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Computationally Effective and Practically Aware Pareto-Based Multi-Objective Evolutionary Approach for Wireless Sensor Network Deployment

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Abstract: Wireless Sensor Network Deployment (WSND) is an active research topic. Different approaches have been effectively developed for WSND. Multi-Objective Evolutionary Algorithms (MOEAs) are regarded as powerful deployment methods because of their adaptive flexibility in effectively searching and providing numerous deployment options for the user. In this study, a computationally effective and practically aware Pareto-based multi-objective evolutionary approach was developed for WSND. On the one hand, the initialization of the population and crossover operation were modified to obtain solutions that meet the connectivity constraints and improve the computational aspect for producing the solutions. On the other hand, a constraint of the dead zone was added to make the deployment practically aware in presence of restricted areas in the Region of Interest (ROI). The approach of the current study was compared with that of Khalesian and Delavar by generating the values of the lifetime and coverage as the conflicting objectives of the deployment. Results showed that the developed approach outperforms the previous approach with respect to these objectives.

Key words: Deployment, Pareto optimization, multi-objective, restricted area, dead zone, lifetime evaluation, coverage zone evaluation

INTRODUCTION

Wireless Sensor Network (WSN) is a technology developed to address the growing need for the observation and control of environments. Originally, the growth of WSN applications is conducted by military applications. WSN are currently used in various fields, such as medicine, environmental risk monitoring, traffic control, disaster monitoring and industrial process control (Debnath *et al*., 2016) . The various types of sensors as well as the limited need for infrastructure, make WSNs capable of providing continuous measurements in a wide range of environments for a large variety of applications (Juul *et al*., 2015).

A sensor is a device capable of sensing objects in an environment and transforming the data gathered by the network for processing. Each sensor has a low processing unit, small data storage, limited battery and limited coverage and communication ranges (Njoya *et al*., 2016). Sensor nodes are distributed in different places and work together to communicate information gathered from a Region of Interest (ROI) through links that connect them wirelessly and send this information using multi-hop communication to the base station called sink which sends the data to the user or to other networks (Abdollahzadeh and Navimipour, 2016).

WSN deployment is a major step in WSN design and is considered a solution for reducing the effects of sensor limitations (Yick *et al*., 2008). Efficient deployment of the sensors is very important in improving coverage area and prolong lifetime of the network (Juul *et al*., 2015; Tsai *et al*., 2015). Connectivity is another critical issue in designing a sensor network for proper functioning regardless of diverse situations (Debnath *et al*., 2016). One of the major challenges in sensor deployment is finding a trade-off among the conflicting objectives of the network, coverage and lifetime under certain connectivity constraints.

Multi-objective optimization has been used as an effective mathematical tool for addressing this type of optimization (Debnath *et al*., 2016). Multi-objective considers several conflicting objectives simultaneously. In such a case, a set of alternatives with different trade-offs, called Pareto optimal solutions or non-dominated solutions generated instead of single optimal solution.

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In a practical environment, restricted areas such as rivers, lakes and unsafe areas can block the connectivity of sensor nodes. Connectivity blocking is an important challenge in WSND (Wahab *et al.*, 2016a, b).

Most of the existing studies on WSN assume that homogeneous sensors can be deployed anywhere (not regarding "restricted areas" that exist in practical situations). Khalesian and Delavar (2016) proposed the Constrained Pareto-based Multi-objective Evolutionary Approach (CPMEA) to maximize coverage and minimize energy consumption. They also designed a genetic-based operator which involves crossover and mutation for ensuring an effective search for optimal solutions. However, their work not aware for some areas in practical environments that are not suitable for sensor deployment. Another criticized aspect of the work by Khalesian and Delavar (2016) is their design of crossover operation from the perspective of computational complexity. In this study, we improve the CPMEA with the following objectives:

- Make CPMEA a Computationally Effective and Practically Aware Pareto-based Multi-objective Evolutionary Approach (CE-PA-PMEA)
- Evaluate CE-PA-PMEA and compare it with CPMEA

Literature review: Many researchers have proposed approaches to enhanced the sensor deployment problem for monitoring and surveillance in many environments and to improving networks and their functionalities (Syarif *et al.*, 2014).

The existence of restricted areas or obstacles in an ROI may degrade WSN functionality and these obstacles may cause loss of connectivity links between sensor nodes, thereby causing the network to break down. Wang and Ssu (2013), proposed a scheme for detecting obstacles in the ROI by identifying the size and location of these obstacles using radio units fitted in each sensor. The scheme recognizes the obstacles by marking the sensor nodes around the obstacle boundaries. Jourdan and de Weck (2004), proposed a multi-objective algorithm that is based on the genetic approach to optimize WSN deployment by providing Pareto-optimal (non-dominated) solutions to maximize the coverage and lifetime of the network. Jameii *et al.* (2015), proposed an algorithm that is based on Non-dominated Sorting Genetic Algorithm (NSGA-2) to optimize coverage, number of active nodes and energy consumption by putting some sensor nodes in sleep state. Liu and He (2014), proposed an approach that is based on ant colony optimization with a greedy mechanism to solve the problem of grid-based coverage with low cost and connectivity maintenance. This approach can dynamically adjust the sensing and communication range to reduce energy consumption, thereby prolonging network lifetime. Zorlu and Sahingoz (2016), proposed a Genetic algorithm for sensor deployment optimization to maximize WSN coverage with the minimum number of homogeneous sensors. Syarif *et al.* (2014a, b), used a multi-objective approach for WSN deployment with some fixed obstacles. This approach which is based on NSGA-2, aims to optimize coverage and connectivity for WSN deployment by dividing the ROI into grid cells to identify the obstacles. They also proposed fitness and ranking functions for defining the best solution from Pareto Fronts (PFs). Sengupta *et al.* (2013), provided a method that depends on a multi-objective evolutionary algorithm and uses a decomposition approach to convert the problem of PF approximation into several single-objective optimization problems.

The deployment problem: In this study, the deployment problem is defined and the related objectives are introduced with mathematical formulations.

Problem definition: This research considers a two-dimensional rectangular environment ROI where K homogeneous sensors are deployed. This environment is subject to some restricted areas. The sensors have a pre-defined coverage zone for the sensing and a communication zone for connecting with one another. The sensors send data directly or via. multi-hop communication to the single sink node (unlimited energy node), assuming that the sink is located at the center of the ROI. No movement is involved as the sensors are assumed stationary.

Problem formulation: The formulation of the wireless deployment problem as a multi-objective optimization is as follows:

$$F(x) = \left[f1(x), f2(x)\right] \rightarrow \text{Max}$$

- The first objective f1 represents the coverage
- The second objective f2 represents the lifetime

Decision variable x:

- xi, yi: represents the location of sensor node_i
- x = x1, y1, x2, y2, ..., xk, yk: represents the location of the sensor nodes as the decision variable

where, x represents the feasible solutions with problem constraints.

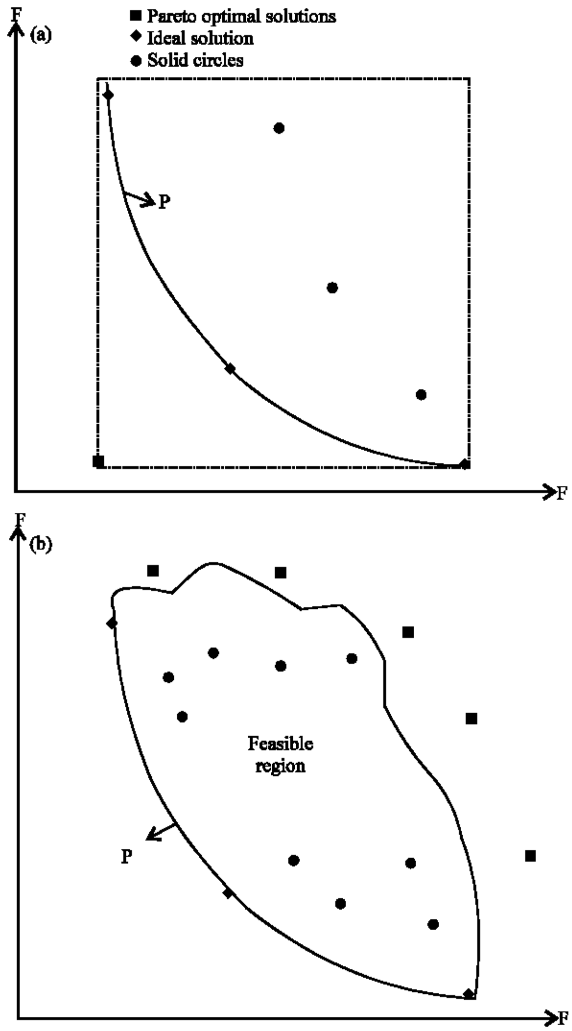

Fig. 1: The Pareto front of multi-objective problem MOP

A solution x* dominates the other solution x' (if (x*)≥ fi (x'))∀ i ∈ {1, 2, ..., M} and fi(x*)>fi(x') ∃ i ∈ {1, 2, ..., M} is denoted as F (x*)>F (x') where M is the number of the objectives in the problem.

The solution that is not dominated by any other solution in the objective space is an optimal (non-dominated) solution. The set of these optimal solutions is the Pareto Front (PF).

Figure 1a illustrates a PF with two objectives: the Pareto optimal solutions in the PF (marked with an asterisk) provide better values for the objective functions than any other solution in the objective space. The rectangle represents the ideal solution which provides the minimum objective values and is often considered unreachable. The solid circles represent the solutions that are dominated by at least one solution in the PF. In Fig. 1b, the bold curve indicates the PF. The solid circles are the feasible solutions in the feasible region and the remaining solutions outside the feasible region (marked with a triangle) are considered infeasible (Jameii *et al*., 2015). The conflicting objectives, we considered in WSN are as follows:

Coverage: The total coverage of the ROI is the ratio of the areas covered by all the sensors to the total area of the ROI:

$$\text{Cover} = \frac{\sum_{(x_G, y_G)\in ROI} g(x_G, y_G)}{N_G}$$

And:

$$g(x_g, y_G) = \begin{cases} 1\exists i \in \{1, ..., k\}, \sqrt{\Delta x_i G^2} \leq \\ 0 \quad \text{otherwise,} \end{cases}$$

where, $\Delta x_{iG} = x_i - x_G$ $\Delta y_{iG} = y_i - y_G$, N_G is the total number of grids in the ROI and R_s would be the sensing range of a sensor node if the ROI were divided into grid points where each point is covered by at least one node.

Lifetime: The lifetime is the ratio of time taken until one of the sensor nodes runs out of energy (failure) to the maximum network lifetime:

$$\text{Life} = \frac{\min\{T_{\text{failure, i}}\} i=1, ..., k}{T_{max}}$$

where, min $\{T_{failure}\}$ is the minimum value of the failure time of the sensor nodes and represents the maximum number of sensing cycles before the energy runs out and T_{max} is the maximum possible number of sensing cycles and represents the maximum lifetime of the network.

MATERIALS AND METHODS

The proposed approach: This study proposes the CE-PA-PMEA for wireless sensor deployment as well as the operators designed and used for this purpose.

The WSN is modeled as a graph G(k) = (Ver, Lnk) where Ver is the set of vertices (sensor nodes), Lnk is the set of links connecting the vertices and K is the number of sensor nodes. A link may exist between any two sensor nodes if the Euclidean distance between them is less than the communication range Rc. Theorem 1 of Khalesian and Delavar (2016) of graph theory is used for checking the connectivity of the produced graphs to ensure the required connectivity of the designed WSN. The general steps of the proposed algorithm are illustrated by a flowchart of Fig. 2.

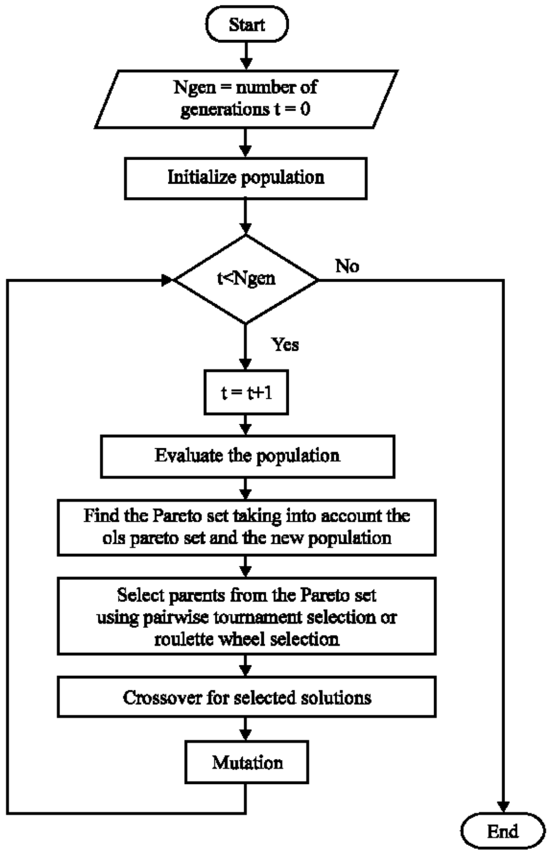

Fig. 2: The CE-PA-PMEA general steps

Theorem 1: Let G be the adjacency matrix of a connected graph and let Y = [yij]i, j = 1, ..., k be the matrix y = $G+G^2$, ..., $+G^{n+1}$. Then G is connected if and only if: $y_{ij} \neq 0$ for all distinct i, j = 1, 2, ..., k.

Initialization: The proposed initialization process aims to produce an initial graph with one node which is the sink node. The first node is randomly generated in the environment while maintaining the avoidance constraint of the restricted areas in ROI by not generating nodes within the boundaries of this areas. Then, the next sensor is also randomly generated but with two constraints: the avoidance constraint of the restricted areas and being in the union of the communication zone of at least one of the preceding sensors until a graph with k nodes and k-1 edges is obtained. With this process, we do not need to check the connectivity of the graph and only need k adding operation thus, the time needed for initialization operation is less than that in the previous approach. This process is clarified by the flowchart in Fig. 3.

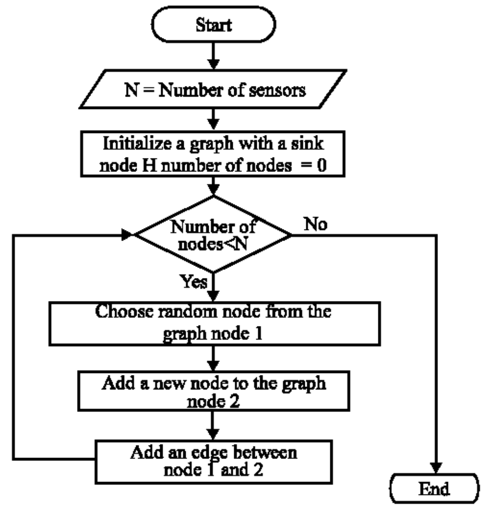

Fig. 3: The initialization steps

Evaluation of the population: After the initialization process, we choose promising solutions from the current population as parents for the next generation.

The values of the objectives should be calculated for the whole population and then the old Pareto solutions are combined with the population. Then, the Pareto set is determined and the two best solutions are selected in terms of Pareto dominance. The coverage and lifetime objectives are computed in study 2. Algorithm 1 shows the evaluation of the lifetime objective which calculated as (Khalesian and Delavar, 2016).

Algorithm 1; Lifetime evaluation:

Input: Number of sensor nodes (k), initial energy of each sensor (E>0), path loss exponent ($\alpha \in [2, 6]$), transmission quality parameter (β), power amplifier energy consumption (amp) and minimum distance between nodes (d_{min})

Output: Lifetime

Step 1: Set E_i (0) = E for all i = 1, 2, ..., k

Step 2: Calculate the minimum transmit energy via. $P_{min} = \beta\, d_{min}$

Step 3: Calculate the maximum possible number of sensing cycles via:

$$Tmax = \frac{E}{P_{min}amp}$$

Step 4: FOR I = 1, 2, ..., k do

Step 4.1: Calculate the shortest path from the sensor node to the sink

Step 4.2: Calculate the traffic load for the sensor node according to node level with the sink

Step 4.3: Calculate the distance from the sensor node to the next node

Step 4.4: Calculate the transmit energy $P_{ij} = \beta\, d_{ij}^{a}$

Step 5: Calculate T failure

$$T_{failure} = \min\left(\frac{E}{P\,amp}\right)$$

Step 6: Set

$$Lifetime = \frac{T_{failure}}{T_{max}}$$

Determining the pareto solutions: For finding the Pareto set in the multi-objective optimization, we calculate the value of the objectives for whole population and combined with previous Pareto solutions. we follow who proposed an approach to determining the non-dominated solutions. This approach is summarized as follows:

- Sort all the solutions in decreasing order of their first objective function and create a list (O)
- Initialize a set S_1 and add the first element of list O to S_1
- For every solution O_i (other than the first solution) of list O, compare solution O_i with the solutions of S_1
  - If any element of set S_1 dominates O_i, delete Oi from the list
  - If O_i dominates any solution of set S_1, delete that solution from S_1
  - If O_i is non-dominated by the elements in set S_1, then update set $S_1 = S_1 \cup O_i$
- The Pareto solutions are in the resulting non-dominated set S_1

Selection operation: The well-known Pairwise Tournament (PT) and Roulette Wheel (RW) selection operators are used. We also use a selection operator equal to 0.5. If the random number generated is greater than 0.5, then the selection will depend on the coverage fitness values; otherwise, the selection will depend on the lifetime fitness values. Selecting parents by PT is explained by Algorithm 2 and selecting parents using RW is explained by Algorithm 3.

Algorithm 2; PT selection:

Input: The values of the objectives of the Pareto solutions and the number of tournament solutions k
Output: The selection of the best solution as a parent
Step 1: FOR each Pareto solution
x (j), j ∈
{1, ..., number of pareto solutions}
f_i (x), ∀ i ∈{1, 2, ..., M}, M is the number of objective functions
IF r and > 0.5 Then
objective Value (j) = f_1(x), …, (Coverage objective)
ELSE
objective Value (j) = f_2(x) … (Lifetime objective)
END IF
END FOR
Step 2: Select k random individuals from the input
Step 3: Select the best individual of k with the highest objective value as a parent

Algorithm 3; RW selection:

Input: The values of the objectives of the Pareto solutions
Output: The selection of the best solution as a parent
Step 1: FOR each Pareto solution x (j), j∈{1, …, number of Pareto solutions}
f_i (x). ∀ i ∈ {1, 2, ..., M}, M is the number of objective functions
IF r and > 0.5 THEN
objective Value (j) = f_1 (x), …, (Coverage objective)
ELSE
objective Value (j) = f_2 (x), …., (Lifetime objective)
END IF
END FOR
Step 2: FOR each Pareto solution x (j), j ∈ {1, …, number of Pareto solutions}

$$\text{Probability ObjectiveValue(j)} = \frac{\text{Objective value}\,(j)}{\text{Sum}\,(\text{objective value})}$$

END FOR
Step 3: Calculate the cumulative sum of the probability objective value
Step 4: Choose the first member of the cumulative sum where:
cumulativeSum≥rand where rand ∈ [0, 1]

Crossover operators: The crossover aims to produce new solutions for the next generation by selecting two solutions from the population; these solutions are called parents and exchange their information with each other with a rate probability (crossover rate) to generate new solutions called children (offsprings). The crossover operation is different from the previous approach. In the proposed approach, we perform the crossover in a light way. Two parents are combined to generate a new WSN with a graph of 2k-2 edges after that a new graph with sink node is initialized and then a random node with its associated edges is selected from the combination and communicated to the new graph with respect to the connectivity constraint of the combined parents graph. we repeatedly select random nodes until a new graph with k-1 edges and k nodes which inherited the positions and their connections from their parents. The crossover process is applied to generate the two children shown in the flowchart in Fig. 4.

Mutation: The purpose of the mutation is to maintain diversity in the population by modified the location of some nodes accordingly to the connectivity constraints with some probability rate (mutation probability). The mutation implemented as (Khalesian and Delavar, 2016).

Termination criterion: When the maximum Number of Generations (N_G) reached, the pareto front returned as optimum solutions in the search space.

Practical awareness for dead zone areas: The previous approach does not process the problem of presence of restricted areas or geographical areas where sensors should not be localized. The network may be negatively affected if the sensors are placed in these areas, thereby causing the sensor nodes to fail and the network to break

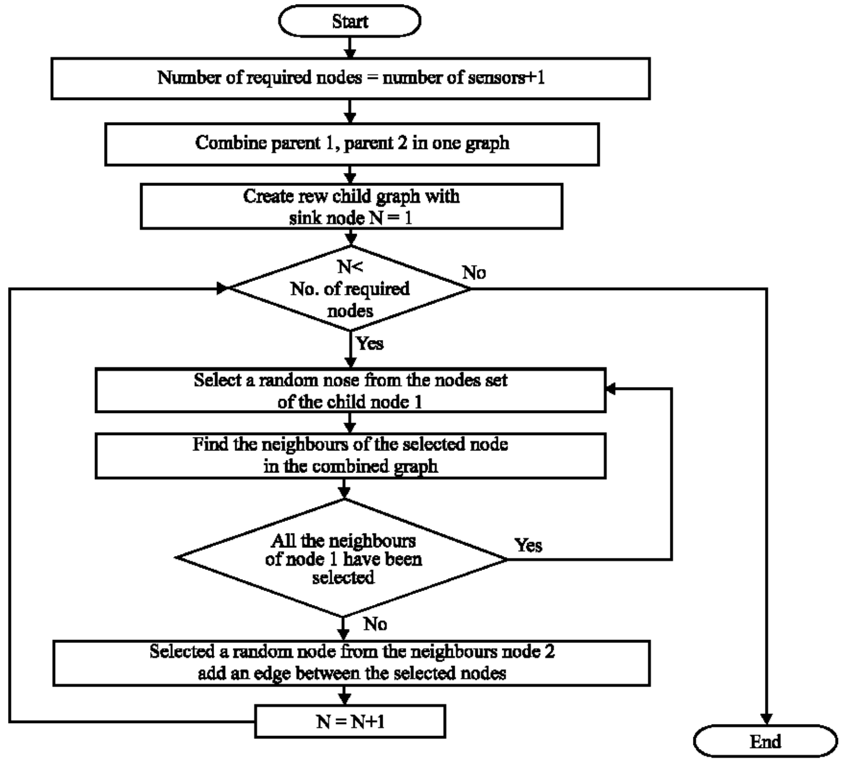

Fig. 4: Flowchart of crossover process

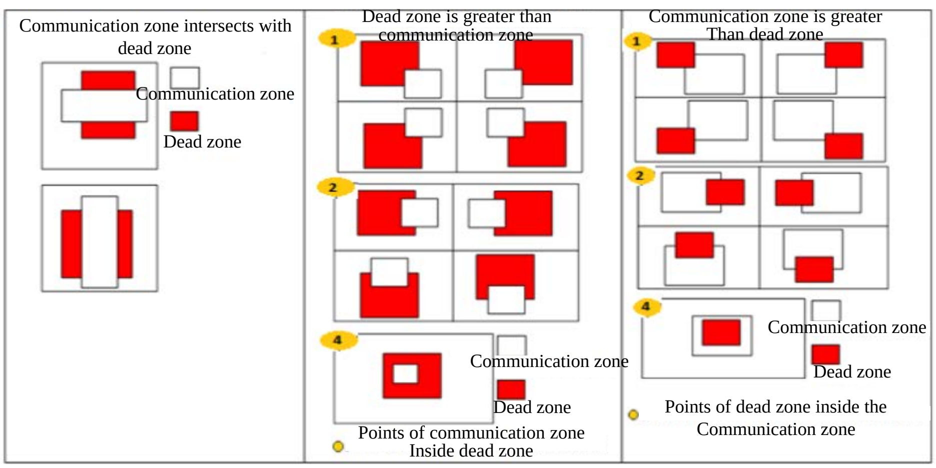

Fig. 5: The several states of crossing between the dead zone and the communicating zone

down. Thus, inside the environment, we assume the presence of a square-shaped area with specific boundaries we called it dead zone in which the sink node should not be placed. During the geometric solution of the initialization and crossover operation, the potential positions of the sensor nodes is tested.

Several states of crossing are founded between the dead zone and the communicating zone because the position of the sensor nodes (xi, yi) should be generating inside a communication area (Fig. 5). These states are processed by redefining the communication area boundaries after exclusion of the dead zone area that defined as inequality constraints: xi<xr1; xi>xr2; yi<yr1; yi>yr2 where, xr1, xr2, yr1, yr2 denoted as the boundaries of the dead zone.

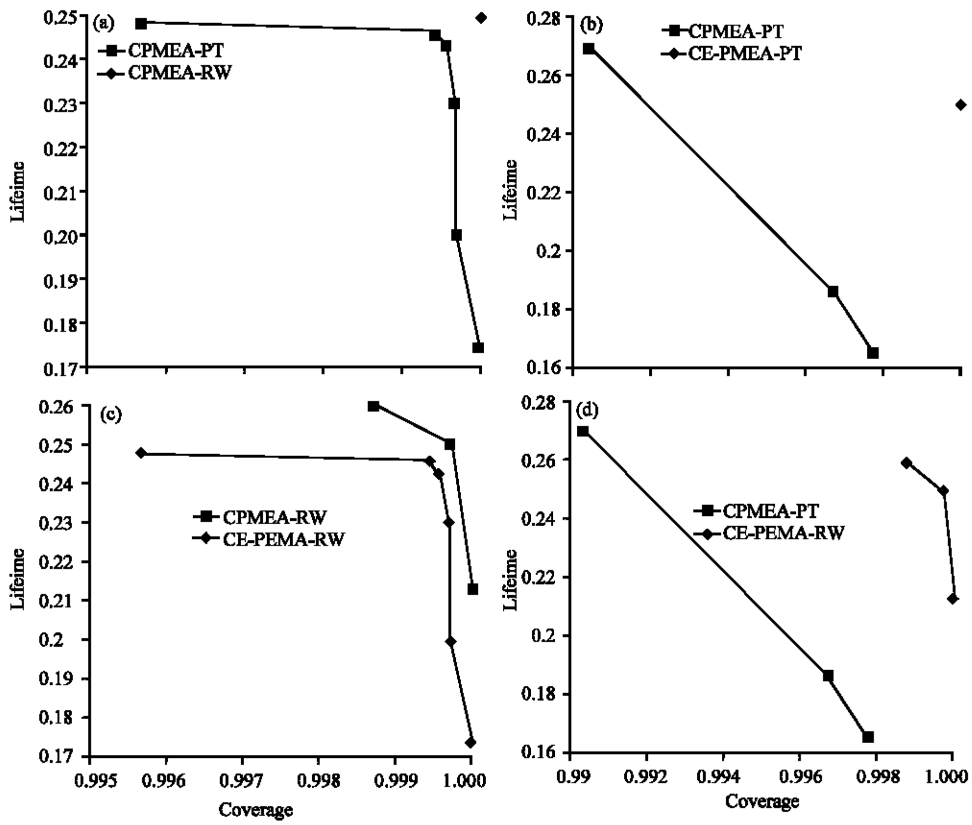

Fig. 6: a- d) PFs of the comparisons between the approaches without dead zone for P1

RESULTS AND DISCUSSION

The efficiency and effectiveness of the proposed evolutionary approach are evaluated by investigating its results and comparing them with those of CPMEA (Khalesian and Delavar, 2016).

We present the evaluation measures of the developed approach with its two selection operations, PT and RW, for both developments CE (Computationally Effective) and PA (Practically Aware) and the Comparison with the Previous Approach (CPMEA) is applied.

Two main scenarios (areas with and without a dead zone) are considered to validate the practical awareness of the developed approach. Moreover, the objectives of the network coverage and lifetime are calculated. The parameters settings considered during the operation of these approaches shown in Table 1.

No dead zones in the ROI: First, we compare the previous and our proposed approaches in the ROI without a restricted area.

CPMEA-PT vs. CPMEA-RW: The performances of the previous approach with PT and with RW are compared.

Table 1: Parameter settings

Parameter setting No.	No. of generations	No. of individuals	Crossover rate	Mutation rate
P1	250	200	0.1	0.1
P2	100	200	1.0	0.1

The PFs for the two approaches are generated for the evaluation. Figure 6a shows the PFs for the parameter P1. The PF generated by PT dominates that generated by RW for the both objectives. Figure 7a shows the Pfs for the parameter P2. The PF generated by PT dominates that generated by RW with respect to the lifetime.

CPMEA-PT vs. CE-PMEA-PT: The previous approach and our computationally efficient approach, both with PT are compared. The PFs for the two approaches are generated. Figure 6b shows the PFs for P1. The solution locations are optimal for the coverage with respect to CE-PMEA-PT and optimal for the lifetime with respect to CPMEA-PT. While Fig. 7b shows the CE-PMEA-PT is optimal for the two objectives for P2.

CPMEA-RW vs. CE-PMEA-RW: The previous approach and our computationally efficient approach, both with RW

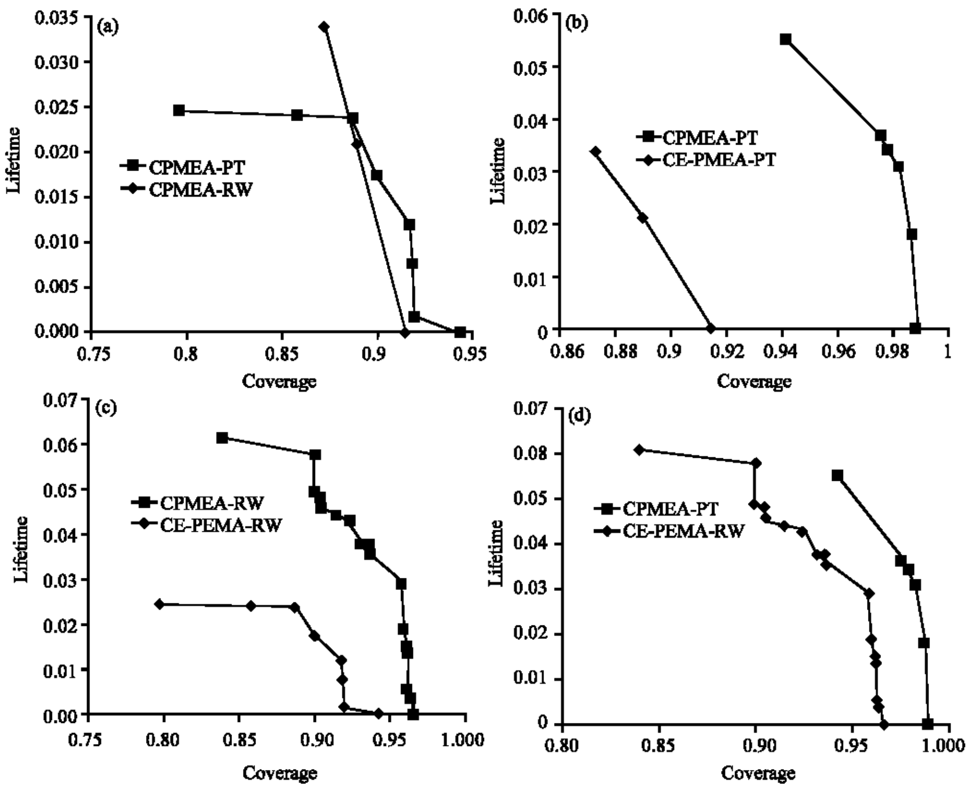

Fig. 7: a-d) PFs of the comparisons between the approaches without dead zone for P2

are compared. The PFs for the two approaches have been generated. Figure 6-c shows the Pfs for P1 and Fig. 7-c shows the Pfs for P2. Both of them shows that CE-PMEA-RW is more optimal for the lifetime and the coverage with respect to the previous approach.

CE-PMEA-PT vs. CE-PMEA-RW: We compare the performances of our computationally efficient approach with PT and with RW for checking which of theme is superior on another. Figure 6d shows the PFs for P1. The PF generated by PT is more optimal for the lifetime than for the coverage. By contrast, the PF generated by RW is more optimal with respect to the coverage than to the lifetime. In Fig. 7d, the PF generated by PT is more optimal for the coverage than lifetime and there is no superiority of one of them over another.

Dead zones in ROI: This set of comparisons is conducted with the assumption of a retracted area intersects with the communication area that lead to the dead zones in ROI.

CPMEA-RW vs. CPMEA-PT: We implement the previous approach in the ROI with a dead zone in which the sensor nodes cannot be placed. The PFs for the two approaches have been generated. Figure 8a shows the PFs for P1. PFs show that the previous approach fails to provide feasible solutions because of its lack of the practical awareness achieved by incorporating the constraints of preventing the dead zone. Figure 9-a shows the PFs for deferent parameter settings.

CPMEA-PT vs. CE-PA-PMEA-PT: The previous approach and our practically aware approach CE-PA-PMEA, both with PT are compared. Figure 8b shows the PFs for P1. We can see that the PF of the previous approach does not appear in this case, thereby indicating that the previous approach fails to provide a solution when a dead zone exists in ROI. Figure 8b show that the PF of CE-PA-PMEA-PT outperform the CPMEA-PT for the two objectives in with respect to P2.

CPMEA-RW vs. CE-PA-PMEA-RW: The previous approach and CE-PA-PMEA, both with RW are compared. The PFs of CPMEA-RW and CE-PA-PMEA-RW are seen in Fig. 8c. The PF for our approach dominates that of the previous approach for the lifetime and the coverage. Figure 9c also shows that CE-PA PMEA-RW outperform the CPMEA-RW for the two objectives.

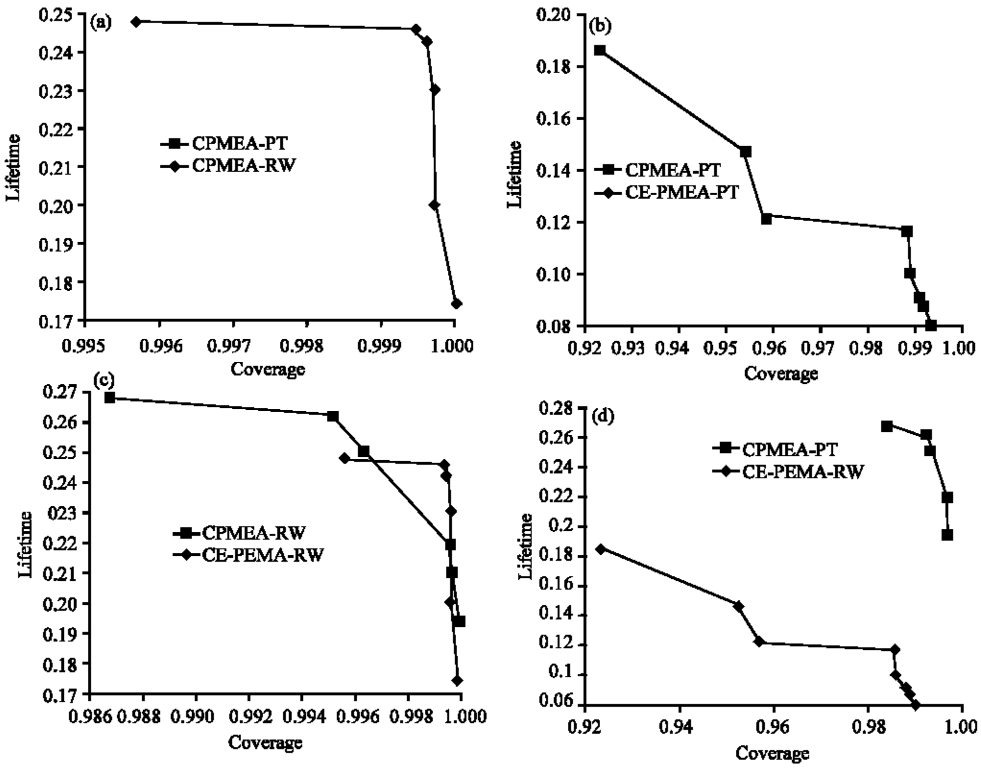

Fig. 8: a-d) PFs of the comparisons between the approaches with presence of dead zone area for P1

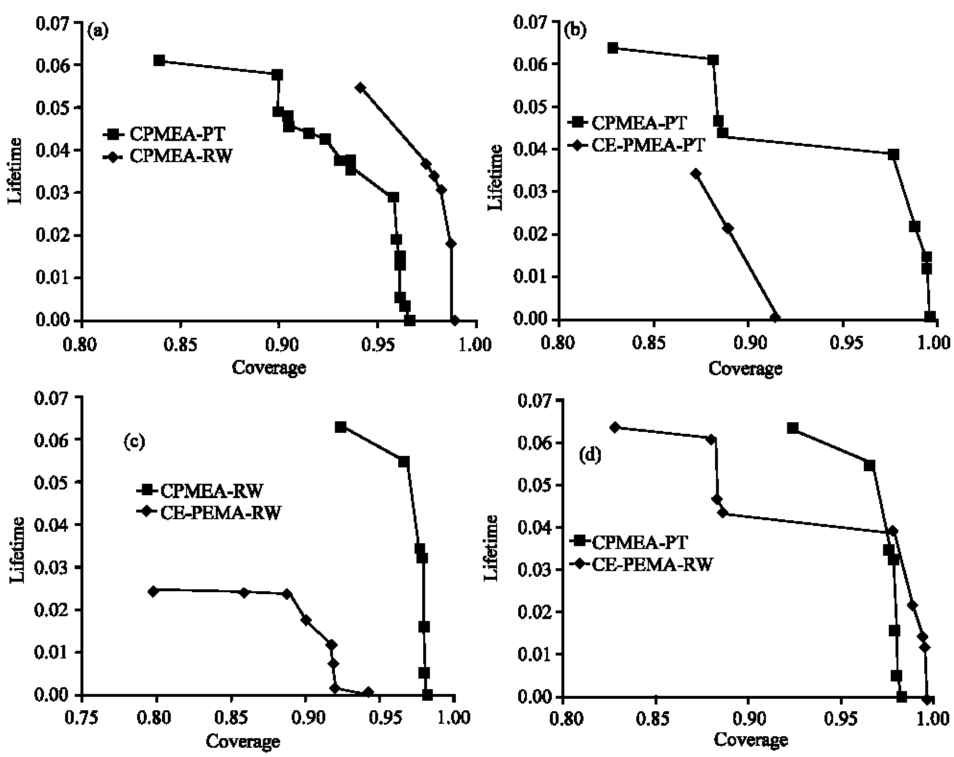

Fig. 9: a-d) PFs of the comparisons between the approaches with presence of dead zone area for P2

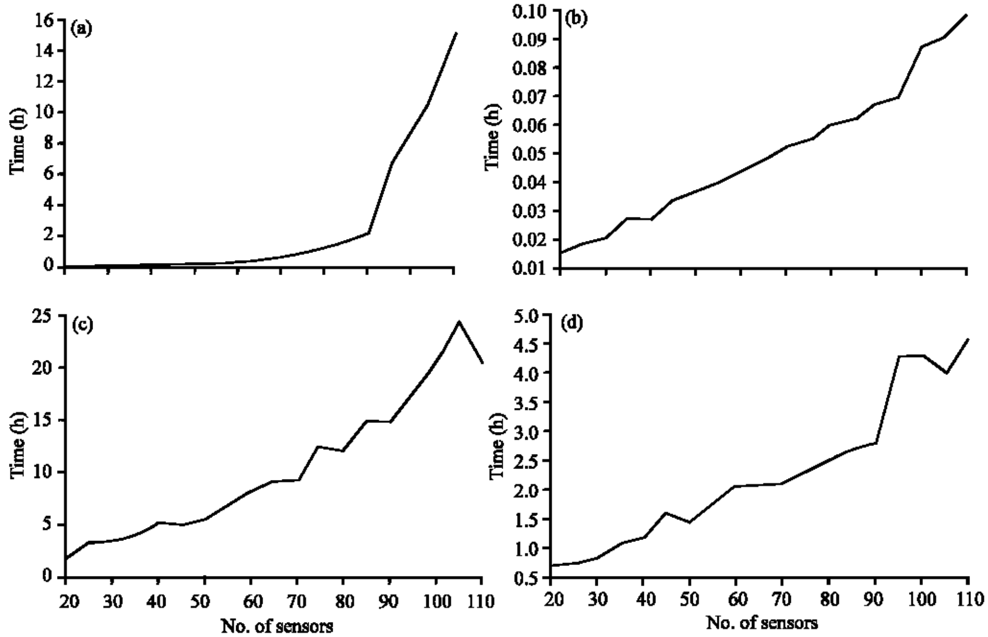

Fig. 10: a- d) The execution time for initialization and crossover for CPMEA and CE-PA-PMEA

CE-PA-PMEA-PT vs. CE-PA-PMEA-RW: Finally, we compare the performances of our approach CE-PA-PMEA with PT and with RW. Figure 8-d shows that PT has a better achievement with respect to lifetime and coverage than RW for P1. Also, Fig. 9d shows that with respect for P2.

Computational time comparisons: A comparison regarding the computational time of the initialization operation and the crossover operation for both previous and proposed approaches was implemented to check the computational complexity, Fig. 10 shows that execution time for the proposed approach outperform that of the previous approach, this prove that the proposed approach is computationally effective.

CONCLUSION

In this study, an improvement of the CPMEA by Khalesian and Delavar has been proposed to maximize coverage and minimize energy consumption that lead to prolong the lifetime of the network. The improvement is concentrated on two aspects: computational performance and practical awareness of the dead zone. The former has been implemented by modifying the initialization and crossover operations and the latter has been implemented by incorporating an additional constraint in the algorithm. Results show the superiority of our developed algorithm over CPMEA with respect to the PF and the two objectives of deployment, lifetime and coverage.

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