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

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Abstract

Deterministic methods used to address the coverage problem in an uncertain deployment environment have not proven to be very successful. For this purpose, the original idea of this paper is to deal with the coverage problem in an uncertain environment with uncertain theories. We consider the imperfection in the deployment environment and in the characteristics of the sensor nodes. The selection of a minimum number of nodes for a minimum number of clusters to guarantee coverage in WSN is uncertain. As a consequence, this paper proposes a hybrid Fuzzy-Possibilistic model to schedule the Active / Passive state of sensor nodes. This model helps to plan the scheduling of node states (Active / Passive) based on the possibilistic information fusion to make a possibilistic decision for the node activation at each period. We evaluated the proposed model with (a) a running example, (b) a statistical evaluation (calculation of the confidence interface), 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) and PEAS with location information protocols. The simulation results highlight the benefits of using the fuzzy and possibility theories for treating the area coverage problem.

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

1 Introduction

Nowadays, the technological progress in Wireless Sensor Networks (WSN) and mobile devices revolutionizes the reliability of the detection, collection, and communication of environmental information. Due to the dynamic physical environments and possible hardware failures, the raw data collected by the 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 [1, 2].

This paper focuses on devices' capacity to detect physical phenomena such as humidity detection, heat, and pressure. We address more precisely the uncertainty that affects these 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 uncertain causes affect the quality of service and decision on the real world information [1, 2]. In many cases where wireless sensor 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.

The atmospheric events, marking the physical environment, influence the position, the power of communication, and monitoring of sensor nodes in the network. This reality makes it necessary to consider the type of uncertainty.

In order to consider uncertainty to address WSN problems, our proposal consists of introducing the fuzziness in the process of scheduling sensor nodes in WSN for several purposes. Among the types of uncertainty configured in WSN [3], there are:

- Uncertainty in radio communication links: The communication power increases if the Euclidean distance increases. In the case of deployment in (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, nonlinear 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 quality, such as node sensibility due to signal interferences thanks to environment objects (*e.g.* foliage) or phenomena (*e.g.* cloud), or node physical state due to possible deterioration (wind, soil state, animals, etc).

This paper addresses the problem of area coverage based on the Possibility and fuzzy set theories. The objective is to extend as much as possible the wireless sensor network to deal with the previous uncertainties and guarantee the quality of service. Thus, it ensures the area coverage with a minimal number of connected node subsets, a minimal cost, minimal number of dominant nodes regardless of the type of deployment used (random or deterministic).

Two case studies are presented: in the first case, the approach has been illustrated through an example, and, in the other one, the proposed protocol has been simulated and compared with MSCR, CMSS, and PEAS with Location Information protocols, 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 area coverage domain. Section 3 presents the foundations of the sets theory. Section 4 exposes the foundations of the possibility theory. Section 6 introduces and explains our proposed methodology. Section 7 shows the evaluation. The conclusion is exposed in Section 8, in which we summarize the benefits, as well as the improvements made of the proposed model, and we quote some future works.

2 Related Work

The coverage is how to monitor the whole area of interest 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 wireless sensor network's lifetime to accomplish different tasks that require more control, monitoring, confidentiality, and continuous time periods. Deployment with a high density of sensor nodes on 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 timestamp since those create the collision in MAC (Medium Access control). On the other hand, the collision in MAC is a consequence of the density of sensor nodes. To maintain the coverage and increase the network's lifetime, it is necessary to apply a process called "scheduling". The best scheduling is to activate a minimum set of sensor nodes at a time and put the rest on standby (off state) until the network is completely exhausted [4]. 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 [5] by decisionmaking processes that are used on a regular basis in optimization and planning services. Solving a scheduling problem can consist to organizing a set of states of tasks to be executed, by using the available resources capacities [6, 7]. This scheduling problem is highlighted by the works in [7, 8].

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 either a state of communication, reception, or idle consumes more energy than in the sleep state. Consequently, it is better for a node to enter in the sleep state to conserve more energy.

The algorithms used to optimize the coverage problem are divided in two types: (a) centralized algorithms and (b) localized algorithms [9]. Centralized algorithms consider the coverage problem as an optimization problem. For such purpose, the linear programming is used to solve this problem, as the works of [4, 5, 10]. Heuristic methods are used in [11]. The authors in [4] and [11] use disjoint sets as a scheduling method and to find the number of minimum sets to activate to ensure the target coverage. This scheduling is based on the mixture of Integer Linear Program. In addition, [11] proves that disjoint set covers (DSC) is an NP-complete problem.

Localized algorithms, such as "Performance measure, environment, actuator, sensor" (PEAS) [12], "Deterministic energy-efficient protocol for sensor networks" (DEEPS) [13], (LBP) [5], consider that a node can go through three transitions: sense / on, sleep / off or vulnerable / undecided. 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 all types of coverage works in WSN (area coverage, target coverage, and barrier coverage). So, The Uncertainty is taken into account in certain works. The work cited in [14] proposes a scheduling mechanism based on timesharing under quantum of time and activates the sensor nodes for each quantum for coverage. The authors in [15] propose probabilistic-based dynamic non-deterministic-K-coverage protocol. This protocol is of Probabilistic K-coverage type, considers that the target movement is uncertain (either the position or the speed), follows the Gaussian law, and the proposed protocol is Optimal Cooperation Scheduling Algorithm (OCSA). The authors in [16] use a Voronoï diagram compromise to balance the sensor nodes and their current energy reserve. The objective of this strategy is to ensure a new type of scheduling to minimize the energy consumed for mobile sensor nodes, to guarantee coverage either partially or perfectly, and to maintain connectivity throughout the network lifetime. The authors in [17] study the partial coverage, by the proposal of two types of scheduling algorithms; "P-percent coverage", and "WASA". A comparison between the different deployment strategies used for Energy-Efficient Coverage TABLE 1. Note that in the table 1: (1) and (2) in column 7 indicates that populating additional (redundant) nodes or mobile nodes is used in the proposal, respectively.

In this context, the coverage problem have been classified in our contributions into two main categories; (a) coverage in sensor networks based on deterministic models and (b) coverage in sensor networks based on uncertain models [32]. In (a) coverage in sensor networks based on deterministic models, we quote: Energetic Sleep-Scheduling via Probabilistic Interference K-Barrier Coverage with Truth-Table Technique in Sensor Network [24], Hybrid Model Approach for Wireless Sensor Networks Coverage Improvement [21], and we quote in (b) coverage in sensor networks based on uncertain models: An Evidential Approach for Area Coverage in Mobile Wireless Sensor Networks [3], Area Coverage Optimization in Wireless Sensor Network by Semi-random Deployment (SRDP) [33], Spiderweb strategy: application for area coverage with mobile sensor nodes in 3D wireless sensor network (Spiderweb strategy)[25], A New Dijkstra Front-Back Algorithm for Data

	Network properties				Deployment		
Ref	Model	Conne ctivity	Coverage	Lifetime	Туре	Tech nique	Targeted Space
[3]	Uncertain	k-path	k-coverage	Node-based	Fuzzy and Evidential- based model	(2)	2-D
[18]	Certain	k-path	k-coverage	Node-based	Random and Geometric-based	(1)	2-D
[19]	Certain	k-path	k-coverage	Network-based	Grid-based	(2)	2-D
[20]	Certain	k-path	k-coverage	Network-based	Random and graph theory-based	(2)	2-D
[21]	Certain	k-path	k-coverage	Network-based	Grid-based	(1)	2-D
[22]	Uncertain	k-path	k-coverage	Uncertain Network-based	Fuzzy/Evidential- based model	(2)	3-D
[23]	Certain	k-path	k-coverage	Node-based	Node-based	(1)	2-D
[24]	Uncertain	1-path	K-Barrier coverage	Network-based	Grid-based	(1)	2-D
[25]	Uncertain	k-path	k-coverage	-	Random	(2)	3-D
[26]	Certain	k-path	k-coverage	Node-based	Geometric-based	-	3-D
[27]	Uncertain	k-path	k-coverage	Network-based	Geometric-based	(2)	3-D
[28]	Uncertain	k-path	k-coverage	Network-based	Probabilistic	(2)	3-D
[29]	Uncertain	k-path	k-coverage	Network-based	Algorithm-based	(2)	3-D
[30]	Uncertain	k-path	Data	Network-based	Uncertainty models	(2)	2-D
[31]	Uncertain	k-path	k-Coverage	Network-based	Uncertainty properties	(2)	2-D

Table 1 A comparison between various deployment proposals in the literature

Routing-Scheduling via energy-efficient Area Coverage in wireless Sensor Network [23], Fuzzy/Evidential Approach to Address the Area Coverage Problem in Mobile Wireless Sensor Networks [22].

3 The foundations of the Fuzzy Sets theory

According to Zadeh [34], 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 belong 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 less strongly to this subset. Formally: Let X be a reference set and let x be any element of X. A fuA fuzzy subset A of X is defined as the set of pairs: zzy subset A of X is defined as the set of pairs:

$$A = \{ (x, \mu_A(x), \text{ with } x \in X \text{ and } \mu_A : X \to [0, 1] \}$$
(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 in the interval [0,1] and $\mu_A(x)$ represents the degree of membership of x to A. We observe the three possible cases:

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

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

$$h(A) = \sup_{x \in X} \mu_A(x) \tag{4}$$

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:

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

$$|A| = \{\Sigma_{x \in X} \mu_A(x)\}\tag{6}$$

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.(c)). Formally:

$$A_{\alpha} = \{ x \in X / \mu_A(x) \ge \alpha \}$$

$$\tag{7}$$

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

4 The foundations of the Possibility theory

The possibility theory presents a formalism allowing to model subjective uncertainties on events [35].Indeed, 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 event studied. 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. taken care of by humans. 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) [36]. Similarly, the possibility measure is an application defined by the following relation:

$$\begin{array}{ccc} A_i & \to & \Omega \\ \pi(A_i) & \to & [0,1] \end{array}$$

 (A_i) : is the measure that evaluates how much 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:

$$\pi(\phi) = 0 \tag{8}$$

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

$$\pi(\Omega) = 1 \tag{9}$$

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

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

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

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

$$\begin{array}{l}
A_i \to \Omega\\
N(A_i) \to [0,1]
\end{array}$$
(12)

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

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

$$N(\phi) = 0 \tag{14}$$

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

$$N(\Omega) = 1 \tag{15}$$

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

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

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

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

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

$$N(A) \le Pr(A) \le \pi(A) \tag{18}$$

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

- $\pi(A) + \pi(\bar{A}) \ge 1$, 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:

$$N(A) - \pi(A) = \theta(A) \tag{19}$$

5 Objectives behind the use of a compromise (Possibility-belief) theory

The main Objectives behind the use of possibility theory and belief theory [37] are:

- The environment is uncertain so must consider that the deployment is uncertain.
- The belief theory is among 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, that it allows us to use possibilities in a formula verifying the measure of necessity.

- The main contribution behind this hybrid model is the automation of the mass function initialization step. Mass function initialization is based on necessity measurements.
- The Beliefs/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 Description of the proposed model

Scheduling is considered one of the techniques used in improving coverage in wireless sensor networks. Scheduling is the process used to choose which node to activate as a cluster-head each time period. The purpose of our work is to make a better, possible and necessary decision regarding the activation of neighboring nodes. The proposed approach is to use the possibility theory in the construction and selection of the potential sensor nodes. This use is to become likely Clusters-Heads in the first place, to choose the cluster-Head node, a step of assigning measures of possibilities and necessities using the fuzzy subset graphs as a function of the Euclidean distance and the energy reserve in the second step. A merge step is used to combine the choice data using fuzzy operators and normalization. The decision stage is realized by the proposition of a probabilistic formula between the measure of possibility and necessity. Fig. 2 represents the possibilistic model proposed as a scheduling process to deal with the problem of coverage in WSN. This model is described by four(5)steps are detailed as follows:

Step 1: Clusters Construction and Candidates Selection: This step is automatic. The

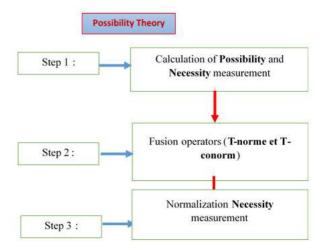


Fig. 1 Possibility theory stages.

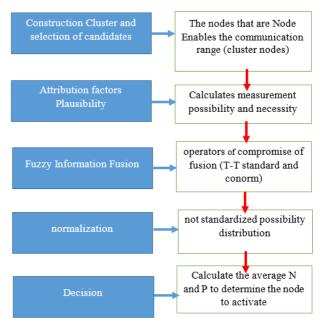


Fig. 2 Pipeline of the our Model for Active/Passive Scheduling.

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

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

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).

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

and reflects the most normal situation in which A is true. For our case study, we consider a universe composed of N node sensors (like singletons) $\Omega = \{u_1, u_2, \ldots, u_i, \ldots, u_n\}$ 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 $\pi(.)$, Constitutes the basic tool of the theory of possibilities. This distribution is equivalent to the membership function of the fuzzy set theory. Indeed, it associates with each singleton sensor node u_i of Ω a value in [0,1] which evaluates, in the light of available knowledge, the possibility of possible activation of this singleton sensor node. Thus, a possibilities distribution is

an application that is defined as defined in (21):

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

Where $\pi(u_n)$ represents the possibility that u_n is the singleton node that has activated. If $(u_n) = 1$, the activation of u_n is considered as 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 from the following way:

o Total Ignorance:

$$\forall u_n \in \Omega, \pi(u_n) = 1 \tag{22}$$

This means that activation of all sensor nodes is possible.

o Complete knowledge:

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

The initialization of mass functions is based on the measurement computation of possibility $(\pi(.))$ and necessity (N(.)). 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, \ldots, u_n a set of neighboring nodes that constructs the cluster C_j . Let $c_1^j, c_2^j, \ldots, c_k^j$ 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):

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

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

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

 $N(u_i) = n(c_1^j) * n(c_2^j) * n(c_k^j)$ represents the merged necessity measure of a node u_i for all criteria $c_1, c_2, ..., c_k$. in a cluster J. and $n(u_i)$ represents the necissity measure of the node u_i . We introduce the following constraints: the energy reserve and the Euclidean distance 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), D_{max} the Euclidean distance from the farthest node to the active node. E_1, E_2, \ldots, E_n respectively represent the current reserves of the neighboring nodes of the active node. D_1, D_2, \ldots, 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 where there are two criteria; the Euclidean distance and the energy reserve, defined by (26).

$$N(u_i) = \pi(c_1^j) \times \pi(c_2^j) \tag{26}$$

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

$$n(u_i) = E_i / E_0 \times (1 - D_i / D_{max})$$
(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 $n(u_i) = 0$

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 illustrated by relations (8), (9), (10) and (11).

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

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

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

Step 4: Normalization:

Normalization of measurement possibility is with non-normalized distributions of possibilities. The height of a distribution $h(\pi)$ is defined in (29) as being the largest possibility value [36]:

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

If $h(\pi) = 1$, the distribution of possibilities is said to be normalized or consistent with the knowledge available. Which 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 nonnormalized (inconsistent), we can define a new measure $Inc(\pi) \in [0, 1]$ as the measure of inconsistency of this distribution (30):

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

Step 5: Decision: As usual, the decision to activate or put back to sleep 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).

$$N_A(u_i) \le P_A(u_i) \le \pi_A(u_i) \tag{31}$$

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).

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

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

7 Evaluation

To evaluate the proposed model, we used three steps: a step of running with real examples to allow knowing if the operation of activation of the node sensor is well chosen, evaluation step by calculating the confidence interval, and another one of simulation. The different evaluation methods should give the same decisions (same results), otherwise, the proposed approach is reliable for some activation cases and unreliable for others. Indeed, for more evaluation, we proposed to use the calculation of possibilities and needs based on T-norm and T-conorm these operations give more real results compared to the use of classical operations. The calculation of the possibilities is done by using

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**

if $\exists u_i \text{ and } (j \neq i)$ then 4: if $N(u_i) > N(u_i)$ then 5: $A(u_i)$ 6: else 7: //In first period and, 8: $A(u_i)$ //In the second period the $A(u_i)$ 9: selection is for the first node where send Hollow message activation to the activate node. end if 10: end if 11: 12: end if

the membership function of the graph representing the distance and the energy consumption.

7.1 The running example:

Let the following nodes used to cover an area of interest $u_1, u_2, u_3, u_4, u_5, u_6$. The base station has selected as the active node u_3 in the first time. For each node, we consider the two metrics: its Euclidean distance to the active node u_3 , and its fuel 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:

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

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

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

 $D_{i,j}$ represents the Euclidean distance between node *i* and node *j* in place and E_i is the energy reserve of the *i* node in joule. The communication radius $R_C = 2.50u$ and the initial energy reserve is 1 joule. To enable a node to the second period by applying our model.

Step 1: Selecting neighboring nodes and building clusters

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

Step 2: Allocation of plausibility measures. We use fuzzy sets to identify opportunities for action. The calculation of possible measures according to the Euclidean distance is based on possibility graph (Fig. 5), and possible measures according to the Energy is based on possibility graph (Fig. 6) respectively.

For this example the possibilities are:

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

So:

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

Step 3: Fuzzy Fusion of Information The necessities of measures for this example are calculated using the following relationships: $N(u_i) = n(c_1^j) * n(c_2^j) * \cdots * n(c_k^j)$ and $n(u_i) = E_i/E_0 * (1 - D_i/D_{max})$ cited above (27).

$$\begin{cases} N_{D,E}(u_1) = (1 - 2.30/2.50) * (0.30/1.00) \\ N_{D,E}(u_5) = (1 - 2.12/2.50) * (0.52/1.00) \\ \end{cases}$$
(37)

So:

$$\begin{pmatrix} N_{D,E}(u_1) = 0.0072 \\ N_{D,E}(u_5) = 0.0411 \end{pmatrix}$$
 (38)

Then, the measure of possibility is defined as follows:

$$\begin{cases} \pi_{D,E}(u_1) = 0.484 * 0.238\\ \pi_{D,E}(u_5) = 0.516 * 0.762 \end{cases}$$
(39)

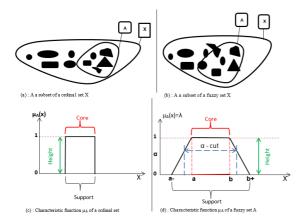


Fig. 3 Foundations of fuzzy and classical sets.

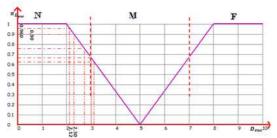


Fig. 5 The calculation of possible measures according to the Euclidean distance fuzzy sets.

So:

$$\begin{cases} \pi_{D,E}(u_1) = 0.1152\\ \pi_{D,E}(u_5) = 0.3932 \end{cases}$$
(40)

Step 4: Normalization To properly apply the probability defined in terms of necessity and possibility, the normalization step is interesting. (1): Normalization of capabilities measures

$$\begin{cases} \pi_D(u_1) = 0.900/(0.9 + 0.96) \\ \pi_D(u_5) = 0.960/(0.9 + 0.96) \\ \text{and} \\ \pi_E(u_1) = 0.125/(0.125 + 0.4) \\ \pi_E(u_5) = 0.400/(0.125 + 0.4) \end{cases}$$
(41)

So:

$$\begin{cases} \pi_D(u_1) = 0.484 \\ \pi_D(u_5) = 0.516 \\ \text{and} \\ \pi_E(u_1) = 0.238 \\ \pi_E(u_5) = 0.762 \end{cases}$$
(42)

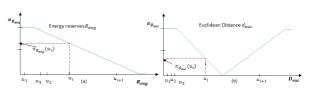


Fig. 4 (a) calculates of necessary measure according to the energy reserves of the node, (b) calculates of possibility measure according to the Euclidean distance.

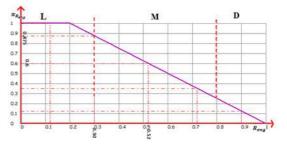


Fig. 6 The calculation of possible measures according to the energy reserve by fuzzy sets.

(2): Normalization of capabilities measures

$$\begin{cases} N_{D,E}(u_1) = 0.0072/(0.0072 + 0.0411) \\ N_{D,E}(u_5) = 0.0411/(0.0072 + 0.0411) \end{cases}$$
(43)

So:

$$\begin{cases} N_{D,E}(u_1) = 0.1491\\ N_{D,E}(u_5) = 0.8509 \end{cases}$$
(44)

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

$$\begin{cases} \pi_{D,E}(u_1) = 0.1152/(0.1152 + 0.3932) \\ \pi_{D,E}(u_5) = 0.3932/(0.1152 + 0.3932) \end{cases}$$
(45)

So:

$$\begin{cases} \pi_{D,E}(u_1) = 0.2266\\ \pi_{D,E}(u_5) = 0.7734 \end{cases}$$
(46)

Step 5: Decision We use the formula defined above: $P_A(u_i) = (\pi(u_i) + N(u_i))/2$

$$\begin{cases} P_A(u_1) = (0.2266 + 0.1491)/2 \\ P_A(u_5) = (0.7734 + 0.8509)/2 \end{cases}$$
(47)

So:

$$\begin{cases} P_A(u_1) = 0.18785\\ P_A(u_5) = 0.81215 \end{cases}$$
(48)

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

7.2 The simulation step

We compared the proposed strategy with some other well-known strategies that study deployment, uses neighbors nodes (exchange their state and location information) as parameters to select active node and the Active / Passive scheduling process. The strategies used in comparison are Probing Environment and Adaptive Sleeping-Location Information (PEAS-LI) protocol [38], Maximum sensing coverage region (MSCR) protocol [39], Spider Canvas Strategy [25], Semi-Random Deployment Strategy (SRDP) [33], and Coverage Maximization with Sleep Scheduling protocol (CMSS) [40], these protocols uses the scheduling process to ensure coverage of the area of interest with a maximum connectivity and minimum energy consumption. The simulation parameters, number of nodes, features, parameter setting are shown in Table 2.

- Probing Environment and Adaptive Sleeping-Location Information (PEAS-LI), characterized by:
 - Maintains only two variables: one is the number of received messages (N), the second is the time necessary to receive these messages (T).
 - PEAS-LI operates in two steps: one is the neighbors exchange their state and location information in order to estimate precisely the coverage, the second is the nodes make their decision to be active, based on the gathered information.
 - PEAS-LI supposes that each node knows its location in the area of interest.
- Maximum sensing coverage region (MSCR) protocol, characterized by:

- MSCR presents a novel gossip-based sensingcoverage-aware algorithm to solve the problem.
- In the algorithm, sensor nodes gossip with their neighbors about their sensing coverage region.
- In this way, nodes decide locally to forward packets (as an active node) or to disregard packets (as a sleeping or redundant node).
- With the distributed and low-overhead traffic benefits of gossip, we spread energy consumption to different sensor nodes, achieve maximum sensing coverage with minimal energy consumption in each individual sensor node, and prolong the whole network lifetime.
- Being sensing-coverage-aware, the redundant node can cut back on its activities whenever its sensing region is k-covered by enough neighbors.
- Coverage Maximization with Sleep Scheduling protocol (CMSS) is characterized by:
 - CMSS is a Sleep scheduling protocol
 - It divides the area of network is divided into grid cells.
 - Each sensor creates a neighbor table and transforms into cell-value table.
 - These tables are used to make decision which mode it should be on each sensor.
- Spider Canvas Strategy objective is to:
 - Weave a wireless sensor network where the spider represents the base station, and the web represents the topology of the WSN network.
 - Use the Archimedes' spiral formula to weave the spider web representing WSN.

The intuition behind this contribution is that:

- 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 a 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

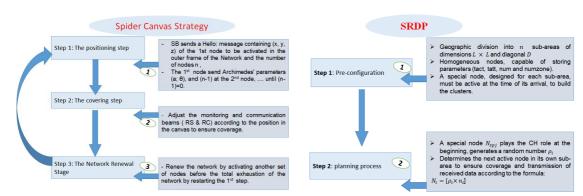


Fig. 7 Spider Canvas Strategy.

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.

Table 2 Simulation parameters

Parameters	Value		
Shape of the monitored area	Square		
Size of the monitored area	$100m \times 100m$		
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		

The simulation results in terms of the number of sensor nodes remaining alive, in terms of the coverage percentage achieved with the 3 protocols and the percentage of coverage after 5 deployment trials in the area of interest are shown in Fig. 9 and Fig. 10 respectively.

We observe that:

• 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

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

strategies (strategies that did not take uncertainty into account as in the treatment of the coverage problem in WSN). On the other hand, Fig. 9 shows that the proposed approach retains an ideal coverage of 99.99% to 90.00% for a long time compared to MSCR and CMSS, and gains a slight difference compared to PEAS-LI. These results explanation is that: (a) The CMSS protocol uses a strategy never guarantees the perfect coverage of the area of interest because the intersection between the coverage of neighboring nodes The rays never guarantee perfect coverage. More than that, the large number of nodes that they must activate at once causes the fast exhaustion of the network nodes which produces the fall of the coverage rate as indicated 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. On the other hand, the fatigue of these protocols is corrected by the application of our protocol that activated only one sensor node at a time in each cell under warranty coverage and connectivity conditions.

• In terms of coverage according of nodes number deployed for 5 AoI trials :

Fg. 10 shows the average coverage percentages as a function of the number of nodes deployed for 5 AoI trials (200, 150, 100, 80, 70 nodes) after 100 units of time. The deployment is evenly dispersed and with different densities. The proposed method ensures an increasing coverage of the area of interest according to the

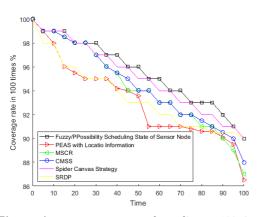


Fig. 9 Average coverage rate depending on 100 times.

number of sensor nodes deployed. This growth shows the effectiveness of the model in terms of coverage. The choice of the sensor node by a method using uncertainty theories in an uncertain environment. This node plays a multiple role: (a) cluster leader and (b) build clusters, (c) cover the cluster and (d) guarantee connectivity and (e) communicate data makes sure that coverage remains preserved for a long time, especially when the density of nodes is dense.

7.3 Statistical evaluation: Asymptotic Confidence interval (ACI) calculation

The objective behind this study is to justify the results obtained statistically and to show the effectiveness of the proposed strategy. Asymptotic Confidence Interval is a robust method for proving uncertain and subjective phenomena where mathematical modeling is often approximate and uncertain.

Let f be the frequency of a character (in sample size n). In our case the character is "coverage".

Asymptotic Confidence Interval proportion is defined by the relation (49):

$$I_C = [f - u_\alpha \frac{\sqrt{f(1-f)}}{\sqrt{n}}, f + u_\alpha \frac{\sqrt{f(1-f)}}{\sqrt{n}}]$$
(49)

After the application of ACI, we can deduce that the proportion of sub-areas that are covered belong to this ACI interval with a confidence level equal to 95%. Where u_{α} is defined by the relation

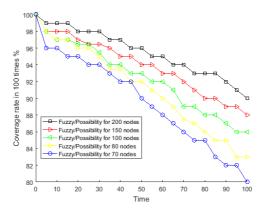


Fig. 10 Average coverage rate depending on 100 times for 5 trials of nodes deployment.

(50):

$$u_{\alpha} = \psi^{-1} (1 - \alpha/2) \tag{50}$$

In our case study:

- The used nodes number is 200.
- $95\% = 1 \alpha$ then $\alpha = 0.05$ and $1 \alpha/2 = 0.975$ In conclusion, $\psi^{-1}(0.975) = 1.96$. Frequently used values of Ψ^{-1} are illustrated by the following table (TABLE 3):

Table 3 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 the TABLE 4. Therefore, the average coverage

 Table 4
 ACI obtained results

Coverage Pourcentage %	Covrage Ratio	$[f-u_\alpha\times \frac{\sqrt{f(1-f)}}{\sqrt{n}}$	$[f+u_\alpha\times \frac{\sqrt{f(1-f)}}{\sqrt{n}}$
[10090]	[1.000.9]	[1.000.86]	[1.000.91]
Average :		92.94	96.27

reliability at 95% is between [92.94, 96.27].

8 Conclusion and Future Work

Deterministic methods used to address the coverage problem in an uncertain deployment environment have not proven to be very successful. The original idea of this paper is to deal with the coverage problem in an uncertain environment based on uncertainty theories model. This paper focuses on the coverage based on sensor network issue and Belief-Possibility strategy in uncertain environment. It is important to select a minimum number of sensor nodes activated in order to keep a perfect connectivity with a minimum amount of energy consumed, and, therefore to increase the network lifetime. An optimization uncertain model type is proposed in this paper to find the optimal positions of nodes on the AoI. Its objective is to jointly minimize the total energy consumed, maximize the minimum residual energy, and guarantee the perfect coverage by maintaining the connectivity during the life of the network.

In this paper, we proposed a fuzzy, scheduling strategy in a wireless sensor network, based on hybrid model (Belief-Possibility) to guarantee a maximum 1-coverage. The AoI is divided into square sub-areas according to a pre-established grid. Then, the steps in this model are used to activate the best neighbor node based on the best possibility and necessity measures. The decision made is based on the average of the best neighbor node's possibility and necessity measures. The proposal of an area coverage in Wireless Sensor Networks based on a hybrid model (Belief-Possibility) is very interesting for several objectives: (a) dealing with the uncertainty of the node infrastructure at the communication, sensing and data level, (b) dealing with the uncertainty of the deployment environment, (c) dealing with the uncertainty of the cluster-head selection, consequently the cluster construction, (d) and applying a more real scheduling with a hybrid model (Belief-Possibility).

In future work, we will firstly 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. We will secondly extend our study to a heterogeneous network in terms of sensor nodes and their characteristics, topology (static or dynamic), etc.

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- Authors' contributions: All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

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