Smart Placement of Routers in Agricultural Crop Areas

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Abstract: The utilization of technologies in agriculture, which is called precision agriculture, is progressively necessary to optimize crop yields. The purpose of this paper is to present an optimized positioning of routers, seeking a robust topology of the network, in order to cover the sensor monitoring devices spread in an agricultural crop area, sending data such as temperature, soil humidity, incidence of luminosity, etc., which allows the farmer to make better decisions regarding the cultivation of his/her land. For this, genetic algorithms will be used to determine the location of routers in a network through evolutionary techniques associated with a fuzzy aggregation method. Typical application cases are presented and discussed to illustrate the proposal.

1 INTRODUCTION

Family farming is responsible for producing about 70% of the food that is available for consumption by the Brazilian population. It is made up of small rural producers, traditional peoples and communities, foresters, aqua culturists, extractivists and fishermen. The sector stands out for the production of corn, manioc root, vegetables, beans, sugarcane, rice, swine, poultry, coffee, wheat, castor beans, fruit and vegetables. In family farming, the management of the property is shared by the family and the agricultural production activity is the main source of income. In addition, the family farmer has a particular relationship with the land, his place of work and residence. Productive diversity is also a striking feature of this sector, as it often combines subsistence production with production destined for the market. Family farming contributes to the generation of income and employment in the countryside and also improves the level of sustainability of activities in the agricultural sector.

Nowadays, the utilization of technologies in agriculture, which is called precision agriculture, is progressively necessary to optimize crop yields. Challenges include effects of climate change to the agricultural systems which can drastically reduce agricultural productivity. In this direction, a recent work in (Del Felipe et al., 2022) proposes a network of wireless sensors applied to precision agriculture. The sensor network collects data on environmental variables such as soil moisture, temperature, and ambient humidity. This data is sent wirelessly to a head node responsible for uploading the information to an Internet of Things (IoT) platform. Another research paper (Dasig, 2020) shows recent advances in Agriculture 4.0. Business models are discussed in (Medici et al., 2021) to identify possible agribusiness models for developed and developing countries, particularly for the European context and sub-Saharan Africa and South Asia-Pacific area. Smart IoT based approach is proposed in (Sreeja et al., 2020) which consists of three sensors, a Wi-Fi module and a dc motor, to measure and display the different parameters for the crop.

Technological advances have had a great impact on Brazilian agriculture; however, family farming is still taking slow steps in direction. Therefore, it is vitally important to implement technological technical support resources in family farming, relying on government funding and making it possible to increase production efficiency, which leads to an increase in production and, consequently, its gains.

The purpose of this article is to optimize the positioning of routers, seeking a robust topology of the network, in order to cover the sensor monitoring devices spread in an agricultural crop area, sending data such as temperature, soil humidity, etc., which allow the farmer to make better decisions regarding the cultivation of his/her land. However, in practice, the purely random positioning of router nodes can result in poor communication performance with the

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sensor monitoring devices. In addition, the actual deployment may need to consider restrictions and geographic characteristics of the area in question, making it necessary to search for different topologies to distribute them. In fact, layout is a critical aspect in mesh wireless networks. As such a problem is of the NP hard type, one motivation to solve the mesh router placement problem and look for the optimal solution with adequate performance is to follow an approach using evolutionary techniques that involve genetic algorithms, including fuzzy aggregation. A wireless mesh network (WMN) can be understood as a communication network composed of radio links planned in a mesh topology. There are two types of nodes in WMNs: routers and clients. The group of mesh routers, connecting to each other, forms the backbone for the set of clients that aggregate the mesh. Some mesh routers act as Internet gateways to intermediate data traffic between the Internet and the WMN. The low design cost and quick installation of WMNs makes them a cost-effective choice for establishing wireless connectivity for mobile users anytime, anywhere. These characteristics can be useful mainly in regions or developing countries, whose decreasing costs of implantation and maintenance of infrastructure can make possible automations in several levels, optimizing levels of production and income of small family farmers. The good quality and operability of WMNs depends heavily on placing mesh router nodes in the desired area to achieve network connectivity, stability and coverage. The placement of routers in a mesh network is not a trivial problem. Typically, this is a problem that can be solved using traditional evolutionary techniques such as weighted-sum approach genetic algorithms or Pareto-based techniques. Weighted-sum evaluation for genetic algorithms leads to difficult assignment of appropriate weights, while Pareto techniques require the designer to select the most suitable solution among the set of presented solutions.

Several studies using intelligent computational systems have been carried out by universities and research centers around the world. In (Girgis et al., 2014) genetic algorithm and simulated annealing is used to search for a low-cost network with restrictions and determine the minimum number of routers. In (Rezaei et al., 2011) a genetic algorithm coupled with circle packing techniques is proposed which consists of positioning non-identical circles without overlapping within another circle, maximizing connectivity and coverage of the area network. Router Nodes Placement Using Artificial Immune Systems is used in (Coelho et al., 2017), and (Coelho et al., 2015) for industrial applications. Recently, coyote optimization algorithm was used to solve the mesh router nodes placement in wireless mesh networks (Mekhmoukh Taleb et al., 2022). The authors claim good results in simulations carried out for typical scenarios. In this work, we use genetic algorithms to determine the location of routers in a mesh network through evolutionary techniques associated with a fuzzy aggregation method (Coelho et al., 2019).

This paper is organized into four sections. The second section deals with modeling the problem followed by discussion of the case studies in section three. Finally, section four closes the article with conclusions.

2 HYBRID FUZZY- GENETIC PROPOSED MODEL

The model used to solve the mesh router placement issue was developed considering its multi-objective aspect. In addition to the full coverage of the acquisition points (sensor monitoring devices), restriction zones were proposed in two scenarios, making it difficult to install the routers. To meet these requirements, a fuzzy-genetic approach was used, which proposes a fusion of Genetic Algorithm and Fuzzy Logic techniques (Coelho et al., 2019).

The genetic algorithm (GA) is inspired by biological evolution, since it makes use of a selection of individuals, using genetic operators and operates in a random and oriented way, seeking an optimal solution within a population. The main application of genetic algorithms is to solve optimization problems with very large or complex search areas, which makes the use of traditional techniques impractical. In the case of a search, a comparison is made between the evolution of the species and the problem in question: a population of individuals (possible solutions) identified by chromosomes are evaluated and associated with an aptitude and subjected to a process of evolution, through selection. and reproduction, for several generations. Fitness is the quality of the individual result compared to the general fitness transferred (Coelho et al., 2019).

The objective function or fitness is defined based on the problem specification and is critical for successful implementation. In general, the objective function involves only a single criterion. However, most real problems involve more than one objective to be considered, so the objective function must use methods to convert vector quantities into a scalar. The general parameters of the GA influence its performance and can be used to establish a stopping criterion to run the algorithm. Such parameters include population size, maximum number of generations and operator application rate. The choice of parameters must meet established empirical criteria or the specific characteristics of the problem. In order to carry out multi-purpose case studies on genetic algorithms we can use a fuzzy aggregation method.

The use of fuzzy systems makes it possible to simultaneously evaluate all objectives, integrating user preferences in relation to each objective and for each situation. This feature offers a good advantage over multi-objective Pareto optimization methods, as it does not require user interference to choose the best solution at the end of the process, since preferences or specifications are entered before evolution in a simpler and more interpretable way through fuzzy logic, so the evolution process is guided in the direction of pre-established preferences. Each individual in the GA population represents a possible solution to the problem. During the evaluation process, individuals are submitted to the function or model that describes the problem and the results obtained in relation to each objective are used as inputs to the fuzzy system. For each individual in the population, the fuzzy aggregation method is applied, producing a single physical fitness value. Figure 1 illustrates the evaluation model using the Fuzzy Aggregation Method. The selection, crossover, mutation, population size and maximum number of generations rates are defined by the designer before starting the algorithm. The fuzzy aggregator rules are designed to meet the preferences needed to solve the problem, considering each objective. Evolution ends when a certain stopping criterion is reached. The most frequent stopping criterion is specified by a certain maximum number of generations. Another possibility is to establish a fitness value to be reached or stop the execution of the algorithm when there is no evolution for a certain number of generations. After evaluating all individuals of the current generation, the genetic algorithm continues the evolution process. The fuzzy aggregation system presents the usual functioning of a fuzzy inference system. Each system input corresponds to an objective and membership functions are triangular or trapezoidal in shape. The genetic algorithm with the incorporation of the fuzzy aggregator used in this work follows the model presented in Figure 2.

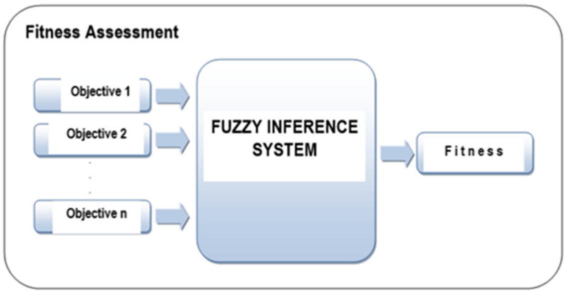

Figure 1: Fuzzy evaluation model with aggregator system.

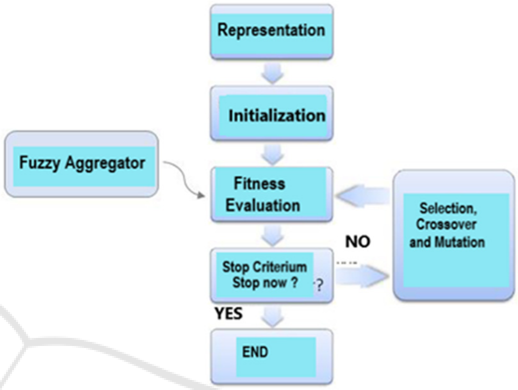

Figure 2: Genetic algorithm and fuzzy aggregator.

3 CASE STUDIES

In this work, three scenarios were considered for case studies whose objective was positioning low power battery operated routers for a mesh network to be used for data acquisition in an agricultural environment of size 50 m x 50 m. In all of them, the Matlab Fuzzy Toolbox was applied.

In the first study, the genetic algorithm was used with the sole objective of positioning the routers so that each monitoring point in the field was covered by at least one router.

In the other two studies, it was considered that, in the same field, there are areas with a higher or hindering installation cost. Therefore, these areas were considered not suitable for installing routers. In this way, the genetic algorithm was used together with a fuzzy aggregation method to perform a multi-objective application where it is desired to position routers so that each monitoring point is in contact with at least one router installed in a low-cost area. The specification of data acquisition points as well as the interconnection between the routers is not part of the scope of this work.

3.1 First Case Study

The environment of this first case study is an agricultural area of 2500 m^2, where the distribution of routers must be carried out in such a way that each monitoring point is covered by at least one router. Each soil condition monitoring device consists of a low power SoC (System On a Chip) IoT microcontroller, equipped with sensors, battery operated, capable of sending data within only 13 meters. Sensors such as temperature, soil moisture, incidence of luminosity and relative humidity. air and soil pH can be connected to the monitoring device. The organization adopted for the routers is homogeneous (all routers have the same characteristics) and irregular. In order to achieve these goals a traditional single-target genetic algorithm is used. The 16 monitoring points are positioned in the area, as shown in Figure 3. It is a single-objective problem, with a strictly objective assessment: to maximize the number of points covered.

The values of the parameters of the genetic algorithm are presented in Table 1. Such values led the algorithm to find a satisfactory solution to this simple case study.

Figure 4 shows the fitness curve of the best individuals and the average population.

Figure 5 shows the location of the monitored points and the positioning of the routers for the best individual reached by the GA. The green square in Figure 5 represents the area of the land in question (50m x 50 m), the smaller blue circles are the monitoring points and the large blue circles represent the area that each of the routers is covering, the routers being represented by the " x" in red.

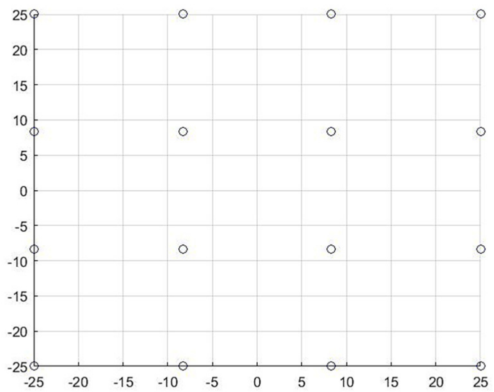

Figure 3: Location of the 16 monitoring points, Case study 1.

Table 1: GA Parameters for case study 1.

Parameters	**Values**
Generations	200
Search Region	X=[-25, 25]; Y=[-25, 25]
Population	300
Precision	50 cm
Fitness	Number of covered points
Selection	Geometric Normalization 8%
Crossover rate	80%
Mutation rate	1%

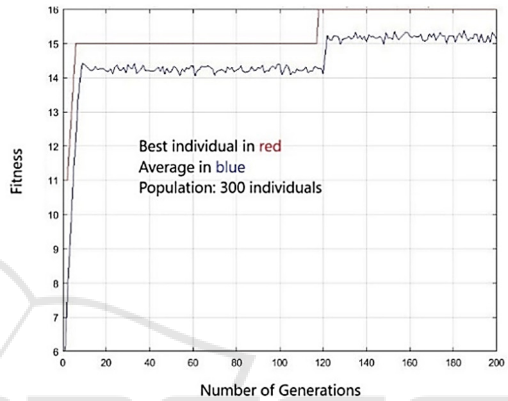

Figure 4: Fitness curve for case study 1.

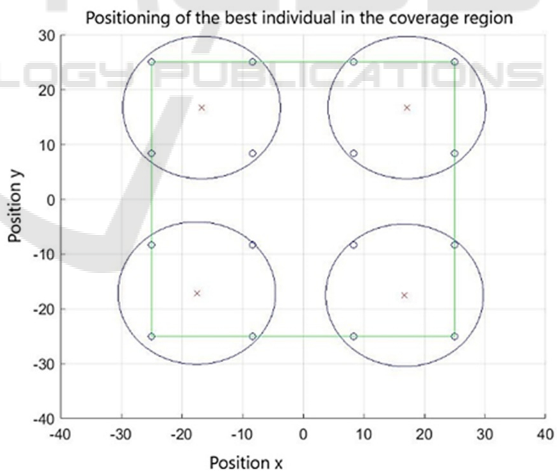

Figure 5: Routers' positioning for case study 1.

It can be seen that the routers were positioned satisfying the established criteria, since each monitoring point is being covered by a router. This first study did not take into account differences in the cost of installing the routers in relation to areas with more difficult access. Considering that cost is something that is important to be reduced in most projects, mesh networks would be no different. Therefore, the proposal of the second case study is to configure the network taking into account the installation costs.

3.2 Second Case Study

As in the first case study, the environment is an agricultural area of 2500 m^2, where the spatial distribution of the routers must be carried out. The monitoring device has a range of 13 m and the organization of the routers is homogeneous (all routers have the same characteristic) and irregular.
For this scenario it is necessary that:

- each monitoring point is covered by at least one router;
- the routers are not positioned in places where the installation cost is high.

So, we have a multi-objective problem: covering the area and reducing costs.

To achieve these goals, a genetic algorithm is used in conjunction with a fuzzy aggregation scheme.

The developed fuzzy system is of the Mamdani type, characterized by being simpler and more interpretable than TSK-type systems, and all rules have the same degree of importance, that is, weights equal to one.

The fuzzy aggregation system has two inputs: “NCS” (Number of Covered Sensor monitoring devices) and "Cost". Both inputs have 3 membership functions. The output is the Fitness that receives an evaluation between 0 and 10, and also has 3 membership functions. The system uses the default Matlab configuration (And method = min ; Or method = max; Implication = min; Aggregation = max).

The Defuzzification method is the mean of maxima (MoM).

Figure 6 shows the fuzzy aggregation system used in this case study.

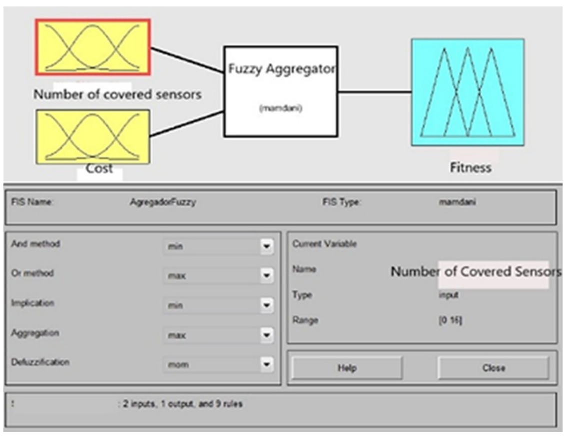

Figure 6: Fuzzy aggregation system for case study 2.

Figure 7 shows the "NCS" (Number of Covered Sensor monitoring devices) input membership functions.

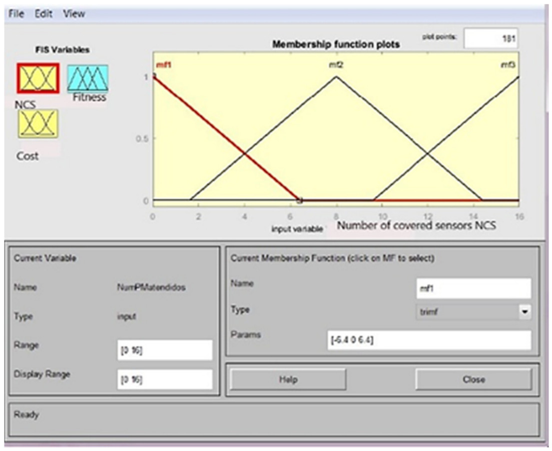

Figure 7: NCS membership functions for case study 2.

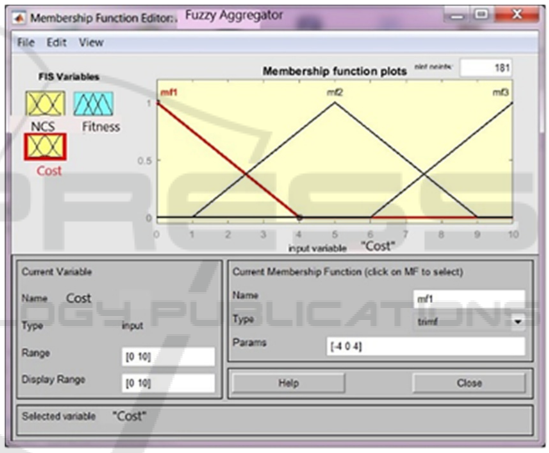

Figure 8: Cost membership functions for case study 2.

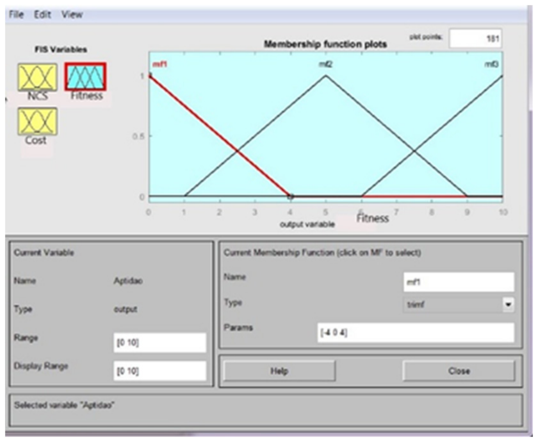

Figure 9: Fitness membership functions for case study 2.

Similarly, Figure 8 illustrates the "Cost" membership functions. Finally, Figure 9 shows the membership functions for the output (Fitness) of the fuzzy system.

The Fuzzy Aggregator rules, as shown in Figure 10, are as follows:

1. If (NCS is low) and (Cost is low)
   then (Fitness is poor)
2. If (NCS is low) and (Cost is medium)
   then (Fitness is poor)
3. If (NCS is low) and (Cost is high)
   then (Fitness is poor)
4. If (NCS is medium) and (Cost is low)
   then (Fitness is poor)
5. If (NCS is medium) and (Cost is medium)
   then (Fitness is poor)
6. If (NCS is medium) and (Cost is high)
   then (Fitness is poor)
7. If (NCS is high) and (Cost is low)
   then (Fitness is good)
8. If (NCS is high) and (Cost is medium)
   then (Fitness is medium)
9. If (NCS is high) and (Cost is high)
   then (Fitness is poor)

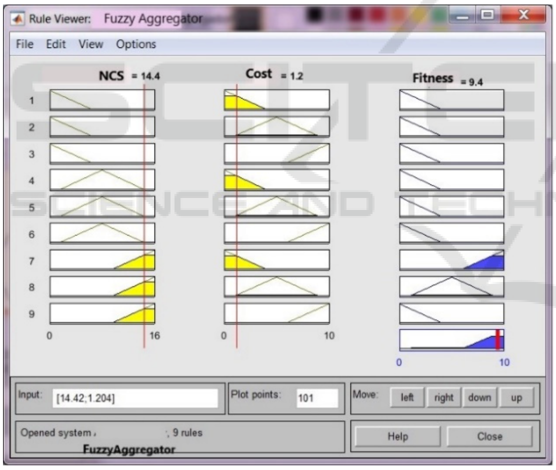

Figure 10: Fuzzy aggregator rules for case study 2.

It should be noted that the system is quite interpretable from the 9 rules presented. In other words, it is important to note that the 9 rules can be reduced to just 5. Indeed, it is noted that when NCS is low or medium, the Cost does not matter. No matter the Cost, Fitness will be poor (2 rules). It only makes sense to evaluate the Cost when NCS is high (3 rules).

Some tests were performed changing the values of the parameters of the genetic algorithm and it was observed that the same parameters of case study 1 also led to good results in case study 2.

Figure 11 shows the area, the location of monitoring devices, and the regions with restrictions on the installation of routers, where warehouses restrict the placement of routers.

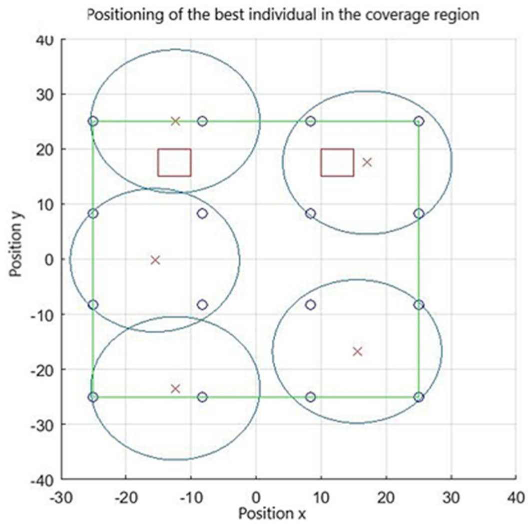

Figure 11: Routers' positioning for case study 2.

Figure 12 shows the curve of the best individual and the average fitness of the population. From the plots it can be seen that the best individual reached the maximum fitness around the 30th generation and the average followed this evolution.

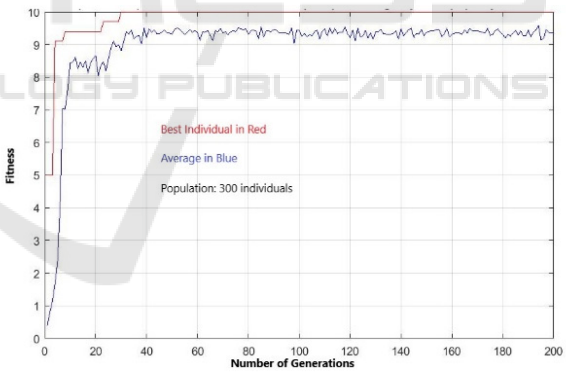

Figure 12: Fitness curve for case study 2.

The green square in Figure 11 represents the coverage area (50 m x 50 m), the smaller blue circles are the monitoring points, the larger blue circles represent the area that each of the routers is covering. The red x are the routers and the red squares are the regions of the area where the cost of installing routers is high. In the same figure it can be seen that the routers were positioned according to the established criteria, since each monitoring point is to be covered by a router and no router was positioned in the area where the installation cost is high. It can also be observed that, with the restriction of positioning the routers in areas of higher cost, it was necessary to use one more router to cover the area, totaling five routers. Such additional cost of routers should obviously outweigh installing a router rather than higher cost. The results obtained in the simulations fulfilled their objective of determining the positioning of routers in the network.

3.3 Third Case Study

In this case, restrictions closer to real scenarios were proposed. Based on the same basic setup as the previous ones, the restrictions in this one are a stream that crosses the land (where, of course, you don't want to place sensors, nor is it possible to install routers) and a 10 m x 15 m tool shed, which also restricts the installation of the routers. Sensors were repositioned out of the waterway.

For comparison purposes, the same parameters as in the previous case were kept in the Fuzzy aggregator. It can be seen that the optimized positioning suggested in this case is different from the previous one, which was in fact expected, given the changes in the restriction regions and sensor positioning. It can also be observed that it takes a few more generations to reach the best individual, given a greater difficulty in the scenario. Figure 13 shows the final location of the routers including the area, the location of monitoring points, and the regions with restrictions on the installation of the routers, where a stream and a shed restrict the placement of the routers. Figure 14 shows the curve of the best individual and the fitness average of the population.

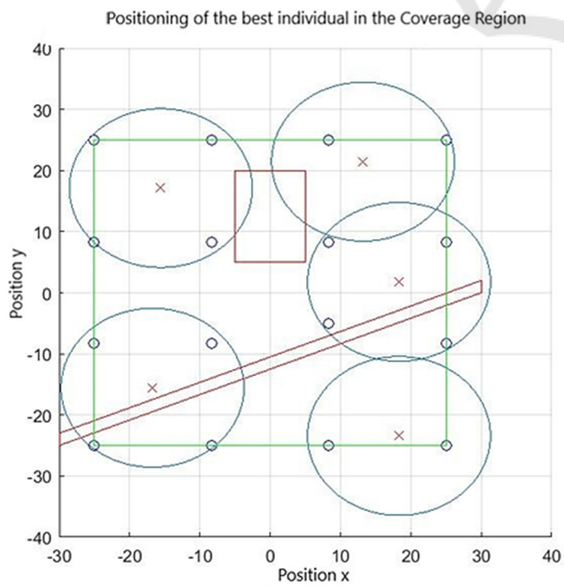

Figure 13: Routers' positioning for case study 3.

From the graphs it can be seen that the best individual reached maximum fitness around the 40th generation and the average followed this evolution.

In both case studies, the presented fuzzy aggregator system simultaneously evaluates the two objectives (maximize NCS - Number of Covered Sensor monitoring devices and minimize Cost), integrating designer's preferences. It offers an interesting advantage over multi-objective Pareto optimization methods, since specifications are entered in a simpler and more interpretable way through fuzzy logic, and so the evolution is guided to pre-established preferences.

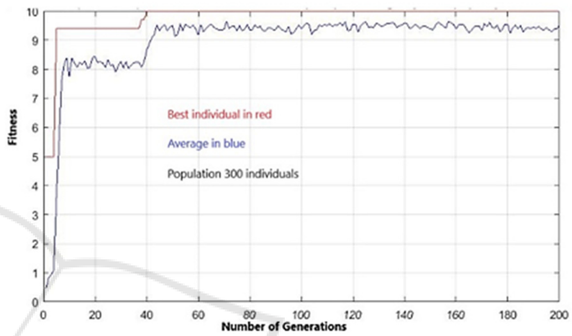

Figure 14: Fitness curve for case study 3.

4 CONCLUSIONS

In this work, case studies were presented with applications in mesh networks, whose objective is to optimize the positioning of routers in a small rural property to optimize the production of family agriculture using sensors with automation for data acquisition. In the scenario of the first case study, with only one objective, a genetic algorithm presented satisfactory solutions. In the other case studies, a hybrid fuzzy-genetic evolutionary technique was applied to a multi-objective system, in which the cost objective was included in the routing issue.

The fuzzy aggregator system makes it possible to simultaneously evaluate all objectives, integrating user preferences in relation to each objective and for each situation. This proposed system offers a good advantage over multi-objective Pareto optimization methods, as it does not require user interference to choose the best solution at the end of the process, since preferences or specifications are entered before evolution in a simpler and more interpretable way through the use of fuzzy logic, so the evolution process is guided in the direction of pre-established preferences.

For future work on precision agriculture, we plan to run experiments with weighted-sum GA and Pareto traditional methods for comparison's sake. It is also expected the inclusion of new targets for fuzzy aggregation and possibly the design of a variable size chromosome in the GA modeling so that evolution can also determine the number of routers suitable for field coverage. In addition, comparisons with other algorithms such as Particle Swarm Optimization (PSO)(Lin, 2013), Whale Optimization Algorithm (WOA) (Mirjalili et al., 2016), Bat Algorithm (BA)(Lin et al., 2014), African Vulture Optimization Algorithm (AVOA) (Abdollahzadeh et al., 2021) etc. are foreseen in future works.

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