Computers and Electronics in Agriculture 138 (2017) 210–223

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

An adaptive approach for UAV-based pesticide spraying in dynamic environments

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ARTICLE INFO

Article history:
Received 19 June 2016
Received in revised form 3 October 2016
Accepted 20 April 2017

Keywords:
Unmanned aerial vehicle
Unmanned helicopter
Evolutionary algorithms
Spraying pesticides
Wireless sensor network

ABSTRACT

Agricultural production has become a key factor for the stability of the world economy. The use of pesticides provides a more favorable environment for the crops in agricultural production. However, the uncontrolled and inappropriate use of pesticides affect the environment by polluting preserved areas and damaging ecosystems. In the precision agriculture literature, several authors have proposed solutions based on Unmanned Aerial Vehicles (UAVs) and Wireless Sensor Networks (WSNs) for developing spraying processes that are safer and more precise than the use of manned agricultural aircraft. However, the static configuration usually adopted in these proposals makes them inefficient in environments with changing weather conditions (e.g. sudden changes of wind speed and direction). To overcome this deficiency, this paper proposes a computer-based system that is able to autonomously adapt the UAV control rules, while keeping precise pesticide deposition on the target fields. Different versions of the proposal, with autonomously route adaptation metaheuristics based on Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing and Hill-Climbing for optimizing the intensity of route changes are evaluated in this study. Additionally, this study evaluates the use of a ground control station and an embedded hardware to run the route adaptation metaheuristics. Experimental results show that the proposed computer-based system approach with autonomous route change metaheuristics provides more precise changes in the UAV's flight route, with more accurate deposition of the pesticide and less environmental damage.

1. Introduction

Agriculture is one of the most important activities in the world economy, which has led to a large variety of studies with different goals, (Baggio, 2005; Daberkow and McBride, 2003; McBratney et al., 2005; Zhang and Kovacs, 2012; Zhang et al., 2002) including: (i) increasing crop productivity and quality, (ii) decreasing production costs and (iii) reducing environmental damage. The use of technology in agriculture can be characterized as Precision Agriculture (PA), as defined by Bongiovanni and Lowenberg-DeBoer (2004): the use of information technology in all agricultural production practices, whether to adapt the use of inputs to achieve the desired results in specific areas, or to monitor the results achieved in agricultural plantations. The demand for larger agricultural production is often reflected in the increase in the amount of pesticides used during cultivation (Faustino et al., 2015; Tsimbiri et al., 2015; Walander, 2015). These products are used for pest[1] control, and creation of a nearly ideal environment for the crop growth. Pimentel (2009) estimates that 3 million metric tons of pesticides are used annually worldwide, but about 40% of all crops are destroyed. One of the main reasons for this problem is the pesticides drift out of the targeted area. In addition to the environmental damage caused by pesticide drift to neighboring areas, prolonged contact with these products can cause various diseases to humans (Dhouib et al., 2016), such as cancer, complications in the respiratory system and neurological disorders.

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[1] Agriculture Department (2003) defines a pest in an agricultural context as any species, strain or biotope of plant, animal or pathogenic agent harmful to plants.

http://dx.doi.org/10.1016/j.compag.2017.04.011
0168-1699/

Pesticide spraying in agricultural crop fields is generally performed in two ways (Sammons et al., 2005), namely: (i) terrestrial and (ii) aerial. In the terrestrial way, which is largely based on ground vehicles, paths are needed within the crop field, as the vehicles require permanent contact with the ground during locomotion. The spraying system must be close the culture, which reduces the drift of pesticides to neighboring areas. Additionally, the terrestrial spraying is able to reach a higher accuracy of spraying distribution in favorable conditions. For example, it can attend particular demands of a specific culture. On the other hand, this spraying approach is usually slow and has contact with the culture, which decreases the production area and can damage healthy plants. In contrast, the aerial spraying allows faster spraying without the need for paths inside the crop field. However, the larger distance between the spraying system and the cultivated area increases pesticide drift to neighboring areas (Nádasi and Szabó, 2011).

The aircrafts usually employed for spraying are manned, therefore requiring the presence of a pilot during the spraying activity. If there is any failure, human or mechanical, during the flight that cause the aircraft fall, can severely harm the pilot. It is important to observe that most of the aerial spraying occur close to the soil (around 3 meters high), which increases the chances of accidents. An alternative to reduce the risk of fatal accidents is to use unmanned (autonomous or remote controlled) aircrafts, like UAVs.

Several studies on the use of tele-operated UAVs to spray pesticides can be found in the PA scientific literature (Bae and Koo, 2013; Huang et al., 2009). However, the use of full or semi autonomous UAVs to perform the spraying operation still has not efficiently addressed the problem of how to autonomously find control parameters able to continuously adapt the flight route of an UAV spraying pesticides in a highly dynamic environment. In the (semi) autonomous operation, an UAV must be able to adjust its flight route accordingly to its velocity and operation height, the velocity and orientation of the wind, and the type of chemical being sprayed (as it might change the size of the droplets).

In this paper, the authors investigate the use of four metaheuristics, two of them population based, to obtain semi-optimal flight control parameter values. The authors believe that these metaheuristics can efficiently search the solution space to find good parameter values for the UAV control rules, increase the accuracy of the spraying process.

Hence, looking to obtain higher accuracy in pesticide spraying and reduce the risk of human exposure to these products, this paper proposes a system called **AdEn** (**Ad**aptation to the **En**vironment) to autonomously adjust the control rules of UAVs spraying operation taking into account possible changes in weather conditions. In the proposed system, four metaheuristics are evaluated regarding their performance in the optimization of the control rules, namely: (i) Genetic Algorithms, (ii) Particle Swarm Optimization, (iii) Simulated Annealing, and (iv) Hill-Climbing. Afterwards, this study will compare the performance obtained in pesticide spraying by using AdEn with the same approach adopted in the literature for the optimization phase (i.e. replacing the metaheuristics by a specific empirical setting of the PSO).

This paper is structured as follows: Section 2 described the main aspects of related works. Next, Section 3 briefly presents the proposed approach for UAVs-based pesticide spraying. In Section 4 there is a detailed description of each component of the approach proposed in this paper. The experimental evaluation process used to assess the performance of the proposed approach is described in Section 5. Finally, a summary of the main conclusions and suggestions for future works are presented in Section 6.

2. Studies of accurate pesticide spraying

Given the benefits derived from pest control with the use of pesticides, several studies have been conducted on how to improve spraying accuracy (Bae and Koo, 2013; Huang et al., 2009; Nádasi and Szabó, 2011; Pérez-Ruiz et al., 2015; Sammons et al., 2005). According to the approach adopted, these studies can be divided into two main groups: (i) terrestrial and (ii) aerial. The main difference between the two approaches is the vehicle used for transporting the spraying system. In the terrestrial approach, the vehicles remain in contact with the ground throughout their route (e.g. tractors). Aerial models use aircrafts with an attached spraying system to fly over the area of cultivation and spray the pesticide on the plantation.

2.1. Terrestrial spraying

An alternative usually adopted for controlling the cultivation and the conditions required for crop growth is the use of greenhouses. These structures can provide a controlled environment whose conditions are closer to the optimum required for production. However, the controlled environment is considered to be harmful to the health of farm workers due to the extreme conditions they are subjected to, like high temperature and humidity (Sammons et al., 2005). Because of the small space between planting trails, pest control in these environments is often performed with manual spraying equipment. As a result, this activity becomes susceptible to human error and can lead to an unbalanced deposition of pesticide. In addition, despite the use of safety equipment, the workers are exposed to the sprayed products. To overcome these hazards and reduce the impact of pesticides on workers' health, Sammons et al. (2005) propose the use of an autonomous robot for pesticide spraying inside greenhouses. For such, a land vehicle uses an auxiliary structure that guides the route of the robot, similar to the way rails are used by trains. This auxiliary structure is fixed between the planting tracks. When the vehicle reaches the end of an alley, a professional enters the greenhouse and positions the vehicle in the next alley. This procedure is continued until all the tracks are covered. The results reported by the authors show that this solution provides a homogeneous and consistent coverage, with an overlapping margin of 10–20%. Despite the good results, this solution is not completely autonomous. Thus, workers are still exposed to the sprayed product when they enter the greenhouse to re-position the vehicle. Furthermore, this solution has poor scalability and high costs due to its dependence on the rails.

Another form of production is the cultivation in open field crops. This allows extensive crop fields and, hence, large scale production. On the other hand, this alternative is the most expensive agricultural production, since it requires a larger amount of machinery and more workers to carry out activities in a timely manner. However, there are limits to the working hours and productivity of agricultural workers, preventing accomplishment of the required tasks the over long periods of time. As a means of overcoming the limitation of working hours and increasing the safety of agricultural work, several studies have investigated the use of autonomous vehicles (Pérez-Ruiz et al., 2015). This approach has achieved good results and has been a more efficient alternative than manned vehicles for agricultural production.

The survey by Pérez-Ruiz et al. (2015) highlighted the considerable progress made in this context, which includes: (i) autonomous tractors, (ii) communication systems and the Global Positioning System, (iii) a design for an intelligent spray bar, (iv) thermal and mechanical systems to control weeds, and (v) an air-blast sprayer. The good preliminary results obtained in these areas show a promising future for the development and use of autonomous vehicles for precision agriculture. Despite making significant advances, land vehicles (whether autonomous or manned) have to use routes within the plantation and this reduces the production area. Moreover, deviations in the route already established can damage healthy plants and further reduce productivity, since these machines enter the crop field several times during the production phase.

2.2. Aerial spraying

Aircrafts equipped with a spraying system are each time more used as an alternative to land vehicles for spraying pesticides on crop fields. This approach does not require routes within the plantation, and, therefore, does not affect healthy plants if there is deviation in their flight paths. In manned vehicles, the pilot has several equipments to carry out cross-checking of information during the flight (Nádasi and Szabó, 2011). To ensure the accuracy of the information provided to pilots, Nádasi and Szabó (2011) describe the concepts necessary for the deployment of Microelectro-MEchanical System (MEMS)-based Inertial Measurement Units (IMU) navigation systems. The main objective of this system is to enable the pilot to know the aircraft geographical position more accurately than when other alternatives, such as Global Position System (GPS), are used. However, this study does not describe the implementation and the results achieved by the proposed system. Regardless of how the described system is validated, it should be noted that the quality of aerial spraying of pesticides depends largely on the experience and skills of the pilot (Nádasi and Szabó, 2011). This is true because, even when information is available, the pilot is still responsible for making decisions during the flight to optimize pesticide spraying.

Regarding the use of unmanned aircraft, sprayed pesticides using fixed-wing aircraft (for example, single-engine aircraft) may cause drift to nearby areas that should not receive the pesticides (e.g. environmental preservation areas) (Antuniassi, 2015). While it is common to use buffer zones to mitigate the damage caused by drift, this hazard can occur 5 to 32 km downwind (Pimentel, 1995), which far exceeds the range of the buffer zones. The use of UAV rotorcraft has been investigated as a safe and high-precision alternative for spraying pesticides (Bae and Koo, 2013; Faiçal et al., 2014a,b; Huang et al., 2009). This occurs because these aircrafts have no pilots on board and their downwash effect[2] is directed to the plantation (Hanson, 2008). The downwash can act as a protective tunnel for pesticide spraying. Taking advantage of this effect, some studies use a spray system attached to an unmanned helicopter for the application of pesticides in the crop field (as proposed by Huang et al. (2009)).

The low-volume spraying system proposed by Huang et al. (2009) has four main components: (i) a metal bar with 2, 3 or 4 nozzles, (ii) a reservoir that stores the product to be sprayed (iii) a pressure pump and (iv) an engine for controlling the operation of the system. This system uses Pulse Width Modulation (PWM) to regulate the pump inlet pressure, which has a linear relationship with the spray flow. Thus, the number and type of fixed nozzles in the metal bar and the PWM setting must be in accordance with specific characteristics required for the spraying process. The system may be loaded with up to 5 kg of pesticide, which is sufficient to spray approximately 14 ha. However, this system was designed and developed to be coupled with the UAV SR200, produced by Rotomotion.[3] This UAV has a combustion engine, which measures 3 m in diameter (for the main propeller) and is able to carry up to 22.7 kg of load. Even though this spraying system is integrated into the UAV control system, which allows it to be adjusted to its geographical position, the accuracy and uniformity of the pesticide deposition have not been evaluated. The uniformity of deposition for unmanned helicopters was analyzed by Bae and Koo (2013), which describes and offers a way of improving the UAV structure to allow a uniform deposition. However, the accuracy of pesticide deposition has not been evaluated in different flight configurations and in dynamic weather conditions.

2.3. Different approaches of spraying

It must be observed that the terrestrial approach employs vehicles that use roads within the plantation to spray the pesticide throughout the cultivation, which can result in soil compaction. The aerial approach, on the other hand, does not require pathways within the plantation and enables the pesticide to be sprayed from a larger distance (when compared to the terrestrial approach). In the latter approach, there is an increase in the drift of pesticides to neighboring areas (Antuniassi, 2015). The drift of pesticides into the environment can cause serious harmful effects on flora and fauna, by contaminating preservation areas and destroying wildlife. Moreover, even though the pesticide is deposited within the crop field, weather conditions can spread pesticides to other areas, expose agricultural workers and the population (end-consumers) to inappropriate and prolonged contact with the products, causing serious health damages (Dhouib et al., 2016).

An architecture based on UAV and wireless sensor networks has been investigated and proposed to reduce the risks of pesticide drifts outside of the target area and to avoid overlapping sprayed areas, by ensuring more precise deposition of the sprayed products. This approach can reduce the amount of pesticides used in agricultural production, without damaging the crop yield.

3. Proposed approach for UAV and WSN for aerial pesticide spraying

3.1. Overview and problem statement

Previous works have investigated the use of UAVs to improve the quality and amount of crop production in several agricultural activities (Huang et al., 2009; Valente et al., 2011). One of the most important of these activities is pesticide spraying for pest control. This activity has had a great influence on the quality and yield of cultivated crops, since pesticides are used to create a near-optimum environment and their inappropriate use can cause environmental and economic damage and lead to health problems. Fig. 1 shows the problem addressed in this paper, resulting from inaccurate spraying pesticides. The weather conditions in the crop field cause pesticide to drift out of the target area. This results in extensive damage, such as overlapping pesticides, non sprayed regions and contamination of rivers, forests and inhabited areas.

3.2. First attempt to solve the problem

In order to deal with the previously mentioned problem, Faiçal et al. (2014b) proposed an architecture based on UAV and WSN for aerial spraying of pesticides in agricultural fields. This architecture enables an UAV to adjust its route to the concentration of deposited pesticides. This information is obtained through a WSN deployed in a matrix format covering the crops in the field. According to experimental results, this architecture makes the spraying process more precise and safer than previous approaches commonly employed for aerial spraying, where a manned aircraft is

[2] In aeronautics, the term *Downwash* means changing the direction of air diverted by the action of the aerodynamic airfoil, wing or helicopter engine in motion, as part of the lifting process (Crane, 2012).

[3] http://www.rotomotion.com/

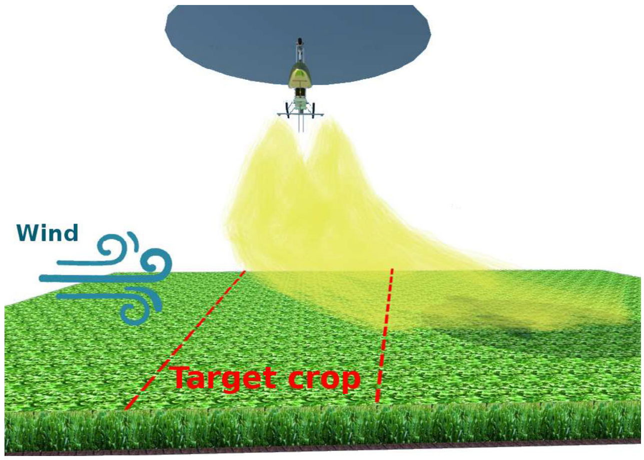


Fig. 1. Problem statement: drift of pesticides from the target crop field in dynamic environments (e.g. a change of wind speed and direction).

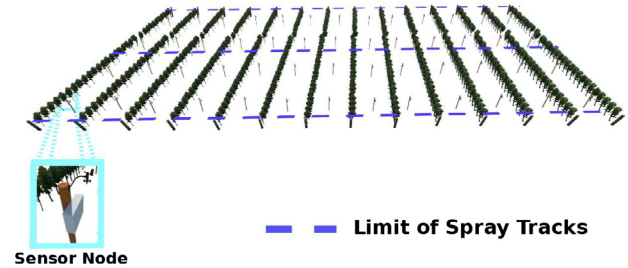
used without the feedback of information about pesticide deposition.

The application scenario exploited by Faiçal et al. (2014b) is shown in Fig. 2. In this figure, the UAV is a spraying element equipped with a programmable trigger system. The control system divides the crop field into parallel spraying tracks and defines a flight path so the UAV can fly over the center of these tracks when spraying pesticide (see Fig. 2(a)). The used architecture allows the spraying process to be interrupted at any time for refueling or pesticide recharge, and resumed at the exact same point. Each track is positioned in a way that pairs of sensors can be placed within the limits of its width. Thus, as the track is covered during the spraying process, the UAV communicates with the sensors in 10 s intervals (see Fig. 2(b)). During the communication, the sensor nodes send information to the UAV control system, such as the concentration of pesticides and weather conditions (wind speed and direction). If the sensors report an imbalance in the pesticide deposition that exceeds a fixed threshold, the UAV control system adjusts the flight path to provide a uniform deposition.

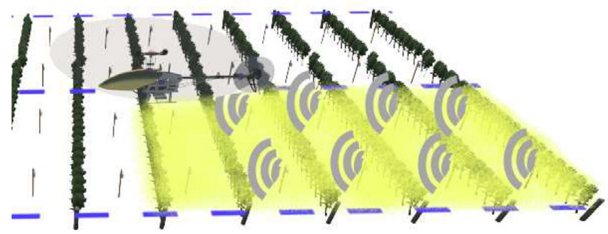
The sensor nodes have a specific hardware to capture information used by the UAV (wind speed and direction and pesticide deposition). To obtain wind-related information, an anemometer can be installed above the plantation height. For the pesticide deposition, a specific chemical sensor may be needed to detect the presence of the active substance used in the pesticide. This is possible because when the pulverized product approaches the crop, the chemical sensors identify the presence of a specific active substance and react to it. It is important to observe that the calibration of the chemical sensors depends on the model and which active substance is used; the calibration must, therefore, be performed in the actual deployment of WSN.

In addition to the WSN operation, the arrangement of sensor nodes (in matrix format) allows the UAV's on-board computer to compare information from two neighboring nodes. This is possible because the definition of the position of the nodes takes into account the range of spraying. Thus, the width of the spray ranges covers two neighboring nodes sensors (in parallel). Finally, regarding WSN architecture, the UAV is considered a mobile node and it is responsible for requesting information from specific fixed sensors (according to their position in the crop field) at periodic time intervals.

The route is corrected by using the route change policy based on feedback received from the WSN, which is to move the UAV in the opposite wind direction. Hence, if for example, the original route of the UAV is in the center of the spray track and there is a wind



(a) The target crop field is divided into spraying tracks to guide the flight path of the UAV. Each track is defined in order to allow pairs of sensor nodes to be covered in its width. These spray tracks are made possible by the WSN that is deployed within the plantation and have a matrix format.



(b) The UAV flies over each spray track, which is defined for the flight path while the pesticides are being sprayed. During the spraying process, the UAV checks the last covered sensors to find out the concentration of pesticide deposited, together with the weather conditions. If the response to the query indicates inadequate concentration (higher or lower than a predetermined threshold), the UAV adjusts its route to balance the concentration in the target crop.

Fig. 2. Standard operation of the proposed architecture by Faiçal et al. (2014b).

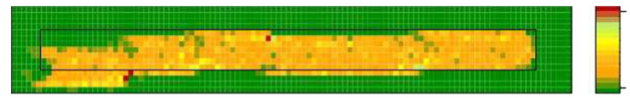
blowing toward the right of the track which is unbalancing the deposition of the pesticide, the policy moves the UAV in the opposite direction to the wind (positioning its route to the left). By this means, although there is drift, the pesticide deposition is balanced in the target track (Faiçal et al., 2014b).

In practice, the route correction policy uses a simple equation to define the time taken by the aircraft to update its route moving its direction in response to wind changes by an angle of 45 degrees (Faiçal et al., 2014b). Finished the direction change, the UAV adapts its route to fly in parallel with the spray track. For such, the route is gradually corrected until the pairs of sensor nodes show a balanced deposition. The *routeChangingFactor* parameter defines the intensity of the route correction, which allows abrupt changes (a longer time for route correction) or mild changes (a shorter time for route correction).

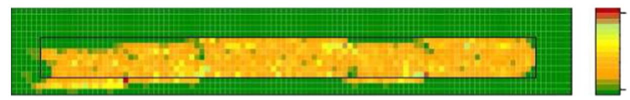
3.3. Discussion of results

The described architecture was experimentally evaluated in different weather conditions. The results from Faiçal et al. (2014b) show that the proposed architecture improved the pesticide spraying accuracy, when compared with a traditional model, which does not allow route adjustments. Despite the good results, it should be noted that the correction of the UAV's course is of the same intensity throughout the whole spraying activity, regardless of the weather in the plantation area. This occurs because the *routeChangingFactor* parameter is set before the flight and remains unchanged. This static behavior is inefficient in dynamic environments, where weather conditions can vary. Thus, an initially good route intensity correction can become bad when the weather condition changes..

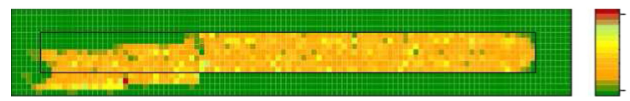
This drawback was partly investigated by Faiçal et al. (2014a), which resulted in the proposal and evaluation of new methods, based on Particle Swarm Optimization (PSO), to optimize the *routeChangingFactor* according to the current weather conditions. According to the experimental results obtained in this study, the use of an adjusted *routeChangingFactor* parameter for weather conditions allows the UAV to make a better route correction. Besides, the UAV was able to spray pesticides with a higher degree of accuracy. Fig. 3 shows that adapting the route correction intensity provides a more accurate measurement. However, the study in (Faiçal et al., 2014a) only considers one type of weather condition, Constant Light Wind (CLW) – which refers to a wind speed of 10 km/h. It is not possible to infer that different weather conditions benefit from the same adjusted *routeChangingFactor* parameter, since this was not evaluated. In addition, Faiçal et al. (2014a) only investigate the use of a metaheuristic to optimize the *routeChangingFactor* parameter for the weather condition; it did not study it as a complete system. To overcome the previously mentioned limitations, this paper proposes the AdEn system, a complete system to optimize UAV flight trajectories where adjustments are made in response to changes in the weather. It must be observed that AdEn is evaluated in different weather conditions and with different computing platforms.



(a) *routeChangingFactor* = 3.000



(b) *routeChangingFactor* = 6.000



(c) *routeChangingFactor* = 7.164

Fig. 3. As shown in Faiçal et al. (2014a), these heat maps represent the chemicals sprayed on the crop. The green area illustrates the plantation and the red area illustrates the concentration of the pesticide. The thin black lines show the crop field that needs to be sprayed by pesticides. (a) and (b) Evaluations with empirical values. (c) Evaluation with *routeChangingFactor* obtained by the PSO. It can be seen that the best adjustments in the UAV track are achieved when employing the *routeChangingFactor* obtained by the metaheuristic. It should be observed that when the simulation starts with wind, the UAV always starts the dispersion of the chemicals outside the boundary. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. The AdEn system – Adaptation to the Environment

The **Ad**aptation to the **En**vironment system (AdEn) is composed by two main components: (i) **Coll**ector and **Act**uating (CollAct), and (ii) **OPTI**mization **C**ore (OPTIC). The first component collects weather information and updates the settings of the UAV control system. The second component is responsible for adapting the *routeChangingFactor* parameter to changes in the weather conditions. It defines the required route correction.

Fig. 4 displays the main features of the AdEn system and the computing platforms where they run, including their internal interactions. CollAct runs on a computer system embedded in the UAV, while OPTIC runs on the Aircraft Control Station. It is worth pointing out that both components (CollAct and OPTIC) run above the Operating System (OS) and in parallel with other processes in their respective computing platforms. The AdEn system is designed to interact with the UAV route correction system (using CollAct to update the flight configurations), making it less dependent on other processes and libraries.

CollAct uses an existing communication link with the WSN to collect weather information about the crop field being sprayed. This information is transmitted to the OPTIC element via a wireless communication link that exists between the UAV and the Control Station. At this time, the OPTIC element is executed and a new value for the *routeChangingFactor* parameter is transmitted back to CollAct, which updates the value of the rule-based parameter adjustment route of the aircraft. The settings are loaded whenever the UAV starts to spray a new subarea.

As previously mentioned, AdEN uses a track structure to guide the UAV's flight path. AdEN creates sequential sub-areas (regions of interest), forming logical divisions at the spray tracks This division defines the regions that will have sensor nodes, which can be queried for weather information and where each optimized value (adjusted intensity) is employed. In the spraying of each track, while a sub-area is sprayed (with the standard operation – spraying and course correction with an intensity set at the beginning of the sub-area), the intensity adjustment (AdEn system) uses weather information from the next sub-area. This process runs sequentially for each sub-area of the track until the end of the spraying process. The spraying of a crop field is concluded after all the tracks are sprayed by the UAV. Fig. 5 shows the logical divisions of the spray tracks, which create sub-areas of interest, and the rest of the crop field in tracks (those without divisions to make it easier to understand the process).

The *routeChangingFactor* parameter is updated during the transition between the current sprayed sub-area and the subsequent sub-area. A procedure based on space-time between the UAV and the crop field was used by the AdEN system to synchronize the UAV activities. Fig. 6 shows the sequence of steps executed by the AdEn system while spraying a track. These steps are performed in parallel with the operation of the architecture proposed by Faiçal et al. (2014b). Thus, the AdEn system runs in parallel with the original architecture, by adapting its route adjustment policy to environmental weather conditions without the route correction system being aware of this process.

Hence, the activities of the proposed system can be summarized as follows: (i) collecting the weather information about the next target sub-area; (ii) optimizing the parameter for the weather and; (iii) updating the parameter value of the *routeChangingFactor* when setting the route adjustment policy. As shown in Fig. 6, the three activities are carried out sequentially to obtain a new parameter value of the *routeChangingFactor* which can be used in the next sub-area. However, in the first sub-area of the spray track, AdEn performs all the activities before starting the spraying. In this case, the UAV control system receives a signal to wait for the *routeChangingFactor* parameter to be updated.

4.1. Querying weather information and updating the route adjustment policy

Querying the sensor nodes located in the next sub-area is performed throughout the wireless communication between UAV and WSN. The querying process executed by the AdEn system for nodes in the WSN, is performed by giving information of the geographic coordinates that define the next target sub-area. Since the sensor nodes have information about their locations, the ones that are deployed within the next sub-area are able to respond to the requests sent by AdEn. Response messages sent by the sensor nodes are destined to the AdEn embedded system in the UAV and have the weather information of the sub-area. This informa-

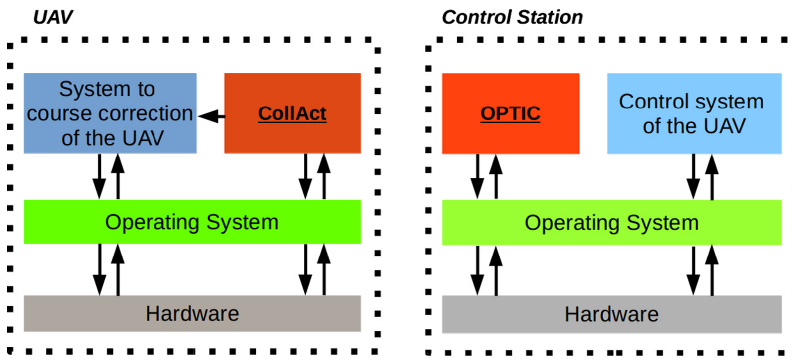


Fig. 4. Elements of the AdEn system (CollAct and OPTIC) in their respective computing platforms, together with the components of the architecture proposed by Faiçal et al. (2014b).

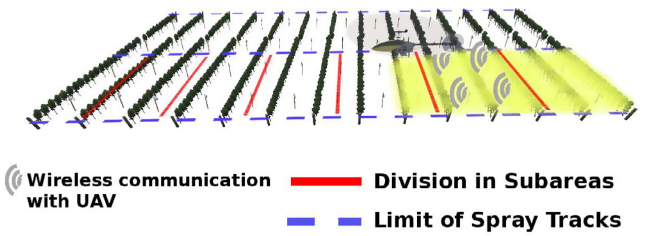


Fig. 5. The spray track is divided into sub-areas of interest, which define the node sensors that will be queried for weather information and the area where each intensity is used. The current sprayed area is highlighted in the whole area to be sprayed. The wireless communication symbols represent the queries about the deposition of the pesticide. Although the query about the weather, used to adjust the intensity of the correction, is not shown (to keep the picture more clear), it is performed with the sensor nodes in the next sub-area to be sprayed.

tion might be the average of the previously acquired sensor data. On receiving these messages, the AdEn system calculates the average weather condition of the sub-area and transmits this information to the OPTIC element in the Control Station.

After sending the information to the OPTIC element, CollAct remains on standby. This state is changed when it receives a message from OPTIC with a new value for the *routeChangingFactor* parameter or in case of a timeout, which can be set according to how long the UAV will take to arrive at the end of the current sub-area. In the event of a failure that prevents a message sent by the OPTIC element (e.g. signal loss from the telemetry system) from being received, two backup settings can be used, (i) keep the last received value and use it for the next sub-areas until the problem has been fixed or (ii) set a default value to be used as a *routeChangingFactor* parameter until a message from the OPTIC element is received.

Finally, the adaptation ends when the UAV reaches the end of the target sub-area and CollAct updates the value of the *routeChangingFactor* parameter in the UAV route correction system. This value is used in the next sub-area to be sprayed, while another intensity adjustment cycle is executed in the next sub-area.

4.2. Optimization of the routeChangingFactor parameter to weather conditions

As previously described, the optimization of the intensity of route correction is carried out by the OPTIC element, which runs in the control station while the previous sub-area was being sprayed. Although the spraying architecture executes the course correction autonomously, the Control Station enables a human operator to take control of the aircraft at any time. Moreover, as previously explained, the control station can also be used as an additional computing platform for processing the decision-making of the UAV control system.

In order to achieve an accurate global spraying, the evaluation of the pulverization accuracy was divided into several sub-problems, each one concerned with the evaluation of the accuracy of the deposition into a sub-area. The combination of adjustments performed in each sub-area allows a better solution to the large (global) problem, which is the adjustment of the intensity of route

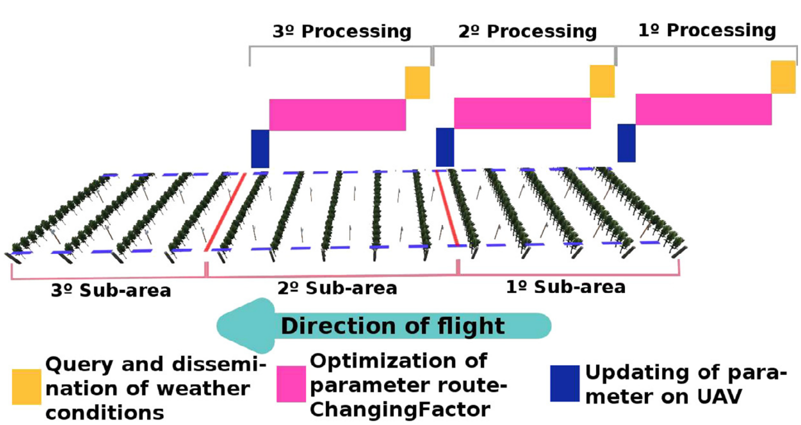


Fig. 6. Spatio-temporal representation of actions taken by AdEn. It is important to observe that the best route correction intensity found is used in the following sub-area, in which the processing steps are executed (e.g.. the result of the 1st processing is used in the 1st sub-area). Initially, the CollAct element queries the sensors from the next sub-area by asking about the weather. It then sends this information to the OPTIC element in the Control Station. After the optimization of the *routeChangingFactor* parameter, the best value is transmitted back to CollAct (in the UAV). Finally, CollAct updates the route adjustment policy with the received value.

correction during the complete spraying of the agricultural field. Even if the pulverization in each sub-area is highly accurate, it is still possible to achieve a globally accurate spraying. The use of sub-areas to evaluate the spraying accuracy can reduce the overall computational cost, making the proposed solution computationally efficient during the online processing.

The optimization problem addressed by the AdEn system (specifically the OPTIC element) is to find non-optimal values of intensity to adjust the route of the UAV in order to minimize the function:

$$Fitness = \sum \vartheta - \sum v$$

where $\sum \vartheta$ is the sum of all the pesticide sprayed and $\sum v$ is the sum of pesticide deposited in the correct region. Thus, this function calculates the amount of pesticide deposited outside the target area. Consequently, the optimal route correction intensity is the one that minimize this objective function (the lower the value, the better the fitness).

In practice, the intensity of the route adjustment is a value inside a search space that allows for different settings (e.g. abrupt, smooth and moderate). The search space is defined by:

$$routeChangingFactor = \{x \in \mathbb{R} | 1.0 \leqslant x \leqslant 10.0\}$$

Fig. 7 shows the operations of OPTIC in the Control Station, with the interactions between its components (Core, Computer Model of the Environment and Metaheuristic). Initially, the Core receives weather information collected by CollAct through the communication link between the Control Station and the UAV (Step 1). Next, it incorporates this information in a computer model that is specifically designed for the given environment (Step 2) and runs a metaheuristic (Step 3). The metaheuristic evaluates various solutions in the computational model (Step 4) to find a route correction intensity value that is close to ideal. The best value found (non-optimal) by the metaheuristic is sent to the Core (Step 5), which sends the value to CollAct (Step 6) by the same communication link used to receive the weather information.

The computer model used by OPTIC was first described in Faiçal et al. (2014b), where it was used to evaluate the accuracy of the platform for route adjustment. However, this model was adapted to run without the occurrence of stochastic interference between the evaluations carried out during the execution of the metaheuristic. This behavior allows a fair comparison between the tested intensities. Yet, the computational model used considers the pesticide spraying architecture without the AdEn system, as this is executed transparently and in parallel with the original architecture.

OMNeT++[4] was used to implement the computational model. This software is a simulator of discrete events based on the C++ language to model networks, multiprocessors and other distributed and parallel systems (Varga, 2010). *OMNeT++* can be used to model several types of networks (for example, networks of queues, wireless and peer-to-peer types) (Wehrle and Mesut Günes, 2005). Because of its generic design, *OMNeT++* has several frameworks established for specific networks, such as *Mixim*[5] 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 (Köpke et al., 2008) layer.

Additionally, the computational model used allows the use of different dispersion models to calculate the physical process of transport and transformation of the product until it reaches the culture. This modular structure allows assessments to be carried out continuously to make it increasingly accurate against the real process without losing deployments ever undertaken. In the current implementation, the Chemical Dispersion Module calculates the fall of the chemical through the position and time of fall of each drop. This chemical dispersion is based on a simplified model of pollutants, which consider (1) the initial velocity vector of the particle, when sprayed; (2) the wind speed vector; and (3) gravity. Calculations are performed for all instants of time for each drop of the pulverized product until reaching the culture (Faiçal et al., 2014b). This dispersion model, although simple, is satisfactory at this stage because the goal is to optimize UAV route. However, it is important to note that the dispersion model can be exchanged for more accurate models according to future research needs.

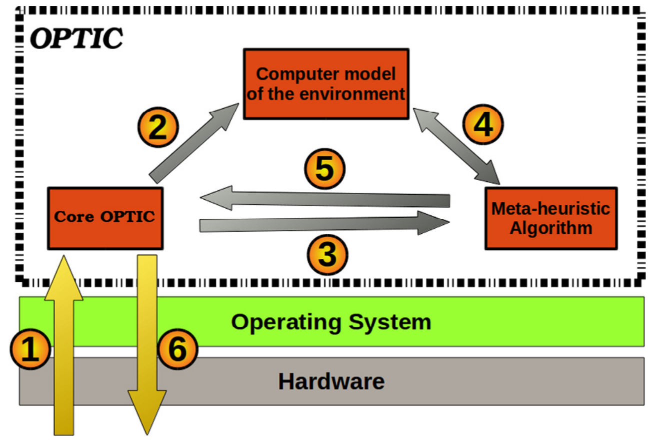


Fig. 7. Execution of OPTIC element in the Control Station to optimize the *routeChangingFactor* parameter for weather measured by the WSN.

Each solution found by the metaheuristic used is evaluating according to the quality its associated route. The quality of a solution is inversely proportional to the amount of pesticide deposited outside the target region. Thus, the lower the amount of pesticide outside the target area, the better the quality of the route. A computational model uses an objective function to evaluate the intensity of route changes and return the best value found for the current weather. The following sections describe the methodology used to assess the effectiveness of the AdEn system.

5. Setting the metaheuristic and evaluating the AdEn system

The optimization of the *routeChangingFactor* parameter is essential for the adaptation of the route correction of the original architecture (proposed by Faiçal et al., 2014b) to the weather conditions. Several metaheuristic were investigated to select the most efficient for this task. The progress made in the use of the route correction intensity adapted to the weather conditions in different scenarios was also evaluated. Due to the short time available for transmitting weather information (Faiçal et al., 2014b) and the need to concentrate on the behavior of the evaluated metaheuristics, it is assumed that the weather information was already incorporated in the environmental computer model. The main focus of this article is on assessing the performance of the metaheuristics. This scenario is similar to that employed in Faiçal et al. (2014a), used here as a benchmark to show the progress achieved in this study.

The experiments are divided into three complementary phases. Initially, Grid Search is used to tune the main parameters of the metaheuristic (see Table 2). Grid search is used to improve the convergence rate of the metaheuristic. In the second phase, the best settings for each metaheuristic is executed on an embedded computing platform. The performance of the metaheuristics in a UAV equipped with embedded hardware is assesses and compared with

[4] OMNeT++ Network Simulation Framework, http://www.omnetpp.org.
[5] MiXiM project, http://mixim.sourceforge.net

the performance achieved by the same metaheuristics in a computer platform used in the Control Station. Finally, the accuracy of the spraying is evaluated to assess if these metaheuristics can be used in different weather conditions (winds of 10 and 20 km/h).

The following metaheuristics were investigated for this study: (**i**) Particle Swarm Optimization – PSO (Eberhart et al., 2001; Engelbrecht, 2006; Faiçal et al., 2014a); (**ii**) Genetic Algorithm – GA (Faiçal et al., 2014; Holland John, 1975); (**iii**) Hill Climbing with the Next-Ascent strategy – NAHC (Forrest and Mitchell, 1993; Muhlenbein, 1991); and (**iv**) Simulated Annealing – SA (Kirkpatrick and Vecchi, 1983). These metaheuristics are widely used in the optimization literature with good results in several applications. It must be emphasized that the implementation of the metaheuristics was based on the article where they were published and their source codes are available at http://goo.gl/tT6qsf. Additional information on the flight conditions of the UAV and about the environment for the development and evaluation of AdEn system can be seen in Table 1.

The main results illustrating the progress made in this work are described next. The results obtained by the GA are highlighted, because, together with the PSO results, they were the best results achieved. PSO was used in the experiments reported in Faiçal et al. (2014a). It is important to notice that two PSO configurations were used in the experiments, (**i**) exactly as proposed in our previous work and; (**ii**) with the same implementation, but modified according to improvements seen in the experiments. All the results are available in https://goo.gl/fiSlcQ.

5.1. Evaluation of metaheuristics used for the optimization of the routeChangingFactor parameter

Metaheuristics have been successfully employed in combinatorial problems to efficiently find non-optimal solutions. The parameter values used in these metaheuristics can influence the quality of the solutions found. The Grid Search Technique is used to reduce the impact of an empirical configuration, searching for parameter values able to improve the performance of the metaheuristics investigated. Table 2 shows the parameters that need to be configured and the limits of the search space covered by Grid Search.

For all metaheuristics, the grid starts with the same uniform positions in the search space. The configuration (indicated by one of the vertices) with the best performance in each cycle, defines the grid's center vertex in the next evaluation cycle. The distance between each pair of vertices is linearly decremented for each evaluation cycle, starting with a distance of thirty units and ending with a distance of five units. Fig. 8 illustrates the execution of the Grid Search. Each assessment cycle of the Grid Search is performed as follows: initially, the settings specified by the vertices are incorporated in the configuration metaheuristic. Next, the metaheuristic performs an optimization of the *routeChangingFactor* parameter ten times using the computational model and assuming an environment with a constant wind of 20 km/h. After 10 runs for the nine settings indicated by the grid, a few statistics are calculated: (**i**) the Convergence Rate for the lowest overall Fitness (considered in this study to be the lowest Fitness found for all the settings in the evaluation cycle), (**ii**) the Mean Execution Time of the metaheuristic for each configuration, and (**iii**) the Total Number of Evaluations provided by the configuration. This information is used to guide the movement of the technique in the search space, named here "search heuristics". Thus, the search heuristic uses the previously described information to indicate a setting that can provide the maximum possible number of ratings for the metaheuristic without exceeding the maximum execution time (the spraying time of a target subarea) and a convergence rate for the best global Fitness larger than 80%.

Table 1
The configuration adopted was defined to provide a fair comparison between the evaluated metaheuristics and the solution in the previous work, when the AdEn system was developed. It must be observed that the Wind Speed parameter had a value of 20 km/h in the proposed system. Now two values (10 and 20 km/h) are used in the evaluation. The UAV's flight height was defined based on related works (Ozeki, 2011; Salvador, 2011).

Element	Information	Value
UAV	Horizontal Position	Middle
UAV	Height	20 m
UAV	Speed	15 m/s
UAV	Direction	East
UAV	Acceleration	0 m/s^2
UAV and WSN	Time between communication	10 s
Crop Field	Target Sub-area Dimension	1000 m $\times$ 50 m
Weather	Wind Speed	10 and 20 km/h
Weather	Wind Direction	North

Table 2
Parameters and limits of the search space used by the Grid Search for configuring the metaheuristics.

Metaheuristic	Parameters	Lower Limit	Upper Limit
GA	Individuals and Generations	1	120
PSO	Particles and Interactions	1	120
HC	Mutations and Jumps	1	120
SA	Disorders and Iterations	1	120

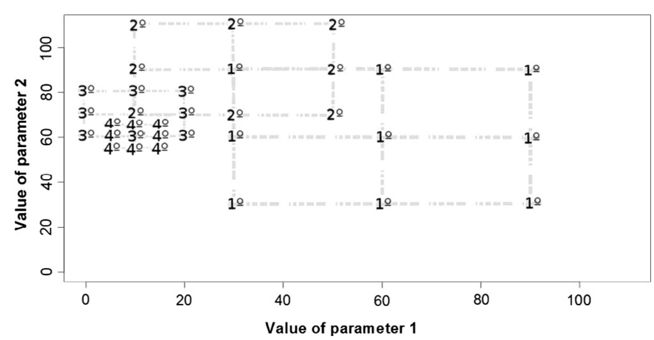


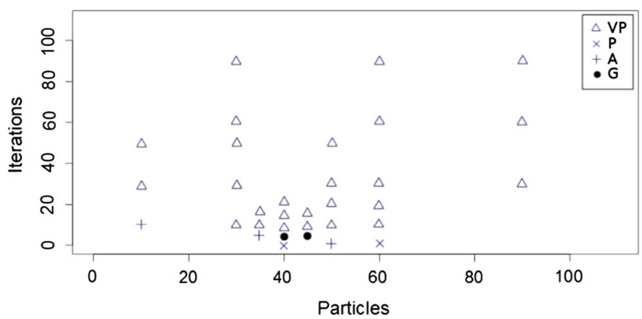
Fig. 8. Scanning in the search space made by the Grid Search to define the configuration of each metaheuristic. An important feature of this implementation of the Grid Search is the convergence and concentration of assessments in a promising region of the search space. The movement of Grid Search is represented by numbered grids listed in the order in which the cycle was analyzed (for example, 1° for the first cycle). The grid formed around a vertex with previous values indicates that this setting resulted in the best performance of the previous cycle.

A virtual computing platform was used to improve the management and control during the experiments. This computing platform has 1 single-core processor at 2.27 GHz, 1 GB of RAM, 10 GB Hard Disk and Ubutu 9.04 operating system. This is the minimum required for the execution of the OPTIC element in the AdEn system. The best configuration found in the evaluation cycle (among the nine tested) is seen as the central vertex of the grid in the next evaluation cycle. In the last evaluation cycle, the best vertex is the final configuration that will be chosen.

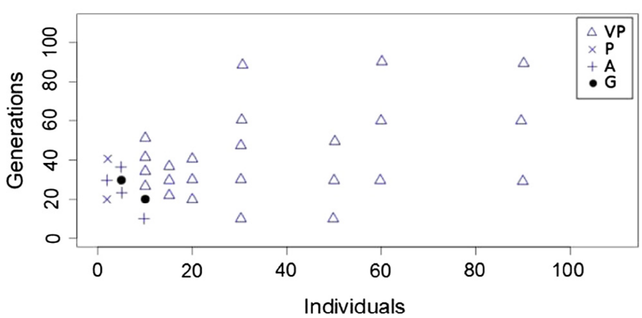
Four classes were created to discretize the behavior displayed by the settings evaluated with each metaheuristic, which are: (**i**) Very Poor; (**ii**) Poor; (**iii**) Average; and (**iv**) Good. These classes represent a behavioral pattern for each setting, which is shown and described in Table 3. Fig. 9(a) and (b) shows the configuration of PSO and GA by Grid Search, with the quality of each configuration evaluated. Initially, the grid starts at the same position for both metaheuristic, but the search direction is different for each metaheuristic. In the fourth round of evaluations, Grid Search converges

Table 3
Discretization of the performance of metaheuristics using the settings evaluated by the Grid Search.

Symbol	Name	Description
△	Very Poor (VP)	Average Runtime higher than available for optimizing the parameter
×	Poor (P)	Appropriate Average Runtime; Convergence Rate less than 0.5
+	Average (A)	Appropriate Average Runtime; Convergence Rate between 0.5 and 0.8
•	Good (G)	Appropriate Average Runtime; Convergence Rate higher than 0.8



(a) Search for configuring the PSO.



(b) Search for configuring the GA.

Fig. 9. Search performed by the Grid Search for configuring the GA and PSO, evaluated to optimize *routeChangingFactor* parameter.

to a promising region of the search space. returning good parameter values for the metaheuristics (indicated by Good class).

Grid Search indicated settings with "Good" class for both metaheuristics, two for PSO and three for GA. These settings are shown in Fig. 9(a) and (b) and marked with •. It is possible to see the behavior of the five settings in Table 4, which are: (**i**) for the PSO, *PART***X***_ITE***Y**, where **X** is the number of particles that compose the swarm and **Y** is the total number of iterations; and (**ii**) for the GA, *IND***X***_GEN***Y**, where **X** is to the number of individuals that comprise the population and **Y** is to the total number of generations.

Although all the settings in Table 4 comply with the criteria set out in the search heuristics and can be classified as "Good", the *PART45_ITE5* settings for PSO, and *IND10_GEN25*, for GA, were better than the other settings. This can be explained by the fact that they have the best convergence rates and further evaluations were conducted during the execution of their metaheuristics. Even tough, these settings keep a reasonable Mean Execution Time. Given the characteristics of environment and flight, the Mean Execution Time is assumed to be reasonable if it is below 66.667 s. The maximum time (Δ) that the execution of the metaheuristic can take is obtained by the Equation:

$$\Delta = \frac{\alpha}{v}$$

where α is the length of the sub-area in meters and v is the UAV speed in meters per second.

Another investigated approach explores the search space and look for settings similar to those highlighted in Table 4, which are later evaluated. To find these new settings, it is necessary to define which numerical combinations of the two parameters of each metaheuristic (PSO and GA) result in the same number of evaluations as the best settings found by Grid Search. To find the new configurations that result in the same amount of evaluations, a procedure calculates $\{i, j\}$ *where* $i \times j == OverallEvaluation$. In this case, *OverallEvaluation* is the maximum number of evaluations allowed for the new settings and i and j represent the metaheuristic parameters. When a numerical combination satisfies this condition, the result is validated. In this study, a blind search for new combinations was carried out, without examining the suitability of each setting in the corresponding metaheuristics. Before the combinations have their feasibility assessed, they must allow a group of elements and evolution cycles with a minimum value equal to five. This prevents the metaheuristic from being suppressed by inadequate settings and being rendered inefficient; for example, using 250 individuals for 1 evolving generation in the GA.

In the experiments, five new settings were found for the PSO and 4 for the GA. These settings, and their respective behavior, are detailed in Table 5. Additionally, the location of each setting in the search space, and the quality class it belongs to, can be seen in Fig. 10. The best settings obtained by Grid Search for each metaheuristic were re-executed together with the new settings that were evaluated to check the stability of their executions. Setting *PART45_ITE5*, indicated by the Grid Search for the PSO increased its Convergence Rate.

This increase may be due to a potential instability in the execution of the PSO with this parameter values. Consequently, the *PART15_ITE15* setting is considered the best found for the PSO, with a Convergence Rate of 0.8 and an appropriate Mean Execution Time. Although other settings have the same behavior, this setting had the lowest Mean Execution Time. For the GA, the setting *IND10_GEN25*, indicated by the Grid Search, maintained its Convergence Rate (1.0) and Mean Execution Time at appropriate level for the application. This behavior indicates a possible pattern of stable execution for optimizing the parameter *routeChangingFactor*. Based on these results, the settings used for the next steps are: *PART15_ITE15* for the PSO and *IND10_GEN25* for the GA. These settings are called PSO-PART15_ITE15 and GA-IND10_GEN25 respectively, in the next experiments.

5.2. The embedded hardware

The single-board raspberry Pi computer was used in the embedded hardware. This computer has the electronic components necessary for the UAV computer system (Vujovic and Maksimovic, 2014). This system requires low power and has a reduced physical size, which makes it easy to use in robotic systems. In light of these characteristics, The PSO-PART15_ITE15 and GA-IND10_GEN25 metaheuristics were executed on the Raspberry pi to evaluate if it can be used for the optimization of the *routeChangingFactor* parameter in the UAV embedded system. This can reduce the UAV communication rate with the Control Station during spraying.

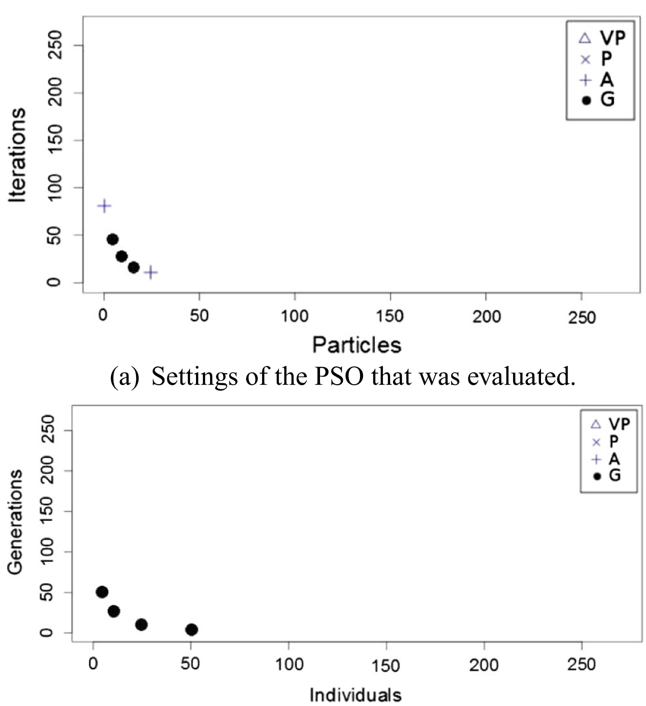
A Raspberry Pi Model B (see Fig. 11) and a virtualized computer (described in Section 5.1), which represented the control station as the computing platforms, were used in the experiments. The hardware used has the following features: Processor Broadcom BCM2835 ARMv6 (700 MHz), 512 MB SDRAM, two USB Ports,

Table 4
Behavior of the "Good" class settings found by Grid Search. The highlighted lines refer to the best settings found for each **metaheuristic**.

Metaheuristic	Settings	Average Runtime (s)	Convergence Rate	Total Ratings
PSO	PART40_ITE5	54.132	0.8	200
PSO	***PART45_ITE5***	**61.369**	**0.9**	**225**
GA	IND5_GEN30	30.992	0.8	150
GA	IND10_GEN20	46.614	0.8	200
GA	***IND10_GEN25***	**57.785**	**1.0**	**250**

Table 5
Parameter values evaluated in the complementary approach.

		Characteristics		
Metaheuristic	Settings	Average Runtime (s)	Convergence Rate	Total Ratings
PSO	PART5_ITE45	63.156	0.8	225
PSO	PART9_ITE25	63.311	0.8	225
PSO	***PART15_ITE15***	***63.112***	***0.8***	***225***
PSO	PART25_ITE9	63.148	0.6	225
PSO	PART45_ITE5	62.401	0.7	225
GA	IND5_GEN50	53.018	1.0	250
GA	***IND10_GEN25***	***59.637***	***1.0***	***250***
GA	IND25_GEN10	63.698	1.0	250
GA	IND50_GEN5	65.139	0.9	250



(a) Settings of the PSO that was evaluated.

(b) Settings of the GA that was evaluated.

Fig. 10. Locations and quality classes for the new settings evaluated in the complementary approach by GA and PSO.

Power Draw/Voltage of 1.2A @ 5 V, 26 pin of GPIO and one Ethernet Port. The Linux operating system version 3.10.37 + for armv6l architecture was installed in an SD Card Class 4 with 8 GB of space. The metaheuristics and source code are the same as those used in previous experiments, but recompiled to run on the embedded system. Thus, the computer platform is the only difference between this experiment and the previous experiment.

Each metaheurstic was run 10 times, to provide more reliable results. The Average Runtime of the device used was 1480.198 s for the PSO-PART15_ITE15 and 1364.898 s for GA-IND10_GEN25. Fig. 12 compares the Average Runtime using Raspberry PI with the use of similar external Control Station platform.

This comparison shows that it is not possible to run the metaheuristics in the embedded platform, since the running time will be longer than the maximum limit required. This occurred because of the high processing power required to run the metaheuristics.

Therefore, the AdEn system was kept as it is in the original proposal. In other words, OPTIC element remains running in the Control Station while CollAct element remains embedded in UAVs.

5.3. Pesticide spraying with route correction adapted to weather conditions

This section evaluated three metaheuristic variations for optimizing the *routeChangingFactor* parameter optimization: (**i**) GA-IND10_GEN25; (**ii**) PSO-PART15_ITE15; e (**iii**) PSO-PART5_ITE20. The first two resulted from evaluations performed in this paper and the third was proposed by Faiçal et al. (2014a). The weather conditions used to evaluate the accuracy of the deposition of the pesticide were as follows: (**i**) constant wind speed – 10 km/h and 20 km/h; and (**ii**) direction of constant wind is in the transverse to the UAV route. A *Constant Light Wind* (CLW) for a speed of 10 km/h and *Constant Moderate Wind* (CMW) for a speed of 20 km/h were adopted (Faiçal et al., 2014b). These and other environmental characteristics are listed in Table 1. It should be noted that the experiments performed in this evaluation stage were repeated 10 times.

The intensity of route correction with the worst fitness for each weather condition was selected for the pesticide spraying. In the case of a tie between the values with the worst fitness, the choice was made at random. By using this approach, it was possible to analyze the worst case scenario that each metaheuristic could provide for pesticide spraying, and the results with the lowest accuracy.

5.3.1. Optimization of the routeChangingFactor parameter

In the experiments for the optimization of the intensity of the route setting using the GA-IND10_GEN25, PSO-PART15_ITE15 and PSO-part5_ITE20 metaheuristics, each metaheuristic was run in the control station for both types of weather conditions (CLW and CMW). The performance and behavior of each metaheuristic in both these conditions are listed in Table 6.

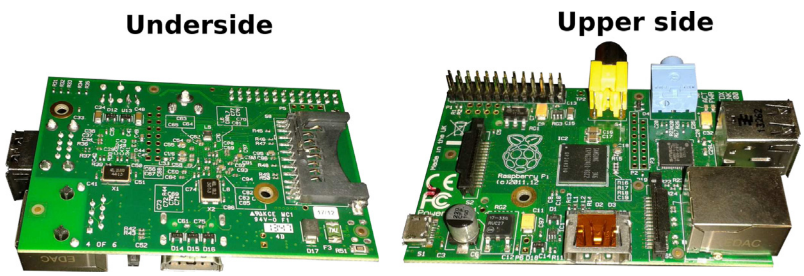


Fig. 11. Embeddable device used as a computing platform to run the PSO-PART15_ITE15 and GA-IND10_GEN25 metaheuristics to optimize the *routeChangingFactor* parameter. This evaluation investigates whether the metaheuristics can be embedded in the UAV to reduce the rate of communication with the Control Station.

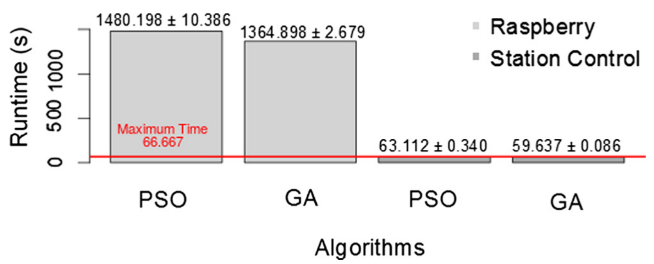


Fig. 12. A comparison between the Average Runtime of the metaheuristics running on the Station Control and on the Raspberry PI. The difference was confirmed with 95% of statistical significance.

The metaheuristics evaluated showed a maximum convergence rate (1.0) and an average execution time suitable for the CLW environment. These results indicate that all the evaluated solutions are suitable for the optimization of the *routeChangingFactor* parameter in this weather. However, for the CMW environment, only GA-IND10_GEN25 reached the maximum convergence rate. The behavior presented by GA-IND10_GEN25 shows an improved stability in different weather conditions, thus being the most reliable for use in AdEn system.

Fig. 13 shows the parameter values obtained by the metaheuristics for different weather conditions. In the graphics, the columns represent the environment (CLW and CMW) and the rows the metaheuristics (PSO-PART5_ITE20; PSO-PART15_ITE15 e GA-IND10_GEN25). Fig. 13(a), (c), and (e) shows a larger interval of values for the same accuracy in the CWL environment, between the 3.343 and 6.616. On the other hand, Fig. 13(b), (d) and (f) suggests that, for the CMW weather condition, the search space is less complex, as indicated by the smaller range of values, between.561 and 3.660 and the best accuracy value found in the experiments. GA-IND10_GEN25 was the only metaheuristic able to keep the convergence rate at 100% for the range of values that provided the best adjustment for the route correction.

5.3.2. Evaluation of pesticide spraying accuracy

The proposed system was validated by evaluating the accuracy of pesticide spraying when the *routeChangingFactor* parameter is adapted to weather conditions. A simulated assessment was carried out to preserve the integrity of the equipment and comply with the first validation of the proposal. This approach is commonly used in robotics, where the first validation is carried out using simulation to identify and resolve potential problems before being actually implemented and deployed in the field (Bergamini et al., 2009; Colesanti et al., 2007; Malekzadeh et al., 2011).

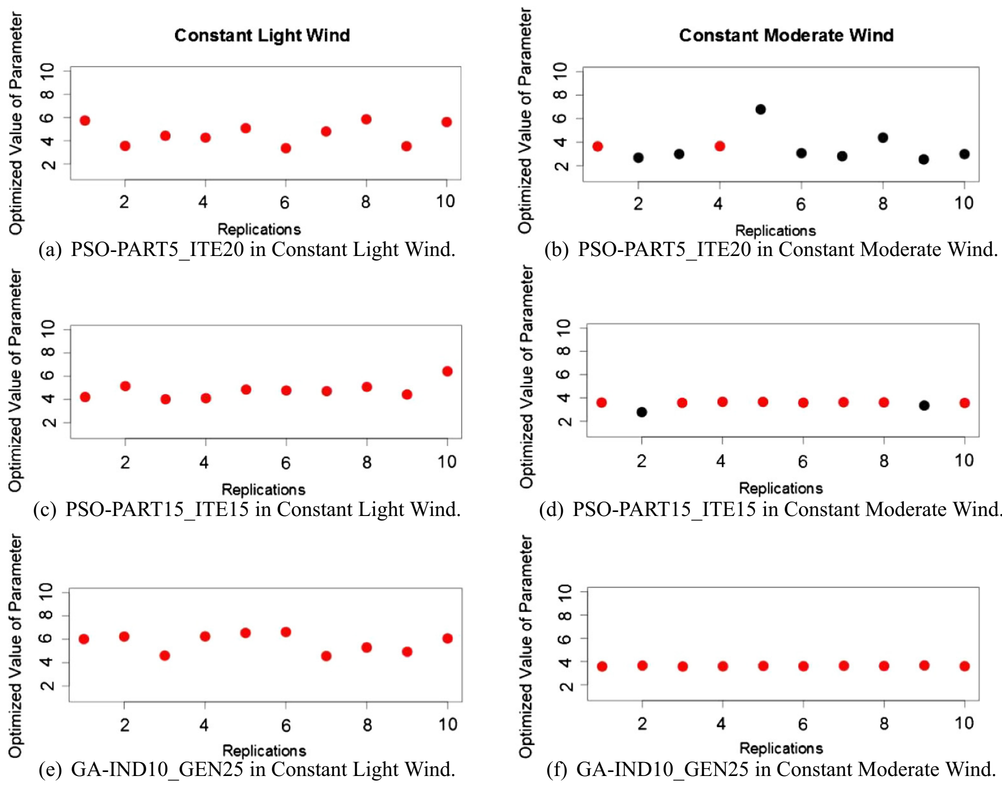
The simulation performed produced an deposition matrix as the result of the pulverization process. The deposition is measured by the amount of particles and the proximity to the target region (Faiçal et al., 2014b), which enables the evaluation of the spraying. It is important to observe that the experiments are performed with stochastic variables to approach a realistic actual behavior. These variables are not used for the parameter optimization phase (making it a deterministic environment), to make the comparison between the different intensities as fair as possible (since they are evaluated with the same environment).

As previously described, after the adaptation of *routeChangingFactor* parameter, the UAV sprays one target sub-area with route correction. The purpose of this experiment is to evaluate the spraying accuracy using the intensities indicated by each metaheuristic (PSO-PART5_ITE20; PSO-PART15_ITE15 and GA-IND10_GEN25). To have more robust results, 70 repetitions were performed for the worst intensity indicated by each metaheuristic. The experiments use different stochastic The metaheuristics presented a similar behavior for the CLW weather conditions.

Fig. 14 shows the percentage of pesticides deposited in the target sub-area (when sprayed correctly) for different approaches investigated in the literature and in this paper. It shows the increase in the accuracy of the pesticide spraying obtained by the proposed approach, when compared with the other approaches from the literature. The results from the PSO-PART15_ITE15 metaheuristic presented more compact quartiles and with a higher median, when compared with the previously proposed PSO-PART5_ITE20. They also show a spraying accuracy improvement when PSO as configured by Grid Search. Finally, GA-IND10_GEN25 presented a spraying accuracy higher to the other metaheuristics. The authors believe that the best results were obtained due to the stability in the Convergence rate, despite the complexity of the weather conditions investigated.

Table 6
Optimization results for *routeChangingFactor* parameter with the GA (IND10_GEN25) and PSO (PART5_ITE20; PART15_ITE15) metaheuristics in all-weather conditions (constant light wind (CLW) and constant moderate winds (CMW) – 10 km/h and 20 km/h).

Weather	Metaheuristic	Settings	Average Runtime (s)	Total Ratings
CLW	PSO	PART5_ITE20	30.705 ± 0.506	1.0
CLW	PSO	PART15_ITE15	65.165 ± 1.478	1.0
CLW	GA	IND10_GEN25	63.031 ± 0.787	1.0
CMW	PSO	PART5_ITE20	28.697 ± 0.361	0.2
CMW	PSO	PART15_ITE15	63.112 ± 0.340	0.8
CMW	GA	IND10_GEN25	59.637 ± 0.086	1.0



(a) PSO-PART5_ITE20 in Constant Light Wind.
(b) PSO-PART5_ITE20 in Constant Moderate Wind.
(c) PSO-PART15_ITE15 in Constant Light Wind.
(d) PSO-PART15_ITE15 in Constant Moderate Wind.
(e) GA-IND10_GEN25 in Constant Light Wind.
(f) GA-IND10_GEN25 in Constant Moderate Wind.

Fig. 13. The values indicated by the metaheuristic for the *routeChangingFactor* parameter. The red dots represent the indicated values that are contained in a range of values that resulted in the best Fitness found among all the optimizations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

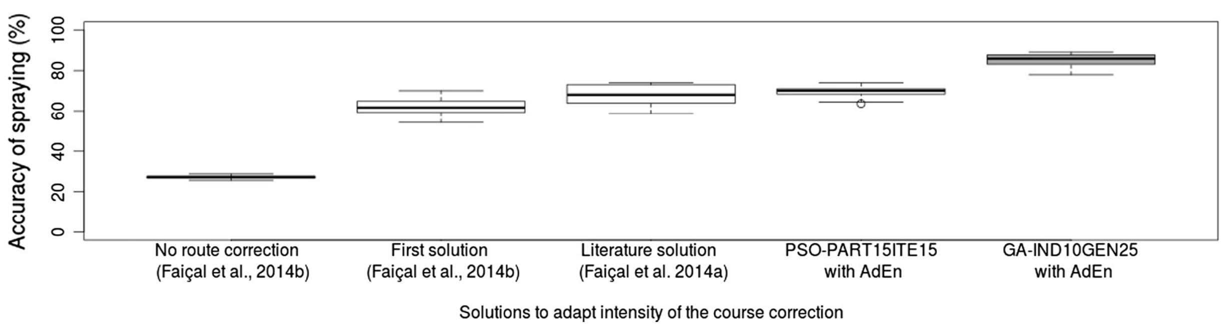


Fig. 14. The degree of pesticides correctly deposited on the targeted sub-area for each solution in CMW weather conditions. It is important to observe that GA-IND10_GEN25, proposed in this study, found a more appropriate intensity to weather in all its executions. This result exceeds the efficiency of the solutions found in the literature.

Statistical tests were conducted to evaluate the obtained results. Initially, the Shapiro-Wilk method was used to verify the adequacy of the sample sets and normal distribution and, hence, to define if parametric or non-parametric methods should be used. The sample sets resulted in a p-value smaller than 0.05. Thus, the normal distribution hypothesis was rejected and the Wilcoxon method was used for the statistical analysis. Therefore, paired comparisons using the Wilcoxon rank sum test (see Table 7) were made to check whether there is a statistically significant difference between the sample sets. Despite the apparent improvement in accuracy when using the PSO-PART15_ITE15 rather than PSO-PART5_ITE20, it is not possible to assume that there is a statistically significant difference between the results obtained. On the other hand, the Wilcoxon test indicates that the accuracy in the spray provided by GA-IND10_GEN25 is better, with statistical significance, than the other metaheuristics evaluated (PSO in both settings).

Table 7
P-values smaller than 0.05 indicate a statistically significant difference between the sample groups. The Wilcoxon test indicates that the accuracy achieved by GA-IND10_GEN25 was better, with statistical significancy, than PSO in both settings.

Wilcoxon Rank Sum Test		
	PSO-PART5_ITE20	PSO-PART15_ITE15
PSO-PART15_ITE15	0.130	–
GA-IND10_GEN25	0.000	0.000

According to the experimental results, GA-IND10_GEN25 seems to be a better caption for the AdEn system. This metaheuristic allowed high-precision spraying in a more complex environment for adaptation of the route correction system. Furthermore, the *routeChangingFactor* parameter optimization process was more stable with the use of the GA-IND10_GEN25 than with any of the other metaheuristic analyzed.

6. Conclusion and future work

This paper proposes AdE, a system that can adapted the route correction rules of a UAV pesticide spray in different weather conditions. This system consists of two elements: (**i**) CollAct, which is responsible for checking the weather of the crop field and updating the *routeChangingFactor* parameter defined in the UAV's control system; and (**ii**) OPTIC, responsible for optimizing the *routeChangingFactor* parameter to adjust the intensity of the route correction according to the sensored weather conditions.

During the AdEn system design, the importance of an efficient optimization process was observed Thus, when validating the proposal and evaluating the progress made, four metaheuristics were assessed as components of the AdEn system. The accuracy of the pesticide spray provided by the values optimized with these metaheuristics was evaluated.

The results of the experiments demonstrated that the proposed AdEn system presented a good performance in the tested scenario, since it uses the control station to process most of the workload. Furthermore, the proposed metaheuristic, GA-IND10_GEN25 (set by the Grid Search technique), was shown to be more efficient and stable than other solutions found in the literature.

In addition to the good results and progress achieved in this work, it opened up several opportunities for further studies, such as: (**i**) the development of a computer model for pesticide spraying with lower computational costs; (**ii**) the optimization of other parameters (e.g. height and speed of the UAVs) to reduce errors in pesticide deposition; (**iii**) investigation of specific characteristics of optimization techniques for dynamic environments (Alba et al., 2013; Yang and Yao, 2013); (**iv**) an investigation of the scalability of the proposed system for implementing a fully-featured prototype model; (**v**) study on the suitability of different dispersion models to make the most accurate computer model the real environment.

Acknowledgements

Bruno S. Faiçal would like to express gratitude for the funding received for his doctoral project by FAPESP (Process N° 2013/18859-8). The other authors would like to express their thanks for the financial support received from FAPESP (São Paulo Research Foundation – process N° 2014/10685-3), CAPES (Capes Foundation, Ministry of Education of Brazil) and CNPq (Brazilian National Council of Technological and Scientific Development). We would also like to thank the Office of Global Naval Research (N° 62909-14-1-N241). Jo Ueyama would like to thank FAPESP for funding the bulk of his research project, FAPESP Grant ID# 2015/21642-6.

The authors would like to thank Geraldo P. R. Filho for his revisions and advice, which were of great value when undertaking this research project.

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