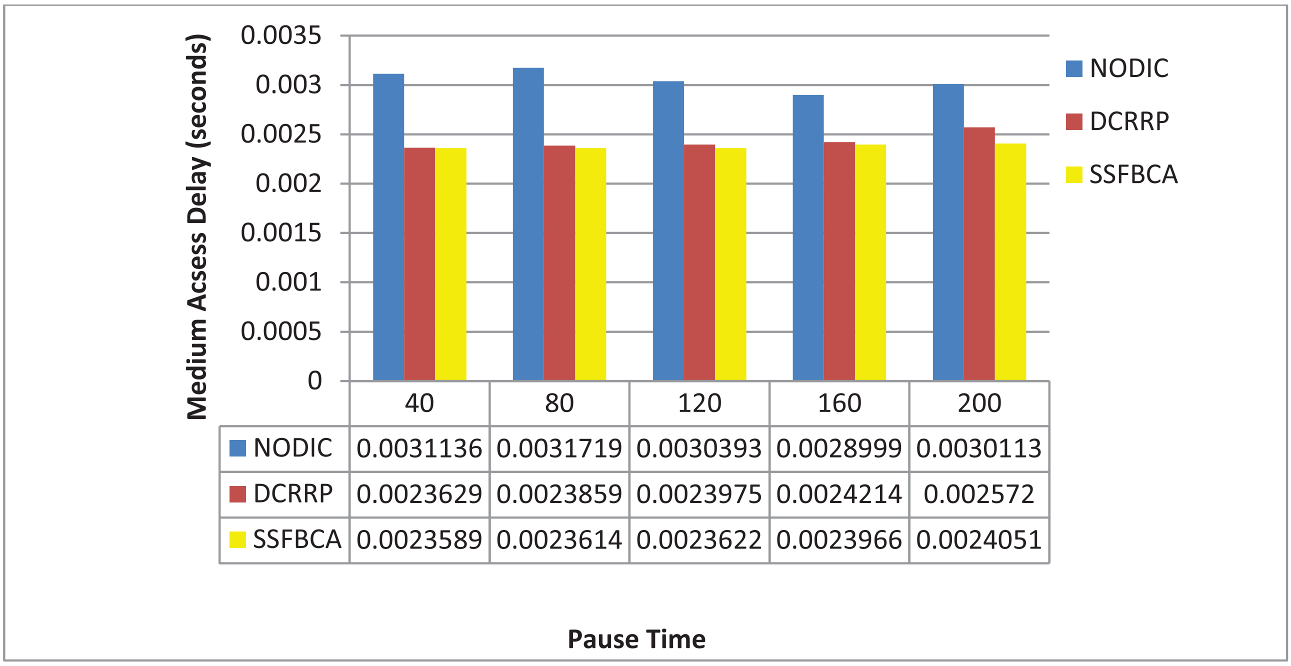


Figure 19 Multimedia access delay in the scenarios without errors.

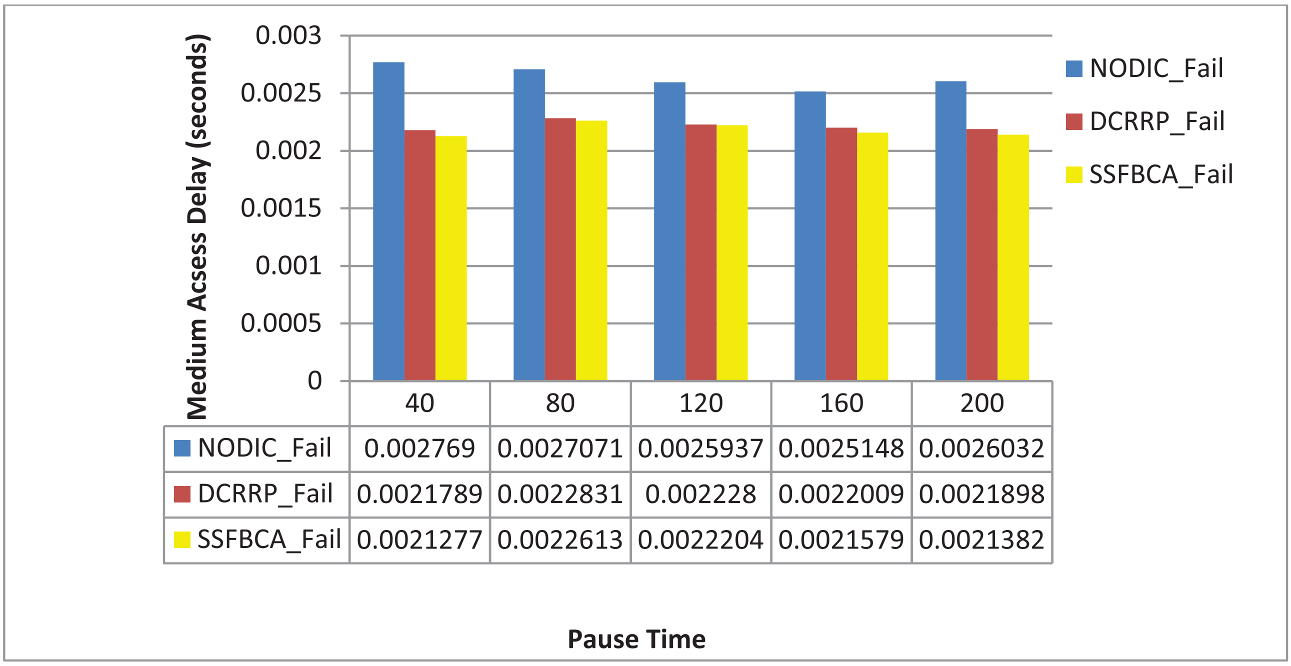


Figure 20 Multimedia access delay in the mode with errors.

the clusterhead, the number of successfully delivered packets to the sink node is high.

Moreover, as depicted in the following figure, the proposed, DCRRP and NODIC protocols were compared in terms of multimedia access delay. The vertical axis denotes multimedia access delay and the horizontal axis refers to simulation time. Multimedia access delay refers to the time period between data packet reception by MAC layer and the time it is completely placed on the wireless media. The justification for investigating this parameter is that many multimedia applications are limited in terms of delay. Hence, after the specific set time, the respcetive application may not have any uses. It was found that the delay of multimedia files increased in the NODIC and DCRRP protocols. It is attributed to the fact that, due to very high data production rate in transmitting video and also, due to the explosive feature, congestion occurrence increases. However, in the proposed protocol, thanks to the movement of the sink and fast data transmission to the sink, the delay of multimedia files is reduced.

Finally, the following figure, the three protocols were compared with one another in terms of multimedia access delay in the scenarios with errors. The vertical axis denotes multimedia access delay and the horizontal axis refers to simulation time. It was observed that, in NODIC and DCRRP protocols, in the mode with errors, the delay of multimedia files increased. Since much energy is required for direct data transmission to the sink at high distances, sensor nodes have to transmit data to the sink node via multi-hops. Hence, due to the heavy display of packets in the sensor nodes which are at the single hop neighborhood of the sink, much energy is depleted and critical points are created. Hence, delay increases accordingly.

5. CONCLUSION

In this paper, a new algorithm, namely SSFBCA, was proposed. It applies clustering by SSO and fuzzy logic algorithm and mobile sink for maximizing energy efifciency. The fuzzy logic is simply one means of describing uncertainty. Also other algorithm such as the genetic algorithm operates imperfectly in local search. Thus we use the Fuzzy logic for fitness value. This method specifies a number of nodes as CHs which results in the formation of appropriate clusters in the network. Within clusters, nodes adopt a single-hop routing for communicating with CH. In this way, in receiving data packets from all the cluster members, they transmit gathered data to the sink node via pre-computed route. Regarding inter-cluster communication, the neighboring node with the maximum remaing energy is selected. SSFBCA prevents data transmission to the sink through long routes. As a result, network power consumption is minimized. SSFBCA, NODIC and DCRRP protocls were simulated in OPNET. The obtained results indicated that SSFBCA performs better with respect to network features such as power onsumption minimization and delay reduction. SSFBCA algorithm is based on spiders' movement towards the best global position which generates an algorithm with less sensitivity and prevents early convergence. Moreover, it encourages spiders to completely discover and identify their suuroundings before converging towards the best global position. Hence, this features provides the global search capability for the algorthm and enhances the exceptional behavior of the proposed approach. In contrast with the other evolutionary algorithms, each response in the SSO algorithm is modeled based on the gender. This condition makes it possible for computational mechanisms to prevent critical faults scuh as early convergence and exploratory balance/false exploitation. Form the optimization perspective, using social spider's behavior, as a metaphor, introduces a pomising concpet to evolutionary algorithms.

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