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A Fuzzy/Possibility Approach for Area Coverage in Wireless Sensor Networks

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Abstract

The literature approaches, devoted to sensor improve network coverage, are deterministic in terms of deployment environment and node configuration parameters. Nevertheless, this type of approaches has not proven to be very successful in uncertain deployment environments. This paper aims to deal with this issue using theories of uncertainty. We consider deployment environment's imperfections and the characteristics of the sensor nodes. The selection of a minimum number of nodes for a minimum number of clusters to guarantee coverage in Wireless Sensor Networks (WSNs) is uncertain. As a consequence, this paper proposes a hybrid Fuzzy-Possibilistic model to Schedule the active/passive State of Sensor nodes Strategy (FP-3SNS). This model helps to plan the scheduling of node states (Active / Passive) based on possibilistic information fusion to make a possibilistic decision for the node activation at each period. We evaluated our model (FP-3SNS) with (a) a running example (that shows the best choice of the active node with a probability of 0.81215); (b) a statistical evaluation (calculation of the confidence interface), where the average coverage reliability at 95% of FP-3SNS use is between [92.94, 96.27]); and (c) a comparison with Maximum Sensing Coverage Region problem (MSCR), Coverage Maximization with Sleep Scheduling (CMSS), Spider Canvas Strategy, Semi-Random Deployment Strategy (SRDP), Probing Environment and Adaptive Sleeping with Location Information Protocol (PEAS-LI) and Variable Length Particle Swarm Optimization Algorithm with a Weighted Sum Fitness Function (WS-VLPSO). The simulation results highlight the benefits of using the fuzzy and possibility theories for treating the area coverage problem and the proposed model maintained a coverage between 99.99% and 90.00% for a significant period of time.

Keywords: Fuzzy set, Possibility theory, Wireless Sensor Network, Area Coverage, Node States Scheduling

1 Introduction

Currently, technological progress in Wireless Sensor Networks (WSNs) and mobile devices is revolutionizing the reliability of the detection, collection, and communication of environmental information. Due to dynamic physical environments and possible hardware failures, the raw data collected by sensor nodes is inherently inaccurate and imprecise. In other words, the raw data can only reflect approximate measurements of the monitored environments and is therefore considered uncertain Youngjoon et al (2018); Wang et al (2017a); Ostad-Ali-Askari (2022).

This paper focuses on the capacity of devices' to detect physical phenomena such as humidity, heat, and pressure. We consider more precisely the uncertainty that affects these detection abilities in a non-deterministic environment. By uncertainty, we mean the hostility of the environment, where the sensor nodes are deployed, caused by the variations of atmospheric circumstances, the modifications of the deployed sensor network topology, the unreliability of the communication radios and reception radios, etc. All these uncertainties affect the quality of service and decision on real-world information Youngjoon et al (2018); Wang et al (2017a). In many cases where WSNs networks are used, non-uniform detection requirements need to be considered depending on the size or the sensitivity of the surveillance zone. For instance, high detection accuracy is required for sensitive regions and low detection for smaller areas.

Atmospheric events, which mark the physical environment, influence the position, power of communication, and monitoring of sensor nodes in a network. This reality makes it necessary to consider the type of uncertainty.

In order to consider uncertainty in a manner that addresses WSN problems, we propose introducing fuzziness in the process of scheduling sensor nodes in WSNs for several purposes. Among the types of uncertainty configured in WSNs Boualem et al (2021), there are:

- **Uncertainty in radio communication links:** The communication power increases if the Euclidean distance increases. In the case of deployment in a three-dimension (3D) environment, mobility, energy power, and connectivity

are constraints that prevent the communication of the network's sensor nodes.

- **Uncertainty in the detection links:** Environmental interference, angle, non-linear distance, noise, sensor types, and other factors can introduce uncertainty in the detection process in sensor networks.
- **Detection uncertainty in the data collection:** When sensors are deployed in hostile environments, different things can affect the collected or detected data's quality, such as node sensibility due to signal interferences caused by objects in the environment (*e.g.* foliage) or phenomena (*e.g.* clouds), or the node's physical state due to possible deterioration (wind, soil state, animals, etc).

This paper addresses the problem of area coverage in uncertain environment with a new strategy based on the theories of possibilities and fuzzy sets. The objective is to guarantee the coverage of an area with a minimum number of subsets of connected nodes, a minimum cost and a minimum number of dominant nodes, regardless of the type of deployment used (random or deterministic). Thus, our approach extends the lifetime of WSNs as much as possible and guarantees the quality of service while taking into account the uncertainties of the environment. To the best of our knowledge, this hybrid model has not been proposed in the literature to deal with such uncertain problems.

All symbols used in the manuscript are listed in Table 1.

Two case studies are presented: in the first case study, the approach illustrated through an example, and, in the second case study, the proposed protocol is simulated and compared with the Maximum Sensing Coverage Region problem (MSCR), Coverage Maximization with Sleep Scheduling (CMSS), Probing Environment and Adaptive Sleeping with Location Information Protocol (PEAS-LI), and Variable Length Particle Swarm Optimization Algorithm with a Weighted Sum Fitness Function (WS-VLPSO) protocols. The results highlight the benefits of using uncertain theories in the area coverage problem. The remainder of this paper is structured as follows: Section 2 highlights the related work on the area coverage domain.

Section 3 presents the foundations of the fuzzy sets theory. Section 4 reviews the foundations

Table 1 The symbols used in the manuscript

Symbol	Signification
u_i	Sensor node i
$D^{(i,j)}$	Euclidean distance between node u_i and node u_j
E_i	Energy reserve of the node u_i
C_1	Selected neighboring nodes of the active node
$\pi_D(u_i)$	Possibility measure of the criterion D for node u_i
$\pi_E(u_i)$	Possibility measure of the criterion E for node u_i
$N_D(u_i)$	Necessity measure of the criterion D for node u_i
$N_E(u_i)$	Necessity measure of the criterion E for node u_i
$\pi_{D,E}(u_i)$	Possibility measure combined between D and E criteria of node u_i
$N_{D,E}(u_i)$	Necessity measure combined between D and E criteria of node u_i
$\mu_A(x)$	Degree of membership of x to A
$P_A(u_i)$	Probability of activation (A) of a sensor node u_i
ACI	Asymptotic Confidence Interval

of the possibility theory. Section 5 introduces and explains our proposed methodology. Section 6 shows the evaluation. In Section 7, we provide a conclusion and summarize the benefits, as well as the improvements, that the proposed model, had on area coverage, and we provide some implications for future works.

2 Related Work

In WSNs, the term coverage relates to how the entire area of interest is monitored with a minimal set of sensor nodes. It can be considered as a measure of the Quality of Service (QoS).

The easiest way to achieve perfect coverage, especially area coverage, is to enable all sensor nodes at once. This activation quickly exhausts the WSN's lifetime to accomplish different tasks that require more control, monitoring, confidentiality, and continuous time periods. Deployment with a high density of sensor nodes in the area of interest produces interference or overlap between the communication and monitoring radii of adjacent (neighboring) sensor nodes in the network. The latter implies that it is unnecessary to activate all the sensor nodes of the network at each times since it creates a collision in Medium Access Control (MAC). To maintain the coverage and increase the network's lifetime, it is necessary to

apply a process called "scheduling". The most effective scheduling process is to activate a minimum set of sensor nodes at each time and put the rest on standby (sleep state) until the network is completely exhausted [Wesam et al \(2019\)](#). This scheduling process is defined by how long each node is active and which node is active at the next quantum of time scheduling, as defined in [Tossa et al \(2022\)](#) by decision-making processes that are used on a regular basis in optimization and planning services. The scheduling problem treatment can consist of organizing a set of tasks according to the energy required to execute them, and then, by using the capacities of available resources [Kaabi \(2019\)](#). This scheduling problem is highlighted by the work in [Garey and Johnson \(1979\)](#).

The reason for using the scheduling procedure is that each sensor node can go through four states-transmit or communication, receive or reception, idle, and sleep. A node in a communication, reception, or idle state consumes more energy than in a sleep state. Consequently, it is better for a node to enter a sleep state to save more energy.

Algorithms used to optimize the coverage problem are divided into two types: (a) centralized algorithms and (b) localized algorithms [Chowdhury and De \(2021\)](#). Centralized algorithms consider the coverage problem as an optimization problem. For such purposes, linear programming is used to solve the problem, as in the works of [Tossa et al \(2022\)](#). Heuristic methods are used in [Wang et al \(2019\)](#). The authors in [Qarehkhani et al \(2022\)](#) use disjoint sets as a scheduling method and to find the number of minimum sets to activate and ensure the target coverage. This scheduling is based on an extension of Integer Linear Programming. In addition, [Katti \(2022\)](#) suggests that Disjoint Set Covers (DSC) are a non-deterministic problem in polynomial time (NP-complete problem) and proposes an approximate solution based on interest finding algorithms. Localized algorithms, such as Performance measure, Environment, Actuator, Sensor (PEAS) [Wang et al \(2015\)](#), Deterministic Energy-Efficient Protocol for Sensor networks (DEEPS) [More and Raisinghani \(2017\)](#), and Load Balancing Protocol (LBP) [Tossa et al \(2022\)](#), consider that a node can go through three transitions: sense/on, sleep/off, or vulnerable/undecided. The PEAS protocol is a localized protocol that defines

the scheduling process by sending a probing message to neighboring nodes. Each node receiving the message responds. A node that has received more than one response will return to sleep. It is noted that this protocol does not guarantee the entire coverage of the Area of Interest (AoI).

Uncertainty affects a variety of work on coverage in WSNs (area coverage, target coverage, and barrier coverage). Thus, the uncertainty is taken into account in certain works.

The work provided in [Hajje et al \(2020\)](#) proposes a scheduling mechanism based on time-sharing under a quantum of time and activates the sensor nodes for each quantum for coverage.

The authors in [Shi et al \(2015\)](#) propose a probabilistic-based dynamic non-deterministic-K-coverage protocol called the Optimal Cooperation Scheduling Algorithm (OCSA). This protocol is a probabilistic K-coverage type, and it considers that the target movement is uncertain (either the position or the speed) following the Gaussian law. The authors in [Abo-Zahhad et al \(2016\)](#) use a Voronoi diagram as a compromise to balance the sensor nodes and their current energy reserves. The objective of this strategy is to ensure a new type of scheduling to minimize the energy consumed by mobile sensor nodes, to guarantee coverage either partially or perfectly, and to maintain connectivity throughout the network's lifetime. The authors in [Charr et al \(2020\)](#) study partial coverage, and propose two types of scheduling algorithms: "P-percent coverage", and efficient Genetic Algorithm (GA) to achieve efficient covers' scheduling with minimal execution time complexity. A comparison of the different deployment strategies used for energy-efficient coverage is presented in the Table 2. Note that in the Table 2: (1) and (2) in column 7 indicates that populating additional (redundant) nodes or mobile nodes is used in the proposal, respectively.

In this article, the coverage problem is classified into two main categories; (a) coverage in sensor networks based on deterministic models and (b) coverage in sensor networks based on uncertain models [Boualem \(2021\)](#). In (a), the coverage in sensor networks is based on deterministic models, such as Energetic Sleep-Scheduling via Probabilistic Interference K-Barrier Coverage with Truth-Table Technique in Sensor Networks [Boualem et al \(2017\)](#), and the Hybrid Model Approach for Wireless Sensor Networks Coverage Improvement

[Boualem et al \(2020\)](#). However in (b), the coverage in sensor networks is based on uncertain models, such as the Evidential Approach for Area Coverage in Mobile Wireless Sensor Networks [Boualem et al \(2021\)](#), Area Coverage Optimization in Wireless Sensor Network by Semi-Random Deployment (SRDP) [Boualem et al \(2018\)](#), Spiderweb strategy: application for area coverage with mobile sensor nodes in 3D wireless sensor networks (Spiderweb strategy) [Boualem et al \(February 2019\)](#), the New Dijkstra Front-Back Algorithm for Data Routing-Scheduling via Energy-Efficient Area Coverage in Wireless Sensor Networks [Boualem et al \(2019a\)](#), and the Fuzzy/Evidential Approach to Address the Area Coverage Problem in Mobile Wireless Sensor Networks [Boualem et al \(2019b\)](#).

3 The Foundations of the Fuzzy Sets Theory

According to Zadeh [Lin et al \(2018\)](#), fuzzy sets theory is a step towards a rapprochement between the accuracy of classical mathematics and the subtle inaccuracy of the real world. In crisp (usual) set theory, there are only two acceptable situations for an element, to belong or not to a subset. The fuzzy sets are characterized by the notion of weighted membership which allows graduations in the membership of an element to a subset, that is to say to allow an element to belong more or less strongly to this subset. Formally: Let X be a reference set and let x be any element of X .

A fuzzy subset A of X is defined as the set of pairs:

$$A = \{(x, \mu_A(x)), \text{ with } x \in X \text{ and } \mu_A : X \rightarrow [0, 1]\} \quad (1)$$

Thus, a fuzzy subset A of X is characterized by a membership function $\mu_A(x)$ which associates, at each point x of X , a real value in the interval $[0, 1]$ and $\mu_A(x)$ represents the degree of membership of x to A . We observe the three possible cases:

$$\begin{cases} \mu_A(x) = 0 \\ 0 < \mu_A(x) < 1 \\ \mu_A(x) = 1 \end{cases} \quad (2)$$

Characteristics of a fuzzy subset: A fuzzy subset is completely defined by the data of its membership function. From such a function, a number of characteristics of the fuzzy subset can

Table 2 A comparison between various deployment proposals in the literature

Ref	Network properties				Deployment		
	Model	Connectivity	Coverage	Lifetime	Type	Technique	Targeted Space
Boualem et al (2021)	Uncertain	k-path	k-coverage	Node-based	Fuzzy and Evidential-based model	(2)	2-D
Ahlawat and Dave (2018)	Certain	k-path	k-coverage	Node-based	Random and Geometric-based	(1)	2-D
Aski et al (2020)	Certain	k-path	k-coverage	Network-based	Grid-based	(2)	2-D
Evangelos et al (2017)	Certain	k-path	k-coverage	Network-based	Random and graph theory-based	(2)	2-D
Boualem et al (2020)	Certain	k-path	k-coverage	Network-based	Grid-based	(1)	2-D
Boualem et al (2019b)	Uncertain	k-path	k-coverage	Uncertain Network-based	Fuzzy/Evidential-based model	(2)	3-D
Boualem et al (2019a)	Certain	k-path	k-coverage	Node-based	Node-based	(1)	2-D
Boualem et al (2017)	Uncertain	1-path	K-Barrier coverage	Network-based	Grid-based	(1)	2-D
Boualem et al (February 2019)	Uncertain	k-path	k-coverage	-	Random	(2)	3-D
Alablani and Alenazi (2020)	Certain	k-path	k-coverage	Node-based	Geometric-based	-	3-D
Nasri et al (2019)	Uncertain	k-path	k-coverage	Network-based	Geometric-based	(2)	3-D
Liu and Ouyang (2018)	Uncertain	k-path	k-coverage	Network-based	Probabilistic	(2)	3-D
Wu and Wang (2017)	Uncertain	k-path	k-coverage	Network-based	Algorithm-based	(2)	3-D
Dogan and Brown (2017)	Uncertain	k-path	Data	Network-based	Uncertainty models	(2)	2-D
Wang et al (2017b)	Uncertain	k-path	k-Coverage	Network-based	Uncertainty properties	(2)	2-D
Boualem et al (2022)	Uncertain	k-path	k-Coverage	Grid-based	Uncertainty properties	(2)	2-D

be studied (Fig. 3.(c)).

Support and Height: These two characteristics, essentially show, to what extent a fuzzy subset A of X differs from a classical subset of X (Fig. 3.(a)). The first is the support and the second is the height (Fig. 3.(c)). The support of a fuzzy subset of A of X , denoted $Sup(A)$, is the set of all elements that belong to it at least a little bit (Fig. 3.(d)). Formally:

$$Sup(A) = \{x \in X / \mu_A(x) > 0\} \quad (3)$$

The height of the fuzzy subset A of X , denoted $h(A)$, is the strongest degree with which an element of X belongs to A (Fig. 3.(d)). Formally:

$$h(A) = Sup_{x \in X} \mu_A(x) \quad (4)$$

Core: A fuzzy subset is normalized if its height $h(A) = 1$. The core of a fuzzy subset A of X , denoted $Cor(A)$, is the set of all the elements which belong to it totally (with a degree 1) (Fig. 3.(d)). Formally:

$$Cor(A) = \{x \in X / \mu_A(x) = 1\} \quad (5)$$

Cardinality: The cardinality of a fuzzy subset A of X , noted $|A|$, is the number of elements belonging to A weighted by their degree of membership (Fig. 3.(d)). Formally, for A closed:

$$|A| = \{\sum_{x \in X} \mu_A(x)\} \quad (6)$$

If A is an ordinary subset of X , its cardinality is the number of elements that compose it, according to the classical definition (Fig. 3.(a)).

α -cut: The ordinary subset A_α of X associated with A for the threshold α is the set of elements that belong to A with a degree at least equal to α . We say that α is the α -cut of A (Fig. 3.(d)). Formally:

$$A_\alpha = \{x \in X / \mu_A(x) \geq \alpha\} \quad (7)$$

The characteristics of fuzzy sets are illustrated in Fig. 3.(b).

4 The Foundations of the Possibility Theory

The possibility theory presents a formalism that allows the modeling of subjective uncertainties on events Pekala (2019). It uses two measures: a measure of possibility that examines the extent to which an event is possible, and a measure of necessity that quantifies the degree of certainty associated with this event. Thus, these two measures make it possible to frame the probability of realization of the studied event. The theory

of possibilities is currently of general interest to researchers who have the need to generalize natural modes of reasoning, to automate decision-making in their field, and to construct artificial systems that perform the usual tasks. Possibility and necessity measures have been introduced to qualify certainty on an event, that is, they apply to ordinary subsets A_i of a reference set X . Within the framework of the theory of possibilities, the uncertainty inherent in an event A is represented by a pair of two measures: the measure of possibility $\pi(A)$ and the measure of necessity $N(A)$ Bouchon-Meunier (2000). Similarly, the possibility measure is an application defined by the following relation:

$$\begin{aligned} A_i &\rightarrow \Omega \\ \pi(A_i) &\rightarrow [0, 1] \end{aligned}$$

(A_i) : is the measure that evaluates how much of event A_i is possible.

Some characteristics of the possibility measure are as follows:

- $\pi(A) = 1$, the event A is the event completely possible (realizable).
- $\pi(A) = 0$, the event A is completely impossible.
- The possibility of an empty set (impossible or empty event) is completely null, formally:

$$\pi(\phi) = 0 \quad (8)$$

- The possibility of the set of references (the set of all possible events) is completely possible, formally:

$$\pi(\Omega) = 1 \quad (9)$$

- The possibility of performing event A or B equals the maximum of their possibilities of realization, formally:

$$\forall A, B \subseteq \Omega, \pi(A \cup B) = \max(\pi(A), \pi(B)) \quad (10)$$

- The possibility of performing event A and B at the same time as equal or less than the minimum of their possibilities of realization, formally:

$$\forall A, B \subseteq \Omega, \pi(A \cap B) \leq \min(\pi(A), \pi(B)) \quad (11)$$

Similarly, the necessity measure is an application defined by the following relation:

$$\begin{aligned} A_i &\rightarrow \Omega \\ N(A_i) &\rightarrow [0, 1] \end{aligned} \quad (12)$$

$N(A_i)$: is the measure that evaluates how much we are certain of the realization of the event A_i .

$$N(A) = 1 - \pi(\bar{A}) \quad (13)$$

Where \bar{A} is the complementary event of A . The necessity measure must satisfy the following properties:

- The need for realization of the empty event is absolutely zero. Formally:

$$N(\phi) = 0 \quad (14)$$

- The need for realization of the set of references (the set of possible events) is absolutely necessary. Formally:

$$N(\Omega) = 1 \quad (15)$$

- The necessity of carrying out one of two events is greater or equal to the maximum of their necessities. Formally:

$$\forall A, B \subseteq \Omega, N(A \cup B) \geq \max(N(A), N(B)) \quad (16)$$

- The necessity of carrying out two events at a time is equal to the minimum of their necessities. Formally:

$$\forall A, B \subseteq \Omega, N(A \cap B) = \min(N(A), N(B)) \quad (17)$$

The probability $P(A)$ of the realization of an event A is delimited by the measurement of necessity $N(A)$ and the measure of possibility $\pi(A)$ in the theory of possibilities. The pipeline of possibility theory is illustrated in Fig.1.

$$N(A) \leq P(A) \leq \pi(A) \quad (18)$$

For this reason, we consider that these types of measurements (possibility and necessity) correspond well to deciding the choice of Active / Passive sensor nodes in the sensor network. The properties characterizing and connecting these two measures are as follows:

- $\pi(A) + \pi(\bar{A}) \geq 1$, the sum of possibility measures of the event A and the opposite event \bar{A} is greater than or equal to 1.
- $N(A) + N(\bar{A}) \leq 1$, the sum of necessity measures of the event A and the opposite event \bar{A} is less than or equal to 1.
- $\max(\pi(A), \pi(\bar{A})) = 1$, the maximum between the possibility of realization of the event A and \bar{A} .
- $\min(N(A), N(\bar{A})) = 0$, the minimum between the possibility of realization of the event A and \bar{A} .
- $\pi(A) < 1 \implies N(A) = 0$,
- $N(A) > 0 \implies \pi(A) = 1$.

We define the distance between $N(A)$ and $\pi(A)$ which can evaluate the level of ignorance $\theta(A)$ on the event A by the following relation:

$$N(A) - \pi(A) = \theta(A) \quad (19)$$

5 Description of the Proposed Model

Active/Passive state scheduling of nodes is considered one of the techniques used in improving coverage in WSNs. Scheduling is the process used to choose which node to activate as a cluster-head in each time period. The purpose of our work is to make better, possible, and necessary decisions regarding the activation of neighboring nodes. The proposed hybrid approach, illustrated in Fig. 2, uses five steps, i.e. (a) construction of the cluster and selection of candidates; (b) plausibility of attribution factors; (c) fuzzy information fusion; (d) normalization; and (e) decision, to activate the best neighbor node in each cluster (sub-area). Thus, the possibility theory is used in the construction and selection of the potential sensor nodes in each sub-area (cluster). The best neighbor node in each cluster becomes the cluster-head. To choose the cluster-head node, it is necessary to first assign measures of possibilities and necessities. The second step is to measure the possibility functions using fuzzy subset graphs to compute the membership functions of the Euclidean distance and energy reserve criteria. A fuzzy fusion step is used to combine the choice data using fuzzy operators in the third step, and normalization operation in the fourth step. The decision step is based on our probabilistic formula, defined

between the possibility and necessity measurements. Fig. 2 represents the fuzzy possibilistic model proposed as a scheduling process to deal with the problem of coverage in WSNs. The five steps of our hybrid model are detailed in the following subsections:

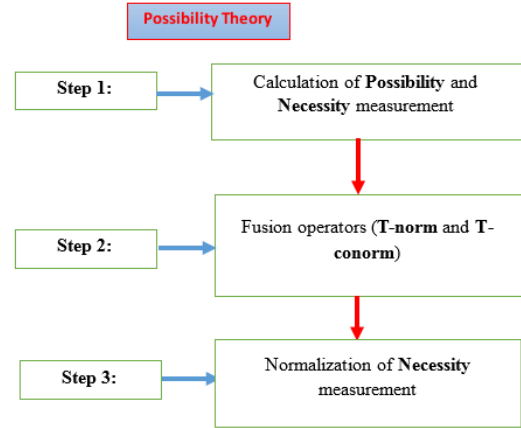


Fig. 1 Possibility theory steps.

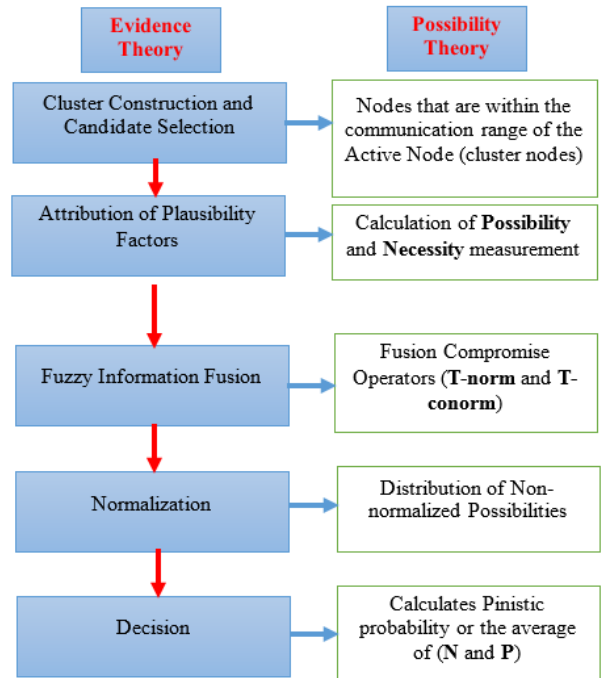


Fig. 2 Pipeline of the model for Active/Passive scheduling.

5.1 Step 1: Construction of clusters and selection of candidates

This step is automatic. The nodes of the same cluster send Hello messages to obtain the energy reserve, the geographical position (to allow the calculation of the Euclidean distance.) The cluster groups of active neighboring nodes, that is to say, the construction of clusters, is based on the two sent criteria (D_{eclud} , R_{energy}), the measurement of communication range (R_C), and the monitoring range (R_S) according to the algorithm described in Pseudo-Algorithm 1.

The sensor nodes that are members of each cluster constitute the set of potential candidates.

Algorithm 1 Pseudo Algorithm of Clusters number and potential candidates

Require: n the number of nodes to deploy

Require: k the number of cluster to construct

```

1: for i=1 to n do
2:   for j=1 to k do
3:     if  $D_{eclud}(ActiveNode, Node_i) < R_S$ 
       then
4:        $C_k = C \cup i = 1^{i=n}(u_i)$ ; //is the
       cluster k to construct  $C_k$ .
5:        $N(u_i) = k$ ;
6:        $\pi_A^E(u_i) = R_{energy}$  //  $\pi_A^E(u_i)$ 
       Energy parameter memory.
7:       if  $K=1$  then
8:          $\pi_A^D(u_i) = D_{eclud}$  //parameter
       memory of the Euclidean distance  $\pi_A^D(u_i)$ .
9:       end if
10:    end if
11:  end for
12: end for

```

In a network of n nodes, the operation to build k clusters requires k steps executed (repeated) n times ($n \times k$ operations). Consequently, the complexity of the Pseudo-Algorithm 1 is polynomial $O(n^2)$.

5.2 Step 2: Attribution of plausibility measures

To say that an event is not possible does not only imply that the opposite event is possible but also that it is certain. Two dual measures are used: the

measure of possibility, and the measure of necessity. The possibility of an event A , denoted $\pi(A)$ is obtained by the formula defined in (20),

$$\pi(A) = \max_{x \in A} \pi(x) \quad (20)$$

and reflects the most normal situation in which A is true. For our case study, we consider a universe composed of N sensor nodes (like singletons), $\Omega = \{u_1, u_2, \dots, u_i, \dots, u_n\}$, and we suppose that we are in a context of uncertainty (i.e. a single sensor node (singleton) of Ω turns on at a time, but we do not know it). The distribution of possibilities, denoted $\pi(\cdot)$, constitutes the basic tool of the theory of possibilities. This distribution is equivalent to the membership function of the fuzzy sets theory. Indeed, it associates with each singleton sensor node u_i of Ω a value in $[0,1]$ which evaluates, in light of the available knowledge, the possibility of possible activation of this singleton sensor node. Thus, a possibilities distribution is an application that is defined as in (21) :

$$\begin{aligned} \pi : \Omega &\rightarrow [0, 1] \\ u_n &\rightarrow \pi(u_n) \end{aligned} \quad (21)$$

Where $\pi(u_n)$ represents the possibility that u_n is the singleton node that has been activated.

If $\pi(u_n) = 1$, the activation of u_n is considered fully possible. However, if $\pi(u_n) = 0$, the activation of u_n is considered to be absolutely impossible. In this formalism, the extreme forms of partial knowledge are expressed in the following way:

o **Total Ignorance:**

$$\forall u_n \in \Omega, \pi(u_n) = 1 \quad (22)$$

This means that activation of all sensor nodes is possible.

o **Complete knowledge:**

$$\exists u_i \in \Omega, \pi(u_i) = 1 \text{ and } \forall u_j \neq u_i, \pi(u_j) = 0 \quad (23)$$

The initialization of mass functions is based on the measurement computation of possibility ($\pi(\cdot)$) and necessity ($N(\cdot)$). The attribution of measures of possibilities in our study will be done by

the fuzzy subsets and according to the Euclidean distance criterion.

Calculation of necessity measure with a probabilistic method

For this model, we have proposed a method for calculating the need to activate a sensor node.

Definition: Let u_1, u_2, \dots, u_n be a set of neighboring nodes that constructs the cluster C_j . Let $c_1^j, c_2^j, \dots, c_k^j$ be a set of metrics generating the sensor nodes of cluster C_j . The activation of the node u_i necessity is defined by the following relationship (24):

$$N(u_i) = n(c_1^j) \times n(c_2^j) \times \dots \times n(c_k^j) \quad (24)$$

The activation of the node u_i possibility is defined by the following relationship (25):

$$\pi(u_i) = \pi(c_1^j) \times \pi(c_2^j) \times \dots \times \pi(c_k^j) \quad (25)$$

$N(u_i)$ represents the merged necessity measure of a node u_i for all criteria c_1, c_2, \dots, c_k . in a cluster J and $n(u_i)$ represents the necessity measure of the node u_i .

We introduce the following constraints: the energy reserve and the Euclidean distance are used to decide whether it is possible and necessary to activate the node u_i (that is, $u_i(A)$).

Let E_0 be the initial energy reserve (before deployment), and D_{max} be the Euclidean distance from the farthest node to the active node. E_1, E_2, \dots, E_n respectively represent the current reserves of the neighboring nodes of the active node. D_1, D_2, \dots, D_n respectively represent the Euclidean distances of the neighboring nodes with respect to the active node u_A . According to relation (24), the necessity of a node $N(u_i)$ in a cluster j is calculated in our case study using two criteria; the Euclidean distance and the energy reserve, defined by (26).

$$N(u_i) = n(c_1^j) \times n(c_2^j) \quad (26)$$

So, the necessity of activation of the node u_i is defined by the relation (27):

$$n(u_i) = E_i/E_0 \times (1 - D_i/D_{max}) \quad (27)$$

The formula defined by (27) led us to define the following properties:

Properties

- if $E_i = E_0$ and $D_i = 0$ then $n(u_i) = 1$
- if $D_i = E_{max}$ then $n(u_i) = 0$

5.3 Step 3: Fuzzy fusion of information

The information fusion is based on the use of fusion compromise operations (T-norm and T-conorm). The operations of the fusion model according to the measure of possibilities are illustrated by relations (8), (9), (10), and (11).

The operations of the fusion model according to the measure of necessity are illustrated by relations (14), (15), (16) and (17).

The information fusion in the proposed model is defined as the following relation (28):

$$N(u_i) * \pi(u_i) > \max_{j \neq i \text{ and } u_i \in C_j} (N(u_j) * \pi(u_j)) \quad (28)$$

5.4 Step 4: Normalization

Normalization of measurement possibility is with non-normalized distributions of possibilities. The height of a distribution $h(\pi)$ is defined in Bouchon-Meunier (2000) as being the largest possibility value, as defined in equation (29):

$$h(\pi) = \max_{u_i} \pi(u_i) \quad (29)$$

If $h(\pi) = 1$, the distribution of possibilities is said to be normalized or consistent with the knowledge available. This means that the normalization or consistency of a distribution depends on the existence of at least one state that is entirely possible.

If the distribution of possibilities is non-normalized (inconsistent), we can define a new measure $Inc(\pi) \in [0, 1]$ as the measure of inconsistency for this distribution (30):

$$Inc(\pi) = 1 - \max_{x_n \in \Omega} (\pi(x_n)) = 1 - h(\pi) \quad (30)$$

Thus, an inconsistency degree of 0 means that the distribution in question is normalized. However, a degree of nonzero inconsistency means that this distribution is non-normalized.

5.5 Step 5: Decision

Usually, the decision to activate a node or to put it back in a sleep mode is based on the Pignistic probability calculus (theories of uncertainty), but in our study, the probability of activation of a sensor node u_i is delimited by the necessity measure $N_A(u_i)$ and the possibility measure $\pi_A(u_i)$ (31).

$$N_A(u_i) \leq P_A(u_i) \leq \pi_A(u_i) \quad (31)$$

In this case, we will use the average between the two possibility measurements of necessity ($N_A(u_i)$) and the possibility measurements ($\pi_A(u_i)$) (32).

$$P_A(u_i) = (N_A(u_i) + \pi_A(u_i))/2 \quad (32)$$

The node u_i becomes active ($A(u_i)$) in the next period if it checks the condition presented in the pseudo-algorithm (Pseudo-Algorithm 2).

Algorithm 2 Pseudo Algorithm of Activation Decision

```

1: if  $N(u_i) * \pi(u_i) > \max_{j \neq i \text{ and } u_i \in C_j} (N(u_j) * \pi(u_j))$  then
2:    $A(u_i)$ ; //  $A(u_i)$  signifies  $u_i$  becomes active in the next period.
3: else
4:   if  $\exists u_j$  and  $(j \neq i)$  then
5:     if  $N(u_j) > N(u_i)$  then
6:        $A(u_j)$ 
7:     else
8:        $A(u_i)$  //In first period
9:        $A(u_j)$  //In the second period, the node  $u_j$ , who requests the activation by sending a Hello activation message and which verified the opposite condition of  $\{N(u_j) > N(u_i)\}$  i.e. " $\{N(u_j) \leq N(u_i)\}$ ", will be effectively activated.
10:    end if
11:  end if
12: end if

```

For n clusters with m nodes in each cluster, the activation operation of the node u_i needs one step repeated n times ($1 \times n$ operations). Consequently, The complexity of the Pseudo-Algorithm 2 is linear $O(n)$.

6 Evaluation

We start this section by citing the motivations and objectives of using the compromise (fuzzy/possibility) to address coverage problems in WSNs. To evaluate the proposed model, we used three steps: 1) a step of running with real examples to clarify whether the operation of activating the sensor node is well chosen, 2) an evaluation step by calculating the confidence interval, and 3) a simulation step. The different evaluation methods should provide the same decisions (same results). Otherwise, the proposed approach is reliable for some activation cases and unreliable for others. As an additional step, we proposed using the calculation of possibilities and needs based on T-norm and T-conorm of these operations to obtain more realistic results compared to the use of classical operations. The calculation of possibilities is completed by using the membership function of the graph representing distance and energy consumption.

6.1 Motivation

The main motivations behind the use of possibility theory and fuzzy theory are:

- The automation of the mass function initialization step is based on necessity measurements.
- The fuzzy/possibilities trade-off is useful for the relevant decision to activate a sensor node in an uncertain environment in order to select a cluster-head playing a multiple role (monitoring and communication).
- In this context, the measure of necessity is calculated based on the possibility of the opposite event, in this case, the opposite event is not the only event that is unknown and difficult to calculate. For these reasons, we will define a formula verifying the conditions to calculate the measure of necessity.

6.2 Objectives

The main objectives behind the use of possibility theory and belief theory Destercke et al (2018) are:

- The environment is uncertain, so we must consider that the deployment is uncertain.
- The belief theory is one of the best methods to deal with uncertainty.

- The selection of potential candidates and the initialization of mass functions in belief theory is manual, and is done by domain experts. This insufficiency pushed us to automate the calculation of the mass functions.
- The possibility and necessity measures are the two essential measures in possibility theory. So, the proposed strategy performs the calculation of the measure of possibility based on membership functions and according to the fuzzy subsets of each fuzzy criterion to make different decisions about the states of a sensor node.
- In contrast, probability and possibility theories adopt an assumption of compositionality pertaining to one connective only (negation for probability functions, and disjunction for possibility functions). So, it allows us to use possibilities in a formula verifying the measure of necessity.

6.3 The Running Example

Let the following nodes be used to cover an area of interest $u_1, u_2, u_3, u_4, u_5, u_6$.

The base station selected u_3 as the active node at first. For each node, we consider two metrics: its Euclidean distance to the active node u_3 , and its energy reserve. According to fuzzy graph of distances (Fig. 4. (b)), the Euclidean distances between u_1, u_2, u_4, u_5, u_6 and the active node u_3 are respectively:

$$\begin{cases} D_{1,3} = 2.30 \\ D_{2,3} = 3.00 \\ D_{4,3} = 3.12 \\ D_{5,3} = 2.12 \\ D_{6,3} = 2.72 \end{cases} \quad (33)$$

The energy reserves of sensor nodes u_1, u_2, u_4, u_5, u_6 according to the fuzzy graph of energy and membership functions (Fig. 4. (a)), are the following:

$$\begin{cases} E_2 = 0.90 \\ E_3 = 0.96 \\ E_4 = 0.12 \\ E_5 = 0.52 \\ E_6 = 0.72 \end{cases} \quad (34)$$

$D_{i,j}$ represents the Euclidean distance between node i and node j in meter and E_i is the energy reserve of the i node in Joule. The communication

radius $R_C = 2.50$ and the initial energy reserve is 1 joule.

Step 1: Select neighboring nodes and build clusters

$$C_1 = \{u_1, u_5\} \text{ Because } R_C > D_{1,3} > D_{1,5}$$

Step 2: Allocate plausibility measures.

We use fuzzy sets to identify opportunities for action. The calculation of possible measures according to the Euclidean distance is based on the possibility graph shown in Fig. 5, and possible measures according to energy are based on the possibility graph depicted in Fig. 6.

For this example the possibilities are:

$$\begin{cases} \pi_D(u_1) = 0.900 \\ \pi_D(u_5) = 0.960 \\ \text{and} \\ \pi_E(u_1) = 1 - 0.875 \\ \pi_E(u_5) = 1 - 0.600 \end{cases} \quad (35)$$

So:

$$\begin{cases} \pi_D(u_1) = 0.900 \\ \pi_D(u_5) = 0.960 \\ \text{and} \\ \pi_E(u_1) = 0.125 \\ \pi_E(u_5) = 0.400 \end{cases} \quad (36)$$

Step 3: Fuzzy fusion of information

The necessities of measures for this example are calculated using the following relationships: the relation cited above (27), where $n(u_i)$ represents the calculation necessity measure of the node u_i , and, the relation (37), where $N(u_i)$ represents the calculation necessity measure of the node u_i computed between E , and D criteria.

$$N(u_i) = n(c_1^j) * n(c_2^j) * \dots * n(c_k^j) \quad (37)$$

$$\begin{cases} N_{D,E}(u_1) = (1 - 2.30/2.50) * (0.30/1.00) \\ N_{D,E}(u_5) = (1 - 2.12/2.50) * (0.52/1.00) \end{cases} \quad (38)$$

So:

$$\begin{cases} N_{D,E}(u_1) = 0.0072 \\ N_{D,E}(u_5) = 0.0411 \end{cases} \quad (39)$$

The measure of possibility is defined as follows:

$$\begin{cases} \pi_{D,E}(u_1) = 0.484 * 0.238 \\ \pi_{D,E}(u_5) = 0.516 * 0.762 \end{cases} \quad (40)$$

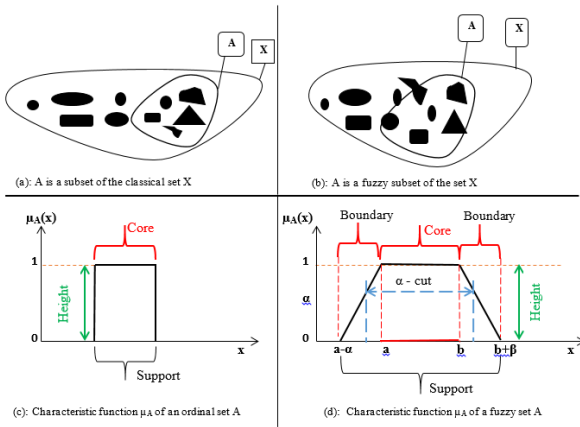


Fig. 3 Foundations of classical and fuzzy sets

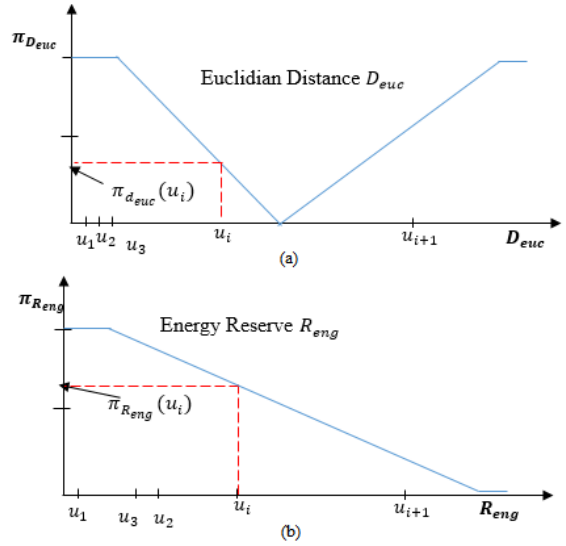


Fig. 4 (a) Calculation of possibility measure according to the Euclidean distance, (b) Calculation of possibility measure according to the energy reserves of the node.

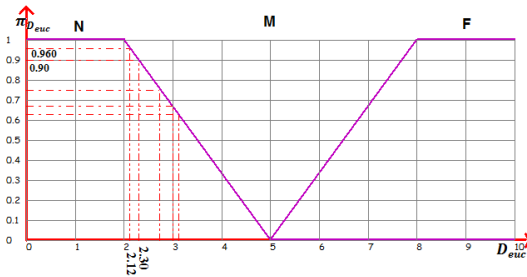


Fig. 5 Calculation of possible measures according to the Euclidean distance fuzzy sets.

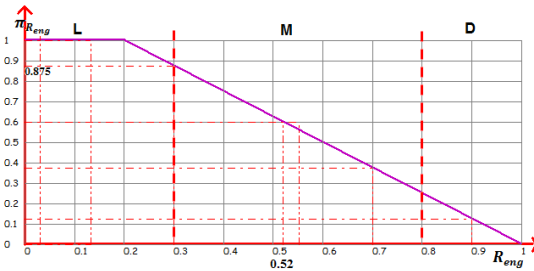


Fig. 6 Calculation of possible measures according to the energy reserve by fuzzy sets.

So:

$$\begin{cases} \pi_{D,E}(u_1) = 0.1152 \\ \pi_{D,E}(u_5) = 0.3932 \end{cases} \quad (41)$$

Step 4: Normalization

To properly apply the probability defined in terms of necessity and possibility, the normalization step is interesting.

(1): Normalization of capabilities of possibility measures

$$\begin{cases} \pi_D(u_1) = 0.900/(0.9 + 0.96) \\ \pi_D(u_5) = 0.960/(0.9 + 0.96) \\ \text{and} \\ \pi_E(u_1) = 0.125/(0.125 + 0.4) \\ \pi_E(u_5) = 0.400/(0.125 + 0.4) \end{cases} \quad (42)$$

So:

$$\begin{cases} \pi_D(u_1) = 0.484 \\ \pi_D(u_5) = 0.516 \\ \text{and} \\ \pi_E(u_1) = 0.238 \\ \pi_E(u_5) = 0.762 \end{cases} \quad (43)$$

(2): Normalization of capabilities of necessity measures

$$\begin{cases} N_{D,E}(u_1) = 0.0072/(0.0072 + 0.0411) \\ N_{D,E}(u_5) = 0.0411/(0.0072 + 0.0411) \end{cases} \quad (44)$$

So:

$$\begin{cases} N_{D,E}(u_1) = 0.1491 \\ N_{D,E}(u_5) = 0.8509 \end{cases} \quad (45)$$

Then, the measures of possibility normalized are defined as follows:

$$\begin{cases} \pi_{D,E}(u_1) = 0.1152/(0.1152 + 0.3932) \\ \pi_{D,E}(u_5) = 0.3932/(0.1152 + 0.3932) \end{cases} \quad (46)$$

So:

$$\begin{cases} \pi_{D,E}(u_1) = 0.2266 \\ \pi_{D,E}(u_5) = 0.7734 \end{cases} \quad (47)$$

Step 5: Decision

We use the formula defined above: $P_A(u_i) = (\pi(u_i) + N(u_i))/2$

$$\begin{cases} P_A(u_1) = (0.2266 + 0.1491)/2 \\ P_A(u_5) = (0.7734 + 0.8509)/2 \end{cases} \quad (48)$$

So:

$$\begin{cases} P_A(u_1) = 0.18785 \\ P_A(u_5) = 0.81215 \end{cases} \quad (49)$$

Then, the node u_5 should be activated in the next scheduling period with a probability of 0.81215.

6.4 The Simulation Step

We compared the proposed strategy with some other well-known strategies that study deployment, and use neighbor nodes (exchange their state and location information) as parameters to select the active node and the Active / Passive scheduling process. The strategies used in the comparison are the PEAS-LI protocol [Beghdad et al \(2016\)](#); (a basic scheduling protocol); MSCR protocol [Danratchadakorn and Pornavalai \(2016\)](#) (a basic coverage protocol); the Spider Canvas Strategy [Boualem et al \(February 2019\)](#); SRDP [Boualem et al \(2018\)](#); CMSS [Danratchadakorn and Pornavalai \(2016\)](#) (a basic scheduling protocol); and the WS-VLPSO protocol [Mohammadi et al \(2021\)](#). These protocols use the scheduling process to ensure coverage of the area of interest with maximum connectivity and minimum energy consumption. The simulation parameters, number of nodes, features, and parameter settings are shown in Table 3.

- WS-VLPSO is a weighted sum version of the particle swarm optimization algorithm with variable length particle vector, and it is considered the best optimization algorithm for

selecting order and optimal filter coefficients. The WS-VLPSO uses a weighted sum as an objective function, and the optimum modeling indicator criterion to:

- Ensure the optimality of a system (the coverage in WSN).
- Ensure the stability of modeled filtering systems.
- Ensure the accuracy and efficiency of the adaptive Infinite Impulse Response (IIR) digital filtering systems modeling such as the coverage problem.
- Ensure the solving of the sensor coverage problem in the real-word variable length optimization problem.
- PEAS-LI, is a protocol that:
 - Maintains only two variables: one is the number of received messages (N), and the second is the time necessary to receive these messages (T).
 - Operates in two steps: one where the neighbors exchange their state and location information in order to precisely estimate the coverage, and the second where the nodes make the decision of whether to be active, based on the gathered information.
 - Supposes that each node knows its location in the area of interest.
- MSCR is a protocol, that:
 - Presents a novel gossip-based sensing-coverage-aware algorithm to solve the problem.
 - Allows sensor nodes to gossip with their neighbors about their sensing coverage region.
 - Lets nodes decide locally to forward packets (as an active node) or to disregard packets (as a sleeping or redundant node).
 - Spreads energy consumption to different sensor nodes, achieves maximum sensing coverage with minimal energy consumption in each individual sensor node, and prolongs the entire network's lifetime using the distributed and low overhead traffic benefits of gossip.
 - Allows the redundant node to cut back on its activities whenever its sensing region is k-covered by enough neighbors.
- CMSS is a sleep scheduling protocol that:

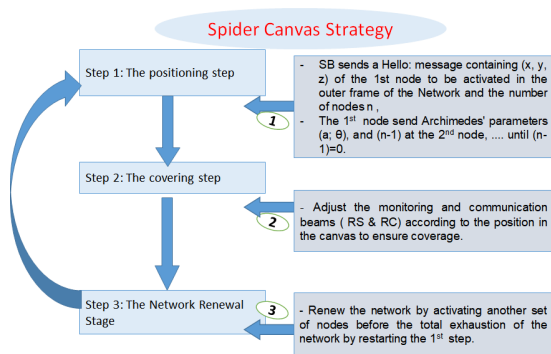


Fig. 7 Spider Canvas Strategy.

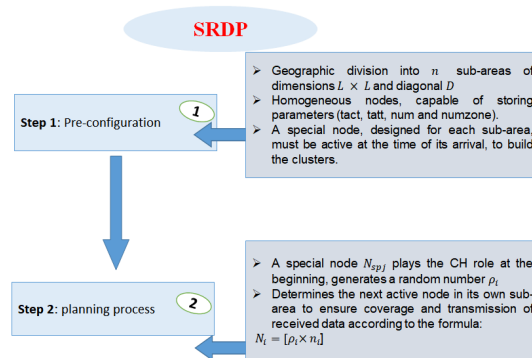


Fig. 8 Semi-Random Deployment Strategy (SRDP).

- Divides the area of a network into grid cells.
- Allows each sensor to create a neighbor table and transforms it into cell-value table.
- Uses these tables to make decisions about which mode each sensor node should use.
- Spider Canvas Strategy is used to:
 - Weave a WSN, where the spider represents the base station, and the web represents the topology of the WSN.
 - Apply the Archimedes' spiral formula to weave the spider web representing the WSN.

The intuition behind this protocol is that:

- The authors have noticed that the spider web is a good example in nature to weave a network against intrusion and provide 3D coverage.
- A strategy is proposed to mimic natural behavior, where the spider is emulated in the construction of its web to cover its own area and chase away its enemies.

The steps of this strategy are illustrated in Fig. 7.

- Semi-Random Deployment Strategy (SRDP): Its objective is to address the problem of area coverage by proposing a new type of deployment that takes advantage of the benefits of both types of deployment (random and deterministic). The steps of this strategy are illustrated in Fig. 8.

The simulation results in terms of the number of sensor nodes remaining alive, the coverage percentage achieved with the six protocols and the

Table 3 Simulation parameters

Parameters	Value
Shape of the monitored area	Square
Size of the monitored area	100m × 100m
Number of sensor nodes	70, 80, 100, 100, 150, 200
Wide-communication range	131.24m
Short-communication range	56.56m
Wide-sensing range	65.62m
Short-sensing range	28.28m
Initial energy	100J
Data transfer ratio	250kbps
Time total of simulation	1000 seconds
Round time	20S
Rounds number	50

percentage of coverage after five deployment trials in the area of interest are shown in Fig. 9 and Fig. 10.

- **Performances in terms of coverage compared with coverage protocols:**

In the Semi-Random Deployment and Spider canvas strategies, some parameters of uncertainty in sensor node characteristics have been taken into consideration and treated by traditional methods. These methods did not use the theories of uncertainty, which gives a slightly better gain than traditional strategies (strategies that did not take uncertainty into account in the treatment of the coverage problem in WSNs). On the other hand, Fig. 9 shows that the proposed approach (FP-3SNS) retains an ideal coverage of 99.99% to 90.00% for a significant period of time compared to MSCR and CMSS, and gains a slight difference compared to PEAS-LI and WS-VLPSO. These results could be explained as below:

- (a) The CMSS protocol uses a strategy that never guarantees the perfect coverage of the

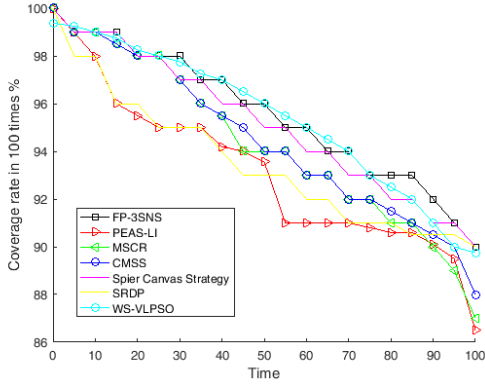


Fig. 9 Average coverage rate

area of interest because of the intersection between the coverage of neighboring nodes. Furthermore, the large number of nodes that must be activated at once causes the fast exhaustion of the network nodes which produces the fall in the coverage rate shown in Fig. 9.

(b) The MSCR uses a grid-based deployment strategy. This deployment also causes the rapid depletion of the energy network that has resulted in the rapid fall of AoI coverage. PEAS-LI is applied in AoI with random deployment based on local information. This process never guarantees full connectivity or coverage. The WS-VLPSO algorithm uses an objective function (weighted sum) and the optimum modeling indicator criterion to determine the selection of the best order and optimal filter coefficient for coverage in WSNs, which depletes the network over time resulting in a loss of connectivity and coverage. This explains the slight gain of FP-3SNS compared to WS-VLPSO. On the other hand, the lack of performances of these protocols is corrected by the application of our strategy (FP-3SNS) that activated only one sensor node at a time in each cell under warranty coverage and connectivity conditions.

- **Performances in terms of coverage according to number of nodes deployed for five AoI trials :**

Fig. 10 shows the average coverage percentages of FP-3SNS according to the number of deployed nodes for 5 AoI trials (70, 80, 100, 150, and 200 nodes) after 100 units of time. The deployment is evenly dispersed and with different densities. The proposed method ensures

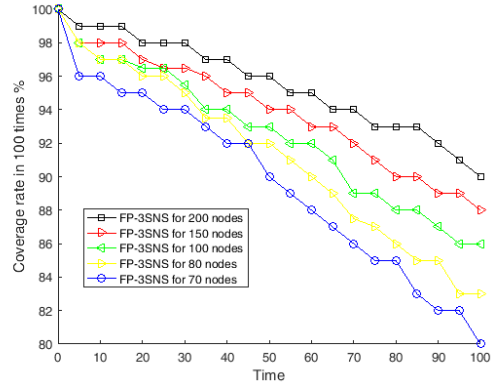


Fig. 10 Average coverage rate for 5 trials of nodes deployment

an increasing coverage of the area of interest according to the number of deployed sensor nodes. This growth shows the effectiveness of the FP-3SNS model in terms of coverage. The choice of the sensor node by FP-3SNS using uncertainty theories in an uncertain environment plays a multiple role: (a) selecting cluster-head; (b) building clusters; (c) covering the cluster; (d) guaranteeing the connectivity; and (e) communicating data and ensuring that the coverage remains preserved for a long time, especially when the density of nodes is high.

6.5 Statistical Evaluation: Asymptotic Confidence Interval

This section aims to study how efficient is the coverage and how confident we can be in it. This type of evaluation is deduced from probabilistic models by statistical techniques of parametric estimation. The important notion is the confidence interval, which allows to evaluate the precision of an estimated value. If $\alpha = 5\%$, we say that we are 95% confident that the IC (Interval Coverage) contains the true coverage value. The reliability and efficiency of the coverage strategy can be established according statistical indices such as variance, correlation coefficient, linear regression, etc.

Asymptotic Confidence Interval (ACI) is a robust method for proving uncertain and subjective phenomena where mathematical modeling is often approximate and uncertain.

Let f be the coverage ratio (the frequency) in sample size n in our case study. ACI proportion is defined by the relation (50):

$$I_C = [f - u_\alpha \frac{\sqrt{f(1-f)}}{\sqrt{n}}, f + u_\alpha \frac{\sqrt{f(1-f)}}{\sqrt{n}}] \quad (50)$$

After the application of ACI, we can deduce that the proportion of sub-areas that are covered have an ACI interval with a confidence level equal to 95%. u_α is defined by the relation (51):

$$u_\alpha = \psi^{-1}(1 - \alpha/2) \quad (51)$$

In our case study:

- The number of used nodes is 200.
- 95% = $1 - \alpha$ then $\alpha = 0.05$ and $1 - \alpha/2 = 0.975$
- $\psi^{-1}(0.975) = 1.96$.

Frequently used values of Ψ^{-1} are illustrated in Table 4:

Table 4 Frequently values of Ψ^{-1}

	90%	95%	98%	99%
ψ^{-1}	1.64	1.96	2.05	2.58

The obtained results are recorded in Table 5.

Table 5 ACI obtained results

Coverage Percentage %	Coverage Ratio	$[f - u_\alpha \times \frac{\sqrt{f(1-f)}}{\sqrt{n}}]$	$[f + u_\alpha \times \frac{\sqrt{f(1-f)}}{\sqrt{n}}]$
[100..90]	[1.00..0.9]	[1.00..0.86]	[1.00..0.91]
99	0.99	0.98	1.00
99	0.99	0.98	1.00
99	0.99	0.98	1.00
98	0.98	0.96	0.99
98	0.98	0.96	0.99
98	0.98	0.96	0.99
97	0.97	0.95	0.98
97	0.97	0.95	0.98
96	0.96	0.93	0.97
96	0.96	0.93	0.97
95	0.95	0.92	0.96
95	0.95	0.92	0.96
94	0.94	0.91	0.95
94	0.94	0.91	0.95
93	0.93	0.89	0.94
93	0.93	0.89	0.94
93	0.93	0.89	0.94
92	0.92	0.88	0.93
91	0.91	0.87	0.92
90	0.90	0.86	0.91
Average :		92.94	96.27

Therefore, the average coverage reliability at 95% is between [92.94, 96.27]. i.e. the efficiency of our

strategy to guarantee the average coverage at 95% is between 92.94 and 96.27.

7 Conclusion and Future Work

Deterministic methods for dealing with coverage problems are not efficient in an uncertain deployment environment. It is important to select the minimum number of sensor nodes to be activated in order to maintain perfect connectivity and consume the lowest possible amount of energy to increase the network's lifetime. Considering the network coverage objectives and the environment uncertainty, this paper proposes an optimization uncertain model, called FP-3SN, to determine the optimal positions of nodes on the AoI. FP-3SN is based on a fuzzy-possibility hybrid strategy. It uses the best possibility/necessity measures of the possibility theory to guarantee maximum of 1-coverage. The AoI is divided into square sub-areas according to a pre-established grid, with each sub-area representing a cluster regrouping a set of neighboring nodes.

As a result, this hybrid model activates the best neighbor node based on the best possibility and necessity measures of the possibility theory. This proposal of area coverage in WSNs is based on a hybrid model (fuzzy-possibility) and is significant for several reasons: (a) the model deals with the uncertainty of the node infrastructure at the level of communication, sensing, and data; (b) it deals with the uncertainty of the deployment environment; (c) it deals with the uncertainty of the cluster-head selection, and consequently the cluster construction; and (d) it applies a more realistic scheduling process using the hybrid fuzzy-possibility model.

In the future, we will first work on defining strategies for a number of challenges: (a) modeling uncertainty in link quality; (b) modeling uncertainty in network connectivity; (c) conscious routing of probabilistic coverage; and (d) data processing and probabilistic applications in the network. Second, we will extend our study to a heterogeneous network in terms of sensor nodes and their characteristics, topology (static or dynamic), etc.

Compliance with Ethical Standards

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Informed consent: No human were involved.

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