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A new optimal strategy for energy minimization in wireless sensor networks

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ABSTRACT

In recent years, evolutionary and metaheuristic algorithms have emerged as crucial tools for optimization in the field of artificial intelligence. These algorithms have the potential to revolutionize various aspects of our lives by leveraging the multidisciplinary nature of wireless sensor networks (WSNs). This study aims to introduce genetic and simulated annealing algorithms as effective solutions for enhancing WSN performance. Our contribution entails two main phases. Firstly, we establish mathematical models and formulate objectives as a nonlinear constrained optimization problem. Secondly, we develop two algorithmic solutions to address the formulated optimization problem. The obtained results from multiple simulations demonstrate the positive impact of the proposed strategies on improving network performance in terms of energy consumption.

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1. INTRODUCTION

Recently, optimal resource management in wireless sensor networks (WSNs) has gained significant importance and is considered a fertile domain for numerous research studies [1], [2]. To support multiple applications simultaneously over a single physical WSN architecture, it is crucial to design and utilize WSNs in an optimal manner, considering their limited computing, memory, and battery power [3], [4]. In this context, ubiquitous sensor networks, which incorporate WSN technologies and internet of things (IoT) paradigms, are rapidly advancing to sense unpredictable environments and provide support to remote clients [5]–[7]. The collected data are processed and trans'

mitted to a cloud system, leveraging the processing and storage capabilities of the resource-constrained devices [8], [9]. Given that most real-time applications in WSNs require substantial resource improvements [10], [11], it is worth mentioning that WSNs consist of numerous sensors deployed in diverse environments to gather data on various environmental phenomena. These networks find applications in earthquake monitoring, marine activity detection, fire detection, smart grids, and intelligent transportation systems [12]. Furthermore, WSNs are extensively used in industrial, medical, environmental, agricultural, and home automation applications [13]–[16].

In WSN, sensor nodes can be deployed in the target area either randomly or deterministically, depending on their applications [17]. These different applications are based on optimizing multiple objectives, which can include bandwidth utilization, storage capacity, and computational capabilities of the sensors. This optimization aims to enhance overall network efficiency, extend sensor lifetime, ensure reliable data transfer, and reduce network maintenance costs. Additionally, optimal resource management facilitates accurate data collection by minimizing packet losses and reducing interference. It also contributes to optimizing the quality of services provided by WSNs, guaranteeing continuous, and reliable monitoring of environmental phenomena. Overall, these resources depend significantly on the energy of sensors. In other words, one of the primary challenges of WSNs is managing energy constraints. Since sensors are typically powered by batteries, efficient management of this limited resource is essential. Excessive energy consumption can significantly reduce sensor lifetime and necessitate frequent battery replacements, which can be costly and impractical. Optimal deployment of nodes, especially the base station (BS) relocation, is considered one of the research issues strongly related to energy constraints in WSNs. Indeed, depending on the chosen communication technology, data transmission may not be guaranteed if the distance between the transmitter and receiver is too large. This challenge is particularly prominent in applications involving surveillance of large areas and deployments with very low density.

The study conducted in this paper aims to minimize energy consumption in WSNs using BS relocation to optimize network performance. This approach has two key advantages: i) it reduces sensor energy consumption and ii) as a direct result of this reduction, it significantly extends the network's lifetime. Our contribution focuses on the development of two optimal strategies: the optimal strategy based on simulated annealing (OSSA) strategy and the optimal strategy based on multi-objective genetic algorithms (OSGA) strategy. This study is connected to various prior works, offering a contextual foundation that emphasizes the significance of energy constraints in WSNs. It reexamines certain mathematical models employed for energy optimization in these networks and references recent research endeavors presenting algorithmic solutions aimed at tackling this issue. In the literature, several research works have focused on the study of optimal resource management in WSNs [18]. Given that the wireless communication module consumes the most energy, the primary objective of these optimization techniques is to minimize the radio module's activity time for different nodes. These techniques can be grouped into two classes: those based on data reduction and those based on sleep/active mode switching.

Yin *et al.* [19] proposed an optimization method based on the Yin-Yang pigeon-inspired optimization algorithm aimed at guaranteeing optimal management of a WSN. To optimize the coverage requirements in WSNs, Elhoseny *et al.* [20] introduced a model that utilized the genetic algorithm for continuous monitoring of specific targets with limited energy resources. Chowdhury *et al.* [21] presented an energy-efficient optimization technique using the Voronoi-glowworm swarm optimization-K-means algorithm. Jebi and Baulkani [22] proposed a multi-objective randomized grasshopper optimization algorithm-based selective activation method for optimal WSN management. Ali and Özdağ [23] elaborated on a new metaheuristic approach using the elfes probabilistic detection model to optimize WSN performance. Zulfiqar *et al.* [24] introduced an optimization algorithm to effectively manage a WSN in terms of energy consumption. Abdulzahra *et al.* [25] presented with the aim of minimizing operational costs and emissions while considering the variability of energy sources.

According to the literature review presented in this section, it is clear that the reduction of energy consumption is a significant research issue in WSNs. Specifically, energy constraints are a critical concern for WSNs deployed in hostile or inaccessible areas and networks with high density. In these scenarios, energy resources are severely limited, making it challenging or even impossible to recharge or replace sensor batteries after deployment. The objective of this paper is to address the energy limitations encountered by WSNs. Specifically, this study aims to enhance sensor performance in terms of efficient communication with the BS, thereby extending the network's lifetime. Our contribution consists of two main phases: phase 1 is mathematical modeling, focusing on formulating the objectives to be achieved as a nonlinear constrained optimization problem. Phase 2 is algorithmic resolution, concentrating on the development of two optimal multi-objective strategies to solve the problem formulated in phase 1. These two phases will be presented in section 2.

Our research methodology unfolds as follows: in the first step, we identify limitations in the existing literature regarding energy constraints in WSNs. In the second step, we address the aforementioned issues using the proposed approach. This approach involves the development of two optimal strategies for BS relocation to improve network performance in terms of energy consumption. These strategies are based on constrained nonlinear optimization algorithms, namely genetic algorithms and simulated annealing. In the third step, we demonstrate and validate the positive impact of the proposed algorithms through simulation results. The rest of this paper is organized as follows: section 2 elaborate on the various phases of the proposed approach; section 3 present the obtained results through multiple simulations, these results are described, analyzed, and interpreted; and section 4 provide concluding remarks and discuss future works.

2. PROPOSED APPROACH

2.1. Optimization problem formulation

In this study, we consider a WSN which is deployed in a defined area. The goal is to contribute to reducing energy consumption in the network, thereby enhancing its performance and extending its operational lifetime. Specifically, our approach aims to optimize sensor performance in terms of energy while using two new optimal relocation strategies to determine the best placement for the BS. To achieve this, we assign a function, denoted as e_i, to each sensor s_i to represent its energy consumption. Based on the Heinzelman model, the energy consumed by a sensor s_i when transmitting a message of l bits over a distance d_i in free space can be expressed as in (1),

$$e_i = l \times E_{elec} + l \times d_i^2 \times E_{fs} \tag{1}$$

Where E_{elec} is the electric energy in pJ/bit, E_{fs} is the free space energy in $pJ/bit/m^2$, l is the message size in bit, and d_i is the transmission distance between sensor s_i and the BS in m.

The distance d_i between sensor s_i and the BS can be calculated using their coordinates $(x_i - y_i)$ and $(x_b - y_b)$ respectively, based on the Euclidean distance as in (3),

$$d_i = \sqrt{(x_i - x_b)^2 + (y_i - y_b)^2} \tag{2}$$

Therefore,

$$e_i(x_b - y_b) = k \times E_{elec} + k \times ((x_i - x_b)^2 + (y_i - y_b)^2) \times E_{fs} \tag{3}$$

Minimizing the energy e_i ensures an improvement in the performance of sensor s_i. As shown in (3), the value of this energy largely depends on the position of sensor s_i relative to the BS. Therefore, a better placement of the BS will positively influence the energy of the sensors and subsequently enhance the network performance. In other words, the objective of this study can be formulated as a key question as follows: 'how to determine an optimal position of the BS that minimizes the energy consumed by the various sensors to improve network performance? Using the previously mentioned notations, we can formulate this objective mathematically as a nonlinear constrained multi-objective optimization problem, as in (4),

$$\begin{aligned} & minF(x_b - y_b) = \big(e_1(x_b - y_b), e_2(x_b - y_b), e_3(x_b - y_b), \ldots, e_n(x_b - y_b)\big) \\ & st\ A \le x_b \le B \\ & C \le y_b \le D \end{aligned} \tag{4}$$

Where n is a number of sensors. $[A, B] \times [C, D]$ represents the area where the sensors are deployed. The formulated problem (4) is a constrained nonlinear optimization problem. To solve this problem by determining the optimal position of the BS, we propose two optimal strategies: OSSA strategy and OSGA strategy, which will be elaborated in the next subsection.

2.2. Developed optimal strategies

2.2.1. Optimal strategy based on simulated annealing strategy

a. OSSA principle

The OSSA strategy utilizes simulated annealing, a meta-heuristic optimization method. It is employed to solve combinatorial optimization problems, particularly when dealing with a large number of sensors. The objective is to identify the best solution among numerous possibilities. Simulated annealing operates by probabilistically exploring the search space, accepting suboptimal solutions in order to escape local minima and discover the global optimum. The technique involves constructing a representation of the problem's solution space, where each point is referred to as a state. Transitions between states occur by making small adjustments to the current solution. To control the convergence of the OSSA strategy towards the optimal solution $\left(x_b^{op}, y_b^{op}\right)$, which represents the best position for the BS, a control parameter denoted as P_k is utilized. This parameter determines the probability of accepting a less favorable solution compared to the current one. In this study, we consider the following three schemes for updating the value of P_k at iteration k: i) exponential update: $P_k = 0{,}95^k$, ii) logarithmic update: $P_k = 1/\log(k)$, and iii) linear update: $P_k = 1/k$

b. OSSA objective function formulation

The OSSA strategy introduces multi-objective optimization to jointly minimize several objective functions. For this, OSSA uses the weighted summation technique to form the objective function to be minimized. Indeed, according to the modeling phase detailed in the previous section, each sensor s_i is characterized by a function e_i which measures its energy. In the context of OSSA's multi-objective optimization technique, the function e_i represents the ith objective function that OSSA aims to minimize. In a network with n sensors, there are n objective functions to optimize. OSSA employs the weighted summation technique to combine these functions and formulate a single objective function F, as indicated in (5),

$$H(x_b - y_b) = \alpha_1 e_1(x_b - y_b) + \alpha_2 e_2(x_b - y_b) + \dots + \alpha_n e_n(x_b - y_b) \quad (5)$$

where α_i is the weight of the objective function e_i. These weights satisfy the condition at (6):

$$\alpha_1 + \alpha_2 + \dots + \alpha_n = 1 \quad (6)$$

c. OSSA flowchart

To achieve the optimal solution, the OSSA algorithm follows a sequence of procedural steps. The initial step entails the initialization of input parameters (S_0: initial solution and P_0: control parameter), where the initial solution is regarded as the current solution, denoted as S_{cur}. Subsequently, the second step generates a new solution S_{new}, based on the current solution. In the third step, we evaluate the objective function F for both S_{new} and S_{cur}, then we compute the difference $\Delta F = F(S_{new}) - F(S_{cur})$. If $\Delta F \leq 0$, the subsequent step involves the generation of a random number r between 0 and 1, then the computation of $\exp(\Delta F / P_k)$. If $r < \exp(\Delta F / P_k)$, S_{cur} value is preserved, and P_k value is updated. If $\Delta F > 0$, we accept S_{new} as the current solution and verify if the stopping criterion is reached in order to determine the optimal solution. The different steps of the OSSA strategy are summarized in the flowchart presented in Figure 1.

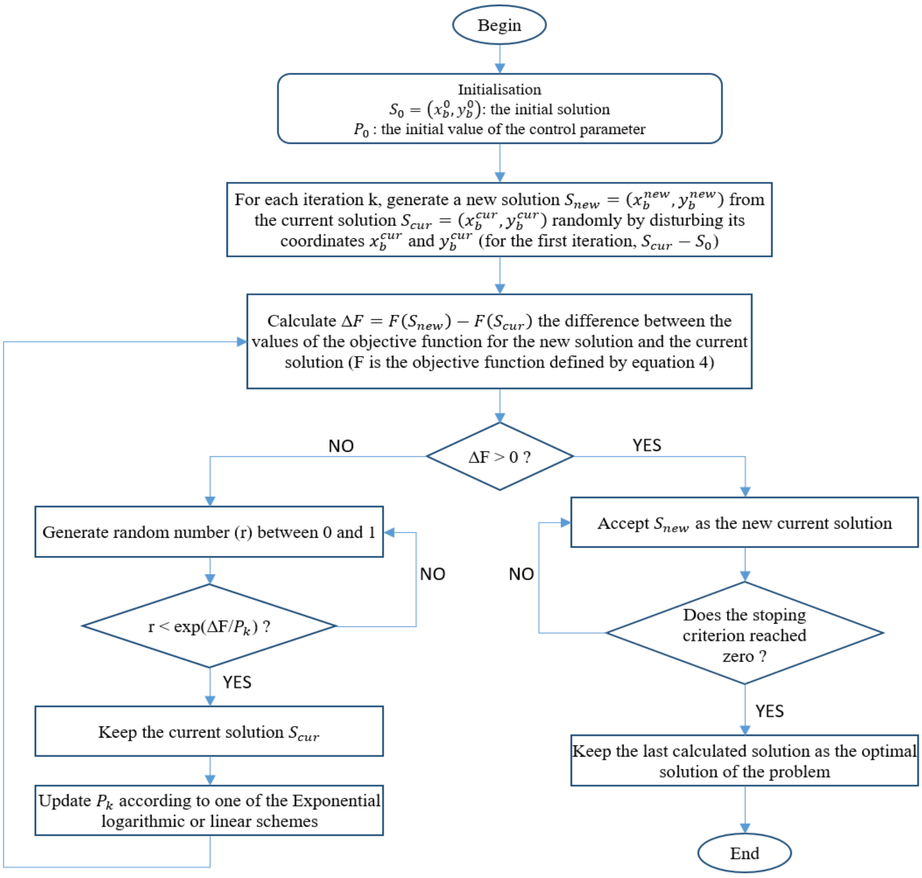

Figure 1. OSSA flowchart

2.2.2. Optimal strategy based on multi-objective genetic algorithms strategy

a. OSGA principle

The OSGA strategy aims to optimize multiple objectives simultaneously by incorporating the principles of multi-objective optimization. This strategy is based on the concepts of Pareto dominance and the search for non-dominated solutions. Pareto dominance is a fundamental concept in the design of OSGA. It enables the comparison and ranking of solutions based on their performance across multiple objectives. In the context of multi-objective optimization, a solution A is considered dominant over a solution B if it is at least as good as B in all objectives and strictly better in at least one objective. In other words, A dominates B if it outperforms B in at least one objective without being worse in any other objective. The basic idea behind Pareto dominance is to search for solutions that cannot be improved simultaneously in all objectives. Instead of seeking a single optimal solution, the focus is on finding a set of non-dominated solutions that represent optimal trade-offs between the objectives. Following this principle, OSSA aims to identify a set of non-dominated solutions known as the Pareto front. In this set, no solution can be improved in one objective without compromising performance in another objective. This approach enables the OSGA strategy to rank solutions based on their performance across multiple objectives, promoting the emergence of a set of non-dominated solutions that represent the optimal compromises between the objectives.

b. OSGA objective function formulation

In order to optimize multiple objectives simultaneously, the OSGA strategy utilizes a fundamental technique that treats these objectives as components of a single objective function represented as a vector. Based on the mathematical modeling presented in section 2.1, each sensor s_i is defined by a function e_i that represents its consumed energy. In the case of a network comprising n sensors, employing the technique introduced by OSGA, the objective function to be minimized can be expressed as (7),

$$G(x_b - y_b) = [e_1(x_b - y_b), e_1(x_b - y_b),\ldots, e_n(x_b - y_b)] \tag{7}$$

c. OSGA flowchart

In order to compute the optimal solution, the OSGA algorithm employs several steps. The first step is to generate a list of initial solutions. To select the best solution, the second step evaluates the objective function for the previously generated initial solutions. In the third step, we check if the chosen solution is optimal according to the Pareto dominance concept. For each computed solution, there are two cases. If the Pareto dominance condition is not met, another list of solutions is generated, and the search space is explored by combining some features of these solutions. To prevent convergence to suboptimal solutions, some potential solutions are randomly modified. If the Pareto dominance condition is met, then the last computed solution is considered as the optimal solution. The various steps of OSGA are presented in Figure 2.

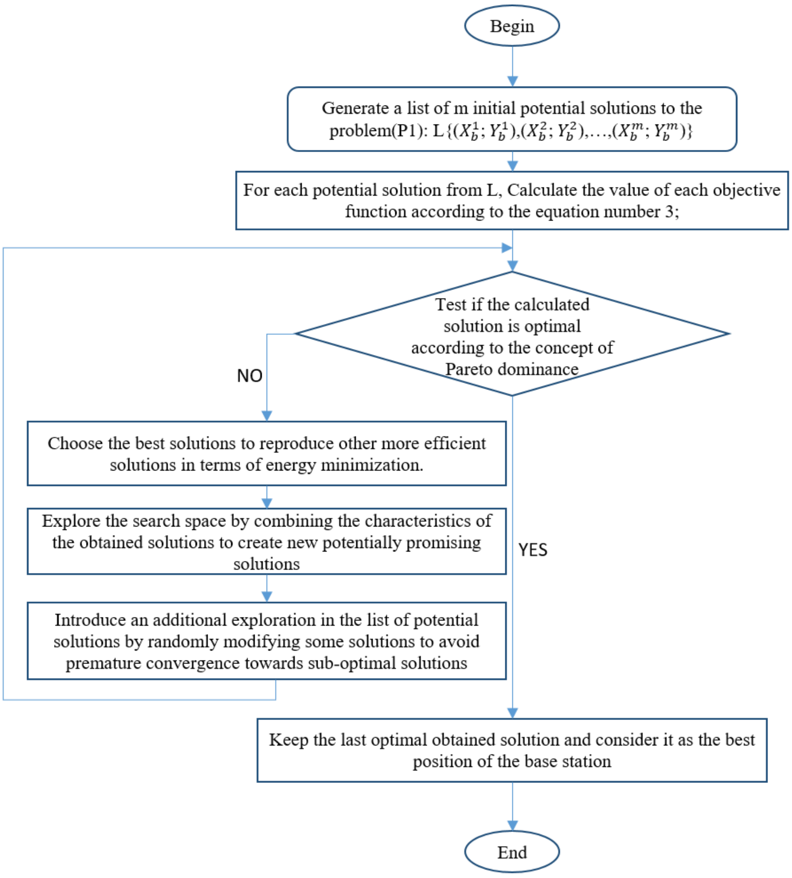

Figure 2. OSGA flowchart

3. SIMULATIONS AND RESULTS

To validate the proposed approach, numerous simulations were carried out using the following parameters: E_{elec} = 50 pJ/bit, E_{fs} = 10 pJ/bit/m^2, the network area = 300×200 m^2, and l = 4,000 bit. As an initial configuration, we considered 10 sensors deployed within a surface area of 140×140. These sensors are connected to a BS initially positioned at the center of the designated area. Although this conventional BS placement strategy ensures complete coverage of the area, it incurs high energy consumption for the sensors. This energy consumption primarily depends on the distance between the sensors and the BS. To address this issue, we conducted a BS relocation using the OSSA optimal strategy. Figure 3 illustrates the results obtained after implementing this optimal relocation. In these results, the value of P_k is updated according to the exponential model.

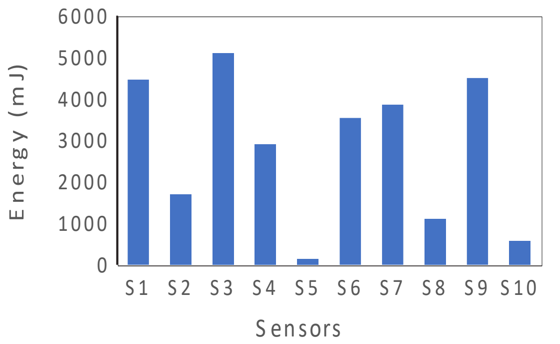

Figure 3. Consumption energy after relocatin BS using OSSA strategy in the initial configuration

3.1. Performances evaluation

3.1.1. Optimal strategy based on simulated annealing strategy

As an initial configuration, we consider 10 sensors deployed in a surface area of 140×140. These sensors are connected to BS which is initially positioned at the center of the designated area. Although this conventional BS placement strategy ensures complete coverage of the area, it incurs high energy consumption for the sensors. This energy primarily depends on the distance between the sensors and the BS. To address this, we conducted a BS relocation using the OSSA optimal strategy. Figure 3 shows the obtained results after performing this optimal relocation. In these results, the value of P_k is updated according to the exponential model.

To evaluate the OSSA performance, we examine multiple configurations by varying the number of utilized sensors. For each configuration, we compute the total energy consumption in the network after relocating the BS using the OSSA strategy. Then compare this energy consumption to that incurred when the BS is positioned at the center of the designated area using the conventional strategy. The obtained results are shown in Figure 4. This figure demonstrates that the OSSA strategy has a positive influence on energy consumption, thanks to the relocation of BS to its optimal position. To control the convergence of the OSSA strategy to the optimal solution (best position of the BS), we conducted several simulations by updating the values of the parameter P_k using the following models: exponential (exp), logarithmic (log), and linear (lin). The results provided by these simulations are presented in Figure 5. According to these results, it can be seen that selecting the exponential scheme enables the OSSA strategy to converge rapidly to the optimal solution, compared to the linear and logarithmic schems. This significant finding favors the exp scheme as it facilitates the control parameter to converge quickly to 0. Consequently, the OSSA strategy can promptly reach the stopping criterion.

3.1.2. Optimal strategy based on multi-objective genetic algorithms strategy

Considering the same initial configuration presented in the previous subsection, we relocated the BS using the OSGA strategy, with the aim of minimizing energy consumption. Figure 6 illustrates the energy consumption levels of the various sensors (S1, S2, ..., S10) following this optimal relocation. Based on the conducted simulations, it has been observed that the OSGA convergence is influenced by the selection of an appropriate value for a critical parameter known as the Pareto fraction (PF). Indeed, to choose PF optimal value in terms of rapid convergence, we performed several simulations by varying the value of PF from 0.1 to 0.9 using the previous configurations. The obtained results are presented in Figure 7. This figure demonstrates that the optimal value of PF, which ensures a rapid convergence of the OSGA strategy, is 0.5. Due to its importance in terms of convergence, in the rest of this paper, all remaining simulations will be performed using this optimal value.

In order to evaluate the efficiency of the optimal OSGA strategy compared to the classical strategy, we investigate several configurations with varying numbers of sensors. For each configuration, we quantify the total energy consumption by the sensors relative to the two aforementioned strategies. The obtained results are presented in Figure 8. This figure clearly shows the significant reduction in total energy consumption achieved by the second optimal strategy proposed in this paper, namely the OSGA strategy. This reduction is attributed to the optimal positioning of the BS, which leverages the advantageous properties of multi-objective optimization.

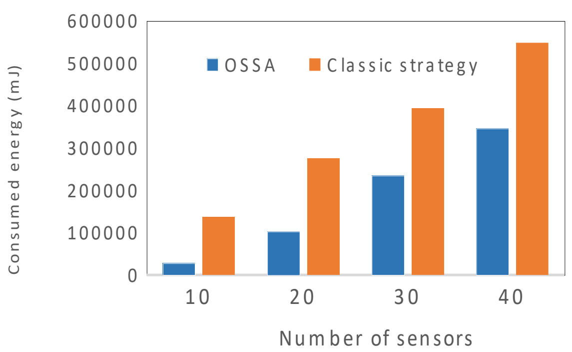

Figure 4. Consumption energy: OSSA compared to classic strategy

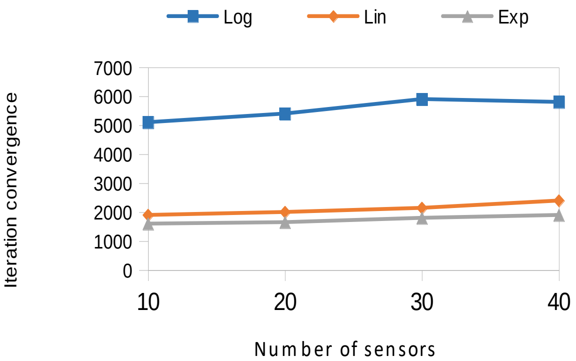

Figure 5. OSSA convergence relatively to P_k update schems

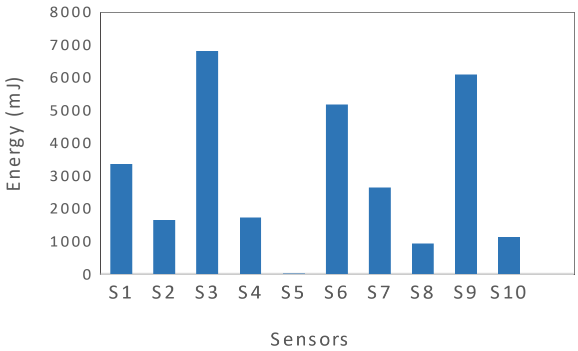

Figure 6. Consumption energy after relocatin BS using OSGA strategy in the initial configuration

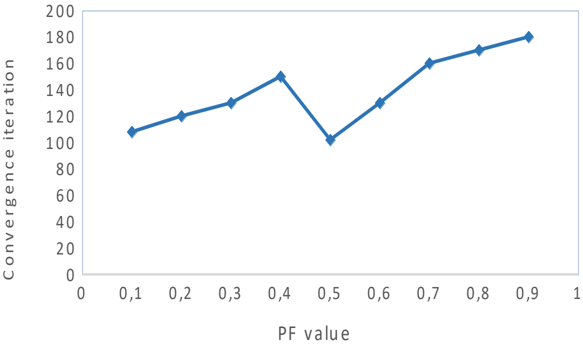

Figure 7. OSGA convergence according to the PF value

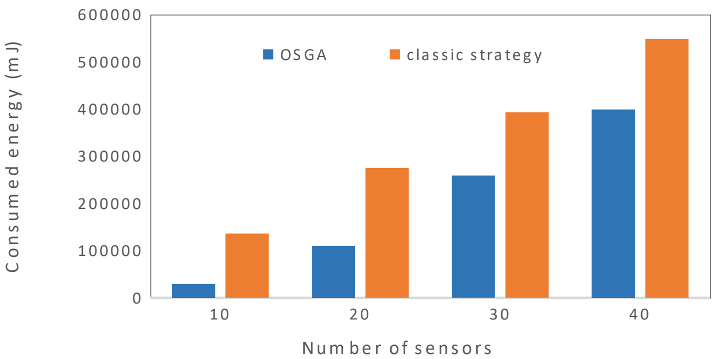

Figure 8. Consumption energy: OSGA compared to classic strategy

3.2. Comparison between OSSA and OSGA
3.2.1. Convergence to the optimal solution

Using various configurations, we conducted numerous simulations to examine the convergence of OSSA and OSGA. the obtained results are illustrated in Figure 9. This figure shows that the OSGA strategy exhibits rapid convergence to the optimal solution compared to OSSA. This advantage can be attributed to the nature of the problem addressed in this paper, which involves the simultaneous optimization of multiple objectives. We particularly emphasize the benefits of the OSGA strategy in formulating the objective function, which facilitates parallelization of the optimization process. This parallelization significantly reduces execution time and positively influences the convergence of the OSGA strategy.

3.2.2. Energy consumption

Using multiple configurations, we calculate the total energy consumed in the network. The obtained results are presented in Figure 10. It shows that relocating the BS using the OSSA strategy results in relatively lower energy consumption compared to the OSGA strategy. This is because the OSSA strategy prioritizes the overall network by minimizing total energy consumption, rather than focusing on individual sensor energy. Consequently, while using this strategy, some sensors may have high energy consumption and others low consumption, but the total energy consumption remains minimal. Conversely, the OSGA strategy primarily focuses on optimizing the energy consumed by each sensor individually. In other words, it achieves a balanced total energy consumption among the different sensors by simultaneously optimizing the objective functions. It is important to emphasize that in these critical scenarios, where certain sensors exhibit high energy consumption leading to battery depletion and a decrease in the network's lifetime, achieving energy balance in the network using the OSGA strategy is considered an effective solution to address such issues.

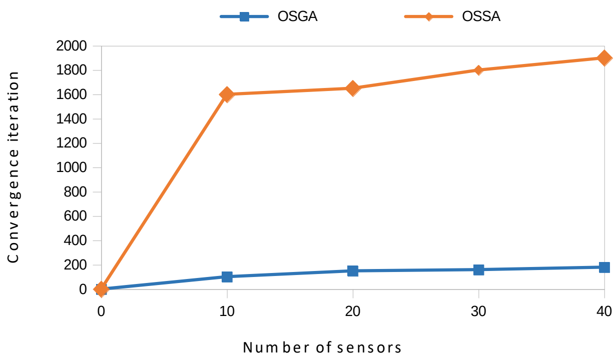

Figure 9. Comparison between OSSA and OSGA in terms of convergence

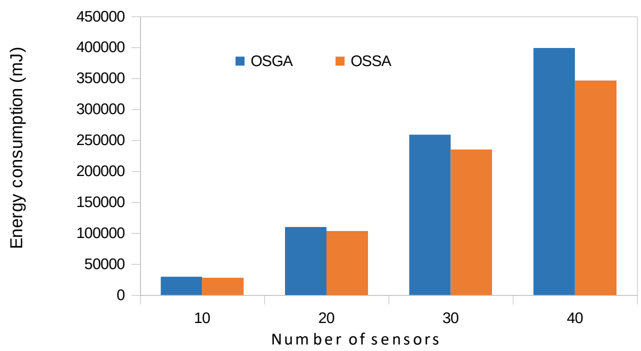

Figure 10. Comparison between OSSA and OSGA in terms of energy consumption

4. CONCLUSION

In this paper, we have presented two new optimal strategies for enhancing the performance of WSN with a focus on energy consumption minimization. These strategies are based on the multi-objective genetic algorithm and simulated annealing algorithm. To elaborate the proposed approach, the objectives were initially formulated as a nonlinear constrained optimization problem. Following that, two algorithmic solutions were developed to address the formulated problem. The obtained results have demonstrated the significance and effectiveness of the proposed strategies in reducing energy consumption within the network. This energy constraint is considered as one of the major research challenges in WSN. The future work will focus on the integration of machine learning techniques and data analytics to enhance the accuracy of predicting network behavior and optimize energy consumption in a more intelligent and proactive manner.

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