Wireless Sensor and Actuator Network Deployment Optimization for a Lighting Control

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Abstract: Wireless Sensor and Actuator Networks (WSANs) are widely used in smart control system as home automation, military service, etc. They consist of hundreds of heterogeneous nodes. Due to this high density, finding an optimal deployment becomes a NP-Hard task. So, determining different node positions, that ensure the highest QoS of these networks, is the most significant challenges. In this paper, we study this problem for light control application. We expose our models for coverage, connectivity and lighting metrics. These proposed models, are adapted and validated by real measurements. The optimization approach is based on Genetic Algorithm for both regular and random deployment. The proposed approach is evaluated for different lighting space shapes, and the results are presented and compared to other studies.

Key words: Connectivity, coverage, genetic algorithm, lighting, optimization, weighted-sum method, WSAN.

1. Introduction

A Wireless Sensor Network (WSN) consists of a set of sensors wirelessly interconnected. It is formed by a hundred of deployed sensors nodes. Its evolution toward Wireless Sensor and Actuator Network (WSAN) has given a promising perspective for different applications such smart lighting control, smart surveillance, smart domestic application, etc. [1]. The integration of actuators nodes with sensors nodes, in WSAN, increases the density of network and adds others constraints for deployment task. Such high density leads to a highly complex network design process and makes finding optimal nodes placement a hard task [2].

Traditionally, nodes deployment is based on a manual process by deploying nodes and iteratively changing the configuration until finding an optimal one. This approach is expensive and does not ensure the optimality of the deployed network. Thus, the need to automate the deployment process. This automation must assist network designers to find optimal architecture and topology in terms of network performance (connectivity, coverage, cost, energy consummation, etc.).

In this work, we present a new approach that allows to automate WSAN deployment for smart lighting system control. Given a deployment environment, sensors and actuators specifications, user's preferences and wireless communication protocols, the proposed approach finds optimal nodes placement that guarantees highest sensing coverage, highest connectivity and ensuring the required lighting level. In this approaches, coverage and connectivity are rigorously defined and modeled. The established models are experimentally validated. Moreover, the optimization task uses a new combination of weighted-sum method and genetic algorithm.

The remainder of this paper is organized as follows: in Section 2, we present related works of deployment problem. Our proposed optimization approach of WSAN deployment is presented in Section 3. Simulations and results analysis are presented in Section 4 Finally, Section 5 concludes the paper and presents some further researches.

2. State-of-the Art

Deployment problem, known by others names as placement or coverage, is to place sensors and actuators nodes in accurate way that ensures high network performance. This performance depends on design objective(s) [3]. Several researches have shown that this problem is NP-Hard [4]. Random deployment, regular deployment and scheduled deployment are the three knowns strategies [5]. In regular deployment, nodes are placed at specified positions. In scheduled deployment, sensors are placed with higher density in areas where the phenomenon and events are concentrated.

To solve the deployment problem, many approaches and algorithms have been developed and proposed in literature. In this section, we draw up a non-exhaustive state of art, focused on models and optimization methods. From this survey we show the limitation of existence approach and the need for a new robust formulation and modeling of the deployment problem.

For optimization, in [6], for example, a multi-objective optimization problem that aims to solve coverage and connectivity WSN problem subjected to node failures was studied. GA and local on-line algorithm were used to find optimal solution. In [7], authors dealt with WSN optimization based on particle swarm optimization and fuzzy logic. This problem aims to maximize coverage, connectivity and lifetime. Furthermore, Woehrle et al. have used evolutionary algorithm to minimize transmission failure probability and network cost [8]. We note that all of these optimization approaches are restricted to specific WSN application or deployment environment.

While solving this problem, different optimized criteria are modeled. Coverage is an important criterion indicating the performance of the network [9]. It measures the ability to control physical events and useful information. In literature, two types of models exist: Boolean model and probabilistic model. In Boolean model, the area of interest is covered if it lies within sensor sensing radius. It is the most used sensing model [10]. Despite of its simplicity, this model does not consider degradation of sensing capacity. Probabilistic models consider realistic parameters of sensors [11]. There are several probabilistic detection models: asymptotic model (polynomial, exponential), Shadow-Fading model, Elfes model [12], etc. For coverage, real sensors do not provide the same sensing capability in every direction. Boolean sensing model do not represent the real sensing capability of sensors. Probabilistic models are more accurate. Therefore, to model the realistic sensing capacity of sensors, an adaptation of Elfes model can lead better results.

The second important metric is network connectivity. Connectivity models are classified in three types: empirical models, deterministic models, and stochastic models. According to [13], the most used propagation models are the Boolean mode, the Free Space Path Loss model (FSPL) [14], the One-Slope model (1SM) [15], and the Multi-Wall-Floor model (MWF) [16]. As for coverage, the Boolean model is used because it facilitates analysis [17]. In [18], authors use binary model for both connectivity and coverage models. Both [19] and [20] assume that sensing range is at least the half of transmission range and then coverage can imply connectivity.

Many approaches are considering metrics separately [19]–[21]. In literature, frequently rectangle environments are modeled [10], [22]. A number of papers consider the optimization of only one type of nodes (sinks or sensors). Many of above-mentioned works simplify the problem by using simplified models [10], [20]–[23]. Lot of works focused on WSN deployment but, for WSAN deployment optimization is not well investigated. In [24], based on linear programming authors aim to optimize communication in terms of routing and sampling rate. An optimization of actor nodes deployment in WSAN using particle swarm optimization is proposed in [25]. Different from WSN deployment that aims to optimize the perceive areas, WSAN deployment aims to cover the area in terms not only perceiving but also being able to influence the environment. For that already existing WSN deployment approach cannot be used for WSAN.

3. Proposed Approach

In our approach, we propose a tool that takes as inputs the environment specifications, user preferences, nodes characteristics, communication protocol and importance of each metrics. It optimizes nodes position for a WSAN dedicated to lighting system. The first step is to determine lighting nodes positions, in regular deployment strategy, that satisfy lighting requirement. Then, we randomly deploy sensor and sink nodes to cover the area of interest and to link sensors, sinks and lighting nodes wirelessly. Fig. 1 illustrates the deployment process of WSAN.

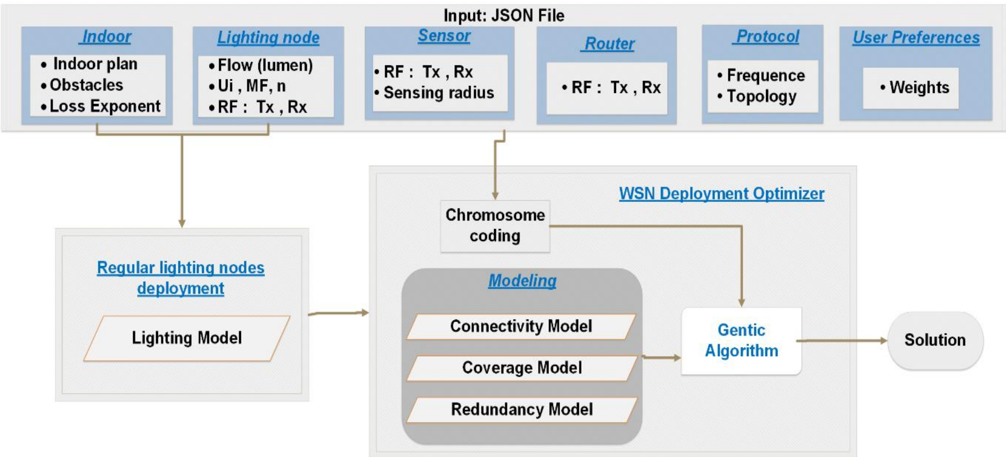


Fig. 1. Proposed approach.

In this section, we start by giving a general description of the proposed approach. We model the deployment space and the WSAN. Moreover, we will study different models. Table 1 summarizes the important symbols used in this work.

Table 1. List of Notations

Notation	Designation
$\|A\|$	Cardinality of the set A.
$\wp(\mathbf{A})$	The power set of A.
$\mathbb{1}(\mathbf{A})$	The characteristic function of the set A.
$\boldsymbol{Cross}(\boldsymbol{O}, (\boldsymbol{i}, \boldsymbol{j}), (\boldsymbol{i}', \boldsymbol{j}'))$	Function that evaluate if the line between (i, j) and (i¨, j¨) is obstructed by the obstacle O.
$\mathbf{d}((\boldsymbol{i}, \boldsymbol{j}), (\boldsymbol{i}', \boldsymbol{j}'))$	Euclidean distance between (i, j) and (i¨, j¨).

3.1. Deployment Space and Network Modeling

The real deployment space is divided into 1m^2 squares called cells and denoted by $c_{i,j}$ where (i, j) are the coordinates of the cell's centroid in a bi-dimensional space. These cells form the modeled deployment space, denoted by C. Different wireless nodes will be deployed in these cells. Our WSAN have three node types: sensor node $s_{i,j}$, sink node $sk_{i,j}$ or lighting node$l_{i,j}$.

Let R_x, T_x, R_{min} and R_{max} be the reception sensitivity, the transmission power, the certainty detection radius and maximum detection radius. lum is the provided luminous flow by the lighting source. Sensor, sink and lighting nodes are defined as follows:

- $s_{i,j} = (R_x, T_x, R_{min}, R_{max})$
- $sk_{i,j} = (R_x, T_x)$
- $l_{i,j} = (lum, R_x, T_x)$

Each node has its own parameters which allows modeling of a heterogenous networks. We define Sk, S and L the sets regrouping respectively sink nodes, sensor nodes and lighting nodes. Fig. 2 shows how a deployment space C is formed.

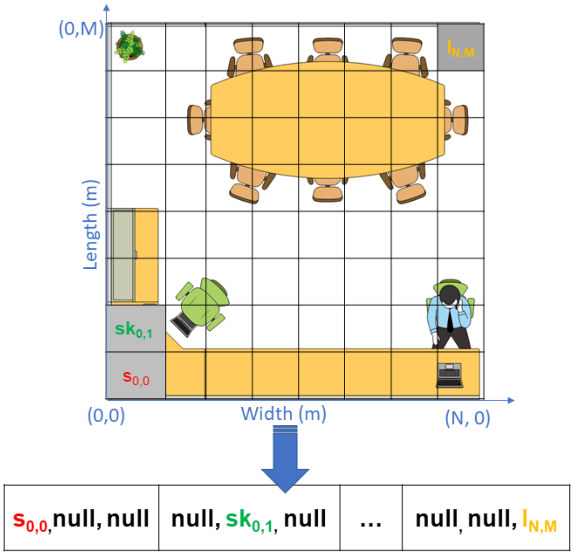


Fig. 2. Deployment space conversion process.

3.2. Lighting Deployment Process

An efficient installation design of lighting system begins by ensuring that lighting is not spread unnecessarily [26]. High quality lighting design includes determining lighting placement. To meet lighting recommendation, we calculate the required number of sources needed. By the next, we find nodes positions in the space to be enlightened uniformity. Number of nodes depends on space dimension and its characteristics (walls color, light loss, nature of activity, etc.) and used lighting sources (luminous flow in lumens). In this work, we calculate the number of sources denoted by NB according the lumen method:

$$NB = \frac{A.B.E}{\text{n}.MF.U_i.f} \tag{1}$$

where A and B are the width and the length of the room. E is the required illuminance (lux). MF is the maintenance factor. n, U_i and f are respectively the number of sources per luminary, the utilization factor and the lumen provided per each source. We implement these NB sources uniformly in the area of the interest. For this purpose, we estimate the allowed inter-distance between two sources as follows:

$$InterDistance = \sqrt{\frac{A.B}{NB}} \tag{2}$$

Fig. 3 shows how lighting sources are installed in the deployment space.

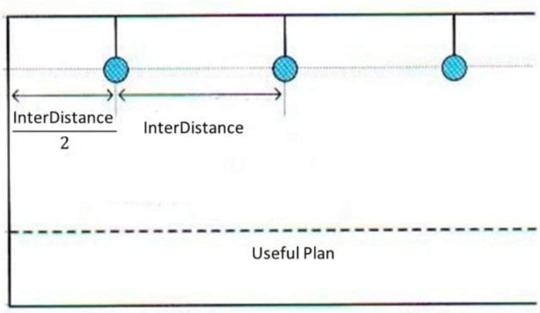


Fig. 3. Lighting nodes inert-distance.

3.3. Modeling Metrics

Sensing model: The main task is to detect events using its sensors. We choose the Elfes model because it introduces the detection uncertainty of a sensor and can be generalized to represent binary model. In this model a cell is considered as covered if the detection probability achieves a minimum threshold. The probability to detect an event at a distance less or equal to d, in this model, is given by equation (3):

$$p_{Elfe}(d) = \begin{cases} 1, & if \, \mathrm{d} \le \mathrm{R_{min}} \\ e^{-\gamma(d-R_{\min})^{\beta}} & if \ \mathrm{R_{min}} \le \mathrm{d} \le \mathrm{R_{max}} \\ 0 & \mathrm{d} \ge \mathrm{R_{max}} \end{cases} \quad (3)$$

where d is the upper bound of distance between the sensor and the event and γ and β are the hardware parameters of the sensor.

To validate the coverage model, detection probabilities have been evaluated for different distances in order to determine the uncertainty radius R_{min}, maximum detection radius R_{max} and then γ and β parameters. The motion sensor used is a VMA314 PIR sensor. For each distance, we measure 20 values and then determine the detection probability. Table 2 illustrates real measurements. Referring to this table, $R_{min} = 4.5$m and$R_{max} = 8.5$m. In order to match real measurements, γ must be fixed to 0.1 and β to 2.2.

Table 2. Sensing Capacity Evaluation

d (m)	Elfes Model	Real Probability
[0-4]	1	1
4.5	0.99	1
5	0.905	0.9
5.5	0.783	0.8
6	0.632	0.6
6.5	0.472	0.5
7	0.326	0.3
7.5	0.207	0.2
8	0.121	0.1
8.5	0.065	0.1
[9-+∞]	0.088	0

To make our solution adaptable and more flexible to application specifications, we evaluate sensing capacity according to network designer preference. A cell in the deployment space C is supposed to be covered if its center is covered by least one sensor node. Let p_{sens}, $p_{Elfe}\left(d\left(\mathrm{c}_{i,j}, \mathrm{s}_{i',j'}\right)\right)$ be respectively the acceptable sensing probability fixed by the network designer and the sensing probability of a cell $c_{i,j}$ by a sensor $s_{i',j'}$ according to Elfes model (equation 2). A cell is said covered if it has a sensing probability greater than p_{sens} and there is no obstacle blocking sensing. Let $c_{i,j}$, $s_{i',j'}$ and Ω_O be respectively a cell from C, a sensor node and the set of obstacles present in C. The coverage of $c_{i,j}$ by a sensor $s_{i',j'}$ can be defined by the following equation:

$$\alpha\left(c_{i,j}, s_{i',j'}\right) = \begin{cases} 1, & if \left(p_{Elfe}\left(d\left(c_{i,j}, s_{i',j'}\right)\right)\right) \geq p_{sens} \\ & and\ \forall O \in \Omega_{O,} \\ & Cross\left(O, (i,j), (i',j')\right) = 0 \\ 0, & \text{else} \end{cases} \tag{3}$$

We define the set of all covered cells in C by the sensor $s_{i,j}$, denoted $\phi\left(s_{i,j}\right)$, by the equation (4).

$$\begin{aligned} \Phi:\quad & S \rightarrow \wp(C) \\ & s_{i,j} \rightarrow \left\{c_{i',j'} \in C, \alpha\left(c_{i',j'}, s_{i,j}\right) = 1\right\} \end{aligned} \tag{4}$$

Respectively, we define the set of sensors from S covering a given cell $c_{i,j}$ by:

$$\begin{aligned} \psi:\quad & C \rightarrow \wp(S) \\ & c_{i,j} \rightarrow \left\{s_{i',j'} \in S, \alpha\left(c_{i,j}, s_{i',j'}\right) = 1\right\} \end{aligned} \tag{5}$$

The coverage of the whole space C denoted by $\mathcal{C}$ is the ratio between all covered cells and the number of cells of C.

$$\mathcal{C}(S) = \frac{1}{|C|}\left|\cup_{s_{i,j} \in S} \phi\left(s_{i,j}\right)\right| \tag{6}$$

A cell can be covered by more than one sensor. In this case, we have redundant coverage. In fact, high coverage redundancy means high energy consumption and more sensor nodes. In order to ensure coverage efficiency, we minimize coverage redundancy. Coverage redundancy, denoted by $\mathcal{R}(C)$ is formally calculated as follows:

$$\mathcal{R}(C) = \frac{1}{|C|}\sum_{c_{i,j} \in C}\left|\left|\psi\left(c_{i,j}\right)\right| - 1\right| \tag{7}$$

<u>Connectivity model:</u> Detected event will be processed by lighting nodes. For this purpose, sensors, sinks and lighting nodes must be connected to each other's. Connectivity evaluation depends on Received Signal Strength (or RSS) calculated at the receiving node. Let $n_{i,j}$ and $n_{i',j'}$ be respectively the sender and the receiver nodes (sensor/sink/lighting node). Tx is the transmission power of $n_{i,j}$. $PL\left(n_{i,j}, n_{i',j'}\right)$ is the path loss between $n_{i,j}$ and $n_{i',j'}$. The RSS is calculated as follows:

$$RSS\left(n_{i',j'}\right) = T_x - PL\left(n_{i,j}, n_{i',j'}\right) \tag{8}$$

PL depends on the connectivity model. The question then arises what model should be chosen. In order to have a reliable model, we performed RSS real measurements and we compared obtained results to the most used models in literature (FSPL, 1SM, MWF). Tests were done using ESP32 microcontroller and Wi-Fi transceiver with 2.4 GHz frequency. It provides a transmission power of $T_x = 0dBm$ and reception sensitivity $R_x = -92dBm$. We evaluated 13 different positions. All nodes are in the same floor. Fig. 4 illustrates tested positions and installation environment.

The point 'A' is defined as the transmitter node and all others nodes are receivers. We fix our transmitter at position (1,4). Then, we recuperate from the receiver the RSS value. The test environment contains obstacles. In order to have more accurate results, we measure different attenuation values caused by presents obstacles. Obtained attenuations values are given by Table 3.

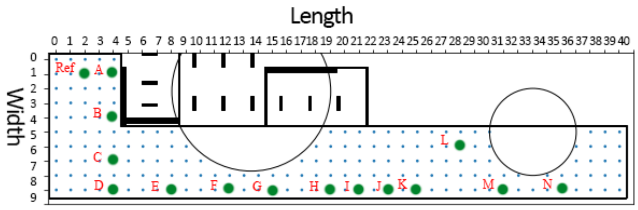


Fig. 4. Tested position.

Table 3. Obstacles Attenuation

Obstacle	Thickness	Attenuation
Wall	20 cm	2dBm
Bolded wall	30 cm	4dBm
Glass	4 cm	6dBm

Fig. 5 illustrates predictions of the RSS (dBm) according models versus measured ones.

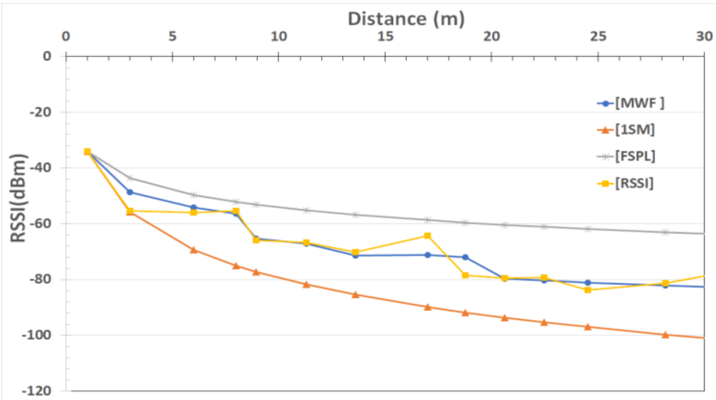


Fig. 5. Models predictions vs. Measured values.

Table 4 illustrates the mean measurements and mean error (%) of different tested models for each location.

Table 4. Obtained RSS Values

Location	d (m)	RSS (dBm)	Error (%)		
			FSPL	1SM	MWF
Ref	1	-34,1	0	0	0
B	3	-55,4	21,31	0,46	12,22
C	6	-55,9	11,25	23,97	3,30
D	8	-55,35	5,85	35,41	1,71
E	8,94	-65,95	19,51	16,98	1,18
F	11,31	-66,75	17,42	22,50	0,38
G	13,6	-70,05	19,02	21,91	1,99
H	17	-64,35	8,85	39,51	10,62
I	18,78	-78,55	24,22	16,80	8,37
J	20,61	-79,45	24,06	17,78	0,31
K	22,47	-79,35	23,02	20,06	1,28
L	24,51	-83,8	26,21	15,73	3,28
M	28,16	-81,35	22,50	22,56	0,95
N	32,01	-75,9	15,48	34,70	9,53

The FSPL assumes propagation in ideal environment without considering obstacles. 1SM is adjusted according to empirical data but it fails to predict the RSS. It can be seen from Fig. 5 and Table 4 that the MWF model is the nearest model to the real obtained measurements. In our work, we adopted MWF model. We adjusted this model to consider all attenuation caused by any crossed obstacles. Formally, path loss between $n_{i,j}$ and $n_{i',j'}$, denoted by $\mathrm{PL}(n_{i,j}n_{i',j'})$ is calculated by equation (9).

$$\begin{aligned} PL(n_{i,j}, n_{i',j'}) &= PL_0 + 10\,\eta \log\left(d(n_{i,j}, n_{i',j'})\right) \\ &+ \textstyle\sum_{k=0}^{|\Omega_O|} Att(O_k)\, Cross(O_k, (i,j), (i',j')) \\ &- G_{T_x} - G_{R_x} \end{aligned} \tag{9}$$

where η=1.8 is the attenuation factor and $Att(O_k)$ is the attenuation due to k^{th} obstacle (built empirically). G_{Tx}, G_{Rx} are respectively transmitter and receiver antenna gains.

According to this model, we evaluate connectivity between two nodes. Two nodes are connected if the RSS calculated at the receiver is greater than its reception sensitivity. Let $n_{i,j}$ and $n_{i',j'}$ be two wireless nodes. $n_{i,j}$ and $n_{i',j'}$ are connected, if and only if RSS calculated at $n_{i,j}$ is greater than its R_x and vice versa. In order to evaluate connections between different nodes, we define for each node its neighbors. In a WSAN, neighbors of a node can be either a sensor, a sink or a lighting node.

Let $n_{i,j}$ be a node from N where N is the set of all wireless nodes ($N = S \cup Sk \cup L$). Formally, $n_{i,j}$'s neighbors, denoted by $\mu(n_{i,j})$, can be defined as follows:

$$\begin{aligned} \mu:\ N &\rightarrow P(N) \\ n_{i,j} &\rightarrow \left\{\begin{matrix} n_{i',j'} \in N, & RSS(n_{i',j'}) > R'_x \\ and & RSS(n_{i,j}) > R_x \end{matrix}\right\} \end{aligned} \tag{10}$$

In our WSAN, nodes should be connected in a mesh topology where each node must have two or more neighbors and every pair of distinct nodes has a path between them. The connectivity of network N can be defined by the equation (11).

$$\Delta(N) = \frac{1}{|N|} \sum_{n_{i,j} \epsilon N} 1_{[2,|\mathrm{N}|[}\left(\left|\mu(n_{i,j})\right|\right) \tag{11}$$

To summarize, our goal consists on maximizing coverage and minimizing coverage redundancy while establishing connection between all nodes and ensuring the required lighting level in the deployment space.

3.4. Problem Formalization

In order to find optimal WSAN, our problem is formulated as problem of maximization and minimization of these metrics. These defined objectives are counterbalanced. Increasing coverage requires using more nodes. Moreover, decreasing coverage redundancy can lead to connectivity hole. In order to address this counterbalance issue, we define a weighted-sum fitness function which allows us to set importance degree of each objective. A weighted-sum fitness function (equation 12) indicates how a solution can satisfy all objectives.

$$Fitness(C, N) = w_1\, \Delta(N) + w_2\, \mathcal{C}(S) + w_3\, \mathcal{R}(C) \tag{12}$$

where w_i is the weight of i^{th} objective and it depends on user preferences which vary from one application to another. It indicates the importance of each objective in the evaluation of the final solution.

3.5. Genetic Algorithm Optimizer

After formulating the problem, we solve it by using Genetic Algorithm (GA). GA has been proven to be an appropriate method to solve this kind of problems [2], [27]. In GA, possible solutions are called individuals. The set of individuals forms a population. The idea is to have an initial population and then apply natural selection. Initially, we start with a set of randomly-created individuals. Then, we evaluate these individuals and we identify the optimal ones according to equation (12). The best individuals survive. Selected ones will be crossed and mutated to create a new generation. Old generation and the new ones are challenged to have a place in the next generation. By replacing the weakest individuals, we improve the average performance level. We iterate for a defined number of generations.

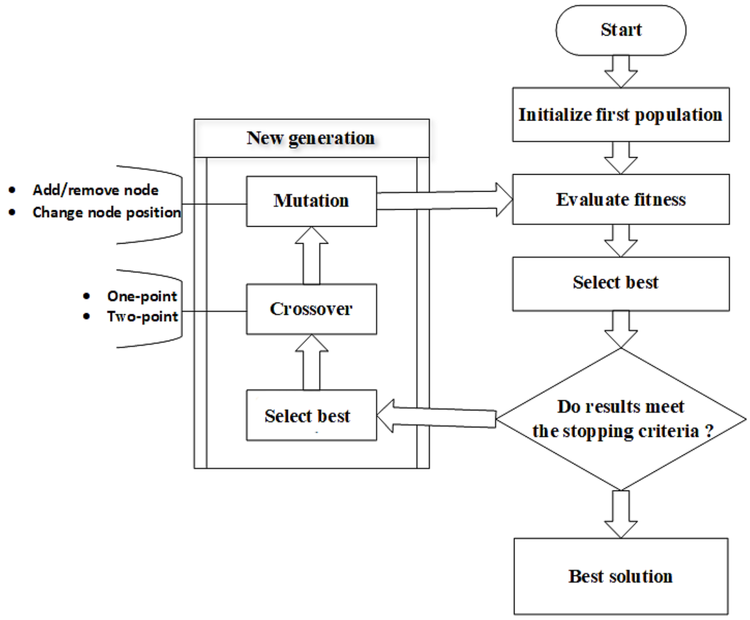


Fig. 6. Genetic algorithm flow chart.

4. Simulations and Results

Before running simulation, the network designer must specify the indoor plan and specifications, nodes characteristics, nature of activity, the required illuminance (lux) and the importance of each metric (w_i). Then, these data are formatted to represent individual which is the entry of our GA optimizer. Our optimization algorithm is developed in Python. We used Python DEAP library under "PyCharm" development environment. Our tool is executed in a PC with an Intel Core 7-5500U, 2.4 GHz processor and 8 GB of RAM. Simulations are executed with the following parameters in Table 5:

Table 5. Simulation Parameters

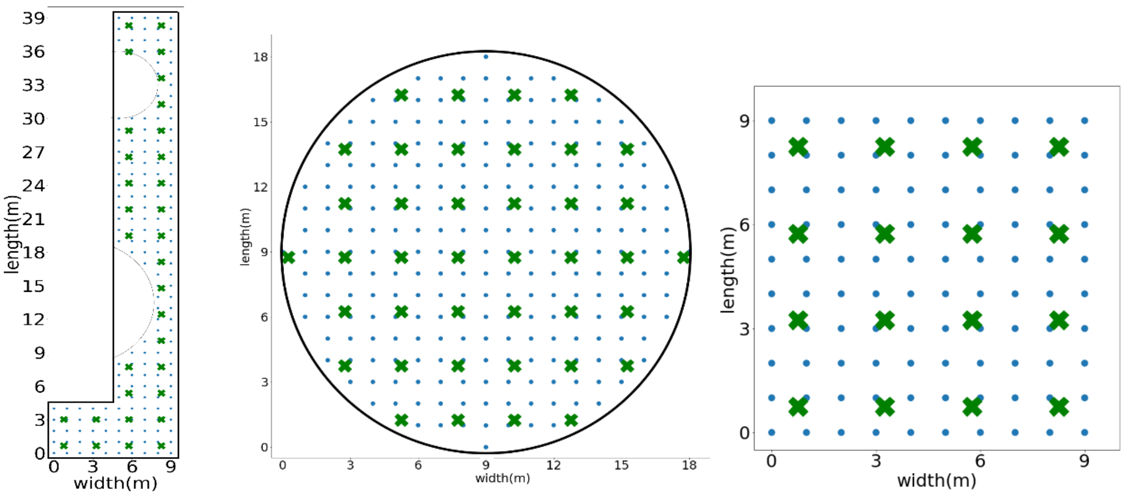
Parameter	Value
T_x(dBm)	0
R_x(dBm)	-90
G_{Tx}	0
G_{Rx}	0
p_{cov}	1
LED/luminary	4
MF	0.98
Lumen/source	700 lumens

In order to evaluate the effectiveness of our approach, we configured our simulation tool to get the optimal WSAN of different deployment space shapes. We execute our tool for 10 instances (10-cross validations) for each described simulation. In the first simulation, the deployment space consists of a corridor that has the shape of an 'L' that covers 225m2. It is a corridor in the National School of Engineering of Le Mans University, France (ENSIM). For this simulation, we assume that $\mathrm{R_{min}} = 4$. In the second one, we optimized WSAN in a square space (10x10m). The third simulation consists of optimizing WSAN deployment in a circular space having a radius of 9m. For these two simulations, $\mathrm{R_{min}} = 1.5$. Simulation results are presented in Table 6.

Table 6. Different Space Shapes Simulations

Sim°	$\boldsymbol{\Delta(N)}$(%)		$\boldsymbol{\mathcal{C}(S)}$(%)		$\boldsymbol{\mathcal{R}_k(C)}$(%)	
	Avg	Best	Avg	Best	Avg	Best
1	100	100	94.27	98.22	0.97	0.66
2	100	100	95.27	98	15	14
3	100	100	91.17	96.31	13.52	17.62

As can be concluded from Table 6, our tools ensure a high QoS in terms of connectivity, coverage, and coverage redundancy. Fig. 7 illustrate the result of regular deployment simulation of each previously described scenario. Green cross marks design lighting nodes. Blue dots are cells' centroid. WASN QoS depends on the application nature. Accordingly, we evaluated weights impact on our solution. We varied weights of different objectives. We reproduced the same parameters as in Sim°2.



(a) Sim°1 (b) Sim°2 (c) Sim°3

Fig. 7. Lighting nodes deployment for Sim°1-3.

Table 7. Different Weights Simulations

$\boldsymbol{w_i}$	$\boldsymbol{\Delta(N)}$(%)		$\boldsymbol{\mathcal{C}(S)}$(%)		$\boldsymbol{\mathcal{R}_k(C)}$(%)	
	Avg	Best	Avg	Best	Avg	Best
$\boldsymbol{w_2 = w_3}$	100	100	95.27	98	15	14
$\boldsymbol{w_3 = \frac{w_2}{2}}$	100	100	98.92	100	20	18

From Table 7, it can be seen that simulation results are influenced by objectives weights.

To validate our work, we compared our proposed approach to [18] and [22]. In these simulations, a similar network scenario is reproduced in order to facilitate comparison. We note that in these two works Boolean connectivity model was used. Table 8 shows a comparison of our work to those obtained results [18] and [22].

Table 8. Results Comparison with Other Works

Work	$\Delta(\boldsymbol{N})$(%)	$\boldsymbol{C}(\boldsymbol{S})$(%)
Our tool	100	96.31
[22]	96	91
Our tool	100	94
[18] MOFPO	100	82
[18] PSO	100	76

As illustrated in Table 7, our tool outperforms [18] and [22] in terms of connectivity. In addition, we have ensured higher coverage rate than the two other studies. Our used models are more real and accurate than the Boolean model adopted in [18] and [22]. Results show that our simulator is an efficient optimizer of WSAN in terms of lighting, connectivity, coverage and coverage redundancy. Our original modeling allowed to have a holistic solution for the different geometric forms of the deployment space. Moreover, it deals with real indoor environment specificity (obstacle, attenuations, sensing blocking, etc.). It takes into account different user preferences (minimal coverage probability, application nature, etc.).

5. Conclusions

In this paper, we have presented a new efficient approach and a tool that determines the optimal deployment for light control by a WSAN. Based on the combination of the regular and the random deployment, this tool automates the generation of optimal WSAN deployment that satisfy requirements and user preferences. We start by placing lighting nodes in a regular deployment. Afterward, sensor and sink nodes are deployed while aiming to maximize both coverage and connectivity and minimizing coverage redundancy.. The originality of this contribution lies in the fact that it is based on credible models which have been tested and evaluated by real measurements. Moreover, the problem was modeled in an original manner to allow incorporating multiple information: as coverage, connectivity, obstacles, sensing probability, application nature, etc. Numerous simulations were performed in this work to prove the effectiveness of our solution. Performance was evaluated under real factors and constraints. In comparison with results in [18] and [22], the proposed approach shows better performance.

In our future research, we intend to concentrate on integrating lifetime and power consumption metrics which is a challenging issue for WSAN. Also, we plan to extend the deployment space from 2D to 3D representation.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

S. E. Bouzid contributed in different research tasks; Y. Serrestou and M. Mbarki verified the mathematical modeling methods; All authors provided critical feedback, helped shape the research, analysis manuscript and approved the final version .

Acknowledgment

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