Airport Surface Planning under Uncertainty

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by

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Preface

This thesis is the result of my research into agent-based methods in order to perform planning under uncertainty for taxiing operations at airports. It has been a challenging and inspiring period in which my eyes were opened for the potentials of decentralized planning methods. I am very glad that I had the chance to work in a very interesting field of study, of which I believe has great potential for the future. Not did this period learned me a lot, I have grown as a person. For that, I am very thankful for all the opportunities offered me by the faculty of Aerospace Engineering and the TU Delft.

I must also be thankful for my daily supervisors, Alexei Sharpans'kykh and Matthijs Spaan, for their support during my thesis. Without them, I probably still was looking around for a better approach. During our meetings, we had great discussions about the project which have helped me a lot. I am glad, the both of you made me part of your world and always helped me with the next step. The door was always open.

I would like to give special thanks to Heiko Udluft, who has helped me with very useful data. But most of all, I am thankful for taking the time for me to help constrain the problem at hand, while sharing your enthusiasm for the potential of the solution. It has given me a lot of positive energy. Many thanks to all of my roommates at the faculty. There was always enough time for a laugh, a discussion, a conversation or just coffee... which kept me going.

Last, I would like to give special thanks to my family, my friends and my girlfriend for all the support they have given me. Without their support, faith and companion I would not have been the person I am today. It wasn't always easy for me, but you have been there for me the whole time. Thank you for that!

J.A. Siebers | 1507729
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List of acronyms

EIBT Estimated In-Block Time

TTOT Target Take-Off Time

SLDT Scheduled Landing Time

CFMU Central Flow Management Unit

AMAN Arrival Manager

DMAN Departure Manager

ATC Air Traffic Control

SMAN Surface Manager

OBT Off-Block Time

IBT In-Block Time

ETA Estimated Time of Arrival

FUM Flight Update Message

FP Flight Plan

EXIT Estimated Taxi-In Time

EXOT Estimated Taxi-Out Time

VTTC Variabel Taxi Time Calculator

TSAT Target Start-up Approval Time

DFW Dallas Fort Worth

A-CDM Advanced Collaborative Decision Making

TOBT Target Off-Block Time

ALDT Actual Landing Time

AIBT Actual In-Block Time

AOBT Actual Off-Block Time

ATOT Actual Take-Off Time

ADS-B Automatic Dependent Surveillance - Broadcast

MDP Markov Decision Process

IATA International Air Transport Association

AMS Amsterdam Airport Schiphol

CDG Charles de Gaulle Airport Paris

LVNL Luchtverkeersleiding Nederland

SMR Surface Movement Radar

GPS Global Positioning System

INRA Institut national de la recherche agronomique

MILP Mixed Integer Linear Programming

GA Genetic Algorithm

BB Branch and Bound

MARP Multi-agent route planning

ATM Air Traffic Management

Summary

Motivation
This report covers the methodology and analysis of an agent-based approach to contribute to a solution for the the ground movement problem, defined by Atkin et al. in 2010 [5]. Due to the rise in air traffic at airports, high throughput is needed. But this throughput comes at a cost, since inefficiencies can be found in ground movement. Complexity of ground movement is high, while regulating this traffic still relies on standard routes and radio communication. Control by Air Traffic Control (ATC) is limited and pilots are responsible for execution of actions. In order to increase performance, centralized methods are proposed to perform scheduling of routing and timing of these aircraft. But due to the lack of control on execution, operational uncertainties disrupt robustness of these systems. Centralized methods have limitations in capturing the complexity and dynamics of the problem at hand. Alternative agent-based methodologies are found that seem to be able to handle the complexity and uncertainty posed by traffic.

Objective and methodology
In order to perform planning, robust to operational uncertainties and dynamic arrival of new aircraft, an agent-based approach is developed. The approach aims to address the following issues: providing solutions within required computational times and robustness to operational uncertainties. Therefore a research is done with the following research objective:

The objective of the research is to develop an agent-based airport surface routing and timing planning model providing multi-objective optimization, robust to operational uncertainty

The project is aimed at providing a solution for large airports like Amsterdam Airport Schiphol. This airport is used as a case. It is chosen to model the taxiing operation within a finite horizon Markov Decision Process with terminal rewards. The system is represented as a sequence of transitions over infrastructure segments, with transition probabilities derived from historic data to capture operational uncertainties. For every aircraft, a unique set of rewards can be found in order to maximize operations value. As a result, the model is able to support on routing and timing to provide the aircraft with the shortest route in time, or provide value optimized planning in order to meet a time window. A data set, based on Automatic Dependent Surveillance - Broadcast (ADS-B) data, gathered over one month is used to set up the state transition probability functions for the western area of Schiphol airport, covering the majority of taxiways.

Results
Through validation, it is found that the model is able to provide the shortest routes in time for aircraft, providing a similar mean time as actual tracks found. A average offset of 5% was found. Within these actual tracks, a higher uncertainty in travel time is found than the results through simulation of the MDP. Only, a variance of 30% from the actual variance was found. It is shown that the model is robust to time offsets, and is able to optimize for different reward sets to cover multiple objectives. It can be explained that the inability of the model to capture full variance is due to conditional probabilities, which are not captured by the MDP. Conditional planning is performed to test the hypothesis of conditional probabilities effecting the result. Transition probabilities are based on data gathered under specific operational conditions, to capture uncertainties under these conditions. Although a relation is found on mean travel time, no benefits in terms of variance were found.

Conclusion and discussion
The model is able to find shortest path in time, and is able to plan on routing and timing for multiple objectives. Optimization is possible for different rewards sets, specified for departures (under CFMU restrictions) and arrivals. Robustness of the model is shown to offset in time, and compu-

tational time is well within the required 2 minutes set as design objective. Therefore dynamics are allowed, for changes in input parameters. Although the model is able to choose start time for departures in order to trade-off travel time with uncertainty in time of arrival, the model insufficiently covers the variance in travel time to be able to assure timely arrival for set deadlines. Uncertainty of later arrival at destination is possible while this uncertainty is not taken into account within the model. Planning under specific conditions is tested to capture reasons for the travel time to be higher or lower than normal, but a too generic conditions is used to conclude effectiveness. With a computational time of 55 seconds, the model can be applied within the major airfields of Europe.
For future research, it is concluded that data quality can be improved through data collection of the airport, providing it offers more flight details and a constant time step. More details on airport conditions within historic data may offer the opportunity to perform better analysis of conditional planning. Another limitation of the current research was the inability of the model to prevent deadlocks. Planning during execution is needed to prevent deadlocks, for which the current model can be used to choose between routing and timing options to resolve conflicts. The model can also be used as the base of multi-agent planning systems, to predict possible conflicts. By recognizing chance of conflict at an early stage, conflicts can be resolved in an effective way.

Contents

1 Introduction

Schiphol is one of the most important hub airports within Europe. Within 2015, more than 450.000 aircraft movements have been made through this airport, and it is expected that this number will grow to 500.000 aircraft movements within 2020. [4] Next to this, also an operation of 4 simultaneously operated runways is discussed. This will increase the number of hourly operations even more, causing more conflicting plans and higher complexity for control. In order to deal with this complexity, pilots and controllers still rely on basic control mechanisms like standard taxiing routes and radio communication. The amount of control over this system is therefore limited. Risk of inefficiencies is significant in a world where performance requirements are high.

In order to increase system efficiency, new planning and control systems are proposed to regulate traffic. Routing and timing freedom is needed within these methods to de-conflict traffic in order to assure shortest travel times and timely delivery. As a result, these methods are able to provide new routing options or regulate time planning in order to taxi free of conflict. But due to the lack of control over execution by pilot, differences in execution pose uncertainty in position over time for aircraft. Current methods are not robust to these uncertainties.

Different research groups have presented centralized methods to plan or control routing and timing over the taxiways. Although, an increase in performance is found, they all suffer under scalability issues due to the high complexity and the dynamic arrival of flights. After time periods, planning needs to be redone for all flights, or even after arrival of a new planning agent. Sub-optimal or constrained solutions are presented, but it is believed that these solutions can also be found by decentralized approaches.

Due to the lack of control over aircraft operating, many types of uncertainties are present within the system. Operational uncertainties haven't sufficiently been identified or implemented within the planning models, where exact solutions in space and time are presented. Due to uncertainty, these plans can easily be invalidated decreasing robustness of these systems. In a time critical system as the airport system, high robustness is needed, and therefore novel methods are needed. Uncertainty should be taken into account to ensure robustness.

Agent-based planning methods are present that are able to deal with different types of uncertainties. But the system should also be able to deal with different objectives presented by different actors involved, like Air Traffic Control and Airline. A trade-off is needed between travel time and time of arrival in order to optimize for all objectives. Preferably with different objectives for all agents, to plan for multiple types of operations and objectives.

To resolve the problems given, a research is presented with the following research objective:

The objective of the research is to develop an agent-based airport surface routing and timing planning model providing multi-objective optimization, robust to operational uncertainty

Within this research, an agent-based planning model will be presented to perform airport surface traffic planning. Not only is it expected that it will perform better in terms of computational time, it will also allow for dynamic arrival of new aircraft in the system. Within this thesis, dynamic arrival is the process of inputting new agents within the planning over time. Allowing dynamic arrival is needed to increase robustness of plans, and ensuring that re-planning is not needed for arrival of new agents. The taxiing operation in this model is presented as a chain of transitions between taxiway segments, captured in a finite horizon Markov Decision Process model. Historical data is used to set up transition probabilities between these segments, in order to capture both speed and conflict uncertainty during operation. A policy will be found, presenting the optimal action for the aircraft at all segments, at all times, to maximize plan value. Value is composed by the amount and type of taxiing operations and the value gathered at the destination segment. A simulation will be performed showing how the model will present a policy that helps getting an aircraft at its goal in the most optimal and robust way.

As a result of this research, a model is presented that provides planning on routing and timing, optimized for travel time and time of arrival (current state of the art). As an objective, this research will focus on an agent-based method that will also capture operational uncertainty and provides multi-objective optimization (contribution). Within the results, the model will be tested on optimization under different start times and for different objectives. Through simulation of agents, value and robustness will be tested.

Within this report, the research performed will be presented. First, a literature review will state the problems found within research on airport surface planning, given in chapter 2. Within this chapter, several problems have been found that have led to a problem analysis given in the research framework in chapter 3. This framework also describes the research objective and sub-objectives that have to contribute to a planning model that will resolve found issues and will contribute to the body of knowledge. The methodology of the model will be presented in chapter 4, where the Markov Decision Process and its required data processing will be explained. Results of the model on optimization and robustness are given in chapter 5, showing performance of the model. A conclusion on the research will be given in chapter 6, followed by model limitations and recommendations.

2

Literature Review

2.1. Ground Movement Problem

The problem at hand can be described as the "Ground Movement Problem", defined by Atkin et al. [5]. It is described as a "routing and scheduling problem and involves directing aircraft to their destinations in a timely matter, with the aim to either reduce the overall travel time and/or to meet some target time windows." Within the problem, safety for aircraft is important and aircraft may not conflict. Atkin found that for larger airports a more complex simultaneous routing algorithm is needed to perform planning. Within this problem description, a couple of operational constraints can be found that are of influence on the result. For instance, the start and end time must be within a specific time span for capacity reasons. These constraint will be discussed later. Atkin also found that multiple objectives can be found, which also will be discussed.

2.2. Planning Mechanism

In order to provide a solution to the Ground Movement Problem, it is important to have an overview of the different planning mechanisms. Within these planning mechanisms, multiple agents are involved with different responsibilities.[13] First of all, the airliner is involved and initiates an operation. Through a Flight Plan (FP) it communicates its intentions to ATC. Within this FP, a Target Off-Block Time (TOBT) and a Estimated Time of Arrival (ETA) is given. Subsequently, ATC instances are able to check whether capacity is available for this flight. First, the ATC of the airport will check if the flight is able to depart, after which it will be assigned a Target Take-Off Time (TTOT). The TTOT will be communicated to the CFMU that will check whether capacity on the requested route is available. If not, the first possible TTOT will be communicated back to the local ATC. After the TTOT is being determined, a Target Start-up Approval Time (TSAT) is calculated and communicated to the airline/aircraft. This is the moment the aircraft is allowed to ask permission to be pushed back and start-up its engines. The last possible moment can be chosen, in order to reduce the amount of fuel used and allowing for a more efficient use of time. Between communication of TSAT and the actual start of the operation, changes may occur through updates. These updates can be expected by all agents involved. An overview of communication within an A-CDM mechanism [13] is given in figure 2.1. After pushback, an aircraft can start taxiing towards the runway it has been assigned to. It will follow a standard route towards the runway, unless ATC will give other instructions. A buffer is place in front of the runway to prevent the runway from running dry, and ATC resolves all conflict on the way.

2.3. Constraints

2.3.1. Start- and End Time

Within traffic planning, the surface planning problem is inferior to runway or airspace capacity planning. Therefore constraints from these planning mechanisms should be taken into account. Within the airport system, use is being made of time slots, which are assigned to flights departing or arriving. Related to the runway capacity, a time slot is assigned through a TTOT or a Scheduled

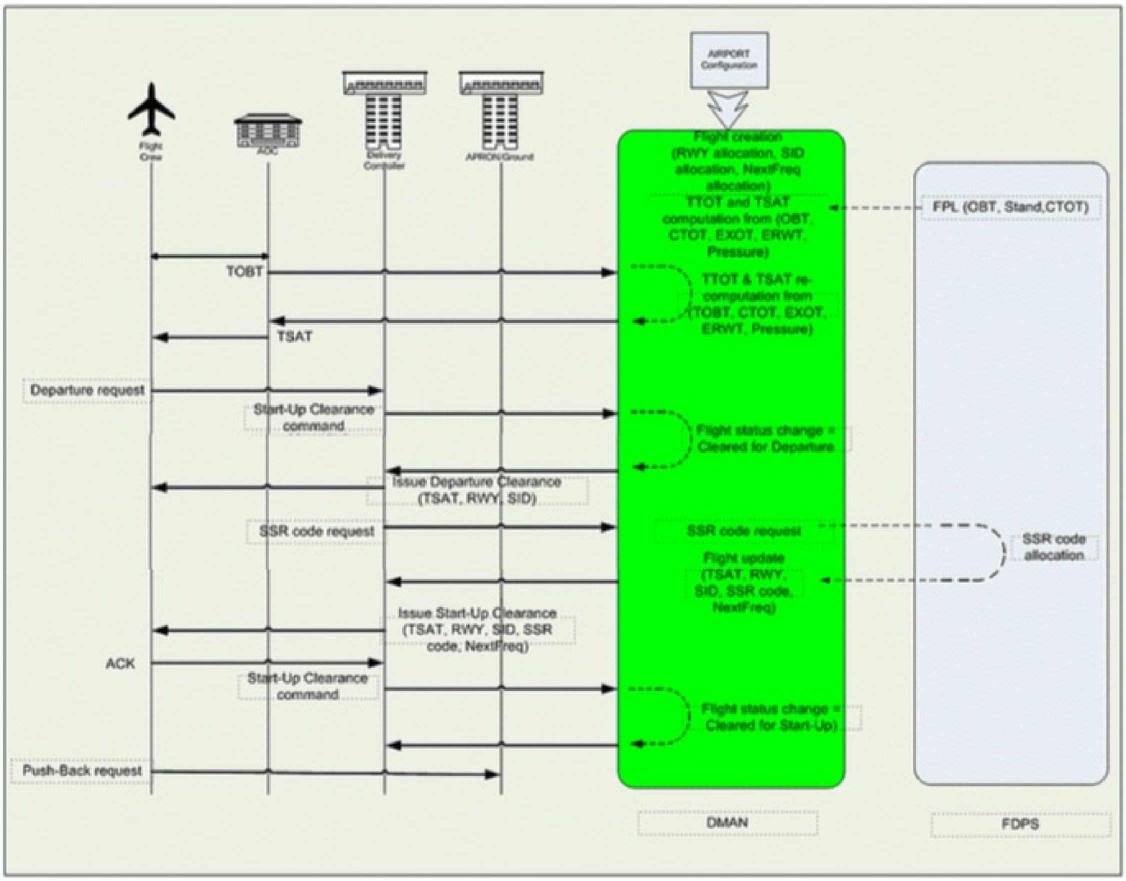


Figure 2.1: Procedure of communication between planning agents within A-CDM before pushback request [13]

Landing Time (SLDT). Offset to this time may result in holding of the aircraft (early arrival) or in reduced runway capacity (late arrival). Another important time constraint is the time slot communicated by the CFMU. Because of capacity constraints within the airspace an aircraft needs to pass, aircraft are only allowed within a time horizon of 15 minutes wide. A take-off time is calculated, where an offset is allowed of 5 minutes before or 10 minutes after. Before this time slot, an aircraft has to stay on the ground. If an aircraft arrives later at the runway, it is not allowed to take-off and has to request a new time slot. Large delays can be found when not making this time slot, and therefore it is highly undesirable. It can be found that Arrival Manager (AMAN) and Departure Manager (DMAN) already take these constraints into account when planning arrival- and departure sequence for the runway. It is up to the Surface Manager (SMAN) or ATC to ensure timely arrival. Two other time instances are of importance, namely Off-Block Time (OBT) and In-Block Time (IBT). These instances describe the other end of the taxiing operation, and are illustrated in figure 2.2. It can be that these times are also constraint by the gate assignment problem. This problem describes the availability of gates, and may only be available between specific time instances. These time instances are of less importance then the slots at the runway.

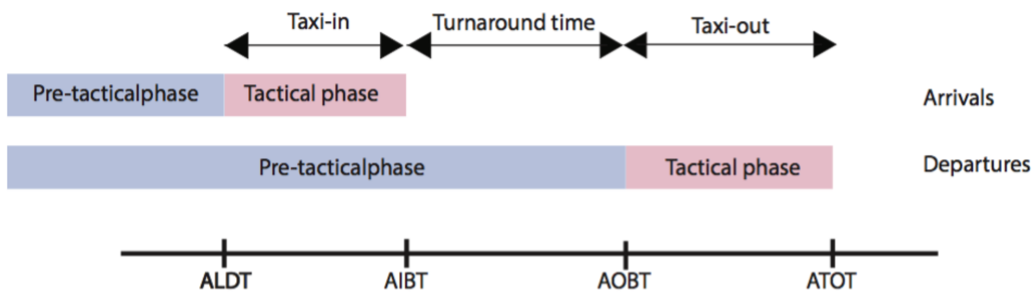


Figure 2.2: Time instances as start and end of the operation, with a pre-tactical and tactical planning phase for landing and departing aircraft

2.3.2. Operational constraints

During taxiing, constraints can be found that are of influence within large airport systems. At large airports with multiple runways in operation, it is likely that routes coincide, and therefore a simple shortest path algorithm is unable to capture risk of conflict. Since conflicts need to be prevented, it is important to know how traffic needs to be separated. First of all, at all times, a separation is needed between aircraft. Roling and Visser [25] defined this safe separation as 200 meters, while Pesic et al. [21] defined this separation as 60 meters. Within current operation, a safe distance needs to be held by pilot by its own insight. A value of 60 to 200 meters therefore seems appropriate, which can also depend on the different types of aircraft involved. Next to this separation, aircraft also are unable to turn around at the taxiways. Therefore, a risk of deadlocks is present. To prevent collision or deadlocks, the conflicts defined by Evertse et al.[14] in figure 2.3 need to be prevented or resolved. This is currently done by procedures and through control of the Air Traffic Controller.

Within planning conflicted plans should be resolved. To resolve these conflicts, different approaches are possible. Timing and routing are two ways to influence traffic. Holding of aircraft cause aircraft to change timing of the taxiing operation, but may block other aircraft. Therefore it can be disruptive for the overall flow at the airport. Another timing option is to wait at the gate, until a conflict free plan is available. At large airports, this may not be efficient. Another way is to differ routing where a different, probably longer, route is chosen that requires less holding and therefore may be shorter in time. Since changing route may stimulate airport flow, it can lead to less conflicts. But longer routes may increase the total taxiing time and emissions at an airport. It is assumed that speed control is not available. Therefore, value for three different operations need to be described: holding, holding at gate or specified holding places and taxiing. A specified holding place may for instance be the taxiway just before the entrance of the runway.

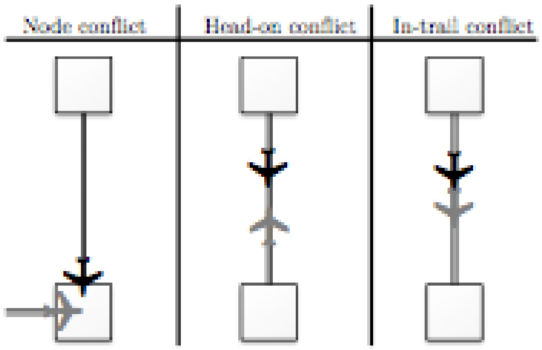


Figure 2.3: Different types of conflicts that need to be prevented or resolved during operation

2.4. Objectives

It can be found in the previous sections that different objectives can be found. Since multiple agents are involved within the operation, a trade-off is needed between these objectives. Four different agents were identified by Potts et al.[22] A further distinction has been made for ATC, since different instances are involved. Potts defined objectives for the air transportation system, for which objectives relevant for the taxiing operation have been filtered out.

- Air Traffic Control
  - Local ATC
    - Maximizing runway throughput
    - Maximizing fairness among aircraft
    - Minimizing arrival/departure delay
    - Minimizing aircraft taxi-in/-out time
  - CFMU
    - Regulate and maintain airspace capacities
- Airline
  - Minimizing operating costs
  - Minimizing engine run time before take-off
  - Maximizing punctuality regarding the landing/take-off time in published timetables
  - Maximizing adherence to the airline priorities within their flights
- Airport
  - Maximizing punctuality relative to the operating schedule
  - Minimizing the need for gate changes due to delays
- Government
  - Minimizing the environmental effects (air pollution)

Value of these objectives differ per aircraft, and therefore for every aircraft a different set is needed. Some objectives have a hard constraint (CFMU slot), but other constraints degrade in value over time (delay on take-off within CFMU slot). Within different studies, also objectives differ. Some studies focus on punctuality, while others focus on minimization of the total taxi time. This is also found by Atkin et al. [5] who found different objectives for arrivals and departures. Following Atkin, arrivals have as objective to minimize taxi time, while departures may have multiple objectives. These objectives can be to reach the runway as fast as possible, to reach the runway in time to attain a pre-determined take-off time or to reach the runway in time to take-off within a specified time window. Within one airport, all objectives described by Atkin can be found, since these objectives depend on the amount of traffic present at the airport or within the air.

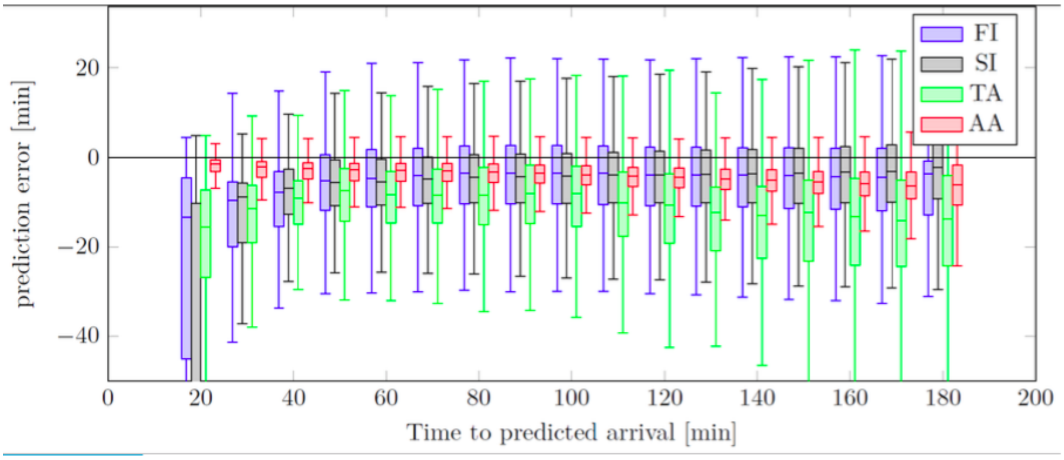


Figure 2.4: Uncertainty in arrival time for Schiphol Amsterdam Airport. In red, the box plots for airborne aircraft that are of main interest. [29]

2.5. Operational uncertainties

When operating, aircraft don't adhere to their original plans. Within different phases of the operation, uncertainty is present that influence the execution of plans. Because of these changes, plans may not be valid any longer, and robustness of plans is low. Therefore these uncertainties need to be taken into account that may influence the robustness of plans. The uncertainties found are split-up in pre-tactical and tactical uncertainties, for which the division of phases can be found in figure 2.2.

2.5.1. Pre-tactical uncertainties

TOBT and ETA or SLDT define the planned start of the taxi operation. A difference exists between planned time and actual time. A target time is communicated from airline to ATC, who in turn determine the place in the runway sequence it can be assigned to. A initial time is communicated 2 to 3 hours before the operation, after which updates are possible through flight update messages (FUM) or radio communication. It is found that for arrivals towards Schiphol, an average of 3 messages per flight are send. [29] Tielrooij also found that the uncertainty decreases when getting closer to the arrival time. This uncertainty can be found in figure 2.4, where the red box diagrams represent the airborne airplanes which is the majority of flights. An uncertainty of around 2 minutes can be found in arrival time when the aircraft is 20 minutes before landing. Next to the start of the operation, it is also unclear where in the infrastructure an aircraft has to go to as end point. First of all, for large airports, it can be that changes occur on configuration of runways. Different configurations are available to minimize environmental pollution or maximize safety. For different wind headings, multiple configurations are available to make sure aircraft can depart or arrive with headwind. Wrong predictions on configurations may lead to large deviations in taxi time. Also deviations in configurations can be found when the amount of traffic differs from the expected demand. A different runway may be assigned for the aircraft to land on or departure off.

2.5.2. Tactical uncertainties

On tactical level, main contributors to uncertainty are: taxi speed, pushback time and conflicting aircraft. Therefore, taxi time cannot be simply calculated from distance of route. Although taken as a constant within optimization tools [25], it is found that unimpeded taxi speed is not a constant, and therefore these uncertainties influence the total taxi time. Different parameters have been found by Ravizza [24] and Capps [7] that show to have a significant correlation with taxi speed, which are:

- Taxi distance
- Arriving or departing aircraft
- Quantity of traffic at airport
- Total turning angle

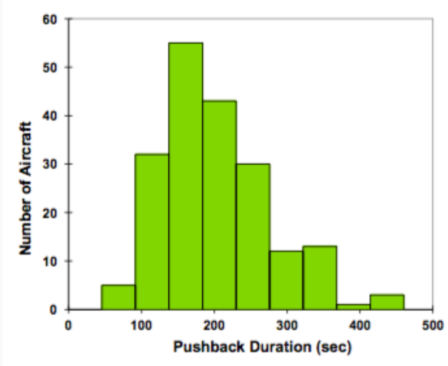


Figure 2.5: Uncertainty in pushback duration time at DFW airport, found by Capps [7]

- Air carrier
- Aircraft type

It is also expected that weather can have significant influence on the taxi speed.
But before an departing aircraft can start taxiing, it needs to be pushed back. A pushback truck will transport it to the taxiways, where it can safely start its engines and start taxiing. Because this operation is performed right after the OBT, it introduces a tactical uncertainty. A case study performed at Dallas Fort Worth (DFW) airport [7] showed that high variance can be found in pushback time. In figure 2.5, the variance in pushback time is shown. The pushback duration data best fit a log-normal distribution. This distribution has a mean of 202 seconds and a standard deviation of 73 seconds.
As a last factor, conflict uncertainty is present within the system. Especially on large airports, multiple aircraft taxi simultaneously. When traffic density is high, chance exists that a conflict will arise. Different types of conflicts were found in figure 2.3. To resolve such a conflict, one aircraft needs to choose for a less efficient plan. For instance an aircraft can be rerouted or put to a hold to resolve a conflict. Capps found that the average additional taxi time when conflicting at an intersection is 29 seconds.[7] During taxiing operation, multiple encounters can take place increasing taxi time.
Conflicts may also arise between aircraft and other traffic present on the taxiways. The chance of these kind of conflicts is expected to be very low, and will therefore not be taken into consideration.

2.6. Planning phases

Within literature, different planning model types have been found. A difference can be found in phase of planning it is used and the freedoms and constraints it holds. Within the pre-tactical and tactical phase, different moments can be found to perform planning. Koeners and Rademaker [15] made a figure in which the different decisions are made clear, which can be found in figure 2.6. The first decision of the airline will be seen as the input of the system, and the take-off request will be seen as the end of the taxi operation. Within the middle, three decisions can be found, which can be taken into account. These three different phases will be discussed.

Moment 1: Sequence planning
One of the first moments is right after receiving the FP, when a landing time and TOBT are given. A Estimated Taxi-In Time (EXIT) and Estimated Taxi-Out Time (EXOT) is needed to connect start and end of taxi operation. At this moment, a runway sequence needs to be made. Within this planning process a lot of efficiencies can be gained because of the large amount of freedom. But since uncertainties are high and fairness between agents is of high value, estimations are needed. It is found that predictions in this phase aren't necessarily worse than within a phase closer to the operation. Pina and De Pablo [10] even found that with taking future conditions into account, predictions of their model even decrease when getting closer to the operation. Therefore planning within this phase would be beneficial. This phase ends around 30 minutes before the operations, since this is the moment a sequence needs to be produced.

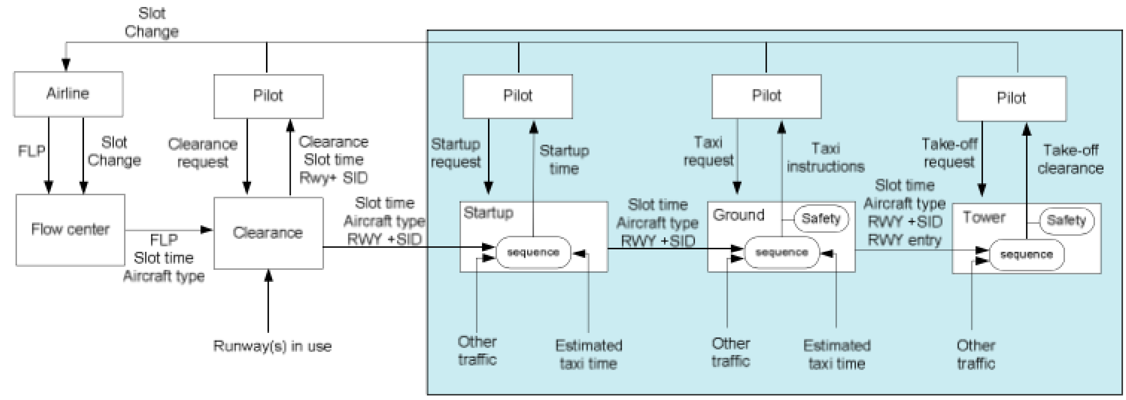


Figure 2.6: Different phases within planning towards take-off with relevant decisions and communication [15]

Moment 2: Startup planning
Another moment can be found within the pre-tactical phase when runway sequence is made. Until TSAT and ETA, pre-tactical planning is possible for aircraft. Within this planning phase, the start times are less uncertain and for departures, the time of starting up the engines can still be determined. Therefore, for departures, holding with engines off at the gate is still possible and may increase efficiency. Considerations possible can be found within the blue block in figure 2.6. When engines are started up and a taxi request is handled, this phase has ended.

Moment 3: Tactical planning
As a last phase tactical considerations need to be handled. Routing and timing considerations are the main tools to gain efficiency. Within this phase, aircraft are taxiing, but also aircraft that are not taxiing yet need to be taken into consideration. Since conflicts can be within the near future, computational requirements are high. Uncertainties on the other hand have a smaller spread and therefore more accurate predictions can be done.

2.7. Optimization methods

For surface traffic planning, different methods are available. Centralized methods are able to compute the optimal solution, but have long computation times and have robustness issues. Within this chapter, different methods will be discussed.

2.7.1. MILP

One of the first methods presented is the formulation by Smeltink. [27] Within this approach, time horizon is split into different time intervals. Aircraft starting taxi operation are planned within their specific time interval, and aircraft plans outside this interval are fixed (planned earlier) or not made yet (planned later). Taxi time is minimized through planning of conflict free routes for a predefined standard route. Smeltink remarked that this was only an initial model and algorithm, he believes that computation time can be reduced. He also found that planning ahead in time prior to the tactical phase has no point since delays would influence planning to much, and solutions would be invaluable. It can be found from the results that the model has significant scalability issues, since an increase by 100% can lead to significant increases in computation time (more than 1500%). This means that computational time is too high for implementation. Last, no uncertainty in pushback time or taxi speed is considered.
Á.G. Marín compared two modeling techniques on computational time. A Branch & Bound (BB) and a Fix and Relax (F&R) method were used to model traffic at Madrid-Barajas airport. He found that the Fix & Relax method performs better on computational time. Computational time is within the proposed maximum of 1 minute, but Marin has not validated his results on a realistic scenario. [19]
Roling and Visser proposed a time-based surface movement plan to de-conflict all plans, and optimizing towards a collective performance goal. Surface planning is made for smaller time horizons, where nodes or links are occupied for a time interval to provide time separation between aircraft.

But taxi speed is taken as a constant, with different values for different aircraft types. For constant speed, the model is not robust to uncertainty within this speed or to delay. Computational time is low, within a couple of seconds, for a full scale schedule with 20 aircraft. [25]
Balakhrishnan also plans for time intervals (30 minutes) where two concepts are tested on. The first is on controlling pushback time, and the second is on changing taxi routes in addition to the pushback time control. Maximal pushback delay is set to ensure a certain degree of fairness between different aircraft. It is found that savings on taxi time up to 14% are possible for high density scenarios. But, speed uncertainty is not taken into account. Although it is said that speed uncertainty can be implemented quite easily, it is not known whether this would influence computational time. [6]
Evertse and Visser developed a real-time taxi movement planning tool, that can refresh planning every 15 seconds to respond to disturbances. Although it is highly reactive, it still is unable to plan on routing and uncertainties. Speed and route are fixed and therefore model complexity is low. Although the model is able to compute a new planning within the 15 seconds, at some time intervals computational times of 150 seconds were found due to the complexity of that situation. A degraded mode was used, where holding at nodes was impossible.[14]

2.7.2. Metaheuristics

Metaheuristic solutions are search methods, and within the current problem context are primarily based on evolutionary biology principles. This principle is called GA. A population is created of solutions from which children are made from the strongest parents. After a couple generations, optima can be found. Mutation is used to escape local optima. It is known as a fast simulation principle, but it is not able to guarantee the global optimum like MILP.
One of the first models was described by Pesic et al. It describes a Genetic Algorithm (GA) for simulating traffic over the taxiways of Charles de Gaulle Airport Paris (CDG). The model is able to make choices on route for every aircraft, and aircraft are allowed to hold at one position during taxi operation. Since the model is stopped after the first feasible solution is found, and no further information is available, it is hard to judge on performance. Also on computational time, no information is given. But for further work, it is concluded that for a realistic tool the uncertainties of the operation should be taken into account. [21]
The research by Gotteland et al. can be compared to that of Pesic. But the method by Pesic is compared to other methods. These methods are used for different purposes. First of all, A* is used to compute the best path between different nodes within an infrastructure. Dijkstra's Algorithm also computes the best paths. Next, a recursive enumeration algorithm is used to find k shortest paths from the result of Dijkstra's algorithm. Last, a Branch and Bound (BB) algorithm can be used to compute alternating paths within a specified maximal elongation of path length. The method proposed by Gotteland et al. is one of the first, within my knowledge, to take speed uncertainty into account. This speed uncertainty is taken as a fixed percentage and it reduces the validity period of predictions. Within the results, a value of zero has been used for speed uncertainty, and therefore it is not taken into account within the results. [16] Gotteland et al. later also implemented CFMU slots within its model, where time offset from the CFMU slot was penalized [17]
Deau, Gotteland and Durand used a two phase method to solve for runway sequence additionally. First, a branch and bound method is used to obtain the runway sequence. After this, both a sequential and GA method is used to plan traffic over the taxiways, of which GA brings significant better results with respect to total delay. Again, a penalty is used for time outside CFMU slot time. [11] Within a second paper an optimization method for runway sequence is further elaborated.[12] Interesting is the defined penalty for arrivals and departures when operated outside target times at runways. This minimization criterion is given in figure 2.7. Interesting is the difference in penalty for arrival and departure.
Next, since missing a CFMU slot can lead to big delay, it is found that a major penalty is given. As second method, a surface management simulation method was refined from its previous paper. A route is chosen from a fixed set of routes, and speed uncertainty is taken into account. It is unclear how this uncertainty is used, since conflicts will be resolved but it is not described what the influence of chance of conflict is on this process. The paper concludes that ground delay should be reduced and the traffic predictions of the DMAN system should be made more relevant. [12]

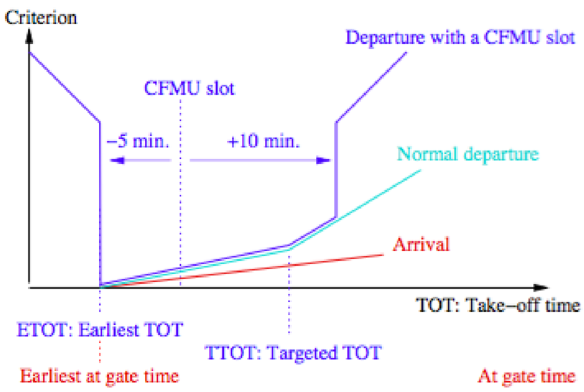


Figure 2.7: Penalty over time for specific times of arrival at end point, given for different types of operations [12]

A more recent study on Genetic algorithms was done by Chen and Stewart. Next to taxiing time, also emissions are taken into account within the objective function. Emissions are becoming of more importance around airports, but it also indirectly justifies prioritization of bigger airplanes. Although speed uncertainty is not taken into account, the model does take different types of taxiway operations into account like turning and acceleration/deceleration. But important is to find that the model can calculate different routes from edges on the runway, only within the pre-tactical phase. Therefore it can't be used within real-time operation. [8]

2.7.3. MARP

Another method was proposed by Ter Mors, based on agent-based planning. Within his method, the aircraft was in charge of planning its route. It can plan for a conflict free route and optimizes for a single agent. Large delays were only found for head-on conflicts. The algorithm was able to change priority of agents, to optimize for individual agents. It is unknown how this can be used for global optimization, but it seems that these local optima perform well. [28] A route planning solution for road travel by cars is presented by Claes and Holvoet. Within this solution, a ant colony inspired system was inspired, where vehicles sent out exploration ants. These exploration ants are able to capture intentions from other vehicles and can decide to change route to avoid dense areas. Intentions then are distributed after which other vehicles can take this vehicles intentions into account. It allows dynamic entrance of vehicles and distributed planning while dealing with uncertainties through Monte-Carlo simulations. [9] It may be possible to gather information of other agents within the information, to take it into account within planning. But the region of multi-agent planning would be entered.

2.7.4. Comparison of models

To find a global optimum, MILP solutions will perform best. But to find this solution, long computational time is needed which is not available. Although some solutions are given that will provide a solution within reasonable time, robustness of plans is not assured. Significant simplifications are made, that influence the value of the solution. Routes are fixed, speed is taken as a constant and other uncertainties are not taken into account. These uncertainties are able to invalidate the solution, requiring a new calculated solution. Metaheuristic models seem to be able to reduce computational time for these complex problem. Although it will not assure the optimal solution, more modeling flexibility is available. Within planning for instance, where multiple routes can be taken into account. Also other planning agents like the departure manager can be taken into account within modeling. Results don't show which planning method are able to capture the optimal result, but metaheuristics and other sub-optimal solution methods have great potential in exploring new planning possibilities.
Multi-agent systems have shown to be capable to work within infrastructures with a high amount of users and are able to deal with uncertainties in a stochastic manner. Therefore they have high potential to work in a highly dynamic environment. Performance with respect to a objective func-

tion is unclear, since they are not widely applied to the airport ground planning system. Communication between agents is needed to gather intentions, and conflicting plans need to be resolved between them. This communication system is not yet present within the airport system. Within table 2.1, an overview can be found of the models stated within this chapter. Unfortunately, no comparison can be done on model complexity and computational time, since no objective number is given. It can be found that only some models can plan a route freely. No models can be found that incorporate stochastic uncertainty of the operation. Within one model a percentage was incorporated on taxi speed, but within the results this value was set to zero. Some models target a low computational time to perform regular updates to cope with uncertainty, but this will bring lots of undesirable changes to the planning.

Model type	Main author	Objective function	Routing	Uncertainty incorporated
MILP	Smeltink [27]	Minimize conflicts	No	No
MILP	Marin [19]	Minimize taxi time	No	No
MILP	Roling [25]	Minimize taxi- and holding time	Yes	No
MILP	Balakrishnan [6]	Minimize taxi time	Limited	No
MILP	Evertse [14]	Minimize emissions, fuel usage, taxiing time and CFMU violations	Limited	No
GA	Pesic [21]	Minimize taxi time	Yes	No
GA	Gotteland [17]	Minimize taxi time and offset time from target take-off time	Yes	No
GA	Deau [12]	Minimize taxi time and offset time from target take-off time	Limited	No
GA	Chen [8]	Minimize taxi time and fuel	Yes	No
MARP	Ter Mors [28]	Minimize taxi time	Yes	No

Table 2.1: Computational models compared on objective function, route consideration and uncertainties taken into account

2.8. Discussion of found design choices

Within literature, a problem definition has been formulated that can be found in section 2.1, called the 'Ground Movement Problem'. Different institutes have put effort to capture this problem, but differences in design choices can be found. These differences can be found in:

- **Planning methods involved**
  Within literature, three different planning methods are recognized: Linear programming, heuristics and multi-agent planning. The linear programming methods are able to provide global optimization, but need to take all scenarios in account. Although optimal, for every freedom implemented an increase in computational time can be found. Therefore, freedoms need to be reduced to find workable computational times. To cope with this scalability issue, heuristics can be used. Heuristics are able to decrease the amount of calculations, but are not able to guarantee a global optimum. While more freedoms can be given within programming, optimality is not guaranteed. Last, multi-agent planning methods are able to find optima for individual aircraft, but global optimization is not guaranteed. Next, communication between aircraft is needed, for which no infrastructure is present yet. Communication may also increase dynamics within planning, what may cause loss of robustness. New inputs may ask for renewed calculations, resulting in multiple plans being made. Through differences in modeling within the models found, it is unclear which way of programming came to the best solutions in terms of optimization performance and robustness. But, an advantage of agent-based modeling through decentralized planning is that input of more agents does not necessarily influence computational times. Especially at large airports this may beneficial, where large amounts of calculations need to be done and lots of agents need a plan.

- **Planning phase**
  Within section 2.6, different planning moments are specified. It is found that methods have chosen for different moments, with which specific freedoms and constraints are chosen. Because of the large uncertainties, it seems risk-full to plan far ahead. Planning of runway sequence is superior over planning on the taxiways, and therefore taxiway planning within this planning phase seems inappropriate. As a consequence, departures are constraint to target times, and timely delivery is needed. Pre-tactical planning can therefore contribute to timely delivery, and minimization of holding. Of these planning systems, robustness to uncertainty was unclear. Although performance seemed high, it is unclear of these systems are able to guarantee timely delivery for departures.

- **Routing and timing options**
  Within planning models, an increase in computational force of computers has led to an increase in planning freedom. The first models took fixed routes into account, where shortest paths were chosen. But later models have increased routing freedom, where k-shortest paths or full routing freedom is possible. For complex airports, a lot of interaction between traffic is present. Different routes with comparable performance are available. Routing freedom seems appropriate to find optimal solutions for these airports. Another option to solve interactions between traffic is timing of paths. Within timing options, next to taxiing, holding is possible. But to maximize traffic flow within a system, holding is only allowed on some specific places. Special holding areas are assigned to take holding traffic out of the flow on the taxiways. Although it may increase performance when allowing holding within the infrastructure, robustness of flow maximization is decreased. Holding on taxiways, and especially on crossings should be punished.

- **Computational time**
  Since planning is performed short before execution, a low computational time is required. After target times have been set, within a few minutes a plan is needed. Planning during execution even requires almost direct feedback to pilot. Most current centralized methods are not able to perform planning within the specified time given. If they do, plans or not robust to operational uncertainties invalidating results presented. Therefore a method is needed that takes a large set of uncertainties into account, while keeping computational time under

2 minutes.

- **Objective function**
  Within the first models, the aim was to minimize the amount of conflicts. For fixed routes, timing of the route was the only option to increase performance. Minimizing the amount of conflicts helped in reducing total taxi time. But with extensive routing options, more options were available to reduce taxi time and prevent conflicts. For realistic implementation, this system is appropriate for arrivals. For departures, timely delivery is of importance and punctuality was included. It can be found that different objectives hold for arrivals and departures. A mix of these two objectives is needed to optimize for both type of operations.

- **Uncertainties incorporated**
  Within the methods, speed is modeled as a constant. Therefore, the position of the aircraft is known, and conflicts were found. A solution is found to de-conflict these aircraft, and optimize taxi time. But when speeds differ, different conflicts may occur, which are not taken into account. Within most models, a recalculation is needed. Since speed planning is not changed, these conflicts may arise late within planning. Time for recalculation is short, and new solutions may not be ideal. Therefore models not taking speed uncertainty into account, fail in predicting conflicts.

- **Optimization methods**
  Different methods are used, both centralized and decentralized. For large complex airports, linear programming methods seem to need too much computational time. Therefore, to offer enough planning freedom, sub-optimal solutions need to be found. Heuristic methods are able to find sub-optimal global solutions, while multi-agent methods find local solutions. But through changes due to uncertainty in operation, multi-agent methods are better able to perform local recalculation. Therefore multi-agent methods perform well under uncertainty.

A set of design choices need to be made, that provides sufficient freedom in planning but constraints the problem so optimization within reasonable computational time is possible.

3 Research framework

3.1. Problem Statement

Within literature, a problem definition is found in section 2.1, called the 'Ground Movement Problem'. Different institutes have put effort to capture this problem, but differences in design choices can be found. Within these methods, the following problems have come forward:

- **High complexity for large airports with multiple aircraft operating simultaneously**
  The following planning methods are found:

  - Centralized approach: Linear Programming
  - Centralized approach: Heuristics
  - Decentralized approach: Multi-agent Planning

  For these methods, different problems have come forward. Centralized methods require high computational times and have high precision in solutions for which offsets cause a need for recalculations. The methods are not suitable to cope with a frequent need for recalculations, especially for large airports. For multi-agent planning, decentralized planning requires less computational time and only single agents plan is sensitive to differences in input changes. But for these systems, high requirements can be found on communication and coordination. Within the current air traffic control, these methods require a high amount of investment.

- **Operational uncertainty causes multiple scenarios to be taken into account**
  Within current methods, uncertainty is insufficiently taken into account. Methods are not robust to different scenarios. Conflicts that are taken into consideration within planning do not necessarily occur during execution. These conflicts can have a high impact on travel time and therefore current methods are not able to model on time of arrival. Chance is present that conflicts will arise, which are not taken into account. They can affect time of arrival, causing a possible decrease in runway utilization. A need to introduce uncertainty in speed and start time is found.

- **Low control by Air Traffic Control**
  Current control during execution is limited to radio communication. Controllers have a limited set of actions available, and execution is under responsibility of pilots. Therefore the system requires a reduced set of simple commands made by ATC. Communication between aircraft is not possible.

- **The airport system has a dynamic objective under different loads**
  During operation, different loads of the system can be found. Under high load, priority of the ATC is to maximize the runway utilization, when runway utilization is of lower importance for lower loads. A queue can be found at the runway under high utilization, increasing the total travel time for aircraft. A trade-off is needed for multiple objectives of both ATC and Airline, where weights differ under different loads and preferably also for different operation

types, like arrival and departure. Currently, aircraft have similar objectives which differ in reality.

Within the current Air Traffic Management (ATM) system, ATC only has limited control over traversal of aircraft over the airport infrastructure. Therefore, it is of importance to take uncertainty of operation into account. These uncertainties affect the time of arrival at the destination of each airplane. Since target times have to be met, it is of importance to provide robust travel times for aircraft. Current methods are unable to provide robustness in travel time, since replanning is needed under uncertainty. Planning methods that are able to capture operational uncertainty and provide routing and timing instructions pose an even higher complexity than already found. New methods are needed that capture the uncertainty in travel time, but are able to provide solutions within low computational time. Decentralized methods are able to reduce complexity of the problem at hand, and are robust to introduction of new aircraft within the planning. Since only limited communication between ATC and aircraft is available, agent-based methods offer a solution to the problem at hand.

3.2. Research objectives

The problem statement has led to the following objective function:

The objective of the research is to develop an agent-based airport surface routing and timing planning model providing multi-objective optimization, robust to operational uncertainty

Within this research objective, some priorities are set that will be of importance throughout this project:

- **Agent-based method**
  It is chosen to decentralize planning in order to reduce computational complexity and to allow different objectives for aircraft operating simultaneously. Within the current system, communication between ATC and aircraft is limited to commanding actions to take. Communication between aircraft is not possible, and therefore implementation of multi-agent systems through communication between aircraft is complicated.

- **Routing and timing planning**
  Control within the system will be through similar actions as found within current system. Within this system, routing and timing actions can be given. Routing defines the set of taxiways to be taken to get from start- to end point. Timing defines the time spans an aircraft is allowed to enter certain taxiways, currently implemented as holding to regulate and prevent conflicts between aircraft.

- **Multi-objective optimization**
  Within the system, objectives from different planning agents are followed. In the objective function a trade-off is needed to minimize the total travel time (airline objective) and to maximize runway utilization (ATC objective). Different objectives for aircraft and priorities under different loads can be translated in agent-based values. Value will be given on actions (holding and taxiing), and for time of arrival at destination. Optimization of value for agents contributes to the system objective of minimization of travel time and maximization of runway utilization.

- **Robustness to operational uncertainty**
  Robustness is needed for speed uncertainty, possible timing actions performed by ATC to resolve conflict and for variation in start time. Planning may not be invalidated by speed variation or possible timing actions performed by ATC, and should therefore be taken into account.

3.3. Markov Decision Process

In this research, methodological steps are taken to solve the 'Ground Movement Problem' by an agent-based approach. The first step is choice of a agent-based planning method that is robust, optimizing agent-based plans through routing and timing and able to perform under uncertainty. As agent-based planning method under uncertainty, a Markov Decision Process is chosen. It is able to provide a policy (set of actions for different states), for systems under uncertainty. Optimization of actions is done in order to maximize value found within states. These characteristics suit the problem at hand. In this section, the base of the method will be given.

Theoretical background
An MDP is a stochastic dynamic programming method based on sequential decisions that have to be made. It can be used to solve stochastic control problems by presenting a policy for value maximization. Different actions within the process represent the desired states that is wanted to become reached. During the process rewards may be gathered, and for time-discrete processes finite horizon or infinite horizon optimization is possible. Literature presents the MDP to be build-up as following: [23]

- A set of decision epochs
- A set of system states
- A set of possible actions
- A set of state and action dependent immediate rewards or costs
- A set of state and action dependent transition probabilities

Within every state, an action needs to be chosen that represents the state desired within the system. The action is based on value optimization of this choice. This value is based on the gathered value within future states. A representation of the sequence of actions and states can be found in figure 3.1. A value needs to be known for future states to base a decision on. Backward programming is

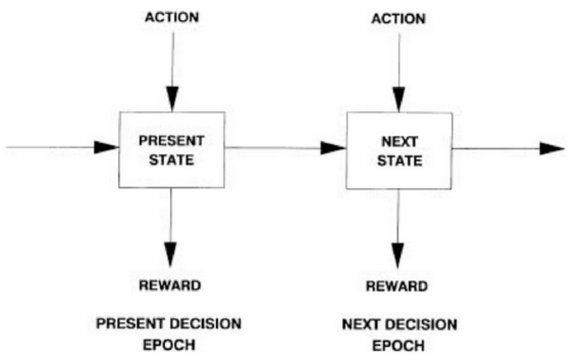


Figure 3.1: Symbolic representation of a sequential decision problem [23]

needed to calculate the value for future states. As an outcome of an MDP, value and policy represent the value that can be captured within a certain state and under a certain policy representing the decision to be made within the different states. For calculating this policy and value, equations 3.1 and 3.2 can be used. The value function is used as objective function in order to optimize routing and timing for aircraft.

$$\pi(s) = max_a\{\sum_{s'} P_a(s,s')(R_a(s) + \gamma V(s'))\} \tag{3.1}$$

$$V_\pi(s) = \sum_{s'} P_{\pi(s)}(s,s')(R_{\pi(s)}(s) + \gamma V(s')) \tag{3.2}$$

Within these equations, actions follow from policy in order to maximize value within the system. This value is based on value of possible states that can be reached and the value that is given for performing an action within a certain state. Within the functions, also a discount factor γ can be found that decreases the value of rewards found later, since more uncertainty on this value is present (value may be different). Modeling of the MDP can be done within programming languages like Matlab [20], by using a toolbox provided by Institut national de la recherche agronomique (INRA) [18]. Within this toolbox, different methods are present to model the MDP. One method may be of particular interest, which is:

Finite Horizon Markov Decision Process
Within the Finite Horizon MDP, a number of decision epochs can be chosen to represent a certain planning horizon. By calculating backwards, value can be calculated from a terminal reward, which represents a end state for the system. This may be a state that needs to be reached to fulfill the goal of the planning. For this model, the inputs given in table 3.1 can be found.
Within this model, a reward can be given specific for state, action and future state. Therefore, a

Input parameter	Description
S	State space
A	Action space
$P(S,A,S')$	Transition probability array
$R(S,A,S')$	Reward array
k	Number of transition stages
γ	Discount factor
$T(S)$	Terminal reward array
π	Policy

Table 3.1: Input parameters for MDP

wide range of rewards can be chosen possibly representing different objectives. It is also possible to decrease the amount of dependencies for this value.

Model definitions
Within the research at hand, parameters of the MDP are defined as following:

- State space S: segments within the infrastructure with a specified heading
- Action space A: taxiing actions with the target connection, or holding action at segment
- Transition Probability P(S,A,S'): Transition probability from one state to another under intent of action a
- Reward array R(S,A): Reward based on action within specific types of states
- Discount factor γ: Factor not used, so set to 1
- Number of stages N: Number of transition possible within planning
- Terminal reward array H(S): Terminal reward for reaching destination state

3.4. Methodological steps

In order to use the MDP, different methods need to be chosen in order to find the uncertainty within the system and to optimize routing and timing for aircraft. The following steps can be found:

1. Choosing uncertainties of importance
2. Data collection and preparation
3. Definition of agent objectives
4. Validation
5. Test robustness through cases

3.4.1. Choosing uncertainties of importance

In order to take uncertainty in execution by pilot into account, propagation uncertainty needs to be found. Differences can be caused by the specifications of the aircraft or pilot, but can also be through the environment it is operating in. Propagation uncertainty also represents the uncertainty of blocking along the path by other aircraft. Since conflicts can't be found during planning through high uncertainties during operation, no resolution of conflict is possible. It is not possible to take possible actions by ATC into account, since no resolution is possible and therefore chance of blocking by other aircraft is taken as uncertainty in propagation. The uncertainties found can be categorized as:

- Location related
  - Sort of taxiway
  - Local traffic density
  - Chance of conflicting paths of aircraft
- Airport related
  - Weather
  - Visibility
  - Traffic load
- Aircraft related
  - Aircraft type
  - Pilot

Since current methods plan for constant speed over the airport, focus is on capturing the uncertainty in propagation over the airport. Since conflicts can be highly disruptive for the system, and many other uncertainties are related to location, location related uncertainties is taken as main focus to capture travel time variation. For uncertainty in both speed as blocking through conflict, propagation of aircraft over the infrastructure can be taken as a way to capture variation in arrival time. Position change over a fixed time span captures both variance in speed as holding through blocking by other aircraft. Within this uncertainty, a split is made between speed uncertainty and conflict uncertainty:

- **Speed uncertainty:** Variation in propagation of aircraft when unimpeded or undisrupted.
- **Conflict uncertainty:** Variation in propagation through blocking of path by other aircraft, or given holding actions by ATC.

3.4.2. Data collection and preparation

First of all, a infrastructure representation is needed. Within this representation, routing options should be straight forward. For these routing options, crossings of taxiways are of importance. A sequence of taxiways is a simple but very useful representation of routing over the infrastructure. Crossings of- and connecting taxiways can be represented as graph with nodes and connections. Location related data is needed to model propagation uncertainty over the infrastructure of an airport. Instead of finding reasoning why variation is present, it is possible to find location related uncertainty by using propagation information found from historic data. Operational data is widely available and can be used to find behavior within the airport infrastructure. Data send from aircraft include location errors, and therefore filters should be set in place to increase data quality. Next, multiple observations are needed to be able to find variation in propagation over taxiways. As airport, Amsterdam Airport Schiphol is chosen for which sufficient data is available within the TU Delft.

3.4.3. Definition of agent objectives

As system objective, minimization of total travel time and maximization of runway utilization is found. In order to optimize for individual agents, agent-based objectives are needed. It is possible to minimize travel time per agent, but individual agents are not able to maximize runway utilization. For departures, it is assumed that a TTOT is given providing a runway slot. This time is communicated by ATC to aircraft, and aircraft is required to comply to this time. Priorities for taxiing and arrival time compliance are of influence on the chance of timely arrival. It is assumed that a small offset to TTOT is allowed, but planning of runway sequence within planning is already done. The planning method is not able to make changes on this sequence, and therefore TTOT and ETA is taken as a fixed input.

3.4.4. Validation

The method is validated by comparison between simulated and actual travel times found for airport infrastructure. Travel times of actual operations is gathered in order to provide mean and deviation in route travel time. It is of importance to check flights with the shortest path in time. By finding the shortest path in time for the method, it can be found whether the representation of propagation over the infrastructure represents the variation in travel time. A simulation of propagation is needed, based on location dependent variations found in the method, to check the travel times found by the method.

3.4.5. Test robustness through cases

In order to check robustness of the system, the following cases need to be presented:

- Results of method under variation in start time
- Results on planning for different objectives of agents
- Analysis of planning for a variation of value sets
- Analysis of computational sensitivity to input parameters
- Planning under environmental (airport) conditions

Variation in input parameters is needed to analyse robustness of the method. These changes in input parameters can be found for changes in:

- Type of agent (departure, departure under CFMU slot and arrival)
- System load (Priority on runway maximization)
- Airport related factors of influence on uncertainty
- Type of airport
- Start time

3.5. Scope

The scope of the project will be limited/defined by the following assumptions. It is important to take these assumptions into account, when evaluating the results.

- **Fixed start time**
  Start time of the operation is assumed to be fixed, and no uncertainty is present within this times. Input by AMAN or DMAN is assumed to be a fixed. On departures, this has a larger implication since pushback duration time uncertainty is bigger than the ETA uncertainty. But implementation of uncertainty within these start times would lead to implementation of other planning agents. This would increase the complexity of the planning, and for the scope of the project this is not wanted. Differences in start time may not affect robustness of the system.
- **Unconditional uncertainties**
  Many reasons for uncertainty are given within literature. These reasons specify uncertainty due to the place the aircraft is at, the traffic situation surrounding the aircraft or the type of aircraft operating. Within the scope of this thesis, uncertainty is assumed to be place specific. It will capture both the unimpeded speed uncertainty of aircraft taxiing on this segment of infrastructure, as the uncertainty caused by traffic situations found for this place within

the infrastructure. These uncertainties are not dependent on any events found previously within the route. Conditions like visibility or time of the day are therefore not taken into account. Since these conditions can be of influence on the result, conditional planning will be performed as a test. Within conditional planning, only uncertainty found within these conditions will be used in order to increase precision of planning. This test is to indicate the gain in performance of conditional planning. It is expected that the found variation in travel time will decrease for conditional planning, but it may also cause recalculations to be needed when conditions differ from planning. Since these dynamics would decrease robustness, conditional planning is only tested but left outside the scope.

- **Deadlocks uncertainty**
  One of the major challenges within route planning is prevention of deadlock situations. These situations can be found when no solutions are available for conflicts given in figure 2.3 or when routing choices are made that send an aircraft into a dead end. A deadlock may be highly disruptive, and therefore must be prevented. Prevention of deadlocks is seen as a task of ATC during taxiing. Since uncertainties may cause multiple scenarios to happen, with multiple possible deadlock situations, deadlocks are not prevented. Possible control actions in timing are expected by ATC to resolve conflicts, and are taken into account as uncertainty in operation. Therefore, current rules for the infrastructure are used, restricting specific taxiways from being used two directional. Other possible control actions are taken into account as uncertainty.

- **Value to objectives**
  Values of different objectives are not necessarily the value that a specific planning agent would give to the objective. Therefore, results may not represent the ideal policy for these agents. It must be taken into account that the current values only give an indication on the different priorities agents might have, and how they would lead to differences in policy. Effort is put into a transparent and fair division of value, but agents are free to get to new values, which can be tested.

- **Uncovered areas within infrastructure**
  Measuring uncertainty within the infrastructure is dependent on historic data. Measured uncertainty is only relevant when enough data is available for each segment of infrastructure. It is assumed that segments without enough data have other purposes, for instance preventing deadlock situations or special operations. Therefore, they are expected not to be relevant for efficient operations. Estimations on transitions are possible if segment of taxiway is of importance.

3.6. Design choices

Within figure 3.2, an overview of the design choices is given based on the requirements found in the literature review and problem statement.

Figure 3.2: Design choices made for thesis project, specified for different requirements

3.7. Impact and Contribution

Within figure 3.3, the proposed method is compared to the state of the art and the expected contribution is given. A division is made between scientific contribution and contribution to the industry.

	State of the art	Contribution
Scientific	• Mixed objectives for Arrivals (minimize total taxi time) and Departures (Maximize time at gate and Minimize offset to target times) • Routing and Timing for aircraft • CFMU slot adherence within planning	• Modelling speed as uncertainty, instead of a constant • Agent-based planning with different objectives • Robust planning for offsets in time • Model learning from historic data (adaptable) • Modelling taxiing operation as a Markov Decision Process
Industry	• Maximization of time at the gate • Minimization of holding on the taxiways "At what time do I have to leave the gate to minimize the taxiing time, but still be in time for my take-off window?"	• Agent-based values for objectives, transparent for industry • Uncertainty planning "What is the uncertainty of time of arrival, and how do I trade-off time of arrival with taxiing time?"

Figure 3.3: Comparison and contribution to state of the art, presented for both science and industry

4 Model

4.1. Model build-up

The basis of the model is a MDP that models transition over the taxiway infrastructure. It is able to capture transition uncertainty, and is able to provide actions both on routing and timing. To model these transitions, historic data is used to set up the probability matrix for the MDP. And the result of the MDP needs to be translated into a routing and timing advise. Within figure 4.1 the set-up of the model can be found.

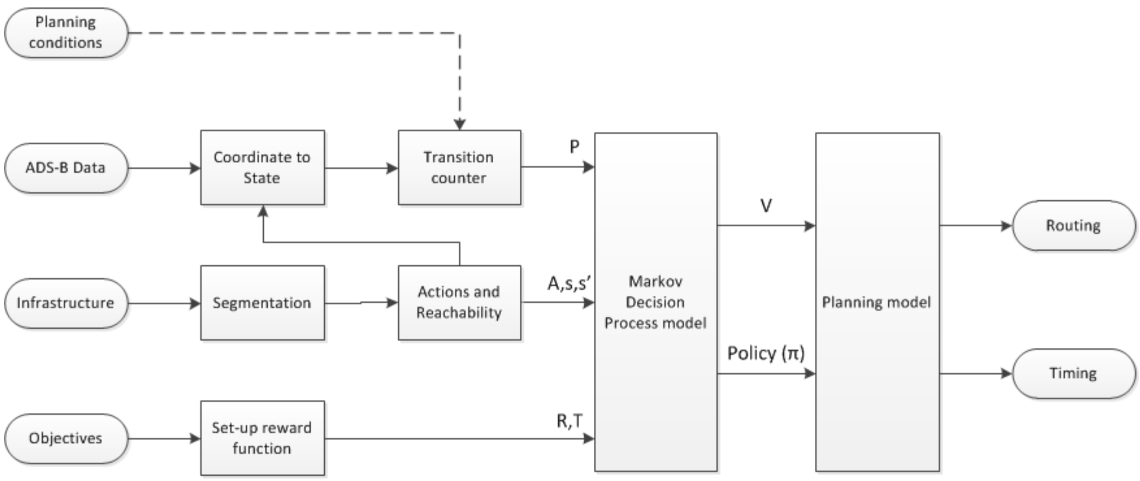


Figure 4.1: Model build-up, from input through data processing towards MDP providing routing and timing advise

Within this chapter, we will discuss the set-up of the model. First, we will discuss the inputs of the model in section 4.2. Then the data processing will be discussed in section 4.3 to get to the inputs of the MDP. The MDP will be discussed in section 4.4, after which we will discuss in section 4.5 how the results from the MDP is translated into a routing and timing advise.

4.2. Model input

Four different categories of input can be found in figure 4.1. These inputs are:

- Infrastructure data
- ADS-B data
- Objectives data
- Planning conditions (Optional feature)

4.2.1. Infrastructure representation

For route planning purposes, an infrastructure representation is needed. A graph of nodes and connections is found, that represents crossings or corners within the infrastructure. This graph representation for AMS can be found in figure 4.2. In red, the 6 runways can be found which are the start or end of the operations. These are also found in figure 4.3. It is based on the graph used by Roling et al. [25], but it is set up for simulation purposes. To better represent the infrastructure, points were added and coordinates were changed manually. When implementing a different infrastructure, it may be needed to specify extra nodes to better represent the corners within an infrastructure. This is of importance when a radar track point is connected to a segment of the infrastructure.

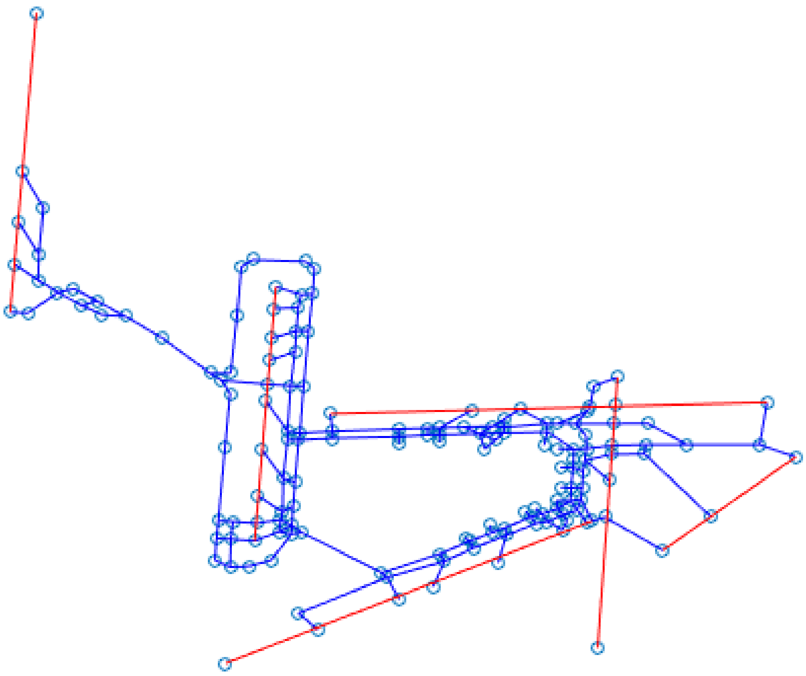


Figure 4.2: Graph representation of AMS, with taxiways in blue and runways in red

It can be found that no gates are specified, but the entrances to the piers are specified instead. It is of importance that tracks can be found on the infrastructure specified by the graph and its connections. Within the infrastructure data set, columns with the following information for the nodes can be found:

- Node number
- X-coordinate
- Y-coordinate
- Connection towards node number, option 1
- Connection towards node number, option 2
- Connection towards node number, option 3
- Connection towards node number, option 4

Within this data set, the direction a taxiway is used can be found. A one-way taxiway can be specified by a connection from node A to node B, but without a connection from node B to node A. The nodes are based on its own reference system, with the first node as origin. To specify it into a MDP,

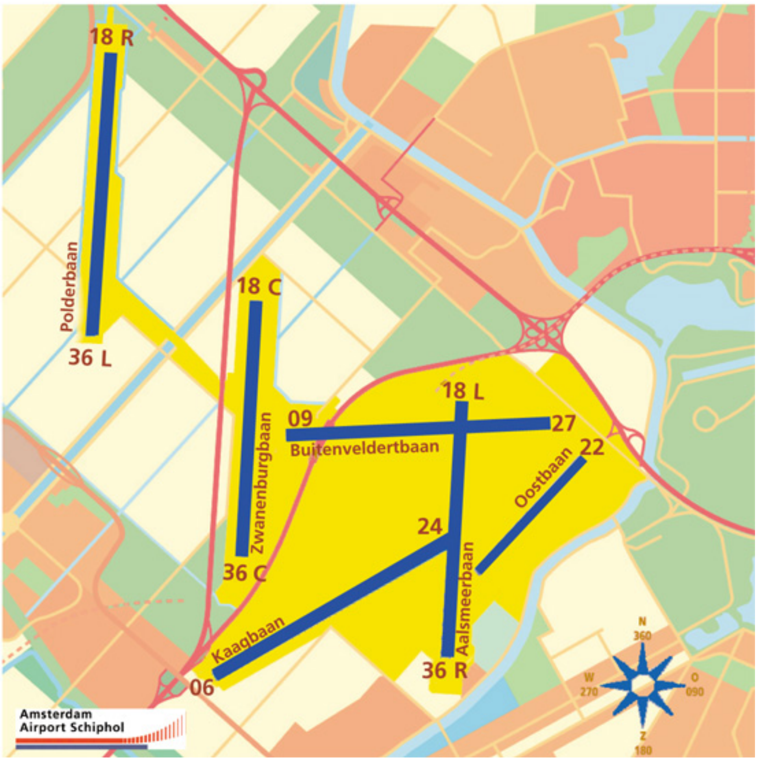


Figure 4.3: Runways of Schiphol, given with name and code to specify direction it is used in [1]

segmentation has to take place of the taxiway into pieces of taxiway of equal length. This is the process this graph will be fed to that will be explained in section 4.3.1.
Of importance is the direction of usage of the taxiways around the terminals. The taxiways are only used within one direction for operational reasons to prevent deadlocks and high number of conflicts. One exception is the taxiway in the south west where only one taxiway is built. Within the ring, the outer ring is used in counter clockwise direction and the inner ring in clockwise direction. This is specified in the connections within the infrastructure data.

4.2.2. ADS-B data to measure uncertainty

The uncertainty present in the airport system is due to speed fluctuations and blocking of path. Within section 2.5, values are given that were found, but they still do not describe the uncertainties an aircraft is posed to during taxiing. Therefore a method is chosen that is able to capture local uncertainty. By describing the uncertainty at each local point within the infrastructure, the model is able to capture route specific uncertainty. ADS-B data has been chosen to subtract this data from. It can be subtracted from FlightRadar24 [3] where it offers the following data:

- Flight ID
- Equipment (Aircraft type)
- Origin (International Air Transport Association (IATA) call sign)
- Destination (IATA callsign)
- Flight Number
- Time (Unix-time stamp)
- Latitude (degree)
- Longitude (degree)
- Altitude (feet)
- Speed (knots)

Out of this data, the propagation over time from a specific location can be found. When gathering multiple observations for one location, propagation variation can be found. For the sake of this research, we are looking for speed and conflict uncertainty. Within this data set, it is unclear

whether the aircraft was unimpeded or close to other traffic. Therefore, no separation can be made between speed and conflict uncertainty. No conclusions on disruptions during execution are possible either.
Within this research, two data sets have been found which are described in table 4.1

Time span	**Number of flights**	**Flight specifications**	**Airport Surface**
25 Jun 2015	1240 tracks	Flight numbers incl.	Total airport
1-25 Feb 2016	12460 tracks	Not specified	North-West region

Table 4.1: Data sets found for this research, with total of 13700 tracks

An observation time of frequent occurrence can be found of 6 seconds, in which traveled distance can be measured. Frequency of time step is plotted in figure 4.4. Also speed is given within the data, but it is tested that integration of speed returns large offsets in calculated distance compared to actual distance and can therefore not be trusted.

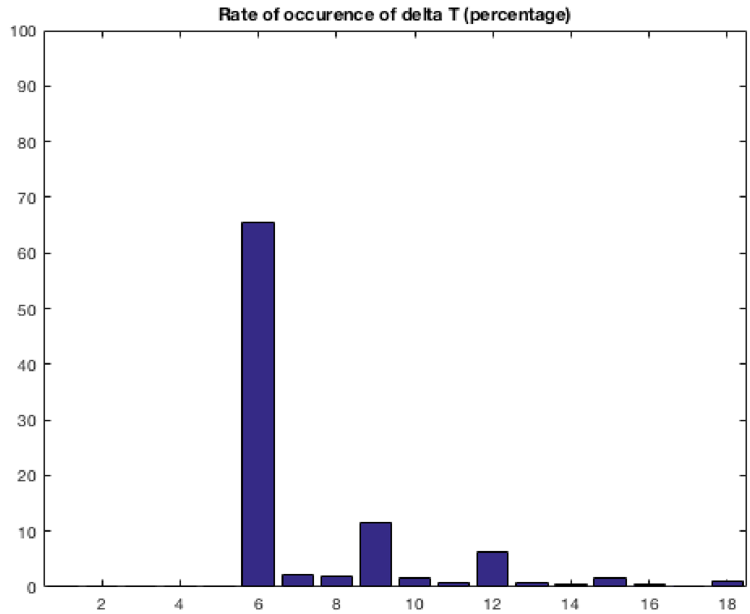


Figure 4.4: Frequency (%) of time step within data, with 67% occurrence of 6 seconds

The speed is measured for regions of the taxiways. Within this research, these regions will be referred to as segments. Track points are gathered for segments, to make a representation of speed within this segment. How the segments will be defined is explained within section 4.2.1. Speed will be defined as the amount of segments an aircraft will traverse within a specified time period. Time period is of influence on the amount of states and the amount of actions within the action space. A small time step increases the amount of states and amount of transitions within one operation, and therefore raises computational complexity. Increasing the time step increases the amount of possible sequences of connections that can be reached, and therefore increases the amount of needed actions. An increase in action space complexity is found, which is unwanted. Therefore a timestep is needed that is accurate, but keeps the amount of actions and states to a minimum. The propagation time period is chosen at 12 seconds, with an allowable offset of 1 second, to capture the majority of possible time steps (50%: both 2x6 and 12 seconds time steps). This time period offers sufficient accuracy for time of arrival, but also keeps the amount of needed actions and states to a minimum.

4.2.3. Objectives for planning

Within planning, different objectives have been found. These objectives will be further specified for three different agents:

- Arriving aircraft
  - Minimize costs of taxiing and holding
- Departing aircraft
  - Minimize costs of taxiing and holding
  - Maximize compliance with TTOT
- Departing aircraft under CFMU slot
  - Minimize costs of taxiing and holding
  - Maximize compliance with TTOT
  - Assure compliance with CFMU slot

For all agents, a trade-off between sub-objectives is needed. These objectives were given as taxi-time and end-time optimization. Priorities within these objectives will be given within the following sections.

Taxi time optimization

Within section 2.4, it can be found that airlines are able to save in costs of fuel by letting aircraft wait at the gate. This is only when early arrival leads to holding at the runway. Under high runway utilization, buffers are in place to maximize utilization. Within the current method, choosing the latest TSAT can increase the value of taxiing, since it can lead to decreasing the need of buffers of aircraft with engines running at the runway. Therefore, holding at the gate has the highest value for the taxiing operation. To get to the target location, taxiing is needed. To minimize taxi time, every additional time period of taxiing needs to be punished. Since fuel is used during taxiing, the value of taxiing is lower than holding at the gate. Last, holding on taxiways is possible. For instance in case of unavailability of the runway or a taxiway for a time period may cause an aircraft to increase its taxi time. Taxiways in front of the runway is also considered as a taxiway. To stimulate flow over the taxiways, holding on the taxiways is unwanted. Therefore, high punishment of holding on taxiways is needed. Taxiing is preferred over holding on the taxiways, but even more attractive is that additional taxi time is spend on assigned parking places. This is less interrupting than taxiing. These possible actions have led to the following order of value:

1. Holding at gate
2. Holding at assigned spots within infrastructure
3. Taxiing
4. Holding on taxiway

A difference can be found within arrivals for which holding at the runway is not possible, for which operation starts on the first taxiway after the runway. Choosing different values for these actions may cause differences in behaviour of the model. Consequences of actions may not weigh up any-more to other consequences when costs for these actions are raised. In order to weigh priorities, it is of importance to know the consequences on operation when different values or priorities are used. Testing of these values is needed within the results. More on the variance in value in section 4.3.5.

End-time optimization

Within this section, it is of interest to discuss the different objectives for possible agents. Arriving aircraft aim to arrive as quick as possible at the gate. Every time instance longer in taxiing operation decreases the value and the method will look for the shortest path in time. The same objective holds for a departure operating under low loads on taxiways and runways. It is assumed that an aircraft is able to depart immediately under these circumstances, and there is no need to put the aircraft into a runway sequence. But when this load is higher, it is likely that a TTOT is assigned to the aircraft. In this case, timely arrival is of importance. Arriving with an offset to this target time may have consequences to capacity. These consequences are higher for late arrival, compared to early arrival, since it decreases runway efficiency. For the airline, a possible CFMU slot is of high influence. When an aircraft has a slot assigned, it is not allowed to depart outside this time window. When it fails to arrive at the runway inside time thresholds, it is not allowed to depart anymore. This can have highly disruptive consequences. Therefore, thresholds are placed wherein value is higher. This has led to the following objectives that need value for the different types of agents:

- Arrival
  - Punishment increasing for later time of arrival
- Departure with TTOT
  - Punishment for offset to TTOT
  - Punishment for later arrival after TTOT
- Departure with TTOT and CFMU slot
  - Punishment for offset to TTOT
  - Punishment for later arrival after TTOT
  - Punishment for arrival outside CFMU slot

Last, it is of importance that the goal of the planning method should be to get to the target point within the infrastructure. Since most actions result in a punishment, a reward is needed to motivate aircraft to taxi towards a specific point within the infrastructure. Within the current research we assume this value to be high enough that in any case, an aircraft will decide to start taxiing. Decisions within real life may also results in cancellation of the operation, but searching for a specific value describing this decision is not within the scope of this research.

4.2.4. Planning conditions

Within section 2.5 uncertainty was found during taxi operation. Other researchers have identified parameters influencing this uncertainty. Some of them are local, but others influence the aircraft operation over the whole infrastructure. It is chosen to model local uncertainty only. But since conditional planning may be of influence on increasing the amount of variation captured of the system within the model, it is tested. Since only a limited dataset of tracks is available, only a limited division in conditions is possible. Parameters that may influence the operation over the whole airport may be:

- Weather conditions (i.e. visibility)
- Traffic number/density
- Configuration of runways

These are just some parameters that may be of influence. Since no conditions are included within the ADS-B data, it requires effort outside of the scope of the project. Since we would like to know in which way conditional planning may be of benefit, a case is set up in which the performance is tested for one parameter. Not only is the condition for which planning will be performed of importance, also the condition for the historic data. Therefore historic data is gathered for one plausible condition. It is chosen to use the configuration of the runways, since it is not only of influence on the uncertainty but also influences the taxiing rules present on the taxiways. For instance during low load on the system on the taxiways, a taxiway over a runway is opened since the runway is not in use. But during peak load, the runway is used and the taxiway over this runway may not be used anymore. This has large implications on the total taxi time and is therefore of importance for the available routes, but also on the uncertainty present during this period. Conditions are gathered for Schiphol from the website of the LVNL, where historic data can be found per 5 minutes interval. [2] This information is gathered for the period found within the data set of radar tracks. First of all, the configurations are gathered for the preferential configurations given in figure 4.5. [26] A lot of different configurations can be found, and less preferential configurations are likely to not be used a lot. Therefore, a division is made in type of configuration: Normal, Departure peak or Arrival peak. Under these conditions, the system can be tested.

Periode 06:00 - 23:00 uur

Preferentie	Landen L1	Landen L2	Starten S1	Starten S2
1	06	(36R)	36L	(36C)
2	18R	(18C)	24	(18L)
3	06	(36R)	09	(36L)
4	27	(18R)	24	(18L)
5a	36R	(36C)	36L	(36C)
5b	18R	(18C)	18L	(18C)
6a	36R	(36C)	36L	(09)
6b	18R	(18C)	18L	(24)

Zichtcondities: goed (1–4)
- zicht tenminste 5.000 m
- wolkenbasis tenminste 1.000 voet
- in daglichtperiode (UDP)

Zichtcondities: goed (5a–5b)
- zicht tenminste 5.000 m
- wolkenbasis tenminste 1.000 voet

Zichtcondities: goed of marginaal (6a–6b)
- zicht tenminste 1.500 m
- wolkenbasis tenminste 300 voet

Nacht (23:00 - 06:00 uur)

Preferentie	Landen	Starten
1	06	36L
2	18R	24
3	36C	36L
4	18R	18C

Figure 4.5: Preferential order of use of runways by LVNL, based on directions specified in figure 4.3 [26]

4.3. Data processing

4.3.1. Segmentation of infrastructure

To capture uncertainty, a distribution is needed expressing the chance of traversing an amount of segments within a specified amount of time. To provide a distribution of propagation per time unit, a range of possible segments is needed. Increase of this amount leads to an increase in amount of states, which is unwanted. A low amount of segments will decrease the focus of speed uncertainty, since transition probability will represent the probability of moving on or not. In order to represent speed uncertainty, a higher number of states is needed. It is estimated that the aircraft needs to be able to end up in one of six different segments. This means that the aircraft is able to travel six segments at a maximum, following assumed maximum taxiing speed. Equation 4.1 is used to calculate segment length. A maximum taxiing speed of 40 knots is chosen (based on speeds within data) and a factor of 0,5144 is used to convert the speed from knots to meters per second. A time step of 12 seconds is chosen, which is explained in section 4.2.2.

$$l_{segment} = V_{max} * 0,5144 * \delta_t / N_{segments} = 41,16m \tag{4.1}$$

- $l_segment$: Maximum segment length
- V_max: Maximum taxiing speed
- δ_t: transition timestep
- $Nd_segments$: Number of segments able to be reached

Based on this segmentation value, taxiways are cut into the lowest amount of equally divided, smaller segments with a maximum segment length. This leads to a new infrastructure with additional nodes and connections, given in figure 4.6.

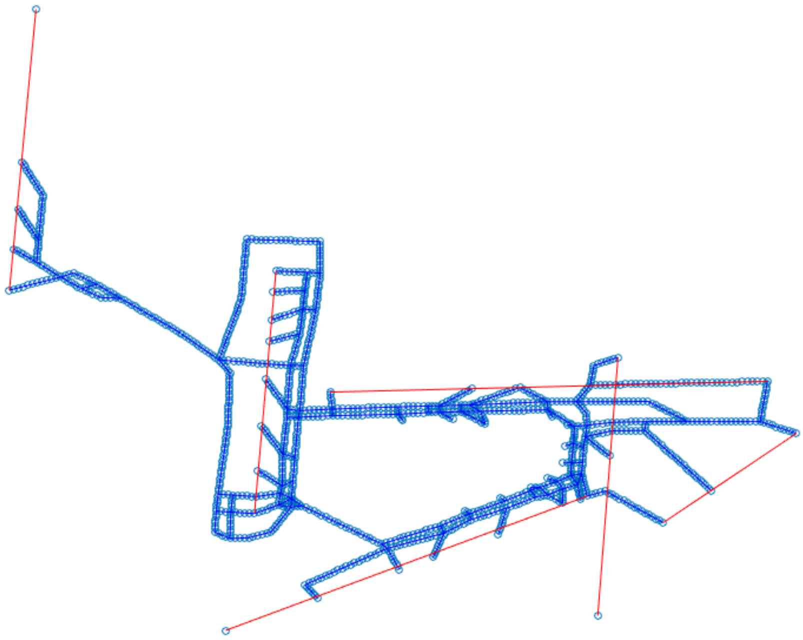


Figure 4.6: New graph representation after segmentation

4.3.2. Action space and reachability

For all states, it is of importance to check whether a transition is possible and which action an aircraft performs. Every state therefore needs an action space and a reachability set of states it can get to in the future to filter outliers. First, the action space is of importance. Not only is it of importance to be able to extract a routing and timing policy out of the MDP, but also to find the right uncertainty for performing a specific action. Actions specify the corresponding connecting segments from the node an aircraft is intended to head towards. An example with two possible intentions, specified as actions, is given in figure 4.7.

The action space is dependent on the set of possible intentions an aircraft may have. For AMS an action space of 4 was found, meaning that from the state an aircraft is in, 4 different other possible connections were found it can be headed towards. Since it is also an objective to do planning on holding, an extra action was included for holding. Within this action an aircraft will remain within the state it is in and transition probability is not based on historic data, but assumed.

Next, it is of importance to check reachability from a particular state by an aircraft. As the heading is given, and depending on the action only a certain amount of future states can be reached. As found earlier in section 4.3.1, transition over only 6 states is possible. It is of importance to filter out future states that in theory can not be reached. For these transitions, it is highly probable that an outlier is found and removed from the data. Transitioning to the same state is possible in case of holding through disruptions.

4.3.3. Coordinates to segments

The ADS-B data found is not ready to use. Outliers of position can be found, and not only aircraft taxiing are present within the dataset. Also ground vehicles from the airport can be found within the dataset. Therefore data processing is needed to get the data ready for subtraction of data. The data processing steps are given in figure 4.8, and will be explained within separate sections.

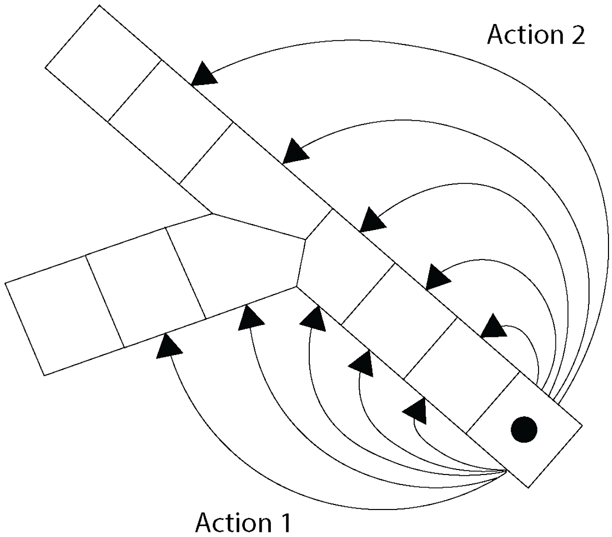


Figure 4.7: Action and reachability space

Figure 4.8: Data processing steps for ADS-B data to label data points with the state it is in

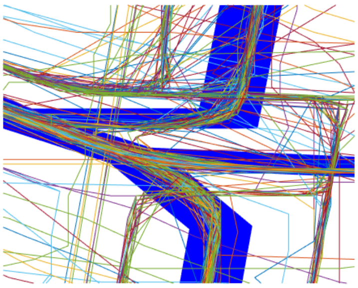
Valid flight check
Within ground operations, altitude for all tracks needs to be zero. Therefore, data is used with an altitude of zero. But, also ground vehicles communicate position data within the area of interest. Therefore, these ground vehicles need to be filtered out. Within figure 4.9 it can be found that lots of tracks can be found belonging to ground vehicles and making use of service roads. A difference can be found in one data set in flight number, where ground vehicles are named "GRND". Ground vehicles can be filtered out within data sets providing flight number. But a data set is found without flight number. For this data set, a different approach is needed. Since we aim at providing routing and timing planning for flights arriving or departing at airports, only data for these type of flights are of interest. These flight tracks have in common that their tracks start or end within the boundaries of a runway. If first or last three data points can be found within the boundary of a runway, this track will be labeled as valid. Other tracks can be of flights with an offset in Global Positioning System (GPS) data, are ground vehicles or of a different type of operation (i.e. moved to a hangar for maintenance). After filtering out faulty flights, a better data set is left shown in figure 4.10.

Couple data point to infrastructure
To couple radar points, use has been made of the *inpolygon* function of Matlab [20]. Within this function, a polygon can be defined for which this function returns whether this point can be found within the polygon or not. The corner points of the polygon have to be defined according to some basic rules:

- With an allowed offset of 23 meters (width taxiway) perpendicular to the connecting line
- On the middle line between two segments from the same node

This leads to the infrastructure lay-out presented in figure 4.11 Within this infrastructure representation, three elements can be found:

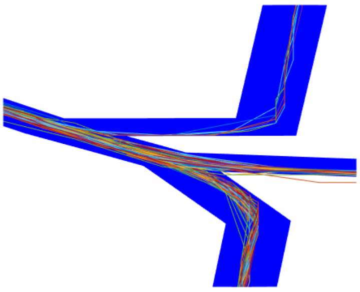
- Nodes
- Connections
- Segments



(a) Ground tracks plotted over infrastructure

(b) Topview of situation

Figure 4.9: Raw tracks plotted over infrastructure



(a) Ground tracks plotted over infrastructure

(b) Topview of situation

Figure 4.10: Filtered tracks plotted over infrastructure

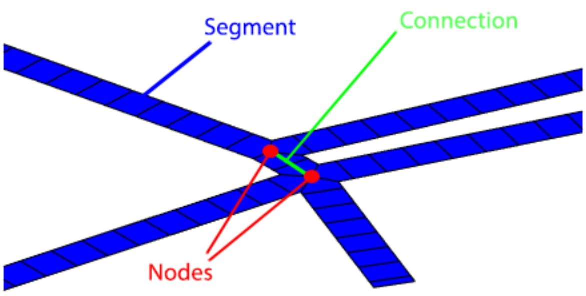


Figure 4.11: Lay-out of the polygons, defined to couple data points to segments

These segments represent the states an aircraft can be in. For Schiphol, a total of 1289 segments can be found. But, possible future states need to be known. Within current infrastructure segments going both ways are reachable. In reality, this is not the case since aircraft are not able to drive backwards or turn around. Therefore it is of importance to specify the direction an aircraft is taxiing in. Within procedures of Schiphol, one-way and two-way taxiways can be found. For the two-way taxiways, it is of importance to specify the direction it is being used. Therefore, another division of the segments is made based on heading on the segment. This is the last division of the infrastructure in the states wanted.

Interpolate holding data Within the data, it is found that data points for periods of holding is excluded. Therefore, gaps in time can be found while aircraft remain within the same position. To include chance of holding, we need to include data points, since they represent a transition. Therefore holding data is included again every 6 seconds. These data points hold the same position and action, but are given interpolated time instances.

Derive heading of aircraft
Therefore, an extra state is defined so the heading on the connection is given. From the track of the aircraft, heading can be derived. Within the process, the following rules were used to find the heading:

1. The sequence of segments within a connection
2. The connection within the track used next
3. The connection within the track used before

If still not found, than data point was filtered out of the data.

4.3.4. Create transition probability matrix

When the data set is corrected, a probability matrix needs to be set up for the MDP. The transition probability space is formulated in equation 4.2 representing the transition probability for all states and under all actions:

$$P(S, A, S') \tag{4.2}$$

S = state space
A = action space
S' = future state space

To set up this matrix, we need to calculate the probability from historic data. Through data processing every data point already holds time, state and action. Another important constraint is that the future state is within the reachability of a state. This constraint is already tested in section 4.3.3. First, a counter will be used that tracks all transitions found in historic data. Within figure 4.12 it can be found that transitions are counted. It can be found that transitions within a different action space, or outside the reachability of a segment are not taken into account. It is of importance to take action into account, since transitions within a different action may influence the transition probability for another action. For instance speed may be lower when approaching a turn (action 1) instead of still heading straight (action 2). Actions are therefore separated.
The transition observations from state s are summed within matrix N, given in equation 4.3

$$N(s, a, s'), \qquad s \in S, a \in A, s' \in S' \tag{4.3}$$

s = state an aircraft is in
a = action taken
s' = state the aircraft is in after t = 12 s

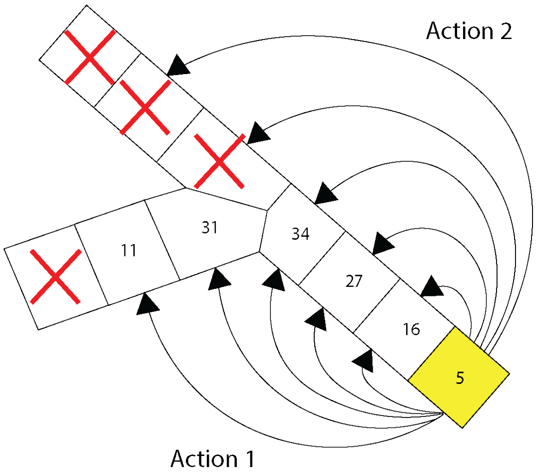


Figure 4.12: Transitions are counted for all future states, filtered for reachability of state

This matrix is used to calculate transition probabilities. These probabilities are calculated following equation 4.4 for which figure 4.13 illustrates the procedure.

$$P(s,a,s') = \frac{N(s,a,s')}{\sum_{n=1}^{S'} N(s,a,s')} \tag{4.4}$$

In case conditions are used, only ADS-B data is used under these conditions. Conditions are coupled by the timestamp found within both data. In order to use conditional planning, new observation counts are needed for ADS-B data under these conditions only.

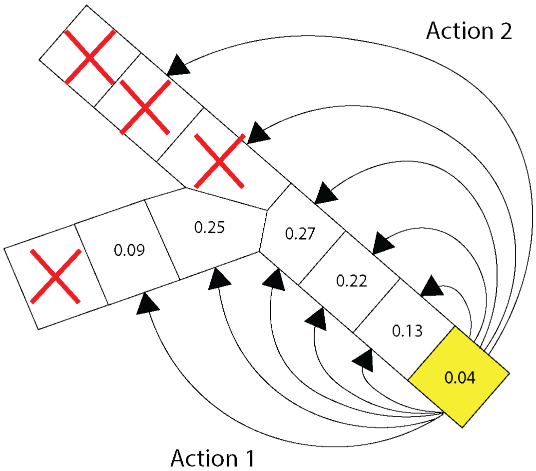


Figure 4.13: Transitions are divided by the total number of transitions to get to probabilities

4.3.5. Objectives translated in rewards

Within section 4.2.3, the objectives were stated in order of preference. Also a function was found in figure 2.7 that illustrates the value for end time. The function found by Deau et al. [12], given in figure 2.7, will be translated to a reward function at the destination within the MDP.
First of all, a high reward is set at the destination in order to introduce motivation for the taxiing operation. The model will look for a way to get to a reward. During operation, taxiing costs may lead to an aircraft not leaving the gate. Therefore, a reward is needed at the end which is allowed to decrease due to punishments and is not able to drop below zero within the planning horizon.
Within the current model, we would like to find the value of the taxi operation. But when reward at

destination is set low, it is possible that situations can be recognized that are not rewarding enough to depart for. For instance outside the CFMU slot, where take-off is not allowed without requesting a new slot time. Recognition of these cases is outside the scope of the project and therefore a reward is chosen that doesn't drop below zero at any place within the infrastructure.
Two different objectives have been formulated, that need to be captured within value. These two objectives are captured within parameters 4.5 and 4.6.

- Reward function, specific for actions performed within states :

$$R(S,A) \tag{4.5}$$

- Terminal reward function, time-dependent, specified for destination states:

$$H(S,A,t) \tag{4.6}$$

Both vectors give a reward that can be found within a state, but the main difference is whether an agent will remain in the planning system. Factor R represents the reward given for an action undertaken within a state, with an action where the agent will remain within the system. Factor T, in contrary to R, represents a terminal reward after which the agent will terminate the planning process. Therefore, R represents the rewards during taxiing while T represents the reward for end time. It is important to find T to be dependent on time.
First, the R factor will be discussed. Within this reward factor, different types of states and actions can be found. For these types of actions, the values can be found in table 4.2

Type of action and state	**Elements**	**Reward**
Holding at start point	$s_{start} \in S, a_{hold} \in A$	$R(s_{start}, a_{hold}) = 0$
Taxiing	$a_{taxi} \in A$	$R(S, a_{taxi}) = -1$
Holding at parking place	$s_{park} \in S, a_{hold} \in A$	$R(s_{park}, a_{hold}) = -1$
Holding on taxiway	$s_{taxiway} \in S, a_{hold} \in A$	$R(s_{taxiway}, a_{hold}) = -2$

Table 4.2: Rewards found for specific actions and states

For the terminal reward, a function over time can be found exclusively for the goal state. For all other states, no reward will be found. The terminal reward will be build according to the objectives given in section 4.2.3. Three different objective values came back that can be found in table 4.3

Objective	**Elements**	**Reward**
Reaching goal	$t \in T$	H(s,a,t) = 1000
Later arrival (than TTOT)	$t >$ TTOT	$H(s,a,t) = -2*(t-\text{TTOT})$
Offset to TTOT	$\lvert t-\text{TTOT}\rvert > 0$	$H(s,t) = -1*\lvert t-\text{TTOT}\rvert$
Outside CFMU slot	$t < t^{CFMU}_{start} \quad OR \quad t > t^{CFMU}_{end}$	$h(s,a,t) = -200$

Table 4.3: Terminal rewards found for time instances at end point

These values have led to the function found in figure 4.14, 4.15 and 4.16. Within these functions, the reward is given for a 30 minutes planning horizon. The blue line indicates the TTOT and the green and red line indicate the begin and end of the CFMU slot.

4.4. Markov Decision Process

Within 4.3, the inputs for the MDP have been defined. Within the current planning process, use will be made of the 'Finite Horizon Markov Decision Process' within the toolbox found from INRA Toulouse [18]. For this toolbox, the following inputs were defined:

- State space S: segments within the infrastructure with a specified heading

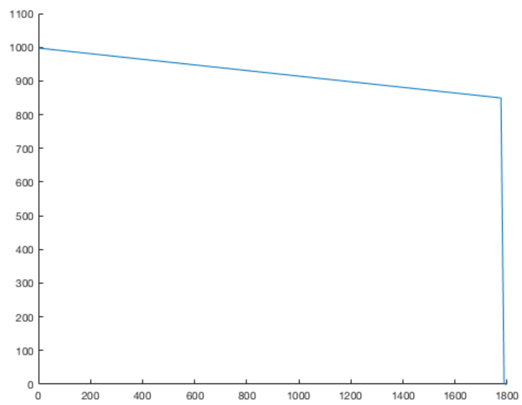


Figure 4.14: Terminal reward function found for arrivals

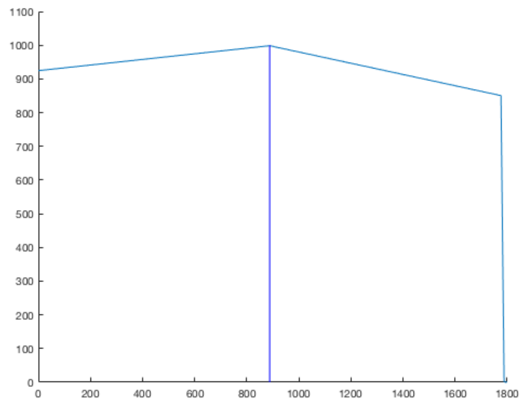


Figure 4.15: Terminal reward function found for departures with TTOT

- Action space A: taxiing actions with the target connection, or holding action at segment
- Transition Probability P(S,A,S'): Transition probability based on historic data
- Reward array R(S,A): Reward based on action within specific types of states
- Discount factor γ: Factor not used, so set to 1
- Number of stages N: Number of transition possible within planning
- Terminal reward array H(S): Terminal reward for reaching destination state

It can be found that almost all inputs have been formulated. But for the terminal reward, it is not possible to differ it over time. Therefore, a modification has been done to the model. To be able to use time specific terminal rewards, the reward has to be changed every transition. Therefore, the MDP will be put in a loop, where value of the states will be transferred to a new transition simulation. Within this simulation, the value represents the value of the future states that can be reached. Backward simulation will therefore still take place, but it is of importance to save the policy and value found per time step. An overview of this loop is given in figure 4.17. The values found for the segments will be translated into the future states value within the next MDP run. Before every run, the value of the end segment will be adjusted with the end states value. For Schiphol, the inputs for the model have the characteristics found in table 4.4. These characteristics are of importance when checking for scalability and will therefore be tested later. Computational time depends on these inputs.

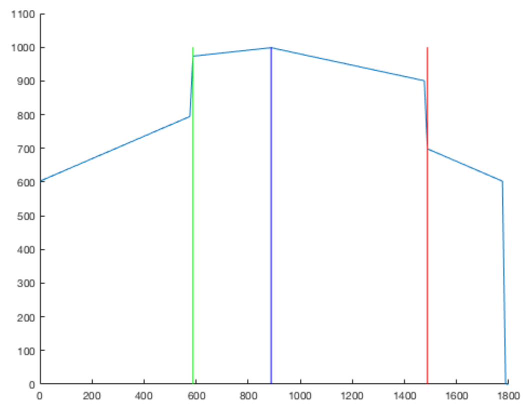


Figure 4.16: Terminal reward function found for departures with CFMU slot assigned

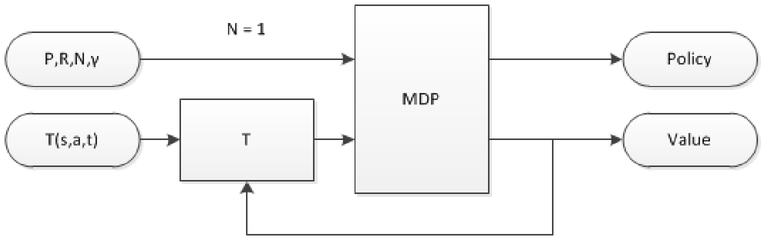


Figure 4.17: Loop for time-dependent terminal reward

Parameter	Build-up	Size
P	SxAxS	2002x4x2002
R	SxA	2002x4
γ	-	1
k	-	1
H	SxT	2002x150

Table 4.4: Parameter characteristics as input for the MDP

4.5. Translation into Routing and Timing advise

When the MDP is modeled over the amount of transitions within the planning horizon, a value and policy are given as output. This value and policy can be used to provide the aircraft with routing and timing advise and are the objective function of the model. Value optimum and policy is calculated through equation 4.7 and equation 4.8, which represent the objective function for each decision epoch.

$$\pi(s) = max_a\{\sum_{s'} P_a(s,s')(R_a(s) + \gamma V(s'))\} \tag{4.7}$$

$$V_\pi(s) = \sum_{s'} P_{\pi(s)}(s,s')(R_{\pi(s)}(s) + \gamma V(s')) \tag{4.8}$$

During taxiing, use can be made of the value and policy function to check which action to undertake within every possible state it can be in. Within the routing advise, taxiing actions will advise on which connection to get to. This advise can be found in the policy space π, which will be dependent on time and state. For departures, the agents will wait at the start point (engines off) till value is maximal (TSAT).

The policy will serve as a 'vector' field that can change over time. Vectors within this field represent actions at time instances, which do not necessarily represent through which actions the value can be found. Therefore routing, but also timing, depend on the time instance an aircraft will reach a certain state and will not traverse a static vector field. It is able to provide the action to take at each state within the infrastructure.
To illustrate how an aircraft will get through this field to capture value at the end of the route, a simulation will be made. Within this simulation, a significant number of aircraft will perform a operation from the start point. By transitioning from state to state, it will simulate through the infrastructure. Tracks of aircraft can be plotted to check which routes are chosen, and which motivations for these routes can be found. The build-up of this simulation can be found in figure 4.18.

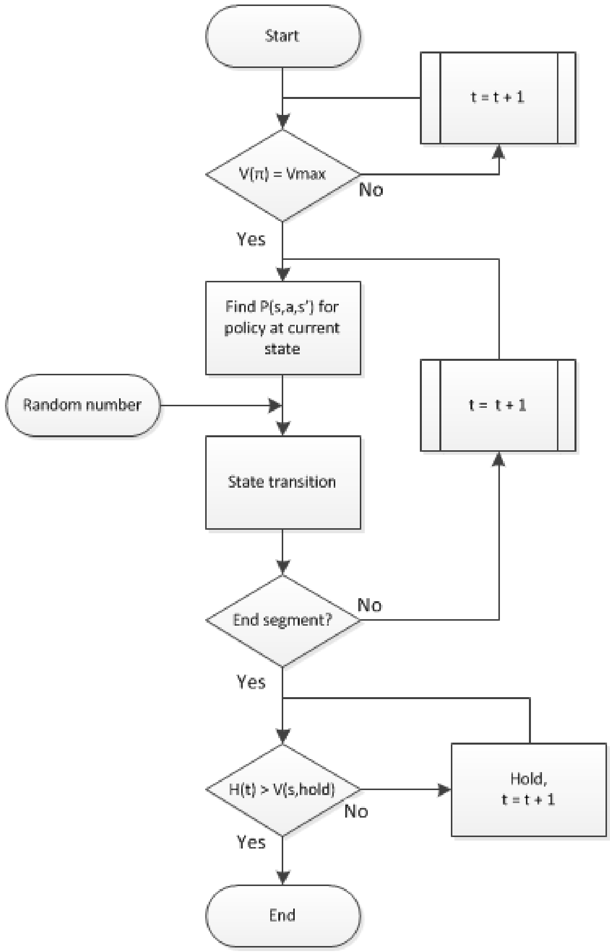


Figure 4.18: Build-up of the simulation tool, starting with waiting for maximum value followed by transitioning to end point, where it will leave for maximum value

After simulation of the MDP for the objectives given, the simulation of aircraft can be done based on value and policy found. At the start the aircraft will look for the optimal time to depart. This can be right away when value at the end keeps decreasing, but may also be later in time. When the maximum value is found for the start position, the aircraft will start taxiing.
Within the policy, the action for that time instant will be found. Following this policy, a probability distribution is found for the possible future states. Probabilities are stacked (to one), and through a random number, a future state is found. The aircraft will transition into this state, after a new transition process will be performed at the next time instance. During this process, actions like taxiing or holding can be found.
After an amount of time, the aircraft will reach the end state, where it will find a terminal reward. When the final state is reached, it will terminate when this terminal reward is the highest value

found. But it is also possible that later in time a higher reward is found that is worth waiting for. In this case, the aircraft will hold at the final state till this terminal value is reached.
This process is repeated for a high number of times to provide insight into the policy provided by the MDP.

5 Results

Within the results chapter, different tests will be performed to give insight into the model under specific circumstances. These tests are needed to validate the model, check the results for different scenarios and objectives and to check computational sensitivity of the model for implementation elsewhere.

5.1. Overview

Within the following sections, the results for the model will be given. The characteristics that are checked are:

Check coverage of airport through data

Significant data is needed to build up the MDP. It is expected that 50 observations are needed for a state to have a representative transition probability function for it. A difference is expected for the map of AMS, since one data set only covers the north-west part of the airport. A map will show for the states how many observations were made.

Validation of model

Second, a validation will be performed in which the model will be tested on shortest path. The scope of the project was to set up a model that is able to capture uncertainty within the operation. This uncertainty is translated into the taxi time. Through propagation uncertainty within the model, arrival time will differ and this uncertainty is of importance. Within this validation, the uncertainty in arrival time will be compared with the uncertainty for aircraft in reality. Routes with a high amount of tracks are used for validation.

Simulate for three different objectives

Three different objectives have been defined within section 2.4. These three objectives will be simulated within the MDP on routing and timing. Routes will be compared within similar start and end points, but under different reward sets and functions.

Simulate for offset in start time

To see which behavior can be expected under a time offset at the start of the operation, aircraft will be send at different start times. Under the three different objectives changes in behavior are expected. The system should be able to offer a plan for the aircraft that is still optimal for the current condition it is in.

Conditional planning

Since circumstances may influence the uncertainty within the whole course of the operation, a MDP will be build based on observations made under the same circumstances. This model will be validated in the same way as performed for the standard model. The simulation will be based on three types of configurations, specific for normal load, starting peak and landing peak.

Computational analysis of sensitivity of the planning method to differences in input
A goal for the project is for the model to be made implementable for other airports. Therefore it is of importance to test computational sensitivity to input parameters. Differences in infrastructure can be found that influence the amount of states and actions. User or ADS-B data found may need a different time step, also the planning horizon may be increased or decreased. Last, different objectives at the airport may call for new input parameters. Sensitivity to these parameters will be tested to check how the system reacts to these changes.

5.2. Airport coverage by data

To set the data to obtain transition probabilities, different data processing steps are followed. The data is processed towards a transition probability matrix. Through different filters, the data is processed and counted within the transition counter. This decreases the amount of data, which is of importance. This decrease can be found in table 5.1.

Data processing step	Data points	Flights
Without filtering	907248	13700
Valid flights	251551	3384
Within segments		
All data	530478	-
Valid flights	231002	-
Transition counter		
All data	324258	-
Valid flights	196100	-

Table 5.1: Data through filters of data processing, reducing the usable amount of data

Segmentation in section 4.3.1 leads to a total of 2002 possible states. Transition probability for these states is based on the amount of transitions made by aircraft from this segment. To represent a transition uncertainty, it is assumed that 50 observations are needed. Within figure 5.1 and 5.2, the amount of transitions for each state is given. One-way segments are left away within the second figure.

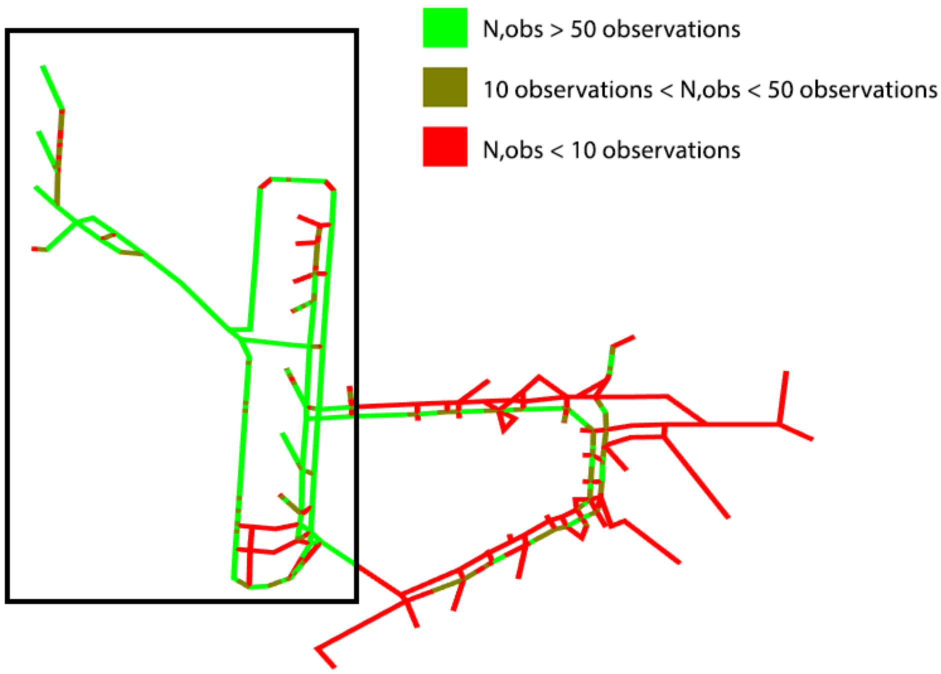


Figure 5.1: Amount of observations made for each state within first heading found for segment, with in black box the coverage of the biggest data set

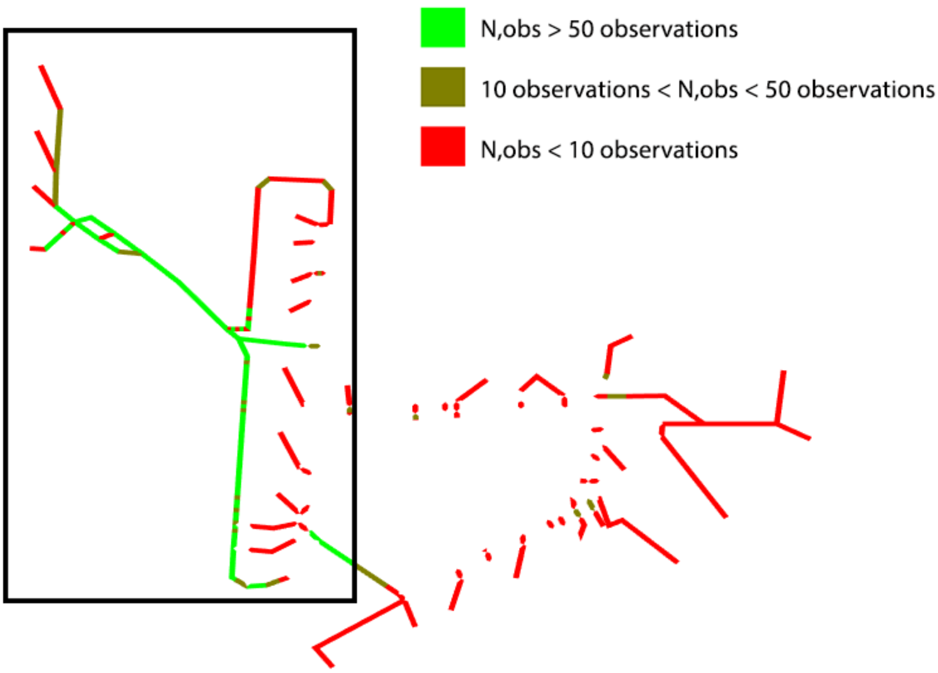


Figure 5.2: Amount of observations made of second heading found for each two-way state, with in the black box the coverage of the biggest data set. One-way segments have been left away

Not for all states, 50 observations are made. A second data set of flights only covers the north-west area of the airport, which can be found within the figure. Even within this area, states can be found with less than 50 observations. But almost all states within the north-west region have been used. The figures are based on transitions counted for all data and not only for the 'valid flights'.
At the entrances of the Polderbaan, in the north-west of the airport, it can be found that most entrances are not used. They are only used as exit for arriving traffic, and the entrance at the south only for departures. It must be said that states within one figure not necessarily represent the states used by arrivals towards the terminal region. For departures only the south entrance is used, which is logical since it offers the longest runway distance to take-off on. For some small parts in the north west region, the coverage is lower than 50. But since they are still covered, it is expected that the effect will be minimal over total taxi distance.
Since the north-west region, given in the black box, provides the most reliable data representation, only this region will be used in further solutions. Within this data two runways are present that can be used and two entrances and exits can be found towards the terminals of the airport. One can be found in the north, where one taxiways functions as exit and one as entrance. The other can be found in the south, which is used in two directions. Not all runways are operated in all possible configurations, since the Zwanenburgbaan is not operated towards/from the south. Within figure 4.5 this option is considered in the fifth preference (Start runway 18C or arrival runway 36C), which is handled only under special circumstances. Therefore it is not strange that coverage is poor. More data is needed to be able to cover the whole airport.

5.3. Validation

To validate the model, it will be tested for shortest path in time. It is possible to set a decreasing reward in time at the end for which the model will look for the fastest way to get towards this reward. As reference, validation will be done with the ADS-B data. Within this data, the start and end time can be found for operations and will be compared to the uncertainty found by the model. Comparison will be done for similar routes.

For this validation, four routes will be compared:

1. Departure Polderbaan from the north taxiways around the terminals, with Zwanenburgbaan open
2. Arrival Polderbaan towards the north taxiways around the terminals, with Zwanenburgbaan open
3. Arrival Polderbaan towards the north taxiways around the terminals, with Zwanenburgbaan closed
4. Departure Polderbaan from the south taxiways around the terminals, with Zwanenburgbaan open

For all four routes, the mean travel time and standard deviation are calculated. For both the simulated and actual tracks, this time is calculated and presented in table 5.2.

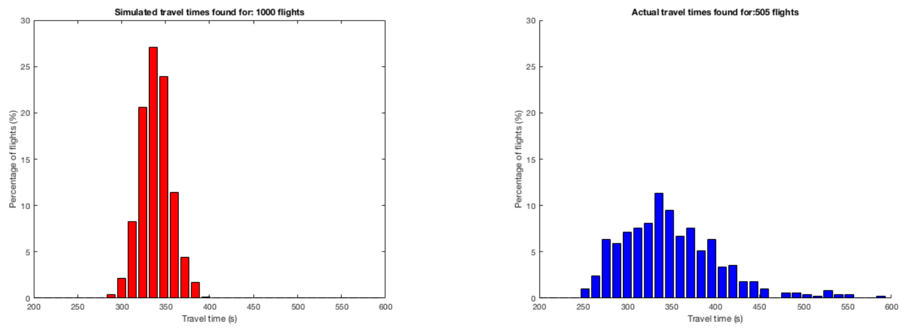
Route number	**# flights**	**Actual flights**		**Simulated flights**		**Offset of mean** (%)	**Captured uncertainty** (%)
		μ	σ	μ	σ		
Route 1	505	355	56	339	18	4,5	32,1
Route 2	1624	345	56	333	16	3,5	28,6
Route 3	361	578	66	576	21	0,3	31,8
Route 4	312	440	70	467	22	6,1	31,4

Table 5.2: Mean and standard deviation given for four standard routes

Within the simulated results, the uncertainty in travel time found is smaller. Within the travel time division in figure 5.3, a wider division can be found for actual travel time. Also outliers can be found in figure 5.4, where travel time is more than two times higher than the fastest operation. Within the simulation, both fastest and slowest travel times are not found. The difference in simulated times, compared to actual times, is not due to the route taken. An explanation can be found in the unconditional transition, captured by the MDP. Within the simulation, after a transition of the maximum amount of segments, it is possible that a transition is found of zero segments. In real operations, an aircraft may taxi faster when traffic density is low and visibility is high. In bad visibility conditions, a pilot may decide to lower its speed for safety reasons. This will lead to a lower average amount of states travelled within a the specified time period and consequently to a longer travel time. These conditions that influence the speed of the whole operations are not captured by the model. Therefore conditional planning is proposed, where data is gathered only for specific conditions as traffic density or visibility. A conditional planning approach is presented later in section 5.7

Another influence on the result can be that holding for conflicts is not fully captured. In literature, an average of 29 seconds was found for holding for conflicts or disruptions. But within the current model, after a transition in which an aircraft has held, a transition representing taxiing with high speed can be found. A chance of 10% for transitioning to the same segments, leads to a chance of 1% that the aircraft will hold twice at that spot. Within actual operations, follow-up holding actions are more related. This is of influence on the spread of the actual results, compared to the simulated operations.

Figure 5.5 illustrates the routes taken, which are similar. Only at the end of the simulated operations, two different routes are taken. On taxi time, this difference in routing is not of influence but is due to different recommended actions within separate states. Although not of influence, it brings in unpredictability of routing behavior that is unwanted. When two different routing options bring in negligible differences, the model may choose different actions within separate states. A way to deal with this behavior is to restrict taxiways to one-way taxiways to stimulate a flow over one taxiway. But this restricts the routing options for the model. Also, it is of importance to see whether this inability to choose a route influences safety, or may lead to deadlocks. For the current segments under consideration, this is not the case.



(a) Travel time for simulated flights

(b) Travel time of actual flights

Figure 5.3: Route travel times from north of terminal to Polderbaan (Zwanenburgbaan crossing open)

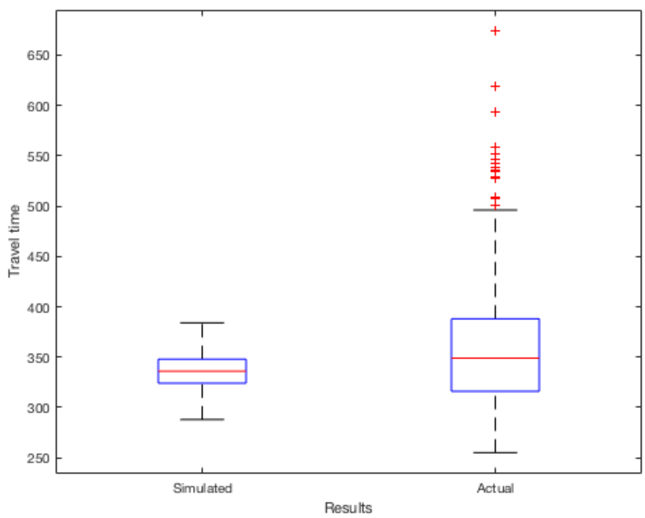
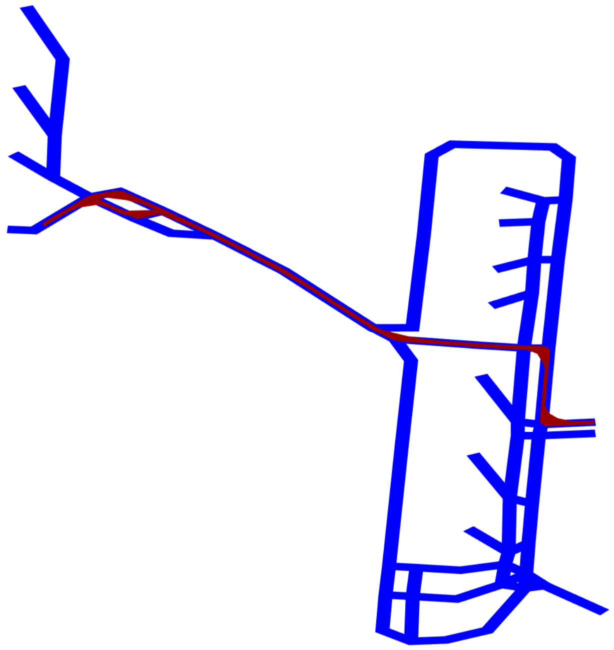
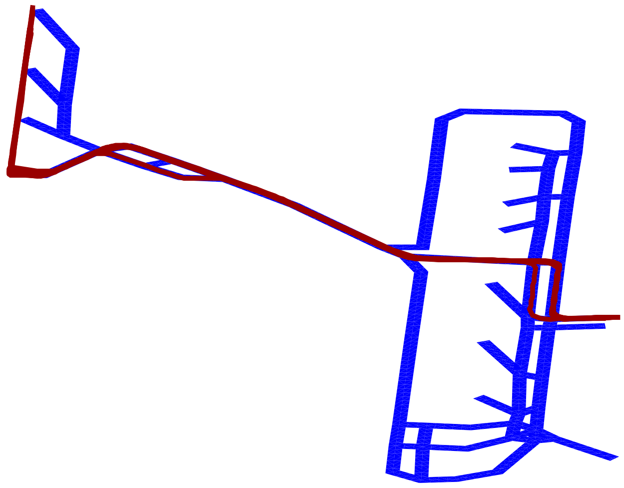


Figure 5.4: Boxplot for taxi times from simulation and actual operation



(a) Simulated tracks plotted over infrastructure (1000 tracks)



(b) Actual tracks plotted over infrastructure (505 tracks)

Figure 5.5: Route tracks from north of terminal to Polderbaan (Zwanenburgbaan crossing open)

Since operational uncertainties represent both speed and conflict uncertainty, a second test case is set-up. Within this test, route 3 is split-up into two parts at the red line in figure 5.6. Within the part on the left, low chance of interaction with other aircraft is expected. The route is only handled by aircraft landing at the Polderbaan, and all will travel in one direction. Catching up is the only conflict that may occur, but this type of conflict only reduces the speed of aircraft. This is the reason that uncertainty will mainly be reflected in speed uncertainty. Since a route along the south needs to be chosen, it can be expected that the 'Zwanenburgbaan' is in operation (most likely for arrivals, exiting on the taxiways south-east), and therefore in the second part of the route more traffic interaction is expected. These aircraft may cross the route at the south entrance towards the terminal, or join the route at the north of the terminal. The effect of conflict uncertainty is expected to be higher within this part of the route. Although average speed is somewhat lower for the second part of the route, which may be due to a higher chance of conflict, a comparable portion of the uncertainty is captured. The mean travel time is comparable, and therefore for both pieces of taxiway the uncertainty is captured and not compensated by capturing one type of traffic uncertainty better. The model therefore does not perform better when conflict uncertainty is expected to be lower. But more research is needed to make conclusions on these effects.

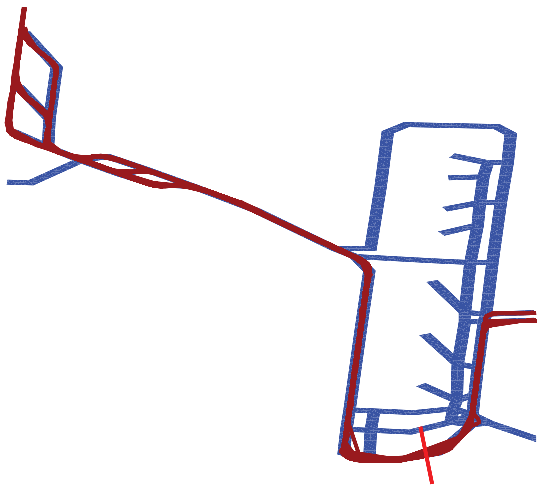
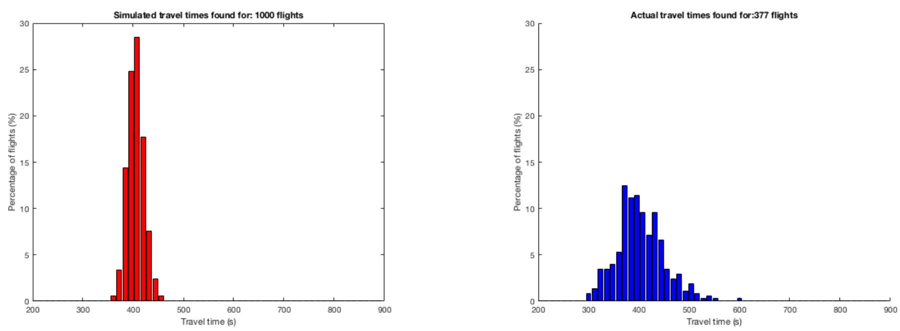


Figure 5.6: Actual route tracks from Polderbaan to north of terminal split into two parts (Zwanenburgbaan crossing closed)

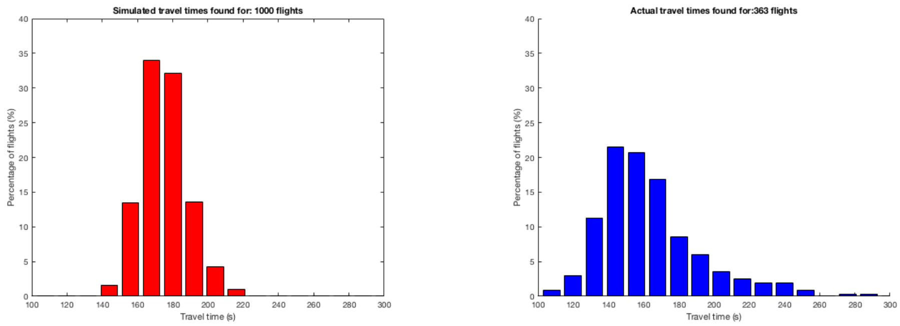
The found taxi times are plotted within figure 5.7 and 5.8. Results are given in table 5.3.



(a) Travel time for simulated flights

(b) Travel time of actual flights

Figure 5.7: Route travel times from Polderbaan to south of Zwanenburgbaan (Zwanenburgbaan crossing closed)



(a) Travel time for simulated flights

(b) Travel time of actual flights

Figure 5.8: Route travel times from south of Zwanenburgbaan to north of terminal (Zwanenburgbaan crossing closed)

Route number	# flights	Avg. speed (m/s)	Actual flights		Simulated flights	
			μ	σ	μ	σ
Route 5a	377	11,4	409	47	405	17
Route 5b	363	10,9	168	29	175	13
Route 3	361	11,3	578	66	576	21

Table 5.3: Mean and standard deviation given for parts of standard route 3

5.4. Simulation for different objectives

Within this section the model will be tested on three different objectives. Values are set-up in section 4.3.5, which are presented again in table 5.4 and 5.5. Differences are most significant in end-time for which different functions can be found. These value functions will be presented. With these values, three different objectives will be tested on routing and timing: arrivals, departures and departures under CFMU slot. A route from the south of the terminal towards the Polderbaan is chosen, with the Zwanenburgbaan unused (open).

Type of action and state	Elements	Reward
1A. Holding at start point	$s_{start} \in S, a_{hold} \in A$	$R(s_{start}, a_{hold}) = 0$
1B. Taxiing	$a_{taxi} \in A$	$R(S, a_{taxi}) = -1$
1C. Holding at parking place	$s_{park} \in S, a_{hold} \in A$	$R(s_{park}, a_{hold}) = -1$
1D. Holding on taxiway	$s_{taxiway} \in S, a_{hold} \in A$	$R(s_{taxiway}, a_{hold}) = -2$

Table 5.4: Rewards found for specific actions and states

Objective	Elements	Reward
2A. Reaching goal	$t \in T$	H(s,a,t) = 1000
2B. Later arrival (than TTOT)	$t > \text{TTOT}$	$H(s,a,t) = -2 * (t - \text{TTOT})$
2C. Offset to TTOT	$\lvert t - \text{TTOT} \rvert > 0$	$H(s,t) = -1 * \lvert t - \text{TTOT} \rvert)$
2D. Outside CFMU slot	$t < t^{CFMU}_{start} \quad OR \quad t > t^{CFMU}_{end}$	$H(s,a,t) = -200$

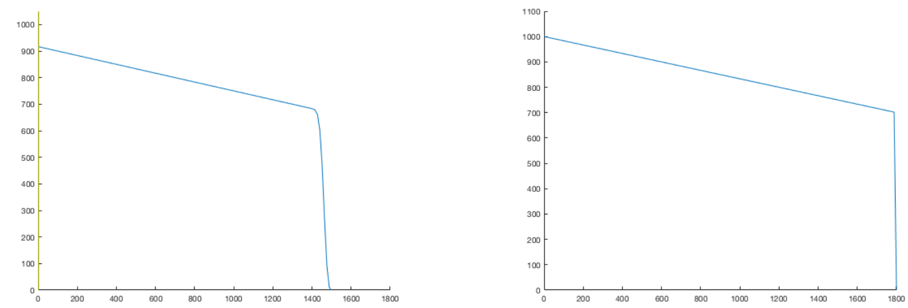
Table 5.5: Terminal rewards found for time of arrival

Arriving flight

First, an arriving flight is discussed. The route chosen is from the Polderbaan towards the north of the terminal, with Zwanenburgbaan not in use (open). This configuration is one of the first preferences and therefore can be found quite often. For this operation, the following objectives are of importance:

- 1B. Taxiing ($R = -1$)
- 1D. Holding on taxiway($R = -2$)
- 2A. Reaching goal ($H = 1000$)
- 2B. Later arrival ($H = -2/\delta s$)

First of all, a goal is set to reach a gate as fast as possible. Therefore, every time instance spent in operation is punished, captured in a cost for taxiing and holding. A later arrival at the gate also costs since crew costs increase over time and chance may exist that passengers will miss a transfer. This value division leads to the value function at the begin and end, given in figure 5.9.

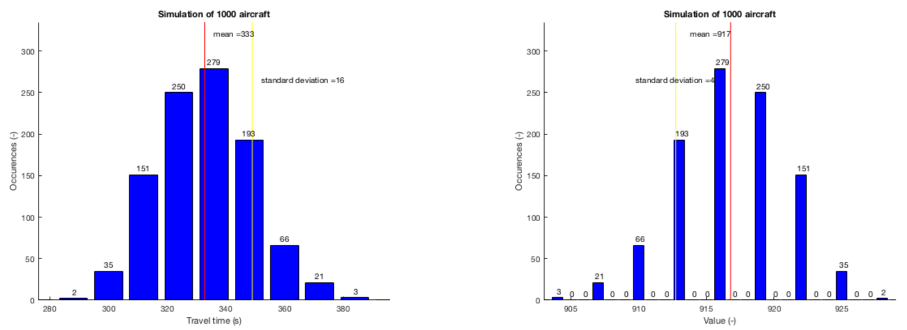


(a) Value function at start point

(b) Value function at end point

Figure 5.9: Value function for arriving aircraft

Within the value function, a decrease in value at the starting point can be found. Although an aircraft is not able to choose its start time to capture optimal value, uncertainty may present a deviation in start time and therefore a different value for the taxi operation is found. At the start point, a high decrease in value is found around 1450 seconds. From this point in time, it is unlikely that the aircraft will reach the gate within the planning horizon. An arrival time outside the planning horizon may still hold value, but a delay causing an aircraft to start after 1450 seconds is highly unlikely. In case of occurence, the model is able to perform new calculations.
The travel time for an arriving aircraft is plotted in figure 5.10, as is the value for the simulated aircraft. A step-wise value division of 3 can be found, which is due to an extra time step of taxiing which costs a value of 1 for taxiing and a value of 2 for later arrival. A division in travel time over 100 seconds can be found, but most results are within 1 minute of each other.



(a) Division of travel time

(b) Values found for simulated aircraft

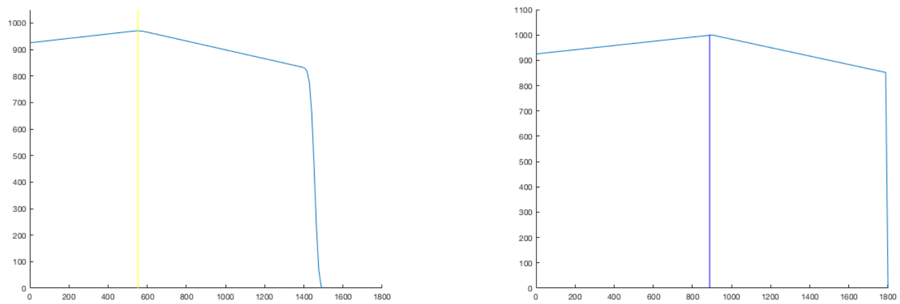
Figure 5.10: Simulation results for arriving aircraft

Departure with TTOT

Second, a departing flight with a TTOT is presented. The route chosen is from the north of the terminal to the Polderbaan, with Zwanenburgbaan not in use (open). For this operation, the following objectives are of importance:

- 1A. Holding at start point ($R = 0$)
- 1B. Taxiing ($R = -1$)
- 1D. Holding on taxiway($R = -2$)
- 2A. Reaching goal ($H = 1000$)
- 2B. Later arrival (than TTOT) ($H = -1/\delta s$)
- 2C. Offset to TTOT ($H = -1/\delta s$)

The rewards found for the departing aircraft differ a little bit with the rewards found for an arrival. For instance, an aircraft is able to hold at the gate with engines off. For this action, no costs are found as it is of lowest cost within the operation. It doesn't however contribute to reaching the goal and therefore taxiing is needed. A cost for offset to TTOT is found, where a higher cost is found for later arrival compared to earlier arrival. Earlier arrival is of less cost than holding, and therefore an aircraft arriving earlier than TTOT is likely to terminate at end point instead of holding there.
This value division leads to the value function at the begin and end given in figure 5.11. A TTOT of 900 seconds (15 minutes) after planning horizon start is set.

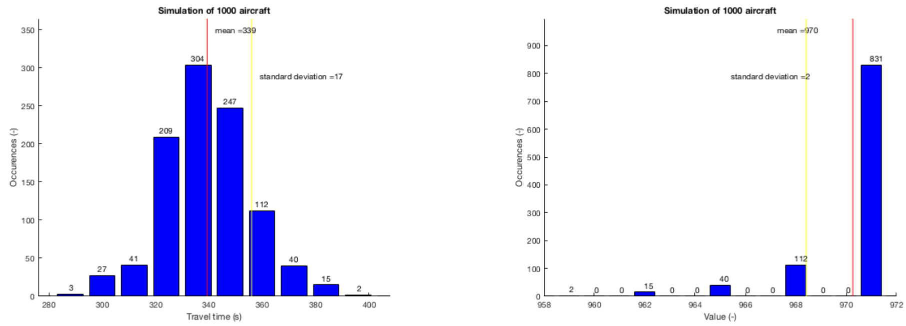


(a) Value function at start point

(b) Value function at end point

Figure 5.11: Value function for departing aircraft

The travel time for a departing aircraft is plotted in figure 5.12, as is the value for the simulated aircraft. Taxiing operation is started at 552 seconds within the planning, which is considered as TSAT within this thesis. The aircraft waits until this time at the gate with the engines off, and therefore saves costs. Within this reward setting, it is likely that in some cases the aircraft won't arrive at the runway in time for the TTOT. Within figure 5.12, it can be found that 169 flights (16,9%) have a taxi time longer than the 348 seconds left to taxi. All other flights are in time. Since arriving a time step earlier than TTOT decreases costs of taxiing by 1, but since value at the end is also decreased by 1, all values result to 971. By changing the degradation in reward for flights later than TTOT, a change in on-time ratio is expected. This sensitivity will be explored within section 5.6.



(a) Division of travel time

(b) Values found for simulated aircraft

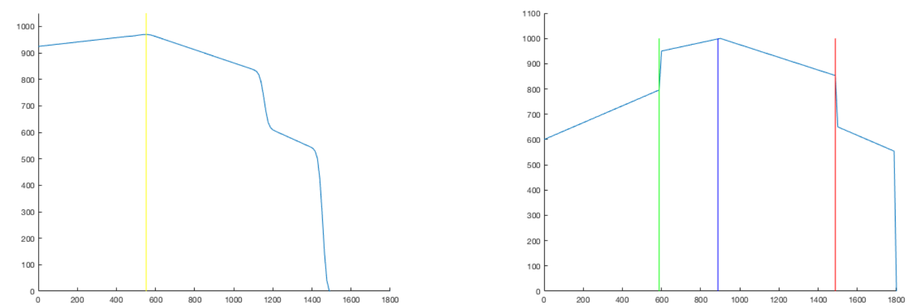
Figure 5.12: Simulation results for departing aircraft

Departing Aircraft under CFMU slot constraints

Last, a departing flight with a TTOT and CFMU slot is presented. The route chosen is from the north of the terminal to the Polderbaan, with Zwanenburgbaan not in use (open). For this operation, the following objectives are of importance:

- 1A. Holding at start point ($R = 0$)
- 1B. Taxiing ($R = -1$)
- 1D. Holding on taxiway($R = -1,5$)
- 2A. Reaching goal ($H = 1000$)
- 2B. Later arrival (than TTOT) ($H = -2/\delta s$)
- 2C. Offset to TTOT ($H = -1/\delta s$)
- 2D. Arrival outside CFMU slot ($H = -200$)

A decrease in value is found for arrival at the runway outside the CFMU slot times. This decrease is significant, since outside the CFMU slot, an aircraft is not allowed to depart from the runway. Within the uncertainty of simulation, it is highly unlikely that an aircraft will arrive outside the slot time when choosing a start time, but it may become of interest when an offset in start time is found. Since within the departure route presented before the aircraft would not hold but would exit at the end, the value for holding is decreased and the value for late arrival increased. This value division leads to the value function at the begin and end given in figure 5.11.



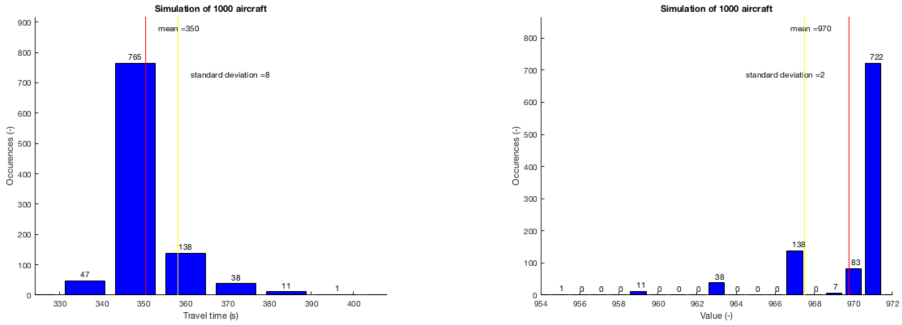
(a) Value function at start point

(b) Value function at end point

Figure 5.13: Value function for departing aircraft under CFMU slot

The travel time for a departing aircraft is plotted in figure 5.14, as is the value for simulated aircraft. No travel times shorter than 330 seconds was found, while these taxi times were found for normal departures. It can be found that the aircraft holds during travel, shown in figure 5.15. Within routes of the simulations it can be found that holding is performed at the end of the route,

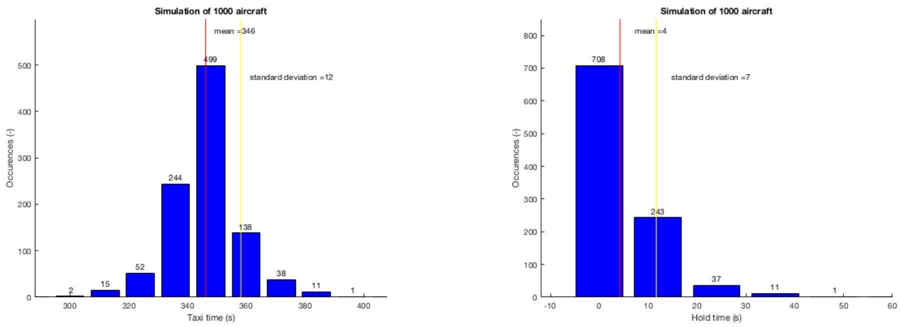
what is logical since timely arrival at the runway is ensured for these flights.
Since no significant difference in value degradation is found after TTOT, no other start time is found than for normal departures.



(a) Division of travel time

(b) Values found for simulated aircraft

Figure 5.14: Simulation results for departing aircraft under CFMU slot



(a) Division of taxi time

(b) Division of hold time

Figure 5.15: Simulation results for departing aircraft under CFMU slot

Summary for objectives
Within table 5.7, the results for the simulations under different objectives are summarized. The suggested start time is found for departures, which returns the highest value captured by the model. This start time presents a trade-off between travel time and portion to be late for target times. Within the departure under CFMU, the reward for holding was lower than for terminating at end segment and therefore a longer travel time is found.

Parameter		Arrival	Departure	Departure under CFMU
Simulation time (s)		17	17	18
Value (-)	μ	917	970	970
	σ	4	2	2
Travel time (s)	μ	333	339	350
	σ	16	17	8
Start time (s)		0	552	552
Max. value at start (-)		916	970	970

Table 5.6: Parameters for different objectives, with specific taxi times and start times per objective

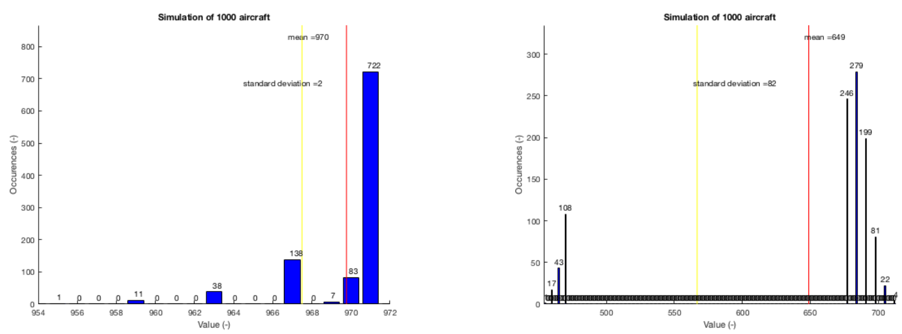
Influence on taxi behavior through rewards Within this section, it is shown that through different sets of rewards, taxiing behavior can be manipulated. Differences in reward for actions, like taxiing and holding, can influence behavior. But these rewards can also be set for performing these actions within single states. Also at the end, different sets of rewards over time are available. A reward can increase or decrease over time, but also hard threshold can be set. Therefore both offset to target times as deadlines can be modulated within the reward function. Behavior of the model under different reward sets will be given in section 5.6.

5.5. Behavior under offset in start time

By setting an offset to the start time, we can check in which way the operation is influenced on routing and timing. Larger variation is found within actual results, and therefore analysis of robustness under offset in start time is needed to check behavior of the model. Since pre-tactical uncertainties may cause an aircraft to depart later or maybe earlier, the system needs to be robust to this uncertainty. For the route considered, arrival within the area of interest may be earlier or later. For this section, it has been chosen to analyze the departure under CFMU, since the most constraints can be found. Values will be chosen that stimulate taxiing over holding, but also a high degradation in value outside target times can be found. We therefore model towards arriving just in time, which is of importance to prevent the model from holding just in front of the end state. The values used are set as following:

- 1B. Taxiing ($R = -1$)
- 1D. Holding on taxiway($R = -2$)
- 2A. Reaching goal ($H = 1000$)
- 2B. Later arrival (than TTOT) ($H = -2/\delta s$)
- 2C. Offset to TTOT ($H = -4/\delta s$)
- 2D. Arrival outside CFMU slot ($H = -200$)

First, an offset in time of 10 minutes is simulated where aircraft depart later than the suggested start time. Therefore, aircraft are not able to arrive in time for the TTOT. But this time of departure is also at the border of the CFMU slot. Simulation results for the delayed operation can be found in figure 5.16. First of all, the mean value for the delayed aircraft are lower than found for normal aircraft. This is logical, since aircraft are held at the start point for 10 minutes longer, increasing the chance of late arrival. But it can be found that a chance is present that the aircraft will not arrive in time for the CFMU slot or other hard time constraints. Therefore, a decrease in value is found for 16,6 % of the flights. This chance creates the large gap in value, and can therefore be very important. Within validation it can be found that outliers with longer travel times can be found, which are not found by the model. Failure of the current model to capture all uncertainty increases the chance of missing deadlines. Therefore, a buffer is needed of around 1 to 2 minutes to be able to assure timely arrival by following actions of the model.



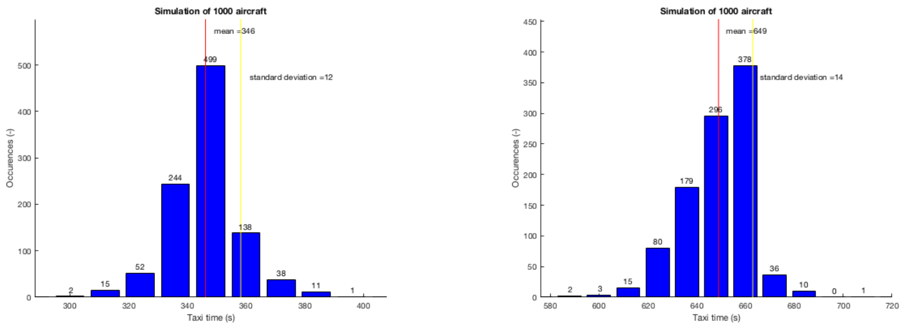
(a) Value division for normal start time

(b) Value division for late start time (10 mins)

Figure 5.16: Simulation results for departing aircraft under CFMU slot, where large drops in value can be found for aircraft arriving too late

Another case considered is the early start, for this case 5 minutes earlier. Since values are set for which taxiing is the most value decreasing action, routing solutions are expected. Within figure

5.17, it can be found that an increase in taxi time can be found for early start time. For aircraft without an offset, a start time of 540 seconds is suggested to get in time for the TTOT. For these flights, 5 % of flights are late for TTOT. Within simulated flights, an equal share is still late for the TTOT. Routing solutions have been found that increase the taxi time, and holding time stays low. Due to a lower reward for taxiing than for holding, elongation of path is chosen. This elongation still poses the chance of late arrival. Behavior for different reward sets is needed. Within figure 5.18, the routes for these simulated flights can be found.



(a) Taxi time for normal start time

(b) Taxi time for early start time (5 mins)

Figure 5.17: Simulation results for departing aircraft under CFMU slot, where chance of arrival decreased for aircraft with early departure

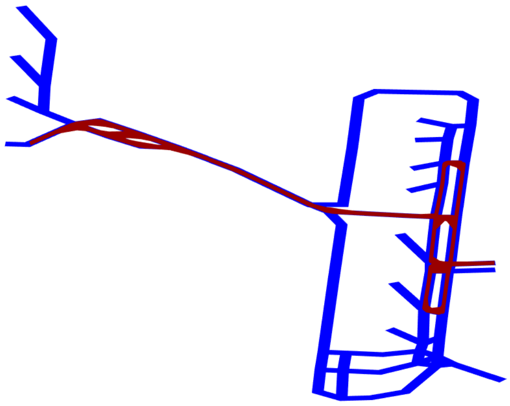


Figure 5.18: Routes for simulation of aircraft with start of 5 minutes earlier, where loops are made to elongate path

Within the routes performed in the simulation, extension of route is done through loops on the taxiways. These loops have extended the time before an aircraft takes the route towards the Polderbaan and over the Zwanenburgbaan. Also at the end, near to the Polderbaan, small loops can be found performed by flights to extend the taxi time. A smaller cost for holding could prevent simulated flights from performing these loops. But also segments can function as parking space, which would lead to holding at these spots when they can be reached in time and don't elongate the route too much.

The loops made within the simulation in the beginning of the operation are problematic. Since actual results indicate that larger offsets in travel time can be found. When loops are been made in the beginning to increase taxiing time, no buffers are present any more to cope with non-captured uncertainty during the rest of the operation. Therefore, an aircraft needs to be stimulated to keep

its buffers till later in the operation, where it can try to maximize value of the operation.
Results for different start times are presented in table 5.7. For early start times it is found that travel time increases with the same amount of time to arrive just in time for the optimal value at the end. But for later start times, the fastest route is taken. A large drop in value can be found around 10 minutes delay where chance of not arriving in time for the CFMU slot is present.

Start time		**No offset**	**-1 min**	**-2 min**	**-5 min**	**+ 5 min**	**+9 min**	**+10 min**
Simulation time (s)		17	18	17	18	17	18	18
Value (-)	μ	969	962	958	943	865	712	649
	σ	2	3	2	2	4	10	82
Travel time (s)	μ	354	421	480	660	865	339	339
	σ	11	5	5	5	16	18	17
Start time (s)		540	480	420	240	840	1080	1140

Table 5.7: Parameters for different objectives, with value and travel times for offset in start times

5.6. Sensitivity to rewards

One objective of this research is to introduce different rewards that can be given to perform agent-specific optimization for multiple objectives. Within this section, the behavior is analyzed for different rewards. First, the rewards will be given in different orders of priority after which they are varied in end value. The rewards of interest are presented in table 5.8 with the different values used in the cases. Since differences in actions for aircraft starting execution too early are of most interest, aircraft are released 2 minutes earlier. In these cases, choices in behaviour are more obvious.

Parameter		**Case 1**	**Case 2**	**Case 3**
Type of flight		Departure	Departure	Departure
TTOT		15 min	15 min	15 min
R (-)	hold	-1	-2	-1
	taxi	-2	-1	-1
H(offset)		-3	-3	-3
Value (-)	μ	932	960	961
	σ	2	2	0
Time (s)	Taxi	342	458	360
	Hold	126	10	108
Travel time (s)	μ	468	469	468
	σ	2	6	1
Start time (s)		432	432	432

Table 5.8: Parameters for differentiated rewards, with differences in holding and taxiing time

Interesting to see is that in case costs for taxiing is higher, the airplane will hold at the end of the route. But when taxiing is of less cost, the airplane will consider different routes at the start to extend its path and will return onto original route. When these costs are set similarly the aircraft still considers these loops at the end, when chance of arriving late is still small. Therefore a wide spread in taxi times can be found, illustrated in figure 5.19. Holding has to be set at most equal to taxiing cost, in order to make sure the aircraft doesn't spend its buffers at the beginning of the operation. Since holding is not of benefit in getting to the goal of the operation, there is no harm in setting holding with a lower cost than taxiing. In order to make sure important taxiways are not blocked by holding aircraft, a lower holding cost can be given at areas where currently multiple routes are chosen. For instance at the end of the route, where the route splits and comes together later on.

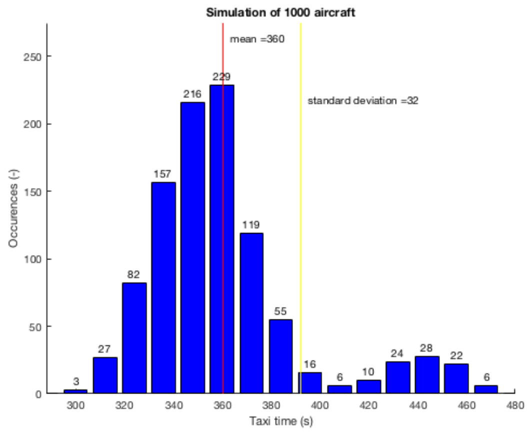


Figure 5.19: Taxi times found for simulation of equal costs for taxiing and holding

Second, a variation in costs for late arrival is considered. To make a trade-off between operational costs for taxiing and loss of runway efficiency, values need to be compared. The value of operational efficiency is captured within costs for offset to time of arrival. Variation leads to differences in start time of the aircraft, captured in table 5.9. Operational costs are increased by a small amount in order to prevent high costs for runway efficiency. Therefore the need of timely arrival can be expressed within this value.
An earlier start time is chosen to decrease the chance of late arrival. Both holding as path elongation are used to increase on-time performance, trade-off to start time. Therefore it is shown that aircraft take chance on offset in arrival time into account when planning start time, routing and timing.

Parameter		**Case 1**	**Case 2**	**Case 3**	**Case 4**
Type of flight		Departure	Departure	Departure	Departure
TTOT		15 min	15 min	15 min	15 min
R (-)	hold	-1	-1	-1	-1
	taxi	-1	-1	-1	-1
H(offset)		-1	-3	-6	-10
Value (-)	μ	971	970	969	969
	σ	2	3	4	11
Time (s)	Taxi	339	344	348	348
	Hold	0	6	13	13
Travel time (s)	μ	339	344	348	348
	σ	17	8	7	7
Start time (s)		564	552	540	540

Table 5.9: Parameters for differentiated rewards, with earlier start time for higher costs for late arrival

5.7. Conditional planning

In section 5.3, a higher variation in taxi time is found for actual travel times. It is concluded that modeling of uncertainty without considering conditional probabilities can cause higher variance in travel time. Therefore, a case is set up in which travel times for different types of configurations is set-up. Since coverage of states needs to be ensured with the limited data sets available, data may only be split-up into some conditional data sets. As condition, configuration is chosen in which a split up is made based on the load/demand on the runways. Different runways are used, causing the set of possible configurations to be big. But a split up is possible between normal load, high departure load and high arrival load. Within these different types of configurations, at least two runways are in use. But an extra start or landing runway can be in use to deal with a peak load in one of the operations. To be able to simulate under different types of configurations, all data needs to be labeled. Configuration data is gathered of Schiphol, collected on the website of LVNL, providing historic configuration data for the airport [2]. The time of the data point is coupled to the configuration used at that time. Next, within the counter to set up the transition probability matrix only data for specific configurations is used. Unfortunately also data is gathered where a switch of active runways was done, and therefore data could not be labeled. The amounts of transitions under the configurations given can be found in table 5.10.

Runway configuration type	Amount of data points
No configurations specified	530478
Normal load	281399
Landing peak	98196
Start peak	62310

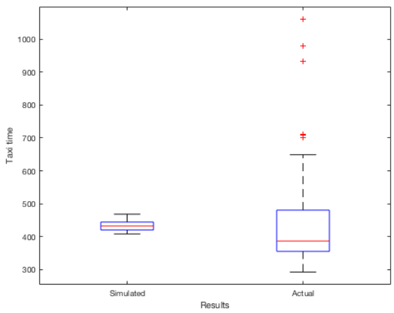
Table 5.10: Amount of transitions found to set up transition probability matrix for different types of configurations

Not all data that is available was captured by this method into specific conditions, since only the preferences specified by LVNL are used found in figure 4.5. Differences in configuration are not registered and data gathered during switches or deviations of configurations are therefore not labeled. Still, the amount of data is high enough to base modulations of popular routes on.
Now a transition probability is specified per type of configuration, analysis of route can be done within these conditions. The specific P-matrix is loaded into the MDP, and runs are done for the arrival route from the Polderbaan towards the south entrance of the taxiways around the terminal. This route is given over the passage of the Zwanenburgbaan. The shortest route is equal for simulated and actual routing of aircraft. The results of the simulation are presented in table 5.11 and figure 5.20 against the actual numbers.

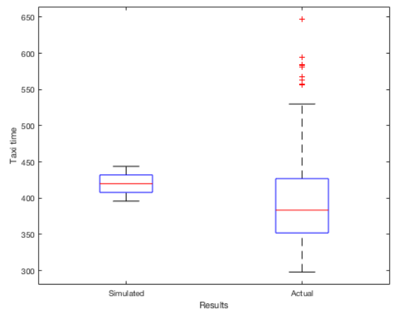
Parameter		All flights	Normal demand	Landing peak	Start peak
Amount of flights (-)		1229	376	262	216
Taxi time - Simulation (t)	μ	432	435	418	409
	σ	19	16	14	13
Taxi time - Actual (t)	μ	412	421	395	389
	σ	77	98	62	68
Offset of mean (%)		4,9	3,3	5,8	5,1
Captured uncertainty (%)		24,6	16,3	22,5	19,1

Table 5.11: Found results for different types of configurations, compared to result of general solution

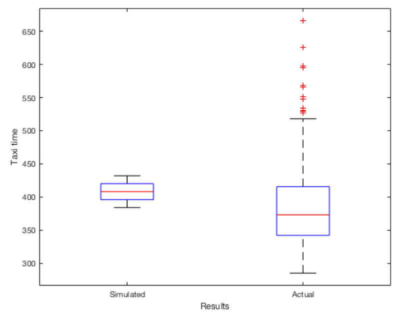
Within the box plots, it can be found that within actual data the spread did not necessarily become more narrow, while this did happen to the spread found in the simulated data. Therefore it seems that within the single data, some relations have been found. But the main contributors to uncertainty have not been found by dividing the data with the current division criteria. The data seems to follow the trend given in the taxi time for the different types of configurations. But in contrary to an expected increase in taxi time for higher demand on the taxiways, the taxi time did decrease instead. Especially during the configurations for normal/average demand, a higher variation is found. A possible reason can be that during peak hours, bigger airplanes land and depart from Schiphol with different speeds and behavior Or at least the mix of aircraft types is different. During normal demand, a bigger mix of different types of aircraft may be found, causing a mix of taxi speeds. But this assumption cannot be supported by data since flight information of equipment is not included in the current data set. Different types of conditions need to be chosen to be able to capture conditional probabilities, or equipment data should be gathered to test this hypotheses.
Since uncertainty found by the model also decreases for conditional planning, a condition is found that explains a mean travel time for aircraft. But the conditional planning did not increase the models ability to capture all operational uncertainty, since its own spread in travel time also decreased. The current conditions are therefore too general to capture specific uncertainties.



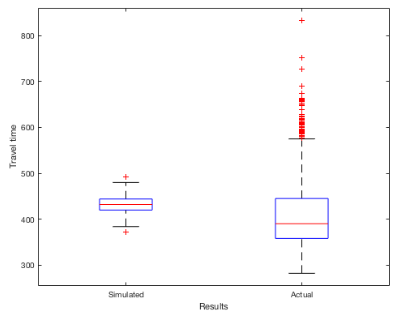
(a) Taxi time division for normal demand configurations, actual data of 376 flights



(b) Taxi time division for landing peak configurations, actual data of 262 flights



(c) Taxi time division for start peak configurations, actual data of 216 flights



(d) Taxi time division for entire data set, actual data of 1229 flights

Figure 5.20: Simulation and actual results for different configuration types, expressed in box plot showing median and quartiles

5.8. Analysis on sensitivity of computational time to input parameters

Different parameters are of influence on the computational time. These parameters may vary for different airports. But first of all, the used computer to do calculations may be of influence. Computational time for the current model is around 17 seconds, performed on:

Apple MacBook White Mid 2010
2,4 GHz Intel Core 2 Duo Processor
8 GB 1067 MHz DDR3 RAM-memory
MathWorks Matlab R2016a (64-bit)

Only infrastructure is of influence on the size of parameters within the model. The influence on computational time is tested for different inputs for these parameters. The parameters and the standard values used can be found in table 5.12. Different parameters are varied, while all other parameters stay the same, to see what influence this has on the computational time.

Parameter	**Value**
States	1122
Action	4
P-matrix	SxSxA
R-matrix	SxA
H-matrix	S
Planning horizon	30 min
δt	12 s
CPU-time	17 s

Table 5.12: Values of parameters for model used

First, the sensitivity to an increase of states is tested. Results are presented in table 5.13. An increase by a factor of two leads to an increase in CPU time of a factor of 4. This increase is also found in the next steps and therefore a exponential relation is present. This is due to the matrix of P that increases quadratic in size by an increase in amount of states.

States	**CPU-time (s)**
1122	17
2200	65
4400	246
6600	554

Table 5.13: Sensitivity to change in amount of states

Second, the amount of actions are of influence. Computational time for different sets can be found in table 5.14. Within the results, a linear relationship can be found between computational time and amount of actions. It linearly increases the size of R and P. The relationship is therefore logical.

Actions	**CPU-time (s)**
3	13
4	17
6	26
8	35

Table 5.14: Sensitivity to change in amount of actions

Within the toolbox, different inputs can be given in size of R. These options are given in table

5.15. The option for R of size A can be used within the current model since taxiing option would lead to a constant cost, and holding option would lead to a different cost. But through differing reward per state, holding places can be defined where a different reward can be found. As last option a size of SxSxA can be found, where reward can be made dependable on transition from one to another state, under a specific action. Within the current problem it is not of interest, but state transitions over variable lengths may be given a different reward for flow speed reasons. It can be found that this last option is of influence on the simulation time. Therefore it is not wise to use this option.

R-matrix	CPU-time (s)
A	17
SxA	17
SxSxA	46

Table 5.15: Sensitivity to change in size of reward matrix

The planning horizon is of influence, like found in table 5.16. The amount of transitions simulated increase with the time horizon, and therefore a linear relation is found.

Planning Horizon	CPU-time (s)
15 min	9
30 min	17
45 min	26
60 min	35

Table 5.16: Sensitivity to change in planning horizon

Last, the δt is investigated. This factor not only increases the amount of transitions needed for the planning horizon, also segmentation takes this factor into account. Therefore the amount of segments are increased for a smaller time step. This leads to the result in table 5.17, where a large increase can be found. A division of the time step by a factor of 2 leads to an increase in states by the same factor, but also the amount of transitions is increased. Therefore, an inverse exponential relationship can be found.

Timestep δt	CPU-time (s)
6 s	135
12 s	17
18 sec	5

Table 5.17: Sensitivity to change in planning horizon

For computational time of Amsterdam Airport Schiphol, an increase in time can be found due to a higher number of states (2002). No increase in actions is found, and also the planning horizon of 30 minutes is sufficient to model a complete route at all times. Therefore a computational time of 55 seconds is found, what is under the two minutes set as objective within the project goals.

5.9. Discussion of the results

Within this chapter, results for the proposed methodology are presented. Some main topics were found within the results which will be discussed here:

Data processing

A graph of the infrastructure and ADS-B data is used to gather transition probability information of historic data. Within this data processing step, it is found that a lot of data is found outside the taxiways given within the infrastructure. Tracks of ground vehicles are one of the main contributors to portion of invalidated data. A hard constrain is given for valid flights, which may be decreased to

gain more tracks. Only 3384 out of 13700 flights were used, which is small. A decrease in constraint may be that at least 2 out of 3 points are within the runway, or even 3 out of 5. But it must be made certain that ground vehicles are excluded from data, since they also make use of the taxiways. A better option is to gather data, like in the smaller data set, with flight number in which operating aircraft can be split from all other traffic.
That only around 20% of data is used for gathering transitions is through strict data processing criteria. A transition is successfully gathered when track is labeled as valid, and two radar points are found within specific segments within reachable distance, and with a time step of 12 seconds (or allowable offset of 1 second). It is found that only 58% is found within segments, and 70% of data have a time step of 6 seconds and 6% a time step of 12 seconds (for random data a chance of 55% on a time step of 12 seconds). A less strict flight validation criteria may lead to an increase in transitions, but the low amount of useable data is due to quality of the ADS-B data.
Last, the representation of the airport can be improved. Currently, the infrastructure is described as nodes and connections. But the interpolated nodes through segmentation are now placed on a straight line between original nodes. These nodes can also be placed on the hart line of the taxiway, to increase the coverage by the polygons for corners. Extra nodes have been placed to increase this coverage, but a method to follow the heart line would influence quality.
An increase in time step consistency is needed to increase the amount of usable data. An increase in data quality can therefore be reached by:

- Having a constant time step in data
- Include equipment type of flight number
- Increase the polygon formulation for turns
- Gather data for all possible configurations

It is of importance to have the whole airport covered. As can be found, within the north-western region, not all taxiways have been covered since not all runways are used within all possible configurations. Therefore some regions have not been covered (enough). Some of these taxiways are only placed for safety reasons, or only for special operations. Since no transition probability will lead to deadlocks within the planning method, estimations on transition probability are needed. If taxiways are chosen for usage, data can be gathered as well, increasing performance of the model. It is not expected that using these taxiways will lead to deadlocks within the system, when planning method will choose this taxiway to get to the value given at the end.
Currently, for the main routes at the airport, more than enough data is found to perform tests on. Data of one day is already enough to cover some important taxiways within the system. But for coverage of the full system, more data is needed.

Validation of model
Within the validation, it is found that the model is able to find shortest paths in time, comparable to the common routes used to reach a specified end point. The mean time of these routes can be compared to the actual mean taxi times found for this route, with a small deviation of around 5%. But the model did not capture the full spectrum of all possible travel times. Both fastest and slowest travel times were not found by the model. A possible explanation can be that the model is not able to capture conditional probabilities. Therefore all travel times are generalized over the transitions, and spread remains small. Since mean travel time is found, it is not likely that the data processing is of influence.
Since conditional probability may be an explanation for the lack of spread within found travel times, it is tested. Three different configuration types were used to split the data set. Results of this split show that different means were found for the different conditions, indicating that it is of influence on the travel time. Therefore it must be taken into consideration. But the current split did not explain all conditional probability, since a bigger variation in travel time for actual data is found. The conditional planning method also had consequences for the simulated results, since a smaller variation is found. Therefore, a relation is found, but it cannot be concluded that this increases the results of the simulation in terms of uncertainty. To be able to increase the model simulation results, more research into correlations within characteristics of operations is needed.

Rewards within model

Since objectives of agents differ, one major objective of this research was to model for different objectives. Objectives are caught in two main reward functions; action reward R and terminal reward H.
Within the first reward function, costs are expressed based on different actions. Costs for holding at the gate, holding and taxiing were defined. The first cost increased the time of the aircraft spend at the gate. Since engines don't need to be running for this action, it is of the lowest cost. For operations starting at the gate, a TSAT can be calculated specifying the time it needs to wait at the gate to gather maximal value. Once taxiing, every time step costs in order to reach the terminal state within the system. A difference in cost for taxiing and holding influences the way a planning agent tries to arrive on time at the end state to capture highest reward. For delayed flights, the model will look for the shortest path in time. But for flights running before schedule, the model will try to spend additional time in the most cost optimizing way. Since not all variation in travel time is caught, taxiing solutions tend to find elongated routes that don't ensure timely arrival when all uncertainty is not caught. Holding instead tends to spend time at the end of the route, decreasing the uncertainty of timely arrival. Therefore this set of rewards seems to be in common with the current procedures where a cue is found at the entrance of the runway (for departures).
At the end point of the operation, two types of rewards can be found. One reward decreasing or increasing over time, to be able to simulate preference of time of arrival, and the costs related to offset in time. An increase in costs for offset in time results in transition of the trade-off point between timely arrival and taxiing costs, where an aircraft will spend more time within the system to assure timely arrival. Another way is to model deadlines through simulation of drops in value at the end. This drop can also be found at the start, where a high decrease can be found when the model found that chance of timely arrival decreased.
Through these two types of reward functions, three different objectives of flights were modeled. Differences in operations can be found between the different objectives, indicating that objective based modeling is possible. The decisions within the model follow from clear and separated objectives given.

Model characteristics under uncertainty
To check robustness of the system to uncertainties present, but not captured by the model, it is tested under offset in time and on computational time in case of changes in input parameters. The offset in time is tested since pre-tactical uncertainties are still present, but also during operation it may be that uncertainty is different than modeled. It is found that for an offset in time, the model is still holding the routing and timing solution for that situation. The planning horizon is sufficient to cope with a delay of 10 minutes, where also a value is still given. Based on the value found, decisions can be made on input parameters. When not sufficient value is found at the current position it is, based on value at the end, decisions can be made to request different input parameters. For changes in input parameters, the current model is able to get to a new solution within 17 seconds. This is faster than the objective, and therefore it also offers dynamic robustness. For modeling of a full scale airport like Schiphol, computational time of 55 seconds can be found, which also is within the 2 minutes specified in the design choices. Therefore, the model can be adapted within other large airports like Schiphol.

6

Conclusion and discussion

In this report, a novel agent-based method is presented in which the taxiway segment transitions are used in a finite horizon markov decision process. In order to capture operational uncertainties within planning, transition probability between segments of the infrastructure are used to represent the traversal through the taxiway system towards goal. Results have been presented, and within this chapter the conclusions, limitations and recommendations on this research will be stated.

6.1. Conclusion

Through this research, some problems have come forward within the field of surface traffic planning. Different methods are presented in literature that try to increase ground operations performance, but have showed difficulties in terms of scalability, applicability and robustness. Suboptimality of the solution is allowed in order to cope with scalability. In order to reduce complexity of the problem, and to decrease the need for communication, an agent-based approach is chosen in order to decentralize the problem and provide a better robustness in plans by introduction of uncertainty in planning. This led to the following research objective which needs to be answered:

The objective of the research is to develop an agent-based airport surface routing and timing planning model providing multi-objective optimization, robust to operational uncertainty

In order to answer the research objective, the conclusion will be split into the next criteria:

Robustness to operational uncertainty
For the model to have robustness, it needs to fully capture both speed and conflict uncertainty, presented as propagation uncertainty. Based on the results, it can be concluded that the model only partly captures operational uncertainties, since the current representation is not able to capture conditional probabilities. By analyzing the full data set, it only captures part of the uncertainty. The model is able to capture mean taxi time, since offsets are within a 5 % range of the actual mean. But the deviation in travel time found is around 30 % of the actual deviation. Therefore, not all uncertainty is captured successfully and the model is not able to assure timely arrival. To improve planning, conditional planning is tested but did not show improvements. Since differences can be found in mean travel time that are also captured by the model, conditions are of influence on the result and need to be taken into account.
Also of importance is the robustness of the model for offsets in time. The model is able to present routing and timing advise when an offset in time can be found. Both value and policy are given providing the optimal policy in order to capture the highest value. For delays within the planning horizon, the model shows to be robust.

Model efficiency
Within the design choices, it is given that the model needs to deliver the optimal solution within

a computational time of 2 minutes. This maximum computational time is needed since planning of start time needs to be done within half an hour before the operation. It also has to be adaptable for differences in input parameters. It can be found that the model satisfies this requirement. The current model is able to perform calculations within 18 seconds. Since it is dependent on size of infrastructure, it is highly robust for changes in input. It therefore also allows for conditional planning, since it can easily adapt to differences in conditions.

Multi-objective optimization
In order to satisfy the first objective, the model needs to find the shortest route in time. It is found that the model is capable of finding the current shortest routes in time. Not only is it able to present this route, through offering different rewards for specific actions, it is capable of influencing the behavior of taxiing aircraft when additional time is available. Through different values for taxiing and holding, aircraft will look for unique solutions, while timely arrival is assured. But since not all uncertainty is captured by the model it is a possibility to have higher costs for taxiing since the model tends to find longer routes that pose uncaptured chance of late delivery. Therefore costs for holding should at least be as high as the costs for taxiing.
Another objective that could be assigned for aircraft, is a cost for offset in time of arrival. It is shown that different value functions can be found for multiple types of operations. By adjusting these values, the model is able to trade-off taxi time over time of arrival. Setting hard deadlines within the value function is possible, but it should be taken into account that the model doesn't fully capture all uncertainty present in order to assure timely arrival.

Routing and timing planning
The model is able to provide routing and timing advise at all states within the infrastructure, in order to optimize value for the operation. It is shown that multiple routing and timing options are available, and the model can adopt to operational uncertainties.

Scalability
It is expected that the biggest gains in air traffic performance can be made at large airports like Schiphol, where traffic complexity is high. Therefore, the project aimed at providing a solution for full airport infrastructures in the category of Schiphol. It is shown that the model is able to plan within the required computational time for Schiphol airport. Unlike other models that were found in literature, the problem does not scale up with the amount of aircraft within the planning, but on infrastructure. The problem scales with the amount of states, the amount of actions and the number of decision epochs. It is expected that the model is scalable for other major airports, since no significant increases are expected for implementation of other airports.

Main conclusion
It can be concluded that the agent-based model presented successfully plans routing and timing of aircraft over an airport infrastructure. Although it is able to find the shortest path in time, it does not fully capture all uncertainty and therefore is not able to assure timely arrival. Gains have been made in terms of robustness to operational uncertainties. Relations between overall conditions and total travel time have been found, but it is not proven that they are able to improve model results. The agent-based approach has proven to perform well in terms of robustness and scalability. Agents priorities can be manipulated easily by straight forward parameters, and therefore it is able to do multi-objective optimization.

6.2. Limitations

By modeling the infrastructure as a Markov Decision Process, operational uncertainties are found within the taxiing operation that are of influence on taxi time. But some limitations are found that are of influence on the result of the model. Within this section, the limitations are presented. When possible solutions are found that can be fixed with minor effort, they are given.

- Coverage of Data
  - Within the current data, different time steps and offsets in position can be found. There-

fore only a limited amount of data is used, limiting the coverage of the infrastructure by data, and introducing even more uncertainty in transition probability. Also the current infrastructure representation is of influence, since interpolated points have been chosen between nodes that are in a straight line, and don't follow the heart line of the taxiway.
  - Opportunity: In order to increase data quality, use can be made of Surface Movement Radar (SMR) that can be collected by the airport. Since current ADS-B data is dependent on the quality of positioning systems on-board of an aircraft, SMR is able to provide more consistent data. Another advantage is that radar scans the airport area by a constant time interval. An increase in data can be expected.
  - Opportunity: Within future data sets, it is of importance to include flight number. Only aircraft taxiing towards or from the runway will have a flight number assigned, and therefore ground vehicles can be excluded right away.

- TSAT planning based on fixed time
  - Current TSAT is based on value optimization for a single start time at the first segment. Although optimal, through pre-tactical and tactical uncertainties this TSAT may not be assured. Possible offsets in end-time may lead to value degradation that may be unwanted.
  - Opportunity: In order to increase value for TSAT, an additional MDP can be setup that models possible transitions towards TSAT times from TOBT. Chance of different time lengths for pushback can be modeled, and will catch value for different offsets in time for TSAT.

- Conflict resolution
  - The model presented is not able to predict and resolve conflicts between aircraft. Risk of conflict is captured within data, but since a conflict may cause a holding time of around 29 seconds, this offset in time is not fully captured. A small chance on large disruptions is modeled as medium chances of small disruptions. It is an explanation for the model being able to capture the mean time, but not all uncertainty.
  - Another limitation is the chance of possible deadlocks. Since possible conflicts that may cause deadlock situations are not found by the model, regulations are needed to prevent deadlocks from happening. These regulations can be found within the model where multiple one-way taxiways can be found. But these regulations decrease the performance of the found solutions.

6.3. Recommendations

The current model allows for major improvements that require significant efforts. Within this section, these opportunities will be given.

- Conditional planning
  - A relation between results and conditions is found within the current research. But the current condition fails to capture variation in travel time. In order to increase the relation between conditions and travel time, the performance of the model should be checked under different conditions. Uncertainty for different types of airlines and aircraft, but also weather conditions and traffic density may be of influence on speed and its uncertainty. Therefore, results should be checked for these conditions in order to increase performance of the model.
  - In order to allow for conditional planning, a tree based approach is needed to cope with the possible data reductions. Within this top-down approach, transition probabilities should be gathered within one general transition probability matrix. A division is allowed when enough data is gathered for a specific condition, providing conditional probabilities for the major part of the infrastructure, but also ensuring probabilities for all parts of the infrastructure.

- Capturing conflict uncertainty

- In order to capture conflict uncertainty more accurately, a time step increase is needed. When conflicts are not resolved within one time step, the model fails to capture conditional probability that another time step of holding is needed. A bigger time step allows for capturing chance of a longer period of holding for conflict, and should lead to an increase in capturing conflict uncertainty. But, an increase in time step will lead to a decrease in accuracy of time of arrival, and therefore a trade-off is needed.
- Another possibility is resolving conflicts through multi-agent planning. Within the model, probability of presence of an aircraft within a segment at a specific time is captured. By communicating costs for other airplanes to arrive at this segment within the same time period allows for aircraft to look for alternative paths, increasing performance. It is expected that a multi-agent planning approach will lead to an increase performance, but it will also increase the dynamics within the planning system. Recalculations will be needed when aircraft update intentions, or when new aircraft arrive within the planning system. Current computational times allow for dynamics within the planning.

• Increase computational efficiency

- It is possible to increase computational efficiency, by splitting the infrastructure in separate modulated areas. Current efficiency scales quadratic for increases in the amount of states. But modeling for separate parts is possible when after each transition, values of connecting taxiways are transferred towards other sectors. Therefore the increase is made linear, neglecting possible computational time for transferring of values.

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