# Extending the Lifetime of Wireless Sensor Networks Based on an Improved Multi-objective Artificial Bees Colony Algorithm

S. Nebti and M. Redjimi

Original scientific article

***Abstract*— Reducing the sensors' energy expenditure to prolong the network lifespan as long as possible remains a fundamental problem in the field of wireless networks. Particularly in applications with inaccessible environments, which impose crucial constraints on sensor replacement. It is, therefore, necessary to design adaptive routing protocols, taking into account the environmental constraints and the limited energy of sensors. To have an energy-efficient routing protocol, a new cluster heads' (CHs) selection strategy using a modified multi-objective artificial bees colony (MOABC) optimization is defined. The modified MOABC is based on the roulette wheel selection over non-dominated solutions of the repository (hyper-cubes) in which a rank is assigned to each hypercube based on its density in dominated solutions of the current iteration and then a random food source is elected by roulette from the densest hypercube. The proposed work aims to find the optimal set of CHs based on their residual energies to ensure an optimal balance between the nodes' energy consumption. The achieved results proved that the proposed MOABC-based protocol considerably outperforms recent studies and well-known energy-efficient protocols, namely: LEACH, C-LEACH, SEP, TSEP, DEEC, DDEEC, and EDEEC in terms of energy efficiency, stability, and network lifespan extension.**

***Index terms*—Wireless sensor networks, multi-objective optimization, artificial bee's colony optimization, network lifetime extension.**

## I. INTRODUCTION

Wireless communications and mobile computing remain important fields of investigation due to the autonomy of these networks in monitoring and securing inaccessible and highly hazardous environments, such as the bottom of oceans, chemically polluted areas, and volcanic areas. In addition, these networks have come to acquire great importance in many other fields, such as medical or public safety, military, personnel safety, home security, environmental monitoring, earthquake detection, irrigation, and transportation management [1] [2].

Since wireless networks are often deployed in inaccessible and critical detection areas, their prolonged and reliable operation must be sustained.

Routing is one of the primary functions in a wireless sensor network that aims to extend the network lifespan and route the data reliably with reduced delays. It must maintain the network operating even after depletion or replacement of some sensors [3]. Although extensive research has been devoted to the aim of extending the lifetime of wireless networks, there is no optimal routing protocol in terms of energy efficiency without additional computation time.

Therefore, hierarchical routing protocols have been introduced to solve the problem of increased latency in medium and large networks. These protocols reduce the number of messages transmitted to the base station by compressing the collected signals at the level of every CH, reducing the energy consumption. Moreover, this type of protocol alternates the role of CH between the network nodes to ensure a good balance of their energy consumptions avoiding their early death. Hierarchical networks have several advantages over flat networks for many reasons. Their superiority is mainly due to their speed in aggregating the data of each group, their fault tolerance by alternating the role of CH between the network nodes and their scalability for large-scale applications [4].

To ensure an optimal balance of energy consumption between nodes, a multi-objective clustering-based routing protocol is proposed. The main idea is to select the optimal set of cluster heads with their optimal number based on their residual energy and their number as a multi-criteria function to be optimized by a Pareto approach based on the (MOABC) algorithm.

This paper is structured as follows. Section II gives state-of-the-art on different techniques used to extend the lifetime of wireless sensor networks. Section III describes a modified multi-objective artificial bee colony algorithm with its adaptation to solve the routing problem of WSNs. Section IV presents the experimental results with their analysis and discussion. Finally, a conclusion with future research directions ends the paper.

## II. RELATED WORKS

The literature on energy conservation in wireless sensor networks is rich and multifaceted. However, despite its abundance, the design of optimal and energy-efficient routing protocols remains a crucial problem. To achieve a long lifetime of sensor networks, numerous studies have been conducted [5]

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S. Nebti is with the Department of Media and Communications, Emir Abdelkader University, Algeria (e-mail: snebti@live.fr).

M. Redjimi is with the Department of Computer Science, LICUS Laboratory, Université 20 Août 1955 Skikda, Algeria (e-mail: medredjimi@gmail.com).

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such as data aggregation [6], radio sleep & wakeup schemes [7], energy-efficient cognitive radio [8], and energy-efficient routing algorithms that include, multipath routing protocols, relay node placement strategies, sink mobility, clustering-based protocols [9], evolutionary-based protocols and multi-objective optimization based protocols [5]. The relay node placement strategies are energy-efficient techniques to maintain node connectivity and network coverage, while the primary benefit of sink mobility is to improve scalability by connecting sparse networks. Clustering-based protocols have been introduced to maintain connectivity in large-scale networks [5]. This type of routing algorithm has formed the basis of the most recent works as they are known for their scalability, energy efficiency, and self-configuration via alternative CHs in case of failure.

Although, the above studies share the same goal of extending the network lifetime, they cannot ensure a well-balanced use of energy to prevent the rapid death of sensors. To take benefit from global optimization in WSNs, evolutionary algorithms and particularly swarm intelligence optimization-based algorithms have been recently investigated. These algorithms aim to balance energy consumption between sensor nodes to achieve a longer lifetime of WSNs, they are often used to improve well-known hierarchical protocols [14], [16], etc. While the multi-objective-based protocols have been proposed to satisfy several criteria at once because routing is inherently a multi-criteria problem and must satisfy many constraints such as latency, energy saving, packet loss, coverage, and connectivity.

Multi-objective optimization algorithms can be distinguished into two broad classes: multiple objective function-based algorithms optimizing a weighted function of multiple parameters and population-based Pareto approaches, optimizing several distinct criteria. The latter is probably the most promising since the decision-maker solutions are often trade-offs between different parameters [10].

Examples based on multiple objective function optimization, include the work presented in [13], in which Sujeetha proposed a clustering-based multi-path routing algorithm using a multi-objective fuzzy logic (MOFL-MPR) approach. In this algorithm, the best set of cluster heads selection is based on a fuzzy logic approach optimizing three criteria, namely: neighbour density, node energy, and link quality. The achieved results outperform existing solutions in terms of stability, energy efficiency, and data delivery rate.

The work proposed by Choudhary [15] is another multiple objective function-based solution to the WSNs routing problem. In this approach, the CHs selection is based on the Swarm-based Grasshopper Optimization (SGO) by optimizing multiple objective functions consisting of three criteria namely: residual energy, distance from member nodes, and coverage. This algorithm offered better performance compared to other protocols in terms of throughput, delay, energy consumption, and packet delivery ratio.

In [17], Duraimurugan et al. used the spider monkey optimization (SMO) algorithm to optimize multiple objective functions for WSNs clustering and multi-hop routing. The routing path is a set of gateways selected by SMO algorithm based on their minimum distance and their number. Node clustering is performed based on the found routing path by using the same algorithm (SMO). This SMO-based routing method outperforms existing algorithms in terms of energy consumption, delivery ratio, throughput, and network lifetime.

In [11], Natarajan et al used the red fox optimization algorithm to conserve network energy and extend its lifetime. In this study, clustering is performed according to four objectives combined in a weighted function, namely: residual energy, inter and intra-cluster distances, network coverage, and degree of nodes. The routing path establishment between a source node and the BS is based on the node residual energy, the distance between CH and the BS, queue length and the link quality. The proposed algorithm showed better performance in terms of energy conservation, packet delivery rate, end-to-end delay, network throughput and lifetime compared to existing methods.

Several energy-efficient protocols based on Pareto multi-objective optimization have been proposed to increase the network lifetime and be more efficient in terms of energy conservation due to their effective strategy in finding optimal trade-off solutions [26], [27],[28].

Some examples based on Pareto optimality algorithms include the work proposed by Nabavi [26], in which, the whale multi-objective optimization algorithm is used to solve the WSNs routing problem, specifically to find the set of optimal cluster heads in terms of energy conservation and network lifetime extension. The two objectives to be maximized based on Pareto dominance are the residual energy of cluster heads and the number of their neighbouring nodes. Thus, the most preferred cluster heads are those with more energy and more surrounding nodes. The results found showed that this approach significantly outperforms other contemporary methods in terms of energy saving, network lifetime, throughput and stability.

The solution proposed by Wu et al [12], is another Pareto optimality approach based on multi-objective particle swarm optimization to find the best multi-hop routing path between relay nodes, which are used to forward the network collected data to the base station. The optimized criteria are the total network energy consumption and the network delay. The achieved results showed the feasibility of this approach in the routing of WSNs powered by solar cells and batteries with reduced power consumption and reduced network delay compared to LEACH.

Clustering-based protocols are known for their energy efficiency, scalability, and reliability in data delivery. To have an efficient clustering-based routing protocol, it is essential to find the optimal set of cluster heads (CHs) that can act as gateways between nodes and the base station (BS). Finding the optimal set of CHs is an NP-hard problem that can be solved by swarm intelligence optimization approaches [19]. In this context, to take advantage of their optimal strategy in the search for optimum trade-off solutions, Pareto multi-objective optimization algorithms have been proposed for CHs selection.

Specifically, to have an energy-efficient routing protocol, a new multi-objective artificial bee colony optimization (MOABC) inspired by the basic ABC algorithm was presented and adapted to find the optimal set of cluster heads with their optimal number. This MOABC-based approach enabled a significantly longer stability period and a longer life with a high packet delivery rate compared to existing protocols and another implemented protocol based on a slightly modified multi-objective particle swarm optimization.

## III. The Proposed Work

A WSN can be defined as a set of nodes (sensors) powered by batteries with limited capacity and dispersed in an environment for its monitoring. The sensors continuously send the collected data to the base station using radio signals.

The basic idea of the proposed protocol is to search the set of CHs having the maximum capacity of energy and to control their number by a multi-criteria approach. This algorithm is hierarchical in which several nodes act as cluster heads to receive the data packets from their neighbouring nodes and then aggregate, compress and transmit the received signals to the base station.

In this work, two algorithms based on swarm intelligence are proposed to solve the routing problem of WSNs.

In the first one: a slightly modified version of the multi-objective particle swarm optimization (MOPSO) described in [20] is adapted to solve the routing problem of WSNs. In this algorithm, the Global Leader is the last inserted non-dominated solution into the repository, instead of a randomly chosen solution from the densest hypercube in the repository. Choosing the global leader in such a way allows better results in terms of stability and network lifetime.

In the second: a new MOABC is proposed, and then adapted to solve the routing of WSNs. This approach gave the maximum extended lifetime compared to the first solution and other energy-efficient protocols.

In our representation, a bee (or a particle) is a vector of nodes initialized by random values between -3.83 and 3.83. These values are then normalized by (“0” and “1") to evaluate their finesses, a “1” means that this node is elected as cluster head, and “0” means a normal node that joins the closest CH node.

The objective is to balance energy consumption between nodes to maximize the network lifetime. For this, optimal solutions based on swarm optimization have been proposed.

The used objective functions are the number of cluster heads and the sum of their residual energies

$$\mathrm{f}(CHi) = \max\left(\textstyle\sum_{i=1}^{Nb\ CHs} Er_{CH\ i}\ ,\ \ Nb_{CHi}\right) \tag{1}$$

where $Er_{CH\ i}$ is the remaining energy of a cluster head CH i and $Nb_{CHi}$ is the number of cluster heads in the current round.

The objective is therefore to choose the most powerful CHs with a reasonable number by optimizing these two criteria.

### *A. The Setup Phase*

In this work, CHs selection and nodes clustering are dynamic and centralized in the base station. The nodes periodically send their remaining energy’ amounts to the base station. The received information is then used by MOPSO or MOABC for CHs selection. The IDs of the best-found CHs according to the optimized criteria are then sent to nodes. Each node joins the closest CH node in terms of the strength of its received radio signal (RSSI), by sending a request message (Join-REQ) using the CSMA (carrier-sense multiple access) MAC protocol. To avoid cohesion between nodes data, each CH establishes scheduling based on TDMA protocol (Time-division multiple access) to communicate with its member nodes and aggregates the received data if necessary before their transmission to the base station. The data transmission from each cluster head to the base station is based on CSMA MAC protocol to check the channel availability, if so the CH transmits the gathered data to BS, otherwise, it remains in a waiting state [25].

#### A.1. The MOABC for CHs selection

In multi-objective optimization, the best solution is no single but a set of so-called Pareto-optimal solutions that are in fact “the non-dominated solutions”. Thus, to solve a multi-objective problem by a population-based Pareto approach (NSGA, MOPSO, MOABC,...), one must first find the set of non-dominated solutions, and then a single solution would be selected from this optimal set by a multi-criteria decision-making method [18].

The Pareto approaches are based on the concept of dominance and scoring methods to compare and rank solutions for their selection [29].

#### *Pareto Dominance*

A multi-objective optimization problem of N objective functions $\mathrm{f_i}$ can be formulated as:

$$\min \mathrm{f}(\mathrm{x}) = \left(\mathrm{f}_1(x), \mathrm{f}_2(x), \dots \dots, \mathrm{f}_\mathrm{N}(x)\right) \tag{2}$$

$x \in \mathrm{X}$: X is the set of feasible vectors

A feasible solution $x_1 \in \mathrm{X}$ is said to dominate the solution $x_2 \in \mathrm{X}$, noted as $\mathrm{x}_1 \succ \mathrm{x}_2$ if and only if the two conditions below are realizable [19]:

• In all the considered objective functions, the solution $x_1$ is equally good or strictly better than solution $x_2$.

• $x_1$ is strictly better than $\mathrm{x}_2$ in at least one objective function.

This can be formally expressed as follows [30], [31]:

$$x_1 \succ\ x_2 \text{ if } \begin{cases} \forall\ i \in \{1 \dots \mathrm{N}\}, & \mathrm{f}_i(x_1) \le \mathrm{f}_i(x_2) \\ \exists\ i \in \{1 \dots \mathrm{N}\}, & \mathrm{f}_i(x_1) < \mathrm{f}_i(x_2) \end{cases} \tag{3}$$

#### *Pareto Optimality*

A Solution x* is Pareto optimal if there are no other superior solutions to the problem than x*, while may exist many Pareto optimal solutions, which are equally good. The Pareto optimal set is the set of non-dominated solutions concerning each other and the plot of their objective functions is called the Pareto front [20]. This later represents the trade-off surface in the objective space. Instead of finding the best solution in terms of a fitness function in mono-objective optimization, these methods converge to the Pareto front [19].

The proposed multi-objective ABC is based on two key ideas:

First: the dominant solutions are privileged in the update of employed and onlooker bees.

Second: the selection of a food source by an onlooker bee is based on the roulette wheel principle used in MOPSO to find the global leader [20].

Based on the ABC optimizer [22], the proposed MOABC is summarized in the following steps (Algorithm 1):

*Algorithm 1: MOABC*

**Begin**
  Bees Initialization
  **For** each iteration do
    Employed bees phase
    Repository update
    Onlooker bee's phase
    Scout bees phase
    Repository update
  **End for**
**End**

As in the ABC algorithm [23], the proposed MOABC uses the following equation to produce new d-dimensional food sources ($NB_{id}$) based on the old ones ($B_{id}$).

$$NB_{id} = B_{id} + \alpha\varphi_{id}(B_{id} - B_{kd}) \quad (4)$$

"$k$" is a randomly chosen employed bee different from "$i$",$\varphi_{id}\epsilon[-1,1]$, and $\alpha = 6$ in our experimental study.

This equation represents the local search principle of this algorithm in the neighbourhood of the old food sources.

In each employed bees phase, a new employed bee is produced based on the old one using equation (4), if it is better in terms of Pareto dominance then the old employed bee is replaced by the news. After the employed bees phase, a new list of non -dominated employed bees is obtained and the repository is updated using the following rules [21]:

- Insert into the repository each solution not dominated by any element of the repository.
- Delete each solution from the repository if dominated by any element of the current non-dominated set of solutions.

If the size of the repository exceeds a predefined limit, favour repository elements located in the less dense regions of the criterion space to maintain diversity.

After that, the repository solutions (called hyper-cubes) are ranked based on their dominant employed bees of the current cycle. The rank of each hypercube represents its density in dominated solutions and it is calculated by dividing a constant over the number of dominated employed bees of the current iteration, a probability for selection is then assigned to each hypercube, which is the ratio between its rank and the sum of the ranks of all the hyper-cubes. Finally, the roulette wheel is applied to select the densest hypercube [20].

In the onlooker bee's phase, a food source is randomly chosen from the densest hypercube, a new food source is then produced using equation (4), if better than the new replaces the old food source. In the scout bees phase, the solutions (employed or onlooker bees) that cannot produce other better solutions will be initialized randomly. A new list of non-dominated solutions is then calculated and the repository is updated.

Algorithm 2 summarizes the MOABC Steps:

*Algorithm 2: The MOABC Steps*

*Step1: Bees initialization*

Initialize randomly the employed bees in the range [-3.8, 3.8] with a size equal to the number of sensor nodes

*Step2: The employed bees phase*

**For** each employed bee **do**
  Produce a "NewBee" in its neighbourhood by eq.(4).
  Normalize them to binary
  **If** "NewBee" dominates the current employed bee
    Replace the current bee with the "NewBee"
  **Else**
    Increase the inefficiency counter of the current employed bee
  **End if**
**End for**

*Step3: The repository update*

Extract the list of non-dominated employed bees
Update the repository according to the rules mentioned above.
**For** each repository hypercube **do**
  Calculate its rank
  Calculate its probability for selection
**End For**

*Step 4: The onlooker Bees phase*

**For** each onlooker bee **do**
  Select the densest hypercube by roulette wheel on the calculated probabilities
  Choose randomly an employed bee "G" from the selected hypercube.
  Produce a NewBee in the neighbourhood of "G" by eq. (4)
  Normalize NewBee and bee(G) to binary
  **If** NewBee dominates bee(G) **then**
    replace bee(G) with NewBee
  **Else**
    Increase bee "G" inefficiency counter
  **End if**
**End For**

*Step5: The Scout bees phase*

Initialize ineffective solutions having an inefficiency counter upper than a predefined Limit in the range [-3.83, 3.83]

*Step 6: Repository update*

Extract the new list of non-dominated solutions.
Update the repository according to the rules above

At the end of the MOABC, the last inserted non-dominated solution into the repository is used for CHs selection.

### *B. The Steady-state Phase*

Several energy models have been proposed to simulate energy consumption by nodes in wireless sensor networks such as the first order radio model [25], the discrete radio model [35], the realistic energy consumption model [19], and many other assumptions to approximate the realistic energy dissipation by sensor nodes [33-37]…etc.

The first-order radio model is one of the most used energy models in clustering-based protocols [32]. For a reasonable comparison, this model has been implemented in the communication phase of the studied protocols.

The idea behind this model is to simulate the dissipated energy in the electronic circuits of the radio communication system. Since a sensor node is mainly constituted of a radio communication system (the transceiver), micro-sensors, a microprocessor, and a power source. The transceiver is responsible for any transmission or reception of data, this component includes a transmitter, a receiver, and an amplifier (Fig.1) [34]. The first-order energy model tries to evaluate the consumed energy by the electronic components and neglects the dissipated energy by the microprocessor and micro-sensors.

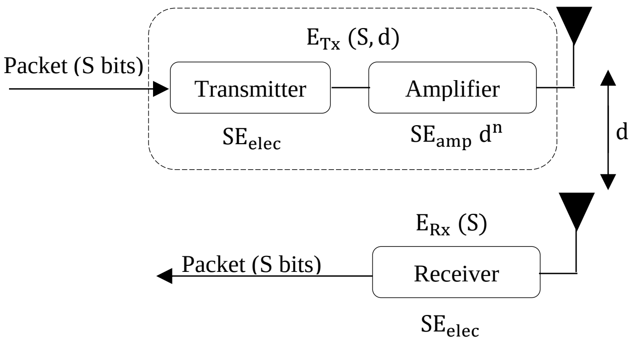


Fig. 1. Radio energy model [25]

In the first-order radio model, the source node dissipates energy using its transmitter and amplifier circuits, while the destination node dissipates energy using its receiver electronic circuit. Furthermore, two types of channels are considered: the free-space channel model and the multipath fading channel model. The first model is used when the distance between the source and destination nodes is less than a predefined threshold representing the threshold of the receiver's sensitivity to the radio signal [38]. While the second model is used to intensify the signal via the amplifier in the case of a distance greater than the predefined threshold to avoid signal degradation [25].

Thus, the energies necessary to transmit $E_{Tx}$ (S, d) and receive $E_{Rx}$ (S) an S-bit packet are as follows [25]:

• To send a packet of S bits to a receiver d meters away, the transmitter consumes:

$$E_{Tx}(S, d) = (S\, E_{elec}) + (S\, efs\, d^2), \qquad \text{if } d < d_0 \qquad (5)$$

$$E_{Tx}(S, d) = (S\, E_{elec}) + (S\, E_{amp} d^4), \qquad \text{if } d > d_0 \qquad (6)$$

$$d_0 = \sqrt{efs/E_{amp}}$$

• To receive a packet of S bits, the receiver consumes:

$$E_{Rx}(S) = S(E_{elec} + EDA) \qquad (7)$$

$E_{elec}$, $efs$ and $E_{amp}$ represent respectively the electronic transmission energy and the amplification energy in free and in multipath fading space. $EDA$ is the data aggregation energy which is set to 5nJ per bit for CH nodes and 0 for member nodes.

## IV. Results & Discussion

In this section, the performances of the proposed algorithms are presented and compared to recent protocols, namely: SEP, TSEP DEEC, EDEEC, LEACH and CLEACH. Experiments run in Matlab 2018. Sensors are randomly deployed. The sink is powered by an unlimited energy source. The initial total energy of the studied algorithms is adjusted to an equal amount for a reasonable comparison and the related data to curves is recorded for every 200 rounds (TABLE II).

### *A. Parameters Initialization*

TABLE I
Initial Parameters

| | | |
|---|---|---|
| WSN parameters | Initial energy | 0.5 J |
| | $E_{elec}$ | 50×10^(-9) |
| | $E_{amp}$ (the amplifier energy) | 100×10^(-12) |
| | EDA | 5×10^(-9) |
| | $s$ (Size of a packet) | 4000 |
| MOPSO parameters | Number of particles | 20 |
| | Archive size | 100 |
| | Cognitive & social factors | 1.49 |
| | Inertia weight | 0.78 |
| | Velocity constriction | [-3.83, 3.83] |
| MOABC parameters | Number of employed bees =Number of onlooker bees | 20 |
| | Abandonment Limit | 20 |
| | a (Acceleration Coefficient) | 6 |
| | Lower & upper bounds | -3.83 & 3.83 |

TABLE II.
The Related Data to Curves in Fig 2

| | Round | Residual energy | Operational Nodes | Time (ms) |
|---|---|---|---|---|
| | MOABC | | | |
| Stability period | 13200 | 6.6701 | 49 | 0.8280 |
| Max round | 24800 | 0.9417 | 5 | 3.0310 |
| | MOPSO | | | |
| Stability period | 2200 | 5.9789 | 47 | 0.0470 |
| Max round | 24800 | 1.1039 | 4 | 0.0470 |
| | EDEEC | | | |
| Stability period | 1200 | 4.8743 | 46 | 0 |
| Total death | 4600 | 0 | 0 | 0 |
| | DDEEC | | | |
| Stability period | 1200 | 3.4925 | 32 | 0 |
| Total death | 3600 | 0 | 0 | 0 |
| | DEEC | | | |
| Stability period | 1200 | 9.0184 | 47 | 0 |
| Total death | 4200 | 0 | 0 | 0 |
| | TSEP | | | |
| Stability period | 1400 | 4.7547 | 49 | 0 |
| Total death | 2200 | 0 | 0 | 0 |
| | SEP | | | |
| Stability period | 1000 | 1.9822 | 38 | 0 |
| Total death | 1600 | 0 | 0 | 0 |
| | CLEACH | | | |
| Stability period | 1400 | 2.5879 | 43 | 0,001 |
| Total death | 3000 | 0 | 0 | 0 |
| | LEACH | | | |
| Stability period | 800 | 5.1494 | 44 | |
| Total death | 2400 | 0 | 0 | 0 |

The Figures below are the obtained curves showing the behaviour of each algorithm, in a detection area of 100×100 m2, in terms of energy consumption, dead nodes, and the number of packets delivered to the base station.

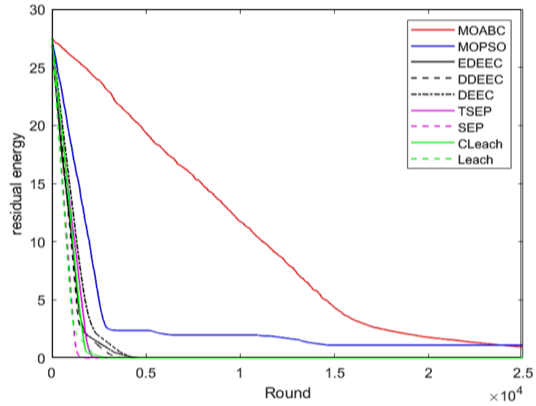


Fig. 2. The behaviour of the studied algorithms in terms of energy consumption in a detection area of 100×100 m$^2$

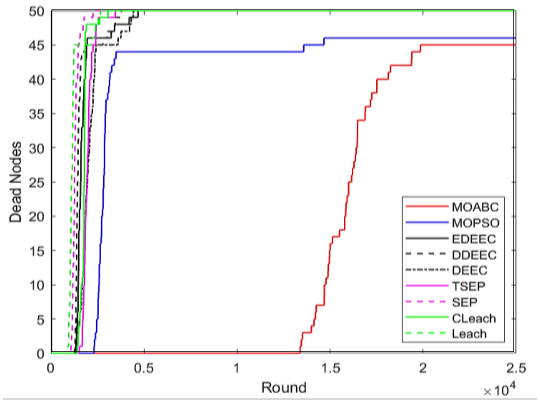


Fig. 3. The behaviour of the studied algorithms in terms of dead nodes in a detection area of 100×100 m$^2$

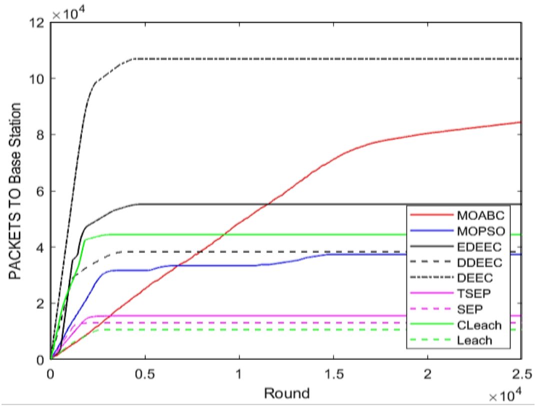


Fig. 4. The behaviour of the studied algorithms in terms of the number of delivered packets to the BS in a detection area of 100×100 m

It can be seen from Fig.2 & 3 that the DEEC-based protocols conserve more energy than LEACH & SEP-based protocols when a small detection area is considered (100×100 m$^2$).

In Fig. 2, 3 & 4, the EDEEC protocol shows a longer lifetime than that of DEEC and DDEEC protocols since it is based on three levels of energy, whereas, in our experiments, DEEC and DDEEC have only two energy levels.

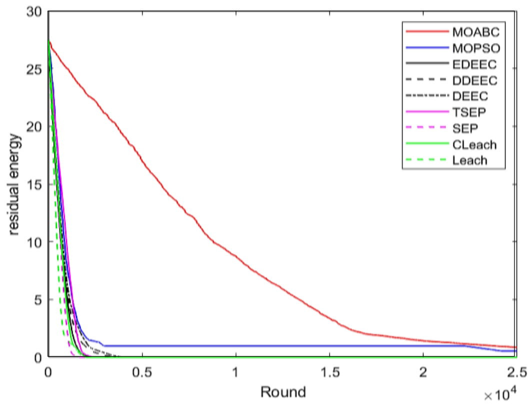


Fig. 5. The behaviour of the studied algorithms in terms of energy consumption in a detection area of 200×200 m$^2$

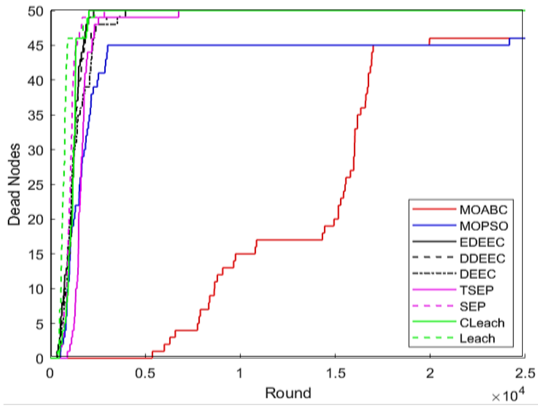


Fig. 6. The behaviour of the studied algorithms in terms of dead nodes in a detection area of 200×200 m$^2$

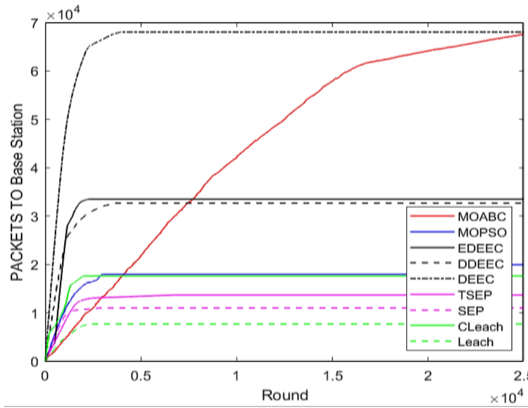


Fig. 7. The behaviour of the studied algorithms in terms of the number of delivered packets to the BS in a detection area of 200×200 m$^2$

According to figures (Fig.2 – Fig.13), which show the curves relating to residual energy, the number of dead nodes and the number of packets delivered to the BS, the proposed approaches, particularly the MOABC-based one is perfectly superior in terms of energy conservation than LEACH, C-LEACH, SEP, TSEP, DEEC, EDEEC, and DDEEC.

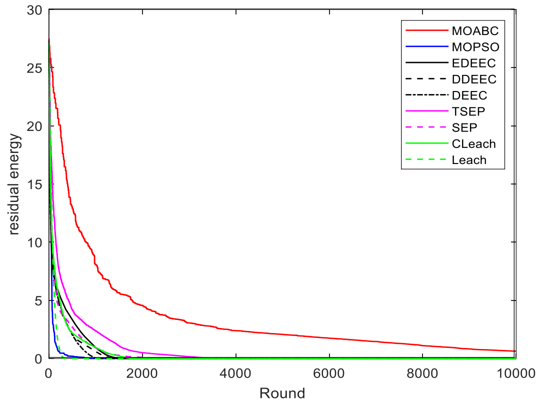


Fig. 8. The behaviour of the studied algorithms in terms of energy consumption in a detection area of 500×500 $m^2$

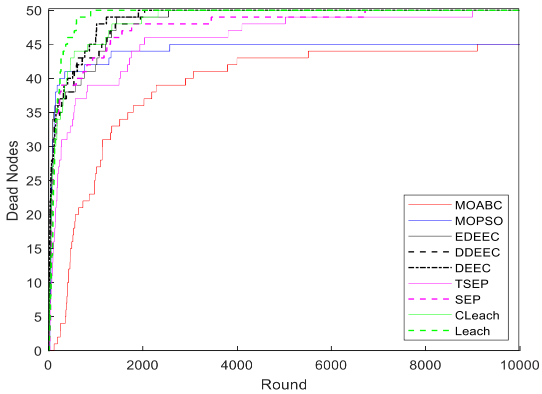


Fig. 9. The behaviour of the studied algorithms in terms of dead nodes in a detection area of 500×500 $m^2$

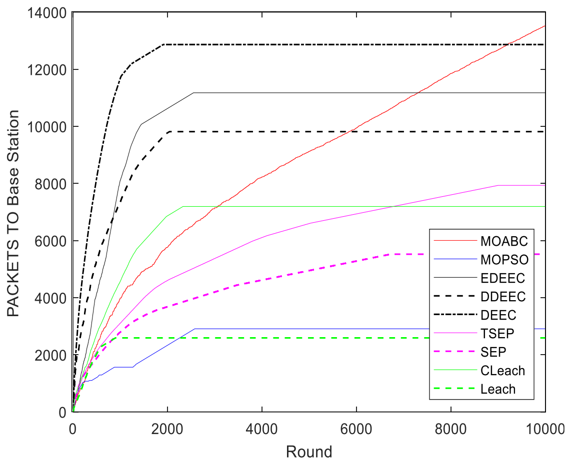


Fig. 10. The behaviour of the studied algorithms in terms of the number of delivered packets to the BS in a detection area of 500×500 $m^2$

The next curves show the results of the considered algorithms when the sum of CHs distances to the base station is taken into consideration in the multi-criteria function.

*B. Evaluation*

In our experimental study, we considered four performance criteria: the network density, its lifetime, the number of dead nodes and the number of packets delivered to the base station.

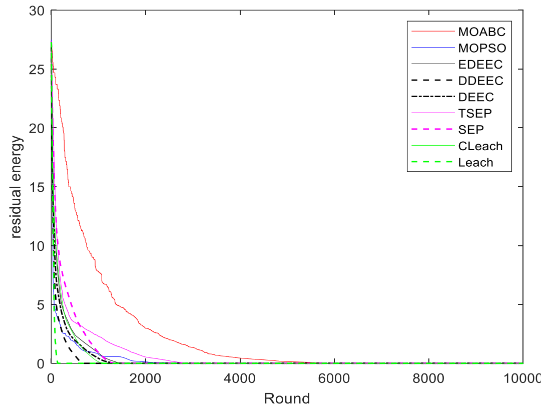


Fig. 11. Energy consumption in the case of a detection area of 500×500 $m^2$ and the second criterion is the sum of CHs distances to the BS

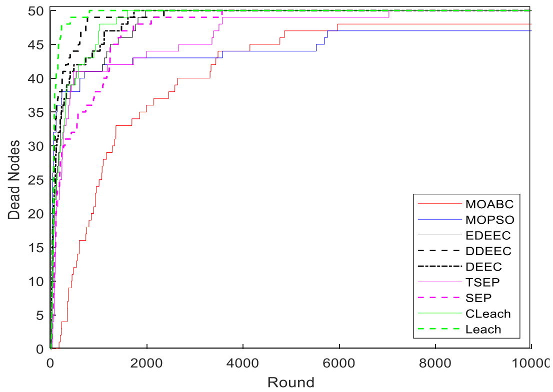


Fig. 12. Dead nodes in the case of a detection area of 500×500 $m^2$ and the second criterion is the sum of CHs distances to the BS

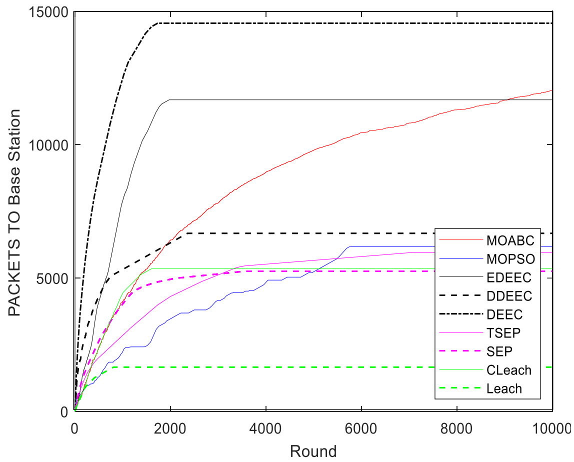


Fig. 13. The number of delivered packets to the BS in the case of a detection area of 500×500 $m^2$ and the second criterion is the sum of CHs distances to the BS.

B.1 The network density

Through the various performed experiments, we have found that the network density can affect the performance of the studied algorithms.

The denser the network is, the longer its lifespan for all algorithms. The performance of these algorithms is degraded in the case of a large detection zone. This leads to too large distances between CHs and the base station and consequently causes their fast depletion.

We note that for 100×100 $m^2$ and 200×200 $m^2$, the MOABC and the MOPSO-based protocols (the best ones) continue operating up to 25000 rounds. Whereas for 500×500 m2 the best algorithm stops working in about 10000 rounds.

B.2 The lifetime and dead nodes of the network

By analysing the related data to Fig.2 in TABLE II, we found that the MOABC-based approach is perfectly superior in terms of stability and lifespan extension. Additionally, we observed the long stability period of the MOABC-based approach that keeps all nodes operational up to 13,000 rounds.

The first deaths are observed with the LEACH protocol (in round 800) with an acceleration of sensors' death until the network's total death, thus reducing its lifespan to 2400 rounds. This acceleration is due to the excessive consumption of the CHs energy as well as the energy of their member nodes, since the CHs selection in LEACH does not take into account their residual energy.

The CLEACH protocol delays the first death of the network until round 1400 with a slightly slower sensor death rate than LEACH (from round 1400 until round 3000), because the selection of CHs is based on the network's average energy.

The CLEACH and TSEP protocols seem to be the best way to delay sensor death. Indeed, the CLEACH and TSEP protocols record their first death in round 1400. However, the number of dead sensors will reach the total number of sensors in 3000 and 2200 rounds respectively.

Obviously, the DEEC-based protocols will perform better than TSEP and CLEACH if advanced and super-nodes have more initial energy. In this work, we adjusted their energy for a fair comparison.

The MOABC protocol delays the first network death until round 13200 with a slower increase in the number of dead sensors compared to MOPSO (its first death in round 2200) and the rest of the protocols. Additionally, for significant periods, the MOABC protocol is successful in maintaining a slow number of dead sensors. In addition, the MOABC protocol extends the lifetime of the network up to 25000 rounds thanks to its optimal strategy of searching for the most powerful CHs.

To conclude this performance summary, it is important to note that when the network totally dies with the other protocols, MOABC keeps 100% of the network alive. Therefore, the MOABC protocol is of great interest as it extends the lifetime of the network up to 11 times the lifetime of the other protocols.

B.3 Number of Packets Delivered to the Base Station

From Fig. 4, 7, and 13, we have seen that the number of packets delivered to the base station with the DEEC protocol is the highest due to its almost completely distributed strategy, i.e. the nearest nodes to BS often send their packets directly to the base station without going through the CHs. In other words, the data passes without aggregation.

We also found that the number of packets delivered to the BS with the MOABC protocol is the highest compared to the rest of the protocols, this is due to its longer lifetime compared to the other protocols (LEACH, CLEACH, SEP, TSEP, EDEEC, DDEEC, and MOPSO).

We also observed that the MOABC continues to send packets longer than MOPSO, as it remains operational for a longer time than MOPSO and the other protocols.

We found that the LEACH protocol is still the least efficient protocol. This is due to the neglect of the energy parameter in the CH selection process.

*C. Findings*

Through multiple experiments to assess our contributions, we can list some findings as follows:

The proposed solutions and particularly the MOABC are perfectly superior to the existing solutions in terms of stability, energy-saving, lifetime extending, and the number of packets delivered to the base station.

The MOABC-based approach proves its efficiency in terms of energy conservation. However, it remains relatively penalizing in terms of latency or response time.

The large-scale deployment of nodes has led to very significant results of the MOABC-based approach, even for the number of packets delivered to the BS.

The proposed approaches offer a considerable energy gain by ensuring an equitable distribution of the CH role between nodes.

Through the obtained results, we can affirm that this type of algorithm offers considerable potential in terms of optimizing the network lifetime.

The DEEC-based protocols are better than SEP and LEACH-based protocols in the small size (100×100$m^2$) detection area, while SEP-based protocols are slightly better than DEEC and LEACH-based protocols in medium and large detection area (200 and 500 $m^2$).

The use of the distance parameter in the CH selection process leads to an increase in delivery time with no improvement in the network lifetime extension or the stability period compared to previous results based only on residual energy and the number of cluster heads.

Performance analysis shows that the reference protocols (LEACH, SEP, and DEEC) outperform the proposed algorithms in terms of delay and response time.

Population-based multi-objective approaches such as the proposed ones are lower power dissipation but impose higher delay compared to standard probabilistic protocols. To solve this problem, there exist some population-based solutions in the literature, which take into account the delay as a criterion to be optimized as in [39].

### D. Discussion

The MOABC protocol reduces its energy consumption thanks to the following advantages:

The cluster formation process is performed centrally by the base station. This advantage prevents the sensors from expending energy during the cluster formation process.

The sensors are allowed to send their data only to their CHs, which greatly reduces the energy dissipated from each node.

CH selection is not energy-intensive; this selection only requires the sending of nodes' residual energy to the base station.

It can be seen that the protocols cited above and used for comparison have a competitive and comparable lifetime. This is due to their very similar principle, which is based on the probabilistic alternation of CHs roles between nodes. However, the proposed approaches follow a multi-criteria optimization principle to ensure a well-balanced distribution of CHs roles between nodes, and a minimum dissipation of energy compared to LEACH, CLEACH, SEP, TSEP, DEEC, DDEEC, and EDEEC.

The modification of the multi-objective function by taking into account the distance between CHs and BS or the distances between nodes and CHs made the algorithm cumbersome, even impractical, without no improvement compared to the simple multi-objective function based on residual energy and the number of CHs. This is explained by the fact that the CHs selection based on their energies permits to better alternate the CH role between nodes by choosing the most powerful CHs in terms of energy to forward packets to the SB, avoiding in that way the quick depletion of nodes. In addition, if the proximity of the CHs to the base station is required, the algorithm focuses on the closest CHs even if their energies are insufficient to transmit all the packets of the group, which exhausts the nodes quickly.

We found that the DEEC-based protocols in particular (DEEC, EDEEC & DDEEC) provide a longer lifetime than SEP protocols mainly in small networks due to their CH selection mechanism which is based on nodes' residual energy and the network average energy.

In addition, SEP-based protocols provide a longer lifetime than LEACH-based protocols, because SEP protocols favour the advanced nodes that have more energy in the CHs selection.

While the superiority of our algorithms is mainly due to the use of multi-objective optimization to select the nodes with the highest energy capacity as cluster heads, which allowed a more accurate selection than the probabilistic one.

The proposed algorithms can be dedicated to certain categories of applications, namely the ones that are tolerant to the delivery time, such as environmental monitoring and health monitoring.

## V. Conlusion & Perspectives

In this paper, two new clustering-based protocols based on the multi-objective optimization of the artificial bee colony algorithm or the multi-objective PSO are presented. The main purpose of these protocols is to conserve the sensors' energy in order to ensure a longer lifetime even for large-scale networks.

The CH selection is adaptive and is based on two criteria, namely, the maximization of the sum of CHs residual energies and the number of CHs. The selection of the optimal set of CHs in terms of their energy and their number led to the maximum extension of the network lifespan.

The obtained results demonstrate that the proposed protocols provide superior performance in terms of energy-saving, network stability, network lifetime extension, and the number of packets delivered to the base station compared to well-known energy-efficient protocols such as LEACH, SEP, TSEP, and DEEC-based protocols. The MOABC-based approach significantly reduces energy consumption by choosing the best sensors in terms of energy capacity and proximity to the base station. This approach allowed an optimal balanced selection of cluster heads compared to the MOPSO-based approach and the other studied protocols.

For future work, the following perspectives can be considered:

Adaptation of this protocol to build real sensor systems of the Internet of Things IOT.

In the proposed approaches, the nodes send their data to their closest CHs, even if they are closer to the sink, so these results can be further improved by sending data directly to the sink from its neighbouring nodes.

Studying the mobility of the base station: The BS movement reduces the distance between nodes and the BS, and therefore minimizes energy consumption.

The proposed solutions as well as those in the literature that are used for comparison do not practically correspond to a realistic model taking into account the area coverage and the preservation of connectivity between nodes within a radio range. It would be interesting to study the behaviour of these algorithms by considering these constraints, specifically, on large-scale WSNs. A hierarchical multi-hop routing protocol can be adopted in this case.

In addition, it would be interesting to explore the capabilities of the proposed multi-objective ABC, because this algorithm has shown an extremely high ability to locate the optimal solution to the routing problem.

Another possible solution would be to explore the use of several sinks in order to ensure short-distance transmissions, and thus preserve more energy of sensor nodes.

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**Salima Nebti** received her Ph.D. degree in computer science from the University Ferhat Abbas of Setif, Algeria in 2013 and she received the HDR degree from the same University of Setif in 2017. Currently, she is a Lecturer at university of Emir Abdelkader of Constantine, Her research interests include Artificial intelligence, image processing, Machine learning, Data Mining and Wireless Networks.

**Mohammed Redjimi** is full professor of computer science at the University 20 Aout 1955 of Skikda – Algeria. He received his PhD degree from the University of Technical Sciences of Lille I – France in 1984. He received the HDR degree from University Badji Mokhtar of Annaba – Algeria In 2007. He was Head of computer science department and Dean of Engineering and Sciences Faculty at the University 20 Aout 1955 of Skikda. He is reviewer in several international journals and conferences. He is currently the head of the team: modeling and simulation of complex systems at the "Computer science and Communication" Laboratoiry of the University 20 Aout 1955 - Skikda (LICUS) and the director of this laboratory. His research interests include image processing, complex systems, modelling and simulation, SMA concepts and platforms and DEVS formalisms and wireless Sensor Networks (WSN).