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Abstract Recently, the efficient deployment of Wireless Sensor Networks (WSNs) has become a leading field of research in WSN design optimization. Practical scenarios related to WSN deployment are often considered as optimization models with multiple conflicting objectives that are simultaneously enhanced. In the related literature, it had been shown that moving from mono-objective to multi-objective resolution of WSN deployment is beneficial. However, since the deployment of real-world WSNs encompasses more than three objectives, a multi-objective optimization may harm other deployment criteria that are conflicting with the already considered ones. Thus, our aim is to go further, explore the modeling and the resolution of WSN deployment in a many-objective (i.e., optimization with more than three objectives) fashion and especially, exhibit its added value. In this context, we first propose a many-objective deployment model involving seven conflicting objectives, and then we solve it using an adaptation of the Decomposition-based Evolutionary Algorithm "θ-DEA". The developed adaptation is named "WSN-θ-DEA" and is validated through a detailed experimental study.

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1 Introduction

Being a key concept in advanced technologies that have created new opportunities for supporting decision making and improving quality of life, Wireless Sensor Networks (WSN) have been significantly an area of interest for industries' research [38, 35, 31, 43]. The advances in WSNs have contributed to the expansion and the development of multiple technologies such as the Internet of Things (IoT) and the Industrial Internet of Things (IIoT). WSN refers to a group of spatially distributed sensors for monitoring and recording the physical conditions of the environment and organizing the collected data in a central location [12]. Numerous domains have benefited from the usage of WSNs, essentially the Industry 4.0, smart cities, health and environmental monitoring and so on.

Based on recent surveys [22, 19], several problems related to WSNs could be modeled as optimization problems and then efficiently solved using metaheuristic algorithms. It has been shown that these problems are multi-objective or many-objective by nature as usually different conflicting criteria should be considered simultaneously to come up with better solutions. Several works have demonstrated the benefits of considering two or three objectives instead of a single one. According to the above state-of-the-art survey papers, there does not exist any work that considers the simultaneous optimization of more than three conflicting objectives (seven for our case) for the deployment task. The optimization of more than three objectives is called many-objective optimization and is still so far, a very challenging research field [30]. The main originality of our research work is to propose for the first time a many-objective modeling and resolution of the WSN deployment problem with the aim to show the added-value that could be obtained by the simultaneous optimization of seven conflicting objectives. From a resolution viewpoint, a decomposition-based many-objective evolutionary algorithm, θ-DEA [45] was adapted and then used to solve the proposed model. To achieve this target, the existing optimization models of WSN deployment have been reviewed by examining their objectives and constraints. Second, the conflicting relationship among the identified objectives have been studied, by means of a conflicting matrix, to identify the objectives that can be gathered into the same model. After that and from a resolution viewpoint, a decomposition-based many-objective evolutionary algorithm, θ-DEA [45] was adapted and then used to solve the proposed model. The research goals of this work are summarized as follows:

- **Proposing a many-objective optimization model for WSN deployment**: For the best of our knowledge, this would be the first work proposing a many-objective WSN deployment model. The model includes the optimization of seven conflicting objectives. The resulting adaptation is named "WSN-θ-DEA". To achieve this target, the existing optimization models of WSN deployment have been reviewed by examining their objectives and constraints. Then, the conflicting relationships between the identified objectives have been studied, by means of a conflicting matrix, to identify the objectives that can be gathered into the same model.
- **Adapting an existing decomposition-based many-objective evolutionary algorithm, θ-DEA [45]**: As traditional Multi-Objective Evolutionary Algorithms (MOEAs) are unable to approximate the Pareto Front (PF) of models with more than three objectives, we have chosen θ-DEA as a MaOEA to solve our framed seven-objective deployment optimization model. The algorithm is chosen according to its ability to produce an efficient set of optimal solutions using a decomposition-based strategy.
- **Demonstrating the benefits of considering the many-objective formulation and resolution over multi-objective and single-objective models**: Results obtained from the optimization of mono- and multi-objective models, considering a set of objectives already involved in the many-objective model, are compared to results provided by "WSN-θ-DEA". The comparison demonstrates the out-performance and the merits of our proposed many-objective modeling and resolution approach.

Investigating the added value of the many-objective optimization in the WSN deployment context constitutes the principal purpose of our work. Hence, in this work we have not introduced new objective equations definitions and we emphasize that the majority of the objective functions, the constraints are taken from literature.

This paper is structured as follows. A literature review related to WSN deployment is provided in Section 2. The fundamentals and main concepts for an optimization problem as well as for the θ-DEA algorithm are presented in Section 3. In Section 4, we present our proposed many-objective deployment model involving seven objectives while illustrating the adaptation of θ-DEA to our proposed model. Sections 5 and 6 illustrate the experimental setup and the discussion of the obtained results, respectively. The conclusion and future work are presented in Section 7.

2 Related Works

Despite the existence of very recent optimization techniques such as [2,34,1], in this section, we mainly focused on optimization techniques that have been proposed to solve the fundamental issue in WSN designing; which is the deployment problem. This specific problem is also known as placement, layout, coverage or positioning problem in WSNs. WSN deployment encompasses the determination of positions for sensor nodes in order to achieve intended coverage, connectivity and energy efficiency while keeping the number of nodes as minimum as possible [5]. Being similar to many real-world design problems related to engineering, the deployment problem is inherently characterized by the presence of multiple objectives which may or not conflict with each other. A wide range of objectives can be considered when dealing with the deployment of WSNs such as network cost, coverage, connectivity, energy consumption, network lifetime, reliability, accuracy of measurements, fault tolerance, throughput and so on [7].

Several works in literature treated the optimization of WSN deployment as a mono-objective problem. Besides, an important number of practical scenarios related to WSN deployment are modeled as a multi-objective formulations where a set of desirable objectives are optimized simultaneously. These objectives are usually conflicting with each other and the decision maker has to choose one of the trade-off solutions. In this sense, we depicted a number of works that considered the optimization of WSN deployment problem with more than one objective. As an important part of solving an optimization problem, several Multi-Objective Optimization (MOO) techniques have been customized to tackle the WSN deployment problem and strike trade-offs between different optimization objectives. Evolutionary Algorithms (EAs) have been the most frequently used techniques in WSN deployment optimization. In [39] a multi-objective evolutionary algorithm has been proposed for solving sensor deployment problem. The proposed approach has been used to optimize simultaneously coverage and connectivity. In [28], an evolutionary multi-objective algorithm has been also used to optimize the deployment of WSN while considering coverage, reliability and an average number of hops. Optimal node redeployment has been investigated in [26] to maximize sensing, coverage and lifetime. The optimization of coverage, energy efficiency and differentiated detection levels was addressed in [24], where authors have proposed an evolutionary multi-objective approach in a $3D$ area. In [23], a multi-objective genetic algorithm was used to optimize coverage and network lifetime. A multi-objective formulation was suggested in [11] for the optimal deployment of WSN. The proposed approach obtained a trade-off between energy consumption and detection capability.

Recent works such as [10, 9, 8, 6, 21] have been proposed to tackle the WSN deployment problem from an optimization perspective. In [10], authors proposed an optimal three-objectives deployment method for practical heterogeneous WSNs which gives a deep insight into the trade-off between the reliability and deployment cost. Specifically, they provide the optimal deployment of sensor nodes to maximize the coverage degree and connection degree, while minimizing the overall deployment cost. In [9], a multi-objective optimization model named MLPGA is formulated to simultaneously satisfy three optimization objectives including the longest network lifetime, the highest network connectivity, and reliability. Under this model, the principal component analysis algorithm is adopted to eliminate the various optimization objectives' dependencies and rank their importance levels. Considering the NP-hardness of wireless network scheduling, the genetic algorithm is used to identify the optimal chromosome for designing a near-optimal clustering network topology. Similarly, in [8], authors proposed to simultaneously consider three objectives to be optimized which are security, lifetime, and coverage. The proposed approach aims to deploy sensor nodes and relay nodes in an industrial environment to analyze the multi-path routing for enhancing security. In [6], a new approach we called MOONGA (multi-objective wireless network optimization using the genetic algorithm) was proposed to optimizing the problem of node placement. MOONGA makes it possible to generate an optimal deployment according to the topology, the environment, the specifications of different applications and the preferences of the network designer users. Specifically, MOONGA considers the simultaneous optimization of five objectives only which are: the coverage, connectivity, lifetime, energy consumption and cost – which are closely linked to the position of the nodes in the network. Also, in [41], a non-dominated sorting multi-objective flower pollination algorithm (NSMOFPA) was proposed with optimization objectives for coverage rate, node radiation overflow rate and energy consumption rate.

Although they are less frequently used in WSNs, there are also other MOO techniques that have been capable of achieving good performance in the WSN deployment optimization context such as swarm intelligence-based optimization algorithms, artificial neural network, fuzzy logic, game theory and so on [19]. For instance, authors in [32] considered a bi-objective energy-latency model allowing the analysis and the comparison of different algorithms including uniform algorithm and cluster algorithm. In [37], authors developed a multi-objective particle swarm optimization and fuzzy based algorithm to handle a model optimizing simultaneously coverage, connectivity and network lifetime. Another multi-objective model has been proposed in [27] where authors made use of the multi-objective artificial ant colony algorithm and the multi-objective firefly algorithm, and compared the obtained results by applying each one of these in addition to other EAs.

State-of-the-art works related to the WSNs optimization prove that the trends are to consider problems with multiple objectives. This choice was not at random but rather the advantages offered by the multi-objective optimization compared to the mono-objective one revealed that optimization with multiple objectives is more suited when dealing with a real-world problem in general. However, these state-of-the-art works either fail to incorporate several specific application requirements into the performance evaluation or suffer from limited objectives. Since the deployment of real-world WSNs encompasses more than three objectives, a multi-objective optimization may harm other deployment criteria which are conflicting with the selected ones. Thus, our aim is to go further and explore the modeling and the resolution of WSN deployment in a many-objective fashion by proposing our WSN-θ-DEA model.

The fundamentals and main concepts for an optimization problem as well as for the θ-DEA algorithm are presented in the next Section.

3 Formulation of optimization problem and the θ-DEA model

The optimization with multiple objectives deals with problems involving more than one objective function. Depending on the number of objectives, the process of optimizing simultaneously a collection of objective functions can take different names. If only two or three objective functions are dealt with then we refer to a Multi-Objective Optimization (MOO) problem. If there are more than three objective functions then we refer to a Many-Objective Optimization (MaOO) problem.

3.1 Multi-objective problem general formalization

The general Multi-Objective Problem (MOP) formalization consists of a minimization or a maximization function under a finite number of constraints that must be satisfied. The general formalization of a multi-objective minimization problem can be described as follows [17]:

$$\begin{aligned} \text{minimize } & f(x) = [f_1(x), f_2(x), \ldots, f_M(x)]^T \\ \text{subject to } & g_i(x) \geq 0, j = \{1, \ldots, P\}; \\ & g_k(x) \geq 0, k = \{1, \ldots, Q\}; \\ & x_i^L \leq x_i \leq x_i^U, i = \{1, \ldots, n\}. \end{aligned} \tag{1}$$

where M is the number of objective functions. In the case of a MOP, a solution x is a vector of n decision variables. The first subset of constraints (P constraints) corresponds to the inequality constraints, the second subset of constraints (Q constraints) represents the equality constraints, and the last subset of constraints adjusts the lower and upper bound of each decision variable which are called variable bounds. A feasible solution x should, imperatively, satisfy the $(P+Q)$ constraints and the N bound constraints. On the other hand, any solution that does not satisfy the entire set of constraints is considered as an infeasible solution. Based on the duality principle, we can convert a minimization problem into a maximization one by multiplying each objective function by (-1) and transform the constraints accordingly. Since the resolution of a MOP yields to a set of Pareto optimal solutions called non-dominated solutions, the resolution algorithms make use of the concept of dominance. Hence, in the following, we define the dominance principle and some related terms [14]:

- **Definition 1.1 - (Pareto optimality)** A solution $x^* \in \Omega$ is optimal if $\forall\ x \in \Omega$; where Ω denotes the feasible search space; and $I = \{1, \ldots, M\}$; either $\forall m \in I$, we have $f_m(x) = f_m(x^*)$ or there is at least one $m \in I$ such that $f_m(x) > f_m(x^*)$. A solution x^* is Pareto optimal only if no other solution x exists which would improve at least one objective while other objectives values remain the same as values proposed by x^*.
- **Definition 1.2 - (Pareto dominance)** A solution $u = (u_1, \ldots, u_n)$ is said to dominance another solution $v = \{v_1, \ldots, v_n\}$ if and only if $f(u) < f(v)$. In other words $\forall I \in \{1, \ldots, M\}$, we have $f_m(u) \leq f_m(v)$ and $\exists m \in \{1, \ldots, M\}$ where $f_m(u) < f_m(v)$.
- **Definition 1.3 - (Pareto optimal set)** For a given MOP $f(x)$, the Pareto optimal set is $P^* = x \in \Omega \mid \nexists x' \in \Omega, f(x') \leq f(x)$.
- **Definition 1.4 - (Pareto optimal front)** For a given MOP $f(x)$ and its Pareto optimal set P^*, the Pareto optimal front is $PF^* = f(x), x \in P^*$
- **Definition 1.5 - (Ideal point)** The ideal point $Z^I = \{Z_1^I, \ldots, Z_M^I\}$ is the vector composed by the best objective values over the search space Ω. The ideal objective vector is expressed by:

$$Z_M^I = min_{x \in \Omega} f_m(x), m \in \{1, \ldots, M\}$$

- **Definition 1.6 - (Nadir point)** The nadir point $Z^N = \{Z_1^N, \ldots, Z_M^N\}$ is the vector composed by the worst objective values over the Pareto optimal set. The nadir objective vector is expressed by:

$$Z_M^N = max_{x \in P^*} f_m(x), m \in \{1, \ldots, M\}$$

3.2 θ-DEA : Theta-Decomposition-based Evolutionary Algorithm

3.2.1 Context

Since the early stage of MOO, different techniques have been used to deal with the resolution of a MOP. A general process of the traditional MOO is characterized by the aggregation of the set of objective functions into a single function. The whole trade-off is then discovered by repeating the process several times with different settings' calibrations. Since the decision maker is responsible of the choice of the aggregative weights, the main drawback to this approach is that, weights are difficult to determine precisely due to insufficient information or knowledge concerning the optimization problem. Other methods have also been used such as the use of penalty functions [40]. Although aggregative and penalty function-based methods offer advantages, they often have some disadvantages especially when some critical parameters are chosen by the decision maker. The Multi-Objectives (MO) evolutionary algorithms propose a more suitable alternative to solve a MO problem mainly because of their wide applicability and their ease of use. Unlike the above mentioned methods, the Multi-Objective Evolutionary Algorithms (MOEAs) are able to approximate the whole Pareto front in one single run.

According to the dominance criteria, the MOEAs could be classified into two classes: the non-Pareto-based EAs such as the Non-dominated Sorting Genetic Algorithm (NSGA-II) [17], the Strength Pareto Evolutionary Algorithm 2 (SPEA2) [48], and the Indicator Based Evolutionary Algorithm (IBEA) [47], and the Pareto-based ones. The main difference between these two classes is that the Pareto-based EAs are founded on the dominance principle.

Most of the algorithms that have been widely used in multi-objective optimization use the Pareto-dominance relation to compare solutions. However, when the number of objectives is greater than three, these algorithms struggle to solve the concerned problems. Thus, although the above mentioned algorithms are suitable for the resolution of problems with small number of objectives, good results are not guaranteed when dealing with many-objective problems (i.e., more than three objectives). One of the most used methods to encounter a MaOP are the decomposition-based algorithms. Decomposition is one of the basic strategies used in both of the multi-objective and many- objective optimizations. A decomposition-based method decomposes the problem into N sub-problems to deal with the problems complexity. Among the mos commonly used decomposition-based algorithms, we name the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [46], the Non-dominated Sorting Genetic Algorithm III (NSGA-III) [16], and the Theta-Decomposition-based Evolutionary Algorithm (θ-DEA) [45]. In what follows, we mainly focus on the description of of θ-DEA as it presents the key component of our proposed WSN-θ-DEA solution.

3.2.2 The θ-DEA model

θ-DEA is a new evolutionary algorithm which is based on a new dominance relation for many-objective optimization and it was proposed in [45]. θ-DEA, the non-dominated sorting technique is employed to rank solutions in the environmental selection phase, ensuring both convergence and diversity. The framework of θ-DEA is presented in Algorithm 1.

First, θ-DEA begins by generating a set of N reference points which can be denoted as $\lambda = \{\lambda_1, \ldots, \lambda_N\}$. For a m-objective problem, λ_j; ($j \in \{1,\ldots, N\}$) is a m-dimensional vector presented by: $\lambda_j = \{\lambda_{j,1}, \ldots, \lambda_{j,m}\}^T$, where $\lambda_{j,k} \geq 0$, $k = \{1,\ldots, m\}$, and $\sum_{k=1}^{m} \lambda_{j,k} = 1$. After that, an initial population P_0 is randomly generated. The ideal point z^* is also initialized in step 3. Since it is often very time consuming to compute exact z_i^*, it is indeed estimated by the minimum value found so far for objective f_i, and is updated during the search. In step 4, the Nadir point z^{nad} is assigned to the largest fitness value in the initial parent population, and it is also updated in the normalization procedure.

Algorithm 1 θ-Decomposition-based Evolutionary Algorithm

```
Generate reference points λ;
Generate randomly the initial population P_0;
Initialize the ideal point z*;
Initialize the Nadir point z^nad ;
Set the number of iterations t to zero ;
while the termination criterion is not met do
    Perform the recombination operators to P_t and create
an offspring population Q_t;
    Fill R_t with individuals from Q_t and P_t
    Sort R_t according to the Pareto dominance relation and
fill S_t with the non-dominated levels ;
    Compare solutions within S_t to z* and update the ideal
point
    Assisted by z* and z^nad, normalize S_t
    S_t members are clustered in C clusters according to
reference points λ;
    Using the θ-non-dominated sorting,S_t members are
classified into F'_1, F'_2,... levels
    Initialize an empty population P_{t+1}
    Set i to 1;
    while | P_{t+1} | + | F'_i |< N do
        Fill P_{t+1} slots with F'_i individuals;
        Increment i by 1 ;
    Perform a random sort to F'_i ;
    Fill the remaining P_{t+1} slots with F'_i individuals
    Increment t by 1 ;
```

Step 6 is iterated until a stopping criterion is satisfied. At each iteration, Q_t is generated by performing the recombination operator to P_t. Same as NSGA-III, θ-DEA combines the offspring population Q_t and P_t to form a new population R_t. R_t is then sorted according to the Pareto dominance relation and members of the best non-dominated fronts are sorted in S_t. $\bigcup_{i=1}^{\tau} F_i$ where F_i is the i^{th} Pareto non-dominated front of R_t and τ satisfies $\sum_{i=1}^{\tau-1} < N$. Assisted by z^* and z^{nad}, the normalization procedure is executed to S_t for solving problems having the Pareto front whose objective values may be disparately scaled. After normalization, members of S_t are clustered into N clusters $C = \{C_1, \ldots, C_N\}$ according to reference points initially generated, .i.e., the cluster C_j is associated to reference point λ_j. After that, the θ-domination sorting, which is the key concept in θ-DEA, is employed to classify S_t members into different θ-non-dominated levels F'_1, F'_2, ... And finally, P_{t+1} slots are filled using one level at a time, starting from F_1. In the case where the size of the last accepted level exceeds the remaining slots in P_{t+1}, θ-DEA randomly selects solutions, since θ-dominance has stressed both convergence and diversity.

The proposed θ-dominance is defined on population S_t with the supply of a set of reference points λ. Each solution in S_t is associated with a cluster among a set of clusters C by the clustering operator. Let:

$$F_j(x) = d_{j,1}(x) + \theta d_{j,2}(x), j \in 1, \ldots, N$$

where θ is a predefined penalty parameter. The distances $d_{j,1}$ and $d_{j,2}$ are both computed in the normalized objective space.

Generally, $d_{j,2} = 0$ ensures that $f(x)$ is always in L, resulting in perfect diversity, and smaller $d_{j,1}(x)$ value under the condition $d_{j,2} = 0$ means better convergence. Note that there is no competitive relationship between clusters in θ-dominance, and thus, different θ values can be used in different clusters. Figure 3 illustrates the distances $d_{j,1}$ and $d_{j,2}$. The computational complexity of the model was discussed in [45].

4 Many-objective modeling and resolution

4.1 System modeling

Given a square area $A(x, y)$, a set $N = \{n_1, n_2, \ldots, n_N\}$ of nodes which are randomly deployed to cover the whole area, and a High Energy Communication Node (HECN) placed at the center of A, nodes are responsible for monitoring and periodically reporting an event of interest to the HECN. We consider a cluster-based architecture network which states that a node may either operate as a Cluster-Head (CH) allowing the communication with the HECN or it may operate as a sensing node. Two modes of sensing nodes are considered: Sensors operating in a High-Signal Range (HSR) and Low-Signal Range (LSR) modes. Let us consider each sensor is equipped with an initial Energy E and having a sensing range R_S, where R_S of the nodes operating in HSR mode is greater than R_S of nodes operating in LSR mode, and a communication range R_C. Each sensing node must be able to communicate through its corresponding cluster-head with the HECN. Two nodes can communicate only if the distance between the two nodes is less than R_C.

Let us suppose that A is divided into $G = x \times y$ rectangular grids of identical size. All cells within a sensor's sensing disk $\Pi(R_S)^2$ centered at the sensor are considered to be covered by the sensor. This modeling of the system is illustrated in Figure 1 and is inspired by the modeling of systems described in [25] and [20]. To present a comprehensive definition of the WSN-θ-DEA model, in what follows, we define the adopted objectives and present the considered assumptions related to each objective.

Table 1 gives a summary of the used symbols in the description of the seven-objective WSN deployment model.

4.2 Adopted objectives

The goal of our work is to investigate, for the first time, the added value of the seven-objective optimization of WSN deployment while reproducing some of the existing objectives and constraints equations given in literature. Hence, in this work, we have not introduced new objective equations definitions and we emphasize that the majority of the objective functions, the constraints are taken from literature in order to reconcile the existing works tackling the same optimization problem.

The WSN-θ-DEA model considers seven conflicting objectives, namely, the number of clusters, the number of HSR nodes, the number of LSR nodes, the coverage, the network connectivity, the energy consumption and the throughput. In what follows, we provide the definition and the mathematical expression of each objective. First, the installation of an additional node increases the overall network cost since each node imposes a certain cost, including its production, deployment and maintenance [19]. Hence, the minimization of the number of nodes generates a significant decrease of the network cost as the deployment of a node is supposed to be highly expensive. As three types of nodes are considered in our model, i.e., cluster heads, HSR and LSR nodes, different costs are assigned to each type of nodes depending on the operating mode. The placement of a node operating in CH mode is supposed to be more expensive than the deployment of a sensor operating in HSR mode. Meanwhile, the placement of the latter is supposed to be more expensive than the deployment of a node operating in LSR mode. The objective of minimizing the number of nodes is divided into three sub-objectives since they may be conflicting with each other. These objectives are the number of clusters, the number of HSR nodes, and the number of LSR nodes. In addition, our WSN-θ-DEA model considers the coverage, the network connectivity, the energy consumption and the throughput objectives; all described as follows:

4.2.1 Number of clusters

The minimization of the number of clusters intuitively leads to the minimization of the number of nodes op-

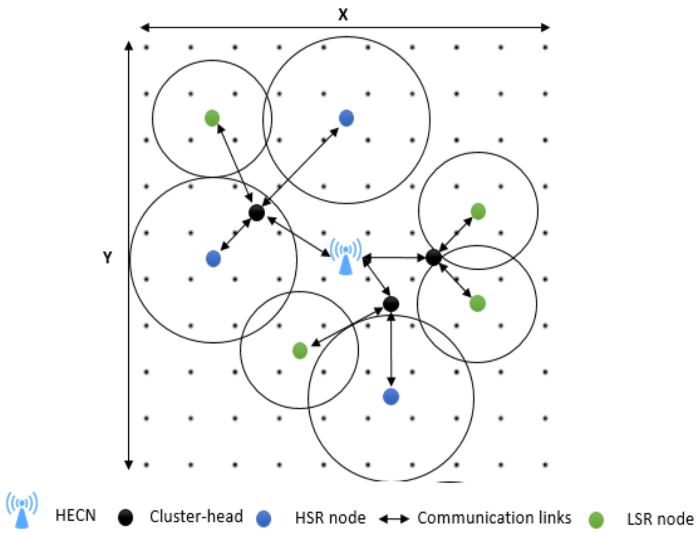

Fig. 1 System illustration

erating in CH mode. Given nch the number of clusters in the network, the number of clusters minimization is expressed as:

$$\min : nch \tag{2}$$

4.2.2 Number of HSR nodes

Nodes operating in HSR mode are sensing nodes with a high signal range covering a greater region than LSR nodes. Given nhs the number of HSR nodes, the objective of the minimization of nhs is expressed as:

$$\min : nhs \tag{3}$$

4.2.3 Number of LSR nodes

Given nls the number of nodes operating in LSR mode, nls is minimized:

$$\min : nls \tag{4}$$

4.2.4 Coverage

Since region A is divided into G identical cells, the objective is to minimize the number of uncovered grids. Let (x_i, y_i) be the coordinates of node i. The network coverage $Cv(x)$ is defined as the percentage of uncovered cells over the total cells of A and it is evaluated as follows [25]:

$$\min : Cv(x) = \frac{\sum_{x'=0}^{x} \sum_{y'=0}^{y} g(x', y')}{x \times y} \tag{5}$$

where $x \times y$ is the total number of grids of A and $g(x', y')$ is defined by the following expression:

$$g(x', y') = \begin{cases} 1, & \text{if } \forall i \in \{1, \ldots, N\}, d_{(x_i, y_i),(x', y')} > R_S \\ 0, & \text{otherwise.} \end{cases}$$

$d_(x_i, y_i), (x', y')$ is the distance separating node i from node with coordinates (x', y').

4.2.5 Network connectivity

Ensuring the connectivity of the network encompasses two major aspects. First, each cluster-head should not have more than a maximum predefined number of sensing nodes in its cluster, and second, each sensing node should be within a cluster and is capable to communicate with its cluster-head. Therefore, authors in [20] distinguished two related connectivity parameters:

– Sensor-per-Cluster-head Error (SCE): This parameter is used to ensure that each cluster-head does not exceed the fixed number M of nodes within its cluster. If $nfull$ is the number of cluster-heads that have more than M sensors in their clusters and n_i is the number of sensors in cluster i, then [20]:

$$SCE = \begin{cases} \frac{\sum_{i=1}^{nfull} n_i}{nfull}, & \text{if } nfull > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

– Sensors-Out-of-Range Error (SORE): This parameter is considered to ensure that sensing nodes are affected to clusters and it computes the percentage of unaffected sensors. If nin_i is the number of clusters supporting node i ($nin_i \in [0, 1]$) and n is the number of sensing nodes, then [20]:

$$SORE = \frac{n - \sum_{i=1}^{n} nin_i}{n} \tag{7}$$

Table 1 Nomenclature of the system modeling symbols

Symbol	Description
$A(x, y)$	Square area of $x * y$ grids to be covered by the network
N	Number of deployed sensors in the area
$HECN$	High energy communication node
CH	Node operating in a cluster-head mode
LSR	Sensor operating in a low sensing range mode
HSR	Sensor operating in a high sensing range mode
E	Initial energy for each node
R_c	Communication range of a sensor
R_s	Sensing range of a sensor
R_{SH}	Sensing range of a high sensing range sensor
R_{SL}	Sensing range of a low sensing range sensor
nch	Number of cluster-head nodes within the network
nhs	Number of high sensing range nodes within the network
nls	Number of low sensing range nodes within the network
M	Maximum cluster size
$Cv(x)$	Percentage of uncovered cells of the area
$d(x_i, y_i), (x_j, y_j)$	Distance separating nodes i and j
SCE	Sensor-per-cluster-head error
$SORE$	Sensors-out-of-range error
nin_i	Number of clusters supporting node i
$nfull$	Number of clusters exceeding cluster's maximum size (M)
OE	Operational energy of nodes within the network
CE	Communication energy of nodes within the network
$E_{consumed}$	Total energy consumed by nodes within the network
T	Throughput of the network
NC	Abbreviation for the number of clusters objective
NH	Abbreviation for the number of HSR nodes objective
NL	Abbreviation for the number of LSR nodes objective
CV	Abbreviation for the coverage objective
EC	Abbreviation for the energy consumption objective
CN	Abbreviation for the connectivity objective
TH	Abbreviation for the throughput objective ($1/T$)

Accordingly, considering that the SCE and $SORE$ parameters are of the same importance, the connectivity objective is expressed as follows:

$$\min : SCE + SORE \tag{8}$$

4.2.6 Energy consumption

The energy consumption metric is closely related to the network lifetime. Authors in [20] considered two types of energies consumed by an operating sensor, namely the Operational Energy (OE) and the Communication Energy (CE). OE is defined as the required energy by a node to insure its activity. The amount of consumed OE per node varies depending on the operation mode of the node. Considering the relevance factors for energy consumption of the different operation modes, we assume that during a specific time duration the energy consumed by a CH node is 10 times more than the energy consumed by a HSR node and 20 times more than the energy consumed by a LSR node. Hence, given nch, nhs and nls the numbers of CH nodes, HSR nodes and LSR nodes, respectively, the OE is expressed as [20]:

$$OE = 20 \times \frac{nch}{n} + 2 \times \frac{nhs}{n} + \frac{nls}{n} \tag{9}$$

Besides, CE is calculated based on the distances separating sensing nodes and their corresponding cluster-heads. It is defined as the energy consumed by the communication between network nodes. The expression of the CE is given as [20]

$$CE = \sum_{i=1}^{c} \sum_{j=1}^{n_i} \mu \times d_{ij}^{k} \tag{10}$$

where c is the number of CH, n_i is the number of sensing nodes belonging to the i^{th} cluster, d_{ij} is the Euclidean distance between sensor j and its cluster-head, and μ, k are constants. The minimization objective of the overall energy consumed by the network can, thus, be expressed as:

$$\min : E_{consumed} = OE + CE \tag{11}$$

4.2.7 Throughput

The general definition of the throughput of a network is the data size transmitted from a source to a sink node within a unit time and can be expressed as: $T = \frac{i}{t}$ where T is the throughput, i is the size of transmitted data and t is the amount of time. Authors in [42] considered the optimization of throughput in a single-hop scenario. Let T_i be the throughput achieved by node i in N, T_i is expressed then as:

$$T_i = i_i \times \frac{t_i}{\sum_{j \in N} t_j} = i_i \times \theta_i \tag{12}$$

Intuitively, the throughput is calculated according to the data rate i_i and the time fraction during which node i occupied the transmission channel θ_i. We consider the fairness allocation of the transmission channel time which is achieved when the fractions of times used by the nodes are equal [42], i.e., $\theta_1 = \theta_2 = \theta_3 = ... = \theta_N$. The size of transmitted data depends on the source node operation mode. Nodes operating in CH mode have much important size of data than HSR and LSR nodes, to relay to the HECN node, as it collects data from a set of nodes. Furthermore, HSR nodes have a greater size of data to transmit than LSR nodes since they cover a bigger area. Let us suppose that an LSR node recovers 70% of the data size captured by an HSR node.

In our work, we consider fixed throughput for these two operating modes: 100 and 70, for HSR and LSR modes, respectively. Besides, a node operating in CH mode receives the data from nodes belonging to its cluster. The throughput value of a CH is supposed to be the sum of throughput values of its cluster members. Given th_j the throughput of node j, the throughput objective is the following:

$$\max : T = 100 \times nhs + 70 \times nls + \sum_{i=1}^{nch} \sum_{j=1}^{n} th_j \tag{13}$$

where n is the number of sensors within cluster i and:

$$th_j = \begin{cases} 100, & \text{if sensor } j \text{ is a HSR node} \\ 70, & \text{if sensor } j \text{ is a LSR node} \\ 0, & \text{Otherwise.} \end{cases}$$

Since the proposed optimization model is expressed as a minimization problem, all the objective functions should be formulated as minimization equations. Hence, the throughput objective should be converted into a minimization one.

$$\min : TH = \frac{1}{T} \tag{14}$$

4.3 Adaptation of θ-DEA

4.3.1 Adopted solution encoding

As a solution of the optimisation of our model provides a deployment schema of all the nodes within the network, a solution must include all the information about the N nodes locations and how they are split in clusters. Hence, a candidate solution X consists of N items corresponding to the N sensor nodes. The i^{th} item of X has three parts: a part representing the position coordinates (x_i, y_i) of node i, the second one representing the operating mode of the sensor, i.e., CH, HSR and LSR nodes represented respectively by 1, 2 and 3, and a third part containing the coordinates of the corresponding cluster-head (if the i^{th} node is already a cluster-head, or a sensing node that is not supported by any cluster, the coordinates of the corresponding CH takes $(0, 0)$). Figure 2 visualizes the structure of an individual.

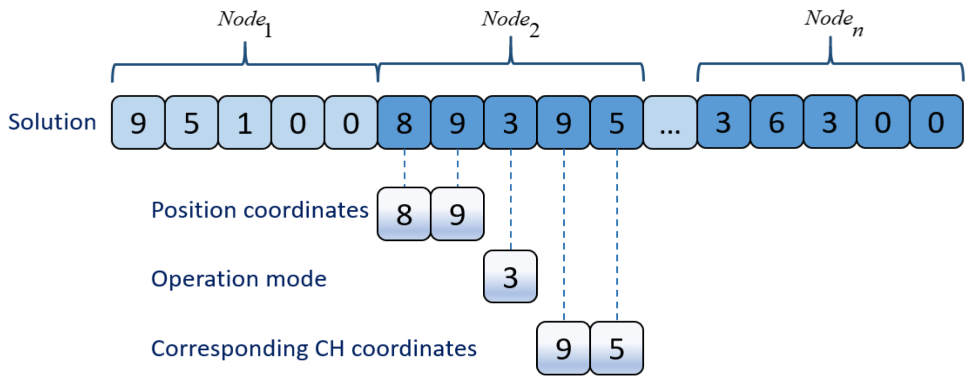

Fig. 2 Solution encoding

4.3.2 Solution evaluation

Being the key concept in θ-DEA, the θ-dominance is used to evaluate solutions while insuring both convergence and diversity. The proposed θ-dominance is defined on the population with the supply of a set of reference points.

In our model, the objective values are disparately scaled and that can present an issue in the optimization process. θ-DEA incorporates the normalization procedure to settle this issue. The set of ideal points $\{z_1^*, z_2^*, ..., z_7^*\}$ and Nadir points $\{z_1^{Nad}, z_2^{Nad}, ..., z_7^{Nad}\}$ found so far are used for normalization purpose. Each objective is expressed as:

$$\bar{f}_i(x) = \frac{f_i(x) - z_i^*}{z_i^{Nad} - z_i^*} \tag{15}$$

where $\bar{f}_i(x)$ is the normalized value of the i^{th} objective for solution x. Once the objective space is normalized, where the ideal point is the origin, the clustering operator is performed to the population. Supposing L is the line passing through the origin with the direction λ_j, and u is the projection of $\bar{f}(x)$ on L. Let $d_{j,1}(x)$ be the distance between the origin and u and $d_{j,2}(x)$ be the perpendicular distance between $\bar{f}(x)$ and L. These two distances are illustrated in Figure 3.

In the clustering phase, only $d_{j,2}(x)$ is involved, by assigning a solution x to cluster C_j (being tied to reference point λ_j) with the minimum $d_{j,2}(x)$ value. Once each member of the population is associated to a cluster C_j, members of the j^{th} cluster are evaluated by:

$$F_j(x) = d_{j,1}(x) + \theta d_{j,2}(x), \quad j \in \{1, 2, ..., N\} \tag{16}$$

where θ is a predefined penalty parameter. The distances $d_{j,1}$ and $d_{j,2}$ are computed in the normalized objective space. Having $d_{j,2}(x) = 0$ generally ensures that $f(x)$ is always in L, resulting in perfect diversity, and a smaller $d_{j,1}(x)$ value under the condition $d_{j,2}(x) = 0$ means better convergence. Note that there is no competitive relationship between clusters in θ-dominance, and thus, different θ values can be used in different clusters. Figure 3 illustrates the distances $d_{j,1}$ and $d_{j,2}$.

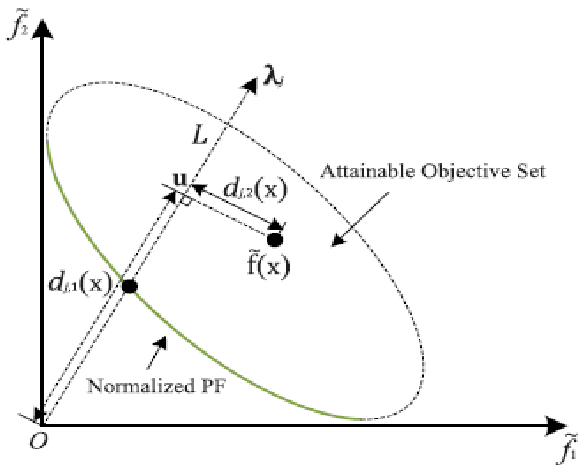

Fig. 3 Illustration of distances $d_{j,1}$ and $d_{j,2}$ [45]

4.3.3 Solution variation operators

The selection of solution variation operators is often delicate in many-objective optimization, since in high-dimensional objective space, distant solutions may be selected for recombination and poorer performance solutions will be probably obtained. Originally, θ-DEA was proposed to solve continuous multi-objective problems. Thus, it varies the population (set of real-encoded chromosomes) using the Simulated Binary Crossover (SBX) and the polynomial mutation operators [15]. Since in our work, each chromosome is encoded as in integer vector, both variation operators need to be sophistically adapted for the following three reasons. First, a candidate solution proposes a possible deployment of N nodes. Each node is presented with 5 serial decision variables: node's coordinates (x_i, y_i), its operating mode, and the coordinates of its corresponding CH (x_j, y_j). Second, the considered decision variables are adjusted with different lower and upper bounds. Finally, a sensing node may have reference to its corresponding CH. Hence, we consider a two-point crossover and a uniform mutation as explained below.

- Two-point crossover: In standard two-point crossover, two parents and two crossover points are chosen randomly in a way that each parent is divided into three parts separated at the crossover points' indexes. Then, each solution of the two offspring solutions takes one part from a parent and two parts from the other parent. In our case, related decision variables should be preserved together. To do so, initial solutions are sorted by clusters, i.e., sensors are presented cluster by cluster and sensing nodes which are not affected to a cluster will be residing in the last positions. Given two parents, for each solution the possible crossover points are detected. Possible crossover positions are points which designate the end of a cluster and the beginning of a new cluster, the separation between a cluster and an unaffected sensor, or the separation between two unaffected sensors. After that, a list of the common crossover points of the two solutions is extracted and two random points from the list are chosen. Then, the crossover is performed.
- Mutation: In this phase, a random node is selected and one of the two possible actions is performed: The first one consists in changing the operating mode of the selected node (Only nodes operating in CH mode which contains other sensors within their clusters are excluded). The second action consists in the assignment of an unaffected sensing node to an existing cluster-head, if possible.
- Repair mechanism: At each phase of the solutions variation, a repair mechanism is used to ensure offspring solutions feasibility, if needed. First, once the crossover is performed, solutions feasibility is ascertained, i.e., if there exist redundant locations of the sensors caused by the crossover, redundancy is removed by assigning new locations to redundant nodes. Second, after each mutation action, the solution is resorted by clusters.

5 Experimental Setup

The main objective of this experimental study is to prove that considering a many-objective deployment model offers a much favorable deployment of the WSN compared to mono- and multi-objective models with respect to the overall trade-off between the considered objectives. Accordingly, optimization results of different models, with different dimensions, are compared to the results obtained by our proposed model. Thus, for each couple of models (WSN-θ-DEA and another model), we look for the answers to the following questions:

- Is the WSN-θ-DEA able to reach optimized objectives values proposed by the confronted model?
- Is the WSN-θ-DEA proposing a better trade-off between all considered objectives?

In this section, we will present the Benchmark of Data and explain the considered experimental comparison protocol.

5.1 System implementation

The model was implemented using a java-based framework for multiple objectives optimization with metaheuristics: jMetal [1]. jMetal includes a number of classic and modern multiple objectives optimization algorithms, a rich set of test problems, and a set of well-known quality indicators to assess the performance of the algorithms. Compared to other existing libraries, jMetal framework offers good usability, components configurability, and extendability.

5.2 Data set

To ensure fairness of comparisons, the WSN related configuration parameters are set to take the same values for the experiments namely, the number of deployed nodes N, the area size (total number of grids) $x \times y$, the communication range R_C, the sensing ranges R_{SH} and R_{SL}, and the maximum cluster size M. Table 2 provides the common WSN system parameters for the conducted experiments and Figure 4 shows an illustrative example.

Table 2 WSN benchmark description

Parameters	Values
Number of nodes (N)	20
Area size ($x \times y$)	100×100
Communication range (R_C)	25
High sensing range (R_{SH})	20
Low sensing range (R_{SL})	16
Maximum cluster size (M)	2

[1] `http://jmetal.sourceforge.net/`

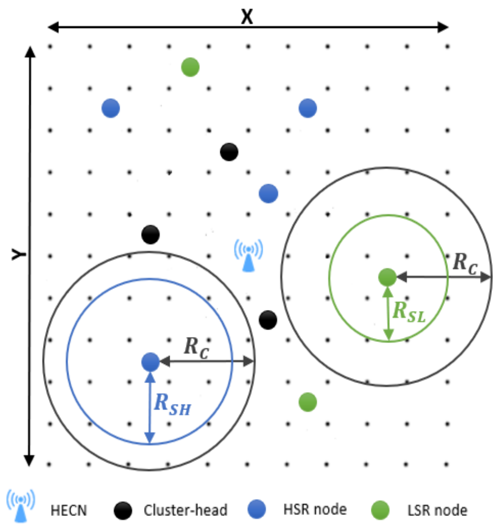

Fig. 4 Illustrative example of WSN-θ-DEA system parameters

On the other hand, θ-DEA related parameters should be also set to take the same values for all experiments. We note that the termination criterion refers to the number of solution evaluations performed during the optimization process. Table 3 shows the θ-DEA related parameter settings.

Table 3 θ-DEA parameters setting

Parameters	Values
Termination criterion	150 000 evaluations
θ	5.0
Parent selection	Binary tournament
Crossover probability	0.9
Mutation probability	0.1

The population size cannot be arbitrary specified for θ-DEA since the size is controlled by the positive integers $H1$ and $H2$ which are considered to set the number of divisions along each objective axis. $H1$, $H2$, and the population size values are reported in Table 4 for each optimization problem size.

Table 4 Number of reference points and population size setting

No. of objectives (m)	Divisions ($H1, H2$)	Population size (S)
2	$(249, 0)$	250
3	$(25, 0)$	351
7	$(5, 4)$	672

5.3 Experimental comparison protocol

Through each experiment, we aim to compare WSN-θ-DEA and a confronted model considering a subset of the seven objectives. We recall that the experiments purpose is to prove that conducting an optimization of a WSN deployment problem in a many-objective manner is better than mono- and multi-objective manners. Thus, we selected the three models represented in Table 5 below to put in competition with WSN-θ-DEA. The experiment results are presented in the next Section.

The comparison of the models effectiveness is based on the objective values provided by optimal solutions, i.e., the best solution is the one optimizing the largest number of objectives. Hence, as only a subset of the seven objectives are incorporated in these models, the remaining objective values of an optimal solution (provided by one of the above models) are calculated based on the proposed deployment schema supplied by the solution. The optimization of these models is also conducted by θ-DEA by modifying the reference points depending on the model size as presented in Table 4. Once the optimization of the WSN-θ-DEA model is performed, we consider at each experiment the optimization of a chosen confronted model. The considered experimental comparison protocol is presented below:

1. **Perform the confronted model optimization**: At each experiment, the confronted model is optimized and the obtained Pareto front is illustrated.
2. **Select the knee point**: In the case where the confronted model is a mono-objective one, the optimal solution is considered. Besides, for the multi-objective models, the optimal solutions belonging to the approximated Pareto front are considered. After that, the knee point is selected. For example, in a bi-objective space, as defined in [13], the knee point of the Pareto front corresponds to the farthest solution from the extreme line L^*. The extreme line is the line defined by the extreme solutions s_1^* and s_2^* (i.e., solutions having minimal objectives' values). Fig. 5 illustrates the knee point for a convex Pareto front.
   Multiple methods for knee point recognition, supporting a high dimensional space, are proposed in literature [4]. We used a recently proposed trade-off worth metric defined in [36]. The trade-off worth metric characterizes two non-dominated objective vectors and can be defined as the net gain of improvement in some objective subset by the accompanying deterioration in some other criteria as a result of substituting an objective vector with another non-dominated one. The expression of the trade-off information for a pair of optimal solutions is given

Table 5 Peer models

Confronted model	NC	NH	NL	CV	EC	CN	TH
Coverage model				⋆			
EC-TH model					⋆		⋆
NH-NL-CV model		⋆	⋆	⋆			

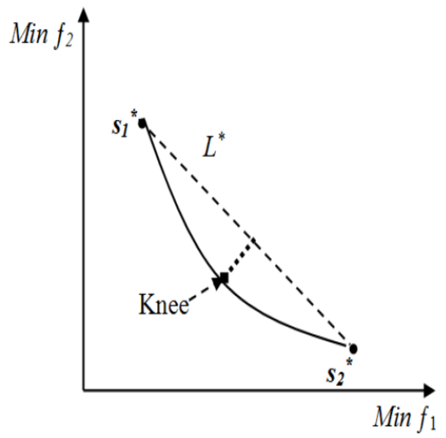

Fig. 5 Illustration of the Knee point for a convex Pareto front [4]

by [4]:

$$T(x_i, x_j) = \frac{\sum_{m=1}^{M} max[0, \frac{f_m(x_j)-f_m(x_i)}{f_m^{max}-f_m^{min}}]}{\sum_{m=1}^{M} max[0, \frac{f_m(x_i)-f_m(x_j)}{f_m^{max}-f_m^{min}}]} \quad (17)$$

where $f_m(x_i)$ corresponds to the m^{th} objective value of solution x_i and f_m^{max}, f_m^{min} are the maximal and minimal values of the m^{th} objective in the population individuals, respectively. In the above equation, normalization is performed in order to prevent some objectives being predominant over others. The numerator and the denominator express, respectively, the aggregated improvement gained by substituting x_j with x_i and the deterioration generated by this substitution. Based on this equation, the following expression is used to compute the worth of a solution x_i, in terms of trade-off, relative to the set of Pareto front solutions S [36]:

$$\mu(x_i, S) = \min_{x_j \in S, x_i \not\prec x_j, x_j \not\prec x_i} T(x_i, x_j) \quad (18)$$

where x_j denotes solutions belonging to the set of non-dominated solutions S. The quantity $\mu(x_i, S)$ expresses the least amount of improvement per unit deterioration by substituting any alternative x_j from S with x_i. Solutions residing in convex knee regions have the highest values in terms of the trade-off metric μ. Based on this, we select the solution having the highest μ value.

3. **Extract the set of nearest WSN-θ-DEA solutions**: The set of the closest solutions from the WSN-θ-DEA front to the knee solution (optimal solution in mono-objective case) are extracted using the Euclidean distance based on the 1, 2 or 3 objectives considered in the confronted model. This approach is explained by the following illustrative example: Let us consider an optimization problem minimizing A, B, C and D objectives. The four objectives' values are supposed to be between 0 and 10 with 0 is the optimal value and 10 is the worth value for all the objectives. We suppose a model optimizing only the first objective A. x_1 is supposed to be the optimal solution involved by the optimization of this model. The set of solutions x'_i, $i = \{1, \ldots, 5\}$, illustrated in Table 6, presents the solutions provided by the optimization of the model considering the four objectives.

Table 6 Illustrative example of the set of solutions selection

	A	B	C	D	ED
x_1	0	8	6	7	
x'_1	0	8	9	8	0
x'_2	1	6	7	5	1
x'_3	1	5	2	5	1
x'_4	6	5	9	7	6
x'_5	8	3	6	7	8

The Euclidean Distance (ED) is computed based on the A objective. Only solutions x'_1, x'_2 and x'_3 are extracted to form the set of the closest solutions since they are too close to x_1 in terms of A objective.

4. **Select the most relevant WSN-θ-DEA solution(s)**: Depending on the alternatives proposed by the set of extracted solutions, one or more relevant solutions are selected to be compared with the optimal solution provided by the confronted model. We reconsider the illustrative example presented in the previous step and the solutions illustrated in Table 6. The aim is to select a close solution to x_1 with respect to objective A and with the intention to have the best trade-off between all the objectives, i.e, the best solution being as close as possible to solution x_1 and having a better B, C and D objectives' val-

ues. Although x'_1 has the same A and B values, it deteriorates the remaining objectives. x'_2 proposes a small deterioration in objective A and only the improvement of B and D objectives. Besides, x'_3 is considered to be the best close solution found as it fulfills the two aforementioned conditions: a close A value and the improvement of all the remaining objectives.

5. **Compare the couple of solutions**: The optimal solution provided by the mono or multi-objective model is compared to the selected WSN-θ-DEA solution according to the overall objectives' values proposed by these two solutions.

We note that as the number of clusters, the number of HSR nodes, and the number of LSR nodes are tied to the overall network cost and the sum of these objectives refers to the total number of nodes, these three objectives will be gathered in one objective for comparison purposes. Let us consider the overall network cost objective as one of the compared objectives which replaces the aforementioned objectives. We recall that nch, nhs, and nls refer to the number of clusters, the number of HSR nodes, and the number of LSR nodes, respectively. The cost objective is:

$$Cost = 4 \times nch + 2 \times nhs + 1 \times nls \tag{19}$$

According to Equation 19, the deployment of a CH node is supposed to be two times more expensive than the deployment of a HSR sensing node and four times more expensive than a LSR sensing node. In addition, it is worth mentioning that during the optimization process of θ-DEA, the objective space is normalized as described in Section 4.3.2. Besides, in the experiments section below, the objectives values are reformed according to the objectives' equations previously illustrated.

6 Discussion of the Results

In what follows, NC, NH, NL, CV, CN, EC, and TH refer to the number of clusters, the number of HSR nodes, the number of LSR nodes, the coverage, the connectivity, the energy consumption and the throughput objectives, respectively.

6.1 WSN-θ-DEA vs Coverage model

In this experiment, we aim to compare the results of the optimization of a mono-objective model and WSN-θ-DEA model. The mono-objective model considers only the optimization of the coverage objective. The obtained objectives' values of the two compared solutions are depicted in Table 7 where the best value for each objective is highlighted in bold.

As can be seen from the table, the solution provided by WSN-θ-DEA has better values in four over five objectives with respect to a little deterioration in the coverage objective by 1.20%. The cost objective improvement is explained by the fact that a CH node was replaced by a HSR node. Besides, connectivity, throughput and energy consumption values improvement is a consequence of a better set of nodes' locations, i.e., the nodes in the WSN-θ-DEA solution are closer to the sink node compared to nodes in the coverage model solution, resulting in:

– A better connectivity (17.81%): 11 connected sensing nodes, 3 non-connected nodes and one cluster exceeds the predefined cluster size.
– A better throughput (8.44%): more connected sensing nodes in the WSN-θ-DEA solution.
– A better energy consumption (6.25%): decrease of the communication energy since nodes are more close to each other.

6.2 WSN-θ-DEA vs EC-TH model

In this section, we consider a bi-objective model optimizing the energy consumption and the throughput objectives. Figure 6 shows the optimal Pareto front obtained by the optimization of the model using θ-DEA (We recall that $TH = \frac{1}{T}$ where T is the throughput expression as illustrated in Section 4). Objectives values of the knee point are compared to another solution obtained by the optimization of WSN-θ-DEA. Results are depicted in Table 8.

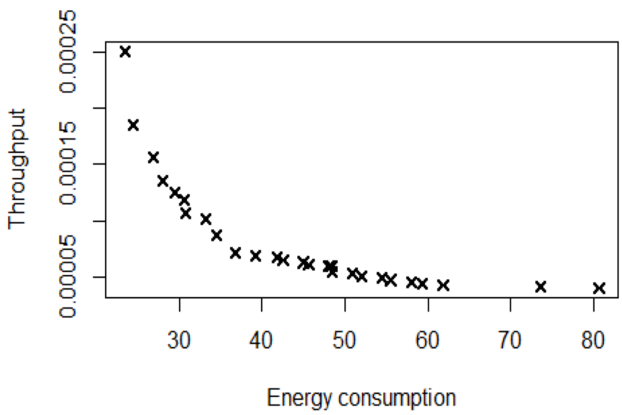

Fig. 6 Optimal Pareto front obtained by one run of the optimization of the Energy consumption-Throughput model

Table 7 Comparative results of WSN-θ-DEA vs Coverage model

	Coverage	WSN-θ-DEA	% difference
Cost (nch, nhs, nls)	52 $(7, 11, 2)$	**50 (6, 12, 2)**	3.85%
Coverage	**1333**	1349	−1.20%
Connectivity	0.0073	**0.0060**	17.81%
Energy consumption	80.4052	**75.3825**	6.25%
Throughput ($\times 10^{-5}$)	4.5872	**4.20**	8.44%

Table 8 Comparative results of WSN-θ-DEA vs Energy consumption-Throughput model

	EC-TH	WSN-θ-DEA	% difference
Cost (nch, nhs, nls)	66 $(13, 7, 0)$	**64 (14, 2, 4)**	3.03%
Coverage	6583	**5815**	11.67%
Connectivity	2.76×10^{-12}	**0**	Optimal
Energy consumption	**36.8351**	37.1245	−0.78%
Throughput ($\times 10^{-5}$)	**7.14**	7.41	−3.78%

The comparison of the two obtained solutions exhibits that the WSN-θ-DEA involves a solution suggesting the improvement of three objectives with a small deterioration in the energy consumption and throughput objectives. The nodes deployment proposed by the WSN-θ-DEA solution is less costly as it deploys 4 nodes operating in LSR mode while the EC-TH solution does not deploy any LSR nodes. As the two solutions deploy an important number of CH nodes, the coverage value is high. Nevertheless, the second solution has the smallest value with 11.67% since the deployed nodes are farther from the sink node. In addition, all the sensing nodes are assigned to clusters and all the clusters' sizes do not exceed the predefined size (connectivity value equals to 0).

6.3 WSN-θ-DEA vs NH-NL-CV model

We consider a multi-objective deployment model optimizing the number of HSR nodes, the number of LSR nodes and the coverage objectives. Fig. 7 shows the optimal Pareto front obtained by the optimization of the model using θ-DEA. We consider the knee point solution provided by the multi-objective model, we look for a near solution obtained by the WSN-θ-DEA model and we compare these solutions. In contrast to the previous experiments, in which only one relevant solution from the WSN-θ-DEA front was found, in this case the solutions' selection phase gives two relevant solutions: Solution 1 and Solution 2 (see Table 9).

Table 9 shows that WSN-θ-DEA is able to provide solutions that dominate solutions obtained by another model. In fact, with respect to the chosen solution, the WSN-θ-DEA offers two alternatives:

- Improve the coverage with an increased cost: Compared to the NH-NL-CV solution, the 1^{st} solution obtained by WSN-θ-DEA improves four objectives including the coverage objective (10.12%) with a little deterioration in the cost objective (−2%). The deployment scheme of this solution is better with respect to the coverage and throughput objectives as it deploys an additional HSR node. The nodes are located in a way that the distances to their corresponding CHs is minimized, involving a better energy consumption value with 11.82%. In addition, the connectivity objective is significantly improved with 33.34%.
- Improve the cost and accept a deterioration in the coverage objective: This alternative is illustrated by the 2^{nd} WSN-θ-DEA solution illustrated in Table 9. Although this solution is also improving connectivity (50%), energy consumption (29.51%) and throughput (13.61%) objectives, the nodes are placed more closer to the sink node resulting in an increased coverage value. The cost improvement (2%) is explained by the substitution of a HSR node by a LSR node.

6.4 Discussion

This section is devoted to discuss the obtained results with an attempt to summarize the conclusions drawn along the experiments. Therefore, it is interesting to note that our proposed many-objective model is very competitive regarding the overall trade-off between objectives. Along the experiments, the model is offering solutions that are too close to solutions obtained by low-dimensions models. Moreover, WSN-θ-DEA is able

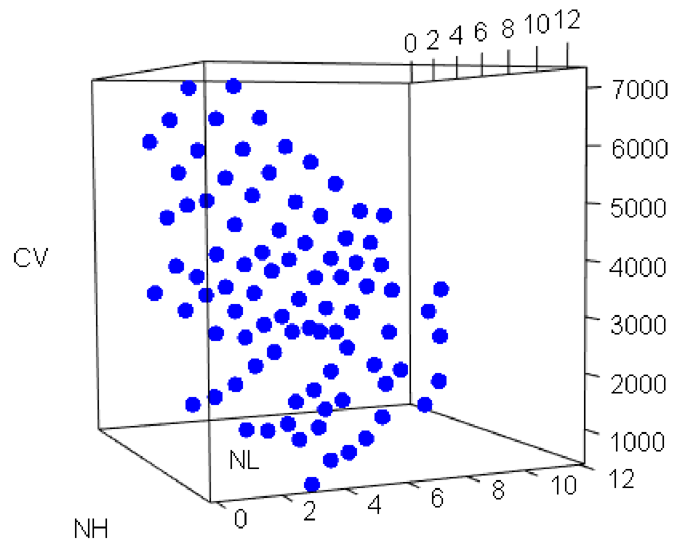

Fig. 7 Optimal Pareto front obtained by one run of the optimization of the Number of HSR nodes-Number of LSR nodes-Coverage model

Table 9 Comparative results of WSN-θ-DEA vs Number of HSR nodes-Number of LSR nodes-Coverage model

	Cost	CV	CN	EC	TH
NH-NL-CV	$50(8,6,6)$	2521	0.012	83.3960	6.54
Solution 1	$51(8,7,5)$	2266	0.008	73.5359	5.59
	-2%	10.12%	33.34%	11.82%	14.53%
Solution 2	$49(8,5,7)$	3439	0.006	58.7822	5.65
	2%	-36.41%	50%	29.51%	13.61%

to provide solutions that are dominating solutions obtained by the confronted models, and it often improves an objective which is already considered with other models. In addition, as illustrated in the third experiment, regarding a given solution provided by a multi-objective model, WSN-θ-DEA shows its capacity to emit different solutions giving more than one alternative to the decision maker.

Last but not least, we note that through all the presented experiments, we considered that all the objectives are of same priority, with identical weights (1/7), where the sum of weights is equal to 1. Thus, it is very important to also indicate that by using our model we can incorporate the decision maker preferences even after the selection of the model objectives. This says that the decision maker can handle the many-objective deployment model with a special focus on the most important objectives by means of different weights attribution while keeping the sum of weights equal to 1. The assignment of different weights to the objective functions will bias the search process towards the Region Of Interest (ROI) and will make the algorithm focusing on solutions that match as possible the decision maker preferences.

To illustrate this aspect, for instance, we consider an example where the coverage and energy consumption objectives have a higher weight. We assume that the number of cluster heads, the number of HSR nodes, the number of LSR nodes, the coverage, the energy consumption, the connectivity and the throughput objectives have different weights: $0,1$, $0,1$, $0,1$, $0,25$, $0,1$, $0,25$ and $0,1$, respectively. According to this example, the coverage and energy consumption objectives are prioritized regarding the other ones. Figure 8 illustrates the knee points obtained by both models with equal weights (without preferences) and this model highlighted, respectively, in blue and orange. These Knee points have been extracted among the generated set of solutions, generated by θ-DEA, using the trade-off worth metric [36].

Keeping in view that the objectives are disparately scaled, solutions have been plotted with normalized objectives values. This figure shows that assigning different weights to the objectives offers an enhancement of objectives with higher weights while accepting a deterioration (or not) for the other objectives with small-scaled weights.

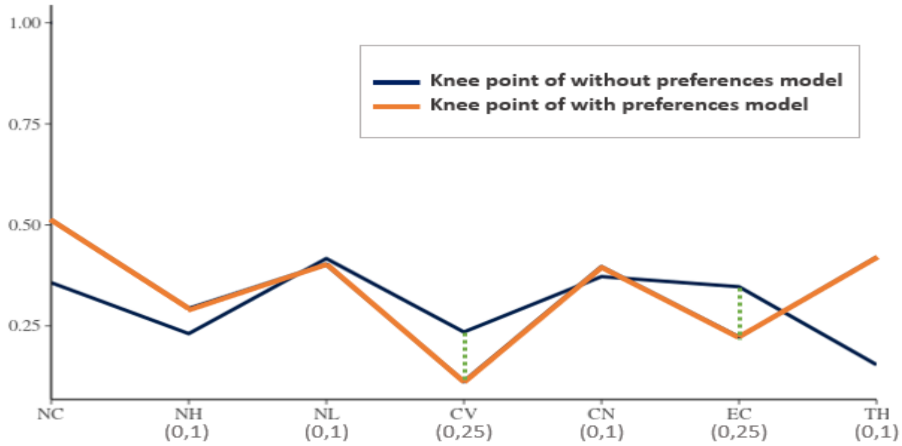

Fig. 8 Parallel coordinates plot of knee points for standard and with preferences WSN-θ-DEA optimization

To measure the efficiency of our proposed approach in terms of latency, we provide a summary of the average resolution CPU time of each model. Our resolution experiments were performed on a computer with Intel®Xeon®Processor CPU E5-2620 v3 and 16 GB RAM using a Java-based framework: JMetal [18]. Mainly, the CPU time varies according to the model objective space: the higher the number of objectives is, the greater the CPU time of the resolution algorithm is. Experimental results for each model resolution are summarized in Table 10:
As shown in table 10, the resolution of the proposed model takes more time than the other models. Otherwise, since the placement of WSN sensors is not a real-time problem, decision-makers willing to optimize as many conflicting objectives as possible, would intuitively adopt the many-objective optimization while accepting longer duration resolution.

According to these interpretations, the most important conclusion to be drawn is that the WSN deployment optimization in a many-objective fashion is a promising alternative.

7 Conclusion and future work

In this paper, we presented the optimization of a seven objectives WSN deployment model while exhibiting the added value of the many-objective optimization compared to mono- and multi-objective ones. For the best of our knowledge, this would be the first work proposing a many-objective WSN deployment model considering more than three objectives. The θ-DEA algorithm was chosen to solve the proposed model, mainly due to its ability to produce an efficient set of optimal solutions using a decomposition-based strategy. The conducted experimental study shows that our approach is promising in the WSN optimization problems field and can reveal extensive perspectives to investigate. In this section, we study the possible threats to validity. We also give proper perspectives to solve the threat issues.

In our proposed model, we incorporated seven of the most used deployment objectives in literature. In fact, a deployment problem encompasses an important number of objectives and the specialized community has been proposing additional ones. Thus, assuming that the WSN-θ-DEA model is versatile, it would be interesting to incorporate new objectives to it (resolved using the same algorithm, since θ-DEA could approximate a Pareto Front (PF) with a respectful quality if the number of objectives does not exceed 15 [45]). Second, from a resolution viewpoint, we have made use of the θ-DEA algorithm as it presents several interesting advantages in comparison to other methods; specifically when focusing on its ability in handling models with more than three objectives. Still, it will be important to examine the resolution of the WSN-θ-DEA model using other many-objective algorithms [29], such as, MOEA/D [46] and NSGA-III [16]. Third, in our experimental study, we accentuated that the decision maker's preferences could be handled, namely, by the weighting of the objectives, allowing additional adjustments in order to take account of special priorities. In this context, we will attempt to propose other preferences handling that take into consideration exceptional circumstances, namely, the fixed positions of certain sensors. Our approach could work well in such setting by making the chromosome (solution) in θ-DEA containing some genes that should be constant (unchangeable) and some other that should be varied for the optimization purpose.

Concerning WSN architecture, we adopted a cluster-based architecture which is the well-known specific type of architectures. However, it will be worthwhile to redefine the objective functions and assumptions to fit

Table 10 Resolution CPU time

Model	Number of objectives	CPU Time (Seconds)
WSN-θ-DEA	7	314
Coverage model	1	58
EC-TH model	2	117
NH-NL-CV model	3	187

other specific deployment architectures. In addition, it is important to investigate another line of research: the dynamic WSN deployment. As a static WSN seldom operates as planned, the basic idea propounded by the dynamic WSN deployment is to approach versatile WSN and enable post-deployment changes in order to fix problems and ensure the network survival and operation [33]. Finally, WSNs have been predominantly used for tracking and monitoring in a vast number of domains. Applications of WSNs include, but are not limited to, industry, environmental monitoring, military tracking and so on [44]. A regular optimization of sensors deployment is, thus, required to handle particular constraints and incidents as in any constrained system there are certain unavoidable trade-offs [3]. Accordingly, it would be beneficial to apply the proposed "WSN-θ-DEA" to real-world setups, as optimal placement of sensors continues to be quite challenging.

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