The use of computational intelligence for precision spraying of plant protection products

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Bruno Squizato Faiçal

Utilizando a inteligência computacional para a pulverização precisa de produtos fitofarmacêuticos

Tese apresentada ao Instituto de Ciências Matemáticas e de Computação – ICMC-USP, como parte dos requisitos para obtenção do título de Doutor em Ciências – Ciências de Computação e Matemática Computacional. *VERSÃO REVISADA*

Área de Concentração: Ciências de Computação e Matemática Computacional

Orientador: Prof. Dr. Jó Ueyama

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This work is dedicated to all the people who helped me get here,
but their stay on this earth did not have enough time to be in that moment with me.

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“Resilience is the ability to recover from crisis situations and learn from it.
It is to have flexible mind and optimistic thinking,
with clear goals and the certainty that
everything will pass.”
(Unknown author)

ABSTRACT

FAIÇAL, B. S. **The use of computational intelligence for precision spraying of plant protection products**. 2017. 115 p. Doctoral dissertation (Doctorate Candidate Program in Computer Science and Computational Mathematics) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2017.

Protection management with the aid of plant protection products makes it possible to carry out pest control programs in agricultural environments and make them less hazardous for the cultivation of products on a large scale. However, when these programs are put into effect, only a small proportion of the sprayed products is really deposited on the target area while much of it is carried to neighboring regions. The scientific literature includes studies on the use of mathematical techniques to calculate the physical transformation and movement and provide a deposition estimate of the product. On the basis of this prediction, it is possible to configure a system which can allow the spraying to be carried out in normal weather conditions in the region for a satisfactory performance, although these conditions can undergo changes and make any statistical configuration unreliable. An alternative way of overcoming this problem, is to adapt the spray elements to the meteorological conditions while the protection management is being undertaken. However, the current techniques are operationally expensive in computational terms, which makes them unsuitable for situations where a short operational time is required. This thesis can be characterized as descriptive and seeks to allow deposition predictions to be made in a rapid and precise way. Thus it is hoped that the new approaches can enable the spray element to be adapted to the weather conditions while the protection management is being carried out. The study begins by attempting to reduce costs through a computational model of the environment that can speed up its execution. Subsequently, this computational model is used for predicting the rate of deposition as a fitness function in meta-heuristic algorithms and ensure that the mechanical behavior of the spray element can be adapted to the weather conditions while the management is put into effect. The results of this approach show that it can be adapted to environments with low variability. At the same time, it has a poor performance in environments with a high variability of weather conditions. A second approach is investigated and analyzed for this scenario, where the adaptation requires a reduced execution time. In this second approach, a trained machine learning technique is employed together with the results obtained from the first approach in different scenarios. These results show that this approach allows the spray element to be adapted in a way that is compatible with what was provided by the previous approach in less space of time.

Keywords: Deposition prediction, Agricultural spraying, Precision agriculture.

RESUMO

FAIÇAL, B. S. **Utilizando a inteligência computacional para a pulverização precisa de produtos fitofarmacêuticos**. 2017. 115 p. Doctoral dissertation (Doctorate Candidate Program in Computer Science and Computational Mathematics) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2017.

O manejo de proteção com uso de produtos fitofarmacêuticos possibilita o controle de pragas em ambientes agrícolas, tornando-o menos nocivo para o desenvolvimento da cultura e com produção em grande escala. Porém, apenas uma pequena parte do produto pulverizado realmente é depositado na área alvo enquanto a maior parte do produto sofre deriva para regiões vizinhas. A literatura científica possui trabalhos com o uso de técnicas matemáticas para calcular a transformação física e movimento para estimar a deposição do produto. Com base nessa predição é possível configurar o sistema de pulverização para realizar a pulverização sob uma condição meteorológica comum na região para um desempenho satisfatório, mas as condições meteorológicas podem sofrer alterações e tornar qualquer configuração estática ineficiente. Uma alternativa para esse problema é realizar a adaptação da atuação do elemento pulverizador às condições meteorológicas durante a execução do manejo de proteção. Contudo, as técnicas existentes são computacionalmente custosas para serem executadas, tornando-as inadequadas para situações em que é requerido baixo tempo de execução. Esta tese se concentra no contexto descrito com objetivo de permitir a predição da deposição de forma rápida e precisa. Assim, espera-se que as novas abordagens sejam capazes de possibilitar a adaptação do elemento pulverizador às condições meteorológicas durante a realização do manejo de proteção. Este trabalho inicia com o processo de redução do custo de execução de um modelo computacional do ambiente, tornando sua execução mais rápida. Posteriormente, utiliza-se este modelo computacional para predição da deposição como função Fitness em algoritmos de meta-heurística para adaptar o comportamento do elemento pulverizador às condições meteorológicas durante a realização do manejo. Os resultados desta abordagem demonstram que é possível utilizá-la para realizar a adaptação em ambientes com baixa variabilidade. Por outro lado, pode apresentar baixo desempenho em ambientes com alta variabilidade nas condições meteorológicas. Uma segunda abordagem é investigada e analisada para este cenário, onde o processo de adaptação requer um tempo de execução reduzido. Nesta segunda abordagem é utilizado uma técnica de Aprendizado de Máquina treinada com os resultados gerados pela primeira abordagem em diferentes cenários. Os resultados obtidos demonstram que essa abordagem possibilita realizar a adaptação do elemento pulverizador compatível com a proporcionada pela abordagem anterior em um menor espaço de tempo.

Palavras-chave: Predição da deposição, Pulverização agrícola, Agricultura de Precisão.

LIST OF ABBREVIATIONS AND ACRONYMS

ANN	Artificial Neural Network
CI	Computational Intelligence
CV	Coefficient of Variation
EC	Evolutionary Computing
GPS	Global Positioning System
ML	Machine Learning
PA	Precision Agriculture
SI	Swarm Intelligence
UAV	Unmanned Aerial Vehicle
ULV	Ultra-Low Volume
WSN	Wireless Sensor Network

CONTENTS

CHAPTER 1

INTRODUCTION

1.1 General Background

The world population has increased rapidly and there has also been a sharp rise in the rate of this growth. It is estimated that by the year 2100, there will be between 9.6 and 12.3 billion people living on the planet (GERLAND *et al.*, 2014). Among the various challenges posed by this growth in population, there is an urgent need to produce and supply food for everybody (JOHNSON, 2016). However, it is believed that in 2014, approximately 0.8 billion inhabitants of the world did not have sufficient food and that the food deficit reached an order of 40 million tons (MARSILY; RIO, 2016).

In light of this, the main exporting countries of agricultural products can be expected (and have the opportunity) to increase their production, reduce the food deficit and supply food for everybody. According to FAO Trade and Markets Division (2014), Brazil is one of the largest producers and exporters of agricultural products in the world. This classification includes it in the list of countries that have this responsibility.

An alternative way of boosting food production is to make already existing areas of cultivated land more productive. For this reason, plant protection products (also known as pesticides) are employed in agricultural management with a view to providing a less adverse environment for the cultivation of products (WEISENBURGER, 1993; FERREIRA; OLIVEIRA; PIETRO, 2009; DORNELLES *et al.*, 2011).

In Brazil, Law 7.802, (11th July 1989) (LEI, 1989), defines plant protection products (pesticides), as follows:

> *"Products and agents derived from physical, chemical or biological processes, that are designed for use in the production sectors, storage facilities and for the benefit of agricultural products, in pasturelands, the protection of forests, (native or planted)*

and other parts of the ecosystem; and also for use in urban, hydric and industrial environments, which result in altering the flora and fauna, with the aim of preserving them from the harmful activities of living beings."

It should be stressed that the unsuitable use of these products, as a result of direct or indirect contact can cause serious damage to people's health. Contact with them can lead to a wide range of illnesses including cancer, respiratory complications and neurological diseases (WEISENBURGER, 1993). It is estimated that about 2.5 million tons of plant protection products are employed around the world each year and this figure is rising (PIMENTEL, 1995; TARIQ *et al.*, 2007). Moreover, it is believed that, on average, less than 0.1% of this amount is enough to control the pests in cultivated land.

This product is used in plantations by spraying the whole cultivated area. The agricultural spraying can be defined as a measure to expel or release products on the crops in an agricultural area (FERREIRA; OLIVEIRA; PIETRO, 2009). This activity is one of the main systems of management and is aimed at protecting the crops against agricultural pests and other problems (such as weeds and harmful insects in the crop fields).

Two methods are widely employed for the spraying of plant protection products in extensive areas (DAVIS; WILLIAMS, 1990; PERECIN *et al.*, 1999; DORNELLES *et al.*, 2011), namely (i) terrestrial and (ii) aerial . Different aspects of these have been fully investigated in the scientific literature (WANG *et al.*, 2016; SAHA; PIPARIYA; BHADURI, 2016; GREGORIO *et al.*, 2016; MINOV *et al.*, 2016; JIAO *et al.*, 2016; SALYANI; CROMWELL, 1992; GHATE; PERRY, 1994), and include the following: the efficiency of the products employed, the resulting environmental impact and the effectiveness of the equipment and techniques that are used.

In terrestrial spraying, a vehicle (usually a tractor) enters the plantation and carries out spraying in the whole of the cultivated area (GHATE; PERRY, 1994; DAVIS; WILLIAMS, 1990; SALYANI; CROMWELL, 1992). This method can only be undertaken with the aid of tracks (which may have to be created) to allow the vehicle to pass through the whole stretch of land. This direct contact between the spray vehicle and the land under cultivation leads to healthy plants being trampled down. These factors (the presence of tracks inside the plantations and harmful contact with healthy plants) lead to a reduction of agricultural production.

The other method involves aerial spraying with the use of an aircraft as a vehicle for transporting the required spraying system . The plane must fly over the whole cultivated area and release the product in the targeted regions, while seeking to cover the crops with the spray (JIAO *et al.*, 2016; DAVIS; WILLIAMS, 1990; XIANG; TIAN, 2011; HUANG *et al.*, 2009; SALYANI; CROMWELL, 1992). If this method is employed, there is no need for tracks inside the plantation or any form of contact of the vehicle with it. However, there is a greater distance from the point where the product is released (the spray nozzles) and the plantation than with the terrestrial method and this causes drift.

The aircraft often employ an Ultra-Low Volume (ULV) system for the application of a greater volume of pesticides in a more versatile manner than the traditional spraying systems, when in ideal conditions (PIMENTEL, 1995). However, in this scenario, only a small amount of the pesticide reaches the targeted crop field, while the rest is carried outside the targeted areas by the weather conditions (PIMENTEL, 1995). The evidence of the plant protection products leading to drift, is usually found at a distance of 48 to 800 m from the targeted field; however, this distance can reach 5 to 32 km, if it is in the direction of the wind (PIMENTEL, 1995).

There has been a notable rise in the use of autonomous vehicles (regardless of whether they are terrestrial or aerial) and these are aimed at increasing the precision of the activities and the duration of the procedure, without affecting the length of time spent each day by the operatives. These vehicles also help to reduce the number of failures caused by human error because they are fitted with a Global Positioning System (GPS) which provides precise navigation and prevents the workers from suffering fatigue as the result of a long day's work. One of the wide range of autonomous vehicles which is under investigation is the Unmanned Aerial Vehicle (UAV) which is used for the spraying of plant protection products (QIN *et al.*, 2016; PEDERI; CHEPORNIUK, 2015; ZHU *et al.*, 2010; HUANG *et al.*, 2009). Currently, it is estimated that approximately 40% of the rice fields in Japan are sprayed by means of these aircraft (PEDERI; CHEPORNIUK, 2015). One of the benefits of these types of aircraft is that they are able to strengthen environmental protection management because they do not have a pilot on board and can be remotely controlled by a professional.

In both spraying methods (terrestrial and aerial), the distance between the spray release bar and the plantation, means that there can be drift outside the targeted region which can cause an overlay of the product on plantations which do not require coverage. For this reason, it is essential to know (and be able to handle) the vehicle correctly, as well as the spraying equipment, so that the product can be applied properly (FERREIRA; OLIVEIRA; PIETRO, 2009). For example, the Coefficient of Variation (CV) is one of the instruments used to estimate the most suitable distance between the nozzles in the spray bar. Different distances between these elements can provide overlapping patterns of varied uniformity and this has a direct influence on the variability of the coverage. There have been several studies that suggest different values for this coefficient depending on the type of product being employed (PERECIN *et al.*, 1998; PERECIN *et al.*, 1999; SMITH, 1992; WOLF; SMITH, 1979).

The distance between the spray bar and the plantation is not the only factor related to the drift of the product. Several other factors influence the trajectories of the droplets before they reach the plantation(SALYANI; CROMWELL, 1992; WANG *et al.*, 2014; RU *et al.*, 2014; DORUCHOWSKI *et al.*, 2013; NUYTTENS *et al.*, 2011), such as the speed and direction of the wind, humidity, temperature, the size of the droplets, the speed of the vehicle and the volume being sprayed.

1.2 Motivation

Despite advances made by the scientific community, the problem of the drift of plant protection products outside the region, remains one of the main challenges in agricultural spraying (NUYTTENS *et al.*, 2011; CUNHA, 2008; CUNHA; REIS; SANTOS, 2006; CUNHA, 2009), since it is regarded as one of the main causes of environmental contamination by agricultural products (FERREIRA *et al.*, 2011). As a result, this issue has been the object of a number of studies by the scientific community, which are all aimed at reducing the damage caused to the flora and fauna and boosting the production of agricultural land (NUYTTENS *et al.*, 2011; DORUCHOWSKI *et al.*, 2013; SALYANI; CROMWELL, 1992; GHATE; PERRY, 1994; JIAO *et al.*, 2016; MINOV *et al.*, 2016; GREGORIO *et al.*, 2016).

FRIEDRICH, RAETANO and ANTUNIASSI (2004) estimates that approximately 50% of pesticide sprays are wasted because they are applied in an unsuitable way. CUNHA, TEIXEIRA and VIEIRA (2005) states that a good result in the spraying of plant protection products (i.e. a low deposition rate), can only be achieved if one knows the nature of the product and carries out practices that are suited to the products and crops that will be sprayed.

In an attempt to mitigate the harmful effects of these products and carry out spraying with greater precision, several studies have been conducted with computational simulations and mathematical models. The purpose of these is to estimate the movement and respective changes of each of the droplets of the sprayed product. These studies have the potential to estimate the spray drift in controlled environments (SALYANI; CROMWELL, 1992; DEVARREWAERE *et al.*, 2016; DORUCHOWSKI *et al.*, 2013; BAETENS *et al.*, 2007).

There are two approaches that stand out in this area (HALLMANN; SCHEURLEN; WITTIG, 1993; BAETENS *et al.*, 2007; DEVARREWAERE *et al.*, 2016), namely those of: (i) Euler and (ii) Lagrange. It should be noted that in some studies a hybrid Eulerian-Lagrange approach is adopted which is based on a statistical description of the dispersion phase in terms of a stochastic process. This is where the particle is attached in a Eulerian statistical representation of the fluid transport phase (SUBRAMANIAM, 2013).

Although good results can be obtained through these approaches (GRIFOLL; ROSELL-LLOMPART, 2012; GUO; FLETCHER; LANGRISH, 2004; NIJDAM *et al.*, 2006a; NIJDAM *et al.*, 2006b), the models that are based on them are expensive to put into effect in computational terms (GRIFOLL; ROSELL-LLOMPART, 2012). The reason for this is that these mathematical models require complex calculations to be made for each droplet at every moment, until the plantation is reached or some final state is satisfied (for example, the complete evaporation of the droplet). As is well known, this approach leads to a huge number of calculations being produced during the numerous iterations that are needed to reach a condition of closure, which causes a considerable delay to the operation.

Owing to the computational costs of these approaches, caused by the number of calculations made by the mathematical models, it is not applicable them in real-world environments when managing the cultivation. This is because the calculation of a particular area can only be finalized after it has already been sprayed. For example, there is a clear need for autonomous vehicles to be adapted to the environmental conditions while the product is being applied. In this way, the vehicle can adjust the spraying configurations to the weather conditions with the aim of reducing the errors in the deposition.

1.3 Research Objective

The aim of this thesis is to allow a rapid and efficient prediction of the deposition of plant protection products. This is to ensure that they can be used during the protection management so that the mechanical behavior of the spray element (i.e. the vehicle fitted with a spraying system) can be adapted to the weather conditions with a view to reducing the drift of these products while the crops are being sprayed. This is because the drift is mainly caused by unsuitable spraying being carried out in an environment with adverse weather conditions. The spraying element must be able to operate in a suitable way in adverse weather conditions to ensure precision. It should be noted that since there are constantly shifting weather patterns in the environment, the spray element must be able to determine the weather conditions and make constant adjustments during the protection management so that it can act with greater efficiency.

The nature of the locality and the concentration of the spray product must be estimated in a rapid and precise way for this adaptation to be feasible. The estimate of the deposition must be carried out at great speed so that it can be put into effect during the activity. At the same time, accuracy is an essential feature because it has a direct influence on the decisions made by the system.

Computational Intelligence (CI) can be defined as a methodology for computing which provides a system with the capacity for learning and dealing with new situations, since it has one or more reasoning attributes such as generalizing, discovery, combination and abstraction. In other words, CI includes practical adaptation and the self-organization of concepts, paradigms, algorithms and implementations that can enable suitable activities to be carried out (i.e. intelligent behavior) in complex and constantly shifting environments (EBERHART; SHI, 2011).

The use of CI concepts allows the computational system of the spray element to adapt to shifting patterns in the environment which are constantly taking place. Thus the computational element must identify the weather conditions of a particular environment and adapt its configurations so that the lowest possible rate of drift will occur.

The combination of the dynamic features of the weather conditions with the computational costs incurred for estimating the deposition of spray products, poses a considerable challenge for this thesis. Initially, a trade-off was made to overcome this problem by seeking acceptable solutions while undertaking the management. This process is carried out in the maximum time possible (which is pre-defined) and in the end, the best solution that is found is used. In other words, the cultivated land is divided into strips for spraying and these strips are subdivided into regions of interest (referred to in this work as sub-area). While the spray element operates in the sub-area, this subdivision allows the computational system to be more suitably adapted to the nearest sub-area. This search is carried out while the whole of the current sub-area is being sprayed and allows the configurations of the spray element to be updated in the period of time preceding the beginning of the operation in the new sub-area.

A meta-heuristic algorithm is used for this method, together with a computational model for management that is designed to seek solutions that allow an adaptation to be made involving a reduction in the estimated error rate. The representation of this model is directed at the next subarea that will be sprayed without the use of stochastic variables, since it is believed that this is the most accurate comparison, of the solutions assessed by the meta-heuristic algorithm. Moreover, the fitness function of each solution is calculated on the basis of the concentration of the product deposited outside the targeted area, including the areas nearby.

The fitness function described here is based on the concept of a set of basic features (JAKOBI; HUSB; HARVEY, 1995; GO; BROWNING; VELOSO, 2004), the minimum use of which have an impact on the relationship between the real world and computed environment. In other words, only factors of great significance are included in the design of the model. The use of the minimum number of factors from the real world, reduces the use of computing resources and speeds up the search for acceptable solutions.

A second approach investigated in this thesis adopts a previous approach to find solutions (or rather, configurations for adaptation) for different weather conditions before the data protection management system is put into effect. These solutions are employed as a knowledge base for training an Artificial Neural Network (ANN) with the aim of provide replies similar to those generated by the meta-heuristic algorithm. The ANN incurs lower computational costs when it is being used during the management of the crops and this allows the configurations to be updated in shorter spaces of time.

The results obtained from both approaches show that if the spray element is adapted to the weather conditions, it will lead to an increase in the precision of the protection management, and thus reduce the drift of plant protection products to neighboring areas. Both approaches proved to be efficient for the purposes of this thesis and succeeded in adapting the mechanical behavior of the spray element to the weather conditions during the spraying. However, the second approach allows the adaptation to be faster and at the same time more efficient, during the management which suggests that it is a more promising method for use in a real-world environment.

1.4 Structure of this thesis

This thesis is written as a collection of papers. All articles have the author of this thesis as the first author and are originated from the studies carried out in this work.

Chapters of this thesis are structured in the following way: after this section, in Chapter 2, the description of the studies for the development of originating articles in this thesis is presented. Chapter 3 contains the article on the validation of the spray platform used as a case study in this thesis. Research on possible approaches to adjust spray element settings starts in Chapter 4, where the article that evaluates the feasibility of using meta-heuristics algorithms in this context is presented. Subsequently, the paper presented in Chapter 5 proposed a system for adapting the spray element configuration and assesses their effectiveness in spraying. In Chapter 6 (Article under review), we conducted a thorough study to investigate the use of different meta-heuristic algorithms in the previously proposed system. A second approach is investigated in Chapter 7 to achieve adaptation behavior more quickly than that provided by the prior approach. Finally, Chapter 8 describes the conclusions reached after carrying out this thesis and makes suggestions for further studies that can complete the work on this field.

CHAPTER

2

BACKGROUND

At the outset, the article with the title *The use of unmanned aerial vehicles and wireless sensor networks for spraying pesticides* (FAIÇAL *et al.*, 2014b) (see Chapter 3) is mentioned as the point of departure for this research study. In this article, a platform is designed that consists of a UAV and a Wireless Sensor Network (WSN) for spray products. The WSN is installed inside the plantation in the form of a matrix and this will receive the plant protection products by means of the spraying carried out by the UAV. During the whole procedure, the UAV maintains active communication links with the WSN which is used to pick up information about the deposition of the spray product and the weather conditions of the region (for example the speed and direction of the wind). If there is an imbalance between the readings carried out by the pairs of sensor nodes in the upper layer and the previously defined threshold, the computational system of the UAV will adjust its route to the flight so that it can maintain the correct balance for the deposition of the product. The published results show that the degree of precision achieved in the spraying with the proposed platform is higher than the spraying carried out with a traditional model (and without any adjustment to the route).

The study undertaken in this article is geared to validating the platform, as the starting-point of the thesis. This platform is essentially designed to be autonomous so that it is able to take previously-defined corrective measures . It should be stressed that the automaticity of this platform derives from its capacity to carry out the spraying without being controlled by a human being. However, the mechanical behavior of the platform does not allow it to adjust to alterations in the weather conditions of the region. As already stated, this gap is effectively filled by this thesis which uses this platform as a case study that can enable its methodology to be transferred to other approaches.

As the research progressed, it was found that the image intensity to which the UAV routes were adjusted, had an influence on the precision of the spraying. In other words, the image intensity that allowed the route to be well adjusted to particular weather conditions, did not have the same degree of efficiency in different situations. As a result, there was an investigation of the use of meta-heuristic algorithms combined with the concepts of Evolutionary Computing (EC) and Swarm Intelligence (SI) with a view to finding more efficient adaptive intensity corrections of the route for the weather conditions. The article *Exploiting Evolution on UAV Control Rules for Spraying Pesticides on Crop Fields* (FAIÇAL *et al.*, 2014) (see Chapter 4), published the initial results of this study, where the feasibility of using these techniques for this objective is analyzed. This means determining if these techniques can converge and provide a satisfactory response in a timely manner. Subsequently, the article *Fine-tuning of UAV control rules for spraying pesticides on crop fields* (FAIÇAL *et al.*, 2014a) (see Chapter 5) broadened the inquiry and assessed the effectiveness of using meta-heuristic algorithms to find intensity corrections of the route and thus provide greater precision in every kind of weather condition. The results achieved show that the use of an adaptive intensity for the weather conditions led to more precise spraying and reduced the amount of drift of the spray product to neighboring regions. These results can be seen as strong indications that the adaptation of the mechanical behavior of the spray element to the weather conditions, can bring about a more precise kind of protection management.

In the work undertaken, there is also a description of the methodology employed for the adjustment of the mechanical behavior of the spray element. A simplified computing model is used for estimating the deposition of the spray product. The deposition is represented in a matrix, the size of which is proportional to the targeted area of the product. The strip of land that the UAV must fly over to carry out the spraying is divided into targeted sub-areas which are used to make the adjustment. It should be emphasized that the adjustment is made in parallel with the original operation of the platform. In view of this, only the methodology employed for the recommended adjustment uses the view of the targeted subareas, whereas the UAV keeps to its task of carrying out the spraying in a previously defined track.

The methodology for adjustment employs a computing model to estimate the deposition of the plant protection products inside the next targeted sub-area, on the basis of the flight parameters, the weather conditions and the dispersion model. This means that, while the UAV sprays the region corresponding to a sub-area, the methodology of adjustment is employed with the aim of improving the performance of the spray element for the next sub-area. At this stage, a meta-heuristic algorithm interacts with the computing model to find an image intensity that provides a greater degree of accuracy for the deposition of the product in the next sub-area. If one kind of intensity proves to be more efficient, the configuration of the UAV is upgraded at the time of transition between the sub-areas. In this way the mechanical behavior of the spray element can be adjusted to the weather conditions collected by the sensors from the targeted sub-area in the recent past.

It should be underlined that the track that is covered by each particle of the spray product is calculated on the basis of a dispersion model implemented in the computing model. These calculations are only applied to the particles that remain in the environment represented by the computing model (which includes a 3-dimensional representation), until they reach the plantation. This feature assists in reducing the computational costs that are required to estimate the extent of the deposition. In addition, the computing model that is employed does not make use of stochastic variables to make an exact comparison between the various image intensities that are assessed.

This approach was broadened in the article: *An adaptive approach for UAV-based pesticide spraying in dynamic environments* (FAIÇAL *et al.*, 2016a) (see Chapter 6) which is currently being revised, and which can be outlined as follows: (i) investigations with four meta-heuristic algorithms (Simulated Annealing, Hill Climbing, Particle Swarm Optimization and Genetic) which are aimed at finding a technique that shows the best results for making the mechanical behavior of the spray element suitable for the weather conditions , (ii) a system is put forward for implementing the methodology outlined in Faiçal *et al.* (2014a) and (iii) there is an investigation of the possibility of putting this approach into effect in a computational component that is fitted on board of the aircraft.

The configurations of the algorithms that were evaluated were defined by the GridSearch technique with a view to reducing the possible interference caused by the empirical configuration parameters. The GridSearch technique undertakes a search which is guided by predefined parameters and a suitable configuration within the search space which is also predefined. On making a determined convergence, the configuration stage is finalized and the algorithms are evaluated with their respectively defined configurations, in an individual way. The configuration for the PSO algorithm, set out in Faiçal *et al.* (2014a), was not recommended by the GridSearch technique but was included in the experiments of this study, because it is concerned with a solution that is found in the literature and employed as a basis for evaluation.

The results published in this article show that the GA achieved a more stable execution than the other techniques (100% of convergence for an intensity range that ensured a lower error rate). Although the proposed system was expensive to put into effect in the aircraft itself, the ground control station can be used as a center for processing the way it is carried out. Despite the fact that the results showed an increase in the precision of the spraying, this system is ideally suited for environments where there is little variability in the weather conditions. This means that this approach cannot lead to a satisfactory performance in environments where the weather conditions are subject to constant alterations. In this scenario, the defined intensity cannot be more suitable when the UAV begins the spraying in the next targeted sub-area, even if meteorological information about the recent past is provided.

As a means of finding a possible way of overcoming this obstacle, the use of a trained ANN was investigated with results (intensity corrections for the route) obtained from the meta-heuristic algorithm in different weather conditions. This approach is described in the article *Fine-Tuning of UAV Control Rules for Spraying Pesticides on Crop Fields: An Approach for Dynamic Environments* (FAIÇAL *et al.*, 2016b) (see Chapter 7). The reason why the ANN technique was chosen for this investigation, is that it has a capacity for interpolating satisfactory data. This allows appropriate intensities to be recommended for unknown weather conditions (and not used during the training stage). The generation of the knowledge base and training stage are carried out before the management protection begins. At the same time, the trained ANN is used during the spraying to allow a faster execution than was provided by the previous approach.

The published results show that the trained ANN is able to recommend results that are similar to those found in the meta-heuristic algorithm where there is less time for execution. This mechanical behavior allows an intensity correction of the upgraded route to be constantly maintained in environments where there are often changes in the weather conditions.

Finally, it is emphasized that the results obtained with this thesis were highlighted in the article *The use of autonomous UAVs to improve pesticide application in crop fields* (FAIÇAL; UEYAMA; CARVALHO, 2016) presented in the 1^{st} Workshop on High Velocity Mobile Data Mining (an event forming a part of the 17^{th} IEEE International Conference on Mobile Data Management), see Appendix A.

CHAPTER

3

VALIDATION OF THE PLATFORM THROUGH A CASE-STUDY

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The use of unmanned aerial vehicles and wireless sensor networks for spraying pesticides

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A B S T R A C T

The application of pesticides and fertilizers in agricultural areas is of crucial importance for crop yields. The use of aircrafts is becoming increasingly common in carrying out this task mainly because of their speed and effectiveness in the spraying operation. However, some factors may reduce the yield, or even cause damage (e.g., crop areas not covered in the spraying process, overlapping spraying of crop areas, applying pesticides on the outer edge of the crop). Weather conditions, such as the intensity and direction of the wind while spraying, add further complexity to the problem of maintaining control. In this paper, we describe an architecture to address the problem of self-adjustment of the UAV routes when spraying chemicals in a crop field. We propose and evaluate an algorithm to adjust the UAV route to changes in wind intensity and direction. The algorithm to adapt the path runs in the UAV and its input is the feedback obtained from the wireless sensor network (WSN) deployed in the crop field. Moreover, we evaluate the impact of the number of communication messages between the UAV and the WSN. The results show that the use of the feedback information from the sensors to make adjustments to the routes could significantly reduce the waste of pesticides and fertilizers.

1. Introduction

Unmanned aerial vehicles (UAVs) have become cheaper because many control functions can now be implemented in software rather than having to depend on expensive hardware. This has allowed single or multiple UAVs to be employed for real-world applications. The UAVs very often require a means of communication so that they can communicate with on-land computers, sensors or other UAVs. As most of the research with UAVs is still in its initial stages, there are a number of open questions that need solving, like mapping and localization schemes [33], route planning [29], coordination and task allocation [30,28] and communication issues [6], among others.

In this paper, we propose an architecture based on unmanned aerial vehicles that can be employed to implement a control loop for agricultural applications where UAVs are responsible for spraying chemicals on crops. The process of applying the chemicals is controlled by means of the feedback from the wireless sensor network which is deployed at ground level on the crop field. Furthermore, we evaluate an algorithm to adjust the UAV route to changes in the wind (intensity and direction) and the impact caused by the number of messages exchanged between the UAV and the WSN. The information retrieved by the WSN allows the UAV to confine its spraying of chemicals to strictly designated areas. Since there are sudden and frequent changes in environmental conditions, the control loop must be able to react as quickly as possible.

The information retrieved by means of the WSN provides the UAV with knowledge of the position and amount of chemicals detected by every sensor of the crop field. However, after the application of the chemicals by the UAV, some areas of the crop may not have a sufficient amount of chemicals; the reason for this is the high speed of the UAV and even though the controls allow the UAV to adjust to sudden random changes of wind as quickly as

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possible, this might not be enough to maintain a perfect lane. As a result, what happens is that we might have some clusters without the correct amount of chemicals being dispersed. Hence, in this paper we also show how to build a chemical concentration map using the data provided by the WSN. The purpose of this is to show clusters where there is an insufficient application of chemicals and the map might be used to perform new UAV applications in designated areas. We show how to build these maps using Instance-Based Algorithms [2] and Density-Based Algorithms [20].

This paper is an extended version of a previous study [10]. It aims to describe the methodology that is employed in a more thorough way, conduct new experiments and discuss the new obtained results. Furthermore, we describe how a chemical concentration mapping can be carried out by using the data obtained from the WSN and we present evaluations with real hardware, where we measure the communication time between the UAV and a ground sensor employing XBee-PRO Series 2.

This paper is structured as follows: in Section 2 we discuss related work on mobile ad hoc network routing protocols and cooperative sensing. Section 3 outlines the proposed method, by describing the proposed system architecture and the details of its development. Section 4 describes the evaluation of all the conducted experiments, the first for the UAV route adjustment, the second for building the chemicals concentration maps (clusters) and the third for the evaluations employing real hardware. The final section concludes the paper and offers some future perspectives.

2. Related work

2.1. Routing protocols

Mobile ad hoc network (MANET) routing protocols can be divided into a few main groups: (i) flat proactive routing, (ii) on-demand reactive routing, (iii) hybrid schemes, (iv) geographical routing and (v) opportunistic routing. Proactive (table-driven) ad hoc routing protocols maintain their routing information independently of communication needs. Status update messages are sent periodically or when the network topology has changed. Thus, a source node gets a routing path immediately if it needs one. This results in low latency and makes them suitable for real-time traffic. When they use proactive routing protocols, nodes proactively update their network state and maintain a route regardless of whether data traffic exists or not. The main drawback of these routing protocols is the high overhead they need to keep the network topology information up-to-date. All the nodes require a consistent view of the network topology.

Reactive (on-demand) routing only establishes routes if they are required. This saves energy and bandwidth during periods of inactivity. It should be noted that a significant delay may occur as a result of the on-demand route discovery. Compared to proactive ad hoc routing protocols, one advantage of reactive routing protocols is the lower overhead control. Furthermore, reactive routing protocols have better scalability than proactive routing protocols in MANETs. One drawback is that reactive routing protocols may experience long delays for route discovery before they can forward a data packet. Reactive protocols perform well in light-load networks.

Geographical routing protocols assume that a source knows its position and can determine the position of the destination. Moreover, each node knows its neighbors' positions. In comparison with flooding-based approaches, geographical routing has a reduced overhead for route discovery. Geographical routing protocols only require neighbor information containing their location to route packets and do not need to maintain per-destination information. Most geographical routing protocols use greedy forwarding as the main method to select the next hop. In order to avoid dead-ends in the routing path, face-routing has been proposed to route around a void.

Opportunistic routing [7,35,27] assumes that an end-to-end communication path may frequently be disrupted or may not exist in a MANET at any time. The routing mechanism forwards the message towards the destination on a hop-by-hop basis and the next hops are selected according to protocol-specific characteristics. This means that it is not essential to have a stable end-to-end connection from the data source to the destination. The packets are forwarded even though the topology is continuously changing.

2.2. Cooperative sensing

Wireless Sensor Networks are networks composed of several wireless nodes. These nodes are often deployed near or inside environments or phenomena with the aim of sensing/obtaining information about it. The information is then routed to a command center, where the data can be examined and appropriate action can be taken [9]. According to [3], those nodes are small embedded systems with the three following components: (i) mote, that is the main component of the sensor node, it is able of communicate wirelessly and should be programmable. Traditionally they are composed of a microcontroller, a radio and an energy source; (ii) a set of sensors, whose objective is to sense the environment and collect data (i.e., temperature, humidity); and (iii) data interface, that can be a USB or a serial port, used to connect the mote to a computer so that it can be programmed. Some motes allow this by means of the wireless interface.

One major issue when dealing with WSN is the limited source of energy, which is normally provided by batteries. Although the batteries can be changed, this can be dangerous for human beings as the sensor nodes might be installed in hazardous environments (i.e., volcanoes, chemical/nuclear affected areas). Furthermore, changing batteries is expensive (and requires both human and financial resources). Some techniques can be employed to increase the lifetime of the nodes. The first of these is the on–off behavior, i.e., the sensor nodes turn off some components to save energy. The best component to turn off is the radio, because it is the component which uses most energy [24]. This procedure makes the sensor node unreachable for some time, so the communication protocols used by the WSN must be aware of it. The second technique seeks to enhance the lifetime of the WSN by using limited radios (low power and bandwidth) because it requires less energy. As a result, the nodes can only communicate with the nearest neighbors. Hence, to send any information from the WSN to a base-station, the message must be routed via several nodes. This method is called multi-hop communication.

The cooperation of several types of nodes in a WSN application, including static and mobile nodes, can be seen in the work by Erman et al. [14]. They have established a platform of heterogeneous wireless sensor nodes with the objective of sensing and monitoring fires in buildings. They propose to deploy nodes inside a building where each node is capable of detecting the temperature of the room. When a fire is detected by the WSN, an UAV is called to fly near the fire and to deploy more sensors, and thus gather more information. When the fire-fighters arrive in the building, they wear a so-called Body Area Network so that they can receive the information from the nodes and also collect information required for the protection of the fire-fighters, such as body temperature and concentration of CO_2 near their mask.

Another project that relies on the cooperation of different types of nodes can be seen in the work by Valente et al. [31], where it is proposed the deployment of sensors in several vineyards to collect information about factors such as temperature and humidity.

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Initially, the collected data were routed to a command center, but as the vineyards are more than 70 m away from each other, they could not exchange the data. The authors tried to use more powerful radios, but this led to excessive battery consumption and the life-cycle of the WSN was drastically reduced. In light of this, the solution was to use an UAV to fly over the vineyards and gather data when the farmer needs it. Following this, the UAV comes back to the command center and the data is sent to a Graphical User Interface system where the farmer can visualize the information about the vineyards and determine the parameters of the watering system.

3. Our approach to spraying pesticides

3.1. UAVs for agricultural application

Fig. 1 shows the application scenario outlined in this paper. The current scenario has one UAV and *n* ground sensors. A UAV is used to spray chemicals on an agricultural field. However, the neighboring field, which may belong to another owner or be a protected area, must not be sprayed. Moreover, the UAV must keep to its lane of operation (i.e., within the boundary). If the UAV used for spraying comes too close to the neighboring field, or if there is a sudden change in the direction of the wind, the chemicals might fall on the neighboring field and this must be avoided. We propose that the UAV gets information from the WSN deployed in the crop field so that it is able to make the necessary adjustment to the trajectory. If a sensor detects an excessive concentration of chemicals, the UAV doing the spraying will be guided away from the border.

The proposed algorithm to adjust the UAV route can be understood with the aid of Fig. 2. Periodically, the UAV broadcasts messages to the sensors in the field to determine the amount of chemicals being perceived. If the sensor receives the message, it responds with a message reporting the amount of measured chemicals and its position. On the basis of this information, the UAV can make a decision about whether to change its route or not. The route is changed when the amount of chemicals perceived by the sensor does not match that of the proposed threshold (each type of chemical must have its own threshold).

An algorithm that requires the sensor nodes to be distributed in the form of a matrix is used to improve the application of the pesticides during the spraying. Fig. 2 shows the flowchart with the rules for changing the route; (1) Periodically, the algorithm sends a message to make queries to the sensor nodes which are scattered on the field. The sensor nodes located at the previous position of the UAV respond to this message with information about the amount of pesticides. (2) With this information, the UAV calculates the difference in the concentration of pesticides between each sensor node (left and right). (3) If the difference is greater than a predefined threshold, the algorithm calculates the route change, otherwise it continues in the pre-defined route and waits for the next query. This threshold may be different for each type of

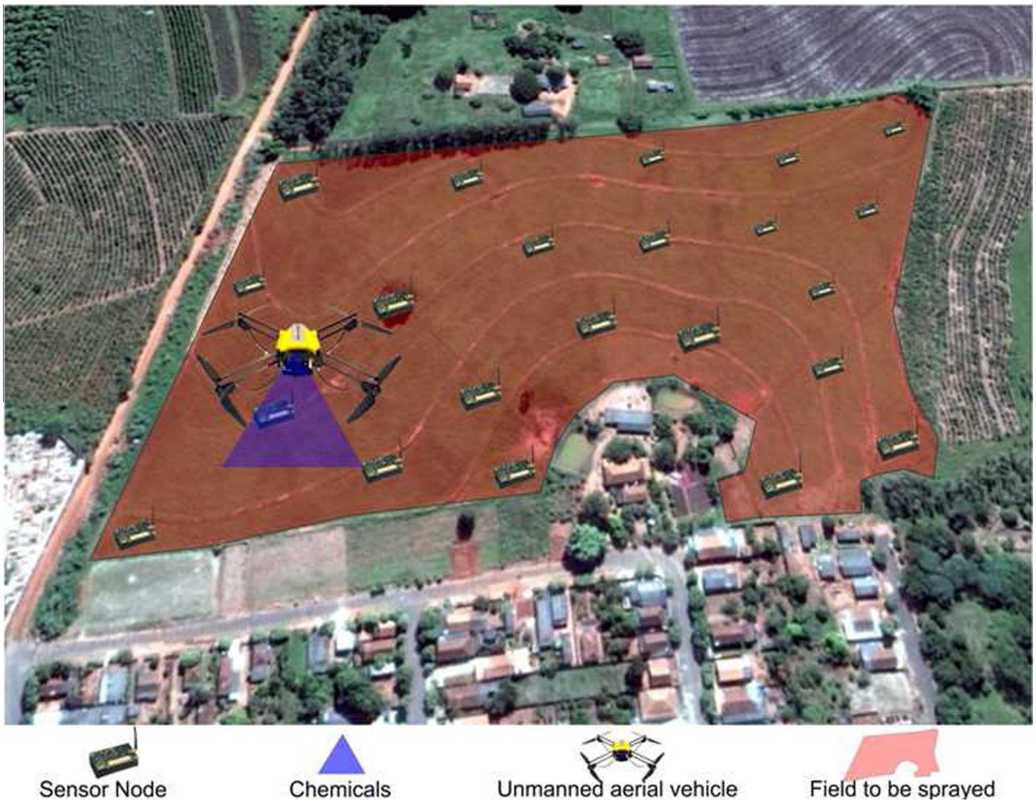


Fig. 1. Sample of application scenario.

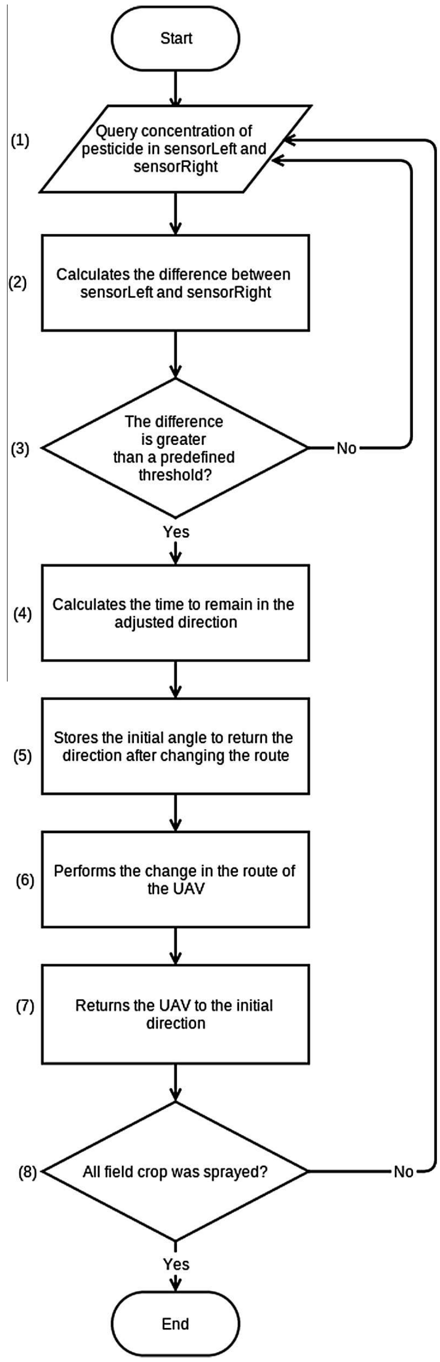


Fig. 2. Flowchart showing the rules for changing the UAV route.

pesticide, so it should be predefined. (4) The dynamics of this solution are revealed by calculating the time that the UAV remains with the changed route before returning to the initial path of the UAV. This computation is based on the difference between the samples and the change in the predefined factors (along with the threshold). (5) The track angle of the initial direction is stored and (6) a trajectory change is performed by the algorithm. The route change consists of turning the UAV at an track angle of 45 degrees to the side where there is less concentration of pesticide. (7) At the end of the predetermined time required for the algorithm to change the route, the algorithm returns to the start track angle. (8) If the spraying of the field crop has been completed, the algorithm ends, otherwise it returns to the query sensor nodes. The algorithm that corresponds to the flowchart can be seen in Algorithm 1. In the algorithm, θ was set to 45 degrees and the *durationTime* that is employed to calculate the time to remain in the new route was equal to 4.0. These values were obtained empirically. It is worth to emphasize that this occurs inside a loop, so, for each query it will maintain the new route for the predefined time. Terrain and environmental configurations are described in Section 4.

Algorithm 1. Adjusting the UAV route

```
diff ← sensorLeft − sensorRight;                  // see Figs. 2(1) and (2)
if (abs (diff) > threshold) then                  // see Fig. 2(3)
    duration ← abs (diff) ÷ durationFactor;       // see Fig. 2(4)
    initialAngle ← angle;                         // see Fig. 2(5)
    if (diff < 0) then                            // see Figs. 2(6) and (7)
        setAngle (angle + θ);
    else
        setAngle (angle − θ);
    scheduleChangeRoute (angle, duration);
```

The algorithm used to adjust the UAV route is based on control theory, that is, the data collected by the ground nodes are used as inputs of a control system, and the output is the track angle which the UAV must take. The system has two inputs, one of which is the chemical concentration perceived at the right-hand side of the plane and the other is the chemical concentration perceived on the left. The system calculates the time the UAV will spend in the new route before returning to the pre-defined route, and attempts to correct the amount of chemicals sprayed by adjusting the track angle of the UAV flight. The algorithm decides the new route on the basis of the data collected by the UAV from the ground nodes.

3.2. System development

There are two main ways to validate large-scale WSN projects: testbeds and simulations [8]. The testbed approach involves a small version of the project, where the system is usually split into modules, each of which is tested separately. The use of a testbed approach has some drawbacks since it is hard to validate the system in a real environment. In addition, Wireless Sensor Networks are faced with other problems that are not found in traditional networks. For example, while the tests are being conducted, the nodes constantly have to store debug messages or even exchange debug messages. This can cause some problems, e.g., the interference of multiple debug messages, or high memory usage, or even battery exhaustion [8]. As a result, the WSN community has been attempting to validate the first stage of a project by adopting a simulation approach [14].

There are several network simulators available (e.g., ns2, JavaSim, SSFNet, Glomosim). However, most of these simulators were designed for specific networks and their usage for wireless network simulation is wide-ranging, and, sometimes, requires the implementation of wireless network protocols and algorithms [22]. In addition, in [22] it is possible to find out more about the features of these available simulators. In carrying out this project, the simulator that is being used is OMNeT++.[1]

The OMNeT++ simulator is a discrete event simulator, based on C++ to model communication networks, multiprocessors and other parallel and distributed systems. This simulator is open-source and can be used for academic, educational and commercial purposes. It has been available for the Unix and Windows operating systems since 1997 [32]. This simulator was not designed to work within a specific network, and as a result, it is used in several kinds of simulations, such as networks with queues, wireless networks and P2P networks [34]. Owing to its generic design, OMNeT++ has a number of frameworks that have been established for specific networks, such as MiXiM,[2] a framework for wireless network modeling. This framework provides detailed models of wireless channels (e.g., fading), wireless connections, models for mobility, models for obstacles and several communication protocols, especially for the MAC layer [19].

There are several systems that can be used to build autonomous helicopters for agricultural applications. Currently, the most promising one, is the Yamaha RMAX, which is designed for agricultural uses, include spraying, seeding, remote sensing and precision agriculture. This includes a liquid sprayer with a tank capacity of 8 litres (2 tanks) and a granular sprayer with a tank capacity of 13 litres (2 tanks). Complete specifications can be seen in [36]. However, the Yamaha RMAX is not fully autonomous yet, hence, studies that adopt intelligent and autonomous approaches are needed to develop new versions. Another technical strategy that can be adapted to autonomous helicopters for agricultural applications, can be found in the work by Huang et al. [18], which examines the deployment of a spraying system for the Rotomotion UAV SR200 [25]. The Rotomotion UAV SR200 has up to 20 kg of payload capacity, although it does not have a spraying system off the shelf. In their work, the requirement was to spray 14 ha of land with a single load, at a low volume spray rate (0.3 L/ha). Hence, 4.2 L of chemical was needed to cover the 14 ha of land.

Furthermore, Ehmke [13] has written a featured research paper in which he describes several aspects of the task of employing unmanned aerial systems in agricultural fields, such as the necessary skills, the costs involved and the privacy policy that is entailed in the crop scouting and mapping by UAVs. As our aim is to study the behavior of the UAV, in our approach, both of the above-cited UAVs can be employed. Naturally, there must be a fine-tuning phase involving the parameters of the algorithm, due to the mechanical characteristics of each UAV. Furthermore, this fine-tuning phase should also take into account the type of crop being handled (soy, rice, corn, grapes, sugarcane) and the type of pesticide to be used.

3.3. Implementation details

The system implementation (currently in a simulation model) has been divided into two modules: (i) the *Behavioral Module* and (ii) the *Chemical Dispersion Module*. In the *Behavioral Module* we simulate the communication between the WSN positioned in the field and the UAV, using OMNeT++ with the MiXiM framework. The *Dispersion Module* was developed by means of Python[3] and SDL[4] library. The two modules run simultaneously, in an integrated way[5] with socket-based communication. The *Behavioral Module* sends the current position of the UAV (x, y, z) to the *Dispersion Module* along with the track angle and speed of the UAV (θ, v). Furthermore, the wind modeling is carried out in the *Behavioral Module*; this emulates changes in wind direction and speed and provides information to the *Dispersion Module* about changes in the environment. Fig. 3 shows an example of a sequence of scenes with the communication between UAV and WSN. In this example, there are 12 nodes representing the sensors in the field and one node representing the UAV.

The *Dispersion Module* calculates the fall of the chemicals, by obtaining the position and fall time of each drop. The WSN, in turn, determines the amount and position of the chemicals and returns this information to the *Behavioral Module*. Periodically, the UAV sends a broadcast message to the ground sensor nodes, requesting the concentration in its area. The ground sensor nodes that receive this message, connect to the *Dispersion Module* and request its concentration using their positions (x, y, z) as parameters. In this way, they can respond by giving details of the concentration in this area to the UAV. By means of these response messages from the ground nodes, the UAV can call a decision manager, for instance, to compute its decision and then change its route if necessary. The chemical dispersion is based on a simplified pollutant model, which considers (1) the vector of the initial velocity of the particle when it is sprayed, (2) the vector of wind speed and (3) gravity. The interactions occur until the particles hit the ground. Nonetheless, in conducting a simulation of how chemical falls, we must not only take account of the height of the UAV, factors like wind speed and direction, temperature, humidity and the droplet size also influences the dispersion, as can be seen in the works by [5,11,16,12]. However, as we are working to achieve a path optimization that can reduce the waste of chemicals, we believe the simulation is satisfactory at this stage. After having a real spraying mechanism, we believe we will be in a position to fine-tune some of the current parameters of the algorithm that adjust the path of the UAV to particular environmental conditions, weather patterns and types of chemical droplets.

Fig. 4 shows the proposed system sequence diagram and we can see the relationship between the nodes. The first activity is wind management which sets the velocity and direction of the wind through the setWind (v, θ) function. This activity can occur at any time, by changing the wind properties in the *Dispersion Module*. After this, while the UAV is moving through the field, it can use the sprayChemicals function, and inform the *Dispersion Module* of its position (x, y, z), velocity and track angle. With this information, the *Dispersion Module* is able to calculate where the chemical particles are going to be sprayed.

Regarding the ideal type of UAV, it must have the following characteristics: (1) be capable of flying at ≈15 m/s, and (2) be equipped with a spray bar that can spray the pesticide. It might be an autonomous airplane or an autonomous helicopter, although in the real-world scenario we are working with helicopters, as can be seen in Fig. 9. With regard to the UAV flying pattern, a traditional technique is mimicked, in which the pilot performs the spraying in predefined tracks. The UAV flies from the beginning to the end of the track and across the field as many times as needed to cover all the tracks. However, in this work the results are based on flights along a single track. With regard to terrain characteristics, the simulation environment considers the sensors deployed as a matrix (this can be understood with the aid of Fig. 8a). It is expected to have random distributed sensors which will be a subject for future studies.

Currently there are some technologies that can identify chemical levels in the air, soil or water. These technologies can calculate the degree of moisture in terms of the percentage of a specific chemical composition in a given area. In addition to determining the degree of chemical concentration, the sensor nodes can be used

[1] OMNeT++ Network Simulation Framework, http://www.omnetpp.org.
[2] MiXiM project, http://mixim.sourceforge.net.
[3] Python Programming Language, http://www.python.org.
[4] Simple DirectMedia Layer, http://www.libsdl.org.
[5] Simulation video available at http://youtu.be/4wFJZZEYAKM.

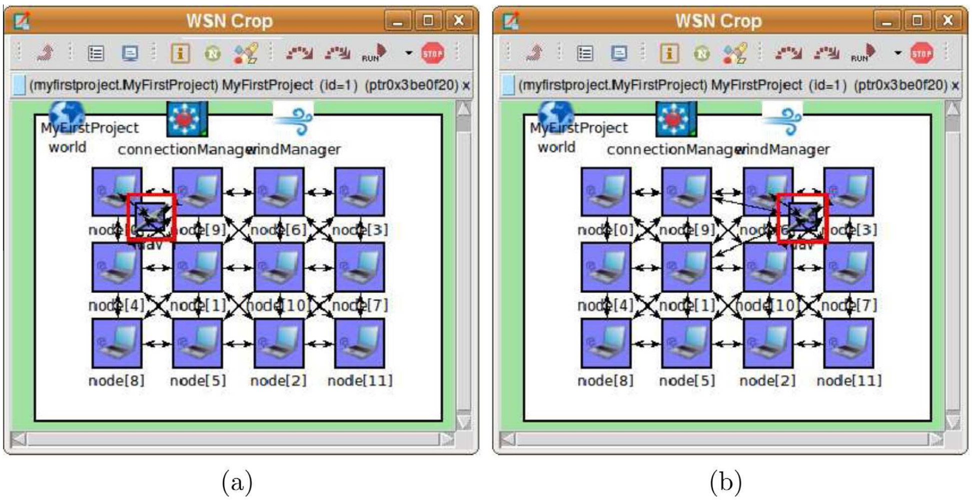


Fig. 3. OMNeT++ project. Figures show the sequence of scenes with the communication between UAV and WSN. The red blocks present the UAV and the arrows present the communication capabilities.

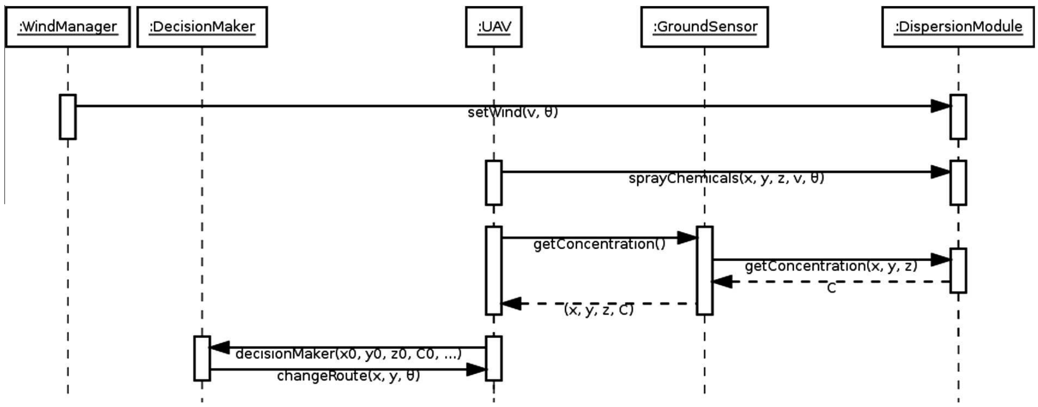


Fig. 4. Sequence diagram of the proposed model.

to detect diseases in plants or insect infestation [17,26,21]. In the current version of this work, we have employed simulated sensors. The use of real electrochemical sensors is also a subject for future work.

We are planning to have a network of UAVs (swarm) and also a network of several sensors (which are currently being simulated). The use of correct routing protocols is very important to minimize battery consumption and maximize communication capabilities, which have to be fine tuned to the specific environment. We have been carrying out an investigation of several routing protocols, as this is a part of the project; however, for the current version, there is only direct communication between the sensor nodes and the UAV.

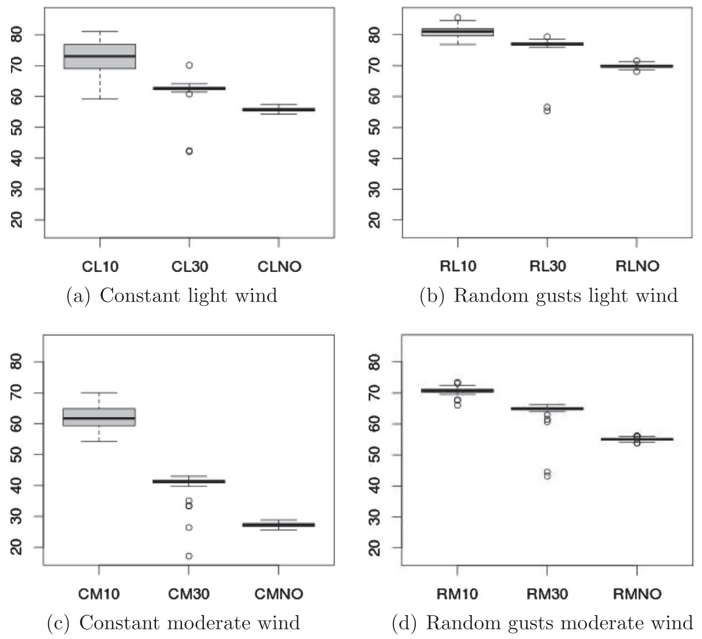
4. Evaluations and results

4.1. Adjusting the UAV route

In evaluating the algorithm to adjust the route for the UAV, we used a wind dataset with data that included wind direction and intensity. With this dataset in hand, we were able to ensure a better area of coverage even in changeable weather conditions. In the evaluation, the UAV was programmed to fly over the crop while spraying chemicals. Moreover, we tried to evaluate whether the number of message exchanges between the UAV and the WSN improved the system performance or not. The set of parameters included in this evaluation can be seen in Table 1.

In this set of evaluations, we carried out experiments including changes in the type of wind, changes in the number of messages between the WSN and the UAV and experiments to point out the behavior of the system while using the proposed algorithm. We performed these 70 times for each parameter set, with different random seeds. Fig. 5 shows the results of these experiments. It should be emphasized that we established an area of 1100 m by 100 m as the size of the simulated crop field. In addition, we only selected a section of the above-mentioned area as the part to be sprayed (i.e., 1000 m by 50 m). The number of sensors inside the crop field is 22 and the UAV velocity and operating height is 15 m/s and 20 m, respectively. We define light wind as 10 km/h and moderate wind as 20 km/h.

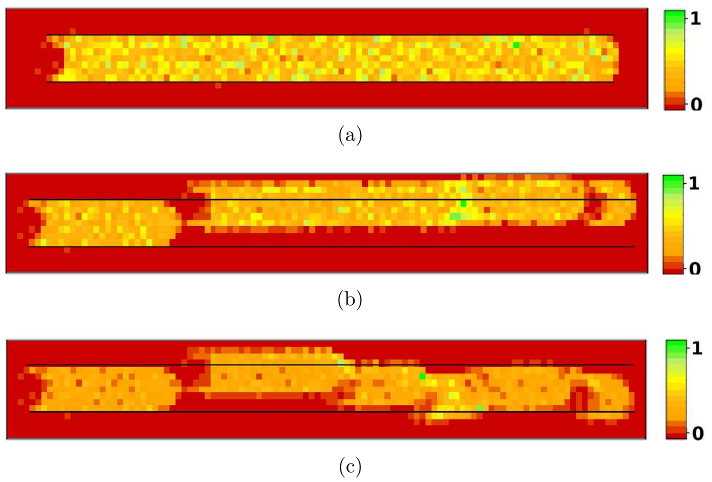
We can see in Fig. 5 that the best results are CL10 and RL10. This makes sense since both CL10 and RL10 are the evaluations that rely



(a) Constant light wind (b) Random gusts light wind

(c) Constant moderate wind (d) Random gusts moderate wind

Fig. 5. Amount (%) of chemicals sprayed inside the boundary (results of 70 runs for each parameter set). The parameters can be seen in Table 1.



(a)

(b)

(c)

Fig. 6. A heat map to represent the chemicals sprayed on the crop at the end of the simulation. The red color represents no pesticide and green represents the most concentrated places. The thin black lines show the crop field that needs to have chemicals sprayed. (a) Evaluation without wind. This shows almost no chemicals outside the lane. (b) Evaluation with wind changes every 15 s and no adaptation in the UAV route – we can see that the wind makes the chemicals fall outside the boundary lane. (c) Evaluation with wind changes every 15 s and when the algorithm is used to adapt the UAV route – we can see that the algorithm adjusts the UAV by attempting to keep the chemicals within the boundary lane. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

on more messages (every 10 s). RL10 is slightly better than CL10 because it has random gusts of wind, which results in having no wind in some parts of the execution. Consequently, the chemical is not affected by the wind the whole time and sometimes goes directly toward the ground. The use of messages every 30 s shows an improvement with regard to the simulation without communication and hence without using the proposed algorithm. In these simulations, the use of messages every 10 s allowed us to improve the chemical dispersion in ≈14% compared with the sets with messages every 30 s and in ≈27% compared with the sets with no messages at all.

We carried out a statistical analysis of the sets to determine if they can be considered to be distinct, and showed the efficiency of the algorithm. First we verified the normal adequacy of the distributions using the Shapiro–Wilk normality test. Most (8 of 12) of the p-values are lower than 0.05, i.e., the hypothesis of normal adequacy is rejected with 95% of confidence. As most of the distributions are not accepted as normal, we carried out a

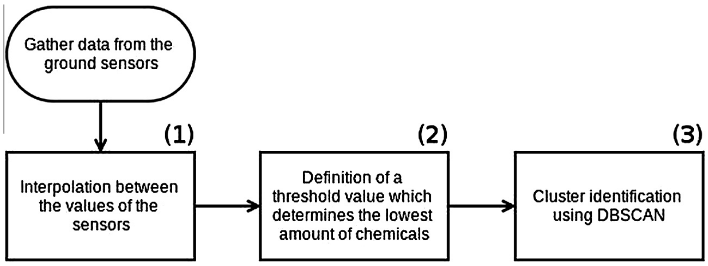


Fig. 7. Steps for mapping the chemical concentration.

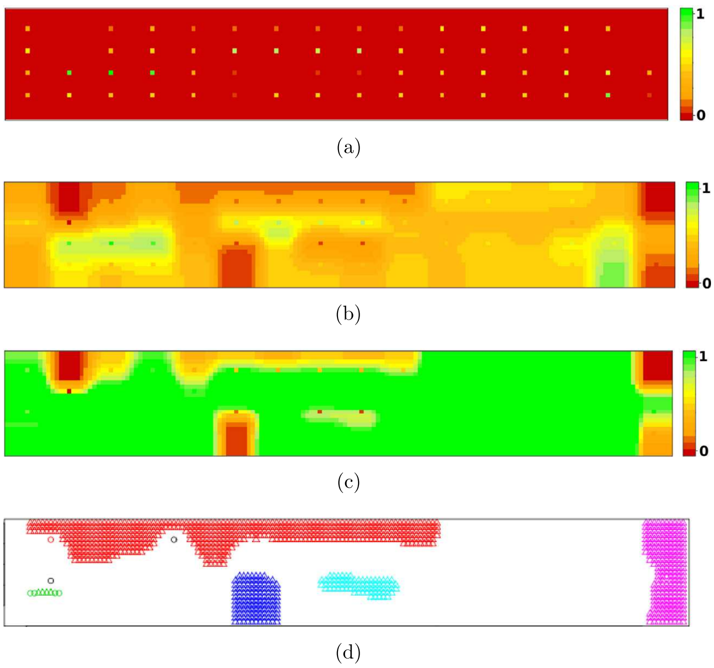


Fig. 8. (a) A crop field represented as a 2D matrix (heat map). A shift from red to green represents less to more perceived chemicals. Most of the area is in red because the sensors are scattered. As expected, the diagram shows a crop field with a non-uniform chemical spraying operation, caused by the highly random wind used in the simulation. (b) Map after the application of the interpolation technique (instance-weighted nearest-neighbor algorithm). (c) Map after the application of the threshold value, which determines the lowest amount of chemicals. (d) Cluster identification using the DBSCAN algorithm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

non-parametric test (Pairwise Wilcox Test) which showed p-values lower than 0.05 in all cases. This means that the algorithm is effective in adjusting the route of the UAV to improve the chemical dispersion. Fig. 6 shows the representation of the chemicals sprayed in the crop field in some of the evaluations. In Fig. 6c we can see how the algorithm adjusts the UAV route and attempts to keep the chemicals within the boundary lane.

4.2. Mapping the chemical concentration

As described earlier, the information retrieved by means of the WSN, provides the UAV with knowledge of the position and the amount of chemicals in every sensor of the crop field. However, after the application of the chemical by the UAV, some areas of the crop might not have a sufficient amount of chemicals; this might occur because the UAV is going too fast and even though the rules allow the UAV to adjust to highly random shifts of wind direction as quickly as possible, it might not be as fast as necessary. As a result, what happens is that there might be some clusters without the correct amount of chemicals. Hence, if we are able to build a chemical concentration map[6] using the data provided by the WSN, we might use this map to show clusters where there is an insufficient application of chemicals.

At the end of the UAV spraying operation, we can build a complete map of the chemical concentration, as we have all the information about the position of the sensors and the amount of chemicals perceived in the UAV memory. The crop field with chemical concentration can be represented as a 2D matrix (Fig. 8a). We represent this map as a heat map, i.e., the amounts of chemicals are represented between the colors red and green, green being the greatest amount.

[6] Source-code and data files used to the mapping scheme are available in http://goo.gl/b0ClX.

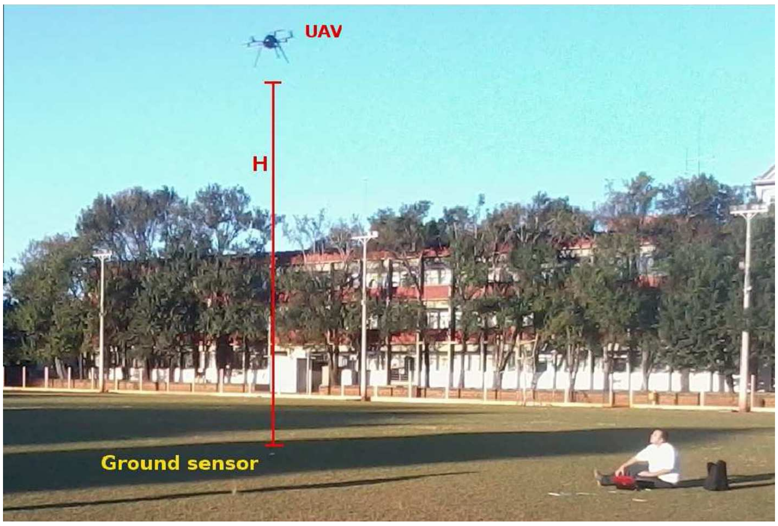


Fig. 9. Example of the real environment used to collect the measurements. We have evaluated *H* with 5, 10 and 20 m.

Table 1
Parameter set employed in the evaluations (with different weather conditions and system characteristics).

Eval.	Wind type	Messages every	Using proposed algorithm
CL10	Constant light wind	10 s	Yes
CL30	Constant light wind	30 s	Yes
CLNO	Constant light wind	–	No
RL10	Random gusts light wind	10 s	Yes
RL30	Random gusts light wind	30 s	Yes
RLNO	Random gusts light wind	–	No
CM10	Constant moderate wind	10 s	Yes
CM30	Constant moderate wind	30 s	Yes
CMNO	Constant moderate wind	–	No
RM10	Random gusts moderate wind	10 s	Yes
RM30	Random gusts moderate wind	30 s	Yes
RMNO	Random gusts moderate wind	–	No

In this simulation, the size of the terrain was set as 1500 m by 150 m. The number of sensors inside the crop field was 64 (4 lines with 16 sensors each). As we were concerned with investigating mapping schemes, we ran this simulation without our proposed adjustment route algorithm and in highly random wind conditions.

We can see in Fig. 8a the representation of the crop field after the application of the chemicals. The red color represents a zero amount, i.e., there is no sensor in that region or the sensor only measured a very small amount of chemicals. In addition, Fig. 8a shows (as expected) a crop field with a non-uniform chemical spraying operation, due to highly random wind.

We ran three stages for cluster identification after obtaining the raw information from the WSN (as shown in Fig. 7). As there are not sensors for every small part of the crop field, it is necessary to make an interpolation between the values of the sensors. Hence, in the first step we use the Instance-Weighted Nearest-Neighbor Algorithm [23] (Step 1 in Fig. 7). This technique is applied in every position of the crop field where there is no sensing information (red area). For each red cell, we calculate the Euclidian distance between its position and the positions of the sensors. Then, the value of each cell will result from a radial function. The closer the chemicals are to the sensor, the higher is their influence on the sensor value. The results of the Instance-Weighted Nearest-Neighbor Algorithm, when applied to the crop field shown in Fig. 8a, can be seen in Fig. 8b.

In the following stage (Step 2 in Fig. 7), we apply a threshold value which determines the lowest amount of chemicals. If the value is below the threshold, it means there were not enough chemicals in the application process. The resulting map after the threshold is adopted can be seen in Fig. 8c.

The last stage (Step 3 in Fig. 7) in the mapping scheme and cluster identification uses a DBSCAN algorithm [15]. The DBSCAN is used to find clusters with an amount of chemicals below the threshold. Using the DBSCAN algorithm, we have to specify a parameter which represents the shortest distance possible between one cell and another to belong to that cluster. Since it aims to provide a completely accurate mapping scheme, this parameter should be measured from real applications. The result of the DBSCAN that is applied in the crop field can be seen in Fig. 8d. We can see five large clusters and three very small ones. We can use the information about clusters to plan a new chemical spraying operation, which is restricted to the delimited areas. Different operations might be taken depending on the size of the cluster (e.g., operations with the UAV or even other types of small autonomous vehicles).

4.3. A step toward a real-world implementation

In the current phase, most of this work has been carried out in simulation environments. With the aim of carrying out evaluations with real hardware, we have measured the communication time between the UAV and a ground sensor, as shown in Fig. 9. We have employed the XBee-PRO Series 2[7] to collect these measurements. Fig. 10 depicts the results obtained from these measurements. The measured communication time consists of the time needed for the UAV to send a request message and receive a response from the ground sensor.

The particular UAV heights (5, 10 and 20 m) were chosen because there is a relationship between the spray angle/coverage and the drone height; the higher the flight, the greater the area covered by the spray. As a result, increasing the distance from

[7] Manufactured by DIGI, http://www.digi.com/products/wireless-wired-embedded-solutions.

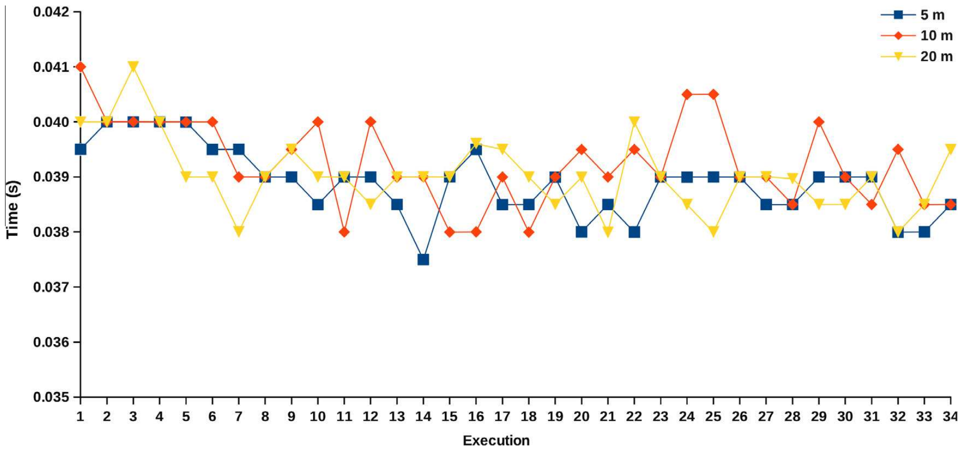


Fig. 10. Time of communication between a sensor ground and the UAV, using XBee-PRO Series 2.

the area where the pulverization is carried out, increases the dispersion of the pesticide. It should be emphasized that environmental conditions also affect the behavior (fall) of the chemicals.

We can notice that the average round trip time for 5, 10 and 20 m is ≈0.04 s. Hence, we carried out a statistical evaluation of the times to check whether there was any significant difference between the 5 m, 10 m and 20 m sets.

Using the Shapiro–Wilk normality test we can observe that there is no evidence that the sets of 5 m and 20 m are normally distributed, with 95% of confidence and the set of 10 m cannot be rejected as a normal distribution, with 95% of confidence. The *p*-values from the Shapiro–Wilk normality test, from 5 m, 10 m and 20 m, are 0.031, 0.056 and 0.006, respectively. Hence, as two of the sets are considered not to be normal, we employ a non-parametric pairwise comparison. The pairwise comparison using the Wilcoxon rank sum test showed that there is no evidence of any difference between the measurements, as all the *p*-values are greater than 0.05. This evaluation has shown that there is no significant difference between the times measured from 5 m, 10 m and 20 m.

5. Conclusions

In this paper we have described an architecture based on unmanned aerial vehicles that can be used to implement a control loop for agricultural applications, where UAVs are responsible for spraying chemicals on crops. The process of applying the chemicals is controlled by means of the feedback from the wireless sensors network that is deployed at ground level on the crop field. Furthermore, we have evaluated an algorithm to adjust the UAV route to changes in the wind (intensity and direction) and the impact related to the number of messages exchanged between the UAV and the WSN. Using the current terrain configuration, we found that the use of messages every 10 s does improve the spraying of the chemical in ≈14% compared to the sets with messages every 30 s and in ≈27% compared to the sets with no messages at all. Moreover, we have also shown how to build a chemical concentration map using the data provided by the WSN. The purpose of this was to show clusters with insufficient application of chemicals which might be used to perform new UAV applications in designated areas. We described how to build these maps using Instance-Based Algorithms and Density-Based Algorithms. The measured communication time between the UAV and the WSN, when the XBee-PRO Series 2 was employed, showed no significant difference for height of 5 m, 10 m and 20 m. All the measured communication times are ≈0.04 s. However this appears to be very short, we have still not been able to assess the actual sensing of the chemicals, which needs to be addressed in the next stage of this research.

6. Future work

The next stages of this project will be as follows: (i) developing the system using real hardware, addressing the reality gap in communications between the UAV and the WSN, the behavior of the UAV and the sensor capabilities, (ii) investigating the use of Evolutionary Techniques [4,1] to build (or tune) an autonomous set of rules (i.e., the behavior of the UAV), and (iii) modeling the system through a UAV swarm technique. As a final observation, since it is necessary to improve the simulation environment (which allows quicker and safer evaluations) other future work should seek to improve the actual chemical dispersion, by also using the mass of the particles, the viscosity of the chemicals and allowing a more realistic interaction between these fluids.

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CHAPTER

4

INVESTIGATION OF THE USE OF META-HEURISTIC ALGORITHMS TO ADJUST THE SPRAY ELEMENT CONFIGURATIONS

Exploiting Evolution on UAV Control Rules for Spraying Pesticides on Crop Fields

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Abstract. The application of chemicals in agricultural areas is of crucial importance for crop production. The use of aircrafts is becoming increasingly common in carrying out this task mainly because of their speed and effectiveness. Nonetheless, some factors may reduce the yield, or even cause damage, like areas not covered in the spraying process or overlapped spraying areas. Weather conditions add further complexity to the problem. Sets of control rules, to be employed in an autonomous Unmanned Aerial Vehicles (UAV), are very hard to develop and harder to fine-tune to each environment characteristics. Hence, 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 an evolutionary algorithm to fine-tune sets of control rules, to be employed in a simulated autonomous UAV. We describe the proposed architecture and investigations about changing in the evolutionary parameters. The results show that the proposed evolutionary method can fine-tune the parameters of the UAV control rules to support environment and weather changes in the simulated environment, encouraging the deployment of the system with real hardware.

1 Introduction

Chemical defensives, also known as pesticides, are commonly applied in agricultural areas to increase productivity. However, these products can cause serious health problems for workers who have direct or indirect contact with them. There are various diseases that can result from the interaction with these chemicals, like cancers, complications in the respiratory system and neurological diseases [15]. It is estimated that about 2.5 million tons of pesticides are applied worldwide each year and that this amount has been growing [12]. Much of the pesticide is lost during the spraying process due to the type of technology employed. Nevertheless, only a small part of the pesticide reaches the target crop field while the rest of it drifts away [10]. Evidences of pesticide drifts are commonly found

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between 48 m and 800 m from the target crop field. Other problems are crop areas not covered in the spraying process and overlapped spraying areas.

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 (WSN), 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 [5], in which the policy parameters were set empirically and applied independent of weather conditions.

This paper is organized in 5 sections. Section 2 presents other studies related to this paper. The proposed methodology is described in Section 3. Results from investigations are presented in Section 4. In Section 5 we present a discussion upon the results; this section also presents the conclusions and describes some future work.

2 Related Work

There are several works that employs UAVs as agents in agriculture and WSN as monitors of the environment, occasionally integrating both [2,7,16]. For example, Huang and collaborators [6] propose a system for spraying pesticide coupled to an UAV capable of carrying as much as 22.7 kg. The UAV model used was a SR200 manufactured by Rotomotion company. The spray system consists of four major components: (i) a metal tube with nozzles, (ii) a tank to store the pesticide, (iii) a pump to move the liquid and (iv) a mechanism for controlling the activation of spray. The spraying system can carry up to 5 kg of pesticide, which was needed to spray 0.14 km^2; and it provides a flight time of around 90 minutes. The main objective of that work was to validate the proposed system and evaluate different spray nozzles. However, the weather conditions were not taken into account. Additionally, a discussion of the evolutionary methodology able to optimize control of this activity is not presented.

Valente and collaborators [13] show a system based on WSNs and UAVs to monitor crop fields of vines. The WSN collects information from soil, climate and the condition of vines and presents this data to the farmer. However, the vine crop groups may be hundreds of meters distant from each other. Because of barriers (eg. rivers and roads) that may occur between crop fields, the usage of cables to connect networks implies in a prohibitive cost. Although the use of more powerful radios in sensor nodes enables communication between WSN, this will result in higher energy consumption implying in the reduction of battery lifetime. Thus, the solution used to overcome such limitations was employ a UAV able to fly over crop fields and collecting the information from each WSN, bringing data back to a processing center.

Faiçal and collaborators [5] proposed and evaluated an architecture formed by UAV and WSN to spray pesticides in crop fields. It is known that the weather conditions in the area of cultivation, such as wind speed and direction, can cause error in the spraying process. The study showed that the proposed architecture allows to minimize error and increase control of this activity. However, the work used a simplistic approach to correct the route of the UAV. The parameters set for the correction of the route are similarly applied in different weather conditions, which can harm the performance of this architecture. As previously mentioned, the objective of this paper is to evaluate and propose an evolutionary methodology to optimize and define the best weather parameter that influences the intensity correction of the UAV route.

3 Methodology

Fig. 1 synthesizes the context of this work. It can be seen that the spraying is carried out using UAVs, which have equipment for pesticide spraying, and a WSN distributed in matrix disposition in the crop field. The WSN is represented only in a target crop field delimited with two dashed lines (from the upper left to the lower right corner) to simplify the visualization. The two arrows indicate the direction of the wind at a specific location. The UAV maintains communication with WSN about the weather conditions (wind speed and direction) in its current position and also about the concentration of the pesticides identified by surrounding sensors. When an imbalance in the pesticide concentration is detected (e.g. the sensor on the left side identified a higher concentration than the one positioned on the right side), possibly caused by winds, the UAV uses its policy to change the position so that the pesticide is applied at a concentration balanced across the width of the target crop field. In addition, constraints prevent the pesticide to be sprayed out of the bounds of the target crop field, which may cause an overlap of the area that was subjected to the defensive chemicals. The adjustment of the route is represented by small arrows between the images

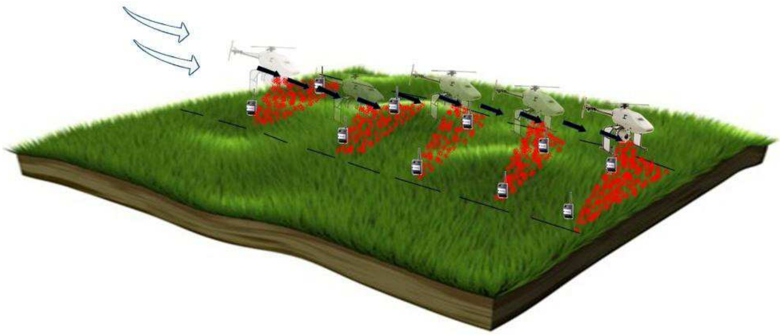


Fig. 1. Spraying using the architecture proposed by [5]. This architecture is formed by a UAV (spray) and WSN (sensing and feedback). If spraying is unbalanced between the sensors (distributed in matrix form on crop field), the UAV can correct your route using a policy with parameter settings defined before starting the activity.

of the UAV in Fig. 1. To adjust the route, the policy has the *routeChangingFactor* parameter, which operates pondering the intensity of alteration (sudden or soft). This parameter is set empirically before the activity and will be constant for all weather conditions.

In this work we extend the architecture proposed by [5], adding an evolutionary module able to optimize the parameter *routeChangingFactor*. Furthermore, the UAV will query the WSN about weather conditions of a target crop field. With this information, the UAV simulates computationally the result of spraying using different possible configurations. These simulations take into account the weather conditions informed by WSN and settings of UAV. The source code contains all instructions necessary to simulate the behavior and communication between the UAV and WSN. It also contains a dispersion model to represent the movement of sprayed particles along the crop field. These simulations use a Genetic Algorithm (GA) which evaluates the results and evolves to find a near-optimal *routeChangingFactor* to be used. This optimization is carried out for each target crop field until the whole desired area is sprayed. It is worth mentioning that the optimization is carried out in parallel to the spraying of pesticides and the *routeChangingFactor* is changed only when the GA finalize and the UAV enters the analyzed crop field.

To investigate the evolution in control we considered a rectangular field 1100 m long and 150 m wide. Moreover, a target crop field was considered to cover a rectangle measuring 1000 m by 50 m. The WSN consists of 20 sensor nodes arranged in matrix form throughout the target crop field. The UAV flies 20 feet high at a constant speed of 15 m/s, communicating with the WSN every 10 seconds.

The fitness function is the sum of pesticide gathered by the WSN outside the boundaries, greater the number means that greater amount of pesticide was placed outside the boundaries; hence, this fitness should be minimized. Current genome has a single real value that represent the *routeChangingFactor*; it is detailed in the next section. We treated the genome as a real value because it could be directed applied to the simulated UAV as an value to the rotors.

3.1 Deployment of the Evolutionary Module

Projects on WSN and UAVs are commonly validated in two ways: (i) testbeds and/or (ii) simulation. The testbed is a smaller version of the project built to conduct experiments. On the other hand, simulation is the act of using computers in formalization, as mathematical expressions or specifications, to mimic a real-world process. The scientific community has used the simulation method to validate WSN environments before real deployment [3,9]. Results from simulation are considered satisfactory in comparison to the results obtained from testbeds [1,8]. Thus, simulation results may be used to justify changes in order to minimize the negative impact in a real environment.

The same platform from [5] was employed to run the simulations. The OMNeT++[1] is a discrete event simulator based on C++ to model communication networks, multiprocessors and other parallel and distributed systems [14]. The OMNeT++ has a wide scope so it can be used to simulate various types of networks. The GA is configured to use a crossing value of 90% in the population and apply a mutation of 10%, besides employing the technique of elitism (where the best individual is kept for the next generation). Table 1 exemplifies the population used by the genetic algorithm, in which each individual is composed of a positive real value for the *routeChangingFactor* and its respective fitness which is calculated by adding all the particles of pesticide that are applied outside the target crop field. Therefore, a lower value of fitness indicates a better individual.

Table 1. Representation of the population used by the Genetic Algorithm

Individual	routeChangeFactor	Fitness
1st	2.136	12,032
2nd	2.532	12,169
3rd	1.465	20,032
4th	4.752	24,878
5th	3.846	22,987

In the experiments five population sizes and three maximum values of generations are evaluated. Each setting of experiments is represented by Ind**M**Ger**N**. Thus, **M** is the number of individuals of the population and **N** the value maximum of generations. As a stopping condition, we define the maximum amount of generations for each experiment, so after running all the pre-defined generations the GA is finished and the best individual of this generation is considered the *routeChangingFactor* more suitable for the weather conditions monitored by the WSN. Each configuration of the experiments were replicated 30 times in order to obtain a sample with high reliability to analyze its results.

The GA evolves the population according to their characteristics already described, and changes the configuration to be evaluated through the assignment

[1] OMNeT++ Network Simulation Framework, `http://www.omnetpp.org`

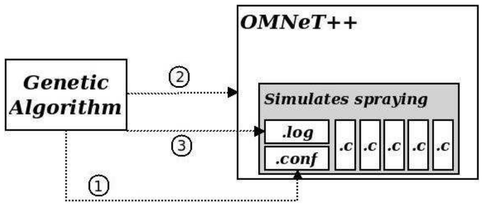


Fig. 2. Interaction between Genetic Algorithm and the simulator OMNeT++

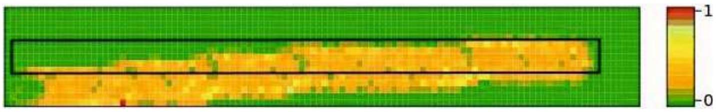
of a new value to the *routeChangingFactor* variable (considering the individual to be tested) in the source code inside the simulator. Fig. 2 shows the interaction between the GA and the simulator. Initially, the GA alters the configuration file of module Simulates Spraying with the value of *routeChangingFactor* of individual to be evaluated (step 1). Subsequently, the GA run the module Simulates Spraying in OMNeT++ (step 2) and finally analyzes the file *log* of the executed plan (step 3). This file stores the result of spraying all over the field (1500 m x 150 m) and the amount of pesticide sprayed wrongly (outside the target crop field 1000 m by 50 m) is considered as fitness of the individual. When the GA has tested all individuals of a generation, it will produce a new generation of individuals until the maximum generation is reached. During this study, we tried to keep the GA simple and fast; this is important because all analysis need to be carried in short time, once the spray occurs at runtime.

4 Results

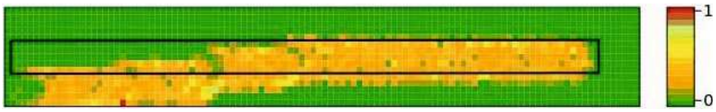
We employed the Genetic Algorithm as an evolutionary method to find the best *routeChangingFactor* to be used at a target crop field, considering the weather conditions identified by the WSN[2]. Fig. 3 shows three heat maps of sprays in the crop field. It can be observed that the target crop field is shown in this image, thus it is possible to identify where the pesticide was actually applied in or out of target field. The values 6.000 and 4.000 were defined empirically, whereas the value 2.140 was obtained by the proposed evolution module. Also is possible observe that the map of the spraying performed using the Evolution Module portrays a most appropriate correction of route considering weather conditions identified by WSN. This optimization provides a spray with lower error rate than the others (see Fig. 3), and provide a setting at runtime this parameter.

To evaluate the results, we performed a series of statistical analyzes. We started using the Shapiro Wilk method to verify the adequacy of normality and consequently to direct it to use parametric or non-parametric methods according to the results. We could observe that all values are less than 0.05, hence, all sets have the hypothesis of normality rejected considering a confidence level of 95%. Thus, we use non-parametric tests in the subsequent analyzes.

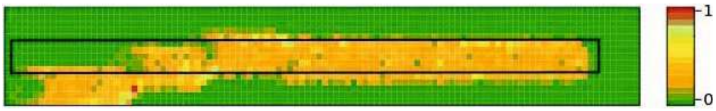
[2] Source code available in `http://goo.gl/9S14T0`



(a) $routeChangingFactor = 6.000$



(b) $routeChangingFactor = 4.000$



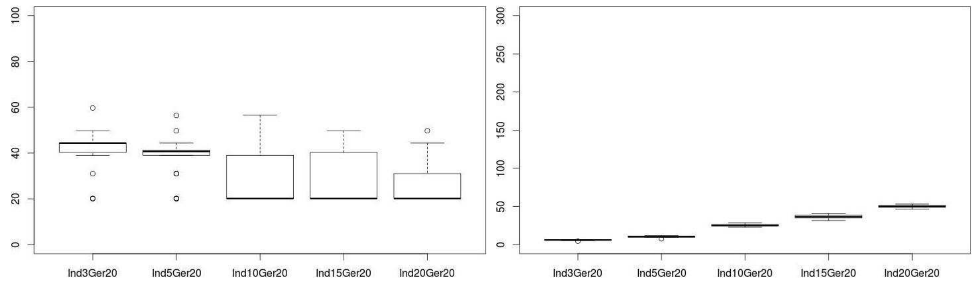
(c) $routeChangingFactor = 2.140$

Fig. 3. 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 genetic algorithm. We can see that when employing the *routeChangingFactor* obtained by the genetic algorithm 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.

As implied in Fig 4(a), there appears to be an improvement in the obtained results (lower error) with the increase of individuals. The pairwise comparisons using Wilcoxon rank sum test shows that there is a significant difference in populations formed by 3, 5 and 10 Individuals but not for populations with 10, 15 and 20 Individuals. This may imply that there is need to further increase the number of generations. Figures 5(a) and 6(a) shows the results with 50 and 100 generations.

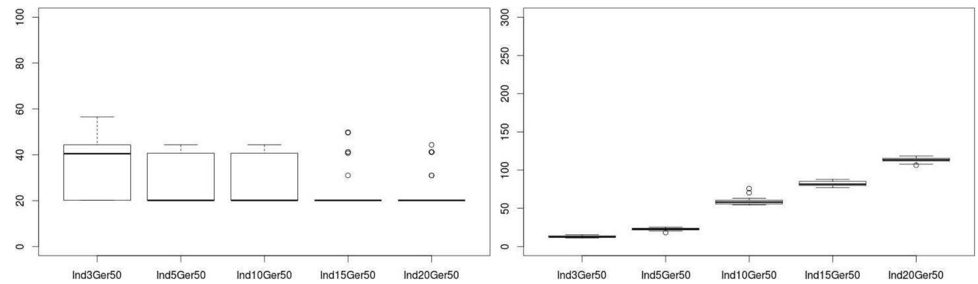
The pairwise comparisons using Wilcoxon rank sum test shows that for experiments using populations with 5, 10, 15 and 20 Individuals for 50 generations there is no significant difference. However, using populations with 5 and 10 individuals have lower accuracy populations when compared with the results of the populations with 15 and 20 Individuals. To the experiments with 5, 10, 15 and 20 Individuals and 100 generations no significant difference and their accuracies are similar. It should be noted that the settings used in the Genetic Algorithm provide results with high accuracies. Therefore, the settings that resulted in the best results are the populations formed with 15 and 20 Individuals to 50 Generations and 5, 10, 15 and 20 Individuals to 100 Generations.

From Fig. 4(b), 5(b) and 6(b), we can see that the average runtime time grows as the population and the amount of generations increase. Considering the settings that correspond to the best results (Ind15Ger50, Ind20Ger50, Ind5Ger100, Ind10Ger100, Ind15Ger100, Ind20Ger100), it is possible to note that the setting Ind5Ger100 has the lowest average runtime of 44.12 seconds. As described



(a) (b)

Fig. 4. Results of the GA employing 20 generations. (a) Fitness. (b) Time (in seconds).



(a) (b)

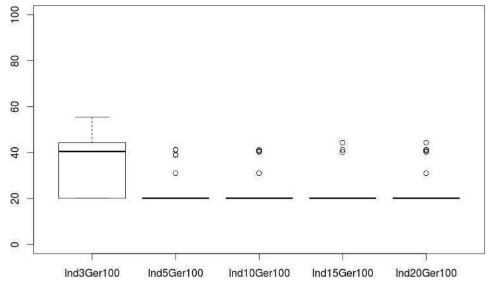
Fig. 5. Results of the GA employing 50 generations. (a) Fitness. (b) Time (in seconds).

above, the UAV flies at a speed of 15m/s in these experiments. Therefore, using the setting Ind5Ger100 to analyze the target crop field the UAV would fly over 661.907 meters. Thus, we can conclude that due to the length of target crop field measuring 1000 meters, this setting allows the later target crop field to be analyzed while the current target crop field is sprayed.

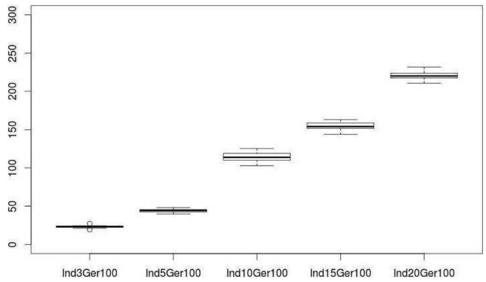
5 Discussion

We have described a methodology to evolve the parameter *routeChangingFactor*, which aims to adjust the UAV route and improve the spraying of pesticides on crop fields. The spraying operation is conducted employing an architecture based on a UAV and WSN. The UAV is the agent which spray the pesticide and the WSN is responsible for the monitoring of (i) weather conditions, (ii) points where the pesticide reached the crop field and (iii) feedback to the UAV. The initial methodology, although functional, have showed some limitations in correcting the route, since this parameter was defined empirically and remained the same for all activity. This limitations is corrected with the proposal described in this work.

Due to the fact that the adjustment of the route is performed using the *routeChangingFactor* parameter. It may be noted that in the experiments that



(a)



(b)

Fig. 6. Results of the GA employing 100 generations. (a) Fitness. (b) Time (in seconds).

we use 20 generations to find the best parameter, settings involving populations with 10, 15 and 20 individuals are not significantly different. However, only 50% of the results achieved is the best possible value. The same happens with the results obtained in experiments using populations with 5 and 10 individuals when evolved by 50 generations. Moreover, the results obtained using 15 and 20 individuals by 50 generations and also 5, 10, 15 and 20 individuals by 100 generations achieved the best possible value and showed greater stability in its results. Considering these results, the configuration Ind5Ger100, corresponding to a population of 5 individuals with 100 generations, has satisfactory behavior for the purpose this study. This configuration is able to achieve good results with high accuracy at relatively low average runtime. Other settings of the experiments not cited in this section are considered unsuitable for solving this problem because of its low accuracy.

It is worth mentioning that the error in no case is less than 20% because the methodology considers that the UAV starts spraying at a fixed point and the route adjustment occurs after some predefined time. Thus, this error occurs at the beginning of the crop field where spraying has the influence of the weather conditions. Therefore, a better understanding of the results is made from the following reading: starting spraying in position X, the best *routeChangingFactor* has value Y, which will result in an error of $Z\%$ in weather conditions informed by the WSN.

Lastly, it is important to remember that the developed methodology, which evolve the *routeChangingFactor*, had as main motivation the possibility of providing to UAV with a intelligent behavior, adjusting its route considering weather conditions. Thus, this becomes a dynamic policy for a naturally dynamic environment. The next stages of this project will be as follows: (i) developing the system using real hardware, addressing the reality gap in communications between the UAV and the WSN, the behaviour of the UAV and the sensor capabilities and (ii) investigating the use of other evolutionary techniques, like NSGA-II [4] and Differential Evolution [11]. As a final observation, since it is necessary to improve the simulation environment (which allows quicker and safer evaluations) other future work should seek to improve the current chemical dispersion module and the physical behaviour of the UAV.

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CHAPTER

5

EVALUATION OF THE EFFECTIVENESS OF ADAPTING TO THE BEHAVIOR OF THE SPRAY ELEMENT

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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 all 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

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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 run-time. 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 system 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.

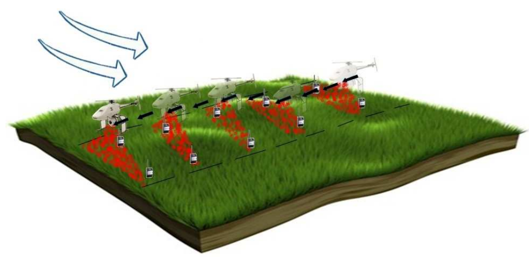


Fig. 1. Example of spraying in crop fields with the architecture proposed by [4]. This architecture consists of a UAV (to spray) and WSN (to monitor). If the WSN identifies an unbalanced spray on its sensor nodes, the UAV changes its route to correct the spraying of the pesticide.

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

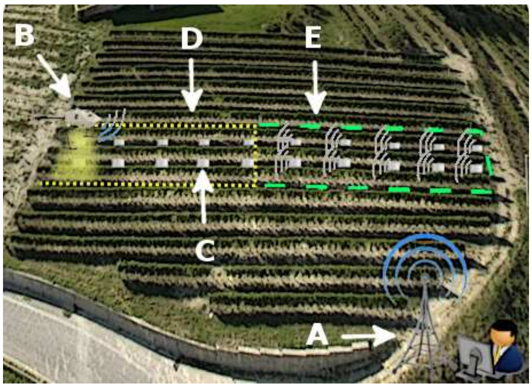


Fig. 2. Behavior of the architecture that employs the proposed optimization methodology. The Control Station (A) is installed outside the target crop field, in a zone that remains communicable with the UAV (B). During the spraying of the current crop field (D), the UAV sends a request for weather information 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.

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 best value of the parameter that is found is sent to the UAV. When the spraying of the current crop field (D) has been finalized, the UAV updates its settings so that the spraying of the next crop field (E) can start. It should be highlighted that the use of a Control Station provides more powerful computation and, in addition, allows a pilot (on the ground) to oversee the flight and, if necessary, intervene in the control of the UAV.

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:

$$\textit{routeChangingFactor} = \{x \in \mathbb{R} \mid 1.0 \leq \mathbb{R} \leq 10.0\}$$

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 $_d$), 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].

$$X_{id+1} = X_{id} + V_{id} \tag{1}$$

$$V_{id} = \begin{array}{c} w_i * V_{id} + C_1 * rand() * (P_{id} - X_{id}) \\ +C_2 * Rand() * (P_{gd} - X_{id}) \end{array} \tag{2}$$

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 (FuncObjetive) 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]OMNeT++ Network Simulation Framework, http://www.omnetpp.org

Algorithm 1: Proposed algorithm to optimize the *routeChangingFactor* parameter.

$InitializeParticles(RandomPosition[1, 10])$
for $MAX\_ITERATION$ **do**
  $PARTICLES \leftarrow FirstParticle()$
  for $ALL\_PARTICLES$ **do**
    $Result \leftarrow FuncObjetive(PARTICLES)$
    if $Result$ is best particle **then**
      Stores the position in particle
    end if
    if $Result$ is the best in the swarm **then**
      Stores the position in swar
    end if
    $UpdateVelocity(PARTICLES)$
    $NewPosition(PARTICLES)$
    $PARTICLES \leftarrow NextParticle()$
  end for
end for
return $BestGlobalPosition$

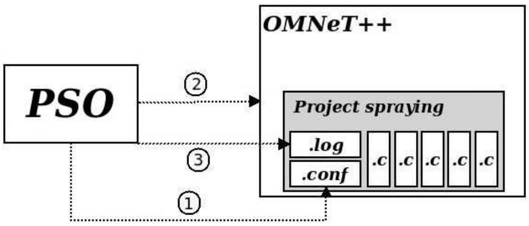


Fig. 3. Interaction between PSO and *OMNeT++*.

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 **P**M (number of particles) **I**H (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 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 P3I20 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

TABLE I. RESULTS OF THE OPTIMIZATION OF THE *routeChangingFactor* PARAMETER. P-VALUE LESS THAN 0.05 INDICATES A NON-NORMAL ADEQUACY, THEM, IT LEADS TO NON-PARAMETRIC STATISTICAL ANALYSIS.

Settings	Convergence rate (%)	Average time of evolutions (s)	Shapiro Wilk p-value
P3I20	96.77	18.617 ± 0.371	0.330
P3I50	100.00	45.927 ± 0.649	0.012
P3I100	100.00	93.854 ± 1.555	0.076
P5I20	100.00	30.705 ± 0.506	0.150
P5I50	100.00	77.162 ± 0.766	0.362
P5I100	100.00	158.995 ± 3.143	0.302
P10I20	100.00	62.549 ± 0.912	0.023
P10I50	100.00	157.957 ± 2.976	0.212
P10I100	100.00	313.335 ± 1.488	0.047
P15I20	100.00	93.606 ± 0.799	0.009
P15I50	100.00	235.189 ± 1.816	0.101
P15I100	100.00	480.359 ± 14.762	0.012
P20I20	100.00	125.088 ± 1.059	0.014
P20I50	100.00	312.894 ± 2.058	0.165
P20I100	100.00	628.324 ± 2.251	0.073

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 ≈ 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

[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.

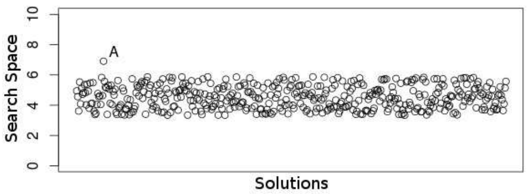


Fig. 4. Representation of the solutions found by the algorithm in the search space.

TABLE II. CORRECT SPRAYING (%) IN THE TARGET CROP FIELD.

Settings	Area with correct coverage (%)
CL10	72.871 ± 4.659
CL30	62.113 ± 3.591
CLNO	55.697 ± 0.657
P3I50	86.220 ± 2.538
P5I20	85.811 ± 2.894
P10I20	85.777 ± 2.520

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.

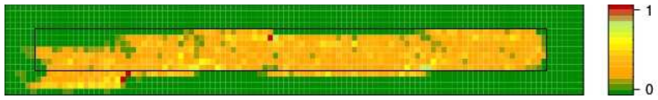
After analyzing the optimization of the *routeChanging-Factor* parameter, we conducted experiments with the aim of evaluating the precision of the spraying by using solution indicated by the algorithm.

B. Spraying on crop fields

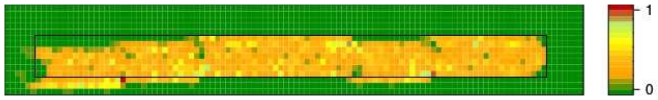
This subsection shows the results of the second stage of the experiments. This involved analyzing and discussing the results of spraying in a crop field by using the solutions found by the PSO. In this stage, the experiments were conducted to support the assessment of the proposal, which entailed optimizing 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].

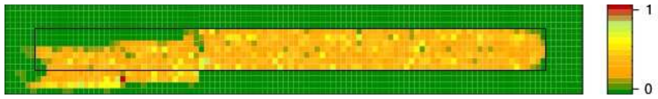
The settings that use optimization parameter are described as follows: *P5I20*, where the algorithm uses five particles and twenty iterations; *P10I20*, where the algorithm uses ten particles and twenty iterations; *P3I50*, where the algorithm uses three particles and fifty iterations. These results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



(a) *routeChangingFactor* = 3.000



(b) *routeChangingFactor* = 6.000



(c) *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.

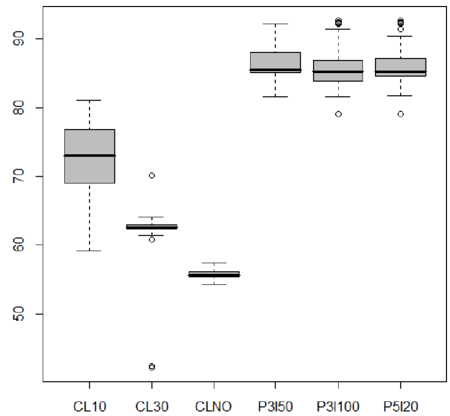


Fig. 5. Percent of pesticide spraying inside the target crop field. In this Boxplot, first three results come from [4]; last three results are obtained in this work by the proposed PSO.

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 aplication of pesticides when employd 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.

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).

	CL10	CL30	CLNO	P3I50	P5I20
CL30	0.000				
CLNO	0.000	0.000			
P3I50	0.000	0.000	0.000		
P5I20	0.000	0.000	0.000	0.52	
P10I20	0.000	0.000	0.000	0.52	0.79

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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CHAPTER

6

VALIDATION IN ENVIRONMENTS WITH A LOW VARIABILITY IN THEIR WEATHER CONDITIONS

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

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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.

Keywords: Unmanned Aerial Vehicle, Unmanned Helicopter, Evolutionary Algorithms, Spraying Pesticides, Wireless Sensor Network

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,

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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.

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 metres 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 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

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

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% to 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] 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/

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, wheather condictions 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. Figure 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 used without the feedback of information about pesticide deposition.

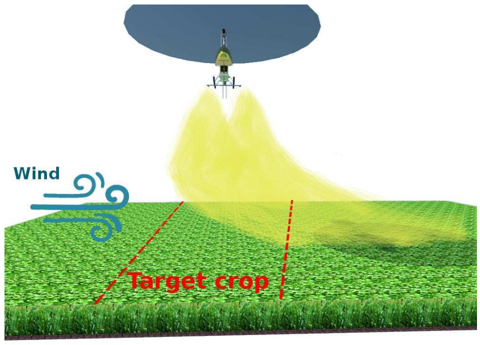
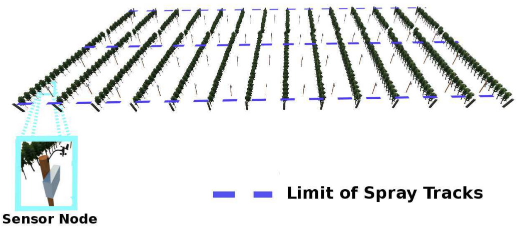


Figure 1. Problem statement: drift of pesticides from the target crop field in dynamic environments (e.g. a change of wind speed and direction).

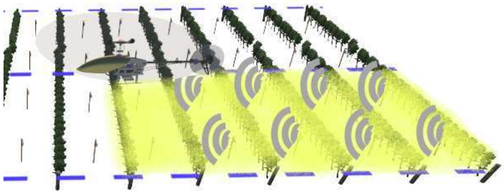
The application scenario exploited by Faiçal et al. (2014b) is shown in Figure 2. In this figure, the UAV is a spraying element equipped with a programmable trigger system. The control system divides the crop field into parallel spraying tracks and defines a flight path so the UAV can fly over the center of these tracks when spraying pesticide (see Figure 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 second intervals (see Figure 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.

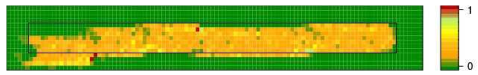


(a) The target crop field is divided into spraying tracks to guide the flight path of the UAV. Each track is defined in order to allow pairs of sensor nodes to be covered in its width. These spray tracks are made possible by the WSN that is deployed within the plantation and have a matrix format.

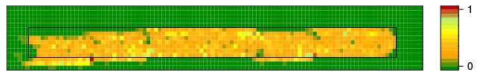


(b) The UAV flies over each spray track, which is defined for the flight path while the pesticides are being sprayed. During the spraying process, the UAV checks the last covered sensors to find out the concentration of pesticide deposited, together with the weather conditions. If the response to the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

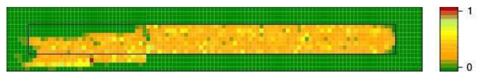
Figure 2. Standard operation of the proposed architecture by Faiçal et al. (2014b).



(a) *routeChangingFactor* = 3.000



(b) *routeChangingFactor* = 6.000



(c) *routeChangingFactor* = 7.164

Figure 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.

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 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. Figure 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.

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.

Figure 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 sub-area.

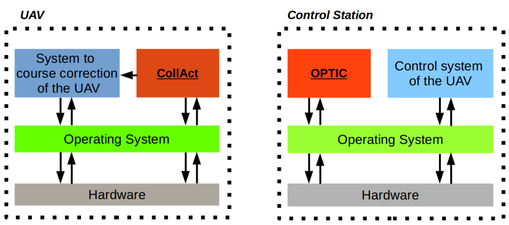


Figure 4. Elements of the AdEn system (CollAct and OPTIC) in their respective computing platforms, together with the components of the architecture proposed by Faiçal et al. (2014b).

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. Figure 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).

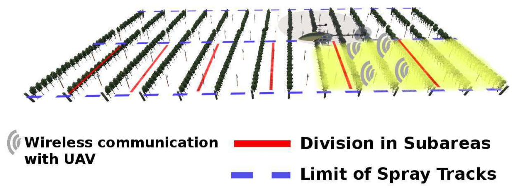


Figure 5. The spray track is divided into sub-areas of interest, which define the node sensors that will be queried for weather information and the area where each intensity is used. The current sprayed area is highlighted in the whole area to be sprayed. The wireless communication symbols represent 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.

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. Figure 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.

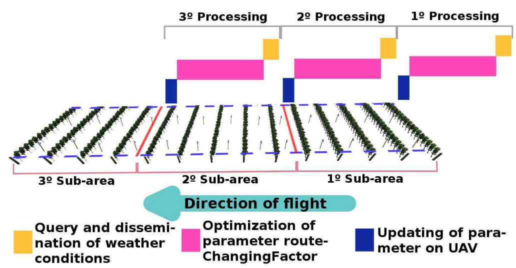


Figure 6. Spatio-temporal representation of actions taken by AdEn. It is important to observe that the best route correction intensity found is used in the following sub-area, in which the processing steps are executed (e.g., the result of the 1st processing is used in the 1st sub-area). Initially, the 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.

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 *routeChang-*

ingFactor when setting the route adjustment policy. As shown in Figure 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 information 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 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:

$$Fitness = \sum \vartheta - \sum \nu$$

where $\sum \vartheta$ is the sum of all the pesticide sprayed and $\sum \nu$ 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:

$$routeChangingFactor = \{x \in \mathbb{R} \mid 1.0 \leq x \leq 10.0\}$$

Figure 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.

[4]OMNeT++ Network Simulation Framework, http://www.omnetpp.org

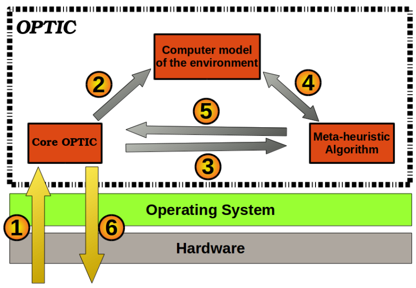


Figure 7. Execution of OPTIC element in the Control Station to optimize the *routeChangingFactor* parameter for weather measured by the WSN.

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) (Klaus Wehrle, 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.

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]MiXiM project, http://mixim.sourceforge.net

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, 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 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 et al., 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 imple-

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 x 50 m
Weather	Wind Speed	10 and 20 km/h
Weather	Wind Direction	North

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).

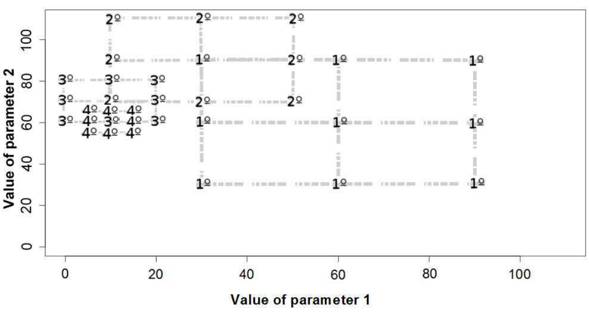


Figure 8. Scanning in the search space made by the Grid Search to define the configuration of each metaheuristic. An important feature of this implementation of the Grid Search is the convergence and concentration of assessments in a promising region of the search space. The movement of Grid Search is 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.

mentation, 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. Figure 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 20km/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%.

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 be chosen.

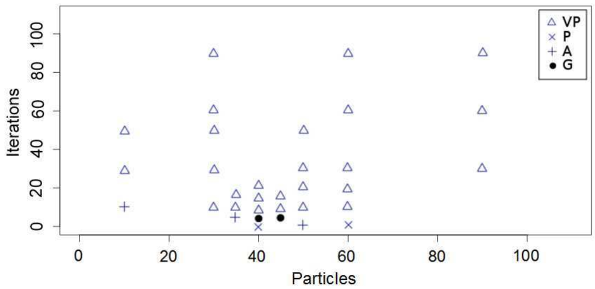
Four classes were created to discretize the behavior displayed by the settings evaluated with each metaheuristic, which are: (**i**) Very Poor; (**ii**) Poor; (**iii**) Average; and (**iv**) Good. These classes represent a behavioral pattern for each setting, which is shown and described in Table 3. Figures 9(a) and 9(b) show 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 to a promising region of the search space. returning good parameter values for 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

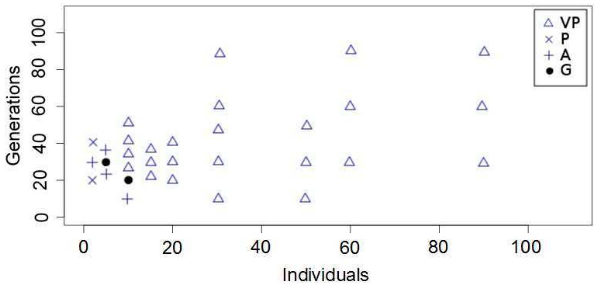
Table 2. Parameters and limits of the search space used by the Grid Search for configuring the metaheuristics.

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

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



(a) Search for configuring the PSO.



(b) Search for configuring the GA.

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

(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 Figure 9(a) and 9(b) and marked with •. It is possible to see the behavior of the five settings in Table 4, which are: (**i**) for the PSO, *PARTX_ITEY*, where **X** is the number of particles that compose the swarm and **Y** is the total number of iterations; and (**ii**) for the GA, *INDX_GENY*, 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:

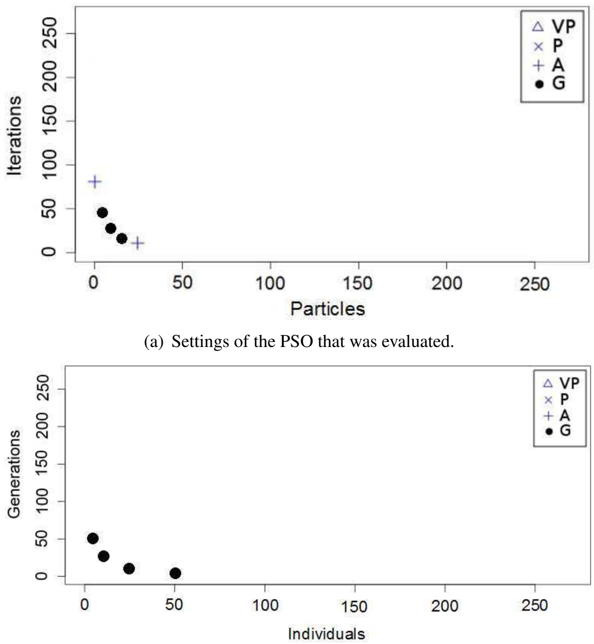
$$\Delta = \frac{\alpha}{\nu}$$

where α is the length of the sub-area in meters and ν 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

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



(a) Settings of the PSO that was evaluated.

(b) Settings of the GA that was evaluated.

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

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 Figure 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 emnbedded 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 Figure 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, Power Draw/Voltage of 1.2A @ 5V, 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 seconds for the PSO-PART15_ITE15 and 1364.898

		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

Table 5. Parameter values evaluated in the complementary approach.

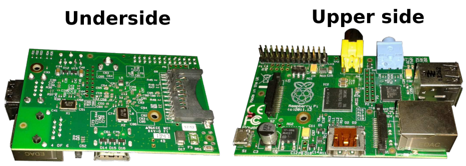


Figure 11. Embeddable device used as a computing platform to run the PSO-PART15_ITE15 and GA-IND10_GEN25 metaheuristics to optimize the *routeChangingFactor* parameter. This evaluation investigates whether the metaheuristics can be embedded in the UAV to reduce the rate of communication with the Control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

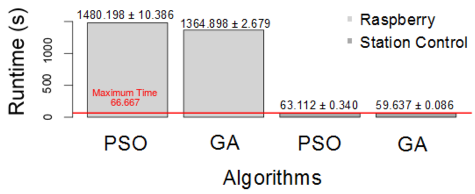


Figure 12. A comparison between the Average Runtime of the metaheuristics running on the Station Control and on the Raspberry PI. The difference was confirmed with 95% of statistical significance.

seconds for GA-IND10_GEN25. Figure 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 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*

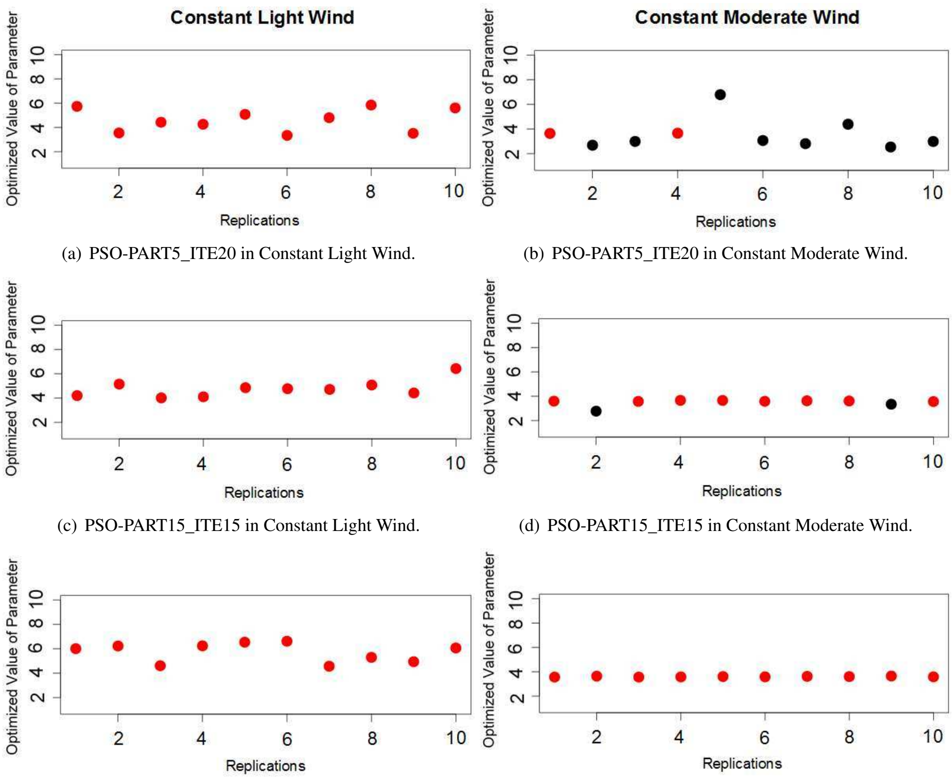
In the experiments for the optimization of the intensity of the route setting using the GA-IND10_GEN25, PSO-PART15_-ITE15 and PSO-part5_ITE20 metaheuristics, each metaheuristic was run in the control station for both types of weather conditions (CLW and CMW). The performance and behavior of each metaheuristic in both these conditions are listed in Table 6.

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.

Figure 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). Figures 13(a), 13(c), and 13(e) show a larger interval of values for the same accuracy in the

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

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).



(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.

Figure 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.

CWL environment, between the 3.343 and 6.616. On the other hand, Figures 13(b), 13(d) and 13(f) suggest 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 metahueristics presented a similar behavior for the CLW weather conditions.

Figure 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.

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).

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 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

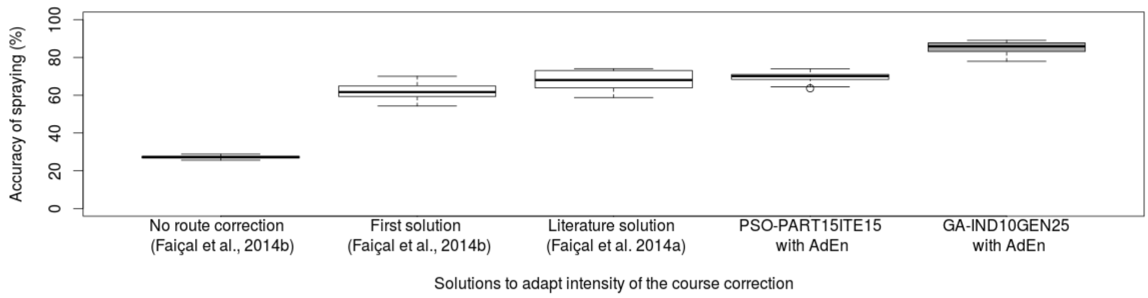


Figure 14. The degree of pesticides correctly deposited on the targeted sub-area for each solution in CMW weather conditions. It is important to observe that GA-IND10_GEN25, proposed in this study, found a more appropriate intensity to weather in all its executions. This result exceeds the efficiency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

Wilcoxon Rank Sum Test

	PSO-PART5_ITE20	PSO-PART15_ITE15
PSO-PART15_ITE15	0.130	-
GA-IND10_GEN25	0.000	0.000

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.

different dispersion models to make the most accurate computer model the real environment.

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CHAPTER

7

AN INVESTIGATION OF HOW TO ADAPT THE SPRAY ELEMENT TO ENVIRONMENTS WITH A HIGH VARIABILITY IN THEIR WEATHER CONDITIONS

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Fine-Tuning of UAV Control Rules for Spraying Pesticides on Crop Fields: An Approach for Dynamic Environments

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Brazil is an agricultural nation whose process of spraying pesticides is mainly carried out by using aircrafts. However, the use of aircrafts with on-board pilots has often resulted in chemicals being sprayed outside the intended areas. The precision required for spraying on crop fields is often impaired by external factors, like changes in wind speed and direction. To address this problem, ensuring that the pesticides are sprayed accurately, this paper proposes the use of artificial neural networks (ANN) on programmable UAVs. For such, the UAV is programmed to spray chemicals on the target crop field considering dynamic context. To control the UAV flight route planning, we investigated several optimization techniques including Particle Swarm Optimization (PSO). We employ PSO to find near-optimal parameters for static environments and then train a neural network to interpolate PSO solutions in order to improve the UAV route in dynamic environments. Experimental results showed a gain in the spraying precision in dynamic environments when ANN and PSO were combined. We demonstrate the improvement in figures when compared against the exclusive use of PSO. This approach will be embedded in UAVs with programmable boards, such as Raspberry PIs or Beaglebones. The experimental results demonstrate that the proposed approach is feasible and can meet the demand for a fast response time needed by the UAV to adjust its route in a highly dynamic environment, while seeking to spray pesticides accurately.

Keywords: Unmanned aerial vehicle; agricultural applications; dynamic environments; neural networks; evolutionary algorithms.

1. 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 to 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 pesticide is wasted during the spraying process due to the type of technology employed. Evidence show that the drift of pesticides is generally found at a distance of 48 m to 800 m from the target crop field; the deviation can range from a distance of 5 km to 32 km downwind.[3]

The use of unmanned aerial vehicles (UAV) to carry out the task of spraying pesticides can have several benefits, 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, by avoiding the presence of chemicals outside the designated areas, which is important to protect the neighboring fields that may have other crops, and protect nature reserves or water sources. The sets of control rules to be employed in an autonomous UAV are very hard to put into effect and even harder to fine-tune to each environmental feature. Due to the technical features of each UAV, a fine-tuning phase must include the parameters of the algorithm. This process must also take into account the type of crop being handled and the type of pesticide being used.

The proposed architecture employs an UAV that has an attached spraying system and is able to communicate with a wireless sensor network (WSN), which is arranged in a matrix-like grid on the crop field. The WSN sends feedback on the weather conditions and determines how the pesticide is actually being applied on the target crop field. On the basis of the received information, the UAV appropriately adopts a policy that allows it to correct its route. Hence, the main contributions of this research are: (i) to investigate an evolutionary methodology capable of minimizing human contact with pesticides, (ii) to evaluate an evolutionary approach that is able to reduce errors when spraying pesticides in areas where vegetables and fruits are grown, (iii) to investigate techniques able to maximize quality in agricultural production, and (iv) to increase the autonomy of the architecture proposed by Faiçal *et al.*,[4] in which the policy parameters were set out empirically and could be applied regardless of the weather conditions.

This paper extends the previous work[5] by presenting a proposal and an evaluation on how UAVs can be controlled in a highly dynamic environment, such as environments with sudden changes in the speed and direction of the wind. To this aim, we devised an ANN to be employed in real-world operations, which was built with evolved values employing a PSO approach. We employ the PSO to find near-optimal parameters for static environments and then train a neural network to interpolate the PSO solutions in order to improve the UAV route in dynamic environments. Neural networks have an intrinsic mapping and generalization features, which make them a good choice for dynamic environments,[6,7] while the evolutionary approach is a good mean to discovering non-trivial parameters.[8,9] Combining the evolutionary technique with the neural approach in this work allowed us to leverage the best capabilities of each technique. In such a way, we propose the use of an ANN for quick decision-making, since in real environments the weather conditions change suddenly and at short intervals of time. The new proposal provides a significant advance in the optimization of an UAV route which can be used in real environments, as a trained ANN is faster than running the evolutionary process of PSO technique over and over again whenever the weather conditions are changeable. Moreover, even if the employed hardware has enough resources to perform the technique PSO quickly, the ANN will enable the intensity of the route adjustment to be adjusted in a shorter time.

This paper is divided into six sections. Section 2 examines other studies related to this paper. Following this, Section 3 provides 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 analyzed and discussed in Section 4, and then compared with the results found in the literature. Finally, Section 5 summarizes the conclusions obtained from the results and suggests how this paper might encourage further studies in this field.

2. Related Work

There are several studies that suggest how UAVs or WSNs can be employed for monitoring agricultural production, occasionally by integrating both technologies.[10–12] However, this work differs in so far as it proposes a particle swarm optimization algorithm to optimize the control rules of the UAV at runtime, based on feedback provided by WSN about weather conditions in the agricultural field.

Valente *et al.*[13] describe a WSN-based system and UAV to monitor vineyards. The WSNs collect information about weather, soil and planting conditions and then make 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 feasible or cost-effective to use cables to connect the WSN. Although the use of powerful wireless devices allows communication between WSNs, this solution leads to higher energy consumption and involves reducing the lifetime of the nodes. One solution that can be adopted to overcome these limitations is the employment a UAV to fly over the crop fields and gather information from each WSN, which can then be conveyed 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 having any adverse effects on the environment.

Huang *et al.*[14] devise a particular system for spraying 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 spraying 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 system can carry up to 5 kg of pesticide, which is enough to spray 14 ha; and it has a flight time of around 90 min. 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 *et al.*[4] proposed an architecture formed of a UAV and WSN to spray pesticide in crop fields. It is known that adverse weather conditions, such as high-speed winds, 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 on pesticide concentrations, the route is gradually changed until the sensor node can identify the correct application of the product. However, the parameters set for the route change are applied in different weather conditions, which might 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 changes in the intensity of the route followed by the UAV.

3. Proposed Approach

3.1. *UAV and WSN architecture for spraying on crop fields*

Figure 1 illustrates how the UAV acts as an agent on the crop fields. The UAV is equipped with a spraying system and a communication module, which enables data exchange with a WSN arranged on the crop fields; it flies over the area and sprays the pesticide in its entire length. The WSN is only depicted within the targeted 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

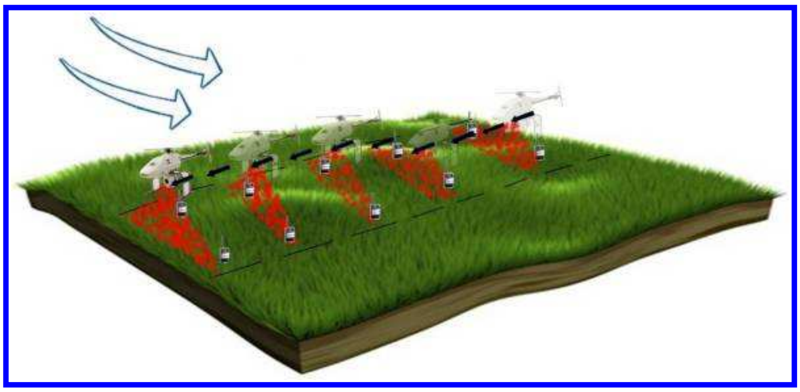


Fig. 1. Example of spraying in crop fields with the architecture proposed by Faiçal *et al.*[4] This architecture consists of a UAV (to spray) and WSN (to monitor). If the WSN detects an unbalanced spray on its sensor nodes, the UAV changes its route to correct the spraying of the pesticide.

the wind direction at a particular 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 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 throughout the whole extent of the targeted 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.

A 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, despite the importance of this parameter to ensure the success of the spraying, its value is set empirically before the beginning of the flight and is used for all weather conditions that occur during the spraying process. 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 detected. Moreover, an increase in the complexity of this environment might cause variable behavior. In other words, the weather conditions can change during the activity, and this is detrimental to the whole architecture if it has a static configuration.

The *routeChangingFactor* parameter is a weighting variable used in the calculation of the period of time assigned for a UAV route change.[4] It defines if the route change will be of mild intensity (low value, resulting in more time for a change of route) or high intensity (high value, resulting in a short time to be re-routed). Equation (1) illustrates the time that the UAV remains in change of route is set. In this equation, ls (left sensor) and rs (right sensor) are data received from the pair of sensors deployed inside the plantation and located in the spraying tracks (see Fig. 1), τ is the *routeChangingFactor* and Δ corresponds to the period of time assigned for the route change.

$$\Delta = \frac{|ls - rs|}{\tau}\,. \tag{1}$$

This equation is used by the UAV control policy, which sets a minimum threshold for the difference between the values from the pair of sensor to decide whether the route change should occur. If the difference is larger than the threshold, the UAV control policy re-defines the duration of the route change (based on Eq. (1)), the angle and the direction required for the aircraft.

To overcome the problems previously mentioned, this paper proposes a methodology based on Particle Swarm Optimization to optimize the parameter *routeChangingFactor*. 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 *routeChangingFactor* (and is close to an optimal solution). Figure 2 shows the behavior of the architecture when the optimization

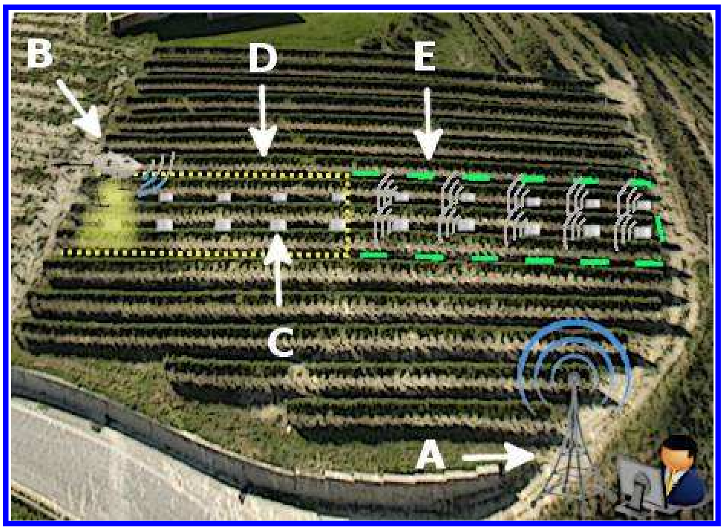


Fig. 2. Behavior of the architecture that employs the proposed optimization methodology. The Control Station (A) is installed outside the target crop field, in a zone within communication range of the UAV (B). During the spraying of the current crop field (D), the UAV sends a request for weather information about the next crop field (E) to the WSN (C). When the requested information 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 back to the 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 is about to begin.

methodology is used. It assumes that a crop field is composed of several small virtual subareas with a rectangular shape. Thus, if all the subareas are sprayed, this results in a complete spraying of the crop field. Each subarea will be called a “crop field” during this study. The UAV’s flight plan is designed to ensure that the next crop field will be sprayed right after the work on the current crop field has been completed. The route change, as described earlier, is made in the current crop field (D). Running parallel with this activity, the UAV (B) queries the WSN (C) about the weather conditions in the next crop field (E). At this stage the request can reach the nodes that are deployed inside the next crop field by using multi-hop links (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 *routeChangingFactor*. At this time, the optimization methodology proposal is executed on the basis of the weather information. At the end of the optimization, the best value of the parameter is sent back to the UAV. When the spraying of the current crop field (D) is finalized, the UAV updates its settings so that the spraying of the next crop field (E) can start. It should be highlighted that the use of a Control Station provides more powerful computation and, in addition, allows a pilot (on the ground) to oversee the flight and, if necessary, intervene in the control of the UAV.

3.2. *Optimization of control rules*

The optimization methodology proposed in this paper is essentially composed of an algorithm based on PSO.[15,16] This algorithm searches for a non-optimal value for the parameter *routeChangingFactor* and in one computation model of the 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 a single crop field (subarea). Hence, the search space is restricted to one zone that has values of different acuteness (e.g. abrupt, smooth and moderate). Additionally, the delimitation of the search space allows a faster convergence.

The optimization process is conducted in two ways simultaneously: (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 (as well as 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 parameter *routeChangingFactor* contained in the 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 Eq. (2) (where: X_{id} is the position and V_{id} is the velocity of particle $_i$ in an instant $_d$), while the velocity is updated in each iteration with Eq. (3) (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 the swarm and, finally, $rand()$ and $Rand()$ are different random values for a good exploration of search space).[17]

$$X_{id+1} = X_{id} + V_{id}\,, \tag{2}$$

$$V_{id} = w_i * V_{id} + C_1 * rand() * (P_{id} - X_{id}) + C_2 * Rand() * (P_{gd} - X_{id})\,. \tag{3}$$

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 the worst case scenarios, when all the iterations have been executed to find one possible solution. Following this, one stop condition can be added with the aim of finalizing the algorithm after confirming that convergence has occurred. It should be noted that the runtime in worst cases should be shorter 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 globally, but is the best of the

Algorithm 1: Proposed algorithm to optimize the *routeChangingFactor* parameter.

1: $InitializeParticles(RandomPosition[1, 10])$
2: **for** $MAX\_ITERATION$ **do**
3: $\quad PARTICLES \leftarrow FirstParticle()$
4: $\quad$ **for** $ALL\_PARTICLES$ **do**
5: $\quad\quad Result \leftarrow FuncObjetive(PARTICLES)$
6: $\quad\quad$ **if** $Result$ is best particle **then**
7: $\quad\quad\quad$ Stores the position in particle
8: $\quad\quad$ **end if**
9: $\quad\quad$ **if** $Result$ is the best in the swarm **then**
10: $\quad\quad\quad$ Stores the position in swarm
11: $\quad\quad$ **end if**
12: $\quad\quad UpdateVelocity(PARTICLES)$
13: $\quad\quad NewPosition(PARTICLES)$
14: $\quad\quad PARTICLES \leftarrow NextParticle()$
15: $\quad$ **end for**
16: **end for**
17: **return** $BestGlobalPosition$

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 (FuncObjetive) contained in the Algorithm, cited in Line 5 of Algorithm 1, refers to an interaction with one project inside the OMNeT++ software. The project is an implementation of a computational model to evaluate the spraying.[4] This interaction tests and analyzes the quality of spraying in each position of all the particles. The OMNeT++[a] is a simulator of discrete events based on C++ language to model networks, multiprocessors and other distributed and parallel systems.[18] The OMNeT++ can be used to model several types of networks, such as networks of queues, wireless and peer-to-peer types.[19] Because of its generic design, OMNeT++ has several frameworks established for specific networks, such as Mixim[b] 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.[20] Figure 3 shows the connection between the algorithm and OMNeT++.

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

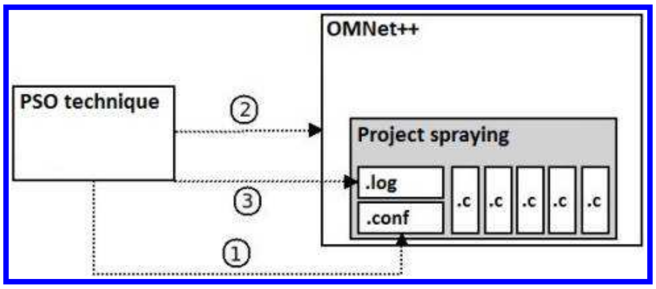


Fig. 3. Interaction between PSO technique and OMNeT++.

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 that, 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 it reaches the planting [plantation ?].[4] The fitness is calculated by estimating the amount of pesticide sprayed outside of the target crop field.

Thus, the objective function used by the PSO technique consists of two stages: (i) the execution of the computational model for the spraying of the agricultural field with the parameters set by the algorithm; and (ii) an analysis of the concentration of pesticide deposited in the agricultural field. In the first stage, the algorithm adjusts the computational model to the received weather conditions and the parameter *routeChangingFactor* being analysed, and runs the simulator to estimate how the spraying will be performed in these conditions. This execution returns a matrix with dimensions proportional to the size of the agricultural field and element values representing the concentration of the product deposited in each square meter. It must be observed that the value of the parameter *routeChangingFactor* will be changed during the optimization process. In the second stage, the pesticide concentration matrix is analyzed and the amounts deposited outside the target area are added to be used as the fitness value. Thus, the smaller the fitness, the better (more accurate) is the spraying carried out with the considered *routeChangingFactor*.

3.3. *Proposed approach for dynamic environments*

One of the characteristics of the PSO is that the search for the best values occurs in static environments. However, the evolutionary approach is often very time-consuming, and hence, it is not trivial to employ it in embedded software for dynamic operations. The operation in this case is dynamic since the UAV can change its speed and height or there may also be a change in the wind itself. Neural networks have intrinsic mapping and generalization features, which make them a good choice for dynamic environments while the evolutionary approach is a good means of discovering non-trivial parameters.

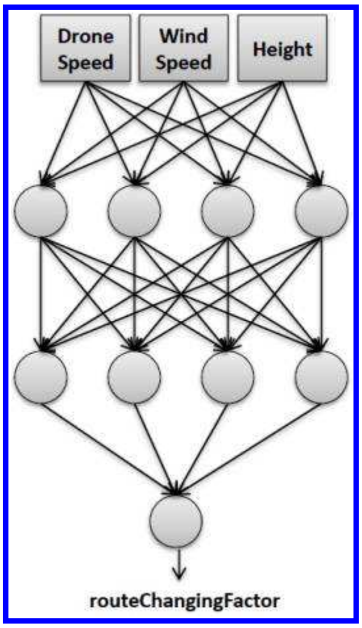


Fig. 4. ANN topology.

For an approach which can handle dynamic environments, we designed and evaluated how a neural network can be built upon data from the evolutionary algorithm. Hence, we ran the evolutionary technique in 27 static different environments and used its results to train the neural network. The 27 different scenarios were built in the light of the following variations: UAV speed (m/s) {10, 15, 20}; wind speed (km/h) {0, 10, 20} and UAV height of operation (m) {10, 15, 20}. We ran the evolutionary algorithm 10 times for each scenario, and obtained 270 different values. These values were then used for training the ANN. It should be highlighted that for each static scenario, the values obtained by the PSO were not the same, but often similar. We evaluated 5 ANN with different topologies to investigate which is the smallest neural network that can achieve the highest degree of accuracy.

Figure 4 shows the ANN topologies. The ANN inputs are the speed of the UAV, wind speed and UAV height and the output is the parameter *changeRouteFactor*. The results of the evaluation are given in Section 4.3.

4. Evaluation and Analysis of the Experimental Results

This section includes a description of our evaluations and examines our results. It is subdivided into three subsections which aim to explain (i) the evaluation of the optimization of the *routeChangingFactor*, (ii) the comparison resulting from the evolutionary approach with pre-programmed rules, i.e. without optimization of rule controls for route changes, as discussed by Faiçal *et al.*,[4] and (iii) evaluation of the application of the neural network for dynamic environments.

Table 1. Results of the optimization of the *routeChangingFactor* parameter. The first column shows the set of evaluated PSO as P#I# meaning P (number of particles) and I (number of interactions).

Settings	Convergence Rate (%)	Average Time of Evolutions (s)
P3I20	96.77	18.617 ± 0.371
P3I50	100.00	45.927 ± 0.649
P3I100	100.00	93.854 ± 1.555
P5I20	100.00	30.705 ± 0.506
P5I50	100.00	77.162 ± 0.766
P5I100	100.00	158.995 ± 3.143
P10I20	100.00	62.549 ± 0.912
P10I50	100.00	157.957 ± 2.976
P10I100	100.00	313.335 ± 1.488
P15I20	100.00	93.606 ± 0.799
P15I50	100.00	235.189 ± 1.816
P15I100	100.00	480.359 ± 14.762
P20I20	100.00	125.088 ± 1.059
P20I50	100.00	312.894 ± 2.058
P20I100	100.00	628.324 ± 2.251

4.1. *Optimization of the routeChangingFactor parameter*

In this stage, the algorithm will search for the best possible value when applying it as the parameter of route changes (taking into account the feedback obtained from the weather information). The evaluated settings are called as: P#I#, meaning P (number of particles) and I (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 ($w_i = 0.1$). This configuration aims at a "quick pull" of the swarm of particles to a place considered promising because it contains a better intensity than the others found so far. Moreover, it is expected that the particles will carry out a thorough search in the region where they are located. It is notable that both the ability not to remain stuck in local minima and the convergence of the algorithm were considered in this study, which showed a satisfactory performance.

Due to the low communication time, measured in Ref. 4, it can be assumed that the communication time between the UAV and Control Station does not have a significant influence on the total runtime. Thus, it can be assumed from this experiment that the weather information is already in the Control Station.

This subsection shows the results when the PSO-based algorithm described in Section 3.2 is employed. Table 1 shows the results of the first stage. Apart from

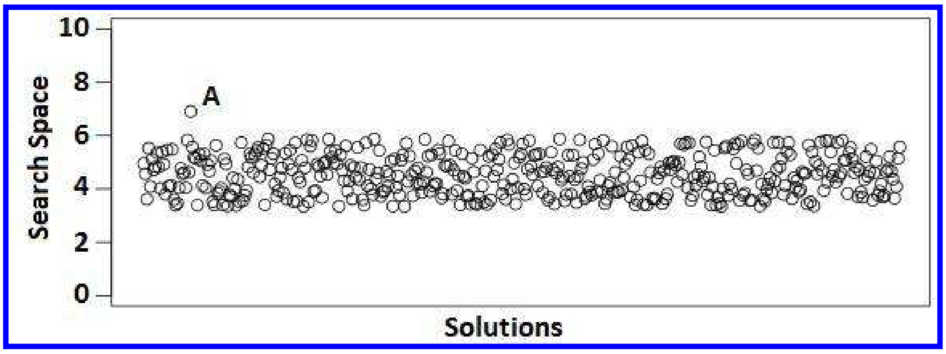


Fig. 5. Representation of the solutions found by the algorithm in the search space.

P3I20 setting, that has a 96.77% convergence rate, all the others have a 100% convergence rate for the same value of fitness. Owing to particular features of the problem, it is possible that a group of solutions has a fitness that is similar but not the same, since the difference between the values of the parameter *routeChangingFactor* may be low enough to have no significant influence on the spraying in specific situations.

It can be seen in Table 1 that the P3I20 setting is the only configuration that does not have a convergence rate of 100%. Another important point in Table 1 is the average time $\pm$ standard deviation (in seconds) for each setting of the algorithm. The spraying of a target crop field is carried out in ≈ 65 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 that are feasible for this application are P3I50, P5I20, and P10I20. These settings allow the optimization of the parameter *routeChangingFactor* with an appropriate time (less than 65 s) and with 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. 5). It can be seen that the proposed algorithm is capable of finding a region in search space where values are appropriate for the parameter *routeChangingFactor* 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 run before the spraying in each crop field is started to reduce the risk of making a wrong decision. The non-converged solution originating from the P3I20 setting, is marked as "A" in Fig. 5. 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 parameter *routeChangingFactor*, we conducted experiments aimed at evaluating the precision of the spraying by using the solution indicated by the algorithm.

4.2. *The spray operation on crop fields*

This stage involves the use of the solution which has best fitness (found in the previous stage) to evaluate the spraying on a target crop field. This selection criterion is used to evaluate the best solution in the group of alternatives generated by replications. If all the replications converge in a group of solutions with equal fitness, one of the solutions is randomly selected. The spraying is carried out by using the value selected as the parameter *routeChangingFactor* and the result is compared with the results without optimization from Faiçal *et al.*,[4] where a fixed value was employed. It is worth noting that the environmental features are the same for all the experiments and this is called *Constant Light Wind* by Faiçal *et al.*[4] This environment has a constant wind at a speed of 10 Km/h. The crop field used has an area of 1100 m $\times$ 150 m and the area of the target crop field is 1000 m $\times$ 50 m. The WSN has twenty-two nodes spread across the target crop field and the UAV initializes the spraying at a height of 20 meters above ground and at a constant speed of 15 m/s. At intervals of ten seconds, the UAV makes requests to the WSN to 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.

This subsection shows the results of the second stage of 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 parameter *routeChangingFactor* 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 the optimization method was used, are compared with the results when there was no optimization as discussed by Faiçal *et al.*[4]

The following settings were adopted: *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. The settings that use an optimization parameter are *P5I20*, *P10I20*, and *P3I50*. These results are obtained by the PSO.

Figure 6 and Table 2 show the results of spraying on target crop field, and compare the results from Faiçal *et al.*[4] with the results of the proposed PSO. It is clear that there is an increase in the area with a correct application of pesticides when the evolved *routeChangingFactor* parameter was applied. The *CL10* is the setting with the smallest error rate among all the non-optimized settings. However, all the optimized settings surpass the precision rate usually achieved when spraying a target crop field. Figure 7 displays a heat map to represent the chemicals sprayed on the crop at the end of the simulation.

The Shapiro Wilk method, employed for the statistical analysis, shows that the hypothesis of normality is rejected for one of the sets when there is a confidence level

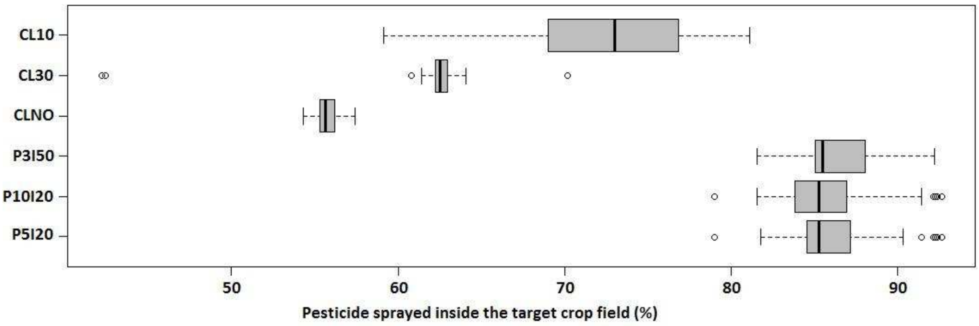


Fig. 6. Percent of pesticide spraying inside the target crop field. In this boxplot, the first three results come from Faiçal *et al.*[4] and the last three results were obtained in this work by the proposed PSO.

Table 2. Correct spraying (%) in the target crop field.

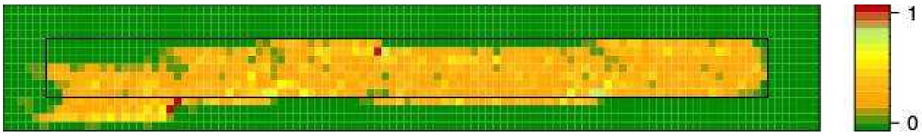
Settings	Area with Correct Coverage (%)
CL10	72.871 ± 4.659
CL30	62.113 ± 3.591
CLNO	55.697 ± 0.657
P3I50	86.220 ± 2.538
P5I20	85.811 ± 2.894
P10I20	85.777 ± 2.520

of 95%. In view of this, we decided to use non-parametric tests in the subsequent analysis.

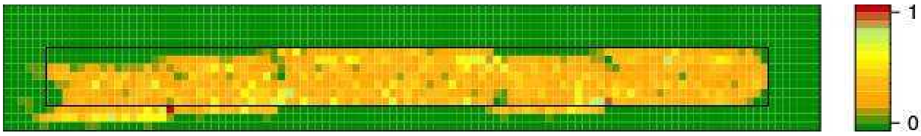
The pairwise comparisons were performed by means of the Wilcoxon Rank Sum Test (see Table 3) and show that there are significant differences between the results that employ the methodology for optimization and the results when this methodology is not used. However, no significant differences were found when only the settings based on 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. 6. As a result, it can be concluded that the use of the optimization method for the parameter *routeChangingFactor* increases the efficiency of the control rules, and reduces the errors when spraying in a crop field.

4.3. *Use of ANNs for dynamic environments*

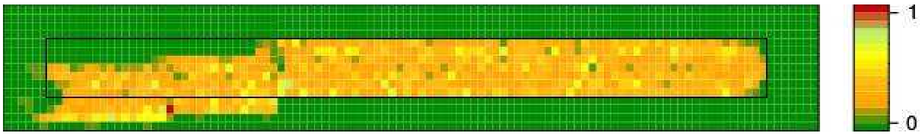
This section analyzes the ANN trained to interpolate and generalize the data from 27 static scenarios evolved by the PSO. As previously stated, the 27 different scenarios were built in the light of the following variations: UAV speed (m/s) {10, 15, 20}; wind speed (km/h) {0, 10, 20} and UAV height of operation (m) {10, 15, 20}.



(a) *routeChangingFactor* = 3.000



(b) *routeChangingFactor* = 6.000



(c) *routeChangingFactor* = 7.164

Fig. 7. (Color online) 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 3. Results of Wilcoxon Rank Sum Test. There are evidences of difference between the evolved values (P*) and the non-evolved values (C*) from Faiçal *et al.*; (p-values less than 0.05). There are no evidences of difference among evolved values (p-values greater than 0.05).

	CL10	CL30	CLNO	P3I50	P5I20
CL30	0.000				
CLNO	0.000	0.000			
P3I50	0.000	0.000	0.000		
P5I20	0.000	0.000	0.000	0.52	
P10I20	0.000	0.000	0.000	0.52	0.79

We ran the evolutionary algorithm 10 times for each scenario, and obtained 270 different values.

We sought to obtain the smallest ANN that would provide the most accurate values, since this also reduces the chance of overfitting during the training and improves the generalization of the ANNs. Hence, we started evaluating neural networks with one hidden layer and with 1 to 5 neurons. No ANN with these topologies

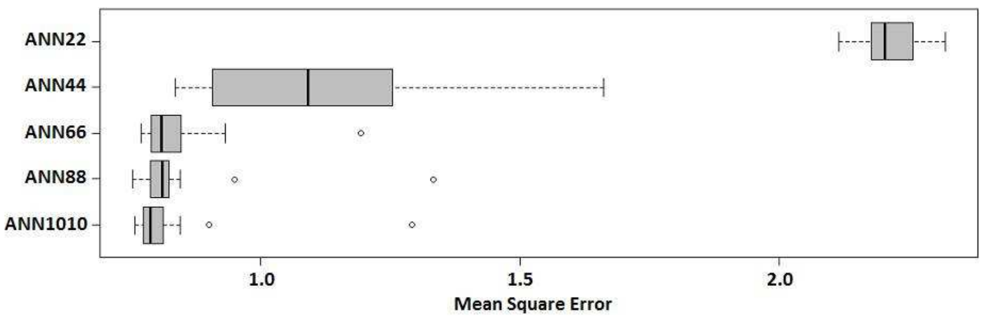


Fig. 8. Mean square error for 30 runs of each ANN topology.

was able to learn an accurate model from the data. therefore, the number of neurons and the number of layers were increased, leading to the following topologies for the first and second hidden layers: $\{2 \times 2, 4 \times 4, 6 \times 6, 8 \times 8, 10 \times 10\}$. The input layer has 3 neurons and the output has one neuron (as described in Section 3.3).

The evaluated ANNs are feed-forward multi-layer perceptron and are trained with the resilient backpropagation algorithm. The ANNs were built and trained by employing the Stuttgart Neural Network Simulator (SNNS).[c] We ran the training 30 times for each of the ANN topologies and employed 3-fold cross validation. The ANNs were trained for 2000 cycles, although we used the values of the best generalization point. The results as mean square error (MSE) can be seen in Fig. 8.

The distributions were evaluated with statistical tests (Shapiro-Wilk) that showed that most of the distributions cannot be accepted as normal distributions. Hence, the comparison between the distributions was carried out with the Wilcoxon-Mann-Whitney test. When 1% of significance is considered, the comparisons between ANN88 and ANN1010 are equivalent. No other comparison of distribution showed equivalence with the ANN1010 distribution. We can see that there is an improvement from ANN22 to ANN88; however, as the statistical test showed that ANN88 and ANN1010 are equivalent, the ANN88 was considered for the deployment.

Figure 9 displays an execution of the ANN88. The black dots represent the expected (original) values and the blue dots represent the values obtained by the ANN. It can be seen that there is a good fit for most of the points; however, there are points in which the obtained values differ from the expected. The reason for this is that the PSO does not obtain single values while performing the evolution, i.e. there is a group of good solutions within a range. Figure 5 can enable us to understand which good solutions are between ≈ 3 and 6, and thus, this PSO response can be interpreted as if the function being evolved has plateau regions. The current ANN topology allows unique outputs for the same inputs, which might be interpreted as a disperse value, although, the type of dispersion shown in the diagram does not

[c]Stuttgart Neural Network Simulator, http://www.ra.cs.uni-tuebingen.de/SNNS

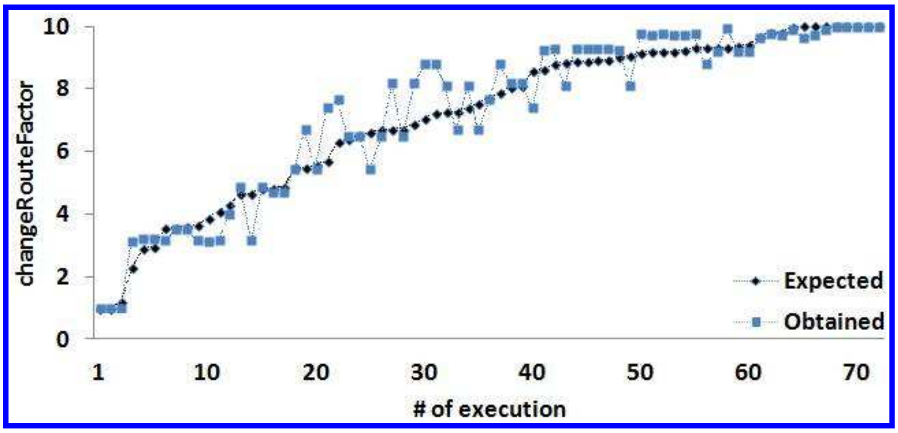


Fig. 9. (Color online) Results of execution of the ANN88 for ≈ 75 different inputs. The black dots represent the expected (original) values and blue dots represent the values obtained by the ANN.

lead to failure in the spraying operation because the obtained values are within a suitable range.

5. Conclusions and Suggestions for Future Work

In this paper, we have proposed and evaluated a methodology based on PSO, for fine-tuning the control rule of a UAV, and on an ANN to increase the support for high dynamic environments. The simulations with PSO provide the optimization of the parameter *routeChangingFactor* and thus reduce the error rate when spraying pesticides on crop fields. In the first experiments, we evaluated a broad set for the optimization method and the results show that it is possible to obtain 100% of convergence. Applying such evolutionary methodology allowed us to increase the precision of spraying pesticides so that ≈ 86% of the product can be applied 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 weather conditions of each target crop field. Although, taking into account that the spraying operation might occur in highly dynamic environment due to changes in wind speed and direction, we devised an ANN to be employed in the real-world operations. The proposed ANN is trained with a dataset of near-optimal parameters obtained by the PSO that evolves for a limited set of static environments. The ANN training process allows it to interpolate the results as so it can be applied dynamically for any configuration of the environment. Combining the evolutionary technique with the neural approach in this work allowed us to leverage the best capabilities of each technique. The presented proposal provides a significant advance in the optimization of an UAV route which can be used in real environments, as a trained ANN is faster than running the evolutionary process of PSO technique over and over again whenever the weather conditions are changeable. Moreover, even if the employed hardware has enough resources to perform the technique PSO quickly, the

ANN will enable the intensity of the route adjustment to be adjusted in a shorter time.

On the basis of the results obtained the following are recommended for further studies: (i) an investigation of how more parameters can be optimized (e.g. the height and speed of the UAV, the best starting-position for the next crop field, and the pressure of the spraying system); (ii) an investigation of different methodologies for the fine-tuning control rules of UAV (e.g. Differential Evolution,[21] Genetic Algorithms,[22] Hill-Climbing,[23] NSGA-II[24]); (iii) an analysis of the feasibility of embedding the optimization methodology in the UAV, leading to an autonomous architecture; (iv) an investigation of the methodologies required for a weather-aware router planner.

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CHAPTER

8

FINAL CONSIDERATIONS

8.1 Conclusions

Precision Agriculture (PA) is one of the alternative ways of increasing agricultural production. PA can be defined as the use of technology in the field and boosting production by processing the needs of the crops in a space-time relationship. In this way, a management system can be carried out which is geared towards the real needs of each agricultural region. This approach makes it possible to increase the yield of agricultural production to a higher level than what was achieved by the use of traditional techniques in a crop field of the same size.

In spite of the well-known and significant advances made in the field of PA, it clearly remains a challenge to carry out the spraying of plant protection products in agricultural plantations with precision. The weather conditions of the region can cause drift from the spray product to neighboring regions which is harmful to the environment and reduces the efficiency of protection management. However, this practice is essential for agriculture where there is a need for pest control to boost production. Studies have shown that if the protection management is not carried out properly (which can be explained as an inappropriate configuration of the spraying system for the weather conditions at the time of its application), only a small amount of the spray product will be really deposited on the targeted region, while most will form a part of the drift that is blown to other areas.

Mathematical models are often employed to estimate the path followed and the physical transformation of each spray particle until its final condition is attained. This condition might be the complete evaporation of the particle or its deposition on a particular surface (for example the soil or the crop). Studies are being carried out on the basis of these calculations of the final position of each particle and these can allow estimates to be made of the concentration of the product deposited in each area. Nonetheless, it should be noted that this approach is expensive in computational terms, both for its execution and management. For example, if an autonomous spray vehicle has to make an estimate of the precision of the spraying procedure, this approach will not allow this to be undertaken during the appropriate time needed for its operation.

This thesis explores approaches which allow estimates to be made of the concentration of plant protection products in targeted areas, rapidly and with a reasonable degree of accuracy. These might involve autonomous sprayers being able to adapt to the weather conditions of the region of interest to achieve a more precise protection management which is less harmful to the environment. For this reason, the thesis investigates the use of Machine Learning (ML) techniques, together with a computing model based on the essential features of the problem being addressed. In addition, a case study was conducted on an autonomous platform for spaying, consisting of a UAV and a WSN. In this study, the UAV is the spray element (a vehicle fitted with a spray system) which flies over the crop field and is guided by the spray tracks so that it can deposit the plant protection products on the crop; and the WSN is the support element that provides information about the remote sensing of the weather conditions and the concentration of the product deposited along the spray tracks for the UAV.

The computing model for the environment calculates the trajectory of each particle on the basis of a dispersion model that takes account of the meteorological information and the features of the spraying system. The trajectory of the particles shows their respective final positions and this makes it possible to estimate the deposition of the product in the targeted area or the amount that is being deposited in neighboring regions. This information is represented by designing a matrix of a size that is proportional to the region of interest, where each cell stores the estimated concentration for the final position of the particles. Furthermore, the model represents the operation of the platform for the spraying in the region of interest and this makes it possible to assess the degree of precision of the spraying in particular weather conditions.

Contributions made by this study to the research field

1. – Adjustment to environments with a low variability of weather conditions

The approach described for the computing model can be linked to meta-heuristic algorithms as a part of the fitness function. This was supplemented by adding an element to the analysis of the deposition matrix to check if the targeted region is being sprayed and giving a response to the question of the number of particles deposited in the neighboring areas.Thus, the fitness of the solutions provided by the meta-heuristic algorithms must have the minimized values to represent a more precise spraying (with less drift). Finally, the fitness function only makes use of deterministic variables in the computing model to ensure that a fair comparison is made between the possible solutions.

The use of meta-heuristic algorithms with the fitness function described earlier, has proved to be an efficient way to estimate the deposition of the spray product with a view to adjusting the image intensity to the UAV route correctly. As a result, it has become possible to adapt the mechanical behaviour of the UAV to the weather conditions of the environment for more precise spraying and thus reduce the drift of plant protection products to neighboring areas.

There was an assessment of the evolving pattern of this approach since its efficiency can be impaired if an environment is chosen with constantly shifting weather patterns and the meta-heuristic algorithm must be repeatedly executed for each new sub-area.

2. – Adjustment to environments with a high variability of weather conditions

Although the execution of the meta-heuristic algorithms requires a relatively long space of time (for example, in scenarios where there is a need to carry out the adaptation in a short space of time), Machine Learning techniques can be used to make the processing more versatile. In Faiçal *et al.* (2016b), it is shown that an ANN can be used to indicate the possible results of the meta-heuristic algorithm without the need for it to be re-executed for each new sub-area. In addition, this approach allows the intensity correction of the route to be indicated with a reasonable degree of accuracy for the unknown weather conditions during the training phase. Hence, an ANN that has been previously trained, can replace the meta-heuristic algorithm to indicate the correction of the route during the spraying of the plant protection products.

Finally, it is believed that the articles that have originated from this thesis show that the new approaches and their evaluation allow the spray element to have their operations adapted to the features of the environment so that a more precise kind of protection management can be provided, even in environments that need to be upgraded in a short space of time.

8.2 Plans for Future Work

After completing this research study, it is possible to envisage areas that might be explored in further studies, such as the following:

- Examining new approaches for the reduction of computational costs, which are incurred by estimating the deposition of the spray product;

- The use of Computational Intelligence concepts to assess show different features of the spray element can be adapted to the environment as a means of reducing the drift of the spray product;

- Investigating the scalability of the proposal in environments where there is more than one sprayer;

- Exploring the feasibility of making adjustments to the performance of terrestrial vehicles;

- Carrying out experiments in real-world environments in which the techniques validated in real hardware are embedded, such as the spraying system that was designed and implemented during the course of this thesis. This system can be found under patent No. BR 10 2016 029353 7[1].

[1] The request for protection was deposited with the Instituto Nacional da Propriedade Industrial (INPI) on December 14, 2016.

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APPENDIX A

DISSEMINATION OF THE RESULTS ACHIEVED IN THIS THESIS

2016 17th IEEE International Conference on Mobile Data Management

The use of autonomous UAVs to improve pesticide application in crop fields

Autonomous UAV, Pesticide application, Optimization, Machine learning

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***Abstract*—The population growth, increase of need for healthy food and concerns regarding wildlife protection put a strong demand in the improvement of agriculture productivity, reduction of the presence of pesticides in fruits and vegetables and of wildlife contamination. Agriculture production needs the application of pesticides to keep the necessary productivity levels. The use of autonomous aircrafts in the application of pesticides can increase the application precision efficiency, reducing the harm to human beings and nature. Weather conditions, like wind intensity and direction during the spraying, make the aircraft control difficult. This talk will present a the use of autonomous UAVs able to self-adjust their routes when spraying pesticides in crop fields.**

I. MOTIVATION

Agriculture plays an important role in the economy of many countries, one of them Brazil. Farm activities in these countries extensively use pesticides to eliminate diseases and plagues in order to increase crop productivity. Noways, the application of pesticides occurs mainly through the use of aircrafts. Aircrafts can avoid problems due to adverse ground conditions that affect the use of ground equipments, like areas with obstacles, like steeply sloping land and tree limbs. Besides being able to avoid ground obstacles, aircrafts can, in the same period of time, cover a larger area than ground equipments. Thus, aircrafts are more advantages when the ground presents obstacles and pesticide application must be carried out in a short period of time.

Usually, these aircrafts are on-board piloted and the pilots must attend several requirements and take specific examinations to become commercial pesticide applicators. However, due to external occurrences, like changes in wind direction and velocity, the precision required by the spraying process on crop fields is frequently is not fulfilled. This occurs because, as a result, pesticides applied by these aircrafts can end up in other areas nearby, affecting recreation areas, other crop cultures and natural resources. Besides, even using personal protective equipments and complying with all safety requirements, pilots of pesticide application aircrafts, can be exposed to pesticides, which can cause serious damages to their health. Unmanned aerial vehicle (UAV) have been used to reduce this problems and there are commercial UAVs for such. However, most solutions use an human pilot who may not be able to react fast to changes in weather conditions, is prone to subjective mistakes and, if close to the crop filed being sprayed, what is usually the case, is still exposed to the pesticides.

II. EXPERIMENTS

This study shows how changes in weather condition and harm to human health can be overcome by using an autonomous UAV. To provide autonomy to the UAV, optimization and machine learning techniques are embed into the UAV. As a result, the UAV can accurately spray pesticides on the target crop field, correct its route autonomously to take into account changes in the environment conditions. The optimization technique is used to find near-optimal flight control parameter values for static environments. For such, several optimization techniques were investigated and, because it presented the best performance, Particle Swarm Optimization (PSO) was used. The machine learning technique is used to induce a model able to make interpolations of the best solutions found by PSO to improve the UAV route in dynamic environments. For such, artificial neural networks (ANNs) were used. This hybrid intelligent approach was embedded in UAVs with programmable boards, such as Raspberry PIs or Beaglebones.

Fig. 1. UAV used in the experiments.

Several experiments were carried out to evaluate the proposed approach. According to the experimental results, the proposed approach is feasible and meets the requirements of a fast response time needed by the UAV to adjust its route in a highly dynamic environment, while accurately spraying pesticides in a crop field. The combination of PSO and ANNs improved the spraying precision in dynamic environments, when compared, during the UAV activity, with the optimization techniques alone. for static environments, such as PSO exclusive use during activity. It is important to observe that PSO needs to perform a large number of evaluations, where they use a simulator that has a high computational cost. Thus, given the time limit required to perform these assessments, the use of just PSO is suitable only in environments with a low rate of environmental change. Figure 1 illustrates the UAV used in the experiments.

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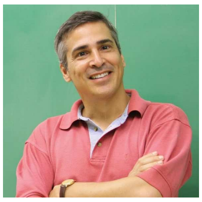
III. NEXT STEPS

The experimental results obtained in the experiments carried out using the proposed approach showed new challenges that need to be addressed, which are (i) Reduce the computational cost of the computational model used for pesticide spraying (ii) optimize other parameters (e.g. height and speed of the UAVs) to improve the precision of pesticide deposition; (iii) incorporate characteristics specific of optimization techniques for dynamic environments; (iv) investigate the scalability of the proposed system for the implementation of a fully-featured prototype model.

BIBLIOGRAPHICAL SKETCH



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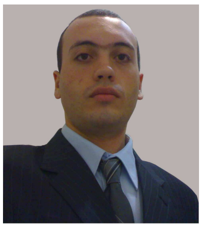

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