



**HAL**  
open science

# A Multi-objective Approach for Unmanned Aerial Vehicle Routing Problem with Soft Time Windows Constraints

Francesca Guerriero, Rosario Surace, Valeria Loscrì, Enrico Natalizio

► **To cite this version:**

Francesca Guerriero, Rosario Surace, Valeria Loscrì, Enrico Natalizio. A Multi-objective Approach for Unmanned Aerial Vehicle Routing Problem with Soft Time Windows Constraints. Applied Mathematical Modelling, 2014, 38 (3), pp.839-852. 10.1016/j.apm.2013.07.002 . hal-00917512

**HAL Id: hal-00917512**

**<https://hal.science/hal-00917512>**

Submitted on 11 Dec 2013

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# A Multi-objective Approach for Unmanned Aerial Vehicle Routing Problem with Soft Time Windows Constraints

F. Guerriero<sup>a,\*</sup>, R. Surace<sup>a</sup>, V. Loscrí<sup>a</sup>, E. Natalizio<sup>b</sup>

<sup>a</sup>*University of Calabria, Italy*

<sup>b</sup>*Heudiasyc - UMR CNRS 7253 - Université de Technologie de Compiègne, France*

---

## Abstract

Aerial robotics can be very useful to perform complex tasks in a distributed and cooperative fashion, such as localization of targets and search of point of interests (PoIs). In this work, we propose a distributed system of autonomous Unmanned Aerial Vehicles (UAVs), able to self-coordinate and cooperate in order to ensure both spatial and temporal coverage of specific time and spatial varying PoIs. In particular, we consider an UAVs system able to solve distributed dynamic scheduling problems, since each device is required to move towards a certain position in a certain time. We give a mathematical formulation of the problem as a multi-criteria optimization model, in which the total distances traveled by the UAVs (to be minimized), the customer satisfaction (to be maximized) and the number of used UAVs (to be minimized) are considered simultaneously. A dynamic variant of the basic optimization model, defined by considering the rolling horizon concept, is shown. We introduce a case study as an application scenario, where sport actions of a football match are filmed through a distributed UAVs system. The customer satisfaction and the traveled distance are used as performance parameters to evaluate the proposed approaches on the considered scenario.

*Keywords:* UAV Routing Problem, Multicriteria Optimization, VRP with Soft Time Windows,  $\epsilon$ -constraint method

---

\*Corresponding author

*Email addresses:* guerriero@deis.unical.it (F. Guerriero),  
rsurace@deis.unical.it (R. Surace), vloscri@deis.unical.it (V. Loscrí),  
enrico.natalizio@hds.utc.fr (E. Natalizio)

---

## 1. Introduction

Technological advances in the area of unmanned aerial vehicles (UAVs, for short), commonly known as drones, are opening new possibilities for creating teams of vehicles able to perform complex missions with some degree of autonomy. A possible application of a team of UAVs, equipped with camera (referred to as camera-drones), is represented by a live sporting event filming, where the use of the camera-drones gives the audience the feeling to be part of the sport competition itself.

This kind of application falls in the general class of dynamic and distributed scheduling problems, whose aim is to ensure both spatial and temporal coverage of given set of point of interests (PoIs). In the specific case of sport event, a PoI could be the movement of the ball that has to be followed and filmed. The spatial coverage implies that the PoI where the event occurs will be “covered”, whereas the temporal coverage is related to a time constraint associated to the event. In practice, the PoI needs to be covered when the event starts and for the whole duration of the event itself. Based on the previous considerations, it is evident that the strategic level of the mission planning needs a dynamic scheduler, deciding what event the system should consider at each time and which drone should be used. In addition, the concept of soft time windows is used to take into account temporal coverage constraints. Soft time concept allows us to find feasible scheduling schemes by introducing a penalty in terms of lower satisfactions of the customers every time a drone is not able to reach “quickly” a PoI.

In this paper, we present a mathematical formulation of the UAVs routing problem in which conflicting objectives are optimized simultaneously. In particular, the proposed multi-criteria optimization model takes into account three objective functions: the total distances traveled by the UAVs (to be minimized), the customer satisfaction (to be maximized) and the number of used UAVs (to be minimized). The customer satisfaction is modeled by using soft time windows constraints. Since the considered criteria are conflicting objectives and thus it is not possible to find a unique optimal solution, the  $\epsilon$ -constraint method [4] is applied to determine the set of efficient solutions. In addition, in order to capture the dynamicity of the considered scenario, a rolling horizon approach is defined.

Since the problem we deal with in this work belongs to the NP-hard

class, we have also considered some efficient heuristics and compare their behavior with the benchmark obtained by using the optimization model, in terms of minimization of distance traveled and maximization of customer’s satisfaction. The rest of the paper is organized as follows. Section 2 is devoted to a presentation of the related works. The UAVs routing problem and the proposed multi-criteria optimization model for its representation are described in Section 3. The solution strategies developed to define the set of efficient solutions are presented in Section 4, whereas their behavior is evaluated experimentally in Section 5. The paper ends with some concluding remarks given in Section 6.

## 2. Related Works

The main motivation for this work comes from the development of UAVs that have many characteristics that make them attractive for cooperative monitoring applications [15]. UAVs can be tailored for a specific mission and are typically low-cost. These characteristics make them very useful in disaster related situations [2] [8] and able for performing complex missions with some degree of autonomy. Typically, this kind of networks is mainly used in Information, Surveillance and Reconnaissance missions (ISR) [11]. In some cases ISR can be represented effectively through dynamic scheduling problems.

In this work we address a task scheduling problem combined with the motion planning one, aimed at reaching a certain coverage degree both spatial and temporal. This specific application belongs to the general class of Dynamic Vehicle Routing (DVR) problem. For this reason, in what follows the terms “vehicle”, “drone” and “UAV” are used in an interchangeable way.

Similarly to [11], we focus on mission planning at the strategic level, deciding what event the system should consider at each time and which vehicle must be used. In [11] authors consider available a probabilistic description of the environments dynamics, whereas we consider a rolling horizon approach to face with the dynamicity of the environment. Moreover, authors in [11] add switching costs penalizing the travel of vehicles between the sites to inspect, while we consider the costs associated to the “transition” of a vehicle from a point to another point, by considering explicitly the distances associated to.

Another example of dynamic scheduling application has been considered in [16]. They consider  $m$  aircrafts tracking the positions of  $n$  submarines with

$m < n$ , so that aircraft has to change task from time to time if each submarine needs to be monitored. Authors consider a restless version of the Multi-Armed Bandit Problem (MABP), in order to accomplish simultaneous events observation with a smaller number of aircrafts. In the specific application scenario we considered in this work, we only consider an active event at each time, but the proposed optimization model is defined to handle simultaneous events and heuristics can easily be tailored to consider events occurring at the same time. Moreover, in [16] authors do not introduce explicitly the soft time windows concept. In fact, while a submarine is under observation information associated to are gained. While it is not, information is being lost. In our approach, we explicitly introduce the satisfaction parameter in order to quantify the degree of observation of the events and we measure the effectiveness of the approaches in terms of degree of satisfaction and in terms of costs, namely, the distance traveled by UAVs.

In [8] the main goal is to provide overview images of certain regions with a specified resolution. Typically they need multiple images in order a certain area to be covered. Optimization criteria are minimizing the number of pictures and energy consumption and maximizing the coverage. They formulate their problem as an integer linear programming model. In practice, they consider only a spatial coverage type while the optimization formulation and the heuristics we derived focus on both spatial and temporal coverage. In fact, we formulate our problem as a particular instance of the VRP.

An example of dynamic UAV routing problem is considered in [6]. Specifically, they focus on scheduling UAVs in military operations subject to dynamic movement and control constraints. In their approach, the authors do not consider explicitly time windows concept while we need to introduce explicitly the concept of time in order to make the dynamic scheduling more effective with time constraints applications. Moreover, they consider a central far controller and take into account of this in the mathematical model. While, we assume UAVs able to communicate and self-organize in a distributed fashion. In [17] authors consider a VRP with soft time windows in a fuzzy random environment. They focus on the minimization of the distance traveled and the maximization of the satisfaction of the customers. The concept of soft time windows is realized through the concept of fuzzy random environment.

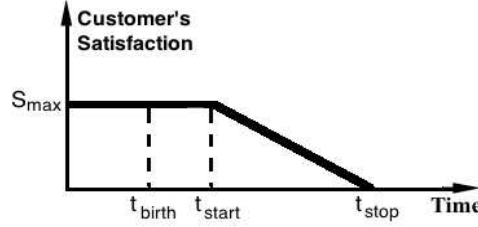


Figure 1: Event soft time window

### 3. Problem Statement and Mathematical Formulation

The considered scenario is characterized by a set of UAVs that fly over a finite dimension area in order to reach all the events, which occur in a finite time horizon. The satisfaction degree achieved by the customer is determined by considering the instant of the time that a drone reaches a particular event location. Indeed, it is a measure of the temporal event coverage.

To better understand how the described scenario can be mathematically represented as a particular instance of the *VRP with Soft Time Windows* (VRP-STW), it is useful to introduce its key components, namely *events*, *UAVs movement* and *customer satisfaction*.

#### 3.1. Events

The particular scenario under consideration is spatially located inside a limited area and temporally placed in a finite time frame. In this space-time location, it is assumed that the events occur in a random way.

An event is spatially characterized by the *x-y-z coordinates*, to identify the location inside the area. The Euclidean distance is used to evaluate the distance among the events.

As far as the temporal dimension is concerned, an event is characterized by a finite time frame, representing its time window (Fig. 1). **In this context, the time is related to the instant at which the drones meet the event to be monitored.**

**The time window associated to each event** is defined by three instants of time:  $t_{birth}$ ,  $t_{start}$  and  $t_{stop}$ . The first,  $t_{birth}$ , represents the event's birth, instead the instant of the time when the event starts working is  $t_{start}$ . The instant in which the event terminates coincides with  $t_{stop}$ .

**In order to better explain the meanings of the three different instant of times in terms of their relation to the events, it is useful to consider the**

following example, related to the refueling of the cars during a car race. Most race cars do not carry enough fuel to complete a race from start to finish. They must return to the pit area for more fuel, which is commonly called *pit stop*. During the pit stop, team’s pit crew quickly puts new tires on the car while fueling to the car.

Let’s consider an area where each race team has a space reserved for the refueling of its car: a car must reach its pit area to be refueled. In our example the event consists of the car refueling. The UAVs, flying over the pit area, must reach all the events in order to film the refueling of the race cars. The three instant of the times characterizing each event, can be described as follows:

- $t_{birth}$ : is the instant of the time when the race car reaches its pit area;
- $t_{start}$ : is the instant of the time when the refueling takes place;
- $t_{stop}$ : is the instant of the time when the refueling operations are completed and the race car leaves the pit area.

Naturally, a UAV knows a new event only when the race car reaches its pit area and the time to achieve that area could be greater than the time between  $t_{birth}$  and  $t_{start}$ . Therefore the satisfaction of viewers will depend on the instant of arrival of the drone.

Another important assumption for the development of the mathematical model is related to the first  $m$  actions. They are dummy event locations used to represent the UAVs initial positions. Thus, no time windows are associated to these events, but they simply are born at the scenario starting time instant and remain active for the all duration of the scenario itself. In addition, since the drones starting positions must not be reached, these events do not influence the customer’s satisfaction degree.

Similar considerations are valid for the last event: it does not contribute to the evaluation of the customer’s satisfaction, but unlike the initial events, a time window is associated with it and it represents a “useful position” that all the drones must reach. The corresponding movements, however, do not contribute to the total distance travelled by the drones. It can be viewed as a meeting place where, for example, it is possible to perform maintenance operations.

All the other events locations must be reached by exactly one drone and it must stay in the event location until the time window ends.

### 3.2. UAVs movement

As far as the characterization of drones movement is concerned, we refer to UAV as any aircraft capable of moving autonomously at constant and homogeneous speed, for which a maximum feasible distance to be traveled is defined. We assume that UAVs are equipped with cameras, a positioning system, storage memory and a wireless transceiver. We assume that the units are able to communicate to each other in a distributed fashion and are able to self-organize. Moreover, they are capable of identifying and localizing a target by some radio frequency identification tag applied on it or by using a sensor network [13] [9] [14] placed at the sides of the field and capable of locating the target and communicating to the drones. They can move in the three-dimensional space. However, for the sake of the simplicity, in this paper the third dimension is not taken into account. Indeed, we assume that the drones lie and move on a plane parallel to the plane where the events occur.

An event is monitored by a drone when the event position represented by the  $x$ - $y$  coordinates coincides with the drone  $x$ - $y$  location.

### 3.3. Customer satisfaction

The customer satisfaction represents a measure of the fulfillment of customer expectations and it is related to the way in which the different events are monitored by the drones.

Consequently, it depends on the instant of time in which a drone reaches the event's location. More specifically, if the drone arrives at the events location before  $t_{start}$ , the customer satisfaction assumes the maximum value. It decreases linearly and it becomes 0 when the event ends before the drone could reach it.

Mathematically, the satisfaction obtained by the customer ( $S_i^k$ ), as in Fig. 1, can be described as follows:

$$\begin{cases} S_{max} & t_{arr,i}^k < t_{start,i} \\ -S_{max} \cdot \frac{t_{arr,i}^k - t_{start,i}}{t_{stop,i} - t_{start,i}} + S_{max} & t_{start,i} \leq t_{arr,i}^k \leq t_{stop,i} \\ 0 & t_{arr,i}^k > t_{stop,i} \end{cases} \quad (1)$$

where  $S_i^k$  is the customer's satisfaction obtained for the event  $i$  reached by vehicle  $k$ ,  $S_{max}$  is the maximum customer satisfaction,  $t_{arr,i}^k$  is the arrival time of drone  $k$  in the position of event  $i$ ,  $t_{start,i}$  and  $t_{stop,i}$  are, respectively, start and stop instant of event  $i$ .



It is worth observing that the initial and final events are not taken into account when evaluating the average satisfaction perceived by the customer.

### 3.4. Modeling through graph theory

The UAVs single-objective routing problem has been introduced in [10]. In this section, we consider the trade-off among three conflicting objectives, namely the total traveled distance, the customer's satisfaction and the number of used UAVs. The mathematical model presented in this paper can be viewed as multi-criteria extension of the model in [10] and it can be described by using the graph theory as follows.

Let  $G = (V, A)$  be a directed graph where  $N = \{1 \dots n\}$  is the vertices set and  $A$  is the arcs set. The vertices  $i$  with  $i = (m + 1) \dots (n - 1)$ , where  $m$  is the number of available UAVs, denote the events to be reached and monitored, these events contribute to the customer satisfaction evaluation, whereas the vertices  $j$  with  $j = 1 \dots m$  identify the drones starting position and  $n$  represents the final event.

A non-negative cost  $d_{ij}$  is associated to each arc  $(i, j) \in A$ , representing the Euclidean distance from vertex  $i$  to vertex  $j$ . It is assumed that  $d_{ii} = \infty$  with  $i = 1 \dots n$ , that is loops on the same event are prohibited.

Let us consider a set of  $m$  ( $0 < m < n$ ) identical drones, constrained by a maximum allowed traveled distance  $d_{max}^k$ ,  $k = 1, \dots, m$  initially positioned at the vertices  $j$  with  $j = 1 \dots m$ , and able to move in two dimensions with constant and homogeneous speed  $v$ . Each drone must follow at most one route, starting from its initial position, including a set of events and ending to  $n$ . Each event should be reached by exactly one drone.

Each vertex is associated with a time window, in which the corresponding event  $i$  remains active  $[t_{birth,i}; t_{stop,i}]$  where  $i = (m + 1) \dots n$ . A drone that reaches an event must stay in the event position until the corresponding time window ends. Each event is associated with a satisfaction function (Fig. 1) and the instant of time in which a drone starts monitoring an event influences the satisfaction obtained by the customer.

The goal is to find a route to be followed by each drone such that all the events are monitored and some criteria are optimized simultaneously.

#### 3.4.1. Notations and Definitions

In order to describe the proposed mathematical model it is useful to introduce the following notations and definitions.

- $A = L \times W$  size-limited area;
- $[0 \dots T]$  time horizon;
- $N = \{1 \dots n\}$  set of events spatially distributed in  $A$  and temporally distributed in  $[0 \dots T]$ ;
- $M = \{1 \dots m\}$  drones (vehicle) able to move in 2 dimensions with constant and homogeneous speed  $v$  ( $0 < m < n$ );
- $d_{max}^k$  maximum feasible distance traveled by vehicle  $k$ ;
- $1, \dots, m$  drones initial positions;
- $n$  drones final position;
- $t_{birth,i}$ ,  $t_{start,i}$  and  $t_{stop,i}$  born, start and stop time instant of the event  $i$   $\forall i \in N \setminus \{1, \dots, m\}$ ;
- $t_{birth,i} < t_{start,i} < t_{stop,i} \forall i \in N \setminus \{1, \dots, m\}$ ;
- $t_{stop,i} < T \forall i \in N \setminus \{1, \dots, m \text{ et } n\}$  and  $t_{stop,n} = T$  (hypothesis in order to conclude the events before the scenario end);
- $d_{ij}$  Euclidean distance between event  $i$  and  $j \forall i, j \in N$ ;
- $t_{arr,i}^k$  arrival time instant of vehicle  $k$  to event  $i \forall i \in N \setminus \{1, \dots, m\}$  and  $\forall k \in M$ ;
- $t_{dep,i}^k$  departure time instant of vehicle  $k$  from event  $i \forall i \in N \setminus \{n\}$  and  $\forall k \in M$ ;
- $t_{i \rightarrow j}^k = \frac{d_{ij}}{v}$  time required by vehicle  $k$  to go from event  $i$  to  $j \forall i, j \in N$  and  $\forall k \in M$ ;
- $x_{ij}^k$  binary variable used to indicate if drone  $k$  travels along the arc  $i$ - $j$

$$x_{ij}^k = \begin{cases} 1 & \text{if vehicle } k \text{ travels along arc (i,j)} \\ 0 & \text{otherwise} \end{cases}$$

- $y_i^k$  binary variable to indicate if drone  $k$  reached the event  $i$

$$y_i^k = \begin{cases} 1 & \text{if vehicle } k \text{ reaches the event } i \\ 0 & \text{otherwise} \end{cases}$$

- $S_i^k$  customer satisfaction achieved when the event  $i$  is reached by drone  $k \forall i \in N \setminus \{1, \dots, m \text{ et } n\}$  and  $\forall k \in M$ . The mathematical description is given in (1);
- $S_{max}$  max satisfaction obtainable by the customer in a single event;
- $\Psi = \sum_{k=1}^m \sum_{i=m+1}^{n-1} S_i^k$  total customer satisfaction, *i.e.* the sum of customer satisfaction perceived in all events;
- $\bar{\Psi} = \frac{\sum_{k=1}^m \sum_{i=m+1}^{n-1} S_i^k}{n-m-1}$  average customer satisfaction;
- $\bar{\Psi}_{\%} = \bar{\Psi} \times 100$  percentage average customer satisfaction;
- $\Psi_{min}$  minimum level of ensured satisfaction;
- $r_k = (v_1, v_2, \dots, v_h)$  with  $v_1 \in \{1, \dots, m\}$ ,  $v_h = n$ ,  $v_2 \dots v_{h-1} \in N \setminus \{1, \dots, m \text{ et } n\}$  and  $\forall k \in M$ . Each drone has to travel a route that starts from its initial position and finish at final position.

It is worth observing that a piecewise linear function is used to represent the customer's satisfaction, given in (1). In order to linearize this function, the following variables are introduced:

- $\delta_{1i}^k, \delta_{2i}^k$  and  $\delta_{3i}^k$  binary variables defined as follows:

$$\delta_{1i}^k = \begin{cases} 1 & \text{if } t_{arr,i}^k \leq t_{start,i} \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_{2i}^k = \begin{cases} 1 & \text{if } t_{start,i} < t_{arr,i}^k \leq t_{stop,i} \\ 0 & \text{otherwise} \end{cases}$$

$$\delta_{3i}^k = \begin{cases} 1 & \text{if } t_{stop,i} < t_{arr,i}^k \leq t_{stop,n} \\ 0 & \text{otherwise} \end{cases}$$

- $z_{1i}^k, z_{2i}^k$  and  $z_{3i}^k$  non-negative variables.

The function (1) for each  $i \in N \setminus \{1, \dots, m\}$  and for each  $k \in M$  assumes the following form:

$$S_i^k = S_{max} \delta_{1i}^k + S_{max} \delta_{2i}^k + \left( \frac{-S_{max}}{t_{stop,i} - t_{start,i}} \right) z_{2i}^k$$

with the variables constrained as follows:

$$\begin{aligned} \delta_{1i}^k + \delta_{2i}^k + \delta_{3i}^k &= 1 \\ 0 \leq z_{1i}^k &\leq t_{start,i} \cdot \delta_{1i}^k \\ 0 \leq z_{2i}^k &\leq (t_{stop,i} - t_{start,i}) \cdot \delta_{2i}^k \\ 0 \leq z_{3i}^k &\leq (t_{stop,n} - t_{stop,i}) \cdot \delta_{3i}^k \end{aligned}$$

#### 3.4.2. Assumptions

- The time and spatial distribution of events are known in advance;
- All the events (except the last one) must be reached by exactly 1 drone;
- Drones start from different positions;
- Drones, that accomplished their tasks, converge towards a dummy location (last event), where maintenance operations on the vehicles can be performed. The distance traveled to reach this final position is not taken into account in the total cost evaluation;
- All events  $\in N \setminus \{1, \dots, m\}$  have their own soft time window already presented in Fig. 1.

#### 3.4.3. Mathematical model

The UAVs routing problem with soft time windows has been mathematical represented by defining a multi-criteria optimization model. The considered objective functions are related to the following three specific aspects: minimize traveled distance, maximize average customer satisfaction and minimize the number of used vehicles.

In the evaluation of the first two objectives, the events corresponding to the initial drones' position and to the last dummy position are not taken into account. The third criterion is determined by considering the number of

vehicles that reach the last event directly from their initial position, without reaching other events. These UAVs represent the vehicles that are not used. The proposed formulation can be mathematically represented as follows:

$$\min \sum_{k=1}^m \sum_{i=1}^{n-1} \sum_{j=1}^{n-1} d_{ij} \cdot x_{ij}^k \quad (2)$$

$$\max \bar{\Psi} \quad (3)$$

$$\min \left( m - \sum_{k=1}^m \sum_{i=1}^m x_{in}^k \right) \quad (4)$$

Subject to:

$$\sum_{k=1}^m y_i^k = 1 \quad \forall i \in N \setminus \{n\} \quad (5)$$

$$\sum_{k=1}^m y_n^k = m \quad (6)$$

$$y_i^k \geq x_{ji}^k \quad \forall i, j \in N, k \in M \quad (7)$$

$$y_i^k \geq x_{ij}^k \quad \forall i, j \in N, k \in M \quad (8)$$

$$\sum_{i=1}^m \sum_{j=m+1}^n x_{ij}^k = 1 \quad \forall k \in M \quad (9)$$

$$\sum_{i=1}^{n-1} x_{in}^k = 1 \quad \forall k \in M \quad (10)$$

$$\sum_{j=1}^{n-1} \sum_{k=1}^m x_{ji}^k = 1 \quad \forall i \in N \setminus \{\{1, \dots, m\} \cup \{n\}\} \quad (11)$$

$$\sum_{j=1}^n \sum_{k=1}^m x_{ij}^k = 1 \quad \forall i \in N \setminus \{n\} \quad (12)$$

$$\sum_{i=1}^n x_{iz}^k - \sum_{j=1}^n x_{zj}^k = 0 \quad \forall z \in N \setminus \{\{1, \dots, m\} \cup \{n\}\}, k \in M \quad (13)$$

$$x_{ii}^k = 0 \quad \forall i \in N, k \in M \quad (14)$$

$$\sum_{i=1}^m \sum_{j=1}^m x_{ij}^k = 0 \quad \forall k \in M \quad (15)$$

$$t_{arr,i}^k = 0 \quad \forall i \in \{1, \dots, m\}, k \in M \quad (16)$$

$$t_{arr,j}^k = \sum_{i=1}^n (t_{dep,i}^k + t_{i \rightarrow j}^k) \cdot x_{ij}^k \quad \forall j \in N \setminus \{1, \dots, m\}, k \in M \quad (17)$$

$$t_{dep,i}^k \geq 0 \quad \forall i \in N, k \in M \quad (18)$$

$$t_{dep,i}^k \geq t_{stop,i} \cdot y_i^k \quad \forall i \in N \setminus \{\{1, \dots, m\} \cup \{n\}\}, k \in M \quad (19)$$

$$t_{dep,i}^k \leq t_{stop,n} \cdot y_i^k \quad \forall i \in N, k \in M \quad (20)$$

$$t_{dep,n}^k = t_{stop,n} \quad \forall k \in M \quad (21)$$

$$t_{arr,n}^k \leq t_{stop,n} \quad \forall k \in M \quad (22)$$

$$\delta_{1i}^k + \delta_{2i}^k + \delta_{3i}^k = y_i^k \quad \forall i \in N, k \in M \quad (23)$$

$$0 \leq z_{1i}^k \leq t_{start,i} \cdot \delta_{1i}^k \quad \forall i \in N, k \in M \quad (24)$$

$$0 \leq z_{2i}^k \leq (t_{stop,i} - t_{start,i}) \cdot \delta_{2i}^k \quad \forall i \in N, k \in M \quad (25)$$

$$0 \leq z_{3i}^k \leq (t_{stop,n} - t_{stop,i}) \cdot \delta_{3i}^k \quad \forall i \in N, k \in M \quad (26)$$

$$S_i^k = S_{max} \delta_{1i}^k + S_{max} \delta_{2i}^k + \left( \frac{-S_{max}}{t_{stop,i} - t_{start,i}} \right) z_{2i}^k \quad \forall i \in N \setminus \{1, \dots, m\}, k \in M \quad (27)$$

$$S_i^k = 0 \quad \forall i \in \{1, \dots, m\}, k \in M \quad (28)$$

$$t_{arr,i}^k = t_{start,i} \cdot \delta_{2i}^k + t_{stop,i} \cdot \delta_{3i}^k + z_{1i}^k + z_{2i}^k + z_{3i}^k \quad \forall i \in N, k \in M \quad (29)$$

The tree objective functions represent the total traveled distance (2) to be minimized, the average customer satisfaction (3) to be maximized and the number of used vehicles (4) to be minimized.

Each event (except the final one) must be monitored by exactly one drone (5), while the last event must be reached by all the drones (6). The event  $j$  must be monitored by the drone that followed the path that goes from event  $i$  to  $j$  (7-8).

All vehicles must start from their initial position and stop in the final event position (9-10). For each event, exactly one path entering and outgoing from it must be present in the final solution (11-13). The drones cannot follow loops, *i.e.* they cannot return to an event previously monitored (14)

and cannot reach the other drones' initial positions (15). The arrival time to the initial position is set equal to the starting simulation instant (16), instead, the arrival time to the event  $j$  (excluding the initial event) by the vehicle  $k$  must be equal to time of departure from event  $i$  added to the time it takes to go from  $i$  to  $j$  (17).

A drone can leave an event only after the simulation time is started (18), the event work is finished (19) and before the end of the simulation time horizon (20).

A drone must never leave the last event, therefore, the departure from final event has only a symbolic value equal to the end of the simulation (21) and a vehicle must reach the final position before the end of the simulation period (22). The constraints (23-29) are used to linearize the customer's satisfaction condition (1).

### 3.5. Case Study: Sport Event Filming Problem

In section 3.4.3, we modeled the UAVs movement in order to make them able to reach a set of events and stay in these positions until the end of the event itself.

The proposed model is useful for representing many real applications [8] [17] [6]. In this paper, we consider the *Sport Event Filming Problem* (SEFP) as a case study.

In many sport events, a very large number of spectators watch the game on TV (or on the Internet) where the event is broadcasted (or streamed). In the last few years, new techniques and devices have been developed by event broadcasting companies in order to attract new spectators. Consequently, new types of cameras, such as automatic cameras and spider cameras, have been developed.

In this context, the challenge is to organize a fleet of drones able to fly over a limited field and film a sport event with the objective of maximizing the satisfaction experienced by customers who watch the game on TV.

In order to apply the proposed model to the SEFP, we assume that a match is the scenario in which a set of game actions (i.e. the events of the generic model) is randomly deployed in space-time PoI. Game action is characterized by a quadruple  $(x, y, z, t)$ , where  $(x, y, z)$  are the coordinates of the position in a 3-dimensional spatial reference system and  $t$  is the time instant of the game action in that position. Drones will follow the actions by moving on the correspondent  $(x, y)$  – *coordinates*. Each game action is associated with a specific Soft Time Window (Fig. 1) where:

- $t_{birth}$ : is the instant time when the possession of the ball is gained by another player;
- $t_{start}$ : is the instant time when the player who has possession of the ball starts performing some movements with it;
- $t_{stop}$ : is the instant time when the player in possession of the ball loses it;
- $T_{fly}$ : is the time interval between the loss of the ball by one player ( $t_{stop}$ ) and the gain of it by another ( $t_{birth}$ ).

An example of game action is given in Fig. 2, where, in subfigure 1, the ball reaches the player 1 and a new game action borns. In subfigure 2, player 1 starts its action by moving and in subfigure 3 player 1 stops its action when he loses the ball, passing it to the player 2. In subfigure 4 the ball reaches player 2 and a new action borns.

We will not use  $T_{fly}$  in optimizing the spectators satisfaction because we assume that an usual camera can follow the movement of the ball from one player to another for the whole event. The goal is to compute the movements of a drones set equipped with a camera, to achieve all the game actions and film them.

An additional requirement in order to adapt the generic mathematical model to the SEF problem is: the events (game actions for SEF problem) must be sequential and not occur simultaneously, in fact the couple player-ball are in only one time-space location at each time and game actions are serial. To ensure these requirements, we set  $t_{stop,i} < t_{birth,j} \forall i, j \in N \setminus \{1, \dots, m\}$  with  $i < j$ . In addition, the constraints (14) are modified as follows:

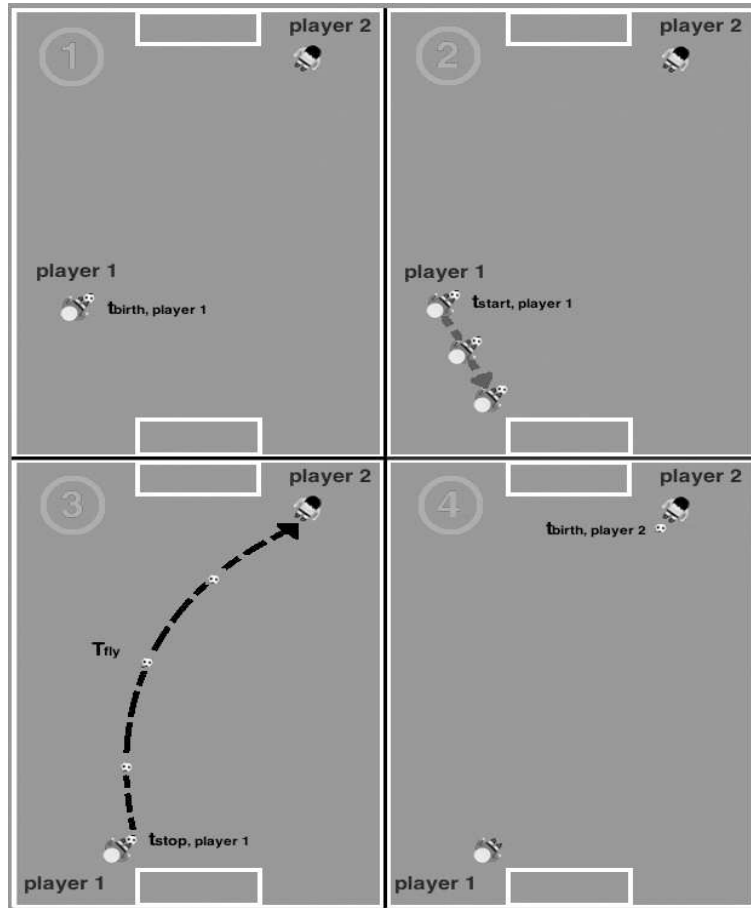
$$\sum_{j=1}^i x_{ij}^k = 0 \quad \forall i \in N, k \in M \quad (30)$$

With the introduction of these constraints, the actions are causal in the time, that is drones cannot reach an action before the action occurs and are forbidden to produce loops.

#### 4. The solution approaches

In this section, the solution approaches proposed to address the multi-objective UAVs routing problem are described in details.





**Figure 2:** Example of game action

Two different solution strategies have been defined to address the UAVs routing problem. The former (i.e., the  $\epsilon$ -constraint method) assumes that all the events are known in advance and allows to determine an approximation of the Pareto front, the latter is a rolling horizon strategy. In what follows, the proposed methods are described in details.

#### 4.1. The $\epsilon$ -constraint method

Several approaches for solving multi-objective optimization problems have been proposed in the scientific literature [7]. In this paper, in order to determine the set of efficient solutions, the  $\epsilon$ -constraint method, introduced in [4], is applied.

The main idea of this method is to select only one of the objective functions to be optimized, whereas all others are converted into constraints. Thus, a set of  $\epsilon$ -constraint problems  $P_i(\epsilon)$ , one for each objective  $i = 1 \dots k$  at a time is solved.

The  $\epsilon$ -constraint method is applied to the bi-objective version of the UAVs routing problem, where the total distance traveled and the customer's satisfaction are taken into account. The third objective is tackled as a parameter of the optimization procedure, in the sense that the number of UAVs to be used is fixed at each iteration of the overall algorithm. However, it is important to point out, that since  $m$  varies within the range of meaningful values that can be assigned to the number of UAVs, the overall optimization process allows us optimizing all the three objectives simultaneously.

Thus, let  $\bar{m}$  a given number of available drones, the following two optimization problems (i.e.,  $P_1(\epsilon_2)$  and  $P_2(\epsilon_1)$ ) are solved iteratively.

$$\text{minimize } \sum_{k=1}^{\bar{m}} \sum_{i=1}^{n-1} \sum_{j=1}^{n-1} d_{ij} \cdot x_{ij}^k \quad (31)$$

subject to:

$$x \in X \quad (32)$$

$$\bar{\Psi} \geq \epsilon_2 \quad (33)$$

$$\text{maximize } \bar{\Psi} \quad (34)$$

subject to:

$$x \in X \quad (35)$$

$$\sum_{k=1}^{\bar{m}} \sum_{i=1}^{n-1} \sum_{j=1}^{n-1} d_{ij} \cdot x_{ij}^k \leq \epsilon_1 \quad (36)$$

where  $X$  denotes the feasible region defined by the constraints (5-13), (15-29) and (30).

Thus in the first model we optimize the total traveled distance and we take into account the customer's satisfaction as an  $\epsilon$ -constraint; in the latter, the customer's satisfaction is optimized and the total traveled distance is handled as an  $\epsilon$ -constraint. At each iteration, the value of the parameters  $\epsilon_1$  and  $\epsilon_2$ , are adequately modified.

#### 4.2. A rolling horizon strategy

We defined a rolling horizon approach in order to capture the dynamicity of the considered scenario. In the static case, it is assumed that all of the events are known in advance, instead in the dynamic case this assumption is relaxed: events can start at any time of the considered time horizon.

In order to handle this specific situation, the route to be followed by the drones are planned by assuming the availability of partial known information about the position and the instant of time in which each event takes place [12]. In particular, let  $n$  be the number of events to be monitored, it is assumed that only a certain number  $r$  of events ( $0 < r < n$ ) is known at each decision epoch. Thus the proposed static model is used to define the best UAVs routing, by considering only the known events and no information on future events is considered.

When a new set of  $r$  events become available (i.e., in the subsequent decision epoch), the new routing is determined by considering as initial drones' positions those obtained in the previous optimization.

### 5. Computational Experiments

The computational experiments have been carried out on Hewlett-Packard m9460it, Intel Core 2 Quad Q9400 2.66 GHz and 4 GB Ram with operating system Windows Vista 64 bit.

To solve the proposed mathematical model, we used LINGO 9.0 ([1]), a tool designed to build and solve different optimization models in efficient way.

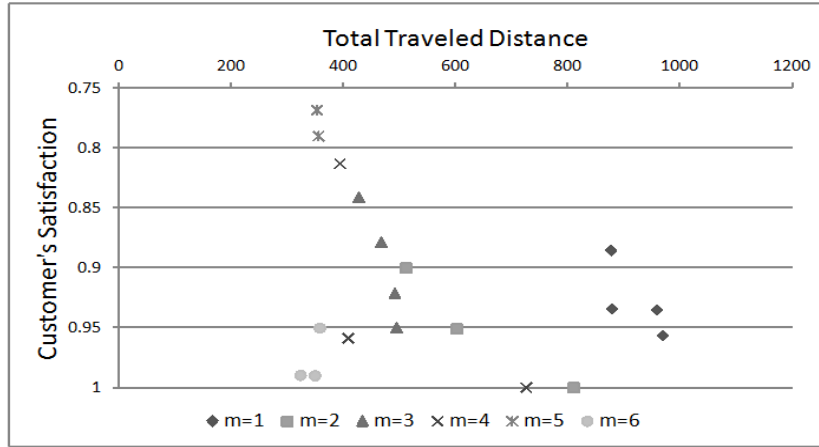
In order to assess the behavior of the considered solution approaches, the SEFP as been considered as a case study. In particular, the specific scenario, whose main characteristics are reported in Table 1, has been considered in the computational phase.

The number of drones  $\bar{m}$  has been varied in the interval  $[1, \dots, 6]$ . We considered 6 as the maximum number of drones since the application scenario is based on a sport event whose field size is small. In fact, we will observe to the follow that difference of performance is not so appreciable when we pass from 5 to 6 drones. The set of efficient solutions obtained by the  $\epsilon$ -constraint method is depicted in Fig. 3.

In order to show the effectiveness of the proposed solution approach, we have also carried out computational experiments by treating the problem as

Parameter	Value
Size of the game field ( $L \times W$ )	$110 \times 80 [m^2]$
Action Min/Max Duration ( $t_{birth} \rightarrow t_{stop}$ )	$\{0.2 \div 6\} [s]$
Number of game actions	20
Ball Min/Max Speed	$\{1 \div 40\} [m/s]$
Coordination Time ( $T_{coord}$ )	0.2 [s]
Max Satisfaction ( $S_{max}$ )	1
Actions Spatial and Temporal Distribution	random
Number of run for each scenario	1000
Confidence interval of	95%

**Table 1:** Values of the relevant parameters used for the experimental testing



**Figure 3:** Graphical representation of the Pareto front obtained with the  $\epsilon$ -constraint method

a single-objective optimization problem, where a convex combination of the three objective functions has been considered.

The related problem assumes the following form:

$$\text{minimize } \alpha \sum_{k=1}^{\bar{m}} \sum_{i=1}^{n-1} \sum_{j=1}^{n-1} d_{ij} \cdot x_{ij}^k - \beta \bar{\Psi} + \gamma \left( \bar{m} - \sum_{k=1}^{\bar{m}} \sum_{i=1}^{\bar{m}} x_{in}^k \right) \quad (37)$$

subject to:

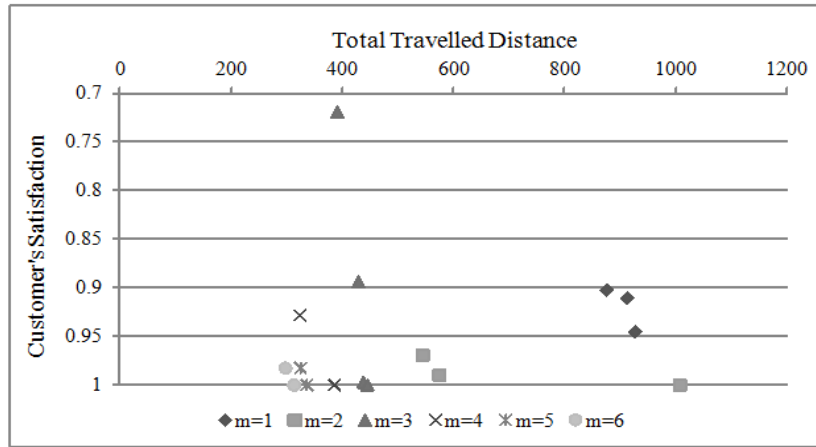
$$x \in X \quad (38)$$

where  $\alpha$ ,  $\beta$  and  $\gamma$  are non-negative parameters chosen in such a way that  $\alpha + \beta + \gamma = 1$ .

To generate non-dominated solutions, the single-objective optimization problem has been solved for different values of these parameters and different values of the number of drones  $\bar{m}$ . Also in this case  $\bar{m}$  has been chosen in the interval  $[1, \dots, 6]$ , whereas  $\alpha$ ,  $\beta$  and  $\gamma$  have been selected as in Table 2. The related results are reported in Fig. 4. By observing Fig. 4, the advantage of the use of the  $\epsilon$ -constraint method is evident. The superiority of this approach is underlined by the results reported in what follows.

$\alpha$	$\beta$	$\gamma$
1	0	0
0	1	0
0	0	1
$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
1	1	1
$\frac{1}{2}$	$\frac{1}{2}$	0
$\frac{1}{2}$	0	$\frac{1}{2}$
0	$\frac{1}{2}$	$\frac{1}{2}$

**Table 2:** Values for the parameters  $\alpha$ ,  $\beta$  and  $\gamma$



**Figure 4:** Graphical representation of the Pareto front obtained by solving the single-objective optimization

More specifically, in order to compare the two considered solution approaches, the quality of the Pareto approximation set is evaluated by considering the diversity of the set. In particular, the spacing metric proposed by Schott in [?] is used. The aim of this metric is to evaluate how evenly the points in the approximation set are distributed in the objective space. It is defined as follows:

$$\Delta = \sqrt{\frac{1}{\eta - 1} \sum_{i=1}^{\eta} (\bar{d} - d_i)^2}$$

where  $d_i = \min_{j=1, \dots, \eta, j \neq i} |f_1^i - f_1^j| + |f_2^i - f_2^j| + |f_3^i - f_3^j|$ ,  $f_1, f_2, f_3$  represent the considered criteria and  $\bar{d}$  is the mean of  $d_i, i = 1, \dots, \eta$ .

The spread metric  $S$  introduced in [5] has been also considered. This metric is used to evaluate if the set of solutions obtained span the entire Pareto optimal region and it is defined as follows:

$$S = \frac{\sum_{m=1}^M d_m^e + \sum_{i=1}^{\eta-1} |d_i - \bar{d}|}{\sum_{m=1}^M d_m^e + (\eta - 1)\bar{d}}$$

where  $d_m^e$  represents the Euclidean distance between the extreme solutions of Pareto optimal front and the boundary solutions of the obtained non-dominated set corresponding to  $m$ -th objective function;  $d_i$  denotes the Euclidean distance between neighboring solutions in the obtained non-dominated solutions set and  $\bar{d}$  is the mean value of these distances. The smaller the value of  $S$ , the better the diversity of the nondominated set.

It is worth observing that this metric works only for bi-objective optimization problems. Thus, in order to evaluate  $S$ , we have considered only two of the three objective functions that is the total traveled distance and the customer's satisfaction.

The obtained results are given in Table 3, they underline that for the considered scenario the  $\epsilon$ -constraint method outperform the single objective optimization approach.

Three different scenarios have been considered to evaluate the performance of the proposed rolling horizon approach, obtained by varying the value of the parameter  $r$ , representing the number of events known at each decision epoch. In particular,  $r$  has been set equal to 3, 4 and 5. In addition, at each time instant of the rolling horizon, for a given number of drones, we solve a single-objective optimization model in which the total distance traveled by the drones is minimized and the customer's satisfaction is handled

	$\epsilon$ -constraint Method	Single Objective Optimization
$S$	19.08	27.50
$\Delta$	1.00	1.13
Number of Pareto Solutions	19	15

**Table 3:** Values of spacing and spread metrics and number of efficient points for the  $\epsilon$ -constraint method and the single objective optimization approach

as a constraint. The number of drones  $\bar{m}$  has been set equal to 1, 2, 3, 4, 5 and 6, whereas the lower limit on the customer’s satisfaction has been chosen equal to 0.50, 0.90. The case in which  $\bar{\Psi}$  is not constrained has been also considered.

The related results are given in Fig. 5, they clear underline that the best performance are obtained when  $r = 3$ .

This behavior can be explained by observing that the lower  $r$ , the higher the number of the times in which the model is solved and thus the better is the representation of the dynamicity of the problem.

In order to evaluate the performance of the proposed rolling horizon strategy, we have compared this approach with the heuristic techniques proposed in [10], where the UAVs routes are re-optimized every time a new action starts. The sub-optimal solution is computed action-by-action by the drones that cooperate by exploiting their communication capabilities in a distributed and self-organized fashion.

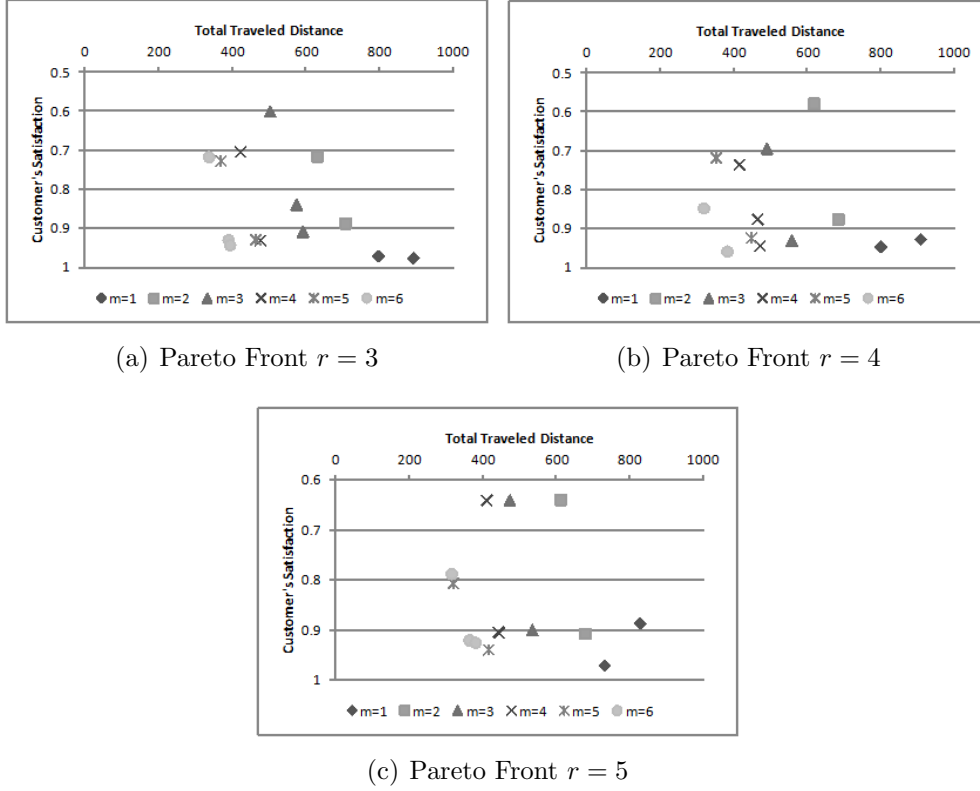
For the sake of completeness, in what follows, we give a brief description of these heuristics.

#### NN Nearest Neighbor

The basic idea of this approach consists in the selection of the UAV closer to the action every time a new event occurs. The Nearest Neighbor technique has been effectively exploited for DVR problems [3].

#### NN-SR Nearest Neighbor with Specular Repositioning

In the *Nearest Neighbor with Specular Repositioning* (NN-SR) technique considers two drones for every action: when one of drones,  $k$ , is chosen to move to film an action for which it is the nearest neighbor, the drone that is closest to the specular position of the action position,  $\bar{k}$ , moves specularly in respect of the first.



**Figure 5:** Pareto Front determined by the rolling horizon approach

### NN-QSR Nearest Neighbor with Quasi-Specular Repositioning

The *Nearest Neighbor with Quasi-Specular Repositioning* (NN-QSR) technique is a generalization of the NN-SR technique. The idea behind the NN-QSR is to make the center of the field be an attractor for  $\bar{k}$  while it is repositioning in the direction of  $k$ 's specular position. The attraction strength on the movement can be modulated through an appropriate *detour factor*,  $0 \leq \beta \leq 1$ . More precisely, if  $(x_a, y_a)$ ,  $L$ ,  $W$  are the positions of the new action, the length and the width of the field, respectively, then  $\bar{k}$  will move to  $(L \cdot (1 - \frac{\beta}{2}) - x_a \cdot (1 - \beta), W \cdot (1 - \frac{\beta}{2}) - y_a \cdot (1 - \beta))$ .

### BMI Ball Movement Interception

The Ball Movement Interception concept is to use the interval of time between  $t_{stop_i}$  and  $t_{birth_{i+1}}$  to forecast the location of next action.



By computing ball trajectory estimation before the ball reaches the next player, UAVs can start moving towards the straight line between the position of the previous action and that of the player expected to receive the ball. So, we introduce a new family of techniques, called *Ball Movement Interception* (BMI), which includes all the previous techniques augmented by this knowledge: *Ball Movement Interception* (BMI), *Ball Movement Interception with Specular Repositioning* (BMI-SR) and *Ball Movement Interception with Quasi-Specular Repositioning* (BMI-QSR).

The heuristic approaches described above have been implemented in Matlab and have been simulated in a MacBook 2.4 GHz Intel Core 2 Duo and 4 GB Ram with operating system Mac OS X 10.5.8.

The related results are given in Tables 4, where for each heuristic and for each number of the available drones, indicated with  $\bar{m}$ , the sum of the distance traveled by each UAV (i.e. the total distance) and the average customer's satisfaction are given.

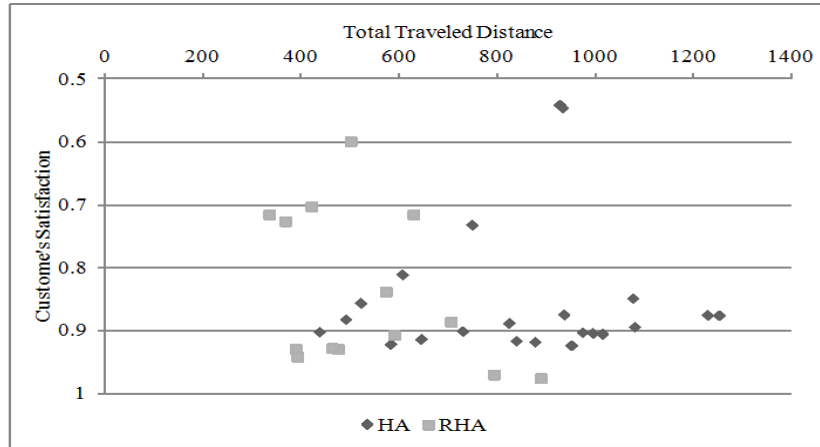
From the results we can argue as, in terms of satisfaction, BMI-based techniques generally behave better than techniques without BMI, when the number of nodes is smaller. In fact, the gap in terms of satisfaction level is around 30% when only a UAV is considered and  $\approx 8\%$  when the number of drones is 3. This better level of satisfaction is paid in terms of total distance traveled. In fact, the difference in terms of distance between the BMI-based and no-BMI-based approaches can achieve values greater than 500 meters when the number of UAVs is smaller than 3. When the number of devices increases ( $\geq 4$ ), we can notice as performance behaviors in terms of both satisfaction and total distance between the two macro-class of approaches (i.e. BMI-based and no-BMI-based) decreases. These considerations allow us to conclude that BMI-approaches are preferable when the number of available devices is smaller.

The set of efficient solutions determined by applying all the considered heuristics is given in Fig. 6.

From the collected results, it is evident that, for the considered scenario, the rolling horizon approach behaves the best. Indeed, the solutions determined by this last strategy dominates those identified by the heuristics.

Heuristic	$\bar{m}$	Total Distance (meter)	Customer's Satisfaction	$\bar{m}$	Total Distance (meter)	Customer's Satisfaction
NN	1	931.91	0.55	2	748.57	0.73
NN-SR	1	926.85	0.54	2	1231.14	0.75
NN-QSR <sub>0.5</sub>	1	937.23	0.54	2	1041.40	0.78
NN-QSR <sub>0.6</sub>	1	929.17	0.54	2	1036.66	0.78
NN-QSR <sub>0.7</sub>	1	935.73	0.54	2	1043.81	0.77
BMI	1	1076.62	0.85	2	935.72	0.87
BMI-SR	1	1084.90	0.84	2	1667.66	0.86
BMI-QSR <sub>0.6</sub>	1	1087.39	0.84	2	1275.02	0.87
BMI-QSR <sub>0.7</sub>	1	1079.75	0.84	2	1252.38	0.88
BMI-QSR <sub>0.8</sub>	1	1085.62	0.84	2	1228.86	0.88
BMI-QSR <sub>0.9</sub>	1	1083.12	0.85	2	1227.86	0.88
NN	3	606.17	0.81	4	520.72	0.86
NN-SR	3	1063.05	0.80	4	849.67	0.85
NN-QSR <sub>0.5</sub>	3	901.14	0.82	4	772.99	0.85
NN-QSR <sub>0.6</sub>	3	890.38	0.81	4	768.49	0.84
NN-QSR <sub>0.7</sub>	3	884.44	0.81	4	755.39	0.85
BMI	3	824.04	0.89	4	728.95	0.90
BMI-SR	3	1371.47	0.89	4	1190.80	0.90
BMI-QSR <sub>0.6</sub>	3	1150.63	0.89	4	1029.34	0.90
BMI-QSR <sub>0.7</sub>	3	1129.05	0.89	4	1014.36	0.91
BMI-QSR <sub>0.8</sub>	3	1100.16	0.89	4	994.94	0.90
BMI-QSR <sub>0.9</sub>	3	1080.28	0.89	4	974.26	0.90
NN	5	490.47	0.88	6	437.09	0.90
NN-SR	5	777.17	0.88	6	682.67	0.89
NN-QSR <sub>0.5</sub>	5	682.63	0.87	6	608.34	0.89
NN-QSR <sub>0.6</sub>	5	670.30	0.87	6	601.73	0.89
NN-QSR <sub>0.7</sub>	5	655.66	0.88	6	578.12	0.90
BMI	5	644.35	0.91	6	582.58	0.92
BMI-SR	5	1060.84	0.92	6	950.95	0.92
BMI-QSR <sub>0.6</sub>	5	929.86	0.91	6	842.67	0.92
BMI-QSR <sub>0.7</sub>	5	915.14	0.91	6	829.30	0.92
BMI-QSR <sub>0.8</sub>	5	876.56	0.92	6	801.88	0.92
BMI-QSR <sub>0.9</sub>	5	838.49	0.92	6	764.37	0.92

**Table 4:** Computational results obtained by the heuristic approaches



**Figure 6:** Pareto Front determined by heuristic approaches

## 6. Conclusions

In this work we proposed a system of Unmanned Aerial Vehicles (UAVs) able to communicate, self-organize and cooperate in order to determine in an effective way a dynamic schedule. The distributed dynamic schedule has to ensure both spatial and temporal coverage of specific targets that evolve both spatially and temporally. We proposed a mathematical formulation as multi-criteria optimization model by consider the minimization of the distance traveled, the maximization of customers and the minimization of the number of used UAVs. Concerning the mathematical optimization model we took into account of the dynamicity of the events by considering the concept of rolling-horizon. Furthermore, we proposed some heuristics and we compared their performance in terms of traveled distance, customer satisfaction and number of vehicles. In order to test and compare the heuristic with the mathematical formulation results, we considered a specific application scenario, that is a football match where the events were the game actions to be followed and our UAVs were equipped with cameras.

## References

- [1] Lingo documentation <http://www.lindo.com/>.
- [2] S.M. Adams and C.J. Friedlan. A Survey of Unmanned Aerial Vehicle (UAV) Usage for Imagery Collection in Disaster Research and Manage-

- ment. In *Proc. of Ninth International Workshop on Remote Sensing for Disaster Response*, Stanford University, California - USA, September 2011.
- [3] F. Bullo, E. Frazzoli, M. Pavone, K. Savla, and S. L. Smith. Dynamic vehicle routing for robotic systems. *IEEE Proceeding*, 99(9):1482–1504, 2011.
- [4] V. Chankong and Y.Y. Haimes. *Multiobjective Decision Making Theory and Methodology*. Elsevier Science, New York, 1983.
- [5] K Deb, A Pratap, S Agarwal, and T Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-II. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, 2002.
- [6] J. Ruck D.K. Ahner, A.H. Buss. In *Proc. of the Winter Simulation Conference*, Training and Doctrine Command Anal. Center, Monterey, CA, December 2006.
- [7] X. Gandibleux M. Ehrgott. A survey and annotated bibliography of multiobjective combinatorial optimization. *OR Spektrum*, 22:425–460, 2000.
- [8] D.W.Struel S. Bhattacharya M. Shah B. Rinner M. Quaritsch, K. Kruggl. Networked UAVs as aerial sensor network for disaster management applications. *Elektrotechnik und Informationstechnik*, 1(127):56–63, January 2010.
- [9] T. Melodia and I. F. Akyildiz. Cross-layer QoS-Aware Communication for Ultra Wide Band Wireless Multimedia Sensor Networks. *IEEE Journal of Selected Areas in Communications*, 28(5):653–663, 2010.
- [10] E. Natalizio, R. Surace, V. Loscrí, F. Guerriero, and T. Melodia. Filming sport events with mobile camera drones: Mathematical modeling and algorithms. Also available at <http://uweb.deis.unical.it/guerriero/wp-content/uploads/2012/06/paperUAV.pdf>, 2012. Technical Report N. 4/12, 2012, Logica Laboratory, University of Calabria, Italy.
- [11] J. Le Ny. *Performance optimization for unmanned vehicle systems*. PhD thesis, Massachusetts Institute of Technology, 2008.

- [12] H.N. Psaraftis. *Vehicle Routing: Methods and Studies*, chapter Dynamic vehicle routing problems, pages 223–248. Elsevier Science, 1998.
- [13] S. Pudlewski and T. Melodia. C-DMRC: Compressive Distortion-Minimizing Rate Control for Wireless Multimedia Sensor Networks. In *Proc. of IEEE Intl. Conf. on Sensor and Ad-hoc Communications and Networks (SECON)*, Boston, MA, USA, June 2010.
- [14] J. Rullán-Lara, S. Salazar, and R. Lozano. Uav real-time location using a wireless sensor network. In *in Proceedings of 8th Workshop on Positioning Navigation and Communication (WPNC)*, pages 18–23, April 2011.
- [15] L. C. Trost. Unmanned Air Vehicles (UAVs) for Cooperative Monitoring. *Sandia Report*, 0185(5):3–44, January 2000.
- [16] P. Whittle. Restless bandits: activity allocation in a changing world. *Journal of Applied Probability*, 25(A):287–298, January 1988.
- [17] Y. Xu, B. Lei, and E. A. Hendriks. Camera network coverage improving by particle swarm optimization. *J. Image Video Process.*, January 2011.