A Fuzzy-Genetic Multi-Objective Optimization Method Applied to Deployment of Routers in Agricultural Crop Areas

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Abstract: High technology is increasingly applied to improving crop fields and coined an area as Precision Agriculture. The main focus of this work is to increase production by performing data acquisition from an agricultural crop area, monitoring sensor devices to measure temperature, humidity, etc. This allows the administrator of the field to make good decisions related to the land management. This paper proposes a hybrid fuzzy-genetic multi-objective intelligent method to place routers in an agricultural crop area so that to cover the sensor monitoring devices spread over it. The method combines a genetic algorithm with a fuzzy aggregation technique to evaluate multiples objectives, in order to determine an adequate location of the routers considering the designer´s preferences. Case studies are presented and show the proposal results.

1 INTRODUCTION

Family farming is at the origin of important debates, both academic and political, and can refer to a diversity of subjects in the collective imagination. Family farming represents a production model structured around the family and which is integrated into different types of markets, whether acquiring inputs and new technologies, or selling the food and raw materials they produce. It is not, therefore, a social group that predominated in the past and remained relatively distant from the market, averse to technology and poorly integrated into society. The family farmer in Brazil typically owns a portion of land ranging from 5 to 110 hectares (one hectare is equivalent to 10 thousand m²). At least half of the labor used in the activity of the property must be family-owned, and income must come predominantly of rural activity. Management must be strictly family-based. According to IBGE (Brazilian Institute of Geography and Statistics), responsible for the census, family farming occupies 23% of the total cultivated area in the country.

The use of technology is already part of several segments in our society, and agriculture would be no different. To seek greater revenue and productivity in the field, the Brazilian farmers need to be increasingly connected with what happens inside and outside their property. Precision agriculture (PA) is largely responsible for bringing agriculture into everyday life in the field. Until a few years ago, they were restricted to certain places and properties, because they were impacted due to the high investment and financial availability of the owners. How can we imagine this in the current scenario, in which the demand for food and its quality grow as the world population increases? It is impossible not to use technology. The term Agriculture 4.0 refers to the industry's upcoming significant trends, such as the internet of things (IoT), using big data and machine learning to make businesses more efficient amid the challenges of population growth and climate change to improve output, efficiency, and support sustainable agriculture by using accurate information to make strategic decisions (Tjhin et al., 2022).

By 2050, it is estimated that there will be 9 billion people on the planet, which will require more production, smaller costs and preservation of natural resources. It is planned that atypical occurrences and climate change represent serious risks to agricultural production. As a result, an increase of 70% or more is expected in food production. The agricultural industry is changing as a result of the adoption of emerging technologies. Using cutting-edge technology like IoT, AI and other sensors, smart

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agriculture will transform traditional farming methods production and international agricultural policies. Agriculture 4.0 looks at its possible benefits and drawbacks of the implementation methodologies, compatibility, reliability, and investigates the several digital tools that are being utilized to change the agriculture industry and how to mitigate the challenges (Gyamfi et al., 2024).

Summing up, precision agriculture combines artificial intelligence, the internet of things and GPS, making the farmer's life easier to achieve greater productivity and efficiency in the field, saving inputs, optimizing the soil and practical operation. Precision agriculture uses an agricultural management system that considers the particularities of each point on the property. Its application was intensified with the improvement of GPS, which made it possible to install receivers in seeders, harvesters and sprayers, associating productivity data with geographic coordinates using satellites. On the other hand, digital agriculture or agriculture 4.0 is a set of technologies that help the producer to monitor rural activities more closely, such as software and devices responsible for collecting and processing data about the farm.

Research in the area of computational intelligence applied to farming is intense currently and there are a large number of papers reporting an increase in crop productivity. Recent works include (Ketheneni et al., 2023) which uses an ensemble model, with four classifiers, to recommending the fertilizer and a sequential convolution neural network to recommending the pesticide for the appropriate crop.

In the recent past, 3D machine vision techniques have been widely employed in agriculture and food systems, leveraging advanced deep learning technologies. Following this path (Xiang et al., 2023) published a survey of 3D vision techniques in food and agriculture applications. (Karunathilake et al., 2023) review recent innovations, challenges and future prospects of precision agriculture and smart farming. For a sustainable production environment (Mallinger et al., 2023) discusses the impact of AI in farming concerning the fusion of AI and autonomous farming machinery (e.g., drones and field robots) in the daily work experience of farmers.

The purpose of this paper is to position a set of routers so to cover the sensor monitoring devices spread in an agricultural crop area, sending data such as temperature, soil humidity, and the like, giving the family farmer the chance of optimal decisions regarding his/her crop. It is intuitive that random positioning of router nodes is not a good choice as can result in poor communication performance with the sensor monitoring devices. Besides, the actual deployment may have restrictions and geographic characteristics of the area in question, making it essential to seek for different topologies to distribute them. Such a problem is of the NP hard type, so that is a good indication for looking for the optimal solution following an approach using evolutionary techniques that includes genetic algorithms with fuzzy aggregation. The placement of routers in a network is not a trivial problem. Usually, such a problem 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.

Research using intelligent computational systems have been taken continuous attention in universities and research centers around the globe. (Waqas et al., 2022) presents an optimal sensor node placement problem in Structural Health Monitoring (SHM) application based on an optimized Wireless sensor network (WSN). The sensor node placement problem is formulated in multi-objective form by considering the energy consumption, sensitivity area and network lifetime. A hybrid optimization algorithm was used by a combination of Chaotic Particle Swarm Optimization (CPSO) with Gravitational Search Algorithm (GSA) to provide optimal sensor node placement in WSN based SHM system. The optimal solution is achieved in the Pareto environment case, which makes the algorithm multi-objective.

In (Akram et al., 2023), a meta-heuristic multi-objective firefly algorithm (MOFA) is presented to solve the layout optimization problem. Their main goal is to cover a number of objectives related to optimal layouts of homogeneous WSNs, which includes coverage, connectivity, lifetime, energy consumption and the number of sensor nodes.

Router Nodes Placement Using Artificial Immune Systems is used in (Coelho et al., 2017), and (Coelho et al., 2015) for industrial applications.

In this paper, we use genetic algorithms to determine the location of routers in a mesh network through evolutionary techniques associated with a new Takagi-Sugeno-Kang (TSK) fuzzy aggregation method inspired by Mamdani system aggregation presented in (Coelho et al., 2019) and (Coelho et al., 2023).

This paper is organized into four sections. The second section deals with the new hybrid fuzzy-genetic proposed model followed by discussion of the case studies in section three. Finally, section four closes the article with conclusions.

2 HYBRID FUZZY- GENETIC PROPOSED MODEL

In this article, we utilized a fuzzy-based system for optimizing router positioning. Fuzzy systems provide a more intuitive and flexible approach to handling imprecise data, which can be easily modeled by the user. Through the implementation of a hybrid fuzzy-genetic strategy, we facilitate the development and adjustment of the objective function, while preserving the optimization strategy of the Genetic Algorithm.

The method to optimize the placement of the routers in the crop area must consider the multiple objective aspects of this issue. For instance, besides the necessity to full coverage of the sensor monitoring devices in the area, it may impose restrictions on positioning the routers due to high cost involved or, in the limit, preventing prohibitive installation costs. A hybrid fuzzy-genetic approach was used based on Genetic Algorithm (GA) and Fuzzy Inference System (FIS).

Genetic algorithms are inspired by biological evolution and some aspects of genetics. Optimization problems are the main application of GAs, particularly in problems with complex or large search areas. In a searching problem, the idea is to establish an analogy between the evolution of the species and the problem. A set of possible solutions (population of individuals) are evaluated, and each individual is associated with a fitness value (quality of the individual). The population is subjected to a process of simulated evolution, through genetic operators (selection and reproduction) for many generations. At the end of the evolutionary simulated process, the best individual (higher fitness value) is associated with the solution.

The fitness evaluation function, also called objective function, is conceived based on problem specification and is very important for obtaining a good result. The traditional GA involves a single criterion, but many real-world optimization problems involve multiples objectives. To deal with multiple objectives, one possible approach is to convert vector quantities (objectives) into a scalar (only one fitness value considering all objectives) by using techniques like the weighted-sum approach or Mamdani fuzzy aggregation.

The utilization of a Fuzzy Inference System (FIS) to aggregate the objectives allows the evaluation of all objectives, integrating designer´s preferences in relation to each objective and for each particular problem. The proposed hybrid method offers an advantage over Pareto optimization techniques because it does not require that the designer chooses the best solution at the end of the optimization process. Specifications and preferences are established a-priori and entered before evolution in a simpler way through the fuzzy system, to guide the evolution process in the direction of pre-established preferences.

It is worth mentioning that each GA individual represents a possible solution to the search problem. During the evaluation process each GA individual is submitted to a particular objective function that represents one aspect of the problem and the results are used as inputs to the fuzzy inference system. The fuzzy aggregation method is applied to each individual in the population in order to produce a single scalar overall fitness value. Figure 1 illustrates the evaluation model using a Takagi-Sugeno-Kang (TSK) Fuzzy Aggregation Method.

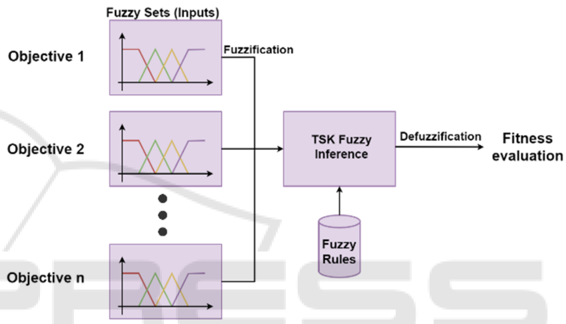

Figure 1: TSK Fuzzy System applied to fitness evaluation.

The values for GA parameters (selection, crossover, mutation, population size and maximum number of generations) must be defined by the designer. The rules for the fuzzy aggregator system are conceived according to the designer´s preferences to solve the problem by considering each objective. To stop the evolution, a certain stopping criterion also must be specified. The most common ones are related to the maximum number of generations and a certain fitness value to be reached.

The fuzzy aggregation method uses an ordinary FIS in which each input corresponds to a particular objective and the membership functions are triangular or trapezoidal in shape for simplicity. The Multiple-objective GA with the TSK Fuzzy aggregator system used in this work is presented in Figure 2.

3 CASE STUDIES

In this study, we explored three scenarios as case studies, aiming to strategically position low-power, battery-operated routers in a mesh network for data acquisition in an agricultural environment, with different size and number of sensors. Throughout the investigations, we leveraged the MATLAB Fuzzy Toolbox. For all experiments, the main objective is to cover all sensors using the routers, while avoiding the positioning in forbidden areas, which might represent places such as rivers, houses, and so on.

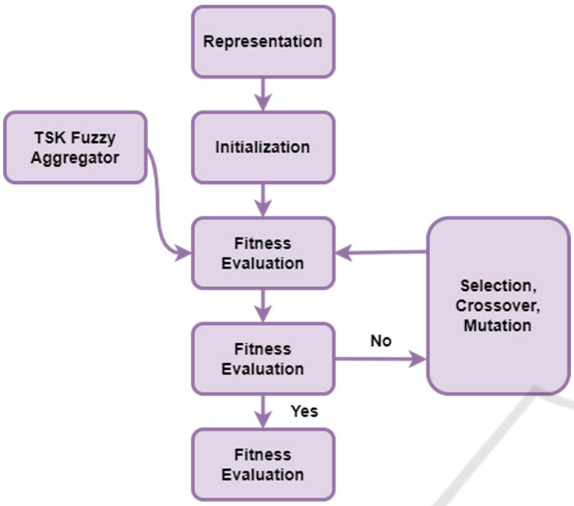

Figure 2: Optimization flowchart with TSK Fuzzy Aggregator.

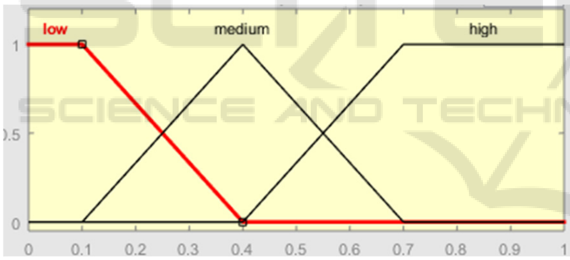

Figure 3: Membership functions for Cost variable.

To investigate the effectiveness of the TSK Fuzzy Aggregator, we compare the results against those obtained using the Mamdani Fuzzy Aggregator (Coelho et al., 2023) across all of the used scenarios in this article. To facilitate a meaningful comparison of results, we configured both the TSK (Takagi-Sugeno-Kang) fuzzy aggregator and the Mamdani fuzzy aggregator to exhibit similar behaviors. This involved maintaining consistency in the information related to the input, specifically the linguistic variables and their associated fuzzy sets.

The fuzzy sets for the number of points covered by routers (SenCovered) are depicted in Figure 3, while Figure 4 illustrates the fuzzy sets for the cost variable (Cost).

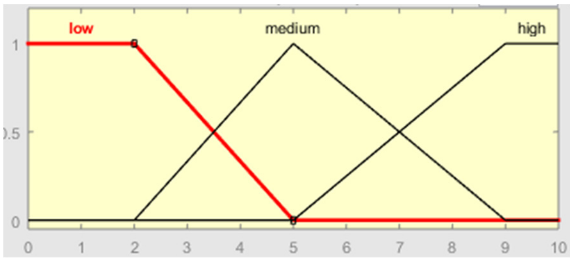

Figure 4: Membership functions for SenCovered variable.

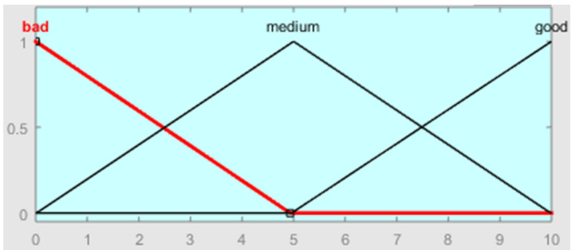

Figure 5: Membership functions for evaluation variable.

Despite the different specifications for the TSK and Mamdani output, both methods employ a common evaluation scale ranging from 0 to 10. Figure 5 displays the fuzzy sets associated with the Mamdani fuzzy aggregator, while the TSK fuzzy aggregator output is described in terms of linear equations for the linguistic variables:

- $overallbad = 0.006\, SenCoved - 0.4\, Cost + 4$
- $attendbad = 4.5$
- $costbad = 0.006\, SenCovered - 0.4\, Cost + 7$
- $good = 0.04\, SenCovered - 0.8\, Cost - 2$

Throughout all case studies, we maintained the rules of the FIS, considering the problem as essentially the same across scenarios. Figure 6 displays the rules for the TSK system, while Figure 7 illustrates the rules for the Mamdani fuzzy aggregator. It is noteworthy that the rules used in the Mamdani system can be simplified to 5 rules.

1. If (SenCovered is medium) and (Cost is low) then (Evaluation is attendbad) (1)
2. If (SenCovered is medium) and (Cost is medium) then (Evaluation is overallbad) (1)
3. If (SenCovered is medium) and (Cost is high) then (Evaluation is overallbad) (1)
4. If (SenCovered is high) and (Cost is low) then (Evaluation is good) (1)
5. If (SenCovered is high) and (Cost is medium) then (Evaluation is costbad) (1)
6. If (SenCovered is high) and (Cost is high) then (Evaluation is costbad) (1)
7. If (SenCovered is low) then (Evaluation is overallbad) (1)

Figure 6: Rules for TSK Fuzzy Aggregator.

1. If (SenCovered is medium) and (Cost is low) then (Evaluation is bad) (1)
2. If (SenCovered is medium) and (Cost is medium) then (Evaluation is bad) (1)
3. If (SenCovered is medium) and (Cost is high) then (Evaluation is bad) (1)
4. If (SenCovered is high) and (Cost is low) then (Evaluation is good) (1)
5. If (SenCovered is high) and (Cost is medium) then (Evaluation is medium) (1)
6. If (SenCovered is high) and (Cost is high) then (Evaluation is bad) (1)
7. If (SenCovered is low) and (Cost is low) then (Evaluation is bad) (1)
8. If (SenCovered is low) and (Cost is medium) then (Evaluation is bad) (1)
9. If (SenCovered is low) and (Cost is high) then (Evaluation is bad) (1)

Figure 7: Rules for Mamdani Fuzzy Aggregator.

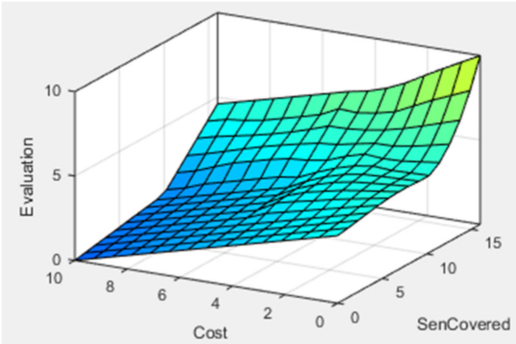

Figure 8: Surface for TSK Fuzzy Aggregator.

The TSK system was designed to progressively reach toward an optimal solution, as illustrated in Figure 8. This approach may be considered an advantageous feature of the TSK system, offering simplicity and precision in its rule-based outputs.

For each case study, we ran the optimization strategy ten times, and compared the results in terms of convergence (basically looking at the output score). As the objective and evaluation for both strategies were tailored to have similar behavior, we compare how good the fuzzy aggregation might be into finding the optimal solution. Also, we aim to observe the consistency of the results provided by the optimization strategies.

3.1 First Case Study

In the initial case study, the scenario unfolds in an agricultural expanse covering 2500 m² (50 m x 50 m), necessitating a strategic spatial layout of routers. Monitoring devices (sensors), with a reach of 13 m, are strategically positioned to achieve two primary objectives: ensuring each monitoring point is covered by at least one router and minimizing installation costs by avoiding high-cost areas. The parameters employed in this experiment using genetic algorithm are outlined in Table 1.

Table 1: GA Parameters for the Case Study 1.

Parameter	Value
Generations	300
Population	50
Mutation	0.01
Crossover	0.6

The results of the first case study are illustrated in Figure 9, showcasing the optimization outcomes employing TSK and Mamdani as fuzzy aggregation strategies. Notably, TSK and Mamdani exhibited similar behaviors in terms of consistency. Both TSK and Mamdani strategies converged to solutions with similar fitness values, which showed that there might be no difference in terms of robustness to achieve an optimal solution. However, it is important to note that the first case study can be considerably easier to obtain a solution that fulfill the requirements.

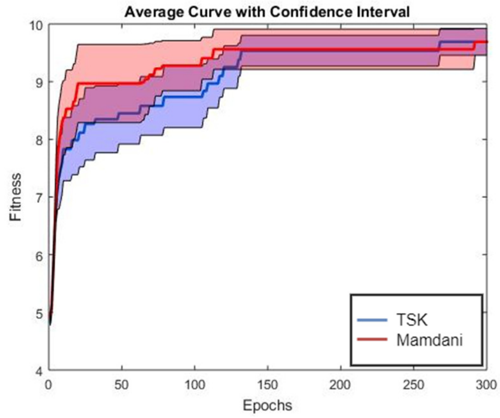

Figure 9: Fitness curve for Case Study 1.

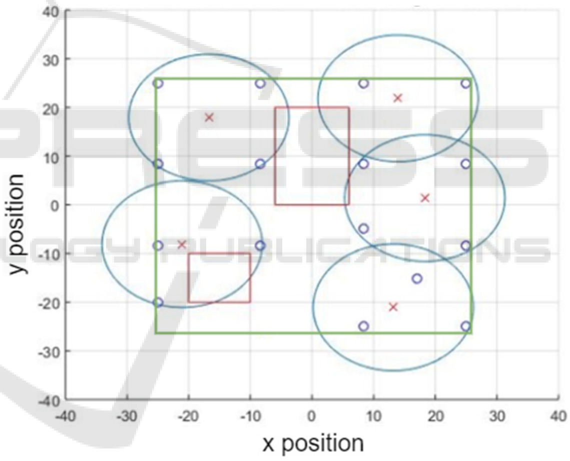

Figure 10: Routers' deployment using TSK Fuzzy Aggregator in Case Study 1.

Figure 10 provides a visual representation of the monitored points and router positions for the best individual identified by the GA. In this depiction, smaller blue circles denote monitoring points, large blue circles represent the coverage area of each router, routers are marked by a red "x," the obstacles are illustrated as red rectangles, and the crop limit area is highlighted in green.

A visual inspection affirms the optimal solution achieved through the optimization strategy. All routers were strategically positioned to enable sensor reach, avoiding forbidden areas, albeit with some proximity to them.

3.2 Second Case Study

For the second case study, we created one more obstacle in the router position, which simulates the obstacle of a house and a river crossing the environment. In this experiment, we kept the experimental setup, except for the number of individuals, as presented in Table 2. The rationale behind this change is based on the complexity of the problem.

Table 2: GA Parameters for the Case Study 2.

Parameter	Value
Generations	300
Population	150
Mutation	0.01
Crossover	0.6

The results of the optimization strategies can be seen in Figure 11. We observed that the Mamdani fuzzy aggregator obtained more unstable results and, in average, noticeable worse results than the TSK strategy. In a more complex scenario (if compared to the previous case study), the TSK fuzzy aggregator obtained results closer to the optimal, which may indicate a more appropriate approach to achieve the desired router placement configuration. We also observed that the Mamdani-type fuzzy aggregator did not converge gradually, but rather took some jumps between the fitness values. For both observations in this case study, the simplified building of the Mamdani fuzzy system may led to worse optimization results, which requires a much larger number of estimates than for the TSK fuzzy aggregator to achieve the best solutions in the optimization process.

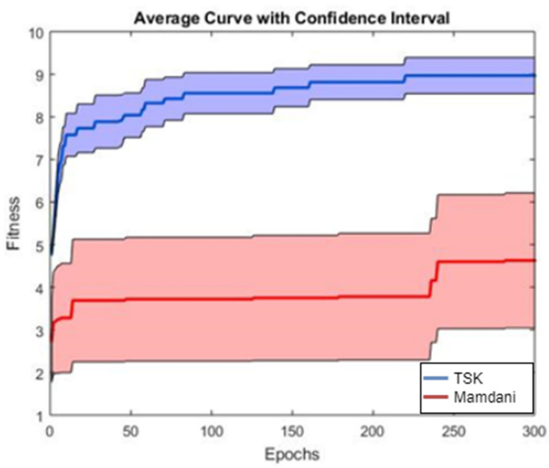

Figure 11: Fitness curve for Case Study 2.

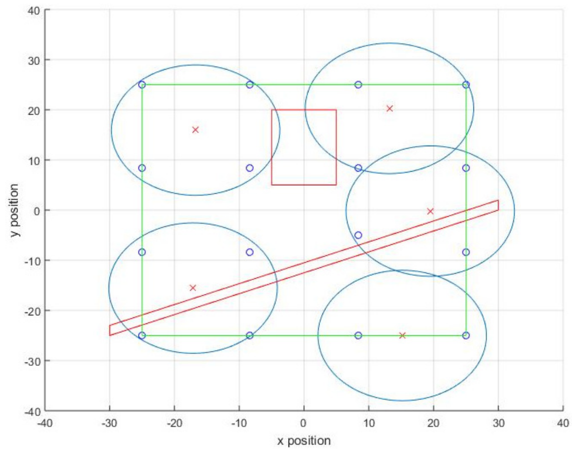

Figure 12: Router's deployment using TSK Fuzzy Aggregator in Case Study 2.

To illustrate the best solutions found in the second case study, Figure 12 shows one of the results using the TSK fuzzy aggregator. As observed in the router deployment, one of the difficulties is that some routers probably need to be placed near one obstacle to accomplish completely one of the objectives. Nevertheless, it was possible to achieve a solution that fulfilled all requirements, showing the effectiveness of finding a set of routers' deployment for this case study.

3.3 Third Case Study

For the third case study, we increased the complexity of the scenario by expanding: the number of sensors (20), number of obstacles (3) and covered area 10000m² (100 m x 100 m). Due to that constraints, we also increased the number of routers to be placed in the environment from 5 to 9.

For the GA parameters, we also increased the number of individuals of population, to balance the increase in the search space. The parameters used in this experiment can be seen in Table 3.

Table 3: GA Parameters for the Case Study 3.

Parameter	Value
Generations	300
Population	300
Mutation	0.01
Crossover	0.6

Figure 13 displays the fitness curve for the third case study. Some of the aspects of the graphs are also present in previous experiments, specifically the predominance of TSK method over the Mamdani. However, we noticed that the Mamdani fuzzy aggregator did not obtain reasonable results, with small increase of fitness score over the epochs.

As depicted in Figure 14, it was possible to obtain a solution that completely achieves all requirements for the router deployment. For a larger area and random positioning of sensors, it is plausible to observe that all routers were allocated to be in range to at least one sensor.

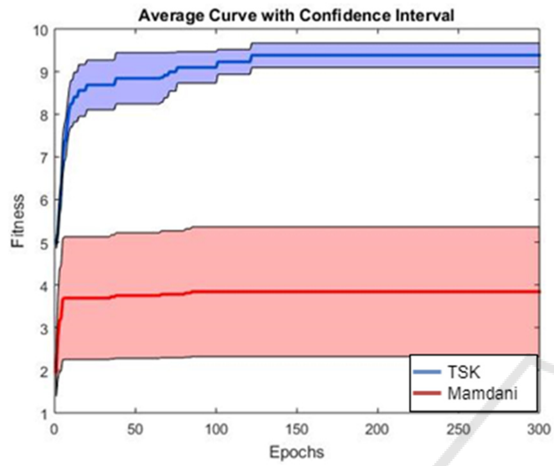

Figure 13: Fitness curve for Case Study 3.

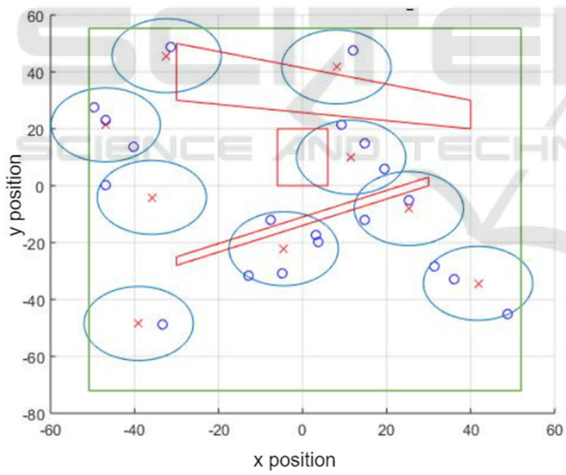

Figure 14: Routers' deployment using TSK Fuzzy Aggregator in Case Study 3.

4 CONCLUSIONS

This paper focused on the placement of routers in a small crop area for data acquisition of sensor monitoring devices to optimize the production of family agriculture. Case studies were presented with scenarios with restrictions closer to real applications. These scenarios consider not only the need to cover all sensors but also the avoidance of areas where routers' installation cost is high. A hybrid TSK fuzzy-genetic multiple-objective optimization method was applied to place the routers in a crop area taking into account the number of covered sensors and the cost objectives in the routing problem.

The multiple-objective technique based on fuzzy aggregation allows the evaluation of the objectives simultaneously, including designer´s preferences before the evolution takes place. This a-priori method offers an interesting advantage over Pareto method because it does not require that the designer chooses the solution at the end of the process. It´s worth noting that both the fuzzy aggregation specifications and designer´s preferences are integrated before evolution in a simpler manner, so the evolution is guided to the desired preferences.

The TSK fuzzy aggregation presented here showed, in two case studies, better performance to this kind of application in comparison with Mamdani fuzzy aggregation (Coelho et al., 2023). It is up to the designer to choose between these two fuzzy inferences which one should be applied to a particular problem. However, it should be stressed that the Mamdani fuzzy aggregation may require a higher effort to achieve a similar behavior, mostly adding new fuzzy sets for inputs, outputs and new rules to increase the granularity of evaluation.

We plan for future works on precision agriculture run case studies with some other a-priori methods, for instance, such as a weighted-sum, and also a-posteriori based on Pareto traditional method for comparison's sake. We also plan to include new objectives for fuzzy aggregation and conceive a model that can also select the adequate minimum number of routers for complete field coverage. In addition, comparisons with other techniques such as African Vulture Optimization Algorithm (AVOA) (Abdollahzadeh et al., 2021), Bat Algorithm (BA) (Yang et al., 2013), Whale Optimization Algorithm (WOA) (Mirjalili et al., 2016) and Particle Swarm Optimization (PSO) (Marinakis et al., 2008) are foreseen in future works related to precision agriculture.

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