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Fine-tuning of UAV control rules for spraying pesticides on crop fields

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Abstract—The use of pesticides in agriculture is essential to maintain the quality of large-scale production. The spraying of these products by using aircraft speeds up the process and prevents compacting of the soil. However, adverse weather conditions (e.g., the speed and direction of the wind) can impair the effectiveness of the spraying of pesticides in a target crop field. Thus, there is a risk that the pesticide can drift to neighboring crop fields. It is believed that a large amount of the pesticide used in the world drifts outside of the target crop field and only a small amount is effective in controlling pests. However, with increased precision in the spraying, it is possible to reduce the amount of pesticide used and improve the quality of agricultural products as well as mitigate the risk of environmental damage. With this objective, this paper proposes a methodology based on Particle Swarm Optimization (PSO) for the fine-tuning of control rules during the spraying of pesticides in crop fields. This methodology can be employed with speed and efficiency and achieve good results by taking account of the weather conditions reported by a Wireless Sensor Network (WSN). In this scenario, the UAV becomes a mobile node of the WSN that is able to make personalized decisions for each crop field. The experiments that were carried out show that the optimization methodology proposed is able to reduce the drift of pesticides by fine-tuning of control rules.

I. INTRODUCTION

Pesticides, also known as agrochemicals, are generally applied in agricultural crop fields to increase productivity, improve quality and reduce production costs. However, prolonged contact (either directly or indirectly) with these products can cause various diseases to humans such as several types of cancers, complications in the respiratory system and neurological diseases [1]. It is estimated that about 2.5 million tons of pesticides are used each year throughout the world and this amount is growing [2]. Much of the pesticides are wasted during the spraying process due to the type of employed technologies. There are evidences that show that the drift of pesticides is generally found at a distance of 48 m and 800 m from the target crop field, the deviation can reach a distance of 5 km to 32 km, downwind [3].

The use of UAVs to carry out the task of spraying pesticides can be beneficial to many reasons, including (i) to reduce human contact with the chemicals, which helps to preserve human health; and (ii) to improve the performance of the spraying operation, avoiding the presence of chemicals outside designed areas, which helps to preserve neighborhood fields, that can be other crops, preserved nature areas or water sources. Sets of control rules, to be employed in an autonomous UAV, are very hard to develop and harder to fine-tune to each environment characteristics. Thus, a fine-tuning phase must involves the parameters of the algorithm, due to the mechanical characteristics of each UAV and also must take into account the type of crop being handled and the type of pesticide to be used. In this paper we present a evolutionary algorithm to fine-tune sets of control rules, to be employed in an simulated autonomous UAV. We describe the proposed architecture and investigations about changing in the evolutionary parameters.

The proposed architecture employs an UAV, which has a system of coupled spray, and it is able to communicate with the Wireless Sensor Network, which is organized in a matrix-like disposition on the crop field. This WSN aims to send feedback on the weather conditions and how spraying actually are falling in the target crop field. Based on the information received, the UAV appropriately applies a policy to correct its route. Hence, the main contributions of this research are as follows: (i) investigate an evolutionary methodology capable of minimize human contact with pesticides, (ii) evaluate an evolutionary approach able to minimize the error in spraying pesticides in areas of growing vegetables and fruits, (iii) investigate techniques able to maximize quality in agricultural production, and (iv) contribute to increase the autonomy of the architecture proposed by [4], in which the policy parameters were set empirically and applied independent of weather conditions.

This paper is divided into six sections. Section II presents other studies related to this paper. Following this, Section III presents an outline of the architecture to clarify the scope of this paper and the optimization methodology proposed in this work. The experiments and results are presented and discussed in Section IV, and then compared with the results found in the literature. Finally, Section V summarizes the conclusions obtained from the results and suggests how this paper might encourage further studies in this field.

II. RELATED WORK

There are several studies that suggest how UAVs or WSNs can be employed for monitoring agricultural production, occasionally by integrating both technologies [5], [6], [7]. However, this work differs in so far as it proposes a PSO to optimize the control rules of the UAV at runtime, based in feedback
provided by WSN about weather conditions in the agricultural field.

Valente and collaborators [8] show a WSN-based system and UAV to monitor the of vineyards. The WSNs collect information about weather, soil and planting conditions and then makes it available to farmers. However, a field crop may be hundreds of meters away from other fields and sometimes there are barriers (e.g., rivers and roads) that separate two crop fields. Thus, it may not be viable or cost-effective to use cables to connect the WSN. Although the use of powerful wireless devices allows communication between WSNs, this solution causes higher energy consumption and involves reducing the lifetime of the WSNs. One solution that can be adopted to overcome these limitations is to employ a UAV to fly over the crop fields and gather information from each WSN, which it can then convey to a processing center. Although this study demonstrates that UAVs and WSNs can be integrated to provide efficient solutions or improvements in an agricultural setting, no methodology is employed for optimization at runtime. Additionally, a UAV is used as a mobile node in a WSN without any chance of having an effect on the environment.

In [9] a specific system is proposed to spray pesticide. This system should be coupled with a UAV that is capable of carrying approximately 22.7 kg. The model used in this work is UAV SR200 manufactured by Rotomotion. The spray system consists of four main components: (i) a metal tube with nozzles; (ii) a tank to store pesticide; (iii) a pump to move the liquid; and (iv) a mechanism for controlling the activation of the spray. The spraying can carry up to 5 kg of pesticide, which is enough to spray 14 ha; and it has a flight time of around 90 minutes. The main objective of this study is to validate the proposed system and evaluate different types of spray nozzles. However, the weather conditions were not taken into account. Additionally, it does not include a discussion of an evolutionary methodology that is able to optimize control of this activity.

Faiçal and collaborators [4] proposed an architecture formed of UAV and WSN to spray pesticide in crop fields. It is known that adverse weather conditions, such as winds of high speed, can cause errors in the spraying process. The study shows how the recommended architecture can reduce the risk of errors and increase control over this activity. With the aid of feedback from the WSN about pesticide concentrations, the route is gradually changed until the sensor node can identify a correct application of the product. However, the parameters set for the route change are apply in different weather conditions, which may impair the performance of this architecture. As mentioned earlier, this paper addresses this limitation by evaluating a methodology that is employed for the fine-tuning of a parameter that ponders the intensity which the route followed by the UAV is changed.

III. METHODS

A. UAV and WSN architecture for spraying on crop fields

Fig. 1 illustrates how the UAV acts as an agent in the crop fields. The UAV flies over the area, equipped with a spray system and a communication module, which enables data exchange (through a communication link) with distributed WSN in the crop fields, and sprays the pesticide in its entire length [4]. The WSN is represented solely within the target crop fields and is bounded by two dark dashed lines (from top left to bottom right) to simplify the viewing image. At the top of Fig. 1, there are two arrows that indicate the wind direction at a specific location. Through its communication link with the WSN, the UAV is able to obtain information about the weather (e.g. speed and direction of the wind) and the concentration of the pesticides sprayed on the crops. If an imbalance is detected in this concentration (e.g. the sensor on the left identifies a higher concentration than the sensor on the right), possibly caused by the wind, the UAV adopts a policy that involves changing its route to balance the application of pesticides in the whole extent of the target crop fields. This policy also helps to prevent overlapping when the chemical is applied. In Fig. 1, the correction of the route is represented by small arrows between the images of the UAV. The parameter called routeChangingFactor is employed in the route change function to set the degree of intensity (e.g. mild or sharp) so that the change can be made. However, although this parameter is important to ensure the success of the spraying, its value is set empirically before the beginning of the flight and is used in all weather conditions that occur during the spraying. This characteristic can affect the quality of the spraying; for example, a sharp correction might be made in an environment where a low wind speed has been identified. Moreover, an increase of complexity in this environment might cause variable behavior. In other words, the weather conditions can change during the activity, and this is detrimental to all the architecture if it has static configuration.

To overcome the problems mentioned above, this paper proposes a methodology based on Particle Swarm Optimization to optimize the parameter of the routeChangingFactor in runtime. As previously mentioned, the parameter of route change has a large influence on spraying and, in addition, the architecture is employed in a dynamic environment. Thus, it is worth investigating a methodology that is able to find a value for the parameter of the routeChangingFactor (and is close to an optimal solution) and which can be used and updated during the spraying. Fig. 2 shows the behavior of the architecture when the optimization methodology is used. It assumes that a crop field is composed of several small imaginary subareas in a rectangular shape. Thus, if all the subareas are sprayed, this results in a full spraying of the crop field. Each subarea will be called a “crop field” during
this study. The flight plan of the UAV is defined to spray the next crop field, soon after work on the current crop field has been completed. The route change, as described earlier, is made in the current crop field (D). In parallel to this activity, the UAV (B) queries the WSN (C) about the weather conditions in the next crop field (E). In this stage the request can reach the nodes that are deployed inside the next crop field by using multihop (not shown in the diagram). Only the endpoints of the communication (source and destination) are shown for a clear image. As soon as the UAV obtains weather information, this is sent to Control Station (A) to optimize the parameter of the routeChangingFactor. At this time, the optimization methodology proposal is run together with the weather information. At the end of the optimization, the Control Station sends the new configuration to UAV. The settings will be updated when the spraying of the current crop field has been completed and the spraying of the next crop field has begun.

B. Optimization of control rules

The optimization methodology proposed this paper is essentially composed of an algorithm based on PSO [10], [11]. This algorithm searches for a non-optimal value for the routeChangingFactor parameter and in one computation model of environment evaluates the accuracy of spraying by applying the weather information received from the WSN. Lastly, the algorithm returns the best solution (value per parameter) and this is assessed so that it can be applied in the next crop field. One important condition of this algorithm is that the computational cost (runtime) should be lower than the time required for spraying one crop field (subarea). Hence, the search space is delimited in one zone that has values of different acuteness (e.g. abrupt, smooth and moderate). Additionally, this delimiting of the search space allows a more rapid convergence. Following the definition of search space:

\[
\text{routeChangingFactor} = \{ x \in \mathbb{R} \mid 1.0 \leq x \leq 10.0 \}
\]

The optimization process is conducted in two ways at the same time: (i) through cooperation (group learning) and (ii) competition (single learning), by considering the particles of a swarm. Each particle is initialized in a random position (possible solution) within a search space. In each iteration of the algorithm, the velocity and position of the particles are updated. The position found by the swarm with best fitness and the positions with best fitness found by each particle individually are considered for updating. As the positions of the particles are possible values for the routeChangingFactor parameter contained in search space, the velocity of the particle indicates how far and in what direction this value will move (to a new position). The new position of each particle is obtained by Equation 1 (where: \(X_{id}\) is the position and \(V_{id}\) is the velocity of particle \(i\) in a moment \(j\)), while the velocity is updated in each iteration with Equation 2 (where: \(w_i\) is the inertia, \(C_1\) and \(C_2\) establish the importance of social trend or individual (cooperation or competition), \(P_{id}\) is the best position found by individual particle, \(P_{gd}\) is the best position found by swarm and, finally, \(rand()\) and \(Rand()\) are different random values for a good exploration of search space) [12].

\[
X_{id+1} = X_{id} + V_{id}
\]

(1)

\[
V_{id} = w_i \ast V_{id} + C_1 \ast rand() \ast (P_{id} - X_{id}) + C_2 \ast Rand() \ast (P_{gd} - X_{id})
\]

(2)

Algorithm 1 shows details of the optimization process. The particles are initialized in random positions inside the search space. The stop condition is defined by the amount of iteration that the algorithm has to run. This stop condition allows the average runtime to be analyzed in worst case scenarios, when all the iterations are run to find one possible solution. Following this, one stop condition can be added with the aim of finalizing the algorithm when identifying the convergence that has occurred. It should be noted that the runtime in worst cases should be lower than the time required for spraying a crop field (subarea). In each iteration, all the particles will have their positions evaluated and if the “fitness” of a particle is the best found by the swarm so far, the algorithm stores this position. On the other hand, if the position is not the best in global terms but is the best of particle the algorithm also stores this position in the particle. Later on, the velocity and the position of each particle are updated. When the algorithm achieves maximum interaction, it is finalized and the best position found by the swarm is returned.

The objective function (FuncObjective) contained in the algorithm, cited in Line 5 of Algorithm 1, refers to an interaction with one project inside OMNeT++ software. The project is an implementation of a computational model to evaluate the spraying [4]. This interaction tests and analyzes the quality of spray in each position of all the particles. The OMNeT++1

\[1\text{OMNeT++ Network Simulation Framework, http://www.omnetpp.org} \]

Fig. 2. Behavior of the architecture that employs the proposed optimization methodology. The Control Station (A) is installed outside the target crop field, in a zone that remains communicable with the UAV (B). During the spraying of the current crop field (D), the UAV sends a request for weather information about the next crop field (E) to the WSN (C). When the information requested is received, the UAV sends it to Control Station (A) where it will be used by the optimization methodology. At the end of the optimization, the Control Station sends the new configuration to UAV. The settings will be updated when the spraying of the current crop field has been completed and the spraying of the next crop field has begun.
Algorithm 1: Proposed algorithm to optimize the routeChangingFactor parameter.

1: InitializeParticles(RandomPosition[1, 10])
2: for MAX_ITERATION do
3: \( \text{PARTICLES} \leftarrow \text{FirstParticle()} \)
4: for ALL_PARTICLES do
5: \( \text{Result} \leftarrow \text{FuncObjective(PARTICLES)} \)
6: if Result is best particle then
7: Stores the position in particle
8: end if
9: if Result is the best in the swarm then
10: Stores the position in swarm
11: end if
12: UpdateVelocity(PARTICLES)
13: NewPosition(PARTICLES)
14: \( \text{PARTICLES} \leftarrow \text{NextParticle()} \)
15: end for
16: end for
17: return BestGlobalPosition

Fig. 3. Interaction between PSO and OMNeT++.

is a simulator of discrete events implemented with base on language C++ to model networks, multiprocessors and other distributed and parallel systems [13]. The OMNeT++ can be used to model several types of networks, such as networks of queues, wireless and peer-to-peer types [14]. Because of its generic design, OMNeT++ has several frameworks established for specific networks, such as Mixim\(^2\) for modeling wireless networks. This framework provides detailed models for wireless channels, wireless connections, mobility models, models for dealing with obstacles and several communication protocols, especially for MAC [15]. Fig. 3 show the interaction between the algorithm and OMNeT++. Initially the algorithm changes the settings and files of “Project spraying” so that the position of the particle can be used as routeChangingFactor, apart from the addition of real weather information (Stage 1). After this, the algorithm runs “Project spraying” in OMNeT++ (Stage 2) and, finally, analyzes the log file to determine the results of the spraying (Stage 3). In the source code of “Project spraying” there is a dispersion model to estimate the movement of pesticide until the planting [4]. The fitness is calculated by estimating the amount of pesticide sprayed outside of the target crop field. Hence the proposed solution is to find, how far the lower value is the best fitness.

IV. RESULTS

These experiments evaluate the use of the proposed methodology by following two essential stages: (i) optimization of the routeChangingFactor parameter; and (ii) evaluation of spraying with routeChangingFactor parameter optimized by means of the proposed algorithm. The results obtained in the second stage of the experiments are validated by comparing them with the results obtained without optimization of rule controls for route changes [4].

The first stage of the experiments is carried out in a virtualized machine with a single core of the processor (with 2.27 GHz of clock) in use. Other features of the computational platform are the use of 1 GB of Memory and Ubuntu 2.6.32-21-generic Operation System (called Control Station in Fig. 2). In this stage, the algorithm will search for the best possible value for applying as parameter of route changes (taking into account the feedback about the weather information). The settings evaluated are called with the standard PM (number of particles) IH (number of interactions). Each configuration is replicated thirty times, to obtain a greater confidence level for future statistical analysis. The algorithm is defined so that it will prefer the social trend \( (C_2 = 0.75) \) to the individual trend \( (C_1 = 0.25) \) in the search. Another important parameter for running the algorithm is Inertia, which is used to strike a balance between local and global searches, and is set to carry out local searches \( (w_i = 0.1) \). Due to the low communication time, measured in [4], it can be assumed that the communication time between the UAV and Control Station does not have a significant influence on the full runtime. Thus, is assumed in this experiment that the weather information already in the Control Station.

The second stage involves the use of the solution which has best fitness (found on previous stage) to evaluate the spraying on a target crop field. This selection criterion is used to evaluate the best solution in group of alternatives generated by replications. If all the replications converge in a group of solution with equal fitness, one of the solutions is randomly selected. The spraying is carried out by using the value selected as the routeChangingFactor parameter and the result is compared with the results without optimization, from [4] where it was employed a fixed value. It is worth noting that the environmental features are the same for all the experiments and is called Constant Light Wind in [4]. This environment has a constant wind at a speed of 10 Km/h. The crop field used has an area of 1500 m X 150 m and the area of the target crop field is 1000 m X 50 m. The WSN have twenty-two nodes spread across target crop field and the UAV initialize the spraying at a height of 20 meters above ground and a constant speed of 15 m/s. At intervals of ten seconds, the UAV makes requests to the WSN for obtain information about the result is compared with the results without optimization, from [4] where it was employed a fixed value. It is worth noting that the environmental features are the same for all the experiments and is called Constant Light Wind in [4]. This environment has a constant wind at a speed of 10 Km/h. The crop field used has an area of 1500 m X 150 m and the area of the target crop field is 1000 m X 50 m. The WSN have twenty-two nodes spread across target crop field and the UAV initialize the spraying at a height of 20 meters above ground and a constant speed of 15 m/s. At intervals of ten seconds, the UAV makes requests to the WSN for obtain information about the quality of the spraying. These experiments are replicated seventy times, to obtain a greater level of confidence for future statistical analysis. In the following subsection, the results are shown and discussed.

A. Optimization of routeChangingFactor

This subsection shows results employing the PSO-based algorithm described in SubSection III-B. Table I shows the results of the first stage. With exception of P320 setting, that has 96.77% of convergence rate, all other settings have a 100.00% convergence rate for the same value of fitness. Due to particular features of the problem, it is possible that a solutions group have the same fitness, since the difference

\(^2\)MiXiM project, http://mixim.sourceforge.net
between the values of the routeChangingFactor parameter may be low enough to have no significant influence on the spraying in specific situations.

For validate the results, was carried out several static analysis. We started using Shapiro Wilk method to verify the adequacy of normality and consequently to lead it to use parametric or non-parametric methods according to the results. Only 53.33% of solution groups have value higher than 0.05 (see Table I), therefore the hypothesis of normality is rejected considering a confidence level of 95%. Thus we use non-parametric tests in the subsequent analyzes.

The pairwise comparisons performed with Wilcoxon Rank Sum Test show\(^3\) that there is no significant difference between the solution groups. Additionally, the Friedman Rank Sum Test shows a p-value of 0.449, which also indicates that there is no significant difference between the solution groups. Both methods have a confidence level of 95%. Despite these results, the P3I20 setting has a lower convergence rate than the other settings. This difference in convergence rate is not indicated by the methods, because the non-converged solution represents 3.5% of all the solutions (i.e. a value less than the confidence level). Other important point contained in Table I, is the average time ± standard deviation (in seconds) for each setting of the algorithm. The spraying of a target crop field is carried out in \(\approx 66,667\) seconds (in accordance with the speed of the UAV) and as mentioned previously the runtime must be less than the time required for spraying a target crop field. Hence, the settings indicated for this application are P5I20, P10I20 and P3I50. These settings allow the optimization of the routeChangingFactor parameter with an appropriate time and a convergence rate of 100%.

In conducting an analysis of the position of the solutions in search space and visualizing the non-convergent solution, we have plotted all the solutions on the basis of their value in search space (see Fig. 4). It can be seen that the proposed algorithm is capable of finding a region in search space where values are appropriate for the routeChangingFactor parameter in specific climatic conditions. This region in search space is closely connected with features of the environment and tends not to be an appropriate region for the next crop field, since it is a dynamic environment. Thus, the algorithm should be run before starting the spraying in each crop field to reduce the risk of making a wrong decision. The non-converged solution originating from the P3I20 setting, is marked as "A" in Fig. 4. Despite its proximity, this solution does not belong to the region of appropriate solutions for the weather conditions reported by the WSN.

After analyzing the optimization of the routeChangingFactor parameter, we conducted experiments with the aim of evaluating the precision of the spraying by using solution indicated by the algorithm.

### B. Spraying on crop fields

This subsection shows the results of the second stage of the experiments. This involved analyzing and discussing the results of spraying in a crop field by using the solutions found by the PSO. In this stage, the experiments were conducted to support the assessment of the proposal, which entailed optimizing the routeChangingFactor parameter and ran parallel with the spraying of a crop field (in the first stage) and applied the results of the optimization to subsequent crop fields (the second stage). The results of spraying where optimization method were used, are compared with the results when there was no optimization [4].

Settings that did not involve the optimization of the parameter are described as follows: CL10, interval of ten seconds between each of the requests of weather information from UAV to WSN; CL30, interval of thirty seconds between each of the requests of weather information from UAV to WSN; CLNO does not change its route. These results came from [4].

The settings that use optimization parameter are described as follows: P5I20, where the algorithm uses five particles and twenty iterations; P10I20, where the algorithm uses ten particles and twenty iterations; P3I50, where the algorithm uses three particles and fifty iterations. These results are obtained by the PSO.

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\(^3\)The results of the Table are not included in this paper due to its size; however, it can be viewed in http://goo.gl/iYR93k.
routeChangingFactor = 3.000

routeChangingFactor = 6.000

routeChangingFactor = 7.164

Fig. 6. A heat map to represent the chemicals sprayed on the crop at the end of the simulation. The green colour represents no pesticide and red represents the most concentrated places. The thin black lines show the crop field that needs to have chemicals sprayed. (a) and (b) Evaluations with empirical values. (c) Evaluation with routeChangingFactor obtained by the PSO. We can see that when employing the routeChangingFactor obtained by the PSO we have the best adjusts in the UAV track, attempting to keep the chemicals within the boundary lane. It is worth to highlight that, as the simulation starts with wind, the UAV always starts the dispersion of the chemicals outside the boundary.

TABLE III. RESULTS OF WILCOXON RANK SUM TEST. THERE ARE EVIDENCES OF DIFFERENCE BETWEEN THE EVOLVED VALUES (P*) AND THE NON-EVOLVED VALUES (C*) FROM [4] (P-VALUES LESS THAN 0.05). THERE ARE NO EVIDENCES OF DIFFERENCE AMONG EVOLVED VALUES (P-VALUES GREATER THAN 0.05).

<table>
<thead>
<tr>
<th></th>
<th>CL10</th>
<th>CL30</th>
<th>CLNO</th>
<th>P3150</th>
<th>P5120</th>
</tr>
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<tbody>
<tr>
<td>CL30</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<tr>
<td>CLNO</td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td>0.52</td>
<td>0.79</td>
</tr>
<tr>
<td>P10I20</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.52</td>
</tr>
</tbody>
</table>

Fig. 5. Percent of pesticide spraying inside the target crop field. In this Boxplot, first three results come from [4]; last three results are obtained in this work by the proposed PSO.

Fig. 5 and Table II show the results of spraying on target crop field, comparing results from [4] with results of the proposed PSO. We can note that there is an increase in the area with correct application of pesticides when employ the evolved routeChangingFactor. The CL10 is a setting where there is less error than between the non-optimized settings. However, all the optimized settings surpass the precision usually achieved when spraying a target crop field. Fig. 6 presents a heat map to represent the chemicals sprayed on the crop at the end of the simulation.

The Shapiro Wilk method, employed to the statistical analysis, presents that the hypothesis of normality is rejected for one of the sets, when there is a confidence level of 95%. In view of this, we decided to use non-parametric tests in the subsequent analysis.

The pairwise comparisons were performed by means of the Wilcoxon Rank Sum Test (see Table III) and show that there are significant differences between the results that employ the methodology for optimization and the results when this methodology is not used. However, no significant differences were found when only the settings that use the optimization methodology were analyzed. Additionally, the Friedman Rank Sum Test is also applied to this data and shows a p-value of 0.000, which suggests that there are significant differences between the results shown in Fig. 5. As a result, it can be concluded that the use of optimization method for the routeChangingFactor parameter increases the efficiency of the control rules, and reduces the errors when spraying in a crop field.

V. CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

In this paper, we have investigated a methodology based on Particle Swarm Optimization for fine-tuning the control rule of the UAV (i.e. the mobile node of WSN). The aim of this proposal is to provide the optimization of the routeChangingFactor parameter and thus reduce the error when spraying pesticides on crop fields. In our experiments, we evaluated several settings for the optimization method. The results show that it is possible to obtain 100% of convergence for a group of values. Thus, the control rule can be adapted to different weather conditions without human intervention. Additionally,
the use of this methodology increases the precision of spraying pesticides so that \(\approx 86\%\) of the product is within a target crop field. The reason for this is that the optimization is performed during the application and thus the parameter can be adapted to the climatic conditions of each target crop field.

Presented results encourage other studies; among these we could cite the following: (i) investigation on optimization of more parameters (e.g. the height and speed of the UAV, the best starting-position for the next crop field, and the pressure of the spray system); (ii) investigation of different methodology for the fine-tuning control rules of UAV (e.g. Differential Evolution [16], Genetic Algorithms [17], [18], Hill-Climbing [19], NSGA-II [20]); (iii) an analysis of the feasibility of embedding the optimization methodology in UAV, leading to an autonomous architecture; (iv) an investigation of the methodologies required for planning route-aware of weather conditions.

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REFERENCES