Wireless sensor network deployment optimization for a smart farming application: comparison of two Multi-Objective Evolutionary Algorithms

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Abstract—As it is one of the main means of insuring food security, agriculture has employed different technologies such as the Internet of Things and wireless sensor networks (WSN), to improve the quality and quantity of agricultural products, while preserving natural resources. But unfortunately, in agricultural plots where we have large surfaces of interest, the optimization of node deployment in a WSN remains among the major problems to be solved. In this work, we proposed a WSN node deployment optimization model for an agricultural application according to classical constraints of coverage, over-coverage, connectivity and nodes number, in addition to the nodes separating distance constraint which affects the quality of physical parameters models. We have applied two variants of Multi-Objective Genetic Algorithms, the Non Sorting Genetic Algorithm II (NS-GA II) and the Strength Pareto Evolutionary Algorithm II (SPEA II). As a result, for a 100 m^2 plot, both algorithms ensured a communication rate of 100% while SPEA 2 presented a lower sensor number and over-coverage rates with a smaller separating distance, and the execution time of NSGA II was shorter with 11 s. Besides, both of them were greedy in terms of computation time with the increase in the size of the plots.

***Keywords*—Precise Agriculture, Wireless Sensor Network, Node Deployment, Strength Pareto Evolutionary Algorithm II, Non Sorting Genetic Algorithm II.**

I. INTRODUCTION

The needs of food production are increasing with the growing population (expected to reach 9.4 and 10.2 billion by 2050 [1]). Therefore, new techniques were adopted in the agricultural field in order to solve the restricted land, water assets, and the climate change issues which represent a huge danger for accomplishing the sustainable farming objectives. PA aims to optimize the yield production by monitoring the irrigation operation, the application of fertilizers, pesticides and the crop growth with the help of direct or indirect measurement of several variables that gives immediate information about the crops [2]. For that purpose, different technologies were used such as the satellite remote sensing [3] and the WSN [4].

The WSN technology uses a group of components to collect, monitor and analyze the sensed data [5]. So as in the field of agriculture, WSN can optimize the crops quality and preserve the natural resources with the use of the deployed sensors which monitor the vital value of physical parameters such as humidity, temperature, and PH level, to define the exact requirements of plants. Furthermore, there are several types of WSNs in agriculture, which are classified according to their mode of deployment into two classes, the first class is the Terrestrial Wireless Sensor Networks (TWSN) where the sensors are deployed above the ground and the second one is Underground Sensor Networks (WUSN) where sensors are deployed inside the soil. The first mode presents more powerful features compared to the second one such as low cost, energy consumption, and the high communication range which can go up to 100 meters [6]. However, the choice between the two modes is influenced by the WSN application type in agriculture. Each WSN is made up of a set of sensor nodes and base stations which work together to detect, transmit, process and interpret information. In addition, each sensor node is composed of a processing unit, a storage unit, a power source, a sensor and a communication module as shown in Figure 1. The components of sensor nodes are defined according to their field of application. For example the most adopted communication technology in agriculture is the Zigbee technology thanks to its properties such as the communication range which varies between 10 and 100 m, and its low energy consumption [7, 8]. Moreover, the WSN confronts several problems that can affect its performance, such as the Quality of Service (QoS), the WSN lifetime, security and the WSN cost. These lasts are related to each other, for example, we have to compromise with the WSN lifetime if we want to guarantee a full area coverage [9]. Therefore, in order to solve this problem

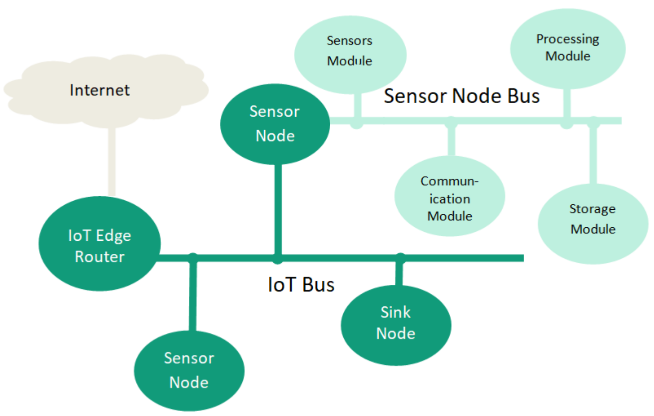

Fig. 1: Architectural model of a WSN.

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we have to deal with a multi-objective issue and for that specific algorithms and techniques have to be applied, the choice of the appropriate technique depends on the functioning of the algorithm, the desired time, the aimed precision and the issues types; Figure 2 illustrates the most important issues of WSN. The cost

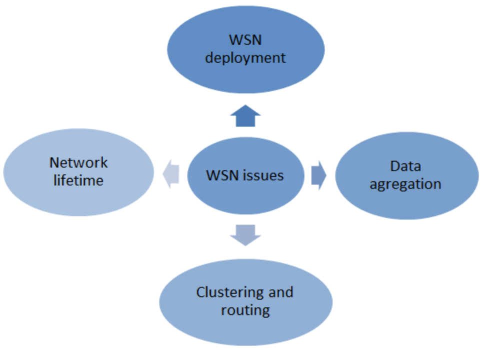

Fig. 2: The most important types of WSN issues.

of installing a WSN is one of the most important criteria for node deployment, of which the number of the used sensor and sink nodes has an impact on the cost of the WSN. Therefore, in this work we were interested in the problem of node deployment in a WSN according to several criteria that we will present in the following sections. In order to optimize the deployment, we chose one of several techniques that we will discuss in the next section. WSN can be defined as a specially appointed organization of an enormous number of nodes, which are miniature sensors equipped for sensing physical phenomena (e.g. sound, light, temperature, motion, seismic action, etc), gathering and sending information in a wireless self-sufficient way, to one or more data collection tanks called sinks [5]. Recently, this innovation plays a key role in several applications such as in PA and became an integral part in the IoTs [10]. One of the most important WSN design's complicated aspects is the node deployment in the region of interest (RoI), because it influences practically the entirety of its presentation measurements, such as connectivity, coverage, quality of service, and network lifetime. So, in order to place nodes in a WSN, there are several strategies which can be categorized in static or dynamic methods.
However, the static methods contain two classes, random and deterministic strategies, the first one aims to distribute the nodes aleatory [11], while the deterministic one aims to decide the location of WSN nodes under some given constraints in order to achieve some WSN goals [12]. Moreover, the dynamic methods are devised in two classes too; the centralized deployment uses a cluster-head to transmit the deployment algorithm to other sensors and the distributed deployment allows each sensor to use its nearby information, like distances to adjoining sensors and obstacles to run the conveying algorithm and self-convey in the upgraded positions.
In literature, the algorithms used for modeling, optimizing and solving the deployment issue, were classified in four main categories based on their mathematical methodology, Genetic Algorithms (GAs), Computational Geometry (CG), Artificial Potential Fields (APF) and Particle Swarm Optimization (PSO). The multi-objective GAs aim to improve the design of a WSN, with typically more than one organization objective [13], while the CG-based Algorithms such as the Voronoi Diagram and Delaunay Triangulation which were demonstrated valuable in evaluating area coverage and discovering coverage holes [14]. In addition, the APF relies on motions, so they are most of time used for Mobile WSNs and conveyed nodes in an ideal manner so that to stay away from any obstacle in artificial field [15], and finally for the PSO, it focuses on artificial intelligence behavior and use a population (swarm) of search points (particles) that move stochastically in the boundaries of the search space optimization problem, in order to calculate moving position of mobile sensors [16].
Furthermore, the four categories can be used in static deterministic deployment or in dynamic centralized deployment, but only CG and APF algorithms can be used in dynamic distributed deployment. So in the case of multiple design objectives being defined, GA and PSO approaches are more qualified for conveying WSNs than CG and APF because multiple objectives can be easily determined using the objective functions of GAs and PSO algorithms [12].
As a result, in our case, we were interested in finding the best Multi-objective GAs between the Non Sorting Genetic Algorithm II (NSGA II) and Strength Pareto Evolutionary Algorithm II (SPEA II), to find the most efficient WSN statistic deterministic node deployment which best meets the constraints of coverage, over-coverage, connectivity, nodes number and nodes separating distance for an agricultural application.
To the best of our knowledge, it is true that in the literature these constraints have already been applied for WSN node deployment optimization as in the [17] study, but the novelty of our study is that they will all be used at the same time. Considering that in agriculture, each of them can have an impact on the performance of the application. For example, if the node separating distance constraint is not taken into consideration, there will be coverage gaps in the deployment plans, so the quality of the physical parameters surrogate models will not be perfect.
Both of the NSGA II and SPEA II has enabled as to find node deployment plans that responds to the 5 previous constraints at the same time. For a 100 m^2 plot, the SPEA II presented better results, but the NSGA II converges faster. The findings of our suggested model were good for agricultural plots of small areas, but the larger the areas, the lower the quality of the solutions of our model and required more computational skills. In addition, our document is arrange as following, the second section presents the related works, the third one explain the details of our proposed model, the fourth discusses the deployment results. Finally, we are going to end our article with some perspectives and future works.

II. Related works

Several works in the literature have been interested in the problem of sensor nodes deployment in WSNs for different fields of use such as smart buildings, military applications, and agriculture, etc. In our study, we were interested in works that have applied GAs in their deployment models.
The GAs are the most famous family of EAs, thanks to their flexibility of application and adaptation to many kinds of complexe problems in practice [18]. In the optimization problems, the GAs evolve a set of solutions according to an already defined number of generations as presented in Figure 3, where each solution is a possible candidate for an optimum of the optimization issue. The representation of solutions in GAs family is in the form of strings of values; they are called vectors in the continuous case and bit strings in the bits case. Constantly, GAs apply

genetic operators as selection, crossover and mutation in order to guarantee diversity in the research space. In the case of WSN

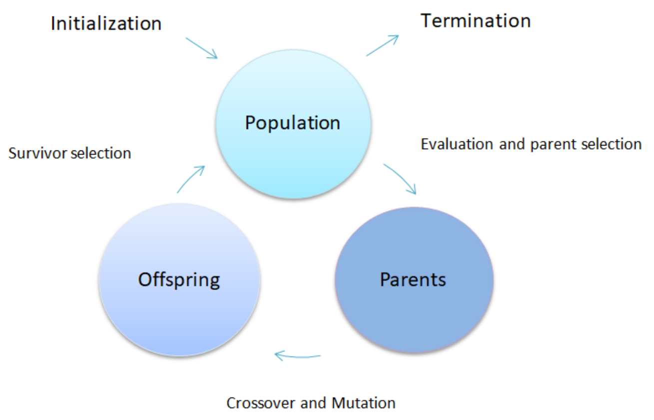

Fig. 3: General Scheme of GA.

deployment issues, where the constraints of coverage, connectivity and the network lifetime play a vital role in the performance and the functioning of WSNs [19], the GAs were widely used, because of their adaptiveness and their support of multiobjective optimization [20]. In literature, we found that Single Objective GAs (SOGAs), Bi-Objective GAs (BOGAs) and Multi-objective GAs (MOGAs) were applied to optimize the positioning of WSN nodes to response to different objectives as shown in Table 1. However, Figure 4 illustrates a comparison between the 16 works presented in Table 1 according to the number of objectives taken into account for the WSNs deployment. We found that 43.75% were SOGAs [21] [22] [17] [23] [24] [25] [26], 25% were BOGAs [27] [28] [29] [30] and 31.25% were MOGAs [31] [13] [32] [33] [34]. The difference between these three types is in the number of constraints to be taken into consideration when deploying nodes. As there are multiple parameters that need to be simultaneously optimized and may potentially conflict with each other. For example, in each WSN deployment, sensors must assure the highest coverage of the interested area with the smallest cost (sensor number). In addition, connectivity and network coverage can be maximized at the same time, but this maximization risks influencing the network lifetime. Therefore, it is remarkable that the more we decrease the number of constraints the more the GAs become more efficient in terms of calculation time, but the quality of the solutions found in the case of SOGAs and BOGAs cannot satisfy all the requirement constraints that affect the sensors locations as the MOGAs solutions.

The presented works aim all to find the optimal sensor nodes deployment according to defined constraints. However, there is a difference between them in the desired objectives. Figure 5 presents the percentage of WSN deployment constraints extracted from the previous works. According to this study, we found that the maximization of coverage and connectivity were the most desired objectives with the percentage of 75% and 50% respectively, followed by the maximization of energy efficiency objective with 25%, than the minimization of sensor nodes number with 18,75% and finally the minimization of over-coverage area with 12,5%. The cited works have proved the advantage and the possibility of applying GAs for sensor nodes deployment optimization in WSN according to single or multiple fitness functions in different fields of use, such as for

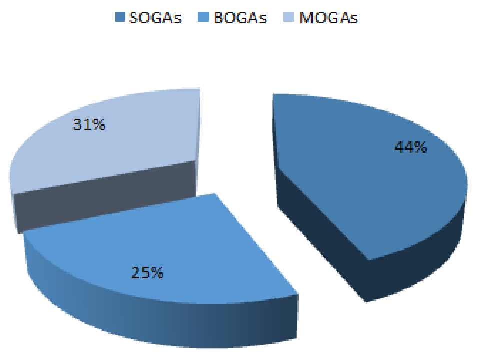

Fig. 4: Comparison of GAs types for WSN deployment.

agriculture. The choice of the GAs type to use, depends on the considered constraints number when deploying WSN. Besides, the computational time and solution qualities are also related to the constraints number. In our study, since it wasn't tested before, we aimed to compare the functioning of two variants of multi-objective GAs according to 5 constraints at the same time for an agricultural application.

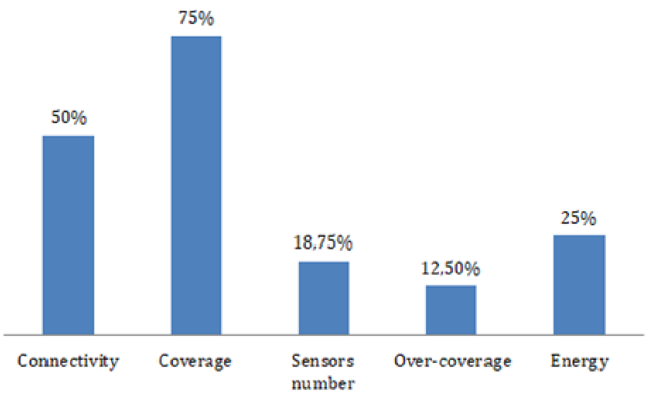

Fig. 5: Percentage of use of the different constraints in the 16 studied works.

III. Proposed Model

In nature, there are real optimization problems which are based on several criteria. These lasts are often contradictory and must be optimized simultaneously as in the case of our study. Therefore the optimization in this case consists in finding a vector of decisions that satisfy the 5 constraints and optimize the objective vector whose elements represent the objective functions, this is called multi-objective optimization.
The NSGA II (Deb et al. 2002 [35]) is made in such a way as to integrate the fronts obtained in the following populations, the crowding distance and the selection by tournament contribute to the obtaining of the diverse populations without losing good solutions, as illustrate the pseudo-code in Algorithm 1.
In addition, in SPEA II there is the mating choice stage, where individuals from the association of population and archive are chosen through twofold competitions. Every individual in the archive has a higher opportunity to be chosen than any population part, as presented in Algorithm 2.
Multi-objective optimization using multi-objective GAs deal with several objective functions at the same time, for this it

Table. I
GAS APPLICATIONS FOR WSN DEPLOYMENT.

Works (year)	Used Genetic Algorithm	Objectives	GA type
Hoffmann, Medina, and Wolisz. (2011) [21]	Hybrid GA with centralized sorting of base stations	Latency Minimization	SOGA
Tripathi et al. (2013) [27]	Genetic Algorithm and Genetic Programing	Coverage and network lifetime maximization	BOGA
Yoon and Kim. (2013) [22]	Genetic Algorithm	Coverage maximization with varying sensing radius of different sensors.	SOGA
Rebai et al. (2015) [28]	Genetic Algorithm	Coverage and connectivity maximization	BOGA
Gupta, Kuila, and Jana. (2016) [17]	Genetic Algorithm-based approach	Maximization of connectivity	SOGA
Gupta, Kuila, and Jana. (2017) [31]	MO-Genetic Algorithm	Maximization of coverage and connectivity and minimum number of sensor nodes	MOGA
Dai and Wang. (2017) [29]	Improved Genetic Algorithm	Maximization of connected confident information and coverage	BOGA
Benatia et al. (2017) [13]	MO Genetic Algorithm	Maximization of coverage and connectivity and minimization of node numbers and over-coverage	MOGA
Karatas. (2018) [23]	Genetic Algorithm-based scheme	Hybrid coverage of heterogeneous WSNs	SOGA
Liang and Lin. (2018) [24]	Genetic Algorithm	Maximization of coverage strategy in MWSN	SOGA
Panhwar et al. (2018) [25]	Genetic Algorithm	Distance based energy optimization	SOGA
Perez. (2018) [30]	Non-Sorting Genetic Algorithm 2 (NSGA II) with local search heuristics	Total number of devices used in the placement and total energy dissipated by the placement	BOGA
Hanh et al. (2019) [26]	Multi-Island Genetic Algorithm (MIGA) and Virtual Force Algorithm (VFA)	Maximization of area coverage	SOGA
Harizan and Kuila. (2019) [32]	Improved Genetic Algorithm	Maximization of connectivity and coverage and energy minimization	MOGA
ZainEldin et al. (2020) [33]	An improved dynamic deployment technique based-on genetic algorithm (IDDT-GA)	Coverage Maximization with the lowest number of nodes and minimizing overlapping area	MOGA
Pal et al. (2021) [34]	Non Sorting Genetic Algorithm II	Strength of received signal, coverage and over-coverage	MOGA

Algorithm 1 Pseudo-code of NSGA II.

$t \leftarrow 0$
$g \leftarrow N$
$s \leftarrow K$
Initialize population of chromosomes P(g=0) randomly size K
Evaluate the P(g=0) objectives according to 5 constraints
Assign Rank level based on Pareto sorting
Generate child population
Select children with binary tournament
Crossover P(g=0)
Mutate P(g=0)
while $g \leq N$ **do**
$gn \leftarrow g + 1$
for each parent and child in population **do**
Assign Rank level based on Pareto sorting
Generate sets of non-dominated solutions
Determine crowding distance
Loop inside by adding solutions to next generation starting from the first front to K size
end for
Select on the lower front with higher crowding distance
Generate child population
Select P(gn) from P(gn-1) with binary tournament
Crossover P(gn)
Mutate P(gn)
Evaluate P(gn)
end while

Algorithm 2 Pseudo-code of SPEA II.

$t \leftarrow 0$
$g \leftarrow N$
$s \leftarrow K$
Initialize population of chromosomes P(g=0) randomly size K
Create empty external archive V
while $g \leq N$ **do**
$gn \leftarrow g + 1$
Evaluate the P(g=n) and and the archive V individuals according to 5 constraints
Copy all non-dominated solutions to archive V
if capacity of V is exceeded **then**
remove individuals from V with truncation operator
else
Fill V with dominated solutions in P(gn)
end if
Select P(gn) from P(gn-1) with binary tournament
Crossover P(gn)
Mutate P(gn)
end while

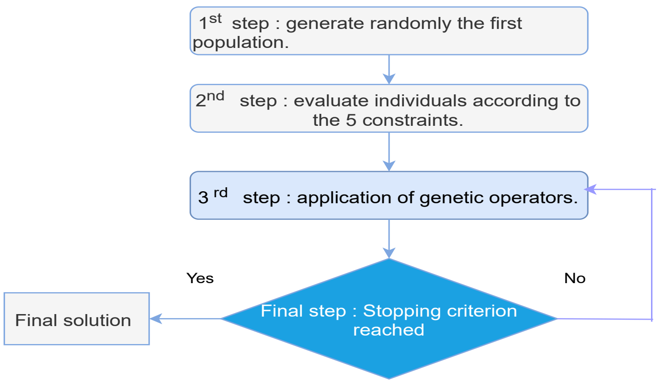

Fig. 6: Our model general evolutionary diagram.

uses the notion of optimal compromise (A solution that satisfies several functions at the same time). The solutions are separated based on the notion of dominance in the sense of Pareto. One solution may be better than another on some goals and less good on others. So there is usually no single solution that simultaneously provides the optimal solution for all of the goals. Therefor, in order to establish a comparison between the SPEA II and NSGA II functioning for an agricultural application, we had followed the same general evolutionary diagram as presented in Figure 6. Each step will be explained in next subsections.

A. *First step*

The modeling of the deployment space is done by dividing it into grids with cells of 1 square meter in size. By applying the binary representation to formulate the chromosomes of the different populations, of which the 1 represents the presence of a node in the cell, and the 0 signifies its absence. We made sure that the first population of individuals is generated randomly, in order to guarantee diversity in the solutions and to avoid at the same time falling on local optima.

B. *Second step*

Our Node deployment problem is considered as a multi-criteria problem, the WSN node network have to minimize the number of sensors used, areas of over-coverage and the nodes separating distance, and maximize coverage and connectivity at the same time [36]. After the generation of the initial population, each individual thereafter will be evaluated by the different 5 objective functions, and we will have as results evaluation vectors of 5 dimensions. Each criterion was therefore represented by a mathematical function as shown in Table 2.

C. *Third step*

In this step, genetic operators will be applied, the first is the selection of individuals who will participate in the offspring of new individuals using the rotation method. Individuals who have better fitness values will be selected, and in case two parents have a similar evaluation, another metric will be applied, which is the Crowding distance [37].
Once the parents are selected, we move on to the crossing operator with a certain probability, the latter defines the proportion of parents in the population that will be used by a crossing operator. in our case we have chosen the crossing at a single point.
After the crossing is applied, we move on to the mutation which

Table. II
MATHEMATICAL REPRESENTATIONS OF EVALUATION CRITERIA.

Evaluation Criteria	Mathematical function		Symbols interpretation
Sensor nodes number rate	$N_{sr} = \frac{N_S}{L \times l} \times 100$	(1)	N_s represents the number of sensor nodes L, the length of the plot l, the width of the plot
Sensor nodes separating distance	$Dist = \sum_{N_s} \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}$	(2)	(x_k, y_k), the coordinates of the K sensor, (x_i, y_i), the coordinates of other sensors
Coverage rate	$C_{vr} = \frac{\sum_x \sum_y Det(x, y)}{L \times l} \times 100$	(3)	$Det(x, y)$, detection coverage matrix
Over-coverage rate	$O_v - C_{vr} = \frac{\sum_x \sum_y O - Det(x, y)}{L \times l} \times 100$	(4)	$O - Det(x, y)$, detection over-coverage matrix
Communication rate	$C_{on} = \frac{\sum_x \sum_y C_n(x, y)}{L \times l} \times 100$	(5)	$C_n(x, y)$, connectivity matrix

allows us to introduce a disturbance into the solution with a mutation rate.

D. Final step

Given that the constraints of our deployment are very contradictory, for example we want to maximize coverage while minimizing the number of individuals. We don't already have a deployment model that we want to achieve. Therefore, the stopping criterian of our algorithms will be to set a generation number that allows the algorithms to properly explore the search space while minimizing the calculation time. Knowing that the number of generations is linked to the size of the agricultural plot.

IV. COMPARISON BETWEEN SPEA II AND NSGA II

A. Definition of MOGA hyper-parameters

In order to establish a comparison between the two variants of MOGA which are NSGA II and SPEA II, we made experimental tests to be able to define the good hyper-parameters of MOGA like the number of generations and the size of the populations. However, these two parameters depend in the first place on the size of the agricultural plot, the larger it is the higher these two parameters are to be able to explore all the research space. Thereby, we chose to work on a plot of dimensions 10 by 10 m^2. therefore our chromosomes will be 100 bits in length.
In addition, to define the hyper-parameters, we have varied the size of the population from 10 to 80 with a step of 10 and generations from 1 to 80. As a result, we found that the execution time is proportional to the population size as shown in Figure 7 and that our model starts reaching a global optimum with 60 individuals in the population at the 70 generation, and reaches it with 70 and 80 individuals as shown also in Figure 7. Therefor, we decided to fix the population size at 70 individual in order to guarantee the convergence of our model with the minimum execution time, and the generation number at 100 in order to give more opportunity to our model to explore the research space.

B. Results and discussion

After having defined the different hyper-parameters of the MOGA, we evaluated the functioning of NSGA II and SPEA II for a 100 m^2 plot, and we evaluated their performance through comparing the fitness value and time efficiency of the two MOGA optimization algorithms. The two algorithms were implemented using Python, and were executed on a PC with an Intel Core i5-4300U, 2.50 GHz CPU and 4,00 GB RAM in order to have a fairly comparison between them. We ended up finding that both of them can give us good results in terms of fitness score, but it turns out that the non-dominated solutions obtained by SPEA II are better than those of NSGA-II in terms of fitness score. Figure 8 shows us the evolution of the 5 objective functions compared to the generation for the two algorithms. In addition, compared to the quality of the solution, the optimal solution presented by the SPEA II offered us better rates of connectivity and over coverage, while minimizing the number of deployed sensor nodes and the distance between the different sensor nodes, while the NSGA II was better in only one objective which is coverage rate, as shown in Figure 9. And according to the execution time, as presented in Table 3, the NSGA II converges to optimal solutions a little faster than the SPEA II. As a result we can conclude that although SPEA II gives better results, NSGA II still provides acceptable results, and still manages to be effective and faster. Figure 10, shows the plan of deployment of the Non-dominated solution of SPEA II.

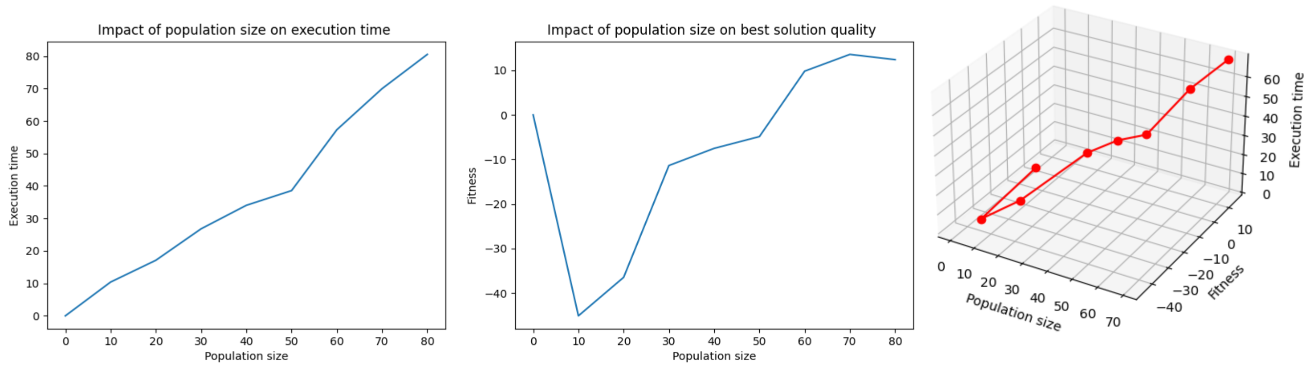

Fig. 7: Impact of population size on best solution quality and execution time.

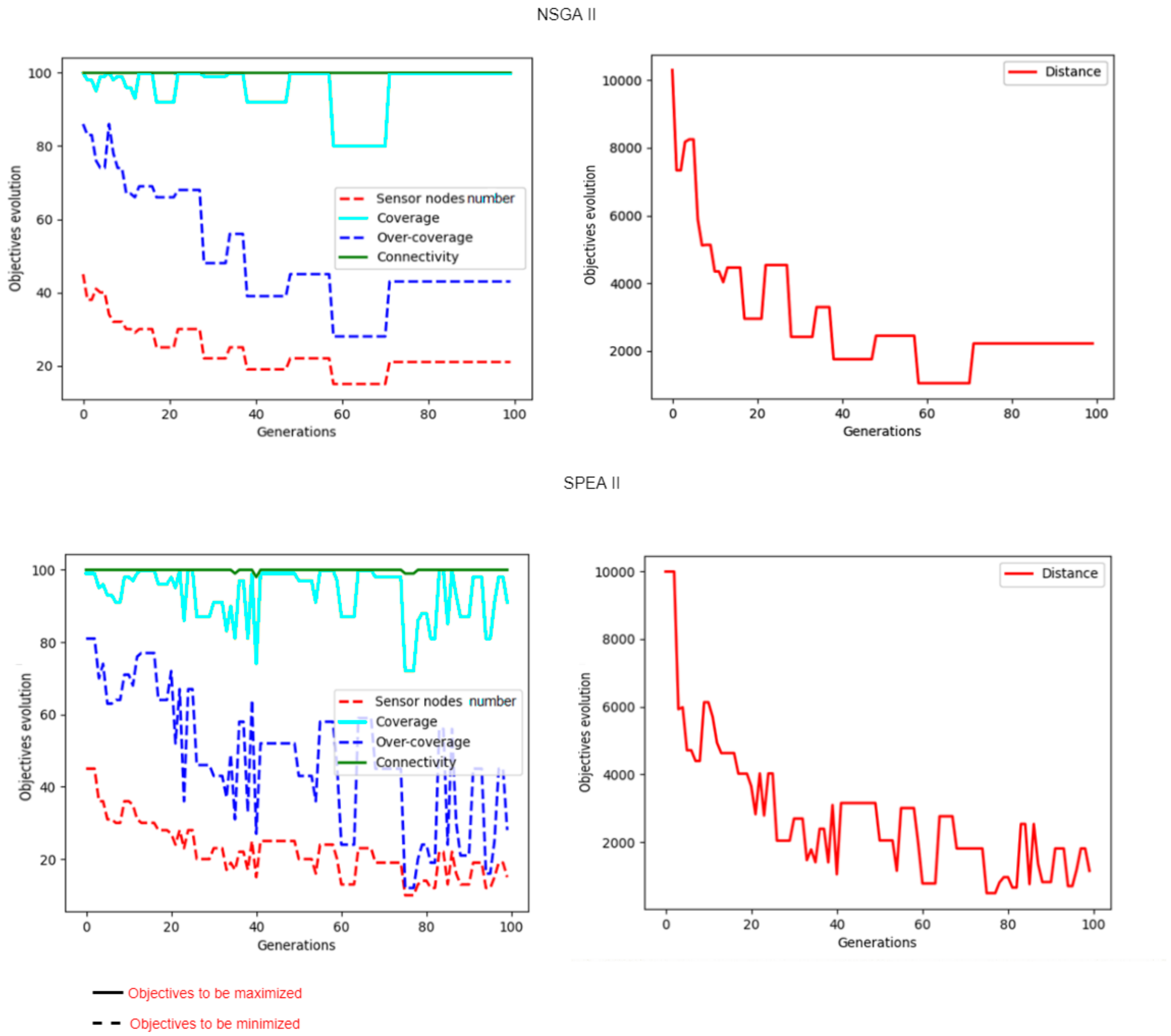

Fig. 8: Comparison between NSGA II and SPEA II according to their objectives functions evolution.

C. Results Generalization

Our proposed model has proven its performance in the deployment of nodes for an agricultural zone according to the 5 constraints described above. But however, we have found that it shows a drastic increase in the computation time, when we increase the size of the agricultural plot as shown in Table 4 (For 400 m^2 the execution time was for about 40 min). The results presented in table 5 are obtained by the execution of the model for different plots of different sizes using the MOGA, SPEA II algorithm. As it presented better results in our tests, the phenomenon of the increase in time can be explained by the increase in the size of the individuals who build the popu-

Table. III
COMPARISON BETWEEN SPEA II AND NSGA II DEPENDING ON THE SOLUTIONS QUALITY AND THE EXECUTION TIME (IN SECONDS).

MOGAs	Execution time (s)	Sensors number (%)	Coverage (%)	Over-coverage (%)	Connect-ivity (%)	Distance (m)	The weighted sum of the fitness objectives
SPEA II	150.54	15.0	93.0	24.0	100.0	1098.98	-188.99
NSGA II	139.12	21.0	100.0	43.0	100.0	2214.94	-415.78

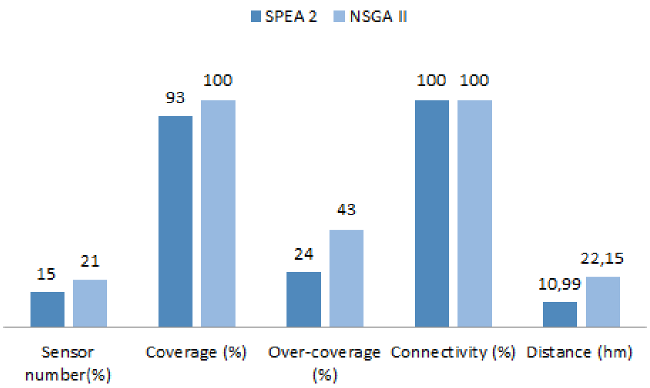

Fig. 9: Comparison between NSGA II and SPEA II non-dominated solutions according to their objective function.

Fig. 10: Sensor node deployment plan for an agricultural plot of 100 m^2 size.

lation because the execution time is proportional to the size of the plot. Thereby, the growing size of individuals will affect the objective function evaluation computation time (Figure 11), which is known as the most time-consuming phase in the GA process [38]. And considering the quality of the solutions, it is essential that if the size of the plot is large, the size of the population and the number of generations must increase more and more in order to better explore the research space. As shown in Table 4, the evaluation of objective functions deteriorates with increasing plot size. Because in our tests, we kept the same hyper-parameters (population size, number of generations) in all the tests. So, we can compare them in a fair way.

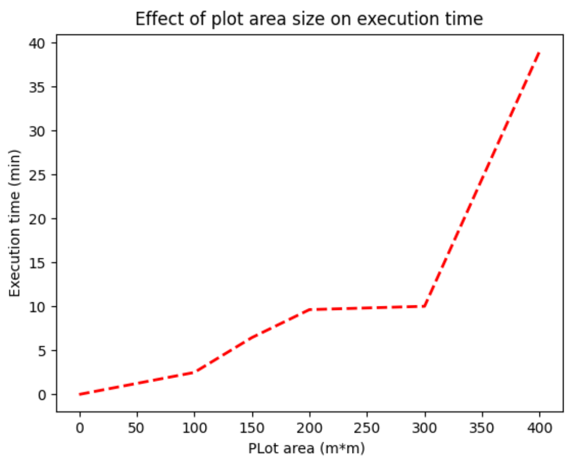

Fig. 11: Effect of plot area size on execution time.

V. CONCLUSION

The application of Multi-objective GAs for WSN node deployment optimization in agriculture using NSGAII and SPEA II showed good results regarding the rates of the different constraints of coverage, over-covera-ge, connectivity, sensor nodes number, and the nodes separating distance.
However, we found that the SPEA II was more efficient but also more demanding in terms of calculation time compared with the NSGA II. The execution time of the two algorithms increases considerably and their solutions quality decreases too, with the increase of the size of agricultural plots. Therefore, as future works, we propose to use a fitness approximation tool. This proposition comes from the fact the evaluation step is the most expensive in terms of calculation time and requires very important computational skills. Besides, we can take advantage of the parallelization nature of GAs, to implement our algorithms

Table. IV
THE RELATION BETWEEN THE INCREASE IN THE SIZE OF THE PLOTS, THE EXECUTION TIME AND THE QUALITY OF THE SOLUTIONS FOR THE SAME HYPER-PARAMETERS OF THE MOGA .

Plot dimensions (m^2)	Execution time (s)	Evaluation of objective functions (N_{sr}, C_{vr}, $O_v - C_{vr}$, C_{on}, Dist)
10 ×10	150.54 (2.50 min)	(15.0, 93.0, 24.0, 100.0, 1098.98)
10 ×15	387.72 (6.46 min)	(19.33, 99.33, 43.33, 100.0, 5520.67)
10 ×20	578.63 (9.64 min)	(22.5, 93.5, 54.0, 100.0, 15584.02)
15 ×20	601.33 (10.02 min)	(22.0, 94.0, 50.5, 99.5, 14793.52)
20 ×20	2342.59 (39,04 min)	(30.5, 99.75, 77.25, 100.0, 151859.30)

on specific hardware computation platforms such as the Multi -Processor System-on-Chip (MPSoC), Field Programmable Gate Array (FPGAs) accelerators, Multicore or Manycore systems and Graphics Processor Unit (GPU).

VI. Compliance with Ethical Standards

The authors have no relevant financial or non-financial interests to disclose.
The authors have no conflicts of interest to declare that are relevant to the content of this article.
All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.
The authors have no financial or proprietary interests in any material discussed in this article.

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