

Hybrid swarm intelligence-based clustering algorithm for energy management in wireless sensor networks

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Abstract

Swarm intelligence-based algorithms are soft computing techniques, which have already been applied to solve a broad range of optimization problems. Generally, clustering is the most common technique, which, balances the energy consumption among all sensor nodes and minimizes traffic and overhead during data transmission phases of Wireless Sensor Networks. The performance scope of the existing clustering protocols is fixed and hence, cannot adapt to all possible areas of applications. In this paper, a multi-objective swarm intelligence algorithm – which is based on Shuffled Frog-leaping and Firefly Algorithms (SFFA) – is presented as a clustering-based protocol for WSNs. The multi-objective fitness function of SFFA considers different criteria such as cluster heads' distances from the sink, residual energy of nodes, inter- and intra-cluster distances and finally overlap and load of clusters to select the most proper cluster heads at each round. The parameters of SFFA in clustering phase can be adapted and tuned to achieve the best performance based on the network requirements. The simulation outcomes demonstrated an average lifetime improvement of up to 49.1%, 38.3%, 7.1%, and 11.3% compared to LEACH, ERA, SIF, and FSFLA in different network scenarios, respectively.

Keywords: Wireless Sensor Networks, clustering, swarm intelligence-based algorithms, firefly algorithm, shuffled frog-leaping algorithm.

1- Introduction

Owing to the rapid advancement of micro electro-mechanical systems (MEMS) as well as wireless communication technologies, Wireless Sensor Networks (WSN) have already received a lot of attention by different scholars. WSN is considered a key technology with paramount importance in the recent century. WSNs consist of several low-cost, low-power tiny sensing nodes randomly dispersed, in a target area, far from human reach without specific infrastructure. Depending on the sensor installed in the node, a particular occurrence, i.e., pressure, temperature or humidity, is sensed by the sensor unit and transmitted to electrical signals, afterwards it is sent to the base station (called sink) via the radio interface. The sink is located between the user and the network and, its function is to collect information from the nodes. Each small sensor includes three sub-units namely, the receiving unit, the processing unit, and the transmitting unit. WSNs have various applications in different areas and, researchers have already developed a variety of techniques to improve their performance in an application specific way. WSNs' aspects – i.e., speed of operation, computation, fault tolerance, network being autonomous, etc. – are applied to identify and track nearby hostile targets in military applications (Sohraby, 2007). Other uses of WSN's in healthcare systems, industry and agriculture surveillance, product quality monitoring, and remote area control, have also been successfully researched.

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Koohi, Nadernejad & Fathi (2010) proposed WSNs to be applied in firefighting. In their work, a distributed algorithm was developed for the sensor network to direct firefighters towards a burning area. This protocol, using the sensor network, guides the firefighters in a stepwise manner and helps them choose the safest path in dangerous zones. WSNs face many challenges, including energy restrictions, security, communication reliability, design, etc. (Musale & Chaudhari, 2017). Of course, it is hard to equilibrium all these challenges because of the conflicts they have with each other. In recent years, many techniques have been proposed to resolve one of the main challenges in WSNs namely, the energy restrictions of sensor nodes. The main objective of such approaches has been to minimize the energy dissipated by the nodes which, will lead to network lifetime longevity. Some of such methods include data gathering, data correlation, energy harvesting, beam forming, resource allocation using cross-layer design, opportunistic transmission schemes (sleep-wake scheduling), portable relays and sinks, optimal deployment, clustering and multi-hop routing (Musale & Chaudhari, 2017). In this paper, authors have focused on the clustering phase of the routing protocols in wireless sensor networks.

1-1- Statement of the problem

One of the soft computing techniques, which has widely been deliberated to solve an extensive range of optimization problems, is swarm intelligence-based algorithms. For example, the genetic algorithm (GA) was employed to improve the efficiency of construction automation system (Wi et al., 2012). Likewise, particle swarm optimization (PSO) was applied to solve many optimization problems in manufacturing (Issam et al., 2013; Thitipong & Nitin, 2011). Similarly, clustering and routing are two renowned optimization problems, which have been researched to develop many nature-inspired algorithms in the field of wireless sensor networks. With the proliferation of WSNs, the wide-reaching appearance of applications has often faced several challenges. Some of these challenges are connectivity, coverage, communication control, bandwidth management, security, energy management and lifetime (Musale & Chaudhari, 2017). Structurally, sensor nodes are small and often have limited irreplaceable energy supply. They send information at short distances. Thus, innovative techniques that minimize energy consumption and maximize the lifetime of the network are significant. Clustering-based routing is one of the most influential energy efficient routing techniques (Pratyay & Prasanta, 2014). In this scheme, sensor nodes are grouped into non-overlapped segments called clusters; each has a preselected node named Cluster Head (CH). Each CH first collects information from sensors nodes, which belong to its cluster and then sends the collected information to other corresponding CHs periodically or after an event. CHs transmit the collected data either directly or through multi-hop scheme to the Sink. The sensor nodes belonging to each cluster send their data only to their own CH. The CH aggregates correlated data and sends it to the sink as, depicted in Fig. 1 (Heinzelman, Chandrakasan, & Balakrishnan, 2000). Clustered networks have some advantages over non-clustered networks; some of these benefits are as follows (Moon, Park, & Han, 2017):

- Clustering provides energy efficiency as well as scalability to decrease the energy dissipation of sensor nodes in WSNs.
- Clustering simplifies routing management by reducing the network overhead, traffic, and improving the network scalability.
- Clustering manages the communication bandwidth by preventing redundant messages from being exchanged during the transmission phase.
- Clustering can implement optimized management strategies in the network.

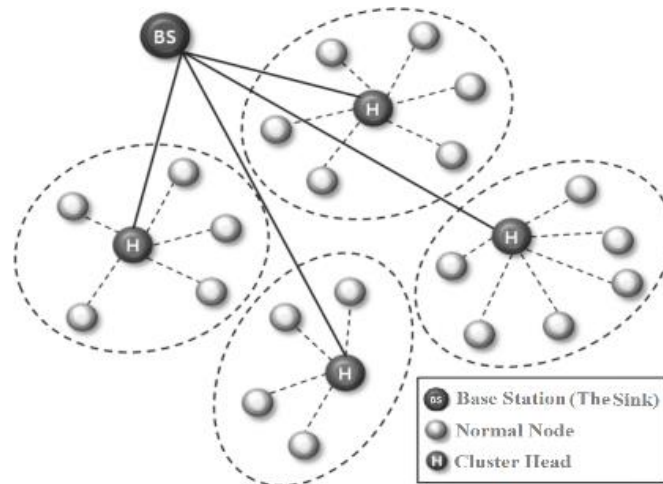


Fig 1. Hierarchical clustering in WSNs

Clustering-based routing protocols include two phases: The setup phase and the steady phase. During the setup phase, CHs are selected and, each node is connected to the nearest CH. At steady phase, to reduce the need for additional and unnecessary data transfers, CHs undertake data aggregation and compression. In large-scale networks, clustering reduces transmission overhead, supports scalability, multi-gateway topologies and data aggregation at cluster heads. For small-scale networks, the participation of fewer nodes in the data transmission can provide efficient use of energy resources (Abbasi & Younis, 2007). Nevertheless, devolving more responsibilities to cluster heads will require more energy consumption to process and transmit each cluster's data, which will result in premature and irregular network depletion (Abbasi & Younis, 2007). Hence, while efforts to reduce the energy consumption have covered different aspects of wireless sensor networks, many important motives remain untouched:

- There is not a general approach to determine and optimize the dissipated energy and the lifetime longevity.
- Current approaches focus on one feature and may load energy consumption in other aspects.
- Existing approaches miss quantitative measures of energy consumption of the entire network.
- NP-hardness of lifetime longevity problem for WSNs endorses metaheuristic approaches.

1-2- Our contribution

In this paper, the authors suggest a new adaptive clustering algorithm for WSNs called SFFA. This algorithm combines two population-based nature-inspired metaheuristic, namely the modified shuffled frog-leaping algorithm (SFLA) and the Firefly algorithm (FFA), in a high-level hybridization way (Talbi, 2009). Roulette wheeled selection (RWS) and some local improvements in the setup phase helps our hybrid approach to converge faster compared to each of the basic algorithms (Talbi, 2009). The main contribution of the present paper could be summarized as below:

- Developing a hybrid swarm intelligence multi-objective metaheuristic algorithm (called SFFA) and employing it as a clustering protocol in WSNs.
- Introducing a new adaptive application-specific multi-objective fitness function, which can be adjusted to the application scope based on the requirements.
- Considering a collection of criteria (e.g., inter- and intra-cluster distances, residual energy of nodes, distances from the sink, estimated energy consumption, overlap and load of clusters) from which to select appropriate cluster heads. The relative significance of these criteria can also be tuned according to the application specifications.
- Performing SFFA in different scenarios to demonstrate its performance against basic and existing protocols, in terms of energy consumption and network lifetime.

The rest of the paper is organized as follows: The related works are presented in section 2. An overview of the basic algorithms is introduced in section 3. The system model including energy, network and lifetime models used, are discussed in section 4. The proposed model including the fitness function derivation, encoding and the proposed algorithm is offered in section 5. Likewise, simulation

and experimental results are presented in section 6. Finally, the conclusion of the paper is presented in section 7.

2- Related works

There is a large number of cluster head selection techniques in clustering algorithms proposed for energy efficiency and lifetime longevity in WSNs (Curry & Smith, 2016). Some of these approaches have been reviewed in this section. Baker and Ephremides (1981) proposed the Lowest-ID Algorithm. In this method, a unique ID is assigned to each node. Then the node with the minimum ID is selected as a cluster head. In this algorithm, the system performance is better than the Highest Degree Algorithm in terms of throughput. However, it does not attempt to balance the load uniformly across all the nodes. Accordingly, Gerla and Tsai (1995) suggested the Highest-Degree Algorithm in which a node x is considered to be a neighbor of another node y , if x takes place within the transmission range of the node y . The node with the maximum number of neighbors is chosen as a cluster head. Experiments prove that the system has a low rate of cluster head change; however, the throughput is low under this algorithm. As the number of nodes in a cluster increases, the throughput drops and system performance degrades. All these drawbacks occur simply because this approach does not impose any restriction on the upper bound of node degree in a cluster. Basagni (1999) proposed an algorithm, called distributed clustering algorithm (DCA) in which, each node is assigned a weight based on its fitness of being a cluster head. A node is chosen to be a cluster head if its weight is greater than any of its neighbor's weights; otherwise, it joins a neighboring cluster head. Results show that the number of updates required is smaller than the Highest-Degree and Lowest-ID algorithms. Since node weights vary in each simulation cycle, computing the cluster heads becomes very expensive and there are no optimizations on the system parameters such as throughput and power control. Amongst the renowned energy-aware distributed clustering methods, LEACH is one of the most promising. This heuristic algorithm has been proposed by Heinzelman, Chandrakasan and Balakrishnan (2002). It selects, randomly and with the probability given in Eq. (1), a predefined number of cluster heads in each period. It organizes other nodes as cluster members, which is assigned to each cluster based on the distance to each CH. The normal nodes (non-CH) transmit their data to the CHs. The optimal number of clusters is calculated by equation (2) which is proposed in.

$$T(n) = \begin{cases} \frac{p}{1-p \times (r \bmod 1/p)} & \text{if } n \in G \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$K_{opt} = \sqrt{\frac{N}{2\pi}} \times \sqrt{\frac{\epsilon fs}{\epsilon mp}} \times \frac{M}{d_{sink} \cdot 2} \quad (2)$$

Where p is the required percentage of CHs (e.g. 10%). r denotes the current round and G is the set of nodes that have not served as the CH in the last $1/p$ rounds. Similarly, N is the total number of alive sensor nodes, M is the maximum length of the side of the square region. Further, d_{sink} is the distance between nodes and the sink. Finally, ϵfs and ϵmp are the amplification coefficients of the power-amplifier in the free space and the multipath fading channel models respectively (Heinzelman, 2002). In order to prevent energy draining in CHs, LEACH vigorously rotates the workload of the CH amongst the sensor nodes (Heinzelman, 2002). However, the main drawback of this approach is that the residual energy of a node is not considered when choosing the CHs. Therefore, nodes with low energy may be selected as a CH, which may die quickly leading to unbalanced energy consumption causing the network to be depleted. Moreover, the CHs send packets directly to sink via single-hop communication, which causes network to be run out of energy sooner and is unrealistic for large scale WSNs (Ramesh & Somasundaram, 2011). Energy-aware Routing Algorithm (ERA) consists of two phases including clustering and routing phases (Amgoth & Jana, 2015). During the clustering phase, each node is assigned an independent timer prior to competing to become a CH. This timer shows the maximum time specified to select CHs. The higher the level of energy, the shorter the period of time to let the node be selected as a CH. If the timer expires and no messages are received from other CHs, the node will introduce itself as a CH by advertising an announcement within a specific range. Alternatively, if a node receives a message from a CH before the timer expires, it turns into a non-CH node. Equation (3)

depicts how the timer of node n is calculated. Here, T_{CH} shows the maximum time needed to select a CH, $E_m(n)$ is the initial energy and $E_r(n)$ is the current energy of node n . In the routing phase of ERA, a multi-hop connection tree is constructed by considering the sink at the root (level=0) and advertising a message in a specific radial range.

$$Timer(n) = \frac{E_m(n) - E_r(n)}{E_m(n)} \times T_{CH} \quad (3)$$

Owing to uncertainties in the WSN environment and overlapping parameters affecting the role of CHs, some protocols have come to utilize fuzzy logic. By using fuzzy variables, inherent uncertainties of WSNs can be handled. Moreover, application of fuzzy logic instead of classical formula in CHs selection reveals comparatively more flexibility (Ran, Zhang, & Gong, 2010). Some of these techniques are discussed in the following: LEACH with Fuzzy Logic (LEACH-FL) is a fuzzy version of LEACH, which qualifies appropriate CHs by performing Mamdani fuzzy inference system. To design the fuzzy inference system of this protocol, three fuzzy variables are chosen as inputs: Energy level, density, and distance of nodes from the sink. At each round, first nodes are sorted in a descending manner according to the fuzzy output. Then, those nodes with the highest output are qualified as CHs. All calculations associated with the fuzzy qualification of CHs are executed over a central processor located in the sink (Ran, Zhang, & Gong, 2010). Multi-Objective Fuzzy Clustering Algorithm, MOFCA (Bagci & Yazici, 2015) is another fuzzy-based clustering approach to reduce the workload of the clusters, which are located close to the sink or have low energy levels. MOFCA selects the appropriate CHs via an energy-aware fuzzy competition from the set of candidate nodes which were filtered using a probabilistic model. In MOFCA, three input variables are defined for the fuzzy system: energy level, density, and distance from the sink. MOFCA has a distributed mechanism for CH-selection, and consequently, sensor nodes make local decisions to calculate the node competition radius and to select candidate and final CHs.

Literature review reveals that managing energy dissipation to prolong lifetime of the wireless sensor networks is a NP-hard problem (Dietrich & Dressler, 2009). Accordingly, many researchers have addressed these problems by means of metaheuristic. Oladimeji and Dudley (2017) proposed a novel Heuristic Algorithm to Cluster Hierarchy (HACH), which sequentially performs selection of inactive nodes and cluster head nodes at each round. Inactive node selection employs a stochastic sleep scheduling mechanism to determine the selection of nodes that can be put into sleep mode without adversely affecting network coverage. Swarm Intelligence Fuzzy Clustering (SIF) is a centralized clustering protocol (Zahedi, Akbari, Shokouhifar, Safaei, & Jalali, 2016), which utilizes Mamdani fuzzy system to select CHs at each round. SIF uses three input variables including energy level, distance to the sink and distance to the cluster centroid. At first, all nodes are clustered via fuzzy c-means algorithm, and then, in each cluster, one node is selected as CH via the Mamdani fuzzy inference system. Ramezani and khodaei (2013) proposed a Shuffled frog-leaping algorithm (SFLA) Based Clustering Algorithm (SBCA) for mobile ad hoc networks. They showed how SFLA could be useful in raising the performance of clustering algorithm. It has the ability to find the optimal or near-optimal cluster heads to manage the resources of the network more efficiently. They modified SFLA by replacing the memplex evolution with the single point crossover operation. Fuzzy SFLA (FSFLA) (Fanian & Rafsanjani, 2018) employs the SFLA algorithm together with fuzzy inference system in a central CPU positioned at the sink to select CHs for single-hop schemes. It considers the remaining energy, the distance from the sink, the number of neighboring nodes, and node histories in CH-selection procedure. Jabeura (2016) proposed a firefly-based clustering approach which includes a micro clustering phase during which, sensors self-organize into clusters. These clusters are refined during a macro-clustering phase where they compete to integrate small neighboring clusters. Simulations show promising results where the number of clusters tend to stabilize independently from the density of the network and the various communication ranges of sensors. A hybrid metaheuristic-based clustering approach based on FFA and simulated annealing was presented by Gupta and Jha (2018) to extend the network lifetime in the heterogeneous WSNs by reducing the overall energy consumption. The algorithm at first tries to find the optimal clustering over the network using the FFA, and then, it attempts to find the best chain inside each cluster using the simulated annealing algorithm.

It could be argued that, in classical approaches CHs are selected via classic formula according to different parameters of sensor nodes. Although these methods are simple and easy to implement, they do not consider appropriate criteria for selecting CHs. In contrast to the classical approaches, fuzzy-based techniques utilize the fuzzy inference system instead of classic formula to determine the relationship between the input parameters and the output (selecting CHs). Metaheuristic-based methods on the other hand, are more efficient compared to the classical and fuzzy-based approaches in terms of selecting appropriate CHs, however, they suffer from high time- and computational-complexity, as an iterative algorithm should be performed to select CHs at each round. The common drawback of the three above categories is that they are not application-specific. In other words, the controllable parameters cannot be adaptively adjusted according to the application requirements. Although these methods may have acceptable performance for some applications, their performance may be dropped for other applications. Moreover, in the most existing protocols, not enough criteria are applied to properly select CHs. To overcome the mentioned drawbacks, the proposed SFFA is introduced in section 5.

3- Overview on basic algorithms

In the following section, two basic swarm intelligence based clustering algorithms are briefly discussed.

3-1- Firefly Algorithm

The first clustering approach is based on firefly algorithm (FFA). FFA was inspired from natural behavior of fireflies and was first introduced by Yang et al. (2008). Fireflies work based on the phenomenon of bioluminescence. Bioluminescence is the process in which Firefly insect yields flashes of short duration (Fister, Yang, & Brest, 2013). Hence, intensity of flash is a vital parameter. There are three rules for firefly approach: First, the attractiveness of each firefly is independent from its gender. Second, when fireflies tend to be attracted towards each other, it depends on the brightness of the flash. Third, objective function helps to determine the brightness of fireflies. Brightness of flash is termed as the attractive factor. This factor depends on the intensity of light. Most common variables within this algorithm are attractiveness factor and light intensity (Mukhdeep & Singh, 2016). In FFA, at first a population of fireflies are randomly generated. Then, the fitness evaluation and population updating are consecutively done until the maximum number of iterations is reached. In the population-updating phase, the movement of firefly i towards another more attractive (brighter) firefly j is done as:

$$x_i = x_i + \beta e^{-\gamma d_{ij}^2} (x_j - x_i) + \alpha \left(r - \frac{1}{2} \right) \quad (4)$$

Where the first term is the current location of firefly i , the second term is due to the attraction to the firefly j , and the third term is a random deviation. d_{ij} is the Euclidean distance between fireflies i and j , r is a random number in the range of $[0,1]$, and α , β and γ are three constant parameters (Mo, Ma & Zheng, 2013).

3-2- Shuffled frog-leaping algorithm

The second clustering approach is founded on another bio-inspired metaheuristic which was initially introduced by Eusuff and Lansey (2003) named shuffled frog-leaping algorithm. SFLA is derived from a virtual population of frogs in which each individual represent a set of solutions. Each frog is distributed to a different subset called a memplex. In each memplex an independent local search, called memplex evolution, is performed. After a predefined number of memetic evolutionary steps, frogs are shuffled among memplexes to interchange message among different subsets and ensure that they move towards an optimal position. Local search and shuffling continue until a definite number of iteration is reached or predefined convergence criteria are met (Xunli & Feiefi, 2015). SFLA can be summarized in the following steps:

1. **Initialization:** Select m and n , where m is the number of memplexes and n is the number of frogs in each memplex. Therefore, the total sample size, F , in the swamp is given by $F = m \times n$.

2. Virtual population generation: An initial population of F frogs is created randomly. For a K -dimensional problem each frog i is represented by K variables, such as $F_i = (f_{i1}, f_{i2}, \dots, f_{ik})$.
3. Sorting and distribution: Frogs are first sorted in descending order based on their fitness values, then the entire population is divided into m memplex, each containing n frogs. In this process, the first frog goes to the first memplex, the second frog goes to the second memplex, frog m goes to the m memplex, and frog $m+1$ goes to the first memplex, etc.
4. Memplex evolution: This step is based on a local search, where in each memplex, frogs with the best and the worst fitness are identified as F_b and F_w , the frog with the global best fitness is identified as F_g separately. Then, an evolution process is applied to improve only the frog having the worst fitness. Accordingly, the position of the frog with the worst fitness is adjusted as follows:

$$D_i = rand() \times (F_b - F_w) \quad (5)$$

$$F_w^{i+1} = F_w^i + D_i, \quad (D_{\min} \leq D_i \leq D_{\max}) \quad (6)$$

Where $rand()$ is a random number between 0 and 1, D_{\min} is the minimum change allowed in a frog's position and D_{\max} is the maximum change allowed. If this process produces a better solution, it replaces the worst frog. If equations (5) and (6) do not improve the worst solution, F_b of equation (5) is replaced with F_g and adjust to equation (7):

$$D_i = rand() \times (F_g - F_w) \quad (7)$$

6. Shuffling: After a predefined number of memplex evolution steps, all frogs of memplexes are collected, and new population is sorted in descending order according to their fitness.
7. Stop condition: If a global solution or a fixed number of iterations is reached, the algorithm stops. Otherwise, go to step (2) and repeat again.

In our suggested hybrid model, there is a modification done in local search part of the original SFLA. This modification takes place on the step, where none of the preceded steps (equations. 5, 6 & 7) would result in local improvement. In this case, a new frog is replaced randomly and uniformly. However, in the approach presented, a Levy flight mechanism is applied for random selection which is proved to be more efficient regarding to exploration (Tang, Yang, & Dong, 2016). Algorithm 1 shows improved SFLA.

Algorithm 1. Modified SFLA: Pseudo code.

Begin;

Generate random population of P solutions (frogs);

Calculate fitness function f value of each frog;

Repeat for specific number of times

Sort population P in descending order of their fitness;

Divide P into m memplexes;

Repeat for specific number of iterations

For each memplex determine the best and worst frogs X_b and X_w ,

Identify the best frog for the entire population X_g ;

Improve the worst frog position using

$$X_w(t+1) = rand() \times (X_b(t) - X_w(t))$$

if $f(X_w(t+1)) < f(X_w(t))$

$$X_w(t+1) = rand() \times (X_g(t) - X_w(t))$$

if $(X_w(t+1) < f(X_w(t))$

$$Levy \sim u = t^{-\lambda}$$

$$X_w(t+1) = X_w(t) + \alpha \oplus Levy(\lambda)$$

End;

Shuffle the evolved memplexes;

End;

Present the best frog X_g .

End;

4- System model

In this section, the system model, including energy, network and lifetime models are discussed:

4-1- Energy model

This paper has employed an energy model named “the first order radio model” (Heinzelman, Chandrakasan, & Balakrishnan, 2002). In this scheme, the transmitter dissipates energy of $E_{Tx}(l, d)$ to manage the radio electronics and the power amplifier, whereas the receiver dissipates energy $E_{Rx}(l)$ when managing the radio electronics, as shown in Figure 2. Depending on the distance (d) between the transmitter and receiver, the free space (d^2 power loss) and the multipath channel fading (d^4 power loss) models were used for all the try-outs carried out.

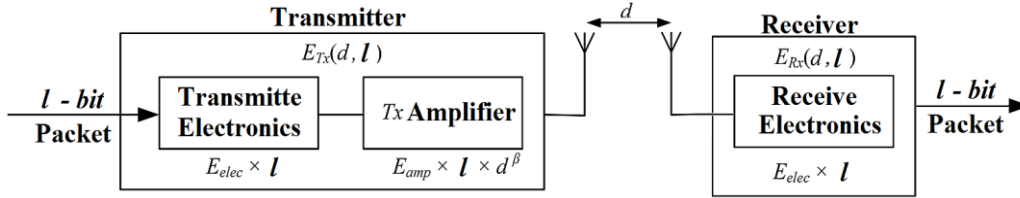


Fig 2. Radio energy dissipation model

The power-amplifier is properly managed such that if the distance was less than a threshold distance d_0 , the free space (*fs*) model would employ else, the multipath (*mp*) model would be used. Therefore, to transmit an L -bit message to a distance d , the radio spends:

$$E_{Tx}(d, l) = E_{Tx_{elec}} + E_{Tx_{amp}} = \begin{cases} l \times E_{elec} + \epsilon mp \times l \times d^4, & \text{if } d > d_0 \\ l \times E_{elec} + \epsilon fs \times l \times d^2, & \text{if } d < d_0 \end{cases} \quad (8)$$

Furthermore, to receive L -bit message, the radio uses energy calculated as:

$$E_{Rx}(d, l) = l \times E_{elec} \quad (9)$$

Equation $d_0 = \sqrt{\epsilon fs / \epsilon mp}$ denotes the threshold distance, and the electronics energy factors such as the digital coding, modulation employed as well as filtering, and spreading of the signal effect E_{elec} . The amplifier energy, ϵmp or ϵfs depends on the distance to the receiver and the acceptable bit-error rate. β determines the dissipated energy according to the distance between transmitter and receiver (Jia, He, Kuang & Mu Y. 2010).

4-2- Network model

According to application research background, the following network assumptions are considered in modeling of the proposed algorithm (Singh et. al 2017):

- All sensor nodes are homogeneous and randomly distributed with few CHs. Once they are deployed, they become stationary, with constant initial energy. Battery recharge and replacement are almost impossible for the entire operation.
- Location of the sink is fixed. It could be placed either inside, or outside of the sensing field, depending on the network scenario.
- To determine the location, all sensor nodes have been embedded with devices (i.e. GPS).
- The communication channel is assumed symmetric. That is, the energy required to transmit data from sensor node s_1 to sensor node s_2 is equal to the energy needed to transmit a message from node s_2 to node s_1 for a particular signal to noise ratio (SNR).
- This scheme supports TDMA protocol provided for MAC layer communication. CHs use slotted carrier-sense multiple access (CSMA) MAC protocol to communicate with the sink.
- Data aggregation is applied using the infinite compressibility model. This idea assumes that cluster heads collect the data from its member nodes and aggregate it into a single packet of fixed

length irrespective of the number of received packets. Nodes, close to each other, have correlated data (Oladimeji, Turkey, & Dudley, 2017).

- The control frames are small in comparison to data frames. Thus, energy consumed in transmitting control frames is negligible in comparison to energy consumed in transmitting data frames and hence, neglected.

4-3- Lifetime model

Network lifetime is perhaps the most important metric for the performance evaluation of wireless sensor networks. Regardless of how the network lifetime is defined, network lifetime strongly depends on the lifetimes of the single nodes, which construct the network. The lifetime modeling of a sensor node depends on two factors: How much energy it consumes over time, and how much energy is available for its later use (Dietrich & Dressler, 2009). Various definition of the network lifetime is given in the literature. The most commonly found definition is *n-of-n* in which, the network lifetime T_n^n ends once the first node fails, thus $T_n^n = \text{Min}_{v \in V} T_v$ with T_v being the lifetime of node v (Dietrich & Dressler, 2009). The sink nodes are excluded from the node set V to show the assumption that a power plug is available at the sink nodes. Other approaches, such as *K-of-N* lifetime and *m-in-K-of-N* lifetime are also introduced. *K-of-N* lifetime presents the duration up to when K CH nodes out of N are alive whereas *m-in-K-of-N* lifetime presents the duration until all m supporting CH nodes and a minimum of K CH nodes are alive (Dietrich & Dressler, 2009). It is important to notice that the network lifetime is defined based on the application, and there is no single suitable definition applicable to all applications (Shokouhifar & Jalali, 2015). For instance, in a medical surveillance network, lifetime is determined as FND, which is distinguished based on the information from sensor nodes. In this case, perishing of a sensor node may generate irreparable damages. Moreover, in some scenarios, network lifetime is considered as the period until the entire sensing region is covered. Lifetime in WSNs can be defined via different criteria based on application specifications, e.g., first node dies (FND), half node die (HND), and last node dies (LND) (Attea & Khalil, 2011). In heterogeneous WSNs with different data packets, the most important criterion is FND, as perishing of even one node may result in irretrievable damages. However, perishing of some nodes is not critical in homogeneous WSNs. In this case, network is trustable as long as at least the determined number of nodes will remain alive. Therefore, lifetime could be defined within different criteria based on node density, application specifications, and distribution of nodes in the network (Shokouhifar & Jalali, 2015). In this paper, authors have used lifetime of the network in terms of round from the start of the network operation until the first node drains its complete energy and stop functioning.

5- Our proposed model

In the suggested model during the setup phase, the sink sends a short message to wake up and to request the IDs – positions and energy levels of all sensor nodes in the sensor field. Based on the feedback information from sensor nodes, the sink uses SFFA algorithm to determine the optimum number of CHs and their locations based on minimization of the dissipated energy on communication process. Then, they broadcast their IDs using CSMA/CA, and MAC layer protocols. Therefore, CH nodes within the communication range of sensor nodes can collect the data of that sensor IDs and send the local network information to the sink. In clustering phase, the sink executes the clustering algorithm. When the clustering is done, all the CH nodes provide their IDs to their cluster members by single hop communication. After that, the CH nodes provide a TDMA schedule to their member sensor nodes for intra cluster communication (Zenga & Dong, 2016). In the following sections, authors present the procedure used for fitness function calculation and population vector initialization. Further, the hybrid-clustering algorithm used will also be introduced.

5-1- Fitness function derivation

Optimal CH selection is deliberated as an optimization problem (Shokouhifar & Jalali, 2015). To maximize network lifetime of a clustered WSN, the most qualified CHs should be selected according to a fitness value calculated by a fitness function for each node. The energy parameters of the sensor nodes ensure that nodes with greater energy be given higher priority in the CH selection process (Shokouhifar & Jalali, 2015). In this part, a multi-objective fitness function is formulated. This multi

objective function is formulated as a weighted average of the five objective functions in equation (10). It comprises five parameters including the ratio of total initial energy of all nodes with the total current energy of the cluster heads, the average Euclidean distance of selected CHs and the sink, the average intra-cluster and inter-cluster Euclidean distance of nodes and load balancing of CHs respectively.

$$OF_{FSFA} = \text{Minimize } \{w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4 + w_5 f_5\} \quad (10)$$

The definition and derivation of these parameters are given as follows:

Suppose a sensing area of size $M \times M$, in which N nodes are randomly distributed. If there are k predefined clusters with $|C_j|$ number of nodes, the ratio of total initial energy of all nodes with the total current energy of the cluster head candidates in the current round E_r introduces the first parameter, $f(1)$ and is defined as in equation (11):

$$f(1) = E_r = \frac{\sum_{i=1}^N E(n_i)}{\sum_{j=1}^k E(CH_j)} \quad , \quad j = 1, 2, \dots, k \quad (11)$$

In which $E(n_i)$ denotes the total energy of the node i and $E(CH_j)$ denotes the total energy of CH_j in the current round. The second objective function $f(2)$ is used to minimize the average distance between the selected CHs and the sink. It can be formulated as Eq. (12), where $d(CH_j, Sink)$ is the Euclidian distance between CH_j and the sink, and the term $M/2$ is used to normalize $f(2)$ near 1. For large-scale networks, this distance should be kept minimized; otherwise, the energy in some nodes will be lost. Whereas, for a small-scale network, that has a few closely located nodes, direct transfer of nodes to sink may be an acceptable option.

$$f(2) = \frac{\frac{1}{k} \sum_{j=1}^k d(CH_j, Sink)}{\frac{M}{2}} \quad , \quad j = 1, 2, \dots, k \quad (12)$$

The third objective $f(3)$, is defined to minimize the average intra-cluster distances of nodes to their associated CHs. It can be formulated as equation (13), where x_{ij} is a binary parameter: It is 1, if the node i is assigned to CH_j ; otherwise, it is set to 0. The term $A/2$ is used to normalize $f(3)$, where A is described in the following (see figure 3).

$$f(3) = \frac{\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^k d(n_i, CH_j) \times x_{ij}}{\frac{A}{2}} \quad , \quad j = 1, 2, \dots, k \quad (13)$$

Where N is the total number of sensor nodes, K is the number of CHs and $d(n_i, CH_j)$ is the Euclidian distance between CH_j and n_i . The fourth objective $f(4)$, defined to maximize the average inter-cluster distances between CHs, can be expressed as equation (14), where CH_k is the nearest CH to CH_j , and the term A is used to normalize $f(4)$. A is described in the following (see figure 3).

$$f(4) = \frac{A}{\frac{1}{|C_j|} \sum_{j=1}^{|C_j|} d(CH_j, CH_k)}, j = 1, 2, \dots, k \quad (14)$$

Finally, the fifth objective f_5 is proposed to balance the load between CHs. The aim is to minimize the maximum load between different CHs as expressed in equation (15), where the denominator is used to normalize f_5 around 1.

$$f(5) = \frac{MAX(|C_j|)}{\frac{1}{k} \sum_{j=1}^k (|C_j|)}; \quad \forall j = 1, 2, \dots, k \quad (15)$$

Here, the normalization terms used for $f(2)$, $f(3)$, and $f(4)$ is explained through an example. Suppose a network area of dimension $M \times M$ with C clusters which are assumed to be distributed symmetrically as seen in figure 3. If A is considered to be the average distance of two neighbor CHs, the intra- and inter-cluster distances in equations (12) and (13) can be normalized via $A/2$ and A , respectively. Moreover, the average distances of CHs to the sink in Eq. (11) can be normalized using $M/2$. The value of the parameter A can be approximately calculated as $A = M/\sqrt{C}$. For example, assuming $M=90$ and $C=9$, A can be calculated as $A=90/3=30$. Thus, each CH approximately covers an area of dimension 30×30 .

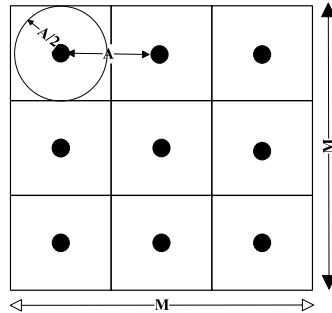


Fig 3. Network area of dimension $M \times M$

5-2- Encoding of individuals

In the proposed approach, each individual of the population can be denoted as a binary string of length N , where N is the number of living nodes. Value of “0” indicates a member node and value of “1” indicates a CH node. This structure is used to represent feasible solutions in both SFLA and FFA. An example of encoding a feasible solution can be shown in figure 4. It should be mentioned that because of the continuous characteristics of the population updating process in both algorithms, the solutions have basically continuous values between 0 and 1. Therefore, only in the fitness evaluation phase, the solutions are rounded into binary structures in order to calculate the objective function. Afterwards, the solutions are updated in the continuous structures.

1	2	3	4	5	6	...	N
0	1	0	0	1	1	...	1

Fig 4. Encoding of the individuals

5-3- Hybrid clustering algorithm

In terms of evolutionary algorithms (EAs), hybridization is done mainly to improve performance via reaching better solutions (Talbi, 2002). For the proposed model, both the SFLA algorithm and the FFA algorithm have their own advantages performing well for an extensive range of optimization problems.

FLA is a collaborative population-based algorithm with high computational efficiency and good global search capability that can solve both discrete and continuous optimization problems (Tang, Yang, & Dong, 2016). FFA, on the other hand, belongs to the group of stochastic algorithms and focuses on producing solutions at the lowest level within a search space (Cheung, Ding & Shen, 2014). Its random search avoids falling into the premature local optimal. This algorithm has a number of advantages over other metaheuristic algorithms. Firefly algorithm is based on absorption and brightness. This will automatically divide the entire population into subgroups with a mean interval, which helps each group crowd around local optima. Among all these local optima, the best global optimum could be attainable. (Cheung, Ding & Shen, 2014). Additionally, this classification allows the search improvement for all nonlinear multi-level optimization problems. The algorithm is set to a ratio of repetition such that convergence can be speeded up by leveraging these parameters. These benefits are faced with clustering, classifications and hybrid optimization (Fister, Yang, & Brest, 2013). In the proposed algorithm, SFFA takes the advantages of both algorithms while trying to minimize any substantial disadvantages at the same time. Moreover, strategy of Roulette Wheel Selection (RWS) is added to compensate probable lack of exploration (Zhang, Liu, Yang, & Dai, 2016). Pseudo code for suggested hybrid clustering algorithm is presented in algorithm 2 in figure 5.

Algorithm 2. The proposed hybrid-clustering algorithm.

Begin;
Divide the initial population P_0 into two sub-populations: P_1 and P_2 ;
Initialize the populations P_1 and P_2 ;
Evaluate the fitness value of each individual according to eq.(10);
Repeat Do in parallel
 Perform FFA operation on P_1 ;
 Perform SFLA operation on P_2 According to Algorithm 1
End Do
Update the global best in the whole population;
Shuffle the two sub-population and regroup them randomly into new sub-populations: P_1 and P_2 ; by means of a Roulette Wheel Selection (RWS)
Until a terminate-condition is met;
End;
Post-process results and visualization;

Fig 5. The proposed algorithm

As depicted in the flowchart of figure 4, at each iteration of the suggested SFFA, in the first step, an initial virtual population P_0 is generated random uniformly. In the second step, P_0 is divided to equal-sized subpopulations FFA and SFLA individuals (P_1 and P_2). In the third step, each individual's fitness value calculated according to the proposed multi-objective fitness function presented in equation (10). In the fourth step, by performing a predefined number of FFA and FLA based evolutionary operations, P_1 and P_2 are evolved in parallel. In the fifth step, global bests of each basic algorithm's population are updated. Afterward in the sixth step, populations of P_1 and P_2 are shuffled and regrouped into new P_1 and P_2 and randomly selected for the next iteration using RWS. Steps of SFFA is repeated until the maximum number of iterations is reached.

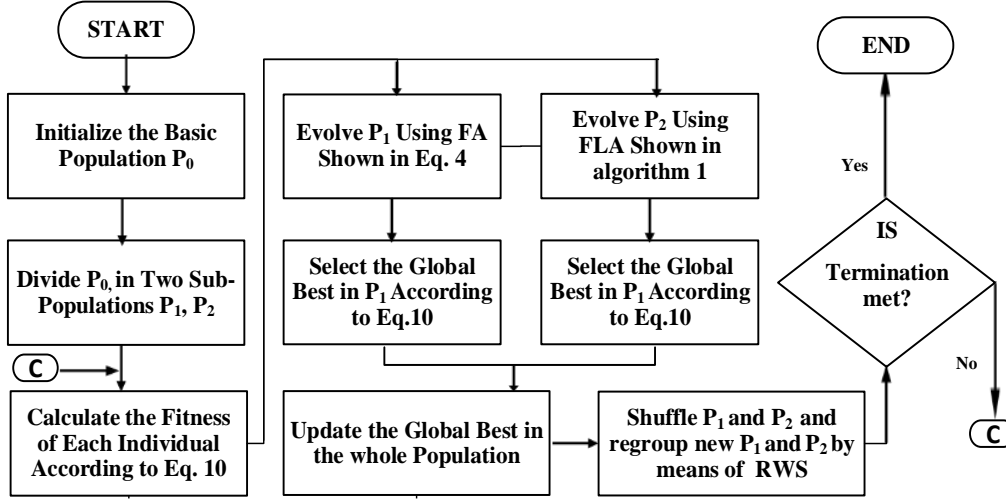


Fig 6. Flowchart of the hybrid SFLA and FFA algorithm in proposed SFFA

5-3-1- Time complexity analysis

Although the metaheuristic based clustering approaches are more efficient in selecting proper CHs, compared to classical and fuzzy based clustering methods, higher time- and computational-complexity is their main drawback(Shokouhifar & Jalali, 2015). In this scheme, prior to data transmission, an iterative time-consuming metaheuristic algorithm should be run at each round causing a probable delay in data transfer. Henceforth, the time complexity analysis is vital not only on behalf of the function evaluation for the hybrid clustering algorithm, but to ensure that higher time consumption would not result in inconvenience and unwanted results – in this subject, delay in transmission may result in data corruption – compared to basic algorithms. Therefore, while the detailed time complexity may depend on the structure of the algorithm implementation (Zhang, Liu, Yang & Dai, 2016), an estimation of the time complexity analysis for the SFFA is summarized in Table 1. In this table, the CH selection via SFFA at each round has a time complexity of $O(N_{iter} \times PopSize \times N \times C)$, where N is the total number of nodes, C is the desired number of clusters, and N_{iter} is the number of algorithm's iterations. Moreover, $PopSize$ is the population of the SFFA, which can be calculated as $PopSize = Pop_{SFLA} + Pop_{FFA}$, where Pop_{SFLA} and Pop_{FFA} are the population size of SFLA and FFA, respectively. Additionally, suppose N_{iter} be the number of iterations for clustering main loop, N_{pop} be the population size of the swarm and $TC_{fitness}$ be the time complexity of the cost function, which is presented by $TC_{fitness} = C \times N_{pop}$.

Table 1. Time complexity for FFA, SFLA and SFFA

Algorithm	Time complexity
SFLA	$O(N_{iter} \times N_{pop_frog} \times Cost)$
FFA	$O(N_{iter} \times N_{pop_firefly} \times Cost)$
SFFA	$O(N_{iter} \times (N_{pop_frog} + N_{pop_firefly}) \times TC_{fitness})$

It can be inferred from table 1 above that, the hybrid approach (SFFA), would not negatively affect the time complexity of the clustering algorithm, as it is linear in terms of both the number of iterations and the population size. Thus, hybrid algorithm is preferred, if it achieves better performance than the other two constituents do. Accordingly, to ensure the fairness of comparisons, all simulations of the SFLA, FFA and the hybrid SFFA are done in the same time complexities. More specifically, the same number of iterations is used for the three techniques. Moreover, the same population size of N_{pop} is used for the SFLA and FFA algorithms, while $N_{pop}/2$ is used for the population size of both SFLA and FFA in the proposed hybrid approach.

6-Simulation and results

In this section, the authors performed massive simulations using MATLAB to analyze and evaluate the performance of the proposed algorithm concerning energy efficiency and network lifetime.

6-1- Performance indices

Several indices concerning energy efficiency and network lifetime longevity have already been introduced to determine the performance of the routing protocols in WSNs. Amongst the different indices; those used in this paper are listed in table 2.

Table 2. Definition of the performance indices used in this paper

Performance indices	Description
First Node Dead (FND)	Number of rounds in which the first sensor node of the network dies.
Half Node Dead (HND)	Number of rounds in which half number of sensor nodes are dead.
Last Dead Node (LND)	Number of rounds in which all sensor nodes of the network are dead.
Total Residual Energy Per Round (TREPR)	Total amount of residual energy of the network versus rounds.
Number of Alive Nodes Per Round (NANPR)	This measure reflects the total number of alive sensor nodes versus rounds.
Throughput	The total rate of data successfully received at the sink versus rounds.

6-2- Algorithm and network parameters

Adjustment of the controllable parameters of metaheuristic algorithms is of utmost importance before testing these techniques. To achieve this purpose, diverse ranges were examined and best values were manually chosen according to experts' recommendations and surveys. List of parameter and their values for the proposed SFFA, including the built-in parameters of the basic algorithms and the multi-objective functions' most appropriate weight values can be summarized in table 3. The weights of the multi-objective functions for clustering in Eq. (10) were tuned to maximize the FND; because, in almost all applications FND is the most important measure (Zenga & Dong, 2016). To do this, several combinations of weight values were examined to attain the best values aiming at FND improvement. However, as previously mentioned, the proposed SFFA has an application-specific approach, which can be adapted with any application through the regulation of five weights expressed in Eq. (10). To evaluate the SFFA, extensive simulations were carried out for WSNs in three scenarios. These scenarios comprise of 50, 100, and 150 sensors nodes randomly deployed in the area of interest with the dimension of 100 m × 100 m. In order to eliminate the experimental error caused by randomness, each experiment was run several times for each WSN. The sink is located at the center of the network. All nodes have an identical initial energy. The simple radio energy dissipation model (refer to section 4-1) is used for communications. Data aggregation is done according to the technique proposed by Seyyit Alper et al. (2014). In this scheme, the size of data packets for a CH after aggregation is calculated using equation (16) and equation (17). In which, S_{comp} represents the value of compressed data, S_{rec} denotes the size of the received data from each cluster member node, R_{agg} denotes the aggregation ratio and N denotes the number of the cluster member nodes excluding the CH node in a particular formed cluster. Total sum of S_{comp} and S_{rec} denotes the size of the aggregated data, S_{agg} . In the simulations performed, the aggregation rate R_{agg} is set to 0.2. Network assumptions for WSNs are listed in table 4.

$$S_{comp} = (S_{rec} \times R_{agg} \times N) \quad (16)$$

$$S_{agg} = (S_{comp} + S_{rec}) \quad (17)$$

Table 3. Parameters of basic algorithms

Parameter	Description	Value
MaxIter	Maximum Number of Iterations	50
PopSize (Pop _{SFLA} +Pop _{FFA})	Population Size	20 (10+10)
α in Eq. (4)	Random Change Coefficient in FFA (Eq. 4)	0.1
β in Eq. (4)	Light Absorption Coefficient in FFA (Eq. 4)	0.5
γ in Eq. (4)	Attraction Coefficient (Eq. 4)	0.05
nMemeplex	Uniform Mutation Range for SFLA	2
nPopMemeplex	Nelder-Mead Standard for SFLA	10
$\alpha, \beta, \gamma, \delta$	Levy distribution parameters for SFLA	0.5, 1, 1, 0.1
w_1, w_2, w_3, w_4, w_5	Weights of Multi-Objective Function in Clustering (Eq. 10)	0.4, 0.2, 0.15, 0.15, 0.1

Table 4. WSNs' network parameter assumptions

Parameters	Value
Area of interest ($M \times M$)	(100 m \times 100 m)
Number of sensor nodes (N) in WSNs 1~5 (scenario #1)	50
Number of sensor nodes (N) in WSNs 6~10 (scenario #2)	100
Number of sensor nodes (N) in WSNs 11~15 (scenario #3)	150
Maximum No. of Rounds	2000
Number of clusters (C)	$0.1 \times N$
Initial energy of sensor nodes (E_{init})	0.2 J
E_{elec}	50 nJ/bit
E_{fs}	100 pJ/bit/m ²
E_{mp}	0.013 pJ/bit/m ⁴
d_0	87.0 m
E_{DA}	5 nJ/bit
Packet Size	4000 bits
R_{agg}	0.2

6-3- Performance evaluation

In the following sub-sections, performance of the proposed model will be explored through comparison of the performance indices calculated in basic algorithms and the hybrid model, as well as with the existing clustering based routing protocols.

6-3-1- Comparison with the basic algorithms

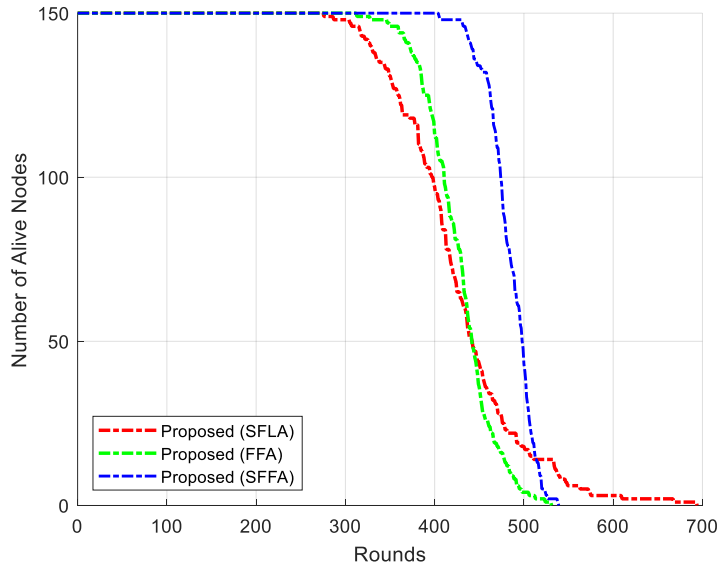
Since SFFA is a hybrid algorithm, it should first be compared with its constituents SFLA and FFA algorithms, in terms of FND, HND and LND. To achieve that, three metaheuristic algorithms utilize the same clustering process with the same parameters which can be reviewed in table 3. The population size of the SFLA and FFA were set at 20, in order to have a fair comparison between different techniques with the same time complexity. Simulation results over each scenario mentioned in table 4, can be summarized in table 5. Additionally, figure 7 statistically qualifies them for the NANPR (on average for five WSNs). According to the obtained results, it can be concluded that the proposed hybrid SFFA algorithm outperforms the SFLA and FFA algorithms, especially in term of the FND. Table 6 shows the total number of data packets successfully received at the sink (Throughput) for each compared algorithm in three scenarios.

Table 5. Comparison to basic algorithms for three scenarios of WSNs, in terms of FND, HND, and LND

Clustering Algorithms	WSNs of Scenario #1			WSNs of Scenario #2			WSNs of Scenario #3		
	FND	HND	LND	FND	HND	LND	FND	HND	LND
Proposed SFLA	411	422	428	343	444	561	275	418	695
Proposed FFA	409	421	434	334	413	478	342	430	560
Proposed SFFA	431	441	446	468	390	468	404	486	562

Table 6. Comparison of basic algorithms for three scenarios of WSNs, in terms of throughput

Clustering Algorithms	WSNs of Scenario #1			WSNs of Scenario #2			WSNs of Scenario #3		
	FND_THR.	HND_THR.	LND_THR.	FND_THR.	HND_THR.	LND_THR.	FND_THR.	HND_THR.	LND_THR.
Proposed SFLA	20550	21074	21118	32800	41881	43729	41250	59188	63485
Proposed FFA	21000	21831	21898	33400	42274	45141	51300	63587	68410
Proposed SFFA	21500	21923	21963	44600	44632	44993	60600	71100	72464

**Fig 7.** Comparison of the NANPR (for scenario #3) for the proposed SFLA, FFA and SFFA

6-3-2- Comparison with existing protocols

In this section, three scenarios with different numbers of sensor nodes in the same network sizes are simulated to evaluate the performance of SFFA against the exemplary existing protocols. The network size remains fixed to emphasize on single hopping scheme (each node sends its data to the sink via one CH). All other simulation parameters including weights of Multi-Objective Function in Clustering are derived from table 3 and table 4. Four existing protocols are used in the simulation, which are LEACH, ERA, SIF and FSFLA. These protocols were selected because they had been studied during the literature review and all had the single hopping scheme in their initial version. To see the results, table 7 contains values of FND, HND and LND for all the five protocols in different sizes. Table 8 shows the throughput values of each network protocol. Additionally, figures 7 to 9 statistically qualify them for the NANPR. Ultimately, figures 10 to 13 compare them for the TREPR.

Table 7. Comparison of the lifetime indices in all scenarios for existing protocols

Exemplary Algorithms	WSNs of Scenario #1			WSNs of Scenario #2			WSNs of Scenario #3		
	FND	HND	LND	FND	HND	LND	FND	HND	LND
LEACH	289	396	449	261	391	477	288	433	570
ERA	330	372	422	279	389	469	294	379	457
SIF	384	402	420	398	420	460	384	405	441
FSFLA	378	396	402	377	405	414	367	390	401
Proposed SFFA	429	442	449	416	451	474	404	486	530

Table 8 Comparison of throughput values of each existing network protocols for all scenarios

Exemplary Algorithms	WSNs of Scenario #1			WSNs of Scenario #2			WSNs of Scenario #3		
	THR_FND	THR_HND	THR_LND	THR_FND	THR_HND	THR_LND	THR_FND	THR_HND	THR_LND
LEACH	14450	19092	19714	26100	36737	38450	35314	61149	63678
ERA	16500	18077	18705	27900	37441	39067	44100	55055	57283
SIF	19200	19872	20053	40000	41495	42002	57600	60066	60720
FSFLA	18900	19624	19726	37600	40090	40338	55050	57889	58359
Proposed SFFA	21450	21923	21986	41600	44632	44993	60600	71100	72464

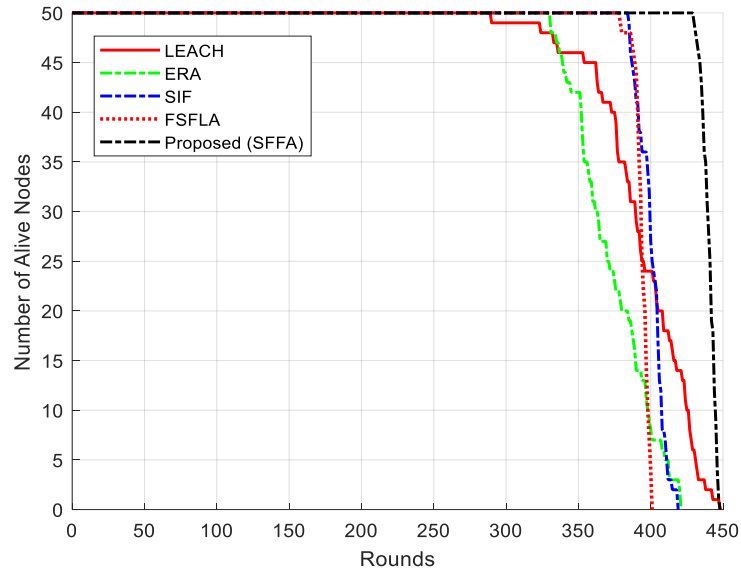


Fig 8. Comparison of the NANPR for scenario #1

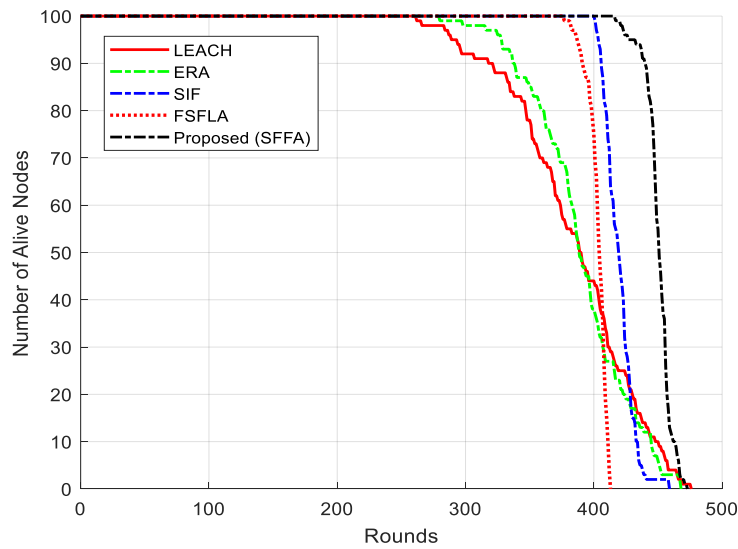


Fig 9. Comparison of the NANPR for scenario #2

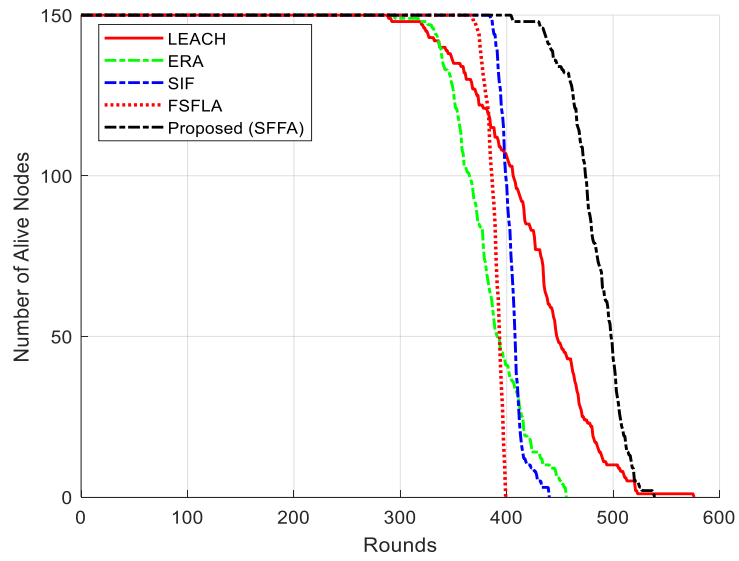


Fig 10. Comparison of the NANPR for scenario #3

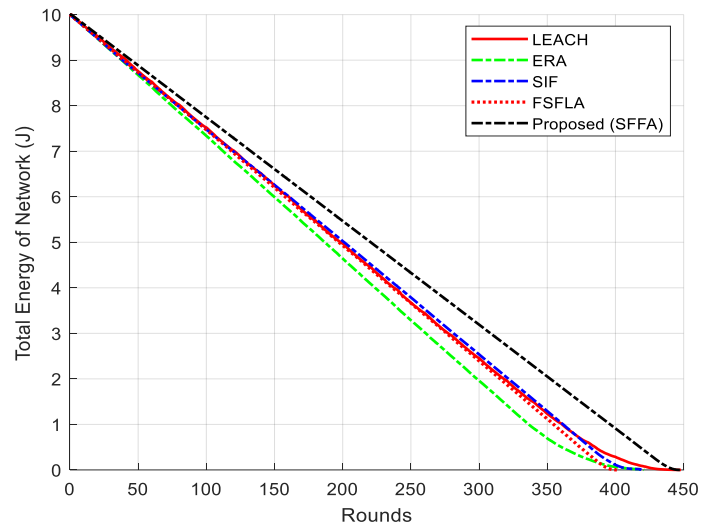


Fig 11. Comparison of the TREPR for scenario #1

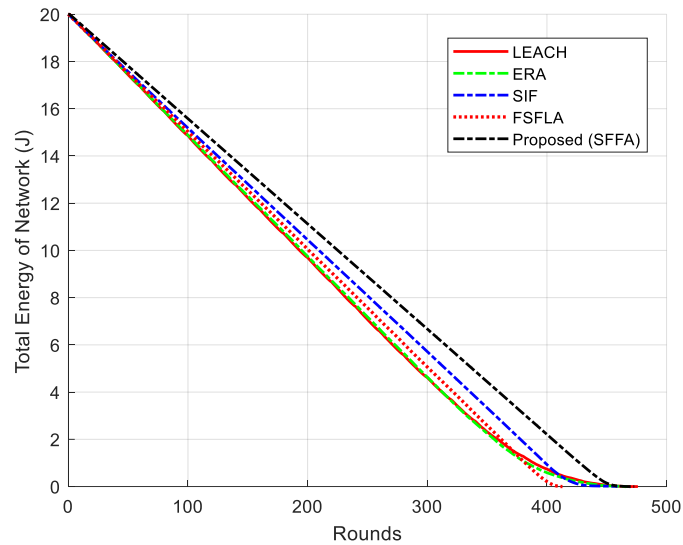


Fig 12. Comparison of the TREPR for scenario #2

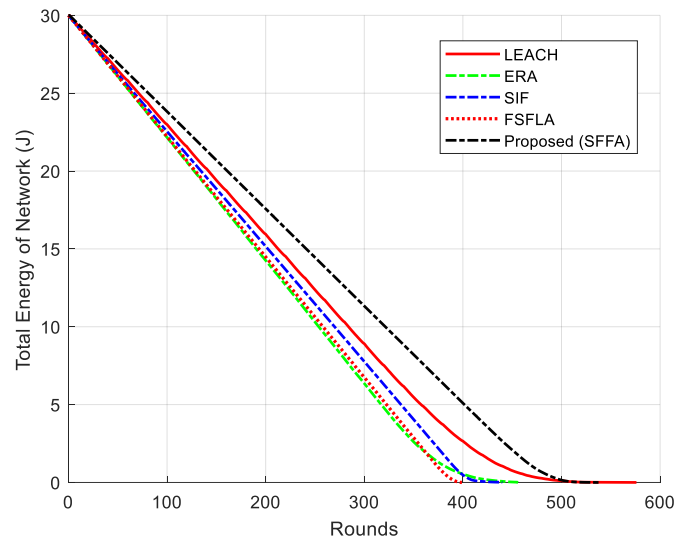


Fig 13. Comparison of the TREPR for scenario #3

6.4 Parameters Analysis

In this section, the impact of input parameters on the performance of the suggested SSFA is presented. To attain this, parameters listed in table 3 and table 4 are investigated respectively. For simplicity of the assessment process, whenever an input parameter is examined, it is recommended to keep other input parameters of the proposed model constant (Suniti et. al 2019). As previously noted in section 6.2, amongst output parameters of models listed in table 2, the FND is of utmost significance. However, for a better inference, other lifetime indices are calculated and examined as well. In regard to clustering parameters listed in table 3, examining the first two input parameters named *MaxIter* and *PopSize* against the lifetime indices of WSNs of scenario 1, illustrated in table 9. The investigation results revealed a minor impact on the performance of the proposed model, because the FND had gotten more accurate values as the population size and the maximum number of algorithm iterations increased. This improvement is likely due to the better local search happened for each basic algorithms. It is worth notifying that, when both parameters dramatically increased at the same time, FND improves nearly by %9. Nevertheless, it is advised not to grow that individual population unboundedly, and consider the lower and the upper limits when dealing with simple to more complex problems (Mo, Ma & Zheng. 2013). This recommendation is noted in the examination

done in the following trials. Figure 13 depicts the effect of MaxIter and PopSize on the performance indices including the FND, HND and The LND.

Table 9. Investigation of the effect of MaxIter and PopSize on the performance indices of WSNs of scenario 1

MaxIter	PopSize = 20 (10 +10)			PopSize = 40 (20 + 20)			PopSize = 60 (30 +30)			PopSize = 80 (40 + 40)		
	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND
30	430	448	453	427	450	470	423	447	453	396	446	469
50	429	442	449	425	457	464	421	461	470	431	438	448
80	421	437	441	430	461	468	431	458	471	429	440	451
100	428	512	596	431	441	469	431	458	460	432	442	450

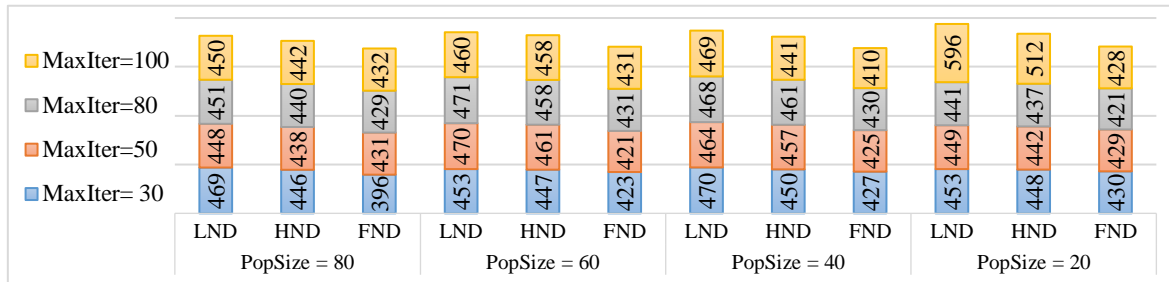


Fig 14. Impact of PopSize and MaxIter on the output parameters FND, HND, and LND

Amongst other input parameters counted in table 3, FFA and SFLA built-in parameters were selected according to the literature reviews. Appropriate parameter values for the proposed FFA, are mainly adjusted based on the guidelines offered by MO et. al (2013). Accordingly, a reasonable range for α is placed in $[0.1,0.2]$, additionally, too small or too big value of γ is not preferred, the optimal values for γ is located in $[1,30]$. Proper value of β depends on the value of β_0 and β_{min} , which are suggested to be 1 and 0.2 respectively. For simpler problems, a population size of 20 to 40 fireflies may be applicable. However, when the problem becomes complicated, it should not be larger than 50. As for the second approach in the hybrid model (SFFA), parameter values for the proposed Levy flight based SFLA, are set in accordance with the Nelder-Mead Standard and the ranges examined and advised by Tang et. al (2016). Weight values of the multi objective fitness function calculated in Eq. (10), have already been discussed in section 6.2. It is emphasized here that these values have been derived via substantial simulations. Afterwards, the best values were manually selected to maximally satisfy the objective function owing to the specific application. Hence, by manipulating five weights in Eq. (10), one could adaptively regulate the outcomes of the suggested model to other application specifications. Thus, to begin the analysis with a set of reliable initial values, experimental values of simulations carried out by Gupta et. al (2018), Amit & Senthil (2017) and Shokouhifar et. al (2015) were chosen within the suggested ranges. To illustrate this, few weight value combinations were provided in table 10 to calculate the FND, HND and LND. Figure 15, demonstrates how proper weight selection positively impacts on the model's performance in terms of TREPR, NANPR, and the throughput.

Table 10 Investigation of the effect of multiobjective fitness function's weights on the performance indices

Weight Combinations					WSNs of Scenario #1			WSNs of Scenario #2			WSNs of Scenario #3		
w_1	w_2	w_3	w_4	w_5	FND	HND	LND	FND	HND	LND	FND	HND	LND
0.4	0.2	0.15	0.15	0.1	438	441	463	286	462	599	404	486	530
0.2	0.2	0.2	0.2	0.2	416	448	495	320	456	622	330	459	677
0.5	0.1	0.15	0.15	0.1	355	447	508	321	453	599	380	458	521
0.6	0.1	0.1	0.1	0.1	320	442	501	239	450	655	190	459	642
0.3	0.3	0.15	0.15	0.1	431	445	461	390	454	490	280	445	601
0.2	0.4	0.15	0.15	0.1	421	436	450	391	452	472	330	457	541

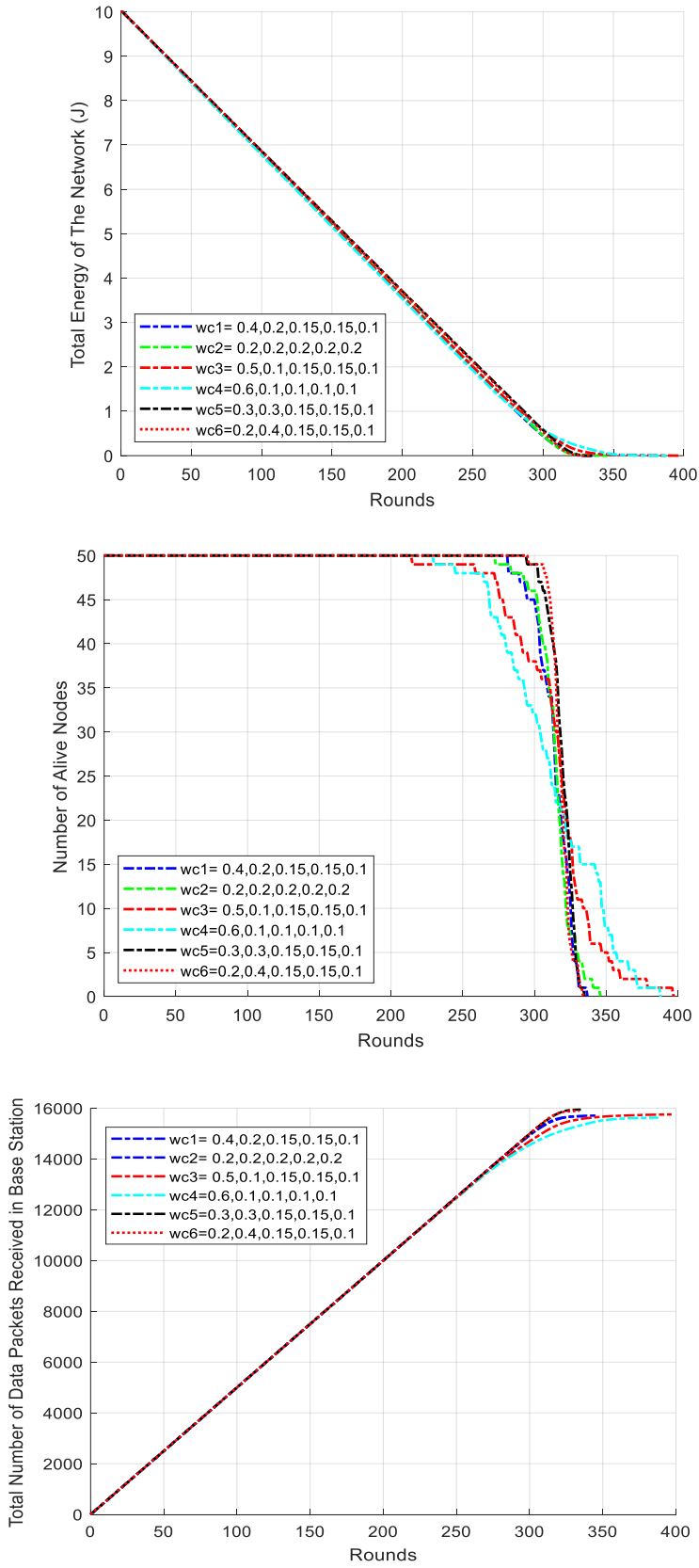
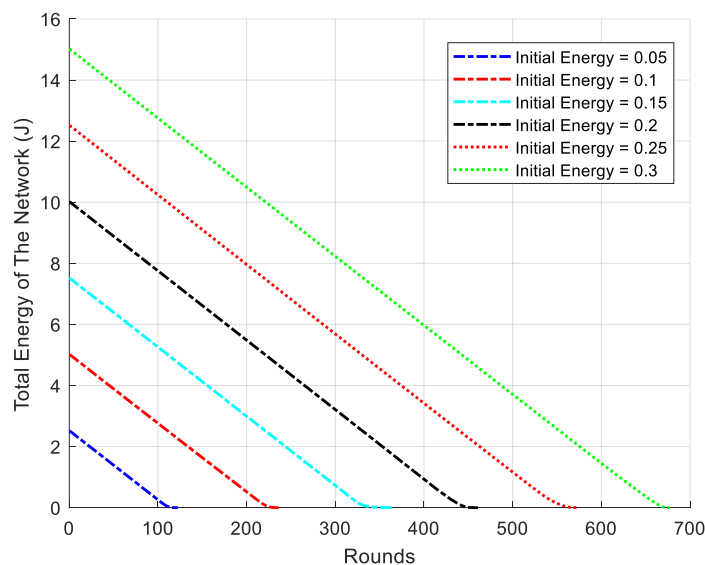


Fig 15. Impact of initial energy of nodes on the output parameters TREPR, NANPR, and the throughput

As for the network parameters inserted in table 4, size of the two-dimensional area of interest is supposed 100 m × 100 m to accentuate the single-hop scheme of the proposed model. The role of parameters N (number of sensor nodes) and C (number of clusters), were previously examined in the form of three scenarios in section 6.3. As it can be reviewed, increasing the number of nodes meaningfully results in throughput improvement. However, for the FND, this relation is not implicit. The effect of changing the initial energy of nodes, E_{init} on the performance of the proposed model is shown in table 11 and figure 13. The higher the energy level of nodes the longest the lifetime indices. Network parameters including E_{elec} , E_{fs} , E_{mp} , d_0 and E_{DA} have taken their values according to the energy model described in section 4.1 and are all constant (Heinzelman, Chandrakasan, & Balakrishnan, 2002). Therefore, two parameters named $Packet_Size$ (length of data packets) and R_{agg} (data aggregation rate) should be investigated. To explore $Packet_Size$ impact on the model's performance, there is an inclusive study done by Suniti et. al (2019). According to this survey, the packet length has direct effect on lifetime performance of the WSN. Selecting long data packets may cause data bit corruption leading to data retransmissions, which ultimately reduces the energy efficiency of the network. On the other hand, shorter packet length may increase data reliability due to fewer chances of data corruption. However, if considering too short data packets, may result in deprivation of energy efficiency due to the standard packet overhead. As can be reviewed in table 12, different data packet lengths were applied as input, and lifetime indices were calculated. It is clear that, the shorter the packet length the longer the FND, HND and LND. Thus, data packet size reversely effects on the lifetime indices of the proposed SFFA in all scenarios regardless of the number of nodes. More exact saying, if the size of the data packet doubles, the FND will be almost halved. Figure 14 depicts the impact of packet length variations on TREPR, NANPR, and the Throughput.

Table 11 Investigation of the effect of different initial energy of nodes on the performance indices

Initial Energy of Nodes (E_{init}) J	WSNs of Scenario #1			WSNs of Scenario #2			WSNs of Scenario #3		
	FND	HND	HND	FND	HND	LND	FND	HND	LND
0.05	90	112	123	88	113	132	85	106	145
0.1	198	218	236	193	221	253	187	236	278
0.15	310	332	351	302	338	375	294	364	413
0.2	430	442	451	416	451	482	404	486	530
0.25	510	553	570	521	540	574	479	581	632
0.3	640	662	688	619	673	721	582	704	792



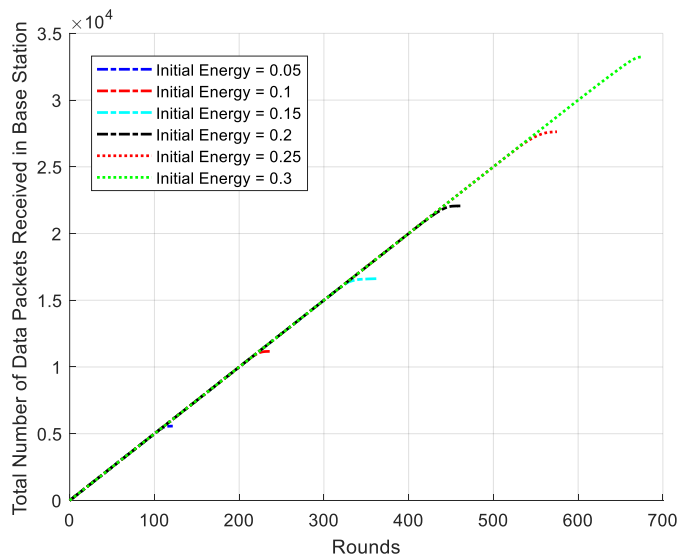
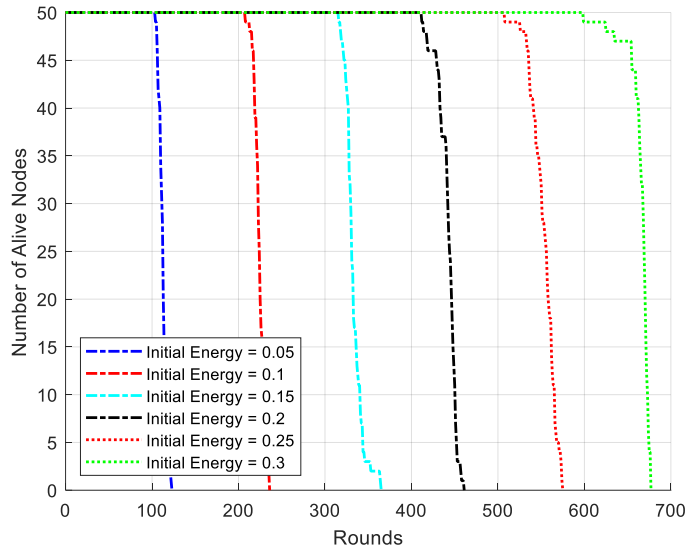


Fig 14. Impact of initial energy of nodes on the output parameters TREPR, NANPR, and the throughput

Table 12. Investigation of the effect of different data packet sizes on the performance indices

Packet Size (bits)	WSNs of Scenario #1			WSNs of Scenario #2			WSNs of Scenario #3		
	FND	HND	HND	FND	HND	LND	FND	HND	LND
1000	1720	1778	1800	1784	1811	1854	1708	1820	2462
2000	859	887	902	856	904	932	821	959	1198
4000	429	442	452	427	452	472	406	496	556
6000	286	289	301	284	298	315	271	326	369
7000	245	252	260	240	261	271	233	280	323
8000	214	221	227	209	228	236	204	245	283
10000	172	176	181	168	182	188	162	196	226

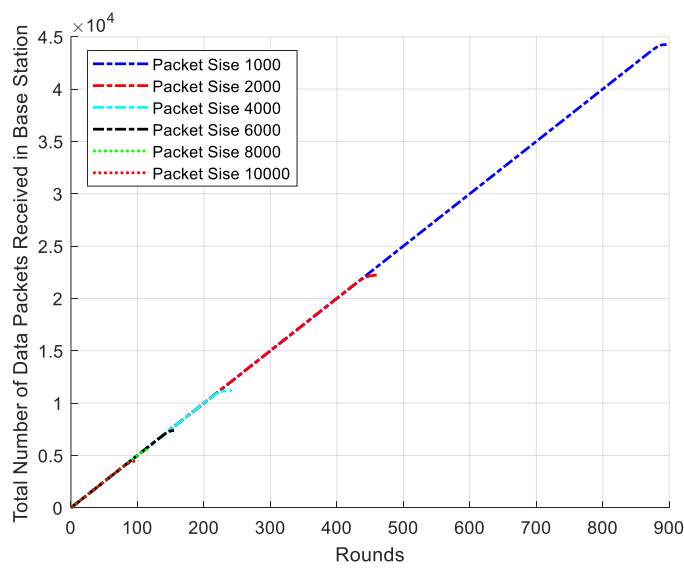
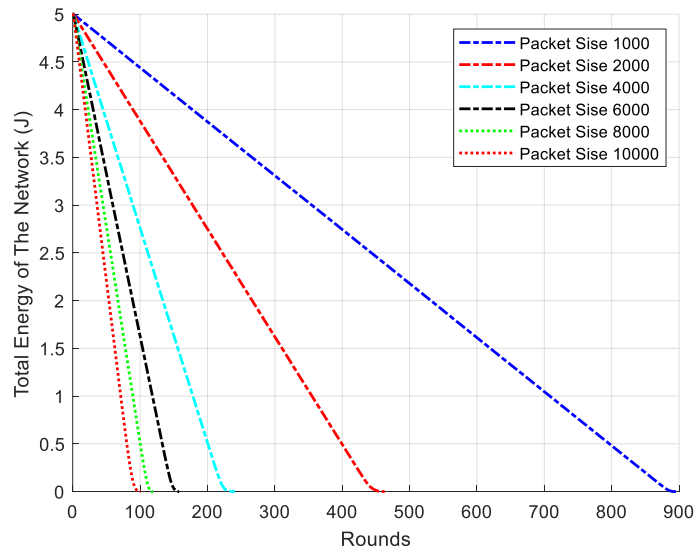
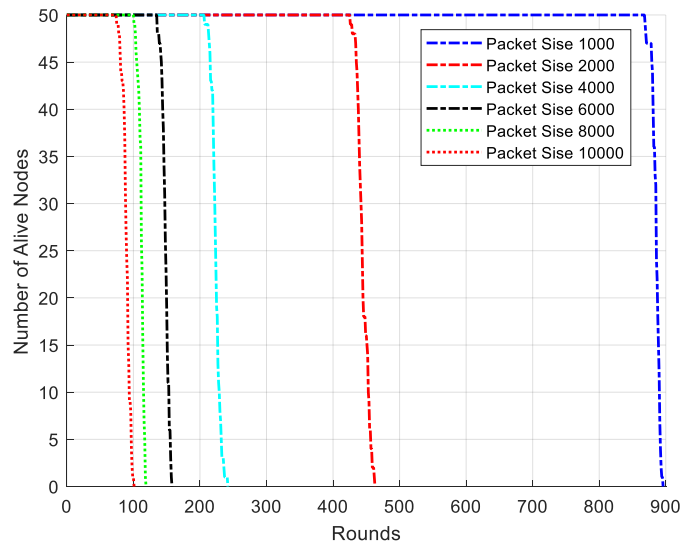
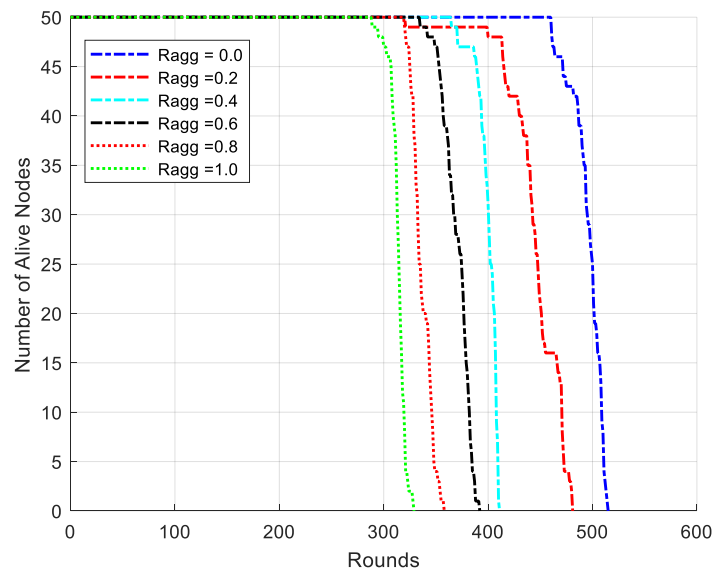
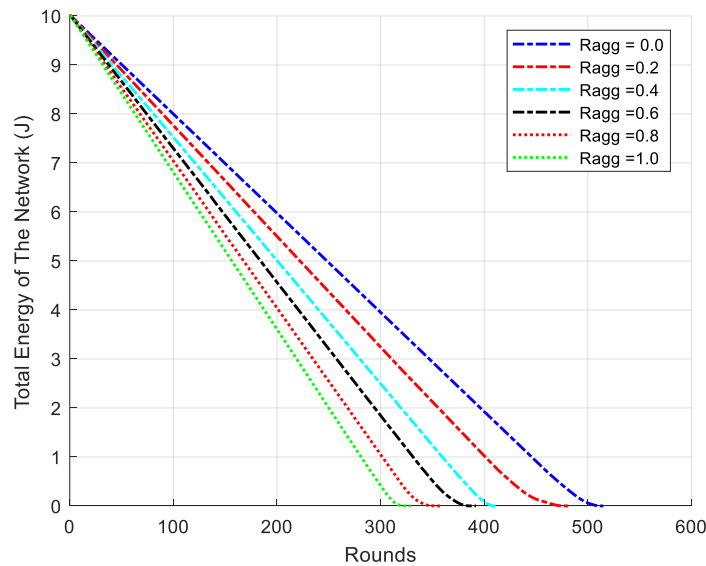


Fig 15. Impact of packet size on the output parameters TREPR, NANPR, and the throughput

As mentioned previously, each selected CH aggregates the received data packets with a predefined ratio (named R_{agg} in Table 4) before transmitting data to the sink. To explore the impact of aggregation ratio on the outcomes of the proposed model, this ratio is set to 0, 0.2, 0.4, 0.6, 0.8 and, 1 respectively. Table 13 and figure16 illustrate R_{agg} impact on the lifetime indices for all WSNs of three scenarios. It should be reminded that in this exploration, for the $R_{agg} = 1$, no data aggregation is done on data packets, whereas for the $R_{agg} = 0$, all data packets will be aggregated first, and then sent to the sink. Outcomes in table 13 show that, if R_{agg} increases the FND increases too. Thus, R_{agg} and FND have a direct impact on each other. However this impact is not linear (Sukhchandani & Sushma 2017).

Table 13. Investigation of the effect of different data aggregation rate on the performance indices

Packet size =4000 (bits)	$R_{agg} = 0.0$			$R_{agg} = 0.2$			$R_{agg} = 0.4$			$R_{agg} = 0.6$			$R_{agg} = 0.8$			$R_{agg} = 1.0$		
	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND	FND	HND	LND
WSNs of Scenario #1	464	497	565	454	463	483	431	441	446	376	398	408	269	338	361	293	315	326
WSNs of Scenario #2	330	530	650	336	482	630	421	461	470	240	417	501	210	342	412	175	330	403
WSNs of Scenario #3	300	518	672	198	493	730	404	486	562	200	420	572	152	354	661	120	332	571



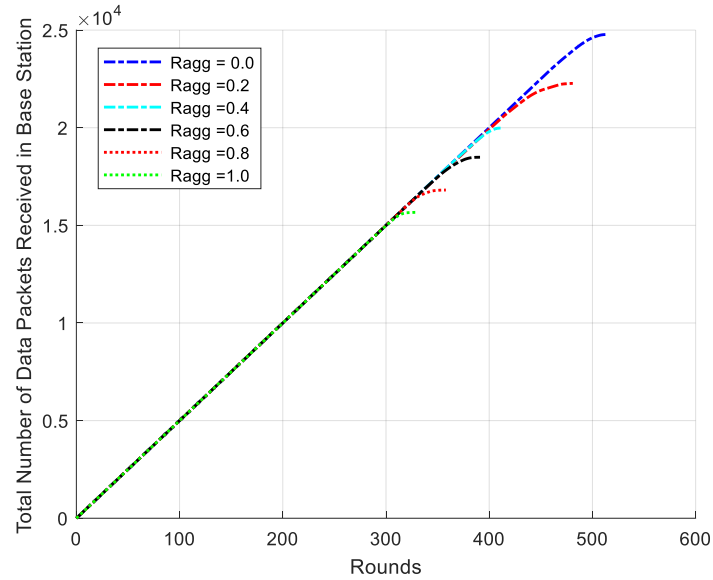


Fig 16. Impact of data aggregation rate on the output parameters TREPR, NANPR, and the throughput

6-5- Discussion

In this section, the average values for all WSNs in the three scenarios are provided in terms of the network lifetime (figure 17) and throughput (figure 18). Considering the mean values in figure 17, the proposed SFFA algorithm can improve the FND by 49.1%, 38.3%, 7.1% and 11.3% compared to LEACH, ERA, SIF and FSFLA in different network scenarios respectively. Moreover, SFFA similarly improves the mean values of HND by 13%, 21%, 12.4% and 15.8% compared to LEACH, ERA, SIF and FSFLA respectively. Likewise, it slightly improves the mean values of LND compared to ERA, SIF and FSFLA. As can easily be inferred from the results, the proposed SFFA can effectively minimize the energy consumption of nodes, and consequently, prolong the network lifetime as well as the overall throughput (figure 18).

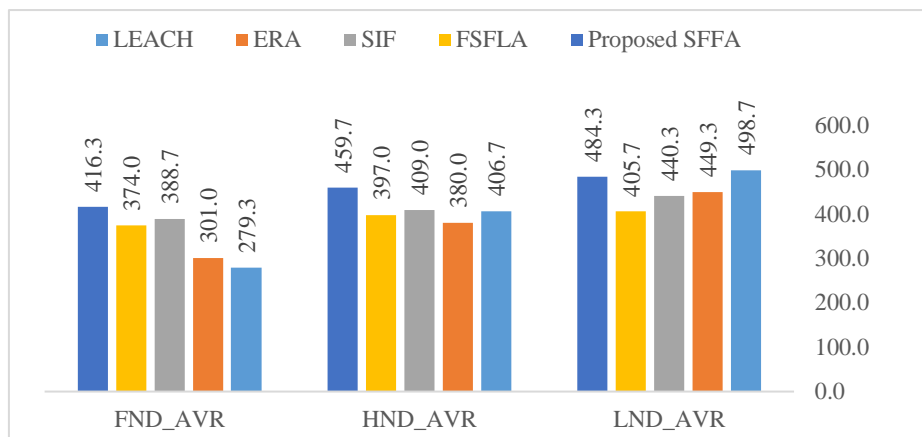


Fig 17. Comparison of the FND (on average) for all WSNs

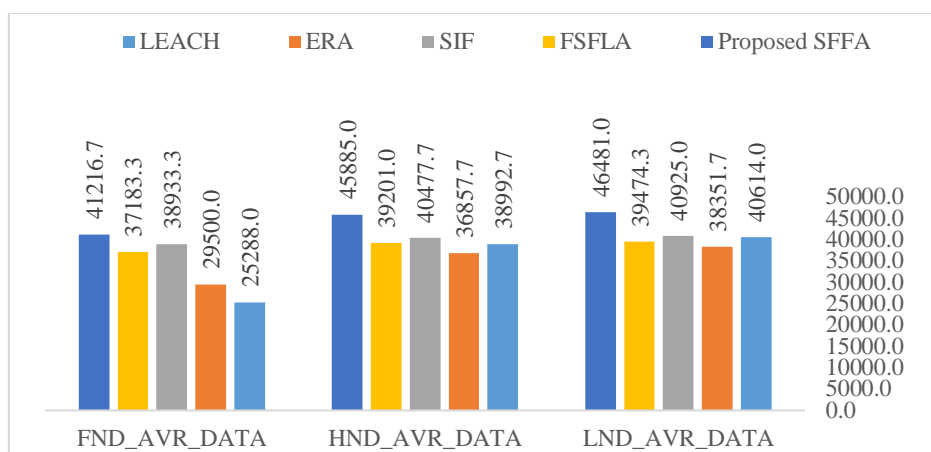


Fig 18. Total average of data packets received successfully to the sink for all WSNs

7- Conclusion

In this paper, a new hybrid clustering Algorithm (SFFA) was proposed which blends two basic nature-inspired metaheuristic algorithms including the firefly algorithm (FFA) and shuffled frog leaping algorithm (SFLA) aiming at energy efficiency and prolonging network lifetime. As presented in Section 6, energy consumption of WSNs as well as the network lifetime were simulated with MATLAB 2017a in different scenarios. Results indicated not only a meaningful performance improvement of the proposed SFFA over its constituents SFLA and FFA in terms of energy dissipation and network lifetime but they also revealed an improvement over the existing protocols including LEACH, ERA, SIF and FSFLA especially in terms of FND and HND. SFFA protocol mainly focuses on the clustering algorithm. Naturally, the routing phase of the protocol should be concentrated on during the next and further studies. Moreover, Although. SFFA has the ability of adapting to new applications through leveraging its controllable parameters; these parameters should be adjust manually. As a future work, Authors aim to utilize an automatic algorithm to tune the controllable parameters of the SFFA based on the application needs.

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