A REVIEW ON THE MCS-OPTW PLANNING APPROACH FOR UAV MISSIONS

Bachelor thesis Econometrics: Quantitative Logistics and Operations Research, Erasmus School of Economics, June 2014

Abstract

In this thesis, different approaches to find efficient tours for Unmanned Aerial Vehicles (UAVs) are implemented. The heuristic developed by Evers et al. (2014), the Maximum Coverage Stochastic Orienteering Problem with Time Windows (MCS-OPTW), is implemented and the results are compared on a new dataset. This approach takes uncertainty in travel and recording times, time sensitive targets and the appearance of new targets into account. The performance of this approach is illustrated with computational experiments in terms of two objectives: the average profit gained by foreseen targets and the percentage of new targets reached in time. In the end, some possible adjustments to the simulation are discussed. All results are compared to a deterministic planning approach.

Wolters, M.A.M.

Student number: 347022

Instructor: Dollevoet, T.A.B.

CONTENT

1. Problem statement

Unmanned Aerial Vehicles (UAVs) are useful in information gathering for military and civilian purposes. An UAV can be used to record target locations or any area of interest. An UAV has no human pilot actually on board, the aircraft is remotely operated from a control station on the ground. Because of time limitations, fuel and the number of available UAVs, not every target can be visited and an effective tour is wished.

In this thesis I implement the methods described by Evers et al. (2014) to execute the use of UAV missions as effectively as possible. Evers et al. (2014) considers three extensions to the standard Orienteering Problem (OP) to model characteristics that are of practical relevance in planning missions of UAVs. First, travel and recording times are uncertain. Secondly, information about the target can only be obtained in a certain time window. Finally, the appearances of new targets during the flight, so-called time-sensitive targets which need to be visited immediately, if possible, are considered.

In the article by Evers et al. (2014), the Maximum Coverage Stochastic Orienteering Problem with Time Windows (MCS-OPTW) is introduced. MCS-OPTW aims at finding a tour with maximum expected profit of the foreseen targets and it directs the planned tour to predefined areas where time-sensitive targets are expected to appear, taking the above stated three extensions into account. Evers et al. (2014) developed a fast heuristic that can be used to re-plan the tour, each time before leaving a target.

The re-planning heuristic is applied on different settings. These settings consider different lengths of the time windows and different locations of new targets to appear. For all of these settings, Evers et al. (2014) found that the MSC-OPTW planning approach outperforms the deterministic (Team) Orienteering Problem with Time Windows ((T)OPTW) approach. The MCS-OPTW approach produces tours that dominate the (T)OPTW approach both in terms of average obtained profit from foreseen targets and the average number of new targets reached in time.

In this thesis this heuristic is applied on a different data set. The objective is to investigate how useful this heuristic in general is. Evers et al. (2014) has investigated the result of another distribution of the travel and recording times than assumed, however this method is not yet applied to completely different data.

Just like Evers et al. (2014) did, different settings will be considered. The results from the data set in this thesis will be compared to the results found by Evers et al. (2014). The average obtained profit from foreseen targets and the average percentage of new targets reached in time will be taken into consideration. Besides, the effects of changing weights in the objective function of the MSC-OPTW are compared. Finally, some adjustments to the simulation are introduced and tested.

2. Data and settings

In this section I will describe the data used in this research. The time limit T of a mission is 150 units. In other words, a tour is supposed to take at most 150 time units. The location of the depot is given. From now on I refer to the location of the depot as 0.

2.1. Foreseen targets

A dataset is obtained on which I am going to implement the heuristic. The dataset includes the location of 30 foreseen targets and a depot. This is the set of foreseen targets N.

2.1.1. Time windows

Further, the data gives the starting time of the time window, l_i, of target i. The ending time of the time window of target i, u_i, is not given. This gives the possibility to investigate the effect of different lengths of time windows. In the article by Evers et al.(2014), $T = 230$ time units and Evers et al. (2014) investigates a dataset in which all time windows are of length 10 time units and a dataset in which 25% of the targets have a length of 10 time units while the others have a length of 170 time units or more. In our case, $T = 150$. For small time windows I set the length of the time windows at 10 time units. For the large time windows I wanted to keep the balances: $170/230 \approx 0.74$, and $0.74 * 150 = 111$. Therefore, I set the length of the large time windows at 110 time units. In the case of 'small time windows', all time windows are of length 10 time units, and in the case of 'large time windows', all time windows are of length 110 time units.

The starting times of the time windows are categorized in three categories: starting between 0 and 50, between 50 and 100 and between 100 and 150. When plotted, it is seen that all categories are spread out. It is not the case that a specific area has more locations with the same category of starting time.

2.1.2. *Travel and recording times*

To calculate the distance between two locations i, given by (X_i, Y_i), and j , given by (X_j, Y_j), I use the formula for the Euclidian distance in two dimensions: $d(i,j) = \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2}$. The average distance between two targets is 8.44 units and the maximum distance is 21.65 units.

The travel times t_{ij} between location i and j are assumed to be gamma distributed with shape parameter k_{ij} equal to the Euclidean distance $d(i,j)$ between these two locations and scale parameter $\theta = 2$. The expected travel time $\overline{t_{ij}}$ is equal to the expected value of the gamma distribution: $\overline{t_{ij}} = E(t_{ij}) = k_{ij}\theta = 2d(i,j)$. This means that the expected travel time is linear in the distance between the two locations. The variance of the travel time is, according to the gamma distribution, $k_{ij}\theta^2 = 4d(i,j)$, also linear in the distance.

The recording times r_i of location i are assumed to be gamma distributed with shape parameter k_i given for all locations and scale parameter $\theta = \frac{1}{2}$. Just like the travel times, the expected recording time $\overline{r_i}$ (given by $k_i\theta = \frac{1}{2}k_i$) and the variance (given by $k_i\theta^2 = \frac{1}{4}k_i$) are linear in the shape parameter k_i . k_i is equal to 3, 6 or 9. The average of the shape parameter k_i is 6.2. The average expected recording time is equal to 3.1 time units. The recording time for the depot is equal to zero.

2.1.3. *Profit*

The targets have a profit of 5, 10 or 15 units. There are 8 foreseen targets with a profit of 5, there are 17 targets with a profit of 10 and there are 5 targets with a profit of 15.

For the targets with a profit of 15, the average distance between two targets is 12.46 units and the maximum distance is 21.47 units. The average of the shape parameters for the recording time of these targets, k_i, is 7.2. For the targets with a profit of 10, the average distance between two targets is 8.88 units and the maximum distance is 19.18 units. The average of k_i is 6. For the targets with a profit of 5, the average distance between two targets is 4.71 units and the maximum distance is 8.22 units. The average of k_i is also 6.

Therefore, I can conclude that the targets with a higher profit are more spread out than the targets with a lower profit. Figure 1 shows that the targets with lowest profit are centered in the middle, and the higher profit more on the outside. Because of the higher shape parameter k_i for the targets with a higher profit, the targets with a profit of 15 units have, on average, a higher expected recording time.

2.2. New Targets

In the dataset, the locations for possible new targets are given. As in the experiments by Evers et al. (2014), this gives the possibility to generate new targets at predefined locations. This is the set of locations of new targets N'. Next to that, the arrival rate λ_i of potential location i is given, this defines the expected number of new targets that appear at this location during the time span $T - t_n$. t_n is the expected travel time from the new target location which is closest to the depot to the depot. It is not known in between which time limit U new targets have to be visited. I decided to set U equal to the length of the small time windows, $U = 10$ time units.

2.2.1. LOCATION NEW TARGETS

If I look at Figure 1, I see that the locations of possible new targets are in two clusters. Evers et al. (2014) considers this setting as well, and gives as example that this situation illustrates important places in two towns.

If I look at the separate clusters, the left cluster seems to be more concentrated than the right. Based on Euclidean distances, the average distance within the left cluster is 2.04 units and the maximum distance is 3.16 units. In the right cluster, the average distance is 4.03 units and the maximum distance is 6.71 units. The average arrival rate is more or less the same in both clusters, respectively 0.27 and 0.24.

Based on the average of the coordinates, I determined the center of the left cluster and the center of the right cluster. The Euclidean distance between the two centers of the clusters is 18.39. The closest distance between a target from the left cluster and a target from the right cluster is 13.60.

2.2.2. RECORDING TIMES

The parameters of the recording times of the new targets are not given. I decided to set the shape parameter of the recording times for the potential new targets equal to 6, as this is closest to the average value of the known parameters for the recording times of the foreseen targets.

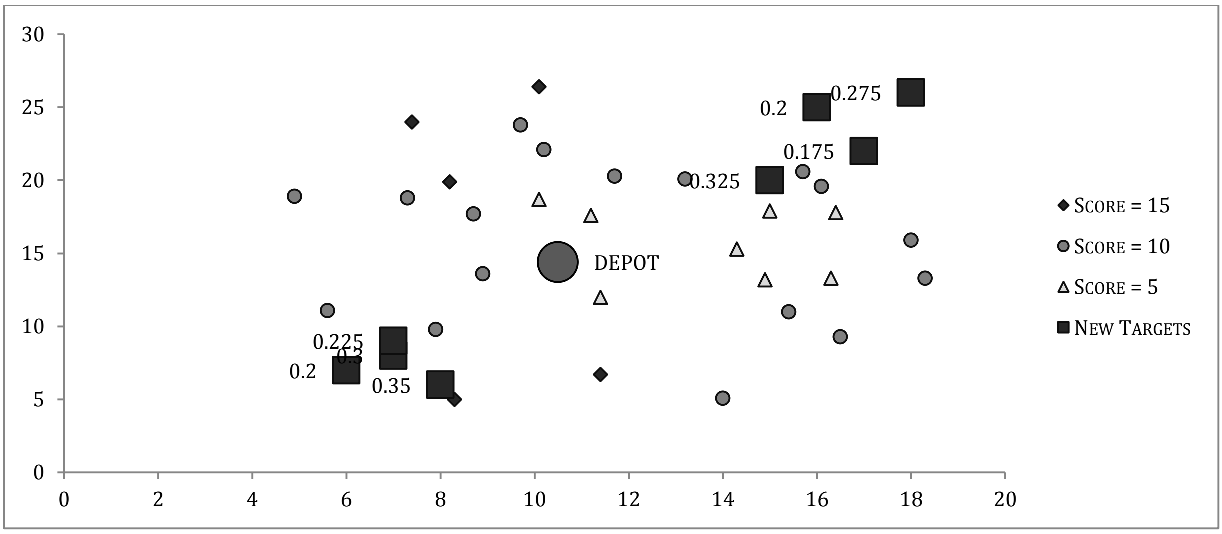

FIGURE 1: FORESEEEN TARGETS, NEW TARGETS AND ARRIVAL RATES

3. RE-PLANNING MODELS

I will shortly describe the two different models that the paper uses, the (T)OPTW re-planning model and the MCS-OPTW re-planning model. With the latter I will explain the weighted location coverage and how the two objectives are balanced in the total objective. The re-planning models are used to re-plan the tour for the UAV each time before leaving a target at time t. 0_t is the location of the UAV at the moment of re-planning, at time t. When planning the initial tour, starting and ending at the depot, the time is equal to zero, $t = 0$, and the current location of the UAV is equal to the depot, $0_t = 0$.

3.1. (T)OPTW RE-PLANNING MODEL

The deterministic (T)OPTW uses the following sets, defined at time t:

$N(t) = the\ set\ of\ foreseen\ targets\ not\ yet\ visited$
$N^+(t) = N(t) \cup \{0\} \cup \{0_t\}, in\ which\ 0_t\ is\ the\ location\ of\ the\ UAV\ at\ time\ t.$

The (T)OPTW is defined on a complete graph $G = (N^+(t), A(t))$. The parameters for the travel time and the recording time are equal to the expected travel and recording time. To each arc $(i,j) \in A(t)$ a binary variable x_{ij} is associated, which has value 1 if arc (i,j) is used in the tour and 0 otherwise. s_i denotes when the recording of target i starts.

The objective of the (T)OPTW is defined as follows: $\max \sum_{i \in N(t)} p_i \sum_{j \in N^+(t) \setminus \{i\}} x_{ij}$. In words, the objective is to maximize the profit obtained from the foreseen targets that are planned to be visited. The formulation of the (T)OPTW is the following:

$\max \sum_{i \in N(t)} p_i \sum_{j \in N^+(t) \setminus \{i\}} x_{ij},$ (1)
subject to $\sum_{i \in N^+(t) \setminus \{0_t\}} x_{0_t i} = \sum_{i \in N^+(t) \setminus \{0\}} x_{i0} = 1,$ (2)
$\sum_{i \in N(t) \setminus \{k\}} x_{ik} = \sum_{i \in N(t) \setminus \{k\}} x_{ki} \leq 1 \quad \forall k \in N(t),$ (3)
$s_j - \overline{t_{ij}} - \overline{r_i} - s_i \geq (x_{ij} - 1)M \quad \forall (i,j) \in A(t),$ (4)
$l_i \leq s_i \leq u_i \quad \forall i \in N(t) \cup \{0\},$ (5)
$x_{ij} \in \{0,1\} \quad \forall (i,j) \in A(t)$ (6)

Constraint (2) in the formulation of the (T)OPTW guarantees that the tour starts at the current location of the UAV and ends at the recovery point. Further, constraints (3) guarantee that, if a target is visited, the UAV only arrives once at that target and also leaves that target once. In constraints (4) M is a large number. Constraints (4) ensure the minimum starting time at each location visited and prevent subtours. Constraints (5) ensure that the recording of a target starts within its time window. The time window of the depot starts at $l_0 = 0$ and ends at $u_0 = T$ (Evers et al., 2014).

3.2. THE MCS-OPTW RE-PLANNING MODEL

The MCS-OPTW re-planning model uses the characteristics of the probability distributions of the travel and recording times. It also takes into account the arrival rates of the locations of potential new targets. This model balances two objectives: the first objective maximizes expected profit by recording foreseen targets and the second objective maximizes the ability of the UAV to be successfully re-tasked to new targets.

3.2.1. WEIGHTED LOCATION COVERAGE

Weighted location coverage (WLC) is used by Evers et al. (2014) as a measure for the ability to reach new targets. At a given moment, a location of a potential new target is said to be covered if the expected travel time from the current location of the UAV to the location of the potential new target is at most U. Evers et al. (2014) introduces two new parameters:

$$b_{jk} = \begin{cases} 1 & if\ location\ k\ \in N'\ is\ covered\ when\ UAV\ is\ at\ location\ j \\ 0 & otherwise \end{cases}$$
$$b_{ijk} = fraction\ of\ arc\ (i,j)\ in\ which\ location\ k \in N' is\ covered$$

If the UAV arrives at location j before the start of the time window, the UAV has some waiting time w_j. Considering a given travel time t_{ij} on arc (i,j) and a given recording time r_j and waiting time w_j at target j, the WLC of arc (i,j) is defined as follows:

$$c_{ij}(t_{ij}, w_j, r_j) = \sum_{k \in N'} (t_{ij} b_{ijk} + (w_j + r_j) b_{jk}) \lambda_k$$

3.2.2. OBJECTIVE

Aim of the MCS-OPTW re-planning model is to find a tour, or a path at time t from 0_t to depot, which balances the two objectives. The two objectives are balanced by α and β, with $\alpha + \beta = 1$. This objective can be used to evaluate any given tour x. The objective maximizes expected values:

$$\mathbb{E}_{tr}(.) = expected\ value\ based\ on\ expected\ values\ of\ t\ and\ r$$

The expected value is determined by evaluating a found solution for a set of scenarios, each containing one realization of the travel time between all combinations of locations and one realization for the recording time in each target. For every scenario, the first part of the objective determines the profit, taking into account that the UAV can arrive too late to start the recording:

$$I_{ixtr} = \begin{cases} 1 & if\ for\ the\ given\ tour\ x, target\ i\ can\ be\ reached\ before\ the\ end\ of\ its\ time\ window \\ 0 & otherwise \end{cases}$$

The objective MCS-OPTW is formulated as follows:

$$\max \alpha \mathbb{E}_{tr}\left(\sum_{i\in N(t)} p_i I_{ixtr} \sum_{j\in N^+(t)\{i\}} x_{ij}\right) + \beta \mathbb{E}_{tr}\left(\sum_{i\in N^+(t)} \sum_{j\in N^+(t)\{i\}} c_{ij}\left(t_{ij}, w_j, r_j\right) x_{ij}\right)$$

In which the first part, with weight α, describing the expected profit obtained from recording foreseen targets and the second part, with weight β, describing the expected ability to reach new targets.

4. HEURISTIC

The route of the UAV should be re-planned each time before leaving a target. For the (T)OPTW, Vansteenwegen et al. (2009) developed a fast heuristic. For the MCS-OPTW, Evers et al. (2014) developed a fast heuristic that differs from the (T)OPTW heuristic in the fact that it takes uncertainty and possible new targets into account.

The heuristic used for both methods consists of four steps:

1. **Initialization**: in this phase the best solution and the current solution contain two locations. First, the current location at time t, and second, the final location, the depot. If $t = 0$ the current location is the location of the depot and if the heuristic is used to re-plan the current location is the location of the target which the UAV is about to leave.
2. **Insertion:** All combinations of targets that could be inserted and placed in the current solution where targets could be inserted without breaking any of the time window constraints are found. Using a certain measure, the best insertion possible is executed. After that, the required characteristics of the targets in the current solution are calculated.
3. **Evaluation:** The objective value of the current solution is determined. If this objective is better than the objective of the current best solution, the best solution is updated.
4. **Shake:** R consecutive targets are removed from the current solution, starting at B. Again, the required characteristics of the targets in the current solution are calculated.

Steps 2, 3 and 4 are repeated until a determined number of times in a row no improvement is found. These steps will be explained further in the following sections.

4.1. (T)OPTW HEURISTIC

The (T)OPTW heuristic stores for each location in the current solution some properties of that target. Consider a sequence of targets i, j and k which are in this order in the current solution. For the middle target, target j, the arrival time (a_j), the time when the UAV can start recording (s_j), the possible waiting time (w_j) and the maximum time the start of recording can be shifted ahead, max shift (m_j) are defined as follows:

$$
\begin{aligned}
&a_j = s_i + r_i + t_{ij} \\
&s_j = \max(a_j, l_j) \\
&w_j = \max(l_j - a_j, 0) \\
&m_j = \min(u_j - s_j, w_k + m_k), m_0 = T - s_0
\end{aligned}
$$

For a_j, s_j and w_j the properties about previous targets in the solution are needed. The arrival time of the first location the UAV flies to in the found solution, a_{first}, is equal to the time of re-planning t plus the travel time between the position of the UAV at the moment of re-planning and the first location. $a_{first} = t + t_{0_t first}$ is used to calculate s_{first}, which is again used to calculate the arrival time for the second location in the found solution, etcetera. m_j uses properties from the targets following up target j in the solution. The last location in the found solution is the depot, for which the max shift is equal to $m_0 = T - s_0$. m_0 is used in calculating the max shift for the second last location in the found solution, etcetera.

The properties of target *j'* can be calculated as if the sequence of target j, *j'* and k is in this order in the current solution. Furthermore, $shift_{j'}$ is the total additional time required to insert target *j'* in the current tour between targets j and k. A target *j'* can be inserted between target j and target k the following conditions are met:

$$
\begin{aligned}
&a_{j'} \leq u_{j'} \\
&shift_{j'} = t_{jj'} + w_{j'} + r_{j'} + t_{j'k} - t_{jk} \leq w_k + m_k
\end{aligned}
$$

The combination of the target and the location in the current solution with the highest ratio $p_{j'}^2/shift_{j'}$ is selected for insertion.

In the 'shake' step, R consecutive targets are removed from the current solution, starting at B. B cannot be the first or last location, as the first target indicates where the UAV is and the last target is the depot to which the UAV should return. B is a position chosen according the uniform distribution between the first and last location in the current solution. R cannot be larger than the number of targets that come after B in the current solution, because the depot cannot be removed, so R is chosen according the uniform distribution between 1 and the number of targets in the current solution minus B.

In the 'shake' step, the heuristic used in this thesis differs slightly from the heuristic for the (T)OPTW developed by Vansteenwegen et al. (2009). In the latter, there are more bounds on B and R.

4.2. MCS-OPTW HEURISTIC

The MCS-OPTW heuristic developed by Evers et al. (2014) takes uncertainty and the appearance of new targets into account. The heuristic takes a set of 100 scenarios for the travel times and the recording times as input. These scenarios are randomly drawn from the gamma distribution with the parameters stated as in the section 'Data'. This heuristics works with two kinds of expected values: first, the expected values based on the probability distribution and second, the expected values equal to the averages of the 100 scenarios. When referred to the properties of the targets it is important to distinguish two types of notations. A '*' refers to an expected value based on the probability distribution. Consider for example the arrival time at target j', $a_{j'}$ is the arrival time based on the expected values based on the average of the 100 scenarios and $a_{j'}^*$ is the arrival time based on the expected values from the probability distribution.

In step 2 and 4 of the heuristic, where the current solution is changed, the characteristics of the targets in the current solution are calculated as in the (T)OPTW heuristic, with the expected values equal to the averages of the 100 scenarios as input.

The heuristic uses characteristics of the probability distributions. $\overline{t_{ij}}$ with σ_{ij}^{t} and $\overline{r_j}$ with σ_j^r define the expected values with the standard deviation of the gamma distribution for the travel times on arc (i, j) and the recording times at target *j* respectively. The heuristic allows travel and recording time realizations to be ρ times the standard deviaton lower than the expected value in the feasibility conditions. Like in the article by Evers et al. (2014), $\rho = 0.5$. This leads to more targets to be allowed for insertion. The earliest realized arrival time of target *j'* to insert target *j'* between *j* and k and the corresponding largest allowed waiting time are now as follows:

$$a_{j'}^{*} = s_j + (\overline{r_j} - \rho\sigma_j^r) + \left(\overline{t_{jj'}} - \rho\sigma_{jj'}^{t}\right)$$
$$w_{j'}^{*} = \max(l_{j'} - a_{j'}^{*}, 0)$$

The feasibility conditions are now defined as follows:

$$a_{j'}^{*} \leq u_{j'}$$
$$shift_{j'}^{*} = \left(\overline{t_{jj'}} - \rho\sigma_{jj'}^{t}\right) + w_{j'}^{*} + \left(\overline{r_{j'}} - \rho\sigma_{j'}^{r}\right) + \left(\overline{t_{j'k}} - \rho\sigma_{j'k}^{t}\right) - \overline{t_{jk}} \leq w_k + m_k$$

To take the uncertainty in travel and recording times into account, the ratio of inserting target *j'* between target *j* and k is calculated as follows:

$$\frac{(P(a_{j'} \leq u_{j'})p_{j'})^2}{shift_{j'}}$$

$P(a_{j'} \leq u_{j'})$ is the probability of the UAV arriving in time to start recording. Considering $a_{j\prime} = s_j + r_j + t_{jj\prime}$ and given that the values s_i and r_i are already realized, this probability depends on the distribution of $t_{jj'}$. In other words, $P(a_{j'} \leq u_{j'})$ can be written as $P(t_{jj'} \leq u_{j'} - s_j - r_j)$, which is gamma distributed as described in the section 'Data'.

The objective value of the MCS-OPTW heuristic is estimated using the given 100 scenarios. With a certain solution, the objective value is calculated for every scenario. The expected objective value, which I am actually looking for, is now the average of all these scenario-specific values.

5. SIMULATION

To test the performance of the heuristic, simulation is used. Each simulation can be regarded as a flight. For every flight, a realization of travel and recording times is obtained. Note that this is a different set than used to evaluate solutions in the heuristic. Besides the travel and recording times, a scenario of appearances of new targets is simulated for every flight. Similar to the article by Evers et al. (2014), the new targets appear according to a Poisson process. As stated in section 2.2., the arrival rate λ_i defines the expected number of new targets that appear at location i during the time span $T - t_n$, therefore the arrival rate per time unit is equal to $\frac{\lambda_i}{T-t_n}$. The inter arrival times are, according to the Poisson process, determined according the exponential distribution with mean $\frac{1}{\lambda}$ (in which λ is the mean of the inter arrival times).

The simulation contains 3 steps, which are repeated until the UAV returns to the depot:

1. **Re-planning heuristic:** Each time before leaving a target and the first time before leaving the depot, the heuristic is applied to find a planned tour. The first target is the target which is the first to fly to according to the found tour. The arrival time (a), the waiting time (w) and the recording time (r) for the first target are determined with travel and recording times of the simulated flight.
2. **Re-tasking:** If one or more new targets have appeared before the ending of the recording of the first, it is decided if the UAV is going to fly to a new target using the re-tasking criterion described

in section 5.1. If more than one target appeared, it is first checked for the target that appeared first. Only if the UAV decides not to fly to this target, the second target that appeared is regarded etcetera.

3. **Objectives:** If the UAV is not sent to a new target, it is checked if the UAV arrived at the first target before the ending of the time window of the first target. If so, it is checked if the recording is completed before the UAV returns to the depot. If the recording is completed, the profit corresponding to the target is gained. If the UAV was sent to a new target, it is checked if the UAV arrived in time. If so, the new target is counted as reached in time. Further, it is again checked if the recording is completed before the UAV returns to the depot and only if this is the case, the new target is counted as recorded.

The UAV returns to the depot if the expected travel time to the depot, according to the probability distribution, equals $T - t$. If more than one target appeared in step 2, these targets are regarded for re-tasking after the potential flying to and recording of the new target. The same holds for targets that appear while the UAV is already on its way to or recording a new target. In these cases the value for U in the re-tasking criterion (explained in section 5.1.) is smaller because of the time that has already passed between the appearance of the new target and the moment that re-tasking is considered.

5.1. Re-tasking criterion

The criterion to fly or not to fly to the new target is defined by Evers et al. (2014) as the re-tasking criterion. The UAV is sent directly to a new target in case the probability of reaching it in time is large enough. The probability of reaching the target at location i in time is defined as follows:

$$P(t_{0_t i} \leq U)$$

$t_{0_t i}$ is the travel time from the current location 0_t to the location of the new target i, which is gamma distributed as described in the section 2.1.2. To find the shape parameter of this distribution, the Euclidean distance, the current location of the UAV needs to be determined. If the new target appeared at time $t_{new\ appearance}$ before the arrival time at the first target ($t_{new\ appearance} < a$), the location is determined according to the fraction of the travel time towards the first target already flown f_{flown} at the moment of appearance. If the location of the previous target (the target at which the re-planning heuristic is applied) is (X_p, Y_p) at time t and the location of the first target is (X_1, Y_1), the current location (X_0, Y_0) at time $t_{new\ appearance}$ is calculated as follows:

$$f_{flown} = \frac{t_{new\ appearance} - t}{a - t}$$
$$(X_0, Y_0) = \left(X_p + f_{flown}(X_1 - X_p), Y_p + f_{flown}(Y_1 - Y_p)\right)$$

If the new target appeared after the arrival at the first, while the UAV is waiting to start a recording or is recording, the location of the UAV is of course equal to that of the first target. With the location of the UAV the probability of reaching the target in time can be determined. This probability is large enough if it is at least $P(a_{new} < 0.85\overline{a_{new}})$. This gives the re-tasking criterion:

$$\text{Re-task if } P(t_{0_t i} \leq U) \geq P(a_{new} < 0.85\overline{a_{new}})$$

a_{new} is the realized arrival time and $\overline{a_{new}}$ is the expected arrival time at the location of the new target at location i, $a_{new} = t + t_{0_t i}$. This gives $P(a_{new} < 0.85\overline{a_{new}}) = P\left(t + t_{0_t i} < 0.85(t + \overline{t_{0_t i}})\right) = P\left(t_{0_t i} < 0.85\left(t + \overline{t_{0_t i}}\right) - t\right)$, which is gamma distributed as described in section 2.1.2.

5.2. Possible adjustments

In this section I introduce three suggestions for adjustments in the simulation.

5.2.1. *RE-TASKING CRITERION*

In the simulation described by Evers et al. (2014), the UAV is sent directly to a new target if the re-tasking criterion is met. It can occur that at the moment of appearance, the UAV is recording a foreseen target. In that case, the recording is stopped and the profit is not gained. It might occur that a nearly finished recording is stopped to fly to a new target, while the new target could have also be reached in time after finishing the recording and profit is lost unnecessary. The variable $r_{0_t,left}$ indicates the recording time that is left at the current location of the UAV at the moment of appearance of the new target. The probability of finishing the recording and reaching the target in time is now defined as follows:

$$P(r_{0_t,left} + t_{0_t i} \leq U)$$

For simplicity in calculations, I assume that once a recording has started, the total recording time is known. The fraction of the recording already completed is given by $f_{recorded}$. This gives $r_{0_t,left}$:

$$f_{recorded} = \frac{t_{new\ appearance} - s_{0_t}}{r_{0_t}}$$
$$r_{0_t,left} = (1 - f_{recorded})r_{0_t}$$

The probability of finishing the recording and reaching the new target in time can now be described as $P(t_{0_t i} \leq U - r_{0_t,left})$, of which the probability distribution is known. The arrival time can be described as $a_{new} = t + r_{0_t,left} + t_{0_t i}$. This gives $P(a_{new} < 0.85\overline{a_{new}}) = P\big(t + r_{0_t,left} + t_{0_t i} < 0.85(t + r_{0_t,left} + \overline{t_{0_t i}})\big) = P\big(t_{0_t i} < 0.85\big(t + r_{0_t,left} + \overline{t_{0_t i}}\big) - t - r_{0_t,left}\big)$, which is gamma distributed as described in section 2.1.2.

5.2.2. *APPEARANCE NEW TARGETS*

The arrival rate λ_i of potential location i defines the expected number of new targets that appear at this location during the time span $T - t_n$. t_n is the expected travel time from the new target location which is closest to the depot to the depot. Due to the return policy, the UAV will not be sent to targets which appear after $T - t_n$(Evers et al., 2014). When a new target appears, the re-tasking criterion is met and the new target is reached in time, the recording of the new target starts. However, if a new target appears just before $T - t_n$, it might occur that the recording of the new target has started but the UAV needs to return to the depot before completing the recording. Therefore, the percentage of new targets reached in time and the percentage of new targets recorded might differ.

Possibly, the UAV is re-tasked while recording a foreseen target, stops the recording of the foreseen target and gains no profit from the foreseen target. The UAV reaches the new target in time, but cannot complete the recording because it has to return to the depot. In this possible scenario, the UAV gains no profit from the foreseen target and the new target is not recorded because of the re-tasking. If the UAV was not re-tasked, it might have completed the recording of the foreseen target and the obtained profit in the flight would have been higher while the percentage recorded remained the same.

Therefore, it is worth investigating the effect of changing the time span in which the UAV can be sent to a new target. In this case, the UAV will not be sent to targets which appear after $T - t_n - r_n$. r_n is the expected recording time of the new target with the smallest expected recording time (in this thesis all new targets have equal values for the parameters for the recording time).

5.2.3. *LESS TIME SENSITIVE NEW TARGETS*

The minimal distance between two new targets in different clusters is 13.60. The time in which the new target has to be reached, $U = 10$, is quite small. The probability of reaching a target in time is therefore relatively small, let alone the probability of finishing a recording and reaching a target in time (as is suggested is in the first adjustment).

If the new targets are less time sensitive, $U > 10$, the results of the simulation might change. New targets are easier to reach in time which will lead to a larger value for the second objective. Further, the effects of the first adjustment could become clearer when the time in which the new target has to be reached is larger because it is easier for the UAV to reach a new target in time after finishing a recording.

6. COMPUTATIONAL EXPERIMENTS

The (T)OPTW heuristic and the MCS-OPTW heuristic are both implemented in MATLAB. All experiments are performed on an Acer Aspire V5 laptop with an Intel Core i7 processor (1.8 gigahertz) and 8.00 GB of RAM. The time needed to run the MCS-OPTW heuristic depends mainly on the setting for the number of no improvements in a row required to accept a solution. Further, it depends on the length of the time windows, larger time windows result in a larger computation time. This can be explained by looking which parts of the heuristic take most time. Approximately the half of the duration of the heuristic is caused by the part in which the heuristic finds all possible insertions. All possible insertions are all combinations of targets that could be inserted and placed in the current solution where targets could be inserted without breaking any of the time window constraints are found. Larger time windows will result in more possible insertions because of less strict time window constraints. The time needed to run the total simulation depends on the number of flights.

6.1. HEURISTIC

In this first section, section 6.1, I discuss the results of running the heuristic once for the starting situation: that means that the current location of the UAV is at the depot ($0_t = 0$) and $t = 0$.

6.1.1. STABILITY

First, I have checked if the heuristics give stable results. To do so, I performed the heuristic five times, each time with the same set of scenarios and settings for the lengths of the time windows. I performed four experiments: First, the MCS-OPTW heuristic with small time windows; second, the MCS-OPTW heuristic with large time windows; third, the (T)OPTW heuristic with small time windows and fourth, the (T)OPTW heuristic with large time windows. For the experiments to check the stability I have set $\beta = 0.3$. Like in the article, the number of no improvements in a row required to accept a solution is set at 1000. The time needed to run the heuristic equals 15 to 35 seconds for small time windows.

For the first and second experiment I calculated the MCS-OPTW objective and the first and second objective separately. For the third and fourth objective I only compared the OPTW objective, as the other objectives are not used in the heuristic. For each objective in each experiment I calculated the mean. Because the number of performances per experiment is so little (five), I do not work with standard deviations. Instead, I calculated the percentage deviation from the mean per performance. The results are given in Table 1. The number of no improvements is set at 1000.

In Table 1 it is shown that, with the same set of scenarios, the percentage deviation from the total objective is never above 5%. Table 1 shows that for the first or the second objective, the percentage deviation is bigger.

In the heuristic only the total objective is maximized, that the first or second objective fluctuates more makes sense. The total objective should be constant. Table 1 shows that the total objective is constant, at least within a margin of 5%. Therefore, I conclude that the heuristic is stable.

As stated at the beginning of this chapter, the time needed to run the heuristic depends mainly on the setting of the number of no improvements in a row required to accept a solution. Because in the simulation the heuristic is called many times, I investigated if the number of no improvements can be set smaller to increase speed while maintaining stability.

TABLE 1: STABILITY HEURISTIC

Results of 5 times running the MCS-OPTW and (T)OPTW heuristic for small and large time windows. Each time the same set of scenarios to evaluate the solution is used. For the MCS-OPTW the results (mean of percentage deviation from the mean) are given in the following form: Total objective/First objective/Second objective. For the (T)OPTW only the total objective is given. If the percentage deviation from the mean is larger than 5%, it is underlined. The number of no improvements is set at 1000. $\beta = 0.3$.

		MCS-OPTW Small time windows	MCS-OPTW Large time windows	(T)OPTW Small time windows	(T)OPTW Large time windows
	Mean	65.25/69.00/56.48	107.59/137.39/38.07	125.00	166.00
Percentage deviation from mean per performance of heuristic	1	0%/12%/-33%	1%/1%/-3%	0%	2%
	2	-1%/3%/-14%	1%/1%/-3%	0%	-1%
	3	-1%/-2%/5%	2%/2%/-1%	0%	-4%
	4	-3%/-10%/17%	1%/1%/-5%	0%	-1%
	5	4%/-3%/25%	-4%/-6%/13%	0%	2%

If the number of no improvements is set at 100, the heuristic needs 1 to 3 seconds to run in case of small time windows, in case of large time windows the heuristic needs 2 to 6 seconds. However, the results are less stable. I have investigated the effects of increasing the number of no improvements by running 1000 times the heuristic for the number of no improvements set at 100, 200 and at 300. With a sample size of 1000, I can apply the Central Limit Theorem to find the standard deviation and the 95% confidence interval. For every heuristic, I calculated the mean, the standard deviation, the confidence interval and the average percentage deviation from the mean for the total objective. The same set of scenarios is used in all heuristics. The results are shown in Table 2.

Table 2 shows that an increase of the number of no improvements results in a higher computation time but also in more stability, as expected. Further, it is observed that the relative decrease in standard deviation or length of the confidence interval becomes smaller when the number of no improvements is increased more.

The percentage with a deviation from mean larger than 5% shows the percentage of observations with a relative large deviation from the mean. In the case that the number of no improvements is set at 300, 95% of all objective values where within 5% of the mean in case of the small time windows and 97% of all objective values where within 5% of the mean in case of the large time windows.

TABLE 2: STABILITY HEURISTIC

Results about stability when the number of no improvements is smaller. The number of no improvements is set at different values. For each value, the MCS-OPTW, $\beta = 0.3$, is performed 1000 times.

	Small time windows			Large time windows		
Number of no improvements	100	200	300	100	200	300
Duration (in seconds)	1 to 4	3 to 6	4 to 7	2 to 6	4 to 9	6 to 16
Mean total objective	64.06	65.15	63.01	104.31	106.40	106.77
Standard deviation	2.07	1.59	1.46	3.39	2.81	2.47
Confidence interval	[60.01; 68.11]	[62.02; 68.27]	[60.15; 65.87]	[97.67; 110.95]	[100.89; 111.91	[102.36; 112.04]
Length Confidence interval	8.10	6.25	5.72	13.28	11.03	9.68
Average percentage deviation from mean	3%	2%	2%	3%	2%	2%
Percentage with a deviation from mean larger than 5%	11%	6%	5%	9%	9%	3%

6.1.2. *BEHAVIOR HEURISTIC*

Now, I want to compare the (T)OPTW heuristic with the MCS-OPTW heuristic using different values for β. Given a set of scenarios and a length for the time windows (small or large), the (T)OPTW heuristic is performed and the MCS-OPTW heuristic is performed for $\beta = 0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9$ and

1. This gives 12 'best' initial tours. For all the tours the objective value is determined. Note that in the case of the (T)OPTW heuristic, the objective value is determined with another formula than in the case of the MCS-OPTW heuristic. Also, the first and the second objective value, from the MCS-OPTW heuristic, are determined for all the tours. In the case of the (T)OPTW, these objectives are not used to determine the best tour. However, for comparison reasons I do determine the first and second objective according the MCS-OPTW for the solution given by the (T)OPTW. Doing so, I can see how the solution given by (T)OPTW performs in case of uncertainty and the capability of covering new targets. The results are shown in Table 3. The number of no improvements in a row required to accept a solution is set at 1000.

TABLE 3: RESULTS HEURISTICS IN INITIAL SITUATION

Results of the heuristic applied on the initial situation, that means that the current location is the depot and the time $t = 0$. The results are given in the following form: Total objective/First objective/Second Objective. Note that for the (T)OPTW approach, the total objective is calculated in a different way than for the MCS-OPTW approach. The number of no improvements is set at 1000. The results from the MCS-OPTW heuristic that outperform the (T)OPTW heuristic are underlined.

Heuristic	β	Small time windows	Large time windows
(T)OPTW	N.A.	130.00/42.20/41.43	155.00/73.90/42.89
MCS-OPTW	0	77.10/<u>77.10</u>/29.86	144.05/<u>144.05</u>/22.63
MCS-OPTW	0.1	74.55/<u>78.65</u>/37.65	128.96/<u>139.35</u>/35.42
MCS-OPTW	0.2	66.17/<u>74.00</u>/34.83	119.77/<u>144.05</u>/22.63
MCS-OPTW	0.3	63.23/<u>62.00</u>/<u>66.11</u>	108.95/<u>129.90</u>/<u>60.08</u>
MCS-OPTW	0.4	63.65/<u>62.00</u>/<u>66.11</u>	102.20/<u>143.85</u>/39.72
MCS-OPTW	0.5	66.43/<u>49.90</u>/<u>82.96</u>	88.06/<u>127.80</u>/<u>48.31</u>
MCS-OPTW	0.6	64.47/<u>62.00</u>/<u>66.11</u>	81.35/<u>110.70</u>/<u>61.79</u>
MCS-OPTW	0.7	68.70/<u>67.70</u>/<u>69.13</u>	75.31/<u>102.90</u>/<u>63.49</u>
MCS-OPTW	0.8	68.63/<u>55.60</u>/<u>71.89</u>	78.93/<u>109.85</u>/<u>71.20</u>
MCS-OPTW	0.9	65.70/<u>62.00</u>/<u>66.11</u>	69.25/<u>78.80</u>/<u>68.19</u>
MCS-OPTW	1	78.22/<u>50.65</u>/<u>78.22</u>	61.11/<u>99.20</u>/<u>61.11</u>

The results in Table 3 are obtained using one set of scenarios for all heuristics and values for β. Note that different sets of scenarios can result in different outcomes. Therefore, I performed the different heuristics with the different values for β for multiple sets of scenarios, the outcomes stated in this section are an example. These outcomes are obtained from one set of scenarios. Further, for the (T)OPTW heuristic the first and second objective can differ a lot, even if the same set of scenarios is used, because these are not used in the heuristic and there are probably many different solutions giving the same objective value in the (T)OPTW heuristic. In the following subsections the main findings about the behavior of the heuristic are described. Because, as stated as above, these findings are based on outcomes of one set of scenarios, I have checked if these findings also hold for outcomes of other sets of scenarios.

6.1.2.1. Influence β

Table 3 shows that increasing the value of β results in a decrease of the first objective and an increase in the second objective. As β is responsible for the weight of the second objective, this is as expected.

In case of the small time windows, the value of the first objective changes relatively more between $\beta = 0$ and $\beta = 0.5$ than between $\beta = 0.5$ and $\beta = 1$. In the case of the small time windows, there is still a quite some fluctuation between $\beta = 0.5$ and $\beta = 1$ for the value of the first objective, though it does not decrease anymore. For the case of the large time windows, the value of the first objective decreases relatively more between $\beta = 0.5$ and $\beta = 1$.

For the second objective most value is gained between $\beta = 0$ and $\beta = 0.5$. The value of the second objective is more than 2 times bigger at $\beta = 0.5$ compared to $\beta = 0$, for the small and the large time windows. Table

3 shows that between $\beta = 0.5$ and $\beta = 1$ the value decreases for the case of the small time windows but increases for the case of the large time windows.

Evers et al. (2014) states that that in the simulation, the values of the objectives do not change significantly anymore between $\beta = 0.5$ and $\beta = 1$, and therefore the results of $\beta = 0.6; 0.7; 0.8$ and 0.9 are left out. With the results shown in this section, it is seen that, in the case of the large time windows, there is still a quite large change between the value for the first and second objective when $\beta = 0.5$ and $\beta = 1$. As stated earlier this section, the results in this section are examples and can change a lot when a new set of scenarios is created. When looking at outcomes from other sets of scenarios, it is sometimes also observed that the value of the second objective changes relatively a lot between $\beta = 0.5$ and $\beta = 1$. This means that with the data in this thesis, for performing the heuristic on the initial situation to get a planned tour, the results could change relatively a lot between $\beta = 0.5$ and $\beta = 1$ and are therefore not left out. If the heuristic in the initial situation behaves like this, this might also be the case in a simulation.

6.1.2.2. MCS-OPTW compared to (T)OPTW

Table 3 shows that the values for the first objective of the solutions of the (T)OPTW are smaller than the total (T)OPTW objective. In outcomes from other sets of scenarios, this is also the case. The total objective, used to determine the best solution, is calculated with the objective of the (T)OPTW in section 3.1. The (T)OPTW objective is simply the sum of the profit of all targets in the found solution. The first objective shown in Table 3 is calculated using the first part of the objective of the MCS-OPTW in section 3.2.2. The first part of the MCS-OPTW objective is the expected value of the sum of the profits of the targets reached before the ending of their time window. If a target is not reached in time, no profit is gained. This results in a difference between the value of the total (T)OPTW objective and the value of the first MCS-OPTW objective for the found solution from the (T)OPTW heuristic. This difference means that, when the travel and recording times are assumed to be known beforehand, as in the (T)OPTW heuristic, the heuristic might result in a too tight planning in which less targets are reached in time when evaluating it by multiple scenarios.

Table 3 shows that if the first objective of the solution of the MCS-OPTW heuristic outperforms the first objective of the solution of the (T)OPTW heuristic in all cases. Therefore, I conclude that adding uncertainty in the objective to determine the best solution is useful.

For the results in Table 3, if the second objective of the MCS-OPTW is compared with the second objective of the value of the solution found by the (T)OPTW heuristic, Table 3 shows that in the case of the small time windows, the second objective is better when $\beta \geq 0.3$ and in the case of the large time windows, the second objective is better when $\beta \geq 0.5$. However, as already stated, the second objective of the solution found by the (T)OPTW can fluctuate a lot. Therefore, it is not correct to draw conclusions from these results about how the (T)OPTW heuristic performs in terms of the second objective compared to the MSC-OPTW heuristic. Though, it is clear that the (T)OPTW heuristic is not useful if a solution with a large coverage is wished with any certainty.

6.1.2.3. Influence length of time windows

Table 3 shows that in the case of large time windows, the objective value is larger than in case of the small time windows, except for the case in which $\beta = 1$. This increase is caused by the increase in the first objective value, therefore the differences in the total objective value are bigger when β is smaller and, in this specific example, the difference disappears if $\beta = 1$. This is caused by the fact that large time windows result in more targets to be reached within their time window. This is a similarity with the results of the simulation of Evers et al. (2014).

6.1.3. TOPOLOGY

Figures A.2-8, found in Appendix A. illustrates 7 examples of solutions obtained by the (T)OPTW heuristic or the MCS-OPTW heuristic with different values for β, for small time windows and large time windows.

Altough these tours can be adjusted after the re-planning step in the heuristic, they give a good illustration of how the tour is situated.

If Figure A.2-8, small time windows, is compared with Figure A.6-8, large time windows, differences can be observed. The small time windows result in tours whith relatively more intersecting arcs, where the tours in case of the large time windows are more smooth. This is a similarity with the results found by Evers et al. (2014). Further, if the same heuristic is applied with the same value for β, the tours planned in case of the large time windows include more targets than the tours planned in case of the small time windows.

When β increases, the number of targets in the tour decreases and the UAV is sent more in the direction of location of potential new targets.

If the tours planned by (T)OPTW are compared with the tours planned by MCS-OPTW with $\beta = 0$, it is observed that the tours planned with (T)OPTW contain more targets. In case of the small time windows, the difference is larger than the case of large time windows. This difference can be explained by the fact that MCS-OPTW takes uncertainty into account and chooses the solution with the most obtained profit over 100 scenarios. To illustrate this, I evaluated the first objective from the MCS-OPTW heuristic for the tour given by both heuristics, in case of the small time windows. The tour from the (T)OPTW heuristic results in a value for the first objective of 53.15, while the tour from the MCS-OPTW heuristic with $\beta = 0$ results in a value for the first objective of 85.35. This confirms the finding in 6.1.2.2.; when the traveltimes are assumed to be known beforehand, as in the (T)OPTW heuristic, the heuristic might result in a too tight planning, too many targets in one tour, in which less targets are reached in time when evaluated by multiple scenarios.

6.2. SIMULATION

As stated in section 6.1.1, the computation time of the heuristic depends on the setting for the number of no improvements. Because a limited period of time available for this thesis, I decided to set the number of no improvements at 300. As shown in section 6.1.1, this gives relatively stable results.

Evers et al. (2014) evaluates the (T)OPTW heuristic versus the MCS-OPTW heuristic for the values of $\beta = 0, 0.1, 0.2, 0.3, 0.4, 0.5$ and 1. In section 6.1, it is shown that the results not only differ between $\beta = 0$ and $\beta = 0.5$ but also differ between $\beta = 0.5$ and $\beta = 1$. Therefore, I decided not to leave out the results of the values of β between 0.5 and 1. However, because of time limits I decided to let out some values of β, and to evaluate the (T)OPTW heuristic and the MCS-OPTW heuristic for the values of $\beta = 0, 0.25, 0.5, 0.75$ and 1.

Note that the adjustments described in section 5.2. are not applied in the simulations unless explicitly said so.

6.2.1. *STABILITY*

The stability of results depends on the number of flights (in other words: the number of simulations) and the number of no improvements setting of the heuristic. Evers et al. (2014) uses 800 simulated flights. If one simulation calls the re-planning heuristic at least 5 times, and the heuristic takes approximately 5 seconds (which it does in case of small time windows and a number of no improvements set at 300), testing a specific value for β for the MCS-OPTW heuristic takes $800 * 5 * 5 = 2000$ seconds, this is more than 5.5 hours. I want to evaluate multiple heuristics, settings for β and settings for the time window. Therefore, it is not possible within the time limit of this thesis to use 800 simulated flights. Evers et al. (2014) states that a smaller number already produces stable results.

Testing stability for different numbers of simulated flights is very time expensive. A larger number of simulated flights will result in a more reliable result. Therefore, I want to set the number of simulated flights as large as possible but I want them to be obtained within 24 hours.

The time to evaluate the (T)OPTW heuristic and the MCS-OPTW heuristic for five different values for β, for small time windows and large time windows, for 200 flights equals approximately 24 hours. This is doable as it can be done over two nights. Therefore, I have set number of flights equal to 200. For all results obtained in this chapter, the same set of 200 flights is used.

6.2.2. *BEHAVIOR SIMULATION*

Table 4 contains the results of the tours found by the (T)OPTW heuristic and found by the different values for β in the MCS-OPTW heuristic. Note that for all results the same set of scenarios to evaluate solutions in the heuristic is used and the same set of simulated flights is used. However, when a new target appears while the UAV is flying and the location and distance to travel is therefore not know beforehand, the travel time has to be determined at that moment. Therefore, when evaluating heuristics with the same flight and if the UAV has by coincidence the same location at moment of appearance of the new target, the travel time can differ.

Evers et al. (2014) shows two different performance measures. First, the average profit obtained by foreseen targets is given. As stated before, this profit is only obtained if a recording starts before the ending of the time window and is completed. Second, the percentage of new targets reached in time is shown. However, it is not clear in the article if the recording of the new target has to be completed to be counted as reached in time. It is possible that a UAV has to return to the depot before the recording of the new target is completed. Therefore, I compared the percentage of new targets reached in time and the percentage of new targets recorded completely. Table 4 shows that there are noticeable differences between the percentage reached and the percentage recorded completely.

I have compared these results with the results obtained by Evers et al. (2014) for the situation in which new targets appear in clusters and the travel and recording times are gamma distributed.

TABLE 4: RESULTS OF THE SIMULATION

Results of the (T)OPTW and MCS-OPTW planning approach for small and large time windows. The number of no improvements in the heuristic is set at 300. The results are based on 200 flights. The results are stated in the following form: Average profit gained from foreseen targets/Percentage of new targets reached in time/Percentage of new targets completely recorded. The results from the MCS-OPTW approach that outperform the (T)OPTW approach are underlined.

Approach	β	Small time windows	Large time windows
(T)OPTW	N.A.	55.43/14.91%/13.62%	45.40/18.00%/16.25%
MCS-OPTW	0	66.93/13.92%/12.41%	94.48/14.32%/12.81%
MCS-OPTW	0.25	68.58/14.94%/13.67%	94.45/13.32%/12.31%
MCS-OPTW	0.5	66.08/17.30%/15.78%	89.00/15.42%/13.93%
MCS-OPTW	0.75	63.55/19.29%/17.26%	78.98/19.50%/18.25%
MCS-OPTW	1	58.35/17.93%/16.16%	72.98/17.75%/15.75%

6.2.2.1. Influence β

Looking at the percentage of new targets reached in time or new targets recorded, I see that increasing β results in a higher percentage for the MCS-OPTW approach, as expected. However, it is noticeable that for $\beta = 1$ the percentages drop a little.

The little drop for $\beta = 1$ in the second objective can be explained intuitively. The potential locations of new targets divided over two clusters. The total arrival rate is the sum of all arrival rates. The total arrival rate of the left cluster is approximately equal to the total arrival rate of the right cluster. In section 2.2.1, I calculated the distances between the two clusters. It turns out that the clusters are too far away from each other for the UAV to cover them both at the same time. The minimal distance between the two targets is 13.60. If the UAV would be in the exact middle of the clusters, the minimal distance to a cluster is 6.80. According to the gamma distribution, this gives an expected travel time of 13.60 time units. The probability that the UAV reaches the closest possible target in the cluster on time, within $U = 10$, is equal to 26.39%. The UAV cannot cover the two clusters at the same time. With $\beta = 1$ the focus is completely on covering possible new targets. The maximum coverage is obtained in one cluster. However, if the focus is for example completely on the left cluster, an appearance in the right cluster is not covered.

Further it is shown that an increase in β results in a decrease of average profit from foreseen targets. The more new targets are visited, the less profit is gained from the foreseen targets.

6.2.2.2. MCS-OPTW compared to (T)OPTW

For the first objective, the gained profit from foreseen targets, the stochastic MCS-OPTW approach outperforms the deterministic (T)OPTW approach. I conclude that taking uncertainty into account is useful in planning a tour. Further, the Table 4 shows MCS-OPTW solutions that are dominant to the (T)OPTW solutions. Dominant solutions are solutions that have resulted in a higher average profit and a higher percentage of new targets reached or recorded. For $\beta = 0.75$, the solution found by the MCS-OPTW approach is dominant to the (T)OPTW solution in case of the small time windows and in case of the large time windows.

It is noticeable that in case of the large time windows, only for one tested value of β the percentage of new targets reached in time or recorded completely found by the MCS-OPTW approach is higher than the results found by the (T)OPTW approach. This might be explained by the fact that a too large value for β does not always result in more new targets reached for the cluster situation of the locations of potential new targets as described in section 6.2.2.1. With large time windows the first objective becomes larger, and therefore the weight of the first objective becomes more important.

6.2.2.3. Influence length of time windows

The large time windows result in better solutions for the first objective. This is in line with my expectations, as in case of large time windows more targets can be planned in a tour and it is easier to meet the time window in the simulation.

6.2.2.4. Topology

The MCS-OPTW planning approach is illustrated by Figure B.9-14, found in Appendix B. These figures show the realized tour (by the black line) and the planned tour (by the dashed line) during several moments in the flight. For these results, the MCS-OPTW heuristic is applied in the case of small time windows with $\beta = 0.3$. Figure B.10 and B.12 show how realized travel and recording times result in a different planned tour. Further, two new targets appeared during this flight. The location of the first new target is too far from the location of the UAV at the moment of appearance, the UAV is not re-tasked. The location of the second new target meets the re-tasking criterion, the UAV is re-tasked to fly directly to the new target. At the moment of appearance of the second target, the UAV was recording a foreseen target. Because of the re-tasking, the recording is not completed and the profit of the foreseen target is not gained.

6.2.3. Robustness

Obtaining the results in Table 4, it is assumed that the distribution of travel and recording times is known beforehand. In this thesis, the travel times are assumed to be gamma distributed. However, it is possible that in reality the probability distribution is different than expected. To check the robustness of the heuristic and the simulation, I have generated a new set of scenarios with travel and recording times according to the normal distribution. This normally distributed set is used to evaluate solutions in the heuristic, while the simulation still uses a set with travel and recording times following the gamma distribution. This way, it is tested how the heuristic performs if the actual probability distribution differs from the assumed one (Evers et al., 2014). For the normal distribution, I used the mean ($k\theta$) and the standard deviation ($\sqrt{k\theta^2}$) found by the gamma distribution. Table 5 shows the results for the MCS-OPTW planning approach for which $\beta = 0.75$. I choose $\beta = 0.75$ because the MCS-OTPW planning approach outperforms the OPTW planning approach on both objectives for the small time windows and the large time windows. For comparison reasons, I included the results of the OPTW and the MCS-OPTW approach in which the heuristics use a set of scenarios for the travel and recording times which are gamma distributed. These values are the values from section 6.2.2.

The MCS-OPTW approach with the travel and recording times assumed to be normally distributed is compared to the MCS-OPTW approach in which the travel and recording times are assumed to be equally distributed to the realized travel and recording times. In case of the small time windows, the profit gained from the foreseen target is larger and the percentage of new targets reached or recorded is smaller when the travel and recording times are assumed to be normally distributed. In case of the large time windows, the values of both objectives are even larger when the travel and recording times are assumed to be normally distributed.

TABLE 5: ROBUSTNESS

Results of the (T)OPTW and MCS-OPTW planning approach for $\beta = 0.75$. The travel and recording times are assumed to be gamma or normal distributed. The realized travel and recording times are gamma distributed. The number of no improvements is set at 300. The results are based on 200 flights. The results are stated in the following form: Average profit gained from foreseen targets/Percentage of new targets reached in time/Percentage of new targets completely recorded. The results from the MCS-OPTW approach that outperform the (T)OPTW approach are underlined.

Approach	Distribution set of scenarios used in heuristic/ Distribution realized travel and recording times	Small time windows	Large time windows
(T)OPTW	Gamma/ Gamma	55,43/14,91%/13,62%	45,40/18,00%/16,25%
MCS-OPTW	Gamma/ Gamma	<u>63.55/19.29%/17.26%</u>	<u>78.98/19.50%/18.25%</u>
MCS-OPTW	Normal/ Gamma	<u>64.10/15.44%/14.43%</u>	<u>80.63/21.30%/19.30%</u>

Table 5 shows that the MCS-OPTW approach in which the travel and recording times are gamma distributed outperform the (T)OPTW approach on all objectives.

These results illustrate that when the assumed distribution differs from the realized one, the MCS-OPTW approach still outperforms the (T)OPTW approach. Therefore, the MCS-OPTW approach seems to be robust. However, in these experiments the distribution differs, but the mean and standard deviation are equal. Evers et al. (2014) has tested the MCS-OPTW approach for robustness by changing the assumed distribution, but also with a smaller expected standard deviation. Evers et al. (2014) shows also with those results that the MCS-OPTW approach is quite robust.

It is noticeable that the results in this thesis show higher values for the first objective in the 'normal' MCS-OPTW approach, the results found by Evers et al. (2014) show the same. A difference between the normal and the gamma distribution is the fact that the gamma distribution is asymmetric. If the heuristic uses the normal distributed set of scenarios, the planned tours contain more targets compared to the heuristic using the gamma distributed set of scenarios. This might be explained by the fact that the gamma distribution has relatively more often higher deviations (because of the asymmetric tail) resulting in relatively more travel and recording times larger than the mean in the scenarios. The fact that the planned tours containing more targets, from the 'normal' MCS-OPTW approach, also result in a realized higher profit, might mean that the planning is too strict when the heuristic uses the gamma distribution, even though the flights are simulated using the gamma distribution. However, further research is needed to investigate this presumption.

6.2.4. *ADJUSTMENTS*

In section 5.2., three possible adjustments are introduced for the simulation. The results of the first and second adjustment are stated in Table 6. Table 6 shows the results of the (T)OPTW and the MCS-OPTW planning approach for $\beta = 0.75$ without any adjustments and the results of the MCS-OPTW planning approach, for $\beta = 0.75$, with the first or the second adjustment applied. Note that the first two adjustments are not applied at the same time. The results of the third adjustment are shown in Table 7. Table 7 also shows the results when the first and third adjustment are applied at the same time.

6.2.4.1. Re-tasking criterion

The first adjustment considers the re-tasking criterion if the UAV is recording a foreseen target when a new target appears. In current simulation, the UAV stops recording if the probability of reaching the new target is high enough. In the adjusted simulation, if the probability of reaching the new target in time is high enough, the UAV finishes its recording if the probability of reaching the new target in time after finishing of the recording is high enough. Table 6 shows that the adjusted MCS-OPTW still outperforms the (T)OPTW planning approach. Compared to the MCS-OPTW approach without adjustments, hardly any differences are observed. Therefore, given the settings I used, the fact that the UAV is allowed to finish a recording has no effect. However, the time in which the new target has to be reached, $U = 10$, is quite small. The probability of reaching a target in time is therefore quite small, let alone the probability of finishing a recording and reaching a target in time. The effects of the first adjustment could become clearer when the time in which the new target has to be reached is larger. This is considered in the third adjustment, of which the results are described in section 6.2.4.3.

6.2.4.2. Appearance new targets

The second adjustment considers the recording time in deciding the last moment to send a UAV to a new target. In the current simulation, the UAV is not sent to targets which appear after $T - t_n$, in the adjusted simulation, the UAV is not sent to targets which appear after $T - t_n - r_n$. Note that targets which appeared after $T - t_n - r_n$ are also not accounted in the total number of new targets that appeared. In the simulated set of 200 scenarios for the new targets to appear, only eight new targets appear between $T - t_n - r_n$ and $T - t_n$, a very small difference. Table 6 shows that the adjusted MCS-OPTW approach still outperforms the (T)OPTW approach. Compared to the MCS-OPTW approach without any adjustments, there are hardly any differences. Instead of the profit gained from foreseen targets to be higher, it is even a little smaller. The percentage of new targets recorded relative to the percentage of new targets reached is more or less the same. Therefore I conclude that, given the settings I used, the smaller time span in which new targets are considered to be visited has no effect.

TABLE 6: ADJUSTMENT 1 AND 2

Results of the (T)OPTW and MCS-OPTW planning approach for $\beta = 0.75$. The number of no improvements is set at 300. The results are based on 200 flights. The results are stated in the following form: Average profit gained from foreseen targets/Percentage of new targets reached in time/Percentage of new targets completely recorded.

- Adjustment 1: Re-tasking criterion takes possibility of finishing a recording and reaching new target in time into account.
- Adjustment 2: UAV will not be sent to targets which appear after $T - t_n - r_n$.

Note that when adjustment 2 is applied, adjustment 1 is not applied. The results from the MCS-OPTW approach that outperform the (T)OPTW approach are underlined.

Approach	Adjustment	Small time windows	Large time windows
(T)OPTW	No adjustment	55.43/14.91%/13.62%	45.40/18.00%/16.25%
MCS-OPTW	No adjustment	<u>63.55/19.29%/17.26%</u>	<u>78.98/19.50%/18.25%</u>
MCS-OPTW	Adjustment 1	<u>64.93/19.64%/17.35%</u>	<u>78.05/18.30%/15.54%</u>
MCS-OPTW	Adjustment 2	<u>62.5/16.24%/14.72%</u>	<u>76.6/22.59%/21.07%</u>

6.2.4.3. Less time sensitive new targets

In section 6.2.2.2 I showed that the UAV can never cover targets from both clusters at the same time. Further, in section 6.2.4.1 it is shown that the first adjustment, the UAV is allowed to finish a recording, has no effect. However, the time in which the new target has to be reached, $U = 10$, is quite small. As explained in section 6.2.4.1., the effects of the first adjustment could become clearer when the time in which the new target has to be reached is larger. Therefore I increased the value of U.

The results of increasing U are shown in Table 7. Table 7 shows that the value for the percentages of new targets reached in time or recorded completely increases with the increase of U. As percentage of new targets reached in time increases, the average profit obtained from the foreseen targets decreases. In section 6.2.2.2. it is explained that, when the UAV is in the exact middle of the clusters, the expected travel time to the closest target in one of the clusters is equal to 13.60 time units. When U is increased to $U = 15$, there are positions in which the UAV can cover two targets from different clusters at the same moment. For a larger value of U, the MCS-OPTW approach still outperforms the (T)OPTW approach in most cases.

Further, Table 7 shows that with a larger value for U, the first adjustment leads to a larger increase in the value for the average profit obtained from foreseen targets. Table 7 shows that the adjustment leads to an increase of 4.02% if $U = 15$. If $U = 30$, the adjustment results in an increase of 11.08%. Because of the larger value for U, it is easier to finish a recording at a foreseen target and to still reach the new target in time. Therefore, I conclude that the first adjustment is useful when the time within a new target should be reached, U, is large enough.

TABLE 7: LESS TIME SENSITIVE NEW TARGETS

Results of the (T)OPTW and MCS-OPTW planning approach for $\beta = 0.75$ when U is increased. The number of no improvements is set at 300. The results are based on 200 flights. The results are stated in the following form: Average profit gained from foreseen targets/Percentage of new targets reached in time/Percentage of new targets completely recorded.

- Adjustment 1: Re-tasking criterion takes possibility of finishing a recording and reaching new target in time into account.

Note that adjustment 2 is not applied. The results from the MCS-OPTW approach that outperform the (T)OPTW approach with the same value for U are underlined.

Approach	U	Adjustment	Small time windows	Large time windows
(T)OPTW	10	No adjustment	55.43/14.91%/13.62%	45.40/18.00%/16.25%
MCS-OPTW	10	No adjustment	63.55/19.29%/17.26%	78.98/19.50%/18.25%
MCS-OPTW	10	Adjustment 1	64.93/19.64%/17.35%	78.05/18.30%/15.54%
(T)OPTW	15	No adjustment	51.53/26.97%/23.16%	47.35/35.00%/32.00%
MCS-OPTW	15	No adjustment	58.50/30.20%/27.41%	75.53/34.18%/30.38%
MCS-OPTW	15	Adjustment 1	60.85/34.61%/32.57%	74.35/36.43%/33.17%
(T)OPTW	20	No adjustment	47.83/45.88%/42.27%	50.68/48.23%/43.97%
MCS-OPTW	20	No adjustment	54.08/47.72%/43.15%	70.95/47.46%/44.16%
MCS-OPTW	20	Adjustment 1	54.65/43.12%/38.44%	74.28/46.33%/41.77%
(T)OPTW	25	No adjustment	44.68/59.79%/53.35%	46.60/59.75%/53.16%
MCS-OPTW	25	No adjustment	50.90/60.61%/54.22%	68.33/61.13%/53.96%
MCS-OPTW	25	Adjustment 1	54.43/61.30%/54.81%	70.85/60.41%/52.79%
(T)OPTW	30	No adjustment	44.35/65.36%/59.38%	48.90/64.89%/57.25%
MCS-OPTW	30	No adjustment	48.93/69.35%/61.56%	66.35/72.94%/63.66%
MCS-OPTW	30	Adjustment 1	54.35/72.87%/63.57%	70.75/69.77%/59.69%

7. CONCLUSION

In this thesis, the methods described by Evers et al. (2014) to plan the use of UAV (Unmanned Aerial Vehicle) missions as effectively as possible are implemented. Evers et al. (2014) compares the Maximum Coverage Stochastic Orienteering Problem with Time Windows (MCS-OPTW) with the deterministic (Team) Orienteering Problem with Time Windows ((T)OPTW). The MCS-OPTW deals with uncertain travel and recording times, time windows for the targets and the appearance of new targets. I have applied the methods by Evers et al. (2014) on a different data set to test how useful the method is in general and if the results found by Evers et al. (2014) hold in different situations. The MCS-OPTW heuristic takes two objectives into account: the planned average profit obtained by the foreseen targets and the ability to cover possible new targets. The ability to cover new targets is expressed by the Weighted Location Coverage

(WLC). The simulation calculates the average profit obtained by the foreseen targets and the percentage of new targets reached in time.

In this thesis, the heuristic and simulation is programmed in MATLAB. This resulted in longer computation times than the implementation by Evers et al. (2014) in Java. I needed to decrease the number of no improvements before accepting a solution in the heuristic and the number of flights in the simulation to obtain results in the time limit of this thesis. Though the results are quite stable, they should have been better and more reliable if I did not have to decrease these numbers. Therefore, it is better to program the heuristic in Java.

For the initial planning, the weights between the two objectives in the MCS-OPTW heuristic has influence on the values of the objectives. The (T)OPTW is not reliable when the ability to cover possible new targets is wished to be maximized, this value can fluctuate a lot because the ability to cover new targets is not taken into account in evaluating solutions in the heuristic. The large time windows result in a higher value for the first objective compared to the tours found in case of the small time windows, as it is easier to reach targets in time with larger time windows. Finally, the tours found by the (T)OPTW heuristic contain more targets than the tours found by the MCS-OPTW heuristic, because the (T)OPTW heuristic does not take uncertainty into account and is therefore less 'careful' in planning.

In the simulation experiments, I have found that the value for the weight for the second objective should not be too small, but also not too big, because of the cluster situation of the locations for the potential new targets. However, I have found a weight in which in both settings for the time windows, small and large, the MCS-OPTW approach outperforms the (T)OPTW approach on all objectives. Further, the MCS-OPTW approach turned out to be robust. If the assumed distribution of the travel and recording times differs from the actual one, the MCS-OPTW approach still outperforms the (T)OPTW approach.

With the results of the simulation I conclude that the methods of Evers et al. (2014) are applicable to the dataset used in this thesis. The MCS-OPTW approach has found solutions that dominate the solutions found by the (T)OPTW approach.

In this thesis, a few adjustments to the simulation are discussed. I have tested the effects of decreasing the timespan in which new targets are considered to be visited. However, this turned out to have no effect. Further, the re-tasking criterion is adjusted. In the simulation of Evers et al. (2014), the UAV always immediately flies to a new target if the probability of reaching it in time is large enough. If the UAV was recording a foreseen target at that moment, the recording is stopped and no profit is gained. In the adjustment in this thesis, the probability of finishing the recording and still reaching the new target in time is determined. In the adjusted re-tasking criterion, the UAV finishes the recording if this probability is large enough. This turned out to have no effect in our settings because of the time sensitivity from the new targets. However, when the new targets where assumed to be less time sensitive, the adjusted re-tasking criterion resulted in a higher profit from foreseen targets.

Future research could focus on adjusting the objective function to make it more specialized for the situation in which the locations of potential new targets are clustered. Further, it can be investigated how strict the planning should be to obtain the best results in realized flights.

8. Appendix

8.1. Appendix A: Initial tours

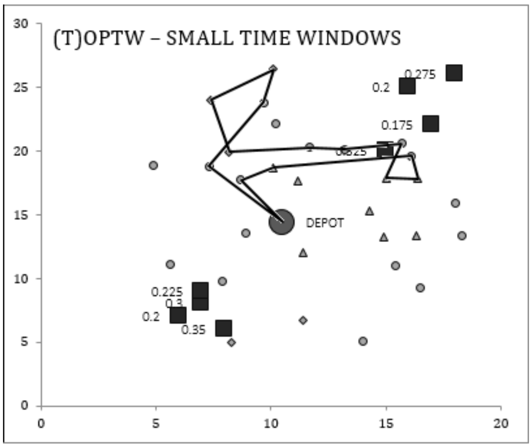

FIGURE A.2

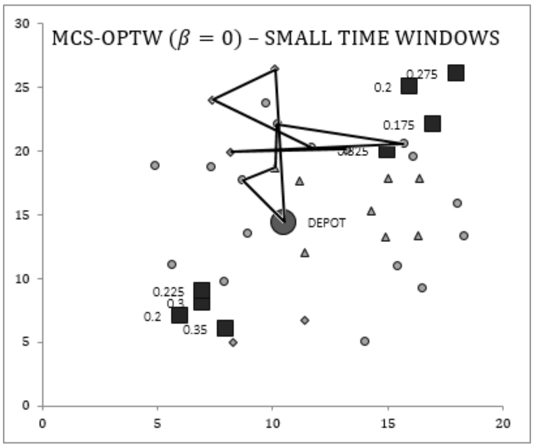

FIGURE A.3

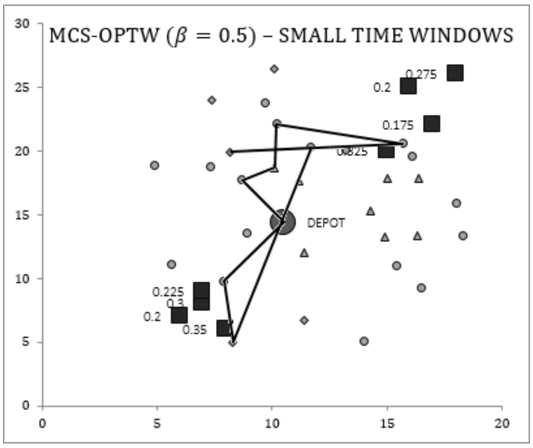

FIGURE A.4

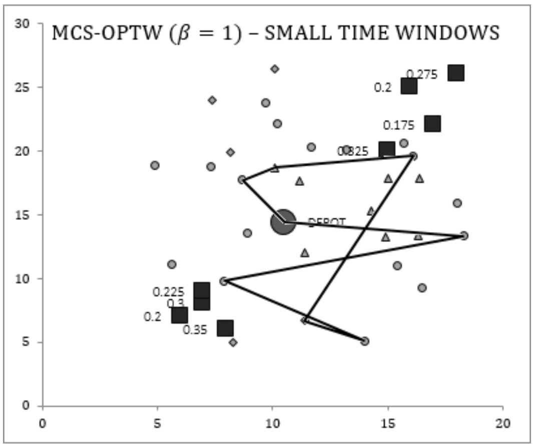

FIGURE A.5

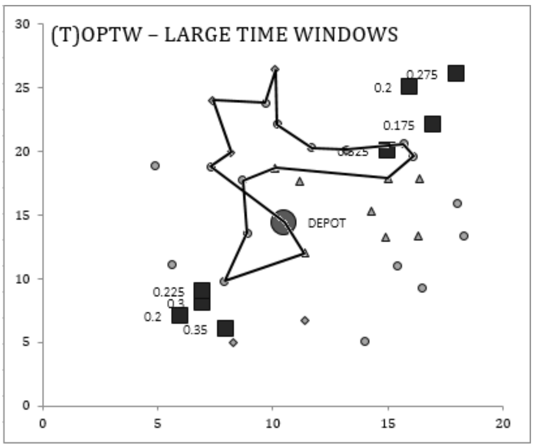

FIGURE A.6

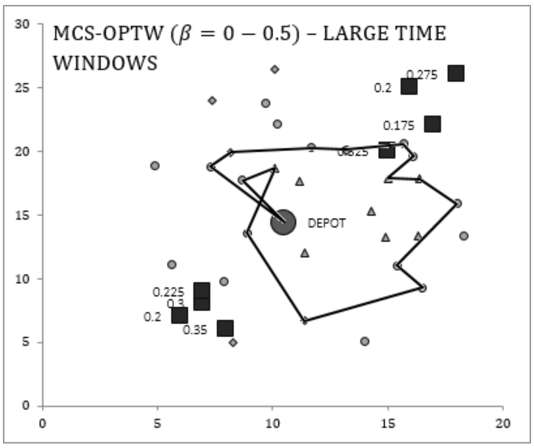

FIGURE A.7

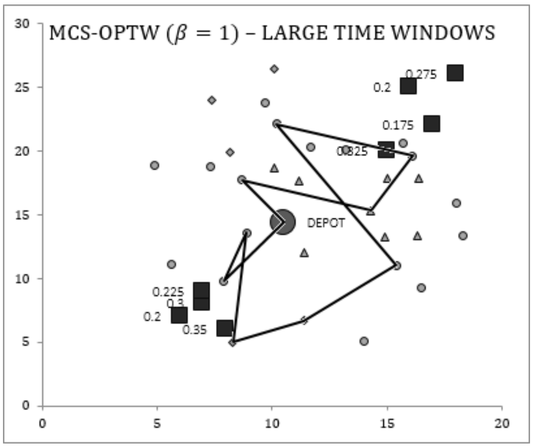

FIGURE A.8

8.2. Appendix B: Illustration MCS-OPTW planning approach

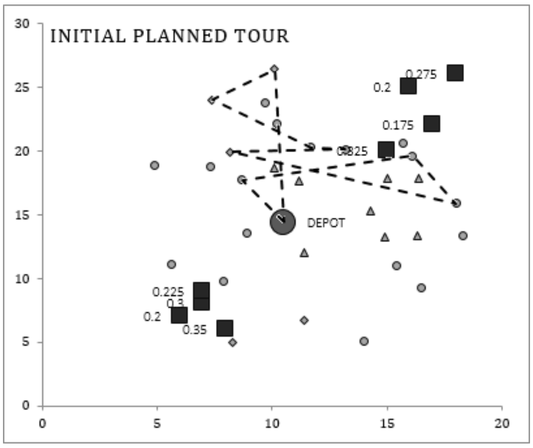

FIGURE B.9

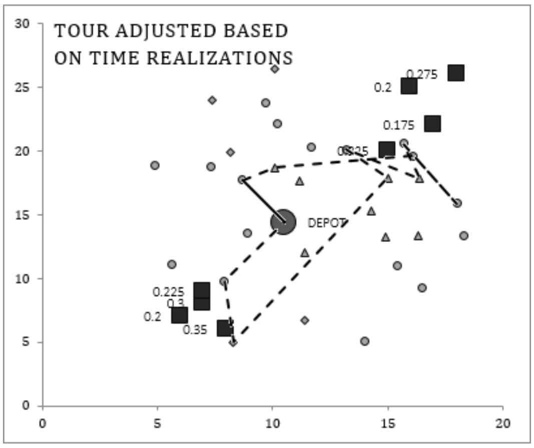

FIGURE B.10

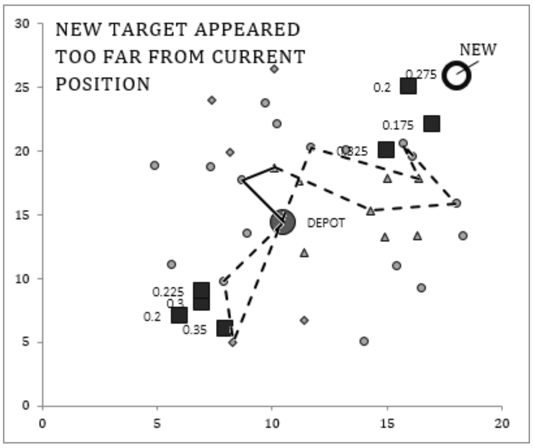

FIGURE B.11

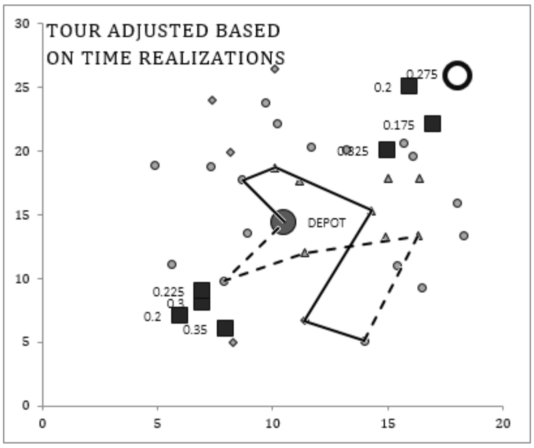

FIGURE B.12

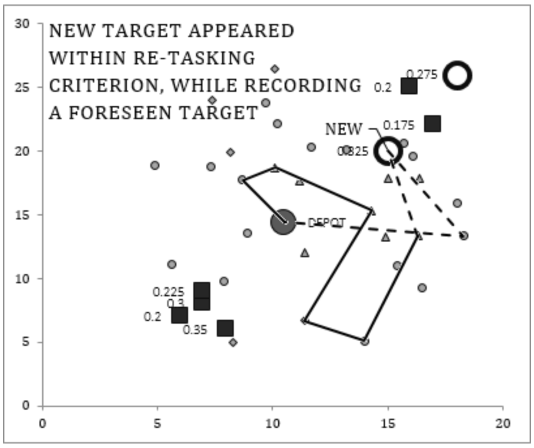

FIGURE B.13

9. References

- Evers, L., Barros, A.I., Monsuur, H., & Wagelmans, A. (2014). Online stochastic UAV mission planning with time windows and time-sensitive targets. *European Journal of Operational Research*, 238(1), 348-362.
- Vansteenwegen, P., Souffriau, W., Berghe, G.V., & Oudheusden, D.V. (2009). Iterated local search for the team orienteering problem with time windows. *Computers & Operations Research*, 36, 3281-3290.