Constrained Pareto-based Weighted-sum ABC Algorithm for Efficient Sensor Networks Deployment

Son Tran[1], Huy Nhat Minh Vu[1], Thanh Tung Pham[2] and Duc Chinh Hoang[1[0000-0002-3018-087X],*]

[1] School of Electrical and Electronic Engineering,
Hanoi University of Science and Technology, Vietnam
[2] University of Fire Prevention and Fighting, Hanoi, Vietnam
*Corresponding author: chinh.hoangduc@hust.edu.vn

Abstract. Wireless Sensor Network performance relies heavily on the effectiveness of the deployment strategy, particularly in building applications. However, the inherent conflicting nature among the optimization objectives poses a significant challenge to achieving a balanced solution. This paper addresses this issue by introducing a constrained Pareto- based deployment algorithm, combining the Artificial Bee Colony and the linear weighted-sum approach. The method is validated through simulations, showcasing the efficacy of theoretical research. The main contribution is the utilization of the bee algorithm to deal with the intrinsic nature of the sensor network. Moreover, a comprehensive procedure integrating the algorithm and the weighting decision-maker is presented to showcase practical application. Nevertheless, the model scope is limited in terms of coverage and energy perspective.

Keywords: First Keyword, Second Keyword, Third Keyword.

1 Introduction

Wireless Sensor Network (WSN) is crucial for recent intelligent systems. Its role is to collect environmental data so that the system can make informed decisions. The working mechanism is to deploy a group of sensor nodes in the monitored area to gather information. Each sensor is required to send the collected data back to the sink node, often located in the middle of the area. Examples of intelligent systems utilizing WSNs are smart buildings [1] and smart agriculture [2], etc.

The working mechanism highlights the coverage and connectivity requirements to collect as much information as possible while maintaining the connection between the sink and other nodes. Another critical requirement is to conserve the network energy and maximize the network lifetime due to the irreplaceable power sources after deployment. Thus, it is essential to formulate and solve the deployment problem that achieves multiple metrics, including (1) Using energy efficiently by minimizing the energy usage, resulting in (2) Prolonging the network lifetime, (3) Maximizing the coverage area, and (4) Maintaining the full connectivity.

Recent research on one of these metrics can be longlisted, such as [3] and [4] try to improve deployment strategy to maximize coverage while [5] aim to solve network lifetime problem. Otherwise, this paper problem is defined as finding the optimal position for the deployed sensor nodes to achieve all the above metrics; thus, it is a combinatorial NP-hard optimization problem [6]. The approximate method is favoured when facing a large-scale problem, especially meta-heuristic solutions. Moreover, these objectives are inherently conflicting in nature as increasing the coverage ratio requires the nodes to be placed far apart; meanwhile, the nodes must be in proximity to each other to increase the lifetime and maintain connectivity. This factor motivates the use of the Pareto optimality principle.

Existing literature utilizes evolutionary algorithms (EAs) [7] to solve multi-objective optimization problems. Reference [8] introduces a flexible algorithm that can be applied to diverse applications. Its flexibility lies in the initialization population, starting with the canonical genome with only three sensor nodes that already satisfy a 2-connected topology. Subsequently, new members are created following the NEAT mechanism [9]. Pradhan's work [10] considers two objectives to maximize both the total coverage and the lifetime. The paper proposes a repeatedly fixing mechanism to achieve a fully connected network during the creation of new members. Moreover, fuzzy decision-making is utilized to distinguish a welter of solutions concentrated in the centre of the Pareto Front.

With the emphasis on connectivity, [12] tackles from a graph theory perspective, ensuring connectivity using Dijkstra's algorithm [13]. The paper integrates the concept of fuzzy dominance in the MOEA/DFD algorithm to differentiate dominance solutions further. In the constrained Pareto-based multi-objective evolutionary approach (CPMEA) [14], instead of randomly generating a network layout without considering the connectivity, the initial population is produced in two dimensions: (1) The topology dimension investigates the network connectivity, and (2) The geometry dimension investigates the network positions. From this perspective, two novel crossover operations are proposed, achieving superiority over the NSGA-II [15] regarding diversity, hypervolume, and generational distance metrics.

Different from the above works, [16] approaches the problem from the application perspective, particularly the building application. Thus, the publication considers the economic value in deployment cost and signal attenuation effects in ZigBee network connection. The network topology is validated using NS-2.35, observing an approximate 0.2s delay and the packet delivery ratio of 98.6%.

In essence, the literature mostly utilizes evolutionary algorithms and does not clearly state how the Pareto set is created and applied to specific applications. Hence, the paper's objective is to tackle this gap. The paper's main contributions are: (1) The paper extends the usage of swarm intelligence-based optimizers in multi-objective deployment problems, particularly the Artificial Bee Colony (ABC) [17]. In creating new solutions, ABC modifies and updates the old solution instead of creating from scratch; thus, it is suitable for WSN deployments as there is more than one optimal solution for the deployment problem. (2) The paper enriches the diversity in the Pareto optimal Set by integrating the linear weighted-sum method during the new solution-creating process. (3) The paper presents a weighting decision-making method to choose the final solution that is applicable to smart buildings.

The paper's structure is as follows: Section 2 presents the mathematical formulation and proposes the solution. Section 3 assesses the algorithm performance through simulation. Finally, Section 4 provides a summary of the paper.

2 Methodology

This section formulates the problem mathematically and introduces the solution. Reference [10] lays the foundation for this paper's network model, particularly the sensor energy model. There is a minor difference in how to use the sensing model [11], but the objective is the same: to calculate the non-coverage ratio.

2.1 Mathematical formulation

The two-dimensional monitored area A has a rectangular shape and can be divided into $x \times y$ identical points. (x_i, y_i) represents a point coordinate. A sensor nodes group $S = s_i | i = \overline{1, N}$ is deployed across the area. Each sensor node has a sensing radius r_s and a communication radius r_c. The notation $\|.\|$ denotes the Euclidean norm. The study introduces several assumptions:

- The network uses the binary Boolean disk sensing model. A point *p*(*x*, *y*) is covered by the sensor if it lies within the sensor sensing range: $\|s - p\| \le r_s$
- The fully connected constraint is defined as there is at least one path from each sensor node to the sink node.
- Sensor s_i are counted as connected with s_j if the distance between them is less than or equal to r_c: $\|s - p\| \le r_c$.
- Each sensor node consumes three energy types: maintenance *ME*, reception *RE*, and transmission energy *TE*. The former maintains the node in the working mode. The two latter energies are crucial in relaying the data packet to the sink in the network. Initially, each node is given a battery capacity *BE*
- Every node is homogeneous, static and synchronized.

Before the mathematical model, the study establishes several definitions:

- The area covered by the sensor group S is defined as:

$$Area(S) = \sum_{i=1}^{N} \sum_{j=1}^{x \times y} P(s_i, p_j), \quad P(s,p) = \begin{cases} 1, \|s - p\| \le r_s \\ 0, \text{ otherwise} \end{cases} \tag{1}$$

- A set N_i is defined as the set of neighbour sensors connected with the i-th sensor

$$\mathcal{N}_i = \{j = \overline{1, N}, j \neq i, \|s_i - s_j\| \le r_c \} \tag{2}$$

A decision variable c is defined as:

$$c_i^k = \begin{cases} 1, & if\ the\ i-th\ sensor\ is\ connected\ to \\ & the\ sink\ via\ k\ sensors, k = \overline{1,N} \\ 0, & otherwise. \end{cases} \quad (3)$$

- A decision vector is a sensor coordinates string (x_i, y_i):

$$x_1\ y_1\ x_2\ y_2\ ...\ x_N\ y_N \quad (4)$$

The energy consumed by each node is calculated as the summation of maintenance, transmission, and packet reception energy. The communication efficiency is guaranteed by transmitting the data in the shortest route.

$$e_i = ME + TE \times c_i^k + RE \times \sum c_i^{k+1} \quad (5)$$

where $k = \{min\{\overline{1,N}\} \mid c_i^k = 1\}$

Additionally, this energy must have a non-negative value and always remain smaller than the battery capacity.

$$0 \leq e_i \leq BE_i, \ \forall i \in S \quad (6)$$

The first objective function is to minimise energy usage at every time cycle, which can be formulated as:

$$f_1 = min \sum_{i \in S} e_i \quad (7)$$

The network energy efficiency is a fundamental metric related to the network performance. The metric is closely related and can be used to calculate the network lifetime. There are different ways of defining the WSN lifetime, but the most common way is the time interval between the network initialization and the battery depletion of any sensor nodes. The mathematical notation is given as: Lifetime = min $\frac{BE_i}{e_i}, \ \forall i \in S$

The second objective function is to maximise the coverage area. However, this function will be formulated as the minimization problem to meet the multi-object problem requirement by assigning a non-coverage penalty to an uncovered area. Thus, the second objective is defined as:

$$f_2 = min\left(1 - \frac{Area(S)}{A}\right) \quad (8)$$

where $\frac{Area(S)}{A} = \frac{\sum_{i=1}^{N} \sum_{j=1}^{x \times y} P(s_i, p_j)}{x \times y}$

Finally, the connectivity requirement ensures each node can transmit the data to the sink node. The constraint is modelled as follows:

$$\text{Subject to } c_i^k \leq \sum c_j^{k+1} \text{ where } k = \overline{1, N}, j \in N_i \tag{9}$$

In essence, the mathematical formulation of the multi-objective problem is to minimise the energy usage (7) and non-coverage penalty (8) while subject to the connectivity constraint (9).

2.2 Proposed solution

Constrained Pareto-based Weighted-sum ABC algorithm. A traditional Pareto Set typically employs either a population or archive updating strategy but mostly focuses on the former [7]. The main idea is to establish an external population to hold the non-dominated solutions that are sorted out at the end of each iteration. In this multi-objective problem, as solution space is pretty large with the size of solution vector size is 1×120, this strategy often exhibits deficiencies in convergence and diversity. Consequently, the results frequently stagnate within local Pareto optima, failing to reach true Pareto-optimal Front.

This paper proposes a novel approach to generate a Pareto Set, combining the linear weighted-sum method with the Artificial Bee Colony algorithm to solve the above issues. Detailed operation of the Constrained Pareto-based Weighted-sum ABC algorithm (CPWABC) follows:

PseudoCode : CPWABC algorithm operation

Input: ABC parameter(MaxIt, nPop, L, a), Update Iteration (UpIt), Cost function f_1 to f_n, Weight Matrix$(W_{w \times n})$

Output: Pareto Set (PS)

1: Setup Parameters , PS= [ ]
2: **for** $i = 1$ to w **do**
3: $f_i = \sum_{k=1}^{n} w(i,k) \times f_k$
4: **for** It =1 to MaxIt **do**
5: ABC generates new solution
6: if new solution satisfies constrain
7: if new $f_i \leq f_i$
8: update new solution
9: else
10: return step 5
11: if It in UpIt
12: PS ← pop
13: **end for**
14: **end for**

CPWABC keeps the general ideas of a typical Strength Pareto Evolutionary Algorithm (SPEA) but with three primary differences: (1) Integrating ABC algorithms with the Pareto method, (2) Changing the objective function every runtime, and (3) Updating the solution mechanism.

Utilizing Artificial Bee Colony optimizer. This ABC algorithm is more suitable for constrained WSN deployment problems than EAs primarily due to the encoding method. The decision vector is decoded as a collection of sensor locations. The EA operators, including crossover and mutation, generate new solutions that are significantly different from the old ones due to the random exchange of parts of the locations. Therefore, the connectivity constraint is difficult to ensure.

Meanwhile, ABC has two steps: global and local search. The former generates new solutions by adding a weighted difference to the old solutions; thus, the new solutions do not change significantly compared to the old ones. Additionally, the local search produces minor modifications to the solution by adjusting the location of several but not the entire topology. Because the cost functions in WSN deployment problems depend vastly on the network topology, these factors showcase why ABC should be utilized.

Dynamic objective function. Instead of allowing the algorithm to run aimlessly without having any certain cost function, a single-objective cost function is implemented to direct the algorithm. This establishes a clear objective for optimizing the solutions. Existing a target is especially beneficial for problems with large solution spaces, where solutions are more likely not to dominate each other.

On the other hand, if the aim is maintained throughout the runtime, solutions will tend to converge to a local Pareto-optima. To bolster the diversity of the Pareto Set and reach near the true Pareto Front, this paper proposes to adjust the cost function at every runtime, which means changing the optimal aim. Therefore, solutions with different aims are anticipated to cover different parts of the solution space, which increases the probability of converging to a global Pareto-optima.

Entire population updating mechanism. In contrast to existing works that primarily focus only on updating the non-dominated solutions, this research emphasizes updating the whole population. The reason is the inherent nature of WSN deployment, especially the connectivity constraints and different solutions sharing the same topology but differences in sensor orders. Thus, it is crucial to investigate the solution space as well as the effect of connectivity constraints on the Pareto Set. For instance, the concavity front can not be shown clearly just by non-dominated points.

Moreover, traditional strategies update solutions into a Pareto Set every iteration. The proposed approach only updates after a number of iterations due to the characteristics of the ABC algorithm. Unlike the widely used EA and its variants, ABC generates new solutions mainly using information on solutions from previous iterations. It evolves by changing its members in a solution little by little to reach the optimal one. This is why, after several iterations, the solutions have been alternated enough to be taken into the Pareto Set.

After the full set are generated, the non-dominated sort is used to find the Pareto Front First Rank. These solutions are not dominated by any other solutions.

Decision maker. The paper's target is to select a final solution that satisfies several conditions. Hence, the weighting method is introduced:

$$\min_{j=1,..,n} \left(\sum_{i=1}^{k} w_i \left| f_i(x_j) - z_i^* \right|\right) \text{ subject to } x \in S \tag{10}$$

with j as the index number of the solution on Pareto Front and k being the number of objective cost functions. Variable w_i, f_i and z_i^* are weighting coefficients, cost function value and ideal vector of objective i, respectively; S is a decision space that contains constrain decided by the decision maker. For example, $k = 2$, as this paper focuses on Coverage ratio and Energy consumption objectives, S can be a condition of a Coverage ratio larger than 80 %.

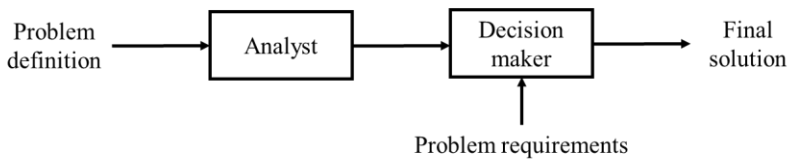


Fig. 1. The proposed procedure to apply in an application

In essence, Figure 1 illustrates the whole application procedure. This paper aims to investigate indoor environmental quality monitoring in buildings, with the problem of deploying a group of sensor nodes in a monitoring area. The analyst is the proposed CPWABC, and the weighting method acts as a decision maker, selecting the final solution from the set of non-dominant solutions with the preferred information.

3 Results and Discussion

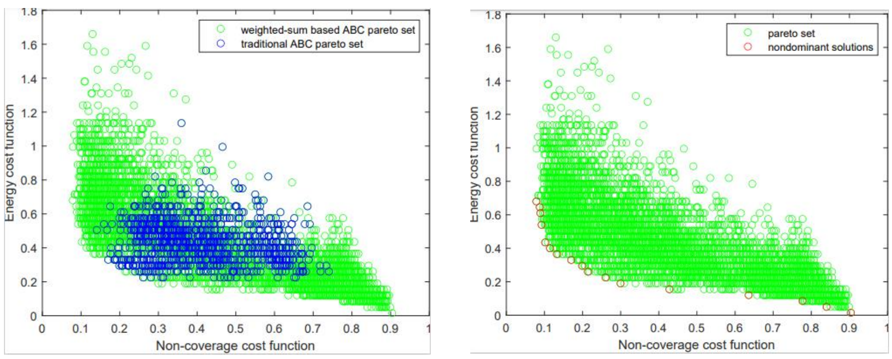
Table 1. The network and solution parameters

ABC Parameter		WSN Parameter	
Max Iteration (MaxIt)	2000	Monitoring area	100m×100m
Population size (nPop)	100	Sensing radius	10m
Limit parameter (L)	1000	Communication radius	10m
Acceleration coefficient (a)	1	Nodes number	60
Update iteration (UpIt)	1100:2000	Battery capacity	1Ah
Weight matrix (W)	[0.1:1;	Maintenance energy	13mA
	0.9:0]	Transmission energy	20mA
		Reception energy	2mA

The section validates the proposed solution performance through MATLAB x64 simulation. Table 1 illustrates parameters used to construct the Wireless Sensor Network deployment problem and operate the Artificial Bee Colony algorithm.

3.1 Diversity enhancement

This subsection shows how our proposed solution enhances the diversity in the Pareto Optimal Set. From the mono-objective optimization, creating the Pareto set in the traditional manner could be seen as linear weighted scalarization by assigning equal weights to each objective. Thus, its solution focuses densely around the centre of the true or global Pareto front, as in Figure 2(a). The usage of dynamic objective functions not only widens the objective space by promoting solution scattering but also achieves higher solution quality. Evidence is the significant reduction in energy consumption, whereas the traditional set only reached the minimum value of 0.2 in the energy cost function.



(a) (b)

Fig. 2. (a) Comparison between traditional and proposed Pareto set and (b) The proposed non-dominant Pareto solutions

Dealing with the conflicting nature of the objectives, Pareto optimality principle finds solutions that cannot be optimized further without deterioration to at least one of the objectives. Figure 2(b) clearly depicts the trade-off between energy and non-coverage objectives through the first rank Pareto Front. In case only non-dominated solutions are updated, the ABC cannot perform modifications on dominated solutions. These solutions, however, have potential to become non-dominant, thereby diminishing the quality of the Pareto Front. With attained solutions, the next subsection determines suitable solution for the application.

3.2 Decision-making integration

The paper aims to apply the results in building applications where the norm dictates that the indoor environmental quality data coverage ratio falls between 80% and 90% to ensure accuracy when applying the interpolation methods. The weighting decision-making method assigns a weight to each objective, thus transforming the multi-objective functions into a single objective function. With the knowledge that the coverage ratio is set to be at least 80% and the lifetime must be maximized, the decision-maker evaluates non-dominant solutions with varying weights to identify the appropriate solution. This yields a non-coverage ratio of approximately 0.19 with a energy cost of 0.295, equivalent to about 3.39 hours of lifetime. Figure 3 shows a selected solution.

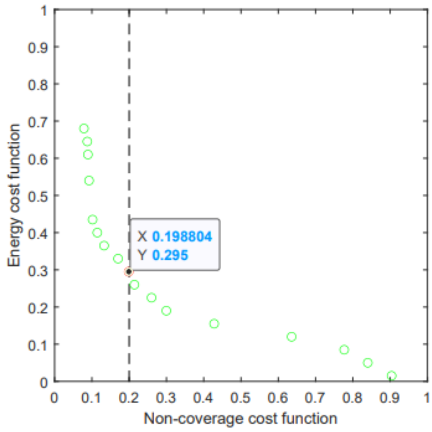


Fig. 3. Integrate weighting decision-making method to find final solution

The final topology is then deployed in the monitoring area. Figure 4(a) depicts final sensor positions. It is crucial to notice that the sensor nodes connecting directly to the sink node would deplete energy much faster because they are responsible for relaying the information of the others to the sink node. For this large-scale problem with 60-node deployment, each of these nodes transmits data on an average of other 7 nodes. When one of these runs out of battery, the network would stop due to network disconnection. The same issue is observed in final area coverage in Figure 4(b) as most of overlapping area surrounds the sink location.

Trade-off between the two objectives becomes apparent when investigating the extreme non-dominant solutions. If the focus is on maximizing network lifetime, all nodes would be deployed around the sink compared to the above final solution. Figure 4(c) illustrates this case in which coverage ratio is almost ignored. All the sensors surround the sink node; thus, the solution achieves operation hours of approximately 67 hours with coverage ratio of about 10%. In the contrast case where the coverage is emphasized, the CPWABC finds the solution with coverage ratio up to 92%, as in

Figure 4(d). Only four nodes connect directly to the sink node, and consequently, the network lifetime is reduced to nearly an hour and a half. It is crucial that in both cases, the solutions are non-dominant; thus, the other objectives cannot be ignored completely.

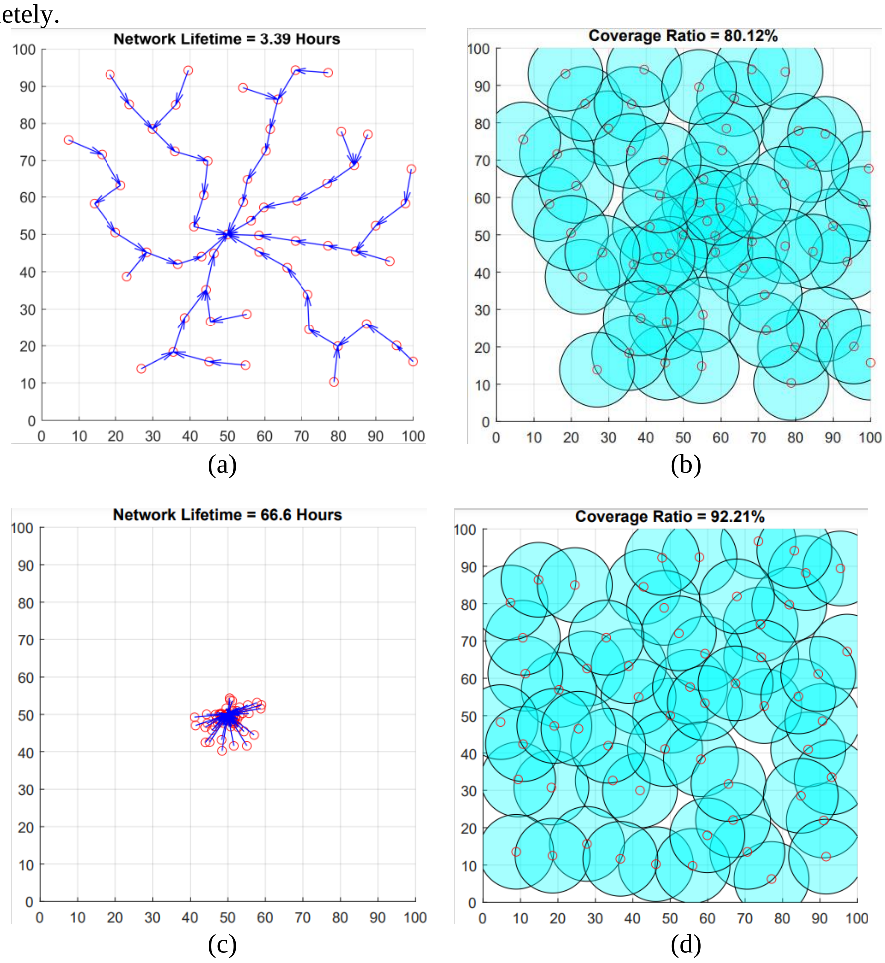


Fig. 4. (a) The final solution topology, (b) The final solution coverage, (c) The extreme lifetime case and (d) The extreme coverage case

4 Conclusion

This paper explores the multi-objective WSN deployment problem, considering four objectives: (1) Energy efficiency, (2) Network lifetime, (3) Coverage, and (4) Network connectivity. A novel approach, combining the constrained Artificial Bee Colony algorithm and the linear weighted-sum method, is proposed to enrich the diversity of the Pareto Set. Moreover, the paper incorporates a weighting decision-maker to select a final solution for the smart building application from the non-dominant solutions. The study's limitation lies in the usage of a simplistic coverage model excluding the uncertainties. Additionally, the energy consumption model eliminates the impact of distance. Thus, future attempts would address these issues and integrate the method with practical systems.

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