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Energy Efficient Clustering in Wireless Sensors Network using Adaptive Lévy-Flight Firefly Algorithm

Mohammed DEMRI[1,4], Abdellatif RAHMOUN[2] and Mohammed OMARI[3]

[1]*Computer Science Department, University of Tlemcen, Algeria*
[2]*ESI-SBA High School of Computer Sciences Sidi Bel-Abbès, LabRI Research Laboratory, Algeria*
[3]*Computer Science and Engineering Department, American University of Ras Al Khaimah, UAE*
[4]*Laboratoire de Developpement Durable et d'Informatique (LDDI), University Ahmed Draia of Adrar, Algeria*

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Abstract: In Wireless Sensor Networks (WSNs), nodes have minimal energy autonomy. Accordingly, designing routing protocols that reduce the total network energy usage is one of the most challenging tasks in this field. Recent deployments of energy-efficient routing protocols for WSNs have used clustering mechanisms . In this regard, choosing optimal placements of cluster heads is an NP-hard problem that can be solved using a variety of biomimetic meta-heuristic algorithms. The Firefly Algorithm (FFA) is considered as one of the most promising and effective algorithms already used for addressing nonlinear optimization problems in general, and the energy-aware clustering for WSNs in particular. However, when solving complex optimization problems, FFA has a high risk of becoming trapped in the local optimum. Since the randomization operator plays a crucial role in updating particle positions and enhancing its global search (exploration) and convergence (exploitation) behaviors, Lévy flight-based random walk has been deployed to improve the firefly algorithm's searching capability and prevent it from the premature convergence, thereby preventing it from trapping in the local optimum. This paper proposes an Adaptive Lévy-Flight Firefly Algorithm-based Protocol (ALFFAP) to increase the energy efficiency in WSN. MATLAB 2018a is used to simulate and assess the proposed approach, and its performance is compared to that of the classical Firefly algorithm (FFA)-based clustering protocol, LEACH, and LEACH-C. ALFFAP outperforms other protocols regarding the number of surviving nodes, total energy consumption, death of the first node, death of half node, death of the last node, stability period, and the number of data packets forwarded to the Base Station.

Keywords: Energy Efficiency, Wireless Sensor Networks, Firefly Algorithm, Lévy Flight, Routing Protocols, Clustering

1. INTRODUCTION

In WSN, node (or mote) is a small, inexpensive, and low-power device that has been recently emerged due to the advances in wireless communications and micro-devices that combine electrical and mechanical components, so called microelectromechanical systems (MEMS) [1], [2], [3]. Generally, wireless sensor mote is made up of four essential units: a communication unit which has the capability to send/receive messages due to its radio module, a sensing unit that is equipped with one or more sensors used for sensing various physical information (temperature, pressure, light, movement . . . etc.) from the environment, a processing unit that is equipped with a microcontroller and a memory that used for data processing and storage respectively, and a power unit that is equipped with a battery that serves as power supply [2], [3]. WSN is composed of tiny nodes (hundreds to thousands) that can be randomly dispersed in the sensing field and communicate among themselves using radio-wave links [3]. The Base station (BS) or Sink is generally a non-energy constraint node, its main role is collecting the different data packets sensed by different nodes. The collected packets are then sent either to other networks or to an end users located in a remote area. These collected data will be exploited for taking decisions [2]. WSNs is used in various applications including military applications, survival monitoring, traffic control, healthcare systems, intelligent buildings, agriculture surveillance and object tracking [3].

In WSNs, nodes are battery powered and spatially distributed in a hostile and non reachable environment, where their batteries cannot be recharged or replaced once deployed. After a given period, sensor nodes dissipate all of their energy, which can directly affect the network lifetime [4], [5]. Accordingly, one of the primary problems to be addressed in building energy efficient WSNs is overcoming the energy restriction. In this regard, clustering-based routing protocols are widely investigated into optimizing the overall energy dissipation and increasing the network lifespan [6], [5], [7], [8].

Clustering-based protocols operate in rounds. Generally,

E-mail address: demri.med@univ-adrar.edu.dz, a.rahmoun@esi-sba.dz, mohammed.omari@aurak.ac.ae

each round comprised two main phases: firstly, in the setup phase, the network is structured in clusters (groups). For each cluster, one of node members is elected to take the role of the leader or cluster head (CH), secondly, in the steady-state phase, the head of each cluster creates a TDMA (Time-Division Multiple Access) table and communicates it to all members within the same cluster. By their role, members wait for their own time slot in the TDMA table to forward their gathered packets to their own CHs. Moreover, each cluster head collects its own packets and send it directly to the sink according to different sets of CDMA (Code-Division Multiple Access) codes [9], [10].

LEACH (Low Energy Adaptive Clustering Hierarchy) is a very popular clustering-based energy-efficient routing scheme [11], [12]. LEACH is distributed and aims at preserving the overall energy of sensor nodes in WSN and hence, maximizing the network lifespan. Each round in LEACH is split into two parts: setup and steady-state. Clusters are formed in the first stage after a random determination of cluster heads. For any given round, all nodes generate an arbitrary number in the interval of (0, 1). Nodes those their randomly generated number is below the calculated threshold, $T(n)$ declare themselves as a final cluster heads. $T(n)$ is calculated using Eq.1.

$$T(n) = \begin{cases} \frac{p}{p*(r \bmod (^1/_p))} & if\ n \in G \\ 0 & elsewhere \end{cases} \quad (1)$$

Here, p stands for the predetermined proportion of cluster heads that should be selected in each round; n denotes the current node eligible to be selected as CH; G stands for the set of nodes non nominated as cluster heads in the previous $1/p$ rounds, and r represents the actual round. In the steady-state step, clusters are formed and for each cluster, members send their own sensed data packets to their own cluster head according to the TDMA table. By their roles, CHs aggregate all data packets received from node members and forwarded to the BS[6].

LEACH offers a significant energy savings and prolonged network lifespan when compared to many energy-aware routing schemes [11]. However, during the clustering process, the remaining energy of nodes is not taken into consideration . Accordingly, even nodes with few remaining energies could be selected as CHs, which leads them to dissipate their battery and decreases the network lifetime[6]. Moreover, using LEACH, the number of cluster heads that was previously predetermined is not taken into account and their positions are not uniformly dispersed on the sensing field [13].

LEACH-C (LEACH-centralized) protocol was proposed in [12] as an improved version of LEACH, were the clustering process is centralized and performed by BS. Similarly to LEACH, LEACH-C operates in two phases. During its setup stage and at the start of each round, nodes communicate their positions and residual energies to the base station. By its role, the BS selects a predefined number of cluster heads using information already received form nodes. To guarantee that the energy usage is equally distributed amongst all sensor nodes, BS firstly calculates the average energy for all nodes, and those with residual energy less than this obtained average, are excluded from being elected to act as final CHs in this current round. For the non-excluded nodes, the challenge of finding the optimal cluster heads is regarded as NP-hard, where the simulated annealing algorithm is applied by the BS to solve it. In LEACH-C, the steady-state phase is analogous to LEACH . According to the findings obtained in [12], LEACH-C considerably brings improvements to LEACH especially regarding the network lifespan, and this achievements are due to its novel strategy of selecting optimal CHs at the base station level.

To enhance the performances obtained using LEACH and LEACH-C algorithms that was involved prolonging the network lifetime, several evolutionary algorithms such as genetic, particle swarms and bee colony algorithms have been investigated in this field [14].

Various meta-heuristic algorithms have been investigated throughout the last decades to resolve hard and complex non-linear optimization issues. However, the majority of conventional optimization strategies utilized to solve several optimization problems are generally deterministic and can easily be trapped in the local optima, and have an unbalanced exploration/exploitation [15].

Xin-She Yang [13] firstly proposed Firefly Algorithm (FFA) as an efficient biologically inspired algorithm to solve nonlinear and complex optimization problems. The simplicity and efficiency of FA are the main motivations behind its use [16]. However, it suffers from premature convergence in most cases and the possibility to get trapped in local minima is very high as well as its global search capability is restricted [13],[17]. Limitations of FFA can be overcome by combining it either with other meta-heuristic algorithms[18] or with the Lévy flight random walk [19].

Lévy Flight (LF) represent a sort of random process (walk) with a strong ability to improve the performances of the optimization algorithms throughout exploration and exploitation stages, thus escaping from local optima [20], [21], [22]. Furthermore, compared to the Brownian random walks, LF has proved its effectiveness in terms of exploring unidentified search spaces [23].

The main objective of this research is reducing the node's energy dissipation during data sensing and transmission. Consequently, this energy saving results in considerably increasing the amount of data packet delivered to the BS. Due to its searching capability, robustness, and self-organization, the swarm intelligence is primarily used in this study. The major contributions of the present work are summarized as the following:

1) Defining the clustering issue that optimizes the energy consumption for each node, consequently, increases the network lifespan for a long period.
2) Applying an Adaptive Lévy-Flight Firefly algorithm-based routing protocol for optimally selecting the best cluster heads positioning, considering their

residual energies as well as their distances to the BS.
3) The investigated methodology is assessed through simulation. The obtained findings are evaluated and compared to those achieved using LEACH, LEACH-C, and FFA algorithms, and this based on different metrics such as the number of living nodes, the network lifetime, the overall remaining energy, the first dead node (FDN), the half dead node (HDN), the last dead node (LDN), the stability period as well as the amount of data packets delivered to the sink.

The forthcoming sections of this research are outlined as follows: In the 2^{nd} section, a brief overview of some prior works in relation to the energy efficiency in WSN is presented. Before giving an overview on the Lévy-Flight Firefly algorithm, both Firefly algorithm and Lévy flight are briefly presented in the 3^{rd} section. The 4^{th} section highlights the deployed model. The proposed approach is explained in detail the 5^{th} section, whereas the 6^{th} section gives the experimental setup and the results obtained by simulating the proposed model. Finally, conclusion and directions for conducting further researches are given in the 7^{th} and last section.

2. RELATED WORKS

Over the last years, biologically inspired meta-heuristic algorithms have been widely investigated in computational intelligence [21], [24], [25]. Clustering based routing strategies in WSN is one of the most motivating areas where these algorithms can be extensively used [7], [10], [14].

A. Nadeem et al.[26] developed a novel energy-aware clustering protocol for WSN using FFA. Herein, aiming at reducing energy usage in each iteration, FFA was used for selecting the optimal CHs taking into consideration the distance of CH candidate to its members as well as its distance to the base station, The obtained results revealed that the death rate of nodes decreases, and this is due to the adoption of FAA to find optimal CHs in WSNs. The main limitation of the conventional FFA, however, is the premature convergence and the high probability of being trapped in the local optimum. Neither of these two issues was targeted in this study.

M. Baghouri et al. [27] applied FFA to optimize the overall network energy usage. In this regard, their approach depends on the maximum number of nodes that are eliminated from being selected as cluster heads. Here, the closest nodes to the BS are excluded from the group of eligible CHs. To extend the network lifetime, the authors employed the FFA to determine the optimal number of cluster heads alongside the number of eliminated nodes. Compared to ITDEEC and TDEEC routing protocols, their findings show that the proposed technique can considerably extend the network lifespan and increase the number of messages sent to the base station. Perhaps the most serious disadvantage of this method is that even nodes with higher energy level will be eliminated from cluster heads selection process. Moreover, authors did not address the global search behavior of their proposed algorithm.

M. Baskaran and C. Sadagopan[28] addressed the premature convergence and local minimum issues by proposing a synchronous Firefly algorithm as a hybrid Firefly heuristic optimization technique for the energy efficiency in WSN. Herein, the light intensity related to each firefly is mapped to its objective function involved for optimally selecting cluster heads positioning in a cluster-based WSN. In terms of reducing the packet loss ratio and improving energy efficiency, their findings have shown that the investigated clustering scheme outperforms both LEACH and Energy Efficient Hierarchical Clustering (EEHC) protocols. However, the proposed approach does not take into account the communication distances, and the hybridization process seems to be complex (selecting best fireflies, crossover, mutation) which may directly affect the overall complexity of the algorithm.

B. Pitchaimanickam and G. Murugaboopathi [29] investigated HFAPSO that stands for Hybrid Firefly Algorithm with Particle Swarm Optimization for determining the optimal locations of Cluster heads for the LEACH-C protocol . Herein, FFA is combined with PSO to improve the global search behavior of firefly particles. To be selected as final CH, node' remaining energy and its distances to the base station are taken into consideration. Their findings revealed remarkable improvements in enhancing the energy effeciency in WSN when compared to the traditional FFA. One major drawback of this approach is the obtained findings that were not compared to those obtained using the classical PSO algorithm since it demonstrated its efficiency in globally exploring the search space.

A. Barzin et al. [30] combined a modified Shuffled frog-leaping algorithm (SFLA) with Firefly algorithm to investigate the use of a hybrid SFFA as an adaptive scheme for designing an optimal clustering-based protocol for WSN. SFFA where the initial population is divided into two sub-populations P1 and P2. FFA runs on P1 and SFLA runs on P2. In SFLA, local search enhancement was achieved on the basis of Lévy flight mechanism. SFFA is a multi-objective swarm intelligence-based algorithm that considers several measures, including residual energy of nodes, intra-cluster and inter-cluster distances, distances from the sink, overlap and the load of clusters into selecting the optimal CH's positioning at each round. The proposed algorithm runs in different scenarios and has demonstrated its effectiveness when compared to LEACH, SIF, and FSFLA algorithms. The main weakness of this approach is that Lévy flight-based random walk was partially applied (only with SFLA) into enhancing its global search capability.

However, even though many researches have investigated using Firefly algorithm for optimally selecting cluster head's positioning in an energy efficient cluster-based WSN, there has been very little research conducted on improving the global search behaviour of fireflies particles by combining FFA with other existing swarm-based meta-heuristic techniques. But, no previous research has adapted Lévy-flight firefly algorithm to be applied as a clustering approach. Therefore, the present work adapted the Lévy-Flight

Firefly algorithm for optimizing the process of clustering in WSN, whereby Lévy flight is combined with FFA to improve its randomness parameter.

3. LÉVY-FLIGHT FIREFLY ALGORITHM

A. *Firefly Algorithm*

FFA is an efficient and promising meta-heuristic algorithms inspired from the nature and was originally created in 2007 by Xin-She Yang [31] to resolve NP-hard global optimization issues. FA is motivated by the blinking property of fireflies to lure others for mating and predation purposes. This biological phenomenon is based on the three major rules [13]:

1) Fireflies are of the same sex; hence, any firefly is always in attraction to others independently of its gender.
2) The attractiveness of any firefly particle is proportionate to its light intensity. Therefore, the less brilliant firefly is always attracted to the more brilliant one. In such a scenario in which no firefly is brighter than a given one, this latest will move arbitrarily in the search area. For any firefly, the luminosity reduces as the distance from it grows. This reduction is due to the light absorption when passing through the medium.
3) For solving any optimization issue, the cost function related to a given firefly particle is always proportional to its light intensity.

The light intensity is utilized to determine the light spread ratio over the surface and at a given distance from the origin. The light intensity changes its value depending on the inverse square law as follows:

$$I(r) = I_0 exp(-\gamma {r_{i,j}}^2) \tag{2}$$

Here, $I(r)$ is the light strength over a distance r, I_0 denotes the intensity of light emitted at the source and γ represents the medium absorption coefficient. For a given firefly, the attractiveness β is given by the Eq. 3.

$$\beta = \beta_0 \exp(-\gamma {r_{i,j}}^m) \tag{3}$$

Where β denotes the attractiveness at the distance $r = 0$ and $r_{i,j}$ indicates the Euclidian distance between two fireflies particles those their locations are x_i and x_j respectively. This distance $r_{i,j}$ is given by Eq. 4.

$$r_{i,j} = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{4}$$

Where, the i^{th} firefly is characterized by $x_{i,k}$ as the k^{th} element of its x_i coordinate; the j^{th} firefly is characterized by $x_{j,k}$ as the k^{th} element of its x_j coordinate and d denotes the dimension size.

```
Algorithm 1: Pseudocode of Firefly Algorithm
Objective function: f(X) ,  X= (x1, ... xd);
Randomly generate an initial population of n fireflies xi ( i=1,2,...,n);
Define the objective function f(xi ) of each firefly xi ;
Define the light intensity Ii at xi according to the cost function f (xi);
Define the light absorption coefficient γ;
While (gen < Max Generation)
  For i = 1: n
    For j = 1:n
      If Ij > Ii
        Move xi towards xj using Eq.(5);
      End if
      Firefly attractiveness is varied with distance r using Eq.(2);
      Evaluate new solutions and update the light intensity;
    End For j
  End For i
  Rank the Fireflies and select the best;
End While
Post-processing the results and visualization;
```

Figure 1. Pseudocode of Firefly Algorithm[31]

A firefly i moves in the direction of a firefly j with higher intensity as the following:

$$x_i = x_i + \beta_0 e^{-\gamma r_{i,j}^2}(x_j - x_i) + \alpha * rand(0, 1) \tag{5}$$

Here, the 2^{nd} expression denotes the firefly's attractiveness, whereas the 3^{rd} expression α represents the randomization operator. According to all the details mentioned above, Fig.1. illustrates the main pseudocode of the conventional FFA.

B. *Lévy Flight*

In 1937, Paul Lévy (1886-1971), a French mathematician, first suggested a stochastic process called the Lévy process [32]. Lévy flight is a class of non-Gaussian arbitrary walk that has been proposed by researchers by studying the foraging pattern of many creatures (spider, fruit flies, monkeys, wasps, humans, jackals...) in nature, and its coherence with the characteristics of the Lévy process, where steps follow a power-law distributed step-length to give random-walk. Steps are drawn from a heavy-tailed distribution that is also called Lévy stable distribution [20], [21], [22].

$$Levy\,(s,\beta) \ \sim |s|^{-1-\beta}, \ \ where \quad 0 < \beta < 2 \tag{6}$$

where s and β denote the step length and the Lévy index,

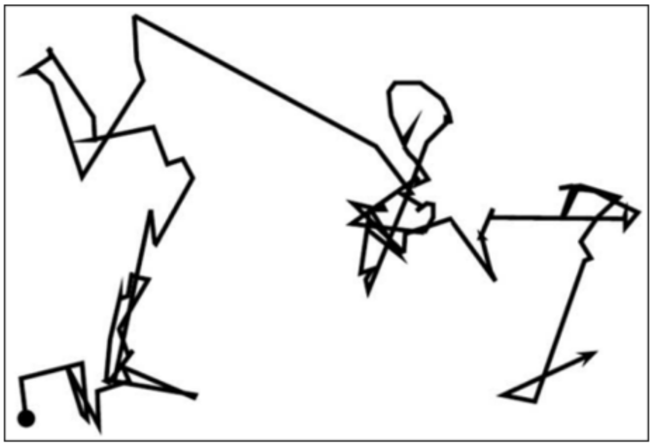

Figure 2. Sequence of 50 consecutive Lévy flights steps

respectively.

For generating a random walk, we must define two features, its step length and direction. The step length follows the Lévy distribution. Several methods can be used to calculate these characteristics, but the basic and powerful one is the so-called Mantegna's algorithm used in the symmetric and stable Lévy distribution [23]

$$s = \frac{u}{|v|^{1/\alpha}} \tag{7}$$

Samples of two normal stochastic variables v and u are derived from a variance of σ_u and σ_v respectively, and Gaussian normal distribution where the mean is equal to zero as the following:

$$u \sim N\left(0, \sigma_u^2\right), \quad v \sim N\left(0, \sigma_v^2\right) \tag{8}$$

The variances can be calculated by:

$$\sigma_u(\alpha) = \left[\frac{\Gamma(1+\alpha)\sin(\frac{\pi\alpha}{2})}{\Gamma\left(\frac{(1+\alpha)}{2}\right)\alpha 2^{\frac{(\alpha-1)}{2}}}\right]^{1/\alpha} \quad and \quad \sigma_v = 1 \tag{9}$$

The distribution for the step s follows the predictable Lévy distribution for $|s| \geq |s0|$, where $s0$ denote the shortest step length and Γ denote the Gamma function that can be estimated using Eq. 10 as follows:

$$\Gamma(1+\beta) = \int_0^\infty t^\beta e^{-1} dt \tag{10}$$

As illustrated in Fig.2, using this pseudorandom number algorithm, 50 different step sizes have been taken to form a series of 50 steps of Lévy flights.

By observing Fig.2, it is evident that the random walk of the Lévy flight suddenly changes big steps after a series of small steps, giving the firefly particle the opportunity to suddenly leap, helping the algorithm jump out of the region where the local optimum is located , preventing premature convergence of the algorithm, and increasing the ability to search globally.

Algorithm 2: *Pseudocode of Lévy-Flight Firefly Algorithm*

```
Objective function: f(X) ,  X= (x1, ... xd);
Randomly generate an initial population of n fireflies xi ( i=1,2,...,n);
Define the objective function f(xi ) of each firefly xi ;
Define the light intensity Ii at xi according to the cost function f (xi);
Define the light absorption coefficient γ;
While (gen < Max Generation)
  For i = 1: n
    For j = 1:n
      If Ij > Ii
        Move xi towards xj via Lévy Flights using Eq.(11);
      End if
      Firefly attractiveness is varied with distance r using Eq.(2);
      Evaluate new solutions and update the light intensity;
    End For j
  End For i
  Rank the Fireflies and select the best;
End While
Post-processing the results and visualization;
```

Figure 3. Pseudocode of the Lévy-Flight Firefly Algorithm [19]

C. *Lévy-Flight Firefly Algorithm*

To eventually improve the standard FA randomness parameter, Xin-She Yang [19] merged Lévy flight random walk with the Firefly search technique to originate the Lévy-Flight Firefly Algorithm (LFA), The pseudo-code shown in Fig. 3. According to LFA, each firefly can move toward anther firefly by modifying Eq. 5 as follows:

$$x_i = x_i + \beta_0 * e^{-\gamma * r_{i,j}^2}(x_j - x_i) + \alpha * sign\left[rand - 1/2\right] \oplus L\acute{e}vy \tag{11}$$

In the above equation, the 2^{nd} expression is related to the attraction as well as the randomization operator via Lévy flights is achieved using the third expression with α as a randomization term. The operator $\oplus$ indicates entry-wise multiplications. While a random step size is being drawn by Lévy distribution, the term $sign[rand - 1/2]$ gives a random sign or direction.

4. THE DEPLOYED MODELS

A. *Network Model*

The following properties of the free space model are considered for simulating the network in our proposed ALFFAP algorithm [7]:

- The BS is stationary and placed in the middle of the sensing area.

- The BS has no restrictions regarding energy, and its computing capabilities are very high.
- Sensors are unaware neither of their precise locations nor locations of other sensors.
- The packet size of collected data from each node is identical.
- All nodes are fixed, randomly deployed, and have a limited energy.
- The task of sensing is performed periodically by all nodes and the sensed data are sent to the BS.
- In each round, all nodes have the same chance to be elected as CH.
- Based on its distance from the receiver, each node can transmit at different power levels.
- The network is designed to work in rounds. Every round starts by a clustering phase followed by a data gathering one.

B. Energy Consumption Model

For computing the energy dissipated by a sensor node while using the radio electronics or the power amplifier , the first order radio model [11] was adopted. The free space channel is utilized in this model in the case where the distance from the sender to the receiver does not exceed a predefined threshold value d_0, and the multi-fading channel is used otherwise. Let E_{elec}, be the energy needed by the electrical circuit and let ε_{fs} and ε_{amp} be the energy of the transmit amplifier in free space and multi-path channels respectively. For sending a packet of k bits over a distance say d , each node consumes quantity of energy according to the following equation:

$$E_{TX}(k,d) = \begin{cases} k * E_{elec} + k * \varepsilon_{fs} * d^2 & d < d_0 \\ k * E_{elec} + k * \varepsilon_{amp} * d^4 & d > d_0 \end{cases} \quad (12)$$

To receive a packet of k bits over a distance say d, the amount of energy dissipated by each node is calculated using Eq.13 as the following:

$$E_{RX}(k) = k * E_{elec} \quad (13)$$

According to the obtained value of a threshold d_0, the distance between tow can be judged as short or long. The value of d_0, is calculated as follows:

$$d_0 = \sqrt{\varepsilon_{fs} / \varepsilon_{amp}} \quad (14)$$

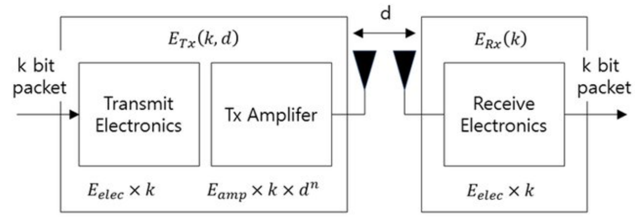

Figure 4. The Energy Model

5. PROPOSED APPROACH

The main issue regarding our proposed approach is designing a novel FFA-based energy-aware routing methodology based on an adaptive Lévy flights-firefly algorithm for choosing the optimal positioning of k different cluster heads minimizing the multi-objective cost function involved in this study.

The proposed protocol is centralized, where the BS runs the clustering algorithm to optimally divide the network into clusters. The proposed algorithm operates in rounds. Each round begins with a setup phase, in which the best k cluster heads are determined and clusters are formed, then ends with a steady state phase, in which the sensed packets are gathered delivered to the sink.

A. Cluster Heads selection

Our approach is inspired from the social behaviors of fireflies combined with Lévy flight random walk, where we suppose that the network contains S sensors (firefly particles). Each sensor s represents a solution (candidate or final CH) with a cost value $f(s)$ that is proportional to the light intensity of its corresponding firefly. The attractiveness β_s represent the power of the firefly s in attracting other fireflies. For a wireless sensor network including S randomly deployed sensor nodes and K clusters. Each cluster CH_i has M nodes members, the network can be clustered as follows:

1) Initially, at the first round the K cluster heads are selected similarly to the LEACH-C protocol.
2) From the second round, cost-based switching takes place in which each firefly that represents a CH looks among its members for one of eligible cluster heads candidates with the higher intensity value for shifting the head's role to it, and this by moving towards it using Eq.11. If it does not exist, the firefly uses the global random search where it moves randomly via Lévy flight according to the stochastic equation for random walk as follows:

$$x_i^{t+1} = x_i^t + \alpha \oplus Levy(\beta) \quad (0 < \beta \leq 2) \quad (15)$$

Where, $\alpha > 0$ represents the step length that can be preset by the user (in most cases, $\alpha = 1$), and its value is dependent on the size of the problem; the product $\oplus$ represents the entry-wise multiplications; β represents the stability index (Lévy index).
Once randomly moved, firefly compares its intensity

to the new eligible cluster head obtained to decide whether shifts the role to it or stay as CH candidate for the next generation.

In our approach, K optimal cluster heads are chosen according a novel multi objective cost function that considers three sub-objectives including the remaining energy of nodes candidates, their distances to the sink and their intra-cluster distances if they are selected as CHs. The cost function adopted for the optimal clustering in ALFFAP is defined as the weighted average of the objective functions involved as following:

$$cost = Maximize\{\alpha_1 * f_1 + \alpha_2 * f_2\} \tag{16}$$

Where α_1 and α_2 are constant for the weighting adjustment of the relative importance of sub-cost terms f_1 and f_2 respectively. The summation of these weights should be equal to 1. Hence, the importance of each sub-cost term involved is proportional to its weight. The first sub-cost function f_1 can be utilized to guarantee that the chosen CHs are those with maximum residual energy level as shown in Eq.(17) as follows:

$$f_1 = \frac{E_{res}(CH_i)}{\sum\limits_{j=1,2,\ldots,M} E_{res}(m_{i,j})} \qquad \forall i = 1, 2, ..., K \tag{17}$$

Where $E_{res}(CH_i)$ and $E_{rem}(m_{i,j})$ are the residual energies of a given CH_i and its members m_j respectively. The chance of a node of becoming a CH increases as its remaining energy increases. Since CHs are in charge of forwarding the gathered data to the BS, it is critical to select CHs with higher energy level. The second sub-cost function f_2 is used to guarantee that selected CHs are in minimum distance with the base station. $f2$ can be expressed as the following:

$$f_2 = \frac{dist_{i=1,2,\ldots,K}(CH_i,\ BS)}{\sum\limits_{j=1,2,\ldots,M} dist(m_{i,j},\ BS)} \tag{18}$$

Where $dist(CH_i,\ BS)$ denotes the Euclidian distance between a given CH_i and the BS, $dist(m_{i,j},\ BS)$ represents the Euclidian distance between a node j assigned to a CH_i and the base station. With minimum $f2$ value, CHs will consume less energy by forwarding huge amount of data packets for short distances.

B. Clusters Formation and data gathering

In this phase, sensor nodes transmit their sensed data packets to their Cluster head within their time slot in the TDMA schedule created by each Cluster head. CHs forward the collected data packets to the Base station. If any node found itself to be an isolated node (has no CH) , it will send its sensed data packets directly to the base station.

Fig.5 illustrates the pseudocode of the adaptive Lévy-Firefly algorithm applied for selecting the optimal cluster heads positioning.

Algorithm 3: *Clustering using Lévy Firefly Algorithm*

```
γ : Coefficient of absorption;
Ii : Light intensity depending on the cost function f (si);
E: Energy level of a node;
Max_Gen: Maximal number of generations;
Begin
  Deploy N nodes randomly;
  Initialize fireflies si (i=1,2 ,..., n);
  Define the cost function of each firefly at si as f(si );
  Define the light intensity of firefly i at si as Ii according to the cost function f(si );
    Set Round =1;
      Run LEACH-C algorithm for the clustering and data gathering;
      Assign one firefly to each node;
    Set Round =2;
    Set Gen =1;
    While Round < Max_Round
      While (Gen <Max_Gen)
        For i = 1: K
          For j = 1:M
            Calculate the light intensity Ii at si by f(si );
            Calculate the light intensity Ij at sj by f(sj );
            If Ij > Ii
              Move Si towards Sj using equation (11);
              Else
                Move Si randomly via Lévy Flight using equation (15);
            End if
            Firefly attractiveness is varied with cost function;
            Set the closest node to Si as CH candidate and update its light intensity;
          End For j
        End For i
        Gen= Gen+1;
      End While
      Rank Fireflies (nodes) and set the best CHs candidates as Final CHs;
      Round=Round+1;
    End While
  Clusters formation and data gathering;
End
```

Figure 5. The pseudocode of the proposed ALFFAP algorithm

Fig.6 illustrates the general flowchart of the adaptive Lévy-Firefly algorithm applied for selecting the optimal cluster heads positioning.

6. SIMULATION RESULTS DISCUSSION

A. Simulation Parameters

The experimental setup and performances of the proposed ALFFAP algorithm are simulated and validated in MATLAB R2018a running on Windows 10 64-bit operating system with an Intel (R) core (TM) i5-4590 CPU and 8 GB of RAM. The motivation behind choosing MATLAB is its high capacity in performing mathematical operations and data analysis. In our simulation, 100 nodes are arbitrarily deployed in a sensing aera with 200m2 of size. The performances of our scheme are analyzed and evaluated when compared to both LEACH[11], LEACH-C [12], and the standard FFA algorithms, and this in terms of various evaluation metrics such as energy consumption, alive nodes, the number of data packets delivered to the base station, FDN, HDN, and LDN. The simulations continued until the death of all nodes. Table I and Table II summarize the various parameters considered for the simulation of the proposed methodology and Lévy-Flight Firefly algorithm respectively. These simulation parameters are the same as those considered in FFA, LEACH and LEACH-C algorithms.

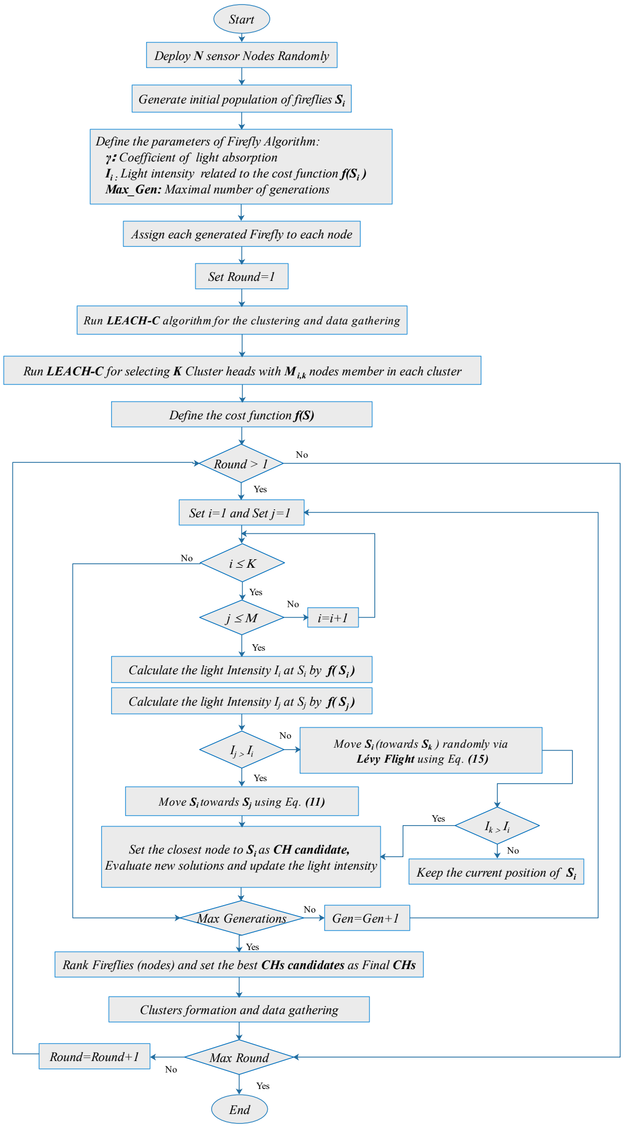

Figure 6. The flowchart of the proposed ALFFAP algorithm

B. Performance Metrics

Several metrics are widely used in the literature to assess the performance of clustering-based routing schemes [30]. In this study, few of these metrics are used for assessing the performances of the proposed algorithm:

1) *Energy consumption*: it defines the sum of energy consumed by sensor nodes during each round.
2) *The network lifetime*: the period that begins with the starting of the network simulation and ends with the death of all nodes.

TABLE I. Radio Model Parameters

Parameter	Value
Sensing field area	200 m^2
Number of Sensors(S)	100
Initial energy	0.1 J
Location of the base station	(50,50)
Packet Size	400 bits
Percentage of Cluster Heads	10%
Transmit amplifier (free space) ε_{fs}	10 $pJ/bit/m^2$
Transmit amplifier (multi-path) ε_{amp}	0.0013 $pJ/bit/m^4$
Transmitter/Receiver Electronics E_{elec}	50 nJ/bit
Data aggregation energy ($_{da}$)	5 $pJ/bit/msg$

TABLE II. Parameters of Lévy-Flight Firefly Algorithm

Parameter	Value
Max of generations	50
Number of particles(Fireflies)	100
α	1
β	1
γ	1

3) *Number of alive nodes*: nodes that are still alive for a given round. The high this number is, the network performance has been improved.
4) *Stability Period*: The period that begins with the start of the network simulation and ends with the death of the first sensor node.
5) *First Dead Node (FDN)*: The number of rounds related to the death of the first sensor node. This metric gives us the time when all the nodes are still alive, and it can also indicate the stability period of the network.
6) *Half Dead Node*: The number of rounds related to the death of the half of nodes. This metric indicates that network performs the data gathering even after the death of 50% of nodes.
7) *Last Dead Node*: The number of rounds that takes the last node to die. This metric specifies the time at which the network is no longer operational.
8) *Number of packets transmitted to the BS*: It indicates the amount of data packets forwarded to the BS during each round. The number of living nodes is proportional to the total amount of data packets sent to the sink. The amount of data packets delivered to the BS demonstrates the reliability of the protocol, if a protocol is sending a greater number of packets then obviously, it has greater lifetime.

C. Results and discussion

Fig.7 reports the sum of nodes remaining energy with respect to the number of rounds, for the proposed ALFFAP algorithm in comparison with standard FFA , LEACH, and LEACH-C routing protocols.

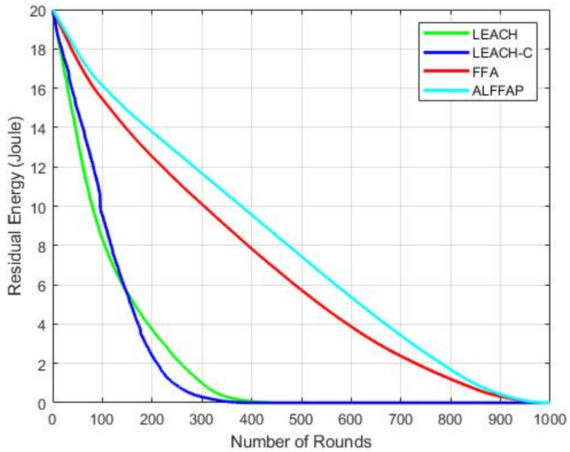

Figure 7. Energy consumption versus number of rounds

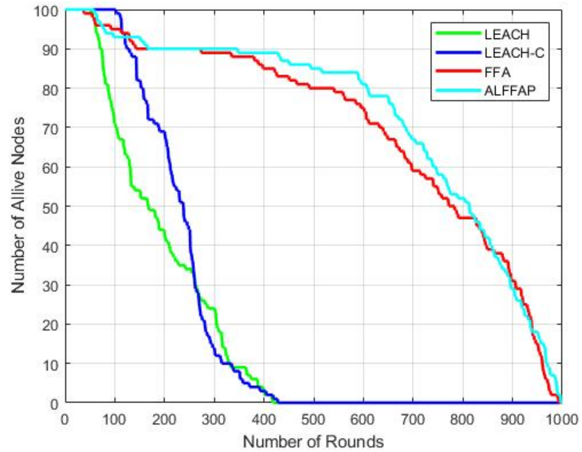

Figure 8. Number of alive nodes over rounds

By observing Fig.7, the remaining energy of nodes gradually decreases with the progression of rounds for all protocols involved. In both LEACH and LEACH-C the entire residual energy of nodes is dissipated at the 400^{th} and the 310^{th} rounds respectively. On the other hand, FFA and the proposed ALFFAP algorithms have the highest values of residual energy and lead some nodes to preserve their energy and remain alive until the 950^{th} and the 1000^{th} rounds respectively. However, the proposed algorithm performs better in reducing the energy consumed by all nodes, and this is due to the fact that it adopts a novel cost function that considers the remaining energy of nodes besides to their distances to the BS before selecting them to act as final CH. Furthermore, using Lévy flight based random walk as searching strategy leads the Firefly algorithm to converge into the optimal CH's positioning by enhancing its global searching capability thus, avoiding being trapped in local optima.

In Fig.8, the network lifetime is defined by the number of living sensor nodes over different rounds for LEACH, LEACH-C, standard FFA, and the proposed ALFFAP methodologies.

As highlighted in Fig.8, it is notable that the number of the remaining living nodes for different investigated schemes gradually decreases with the evolution of rounds; therefore, the increasing number of dead nodes directly affect the network lifetime. Both the proposed ALFFAP and the standard FFA algorithms bring significant improvements into increasing the number of living nodes related to each round then, preserving their lives as long as possible in comparison to the LEACH and LEACH-C algorithms. Indeed, for ALFFAP, some nodes preserve their lives until the 1000^{th} round, whereas in FFA scheme, nodes still living until 996^{th} round. On the contrary, for both LEACH and LEACH-C, all nodes are dead after the 450^{th} and 390^{th} round respectively. This improvement is due to the adopted cost function that excludes nodes with fewer remaining energy form being chosen as CHs, thereby increasing the number of living sensor nodes in WSN.

The network lifetime can be defined as the FDN, HDN and LDN versus number of rounds. Fig.9 reveals that the number of rounds elapsed for the FDN, HDN, and LDN of the network for the proposed ALFFAP approach in comparison the standard FFA, LEACH and LEACH-C algorithms.

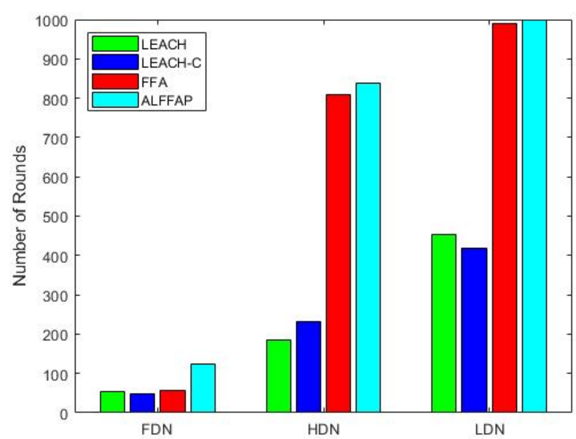

Figure 9. FDN, HDN and LDN vs the number of rounds

It is clearly apparent from Fig.9 that ALFFAP outperforms LEACH, LEACH-C and FFA algorithms in terms of FND, HDN and LDN and the stability period. The first node of ALFFAP dies at the 123^{rd} round whereas the first node of LEACH, LEACH-C, and FFA dies at the 53^{rd} , 49^{th} , and 58^{th} rounds respectively. The half of nodes of ALFFAP dies at the 838^{th} round whereas the half of nodes of LEACH, LEACH-C, and FFA dies at the 158^{th} , 233^{rd} , and 808^{th} rounds respectively. The last node of ALFFAP dies at the 1000^{th} round whereas the last node of LEACH, LEACH-C, and FFA dies at the 418^{th} , 452^{nd} , and 991^{st} rounds respectively. Furthermore, according to the obtained FDN, ALFFAP achieves larger stability period compared to that obtained using others. This significant improvement achieved by the proposed scheme in terms of FDN, HDN, LDN and the stability period is mainly thanks to the optimal selection of CHs which delay the death of the first node, half of nodes, and all nodes.

Fig.10 presents the entire number of packets transmitted to the base station during each round for the three protocols, the proposed scheme, FFA, LEACH and LEACH-C.

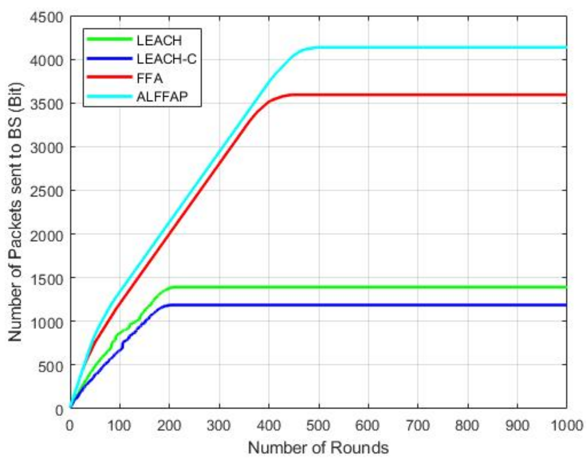

Figure 10. The amount of data packets sent to the BS

From the graph presented in Fig.10 , it is apparent that the amount of data packets forwarded to the sink increases with the progression of rounds. In LEACH and LEACH-C algorithms, no data will be transmitted after the 200^{th} round. Otherwise, for both FFA and ALFFAP protocols the BS still received more data packets until the 420^{th} round and 450^{th} round respectively. These findings prove the efficacy of the investigated scheme in delivering more data packets (4200 bits) especially when compared to LEACH (1400 bits) and LEACH-C (1200 bits). However, the standard FFA (3600 bits) is slightly worse than ALLFAP. This huge number of packets forwarded to the sink achieved using ALLFAP is due to the growing number of alive nodes that forward their sensed packets to their CHs those by their roles deliver these packets to the base station. Furthermore, the less energy consumption provided by ALFFAP leads to a huge extension in the network lifetime thereby, more packets still to be sent to the BS.

7. CONCLUSION AND FUTURE WORK

The FFA is widely used as swarm intelligence-based meta-heuristic technique for solving optimization problems. FFA is simple to implement and rapidly converge towards the optimal solution. However, its primary problem is being stuck in the optimal local solution. In this study, we introduced ALFFAP, a novel energy-aware clustering-based routing algorithm for WSN. In the proposed scheme, the Firefly algorithm was combined with Lévy flight random process to find the optimal locations of cluster heads based on a predefined cost function that considers the remaining energy of sensor nodes, their distances to the base station, and their intra-cluster distances when they are chosen to act as CHs. The simulation results demonstrate that ALFFAP outperforms the standard FFA, LEACH, and LEACH-C when protecting the life of nodes, effectively delaying the death of the first, middle, and last nodes and increasing the network's lifetime. Additionally, the stability period is lengthened, and the amount of data sent to the sink is significantly increased. Because the FFA with LFA as a randomness term can escape from local optima while exploring the search space to find the optimal global solution, the obtained results were entirely predictable. In the future, we intend to investigate MH-ALFFAP, a multi-hop variant of the ALFFAP protocol, to reduce the total energy dissipated by CHs located far from the BS. FFA can also be combined with other randomness parameters (Brownian, Gaussian, etc.), and LFA can be hybridized with other nature-inspired optimization strategies.

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Mohammed DEMRI is currently an assistant professor with the department of Mathematics and Computer Science, Ahmed Draia University of Adrar, Algeria. He received his degree in computer science engineering in 2009 from the Ahmed Tahri University of Bechar, Algeria, and his Magister degree in computer science in 2012 from Abou Bakr Belkaïd University of Tlemcen, Algeria. Presently, he is pursuing his Ph.D. in computer science at the same University and his research activities are focused on energy efficiency in Wireless Sensor Networks and biologically inspired meta-heuristics algorithms.

Abdellatif RAHMOUN is currently a full professor in computer engineering with the Higher School of Computer Science (www.esi-sba.dz); Sidi Bel-Abbès, Algeria. Twenty years in the past, he has been involved in different AI-based research topics including Genetic Programming (GP) , Genetic Algorithms (GA), neural nets, fuzzy systems, hybrid intelligent systems, biometrics, grammar-based GP, strongly typed GP...etc. Presently, He is working on meta-heuristics, machine learning, embedded systems (hardware and software design), and the internet of things.

Mohammed OMARI joined the American University of Ras Al-Khaimah in 2022 as a full professor in the Department of Computer Science and Engineering. He obtained his Ph.D. in computer science in 2005 from the New Mexico Institute of Mining and Technology in the United States. He also obtained a master's degree in computer science from the same university in 2002. In 1995, he obtained a bachelor of engineering degree in computer science from the University of Oran, Algeria. Professor Omari has many research interests, including wireless networks, Adhoc networks, clustering of wireless sensors networks, routing protocols, image and video compression, security, and cryptography.