Socio-Technical Agent-Based Modelling of Decision-Making in an Airline Operational Control Center

Application to an unexpected diversion use case at KLM CityHopper

D.H.Koch

Socio-Technical Agent-Based Modelling of Decision-Making in an Airline Operational Control Center

Application to an unexpected diversion use case at KLM CityHopper

by

D.H.Koch

to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on April 7th 2021.

Student number:	4331141	
Project duration:	August 2020 – April 2021	
Thesis committee:	Prof. dr. ir. H.A.P. Blom	TU Delft, Committee chair
	Drs. P. Fopma	KLM CityHopper, Manager Operations Control
	Dr. O.A. Sharpanskykh	TU Delft, Daily supervisor
	Ir. O. Stroosma	TU Delft, External examiner
	Ir. M. de Raad	KLM CityHopper, Advisor Operations and Control

An electronic version of this thesis is available at http://repository.tudelft.nl/.

TU Delft

Acknowledgements

The research documented in this thesis report concludes my time at the Delft University of Technology. To obtain the master's degree in Aerospace Engineering I researched the decision making in KLM CityHopper's Operational Control Center. This research provided additional insights into the use of different decision-making mechanisms and their application to the operational decision making within KLM CityHopper. I hope the recommendations with respect to the acceptation of decision support tools by the operations controllers and the use of Multi-Criteria Decision-Making will help KLM CityHopper to improve its understanding of operational decision making.

This research would not have been possible without the support and guidance of Alexei, my daily supervisor. Pieter and Maarten enabled the collaboration with KLM CityHopper and motivated and supported me during the weekly meetings. Randolph and Denise provided their expert opinions and helped me to understand the real-life decision making in KLM CityHopper's Operational Control Center from the perspective of an operations controller. Jan helped me with the brainstorming about the different decision-making mechanisms that could represent the decision-making in the Operational Control Center. Ultimately this enabled the accurate modelling of the operations controllers. I would like to thank my brother Mike who advised on modelling choices, supported me in programming and spent a lot of time proofreading this report. Last but not least, I am very grateful to my family who supported me my entire life and always facilitated and motivated me to perform to my best capabilities.

D.H.Koch
Delft, March 2021

Contents

List of Figures

List of Tables

Nomenclature

Abbreviations

AHP	Analytical Hierarchy Process
AMS	Amsterdam Schiphol airport
AOC	Airline Operations Control
AOCC	Airline Operations Control Center
AOP	Agent-Oriented Programming
BDI	Belief-Desire-Intention
CLA	Collective Labour Agreement
CNP	Contract Net Protocol
DAM	Duty Area Manager
DMC	Duty Maintenance Controller
DMGS	Duty Manager Ground Services
DMN	Duty Manager Network
DMOC	Duty Manager Operations Control
DMPS	Duty Manager Passenger Services
DoO	Day of Operations
DST	Decision Support Tool
EOBT	Estimated Off Blocks Time
ETD	Estimated Time of Departure
FC	Fleet Controller
FS	Fleet Scheduling
FW	Flight Watch
GQN	Generic Q-Negotiation Protocol
JADE	Java Agent Development
KLC	KLM Cityhopper
LCY	London City airport
LEADSTO	Language and Environment for Analysis of Dynamics by SimulaTiOn
MCDM	Multi-Criteria Decision-Making
NWI	Norwich airport
SEN	London Southend airport
SOU	Southampton airport
STA	Scheduled Time of Arrival
STD	Scheduled Time of Departure

STS	Socio-Technical System
TTL	Temporal Trace Language
TTS	Timed Transition Syntax

Symbols

λ_{max}	Maximum eigenvalue [-]
A_{burn}	Fuel burn of an Embraer 190 [Liter/Minute]
$C_{\text{cancellation}}$	Cost of a leg cancellation [€]
$C_{\text{canxclaim}}$	Expected claims due to rebookings [€]
$C_{\text{crewreserve}}$	Cost of a single set of reserve crew [€]
C_{crewswap}	Cost of a crew swap [€]
C_{cycle}	Cost of flying an extra cycle [€]
C_{kerosene}	Cost of fuel [€]
C_{reserve}	Cost of reserve devaluation [€/min]
C_{swap}	Cost of a registration swap [€]
$\text{FVL}_{\text{elite}}$	Future Values Loss elite passengers [€]
$\text{FVL}_{\text{non-elite}}$	Future Values Loss elite passengers [€]
$\text{pax}_{\text{elite}}$	Number of elite passenger [-]
$\text{pax}_{\text{non-elite}}$	Number of non-elite passenger [-]
$\text{tax}_i(g)$	The tax that agent i pays for implementation of solution strategy g [€]
A	Set of decision-making agents
A_{ij}	Pairwise comparison matrix [-]
a_{ij}	Pairwise comparison value between criteria i and j [-]
C	Set of criteria
c_1	Extra cycles flown [-]
c_2	Extra minutes of flight [min]
c_3	Leg cancellation count [-]
c_4	Registration swaps in early window [-]
c_5	Registration swaps in late window [-]
c_6	Reserve devaluation minutes [min]
c_7	Crew swap count [-]
c_8	Crew reserve usage [-]
c_9	Bussed elite passenger count [-]
c_{10}	Bussed non-elite passenger count [-]
c_{11}	Rebooked elite passenger count [-]
c_{12}	Rebooked non-elite passenger count [-]
c_{13}	ETD delay minutes [min]
c_{14}	Collateral delay minutes [min]
CI	Consistency Index [-]

CR	Consistency Ratio [-]
F	Set of flights affected by confirmed delays
G	Set of flights affected by collateral delays
g^*	Optimal solution according to Clarke Tax Algorithm [-]
n	Number of criteria [-]
n_{ij}	Normalised value of criterion j for solution strategy i [-]
P_i	Preference value of solution strategy i [-]
r_{ij}	Value of criterion j for solution strategy i [-]
r_{max}	Maximum criteria value [-]
RI	Random Index [-]
S	Set of solution strategies
s	Set of solution strategies [-]
$u_i(g)$	Utility of agent i with respect to solution strategy g [€]
$v_i(g)$	Valuation of agent i with respect to solution strategy g [€]
W_i	Weight of criterion i [-]
WS_i	Weighted sum value of criterion i [-]

Introduction

The research in this report has been performed to obtain a Master of Science Degree in Aerospace Engineering from the Delft University of Technology. Through collaboration with the operational control department of KLM CityHopper, the decision making in KLM CityHopper's Operational Control Center has been investigated. The combination of disruption management and socio-technical agent-based modelling proved to be very interesting.

In the environment of an airline's operational control center (AOCC) digitisation of decision making is a commonly studied topic. Most studies focus on the development of optimisation tools that propose optimal solution strategies to the operations controllers [22]. However, the role and adoption of these optimal solution strategies in the decision-making are not touched upon. Therefore in this research, we developed an agent-based model that contains both human and technical decision-makers. This socio-technical agent-based model has been used to investigate the decision-making in KLM CityHopper's Operational Control Center and determine the effect of increased context comprehension and use of technical systems. To facilitate this, the operations controllers have been simulated to work in four different control modes. With increasing control mode the controllers have increased competence, which has been modelled by varying coordination activities and the use of different decision-making mechanisms.
This research adds to the body of work on the topic of socio-technical agent-based modelling of airline operations control. The inclusion of both social and technical decision making entities and the use of different decision-making mechanisms in the developed model increases the understanding of this topic.

To enable this research KLM CityHopper provided the unexpected diversion case study and inherent data. The operational control experts from KLM CityHopper provided their support to; gain an understanding of the AOCC environment, provide input for the decision-making mechanisms, provide details about the use of decision support tooling in the AOCC and to validate the model. Moreover, they provided their expert opinion for making assumptions during the model development.

The performed research has been reported in three parts. In Part I the scientific paper is presented. This paper summarises the case study, methodologies used, model development, results and discussions. In Part II the literature study in support of the scientific paper is given. Finally, in Part III, the appendices to the scientific paper are given. In Appendix A the workflow diagrams used to model the agents according to the control modes are discussed. The behavioural rules that are derived from these workflow diagrams through the application of the co-ladder framework are elaborated upon in Appendix B. The preference relations used as input for the voting protocols in the scrambled- and opportunistic control modes have been given in Appendix C. In Appendix D the pairwise comparison matrices used for the application of MCDM in the strategic control mode are given. The approximation of the airline's cost model is given in Appendix E. The details of the software implementation are discussed in Appendix F and the specification of the criteria inherent to the available solution strategies to the agents in Appendix G. To conclude the supporting work, the detailed results of the tactical- and strategic control modes are respectively presented in Appendix H and Appendix I.

I

Scientific Paper

Socio-Technical Agent-Based Modelling of Decision-Making in an Airline Operational Control Center

D.H.Koch,*

Delft University of Technology, Delft, The Netherlands

Abstract

This paper proposes a socio-technical agent-based model developed to increase the understanding of decision-making in an airline operational control center (AOCC). In this model human decision-makers, a Decision Support Tool, and technical systems are included. The selected case study encompasses the unexpected diversion of a flight from Amsterdam to London City. The decision-making inherent to the disruption management of this unexpected diversion is studied. In the model, in line with cognitive science literature, the agents are simulated to operate in the scrambled, opportunistic, tactical, and strategic control modes, which differ in the situation awareness and use of technical systems. In these control modes respectively the plurality voting protocol, Borda voting protocol, Clarke Tax Algorithm, and Multi-Criteria Decision-Making (MCDM) are implemented as decision-making mechanisms. The agents in the strategic control mode demonstrated the ability to make adaptive decisions. In the tactical control mode, the agents showed decision-making characterised by adaptive responses and limited anticipation. In the scrambled and opportunistic control modes, the decision-making was characterised by a lack of adaptation and was solely based on experience. The analysis of the decision-making showed that decision-making based on the airline's cost model results in different decisions than decision-making by the human operations controllers. Due to this, the operations controllers are not eager to decide on the implementation of a proposed solution strategy by the Decision Support Tool. It showed that the decision-makers often have to make compromises to arrive at a collaborative decision. Furthermore, scenarios that are characterised by reserve unavailability do not require anticipation in the decision-making and can be handled in the opportunistic control mode, which is the lowest control mode that resulted in adequate decision-making. However, when anticipation is required the CDM and OrbiFly systems are essential resources. It is recommended that the MCDM decision-making mechanism can be used to improve the consistency of the operational decision-making and enables the AOCC to learn from previous occurrences. Hereby, the capability of the AOCC to deal with disruptions through resistance instead of resilience can be extended. Overall, the analysis of the different decision-making mechanisms showed that human operations controllers are essential for adaptive decision-making in the AOCC.

1 Introduction

The operations controllers in an AOCC are faced with many challenges during a day of operations. These challenges originate from (un)known disruptions occurring to the flight, crew, and passenger schedules. To cope with these disruptions the controllers can inform themselves on the diverse information related to the disruption through the use of technical systems. These either provide additional information on the current context or propose solution strategies by means of optimisation [17]. It is up to the operations controllers to process all this information and determine which measures are appropriate in order to manage the disruption [12]. As a consequence, disruption management is largely dependent on situation awareness and human interpretation.

The dynamic variability in an AOCC [18] in combination with human decision-making, makes it challenging to determine the achieved performance level. This performance level can be characterised from the perspectives of robustness [2] or resilience [35]. The impact of the Covid-19 pandemic [21] demonstrates the relevance of resilience for the airline industry. However, also before the pandemic the AOCCs frequently faced unknown disruptions. To cope with these unknown disruptions, the resilience decision-making ability of the airline's operations controllers plays an essential role. This research sets out to investigate this topic, by the development of a socio-technical agent-based model.

An agent-based model enables the analysis of a system by modelling the actors as autonomous agents. These agents operate in an environment in which they can perform actions and interact with other agents. By using an agent-based model the effects of these actions and interactions can be studied. A socio-technical agent-based model is comprised of human agent and technical agents/resources, similar to an AOCC. Therefore, this

*Msc Student, Air Transport and Operations, Faculty of Aerospace Engineering, Delft University of Technology

modelling paradigm is suitable for performing research on decision-making that is inherent to the disruption management in an AOCC.

Socio-technical agent-based modelling in the air transportation context has already been subject to several studies. Bouarfa et al. conducted multiple studies on the subject of socio-technical agent-based modelling of airline operations control [7]-[11]. In a first study [9] they explored the coordination in an AOCC through the application of the theoretical joint activity framework by Klein et al. [23]. In a follow-up study, they used a socio-technical agent-based model to simulate the agents using four different disruption management policies to solve a disruption scenario [10]. Hereafter they combined these policies with different negotiation mechanisms to determine the impact of these policies on the level of performance of the operational decision-making in an AOCC [7]. In a recent study, Bouarfa et al. [8] applied the socio-technical agent-based modelling approach to analyse decision-making under uncertainty in an AOCC.

Zimmer [38] developed a socio-technical agent-based model which included the modelling of personality as a human factor. From this study, one of the results was that increased awareness of social agents improved operational decision-making. Feigh and Pritchet [18] suggest the use of the Contextual Control Model by Hollnagel [20] to use in the design of support systems for dynamic decision-making in airline operations. By using this framework a variety of human behaviour can be captured in the modelling of an AOCC.

Castro and Oliveira [14] developed an agent-based model of an AOCC which can be used by operations controllers as a decision support system. This system has been developed to fill the gap between fully automated decision-making tools and human decision-making. The agents in this model are software agents and interact with the human operations controller by requesting feedback on proposed solutions. Through this feedback, the software agents can learn and propose improved solutions next time [5]. Bouarfa et al. [11] used agent-based modelling and simulation to evaluate the socio-technical and socio-economic implications of using the multi-agent decision support system from Castro and Oliveira [14]. From this evaluation, it followed that the implementation of such a system results in a loss of the experience of the AOCC in handling out of the ordinary disruptions.

To bridge the gap between human decision-making and technical decision-making systems, this research proposes a socio-technical agent-based model that includes both human and technical decision-makers. The research objective that followed from this research gap is: *'To analyse the decision-making in the Airline's Operational Control Center, by the development of a socio-technical agent-based model.'*

The model is simulated for an unexpected diversion case study, provided by the airline. The behaviour of the social agents is simulated in the scrambled, opportunistic, tactical, and strategic control modes [20]. With increasing control mode, the social agents have increased situation awareness and make increased use of the Decision Support Tool and other technical systems. In each of these control modes, the agents are modelled to use different decision-making mechanisms: plurality voting, Borda voting, Clarke Tax Algorithm, and Multi-Criteria Decision-Making. The novelty of this research is the application of these decision-making mechanisms to simulate decision-making in an AOCC. Furthermore, the use of the Decision Support Tool in collaborative decision-making is analysed. The analysis of the decision-making is performed based on the conceptual resilience framework by Vert et al. [35], which adds to the body of research in the AOCC domain.

The remainder of this paper is organized as follows. In section 2 an explanation of the case study used for this research is given. Hereafter the methodological frameworks used are elaborated upon in section 3. The theoretical background on the used decision-making mechanisms is provided in section 4. The proposed socio-technical agent-based model is presented in section 5. The verification and validation of this model are discussed in section 6. In section 7 the simulation setup and results are provided. In section 8 a reflection on the used methodologies is given, the results are interpreted and recommendations are given. Finally section 9 draws the conclusions.

2 Case Study

The case study for this research has been selected through discussions with the airline's operations controllers. The three main requirements imposed on the case study were: the involvement of socio-technical entities, the inclusion of aircraft, crew, and passenger recovery and relevance to the airline's daily flight operations.

The selected use case is the unexpected diversion of a flight en-route from Amsterdam Schiphol Airport (AMS) to London City Airport (LCY):

> *"The current time is 07:10z. KL985 is cruising above the North Sea, nearing the halfway point of the flight. The flight crew is contacted by ATC and informs them of the unexpected closure of LCY airport due to a runway blockage. With this limited information, the flight crew contacts the airline's operational control center. Due to which the unexpected diversion scenario is initiated."*

The details of the LCY rotation are given in Table 1. The underlying data contained in the flight schedule is provided in the appendix [24].

Flight no.	STD	STA	Route
KL985	06:45z	07:50z	AMS-LCY
KL986	08:25z	09:30z	LCY-AMS

Table 1: LCY rotation Flight Data

In this case study, three parameters define the scenario that is evolving: the available holding time of the aircraft, the reopening time of LCY airport and the intertwined availability of fleet and crew reserves. The scenarios that are considered concerning these parameters will be elaborated upon in section 7.1.

In section 2.1 the decision-makers and technical systems included in this use case are described and in section 2.2 the available solution strategies to solve the disruption are elaborated upon.

2.1 Decision-makers and Technical Systems

The case study evolves in the environment of the AOCC of the airline under consideration. Within this environment, a total of 11 social entities and 5 technical entities are relevant for this case study. Only four of the social entities are relevant for the decision-making: the Duty Manager Network (DMN), Fleet Control (FCo), Crew Control (CC) and the Commercial Desk (CD). The goals of these actors are described as:

- *DMN*: Ensure integration of long-haul and short-haul flight operations of the airline.
- *FCo*: Timely and safe execution of the planned flight schedule and ensuring absorbing capacity to counter disruptions.
- *CC*: Making minimal changes to the planned crew schedule and ensuring absorbing capacity of this schedule to counter disruptions.
- *CD*: Ensuring minimal changes to the passenger schedule, maximum flight completion factor and on-time performance.

The technical systems that the agents use to be able to accomplish their goals are the Operational Control System (OCS), Passenger Control System (PCS), Aircraft Communications Addressing and Reporting System (ACARS), Decision Support Tool (DST), Collaborative Decision-Making (CDM) and OrbiFly (OF). The specifications of these systems are:

- *OCS*: The main operational control system used. Allows agents to keep track of the exact details of the flight and crew schedules. All agents in the AOCC have access to this system, but only Fleet Control and Crew Control can apply changes to this system.
- *PCS*: This system allows the Commercial Desk and Duty Manager Network to keep track of the exact details of the passenger schedule. Only the Commercial Desk can apply changes.
- *ACARS*: Means of communicating between the AOCC and the aircraft while in the air and outside of VHF range.
- *DST*: Only accessible by Fleet Control and provides an optimised flight schedule. In this research, this agent has been modelled based on the business rules as provided by the airline [26].
- *CDM*: A web portal provided by Amsterdam Schiphol airport that can be accessed by Fleet Control. This system provides airlines and other operators with additional insights into the turnaround processes and exact slot times at Amsterdam Schiphol airport [3].
- *OF*: This web application can be used to check the current weather conditions, Meteorological Aerodrome Reports (METARs) and Terminal Aerodrome Forecasts (TAFs) at airports all around the world. This system can be accessed by all agents within the AOCC. The application is accessible through '`www.orbifly.com`' and has been developed by the OrbiFly European based FAA flight training organisation.

From these technical systems, only the Decision Support Tool can perform autonomous activities. The other systems are resources that provide the decision-makers with information, but can not make autonomous decisions. Due to this, the Decision Support Tool is regarded to as a technical agent and the other systems as technical resources.

2.2 Solving the Disruption

To solve the disruption the decision-making agents representing the fleet, crew, and passenger domains, negotiate about the solution strategy. During this negotiation, the Duty Manager Network acts as a mediator to which Fleet Control, Crew Control, and the Commercial Desk make proposals based on their preference on solution strategy. This hierarchical decision-making structure is shown in Figure 1.

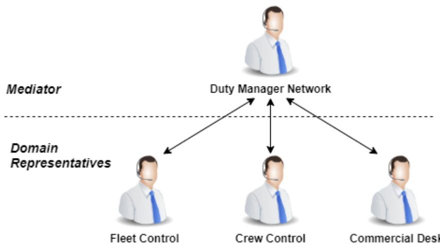


Figure 1: Decision-making hierarchy

In the use case, there are six (A through F) solution strategies that the decision-makers can decide upon to resolve the disruption. These solution strategies have been identified in cooperation with the airline's operations controllers and are explained below:

- *Solution Strategy A*: Flight KL985 is diverted to one of the alternative airports, where it awaits the reopening time of LCY airport. Hereafter continuing the flight to LCY airport.
- *Solution Strategy B*: Flight KL985 is diverted to one of the alternative airports and waits there for the passengers to be bussed from LCY airport to the diversion airport and vice versa. As soon as the passengers of flight KL986 have arrived at the diversion airport, the aircraft departs for the flight back to AMS.
- *Solution Strategy C*: Flight KL985 is diverted to one of the alternative airports, where the passengers are de-boarded, after which the aircraft performs a ferry flight back to AMS. The passengers of the KL985 continue by bus to LCY while cancelling the KL986.
- *Solution Strategy D*: Mid-air return of KL985 to AMS. Upon arrival at AMS, the complete LCY rotation is cancelled.
- *Solution Strategy E*: Mid-air return of KL985 to AMS. The entire LCY rotation is delayed. If the new estimated time of arrival (ETA) is equal to or later than the reopening time of LCY, the flight is allowed to depart AMS.
- *Solution Strategy F*: The aircraft awaits the reopening of LCY airport in a holding pattern.

The next section elaborates upon the main methodologies that have been used to translate this case study into a socio-technical agent-based model.

3 Methodology

To gain an understanding of the methodologies used for the development of the agent-based model based upon the case study, the frameworks that have been used are explained throughout this section. First, a socio-technical agent-based modelling framework is discussed in section 3.1. Hereafter the frameworks used to capture the agents' behaviour are described in section 3.2. Lastly, the resilience framework used to analyse the decision-making of the AOCC is discussed in section 3.3.

3.1 Socio-Technical Agent-Based Modelling

Due to the socio-technical nature of the case study under consideration, a socio-technical modelling approach is followed in to identify the components of the agent-based model. The methodological framework developed by Nikolic and Ghorbani [25], which enables the transformation of a socio-technical system into an agent-based model, has been used. This framework encompasses five iterative phases, as illustrated in Figure 2.:

- *System Analysis*: The AOCC is studied independently of agent-thinking or software modelling. The main goal of this phase is to identify the internal structure of the system under consideration, such that a complex analysis of the respective system can be conducted.
- *Model Design*: Accommodates for the identification of the agents and interactions between the agents in the system.
- *Detailed Model Design*: The required details for the development of a model of the system under consideration are specified. The environment, agents and interaction among agents is modelled.
- *Software Implementation*: In this phase, the actual programming is performed. The goal is to arrive at a model that is compliant with the previous phases.

- *Model Evaluation*: A continuous process of verification and validation during the development of the model. Additionally, experiments are performed to gather the results of the model.

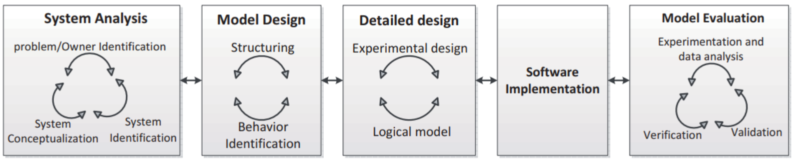


Figure 2: Socio-technical modelling approach [25]

This methodological framework aids in the identification of the main components required for the development of an agent-based model. These main components are the environment which the agents can observe and act upon, the agents and their local properties, the interaction among agents and interaction among agents and the environment [32].

3.2 Agent Behaviour

To model the behaviour of the social agents in the model, the co-ladder framework from Chow et al. [15] is combined with the contextual control model from Hollnagel [20]. The co-ladder framework [15] allows to model the agents' behaviour based on the definition of behavioural rules. In Figure 3 the co-ladder is shown, which helps in the identification of the behaviour rules.

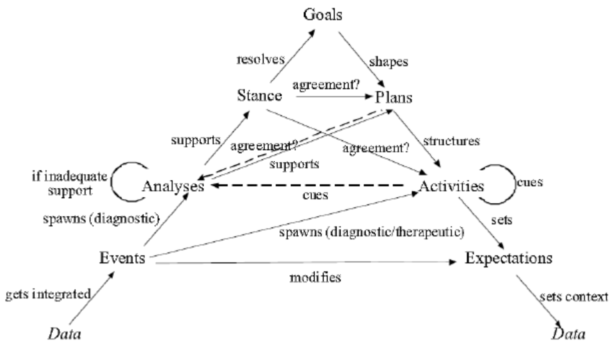


Figure 3: Co-ladder framework [15]

These behavioural rules are triggered by observations of the agents. Observations can be a change in the environment, communication with other agents, or output from a technical system. Upon an observation, the agents can either perform an analysis, action or develop an expectation. An analysis simulates the interpretation of an observation, upon which a task or thought process can be performed. From an analysis a plan evolves, which is the intention of the agent to execute a certain activity or sequence of activities. An activity can either be communication among agents or the application of changes to a technical system. At last, an expectation is based on a observation or the result of an activity. This can be about tasks that might be assigned to the agent in the near future, a change in the environment or events that might result due to changes made to the environment.

The behavioural rules of the agents depend on the contextual control mode that the agents are operating in. Hollnagel [20] captured the following four control modes within the contextual control model:

- *Scrambled Control Mode*: Panic dominates the agents' behaviour. No relation can be identified between the context and the performed actions.

- *Opportunistic Control Mode*: The agents are applying limited planning or anticipation due to a lack of context comprehension. The behaviour of the agents is based on experience from similar situations or frequency of use.

- *Tactical Control Mode*: The agents can match the context to a predefined working procedure or behavioural rule. There is increased planning and anticipation capability. However, this is still limited.

- *Strategic Control Mode*: The agents have a wider time-horizon that allows for higher-level goals to be taken into account and full competence is available. Hereby the agents have the highest context comprehension.

The impact of the control modes on the agents' behaviour results in varying levels of situation awareness and the use of different decision-making techniques. As a consequence varying results are generated, which have been analysed by using the framework as discussed in the next section.

3.3 Analysis of Resilience

To be able to analyse the results of the agent-based model concerning resilience, the conceptual framework from Vert et al. [35] has been used. This framework enables the analysis of the reaction of complex socio-technical systems to events that require a response from these systems. A system can respond with resilience to either an unexpected adverse event or an expected unplanned adverse event. A system can respond with resistance to either an expected unplanned adverse event or an expected planned adverse event. A schematic overview of this framework is given in Figure 4.

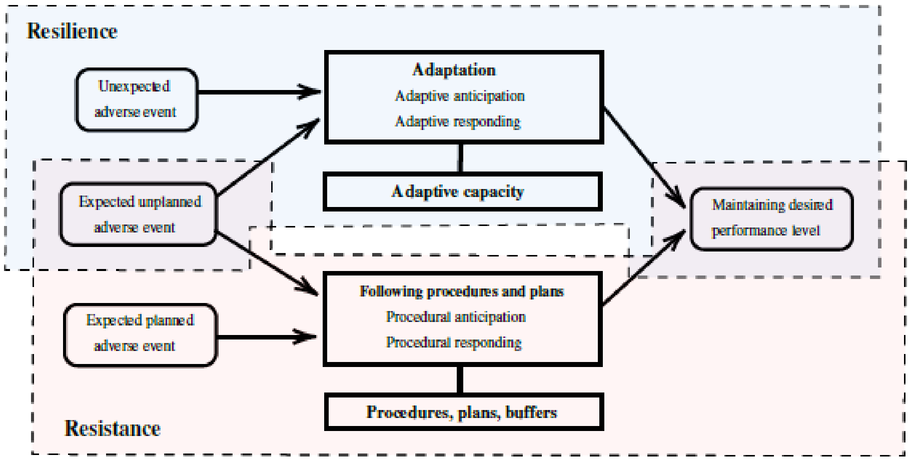


Figure 4: Conceptual framework for resilience [35]

A system responds with resilience to an event when adaptation is required to cope with the events. The types of adaptation are adaptive responding and adaptive anticipation. Adaptive anticipation takes place when the system can make predictions about adversities that are potentially going to affect the system in the near-future and allocate resources accordingly. Based on either the adaptive anticipation or adaptive response, solution strategies are generated to cope with the adversity. Next, these solution strategies are valuated relative to each other upon which one is selected and will be implemented.

Besides resilience, this framework also allows for the analysis of resistance that is exercised against an adversity by the system. Instead of adaptive capacity, the system appeals to predefined procedures, plans, and buffers. Hereby only procedural anticipation and procedural responses are within the capacity of the system. These procedures are described in working procedures or are based on the previous experiences of the system.

This concludes the main methodologies that have been used to conduct the research. In section 4 the theoretical background on the use of decision-making mechanism is given.

4 Decision-making

In the agent-based modelling paradigm, agents have the ability to negotiate to arrive at a common agreement or decision. Especially in the airline operations control context, decision-making is an imminent part of the agent-based model. Within the research conducted in this paper two types of decision-making have been included: Voting and Multi-Criteria Decision-Making (MCDM). These types of decision-making have been used to simulate the decision-making for the agents operating in the control modes as discussed in section 3.2. In the remainder of this section, the theoretical background of these techniques is elaborated upon in section 4.1 and section 4.2.

4.1 Voting

Voting as a decision-making mechanism in the agent-based modelling domain is closely related to social choice theory. This theory captures the combination of individual preference, interests or welfare that leads to reaching a collective decision or a certain amount of social welfare [31]. Voting mechanisms are designed to generate the socially most preferred choice based on the personal preferences of the agents [33]. The voting mechanisms that have been used in this research project are: the Plurality voting protocol, the Borda protocol and the Clarke Tax Algorithm. These voting mechanisms have been used to model the collaborative decision-making of the agents in the scrambled, opportunistic, and tactical control modes. The increasing complexity of these voting protocols has been used to simulate the increasing competence of the decision-makers.

4.1.1 Plurality Voting

In the plurality voting protocol, the mediator agent requests the decision-making agents to vote for the solution strategy they most prefer. The solution strategy that receives the most votes is decided upon.

4.1.2 Borda Voting Protocol

In the Borda voting protocol, each decision-making agent assigns the most preferred solution strategy a value of $|O|$, the second-highest solution strategy is assigned a value of $|O| - 1$ and so on. The decision-making agents provide the Borda votes to the mediator agent, which sums the values across each solution strategy. The solution strategy with the highest sum is selected as the winner of the vote.

4.1.3 Clarke Tax Algorithm

The Clarke Tax Algorithm is a utility-based social choice mechanism [19]. The rationale of this algorithm is that each participating agent will be assigned a tax, of which the amount depends on how the agents utility affects the utility of the rest of the group. The higher the assigned tax, the bigger the influence of the agent on the choice of solution strategy. When the assigned tax is zero, it means that the other decision-making agents would arrive at the same solution strategy when the zero-tax paying agent would not participate. The main advantage of the Clarke Tax Algorithm is that each agents dominant strategy is to tell the truth. Hereby no effort is wasted on counter-speculating each others declared preferences [33][16]. The basis of the Clarke Tax Algorithm is the social choice function as in Equation 1. In this equation, g^* represent the decision and A is the set of decision-making agents. The decision is made by summing the agents' valuation for each solution strategy from which the solution strategy with the maximum sum of valuations is chosen.

$$g^* = \arg\ \max_g \sum_{i \in A} v_i(g) \tag{1}$$

In this function $v_i(g)$ is the valuation of agent i and personal preference g. The tax that is paid by the agents for a certain preference is equal to the amount that the agent's vote lowers the utility of other agents. This relation is presented in Equation 2.

$$\text{tax}_i = \sum_{j \neq i \in A} \hat{v}_j \Big(\arg\ \max_g \sum_{k \neq i \in A} \hat{v}_k(g)\Big) - \sum_{j \neq i \in A} \hat{v}_j(g^*) \qquad \forall i \in A \tag{2}$$

The utility of each agent is calculated by subtracting the tax from the valuation of the agent for the chosen preference, which is illustrated in Equation 3

$$u_i(g) = v_i(g) - tax_i(g) \qquad \forall i \in A \tag{3}$$

The Clarke Tax Algorithm is a prescriptive method and involves the decision-making agents to be able to calculate their valuation of each solution strategy by using utility functions.

4.2 Multi-Criteria Decision-Making

MCDM has been included in this research since it can be used in decision-making that involves the choice of a most preferred solution strategy from a set of multiple potential solution strategies, which are subject to several criteria [28]. Moreover, MCDM is employed to aid people in making decisions according to their preference in situations that are characterised by multiple conflicting criteria and finding the optimal choice among the set of available alternative solution strategies. Hereby it is deemed to be a representative method for the modelling of decision-making in an AOCC.

For the application of MCDM, the first step is to derive the goals of the agents from which the set of criteria and set of available solution strategies can be derived. These two sets are input for the decision-making method that should be chosen based on the nature of the decision problem [28].

In this research, the Analytical Hierarchy Process (AHP) has been selected as the decision-making method. The AHP method is found to be an effective way to deal with decision areas in operations management [27] and has proven to be suitable for application within complex transport decisions [22][29]. In addition, Aziz et al. [6] highlight that the AHP method is suitable for ranking and analysis of complex decision-making problems and allows for checking and reducing inconsistencies in opinions. As a result of the application of the AHP method, a ranking within the set of solution strategies is obtained. This ranking enables the agents to select their personal most preferred solution strategy, based on qualitative judgement [28].

The application of the AHP method involves several steps. Initially, the pairwise comparison matrix should be setup. In this matrix, the criteria are judged against each other by using Saaty's 1-9 scale of pairwise comparison [1][6][13]. This results in the pairwise comparison matrix A_{ij} as in Equation 4, in which C is the set of criteria.

$$
\begin{aligned}
A_{ij} &= \begin{bmatrix} a_{11} & a_{12} & ... & a_{1n} \\ ... & ... & ... & ... \\ a_{n1} & a_{n2} & ... & a_{nn} \end{bmatrix} \quad \forall i,j \in C \\
A_{ij} &= 1 \quad \text{for} \quad i = j \\
A_{ij} &= \frac{1}{A_{ji}} \quad \text{for} \quad i \neq j
\end{aligned} \tag{4}
$$

Hereafter the columns of the pairwise comparison matrix A_{ij} are normalized by dividing each column value with the sum of the column, resulting in the normalised pairwise comparison matrix by using Equation 5.

$$
A_{ij} = \frac{a_{ij}}{\sum_{\forall i \in C} a_{ij}} \quad \forall i,j \in C \tag{5}
$$

To obtain the criteria weights W_i the rows of the normalised pairwise comparison matrix should be summed, and divided by the number of criteria n as in Equation 6.

$$
W_i = \frac{\sum_{\forall i \in C} a_{ij}}{n} \quad \forall j \in C \tag{6}
$$

Upon determination of the criteria weights, the consistency of the pairwise comparison matrix is calculated. The initial (not normalised) pairwise comparison matrix (A_{ij}) is re-used and each column is multiplied with the respective criteria weights (W_i). The resulting matrix rows are then summed to arrive at the weighted sum values (WS), as can be seen in Equation 7.

$$
WS_i = \sum_{\forall j \in C}^{n} a_{ij} \cdot W_j \quad \forall i \in C \tag{7}
$$

For the calculation of the consistency of the pairwise comparison matrix, first, the maximum eigenvalue λ_{max} has to be calculated by multiplying the weighted sum value of each row with the respective criteria weight. Finally dividing the sum of the obtained values by the number of rows. This is shown in Equation 8.

$$
\lambda_{max} = \frac{\sum_{\forall i \in C} (\frac{WS_i}{W_i})}{n} \tag{8}
$$

The obtained λ_{max} serves as input for the calculation of the consistency index CI according to Equation 9.

$$
CI = \frac{\lambda_{max} - n}{n - 1} \tag{9}
$$

Upon this the consistency ratio CR can be calculated according to Equation 10, by dividing the consistency index (CI) with the random index (RI) according to the n number of criteria from Table 2. This ratio is required to be $< 10\%$ in order to have a consistent and valid pairwise comparison matrix [4].

$$
CR = \frac{CI}{RI} \tag{10}
$$

n	1	2	3	4	5	6
RI	0	0	0.58	0.9	1.12	1.24

Table 2: The average stochastic uniformity index target value of judgement matrix [1]

The criteria weights W_i and the consistency of the pairwise comparison matrix have been calculated and hence the validity has been determined. Following this, the decision matrix can be set up, which provides an overview of the available solution strategies (alternatives) and the inherent criteria values [1].

To be able to determine the preference on the alternatives in the decision matrix, the criteria values have to be normalised to enable inter-criteria comparisons. To select a proper normalization technique, the work from Vafaei et al. [34] has been consulted, in which a case study on normalization techniques for use in the AHP method is conducted. From this study, it followed that the linear normalization technique proves to be the most accurate for use in the AHP method. Hence for a criterion that is to be maximised Equation 11 should be used, and for a criterion that is to be minimised Equation 12 should be used.

$$n_{ij} = \frac{r_{ij}}{r_{\max}} \quad (11) \qquad\qquad n_{ij} = 1 - \frac{r_{ij}}{r_{\max}} \quad (12)$$

After the criteria values in the decision matrix have been normalised, the last step is to evaluate each alternative in the set of solution strategies by multiplying the criteria with their criteria weight and summing the resulting values for each solution strategy to obtain the relative final priority of each solution in the set of solution strategies. This is illustrated in Equation 13

$$P_i = \sum_{\forall i \in S} W_j \cdot x_{i,j} \quad \forall j \in C \tag{13}$$

In this equation S is the set of solution strategies, and P_i indicates the preference value of solution strategy i compared to the other available solution strategies.

This concludes the theoretical background on the decision-making mechanisms. In the next section, the development of the socio-technical agent-based model is described in which these decision-making mechanisms are incorporated.

5 The Agent-Based Model

In this section, the details of the developed socio-technical agent-based model are discussed. The environment is specified in section 5.1, the agent behaviour based on the control modes is described in section 5.2, the decision-making of the agents is discussed in section 5.3, and the criteria used in the decision-making are explained in section 5.4. Finally, the software implementation is elaborated upon in section 5.5.

5.1 Environment

The model is developed in the environment of the AOCC of the airline under consideration. The high dynamic variability in this environment is due to aircraft status, crew status, passenger status and airport status.

The environment has been modelled using categorical variables since the exact variability of the processes considered in this research project is unknown by the airline's operational control experts. The categorical variables are listed in Table 3 and are elaborated upon below.

Variable	**Values**
Holding time of diversion aircraft	'Short'/'Long'
Availability of fleet and crew reserves	'Yes'/'No'
Reopening time of LCY airport	08:20z/08:50z/09:20z
Diversion airport	'SEN'/'SOU'/'NWI'

Table 3: Categorical variables in the environment of the agent-based model

- *Holding time*: A short holding time of the aircraft subject to the diversion indicates that the aircraft is not able to stay in a holding pattern and await reopening of LCY airport. However, the aircraft can fly to a diversion airport or return to AMS.
- *Fleet and crew reserves*: The availability of fleet and crew reserves allows the agents to use them in their solution strategies. If they are unavailable, the solution strategies can neither encompass the use of reserve fleet nor reserve crew.
- *Reopening Time*: The reopening time of LCY airport can be set at either 30 minutes after Scheduled Time of Arrival (STA) of the KL985 (08:20z), 60 minutes after STA of the KL985 (08:50z) or 90 minutes after STA of the KL985 (09:50z).
- *Diversion airport*: The available diversion airport can be set to either Southend (SEN), Southampton (SOU) or Norwich (NWI). These are defined as the top three alternative airports for flights with destination LCY airport by the airline under consideration.

5.2 Agent Behaviour and Control Mode

The behaviour of the agents has been modelled to be dependent on the control mode that the agents are operating in. The control modes affect the situation awareness and coordination among the agents. In this research, and in accordance with the Contextual Control Model [20], the agents are modelled to have increasing situation awareness from the scrambled control mode to the strategic control mode. In Table 4 the varying coordination and situation awareness of the agents per control mode is depicted.

Control Mode	Reopening	Div. Airport	Technical Systems
Scrambled	✗	SEN	OCS, PCS, ACA
Opportunistic	✓	SEN	OCS, PCS, ACA
Tactical	✓	SEN, SOU, NWI	OCS, PCS, ACA, DST
Strategic	✓	SEN, SOU, NWI	OCS, PCS, ACA, DST, CDM, OF

Table 4: Agent situation awareness per control mode

In the scrambled control mode, the agents are simulated to act in panic and do not collect information, such as calling LCY airport to inform on the reopening time. The only diversion airport considered is SEN and only the essential technical systems are used.

The agents operating in the opportunistic control mode know from their experience that the reopening time of LCY is essential information for decision-making. Therefore, they make the call to LCY airport resulting in increased situation awareness. However, no additional diversion airport or technical system is considered to simulate the limited anticipation and lack of context comprehension of the agents. Hereby, the agents are simulated to apply limited planning or anticipation due to a lack of context comprehension.

In addition to the previous control mode, the agents operating in the tactical control mode consider all the available diversion airports and use the Decision Support Tool. Hereby simulating increased planning and anticipation of the agents.

The strategic control mode enables the agents to also use CDM and OrbiFly to gather extra information about the situation. The use of these technical systems simulates the agents having a wider time-horizon which allows them to take higher-level goals into account and act with full competence.

The behaviour of the social agents has been modelled through the co-ladder framework [15]. This framework proposes human model constructs that enable the modelling of human behaviour (section 3.2). The relation between these model constructs is defined with behavioural rules. The behavioural rules derived from the co-ladder framework and used in this research project are:

Observation → Expectation
Observation → Activity → Expectation
Observation → Analysis → Plans → Activity → Expectation

All agent behaviour is initiated with the agent making an *Observation*. An observation can be made through interaction with the environment or through interaction/coordination with other agents. Examples of observations are messages from other agents or changes in the flight, crew, or passenger schedules. From an observation either an *Analysis*, *Activity*, or *Expectation* originates.

While performing an *Analysis* the agent is interpreting the observation and performing a task or thought process based on this observation. An example of an analysis is the determination of the preferred solution strategies by Fleet Control, Crew Control, and Commercial Desk.

Following an analysis, *Plans* are made. A plan is the intention of the agent to execute a certain activity or sequence of activities that are the result of an analysis. An example of a plan would be Fleet Control planning to first send information via ACARS to the Flight Crew and thereafter setting up a conference call with other agents.

Activities are modelled as either communication to other agents or an agent applying an action in a technical system. In this case study communication can be in the form of conference calls, ACARS messages, or direct agent to agent communication via phone calls or face-to-face. With technical systems, the agents are modelled to have an input-output relation. An example of this is Fleet Control requesting the Decision Support Tool to propose an optimised solution strategy, upon which the Decision Support Tool outputs the optimised solution strategy.

From either an activity or an observation an agent sets an *Expectation*. Expectations are about the result of an applied action, tasks that might be assigned to the agent in the near future, about a change in the environment, and events that might evolve from changes to the environment.

As a result of the different control modes the behaviour and thus the behavioural rules of the agents are different per control mode. The exact definition of the behavioural rules and the individual components of these rules (observations, analyses, plans, activities and expectations) concerning the control modes, are defined in the appendix [24].

5.3 Decision-Making and Control Mode

Naturally, the control mode that the agents operate in impacts the decision-making. To simulate this in the model, the agents have been modelled to use different decision-making mechanisms per control mode.

Control Mode	Decision-making mechanism
Scrambled	Plurality voting protocol
Opportunistic	Borda voting protocol
Tactical	Clarke Tax Algorithm
Strategic	MCDM - AHP Method

Table 5: Decision-making mechanisms per control mode

The decision-making mechanisms per control mode are given in Table 5. In section 5.3.1 through section 5.3.4 the reasoning for the use of these decision-making mechanisms is elaborated.

5.3.1 Decision-making in scrambled control mode

In the scrambled control mode the agents have no control over the situation and are not able to obtain a good comprehension about the context. They will make decisions based on their gut-feeling. To represent this, the plurality voting protocol is implemented to simulate that the agents can prefer a solution strategy over the alternatives, but can not give any indication of relative preference. As a consequence of the limited situation awareness inherent to this control mode, there is only a limited set of solution strategies available. The solution strategies that the decision-making agents can vote on are:

B C D E

Solution strategies A and F are not in the solution space since the agents are not aware of the reopening time of LCY airport. This knowledge is a prerequisite for these solution strategies.

The votes of the decision-making agents have been identified through discussions with the airline's operational control experts and are described in the appendix [24]. These preferences are based on the scenarios that will be explained in section 7.1.

5.3.2 Decision-making in opportunistic control mode

Increased comprehension of the context is obtained by the agents while operating in the opportunistic control mode. To simulate that the agents are more aware of the impact of a solution strategy relative to the alternatives, but not being able to quantitatively express this, the Borda voting protocol is implemented. This protocol allows the agents to express their experience through the relative priority of the solution strategies. Hereby simulating the human decision-making of the real AOCC. In comparison to the scrambled control mode, an increased set of solution strategies is available due to the awareness about the reopening time of LCY airport. The available solution strategies are:

A B C D E F

To enable the implementation of the Borda voting protocol, preference relations for all scenarios have been derived based upon discussions with the airline's operational control experts. These preference relations are attached in the appendix [24].

5.3.3 Decision-making in tactical control mode

In the tactical control mode, the agents have a thorough comprehension of the context and have full control over the situation. Hereby they are able to compare the available solution strategies in detail. Furthermore, the agents are able to determine the impact of their preferred solution strategy on the other domains. To capture this in the model it is chosen to implement the Clarke Tax Algorithm as the decision-making mechanism. By using this algorithm the agents are able to quantify the impact of each solution strategy and can calculate a quantitative indication of the influence they have on the collaborative decision-making.

Within this research project, the agents' social welfare is expressed by cost functions. As a consequence the agents prefer minimum valuations ($v_i(g)$). Therefore, the social choice function is rewritten in Equation 14. The cost functions used for the valuations are elaborated in section 5.4.

$$g^* = \arg\,\min_g \sum_{\forall i \in A} v_i(g) \tag{14}$$

Conform with this, the taxes are calculated as in Equation 15.

$$\text{tax}_i = \sum_{j \neq i \in A} \hat{v}_j \Big(\arg\,\min_g \sum_{k \neq i \in A} \hat{v}_k(g) \Big) - \sum_{j \neq i \in A} \hat{v}_j(g^*) \qquad \forall i \in A \tag{15}$$

The utility of each agent is calculated by adding the tax to the valuation of the agent for the chosen preference, which is illustrated in Equation 16.

$$u_i(g) = v_i(g) + tax_i(g) \qquad \forall i \in A \tag{16}$$

Due to this, the agents prefer the total obtained utility to be as low as possible. This means that the impact of the implementation of a solution strategy is minimal.

Since the decision-making agents are able to use the Decision Support Tool in this control mode, there is an increase in size of the solution space. For each regular solution strategy there is also a proposal of the Decision Support Tool available. The resulting solution space is:

$$\begin{array}{cccccc} \mathrm{A} & \mathrm{A_{DST}} & \mathrm{B} & \mathrm{B_{DST}} & \mathrm{C} & \mathrm{C_{DST}} \\ \mathrm{D} & \mathrm{D_{DST}} & \mathrm{E} & \mathrm{E_{DST}} & \mathrm{F} & \mathrm{F_{DST}} \end{array}$$

5.3.4 Decision-making in strategic control mode

The strategic control mode simulates the agents having full competence and should be able to make the most thorough decisions. In addition, the agents have plenty of time to make decisions and evaluate all available solution strategies. To capture this in the model, MCDM with the AHP decision-making method is implemented. This method allows the agents to be aware of the details of each solution strategy and make a qualitative comparison between the alternatives. Additionally, it allows the agents to incorporate anticipatory behaviour due to the possibility of pursuing changing goals in different contexts. These contexts result from the use of CDM and OrbiFly by the agents and capture the anticipation of the future state of the environment. Hereby an accurate representation of real-life human decision-making, through qualitative judgement, has been incorporated in the model.

To capture the different contexts in the decision-making, each scenario is evaluated for four different contexts. These contexts are chosen based on the experience of the airline's operational control experts and the regularity of occurrence. The contexts are depicted in Table 6.

Context ID	**Description**
Context 1	Regular day of operations
Context 2	Slot delays at AMS until 10:00z
Context 3	Slot delays at AMS effective from 10:00z
Context 4	Critical passenger connections

Table 6: Contexts strategic control mode

The qualitative judgement and anticipation of the airline's operations controllers in these contexts result in different pairwise comparison matrices, through which the relative importance of the criteria are captured. These pairwise comparison matrices are determined by the airline's operational control experts and are attached in the appendix [24]. A more detailed description of each context is:

- *Context 1*: A regular day of operations is assumed. Hereby the controllers anticipate that no major disruptions are going to impact the airline's flight operations.
- *Context 2*: From using CDM it is noticed that currently all flights at AMS are affected by slot delays. OrbiFly shows that these slot delays are due to bad weather, which is expected to be cleared by 10:00z.
- *Context 3*: Currently the flight operations are not suffering from any disruption. However, by accessing OrbiFly it is noticed that a storm will hit AMS at around 10:00z. This is confirmed by the CDM system, which indicates expected slot delays from 10:00z onward.
- *Context 4*: The CDM system shows that many flights are suffering from unstable slot times. Hereby the agents are aware that the passenger connections are critical.

The available set of solution strategies in this control mode is not changing over the contexts. Hereby the available set of solution strategies is identical to the set of solution strategies available in the tactical control mode:

$$\begin{array}{cccccc} \mathrm{A} & \mathrm{A_{DST}} & \mathrm{B} & \mathrm{B_{DST}} & \mathrm{C} & \mathrm{C_{DST}} \\ \mathrm{D} & \mathrm{D_{DST}} & \mathrm{E} & \mathrm{E_{DST}} & \mathrm{F} & \mathrm{F_{DST}} \end{array}$$

5.4 Agent Decision-Making Criteria

To enable the decision-making agents to express their preferences on solution strategies in the tactical and strategic control modes, respectively the Clarke Tax Algorithm and the MCDM decision-making mechanisms are applied. To enable the application of MCDM, the goals of the agents have to be derived into criteria, on which optimality conditions are applied [36][28]. Additionally, these criteria can then be re-used to develop cost functions that facilitate the application of the Clarke Tax Algorithm.

The criteria and cost functions for the decision-making agents are derived in section 5.4.1 through section 5.4.4.

5.4.1 Fleet Control Criteria and Cost Function

Fleet Control represents the fleet domain in the decision-making. The goal of this agent is two-fold:

'Timely and safe execution of the planned flight schedule and ensuring absorbing capacity to counter disruptions'.

Based on these goals, six criteria have been derived:

- c_1 - *Extra cycles flown*: Refers to the extra cycles flown compared to the planned flight schedule and is a positive integer number. The aim is to minimize this criterion since extra cycles imply more intensive maintenance activities.
- c_2 - *Extra minutes of flight*: Extra flying time results in a higher fuel burn and additional maintenance. The criterion is a positive integer number that is to be minimised.
- c_3 - *Leg cancellation count*: Cancelling a leg is undesirable since it means that the airline loses expected profits. This criterion is a positive integer, which is to be minimised.
- c_4 - *Registration swaps in early window*: Registration swaps of flight with a Scheduled Time of Departure (STD) that is within a time span of 180 minutes from the current time, is said to be in the 'early window'. Registration changes made in this window requires quick re-scheduling for multiple departments: fleet, crew, gate, and turnaround planning. Therefore this is a criterion to be minimised, as a positive integer.
- c_5 - *Registration swaps in late window*: Registration swaps of flight with an STD more than 3 hours from the current time requires less effort to reschedule and is therefore evaluated separately from c_4. It is a positive integer number that is to be minimised.
- c_6 - *Reserve devaluation minutes*: The decrease in the number of minutes of reserve fleet in the flight schedule as a result of the implementation of a solution strategy is captured by this criteria. It is calculated as the scheduled reserve fleet time subtracted by the actual reserve fleet time, hereby it is a positive integer number that is to be minimised.

Based on these criteria the cost function as in Equation 17 is developed. The exact values of the cost variables are based on the airline's cost model.

$$\begin{aligned}\text{Fleet Control Cost} = {} & c_1 \cdot \mathrm{C_{cycle}} + c_2 \cdot \mathrm{C_{fuel}} \cdot \mathrm{A_{burn}} \\ & + c_3 \cdot \mathrm{C_{cancellation}} + c_4 \cdot \mathrm{C_{swap}} + c_6 \cdot \mathrm{C_{reserve}}\end{aligned} \tag{17}$$

In this equation $\mathrm{C_{cycle}}$ is the cost of flying an extra cycle, $\mathrm{C_{fuel}}$ is the cost of fuel, $\mathrm{A_{burn}}$ is the fuel use per minute of flying time, $\mathrm{C_{cancellation}}$ is the cancellation cost, $\mathrm{C_{swap}}$ is the cost of making registration changes, and $\mathrm{C_{reserve}}$ is the cost per minute of reserve devaluation. Criterion c_5 is not included in this cost function, since this criterion is considered to be free of charge in the airline's cost model.

5.4.2 Crew Control Criteria and Cost Function

Crew Control represents the crew domain in the decision-making. The goal of this agent is two-fold:

'Making minimal changes to the planned crew schedule and ensuring the absorbing capacity of this schedule to counter disruptions'.

Based upon these goals two criteria have been identified, which aim at capturing these goals in the decision-making:

- c_7 - *Crew swap count*: Swapping crew introduces a domino effect in the crew schedule and requires a lot of additional work for the crew controllers, moreover introducing instability in the crew rosters and therefore being undesirable. It is a positive integer that is to be minimised.

- c_8 - *Crew reserve usage count*: Crew reserves should be treated delicately due to the working time restrictions imposed by the Collective Labour Agreement (CLA). Additionally, if crew reserves are used, they should be used efficiently due to the stringent rules regarding the flight duty period. This is captured by this criterion, which is a discrete positive count to be minimised.

The cost function that has been developed with these criteria is given in Equation 18.

$$\text{Crew Control Cost} = c_7 \cdot \mathrm{C}_{\text{crewswap}} + c_8 \cdot \mathrm{C}_{\text{crewreserve}} \tag{18}$$

In this equation $\mathrm{C}_{\text{crewswap}}$ is the cost of a crew swap and $\mathrm{C}_{\text{crewreserve}}$ is the cost of using crew reserves.

5.4.3 Commercial Desk Criteria and Cost Function

The last decision-maker for which it is required to define criteria and a cost function is the Commercial Desk. The goal of this agent is three-fold:

'Ensuring minimal changes to the passenger schedule, maximum flight completion factor and on-time performance'.

From these goals, a total of six criteria have been identified. In some of these criteria, differentiation has been made between elite and non-elite passenger. This is done since this differentiation is also made in the airline's cost model which serves as a basis for the cost functions. Elite passengers enjoy more privileges compared to non-elite passengers. Hereby they might be prioritised in the decision-making based upon the context. The derived criteria are:

- c_9 - *Bussed elite passenger count*: The number of elite passengers that have to be bussed from an alternative airport to the planned destination airport. This criterion is a positive integer value, that is to be minimised.
- c_{10} - *Bussed non-elite passenger count*: The amount of non-elite passengers that have to be bussed from an alternative airport to their planned destination airport. This criterion is a positive integer value, that is to be minimised.
- c_{11} - *Rebooked elite passenger count*: The number of elite passengers who need to be rebooked due to cancellation of a connecting flight. This criterion is a positive integer value, that is to be minimised.
- c_{12} - *Rebooked non-elite passenger count*: The number of elite passengers who need to be rebooked due to cancellation of a connecting flight. This criterion is a positive integer value, that is to be minimised.
- c_{13} - *ETD delay minutes*: The total minutes of delay that have been introduced by setting confirmed delays (ETDs). This criterion is a positive integer value, that is to be minimised.
- c_{14} - *Collateral delay minutes*: The total minutes of propagated delay that are a result of ETDs set on other flights. These flights have an unconfirmed delay but are likely to receive a confirmed delay in the future. This criterion is a positive integer value, that is to be minimised.

Combining these criteria with the airline's cost model, the cost function in Equation 19 results.

$$\begin{aligned} \text{Commercial Desk Cost} = {} & c_9 \cdot \mathrm{FVL}_{\text{elite}} + c_{10} \cdot \mathrm{FVL}_{\text{non-elite}} + (c_{11} + c_{12}) \cdot \mathrm{C}_{\text{canxclaim}} \\ & + \sum_{i \in F} \Big(c_{13_i} \cdot (\mathrm{pax}_{\text{elite}_i} \cdot \mathrm{FVL}_{\text{elite}_i} + \mathrm{pax}_{\text{non-elite}_i} \cdot \mathrm{FVL}_{\text{non-elite}_i}) \Big) \\ & + \sum_{j \in G} \Big(c_{14_j} \cdot (\mathrm{pax}_{\text{elite}_j} \cdot \mathrm{FVL}_{\text{elite}_j} + \mathrm{pax}_{\text{non-elite}_j} \cdot \mathrm{FVL}_{\text{non-elite}_j}) \Big) \end{aligned} \tag{19}$$

In this function, F is the set of flights affected by confirmed delays and G is the set of flights that are affected by collateral delays. Furthermore, FVL is the expected future value loss of the airline due to bussing of passengers, $\mathrm{C}_{\text{canxclaim}}$ is the cost of a cancellation claim due to rebooking of passenger, and pax are the number of passengers on a flight.

5.4.4 Duty Manager Network Criteria and Cost Function

The Duty Manager Network is acting as the mediator agent in the decision-making between the fleet, crew, and passenger domains, as has been illustrated in Figure 1. Due to this hierarchical structure, the Duty Manager Network integrates the criteria of the decision-making agents. This integration is performed with the following goal:

'Ensure smooth cooperation between long-haul and short-haul flight operations'.

The criteria that have been derived from this goal are:

- *Fleet*: Captures the relative importance of the fleet domain with respect to the crew and passenger domains.
- *Crew*: Captures the relative importance of the crew domain with respect to the fleet and passenger domains.
- *Passengers*: Captures the relative importance of the passenger domain with respect to the fleet and crew domains.

Since these criteria are of a high level and are not directly related to KPIs within the solution strategies, no optimality conditions have to be applied.

The cost of a solution strategy for the Duty Manager Network is equal to the sum of the costs of the domain representative agents, since this agent integrates the fleet, crew, and passenger domains.

The structure and hierarchy of the complete set of criteria for all agents is shown in Figure 5. These criteria are used in the simulation of the tactical and strategic control mode. In the tactical control mode the criteria are used by the agents in the cost functions for the application of the Clarke Tax Algorithm as decision-making mechanism. The agents operating in the strategic control use the criteria for the application of the Multi-Criteria Decision-Making mechanism. In this mechanism, these criteria allow the qualitative judgment of the airline's operations control experts to be captured in the model.

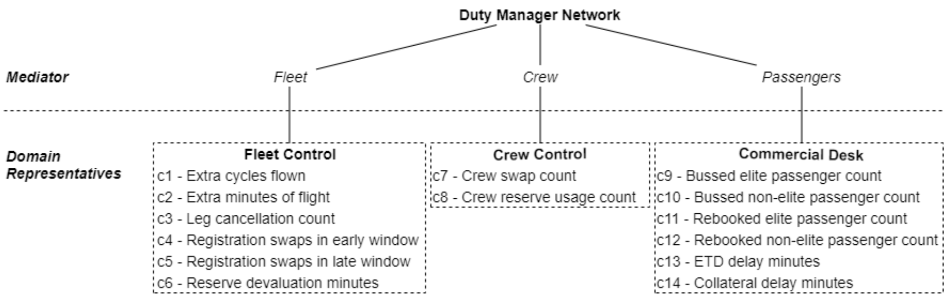


Figure 5: Complete set and hierarchy of criteria

5.5 Software Implementation

The software implementation of this model has been done in the Python programming language. An object-oriented programming structure has been used. The environment, social agents and technical systems have been modelled as individual objects. Through the environment, the agents can interact with each other and make observations. The social agents, if allowed, can access the technical system objects to extract information or apply changes.

For the exact details of the software implementation, one is advised to consult the appendix [24].

This concludes the section about the development of the socio-technical agent-based model. In the next section, the verification and validation of the model are discussed.

6 Verification and Validation

To ensure that the agent-based model generated the desired and expected results, verification and validation have been performed.

Verification has been performed through unit testing during the model development phase. Additionally, errors were tracked while programming through compiling errors. These errors have been resolved at the moment they occurred. For example, the results of the voting protocols (Plurality, Borda, Clarke Tax), the cost functions, and the functions of the agent objects have been verified.

Three major parts of the model needed validation. One of these being the agents' behaviour. To validate the agents' behaviour, trace plots have been outputted and were matched with the airline's workflow diagrams and the implemented behavioural rules [24]. An example trace plot is given in Figure 6. In this figure, the communication between agents is shown. The ATC agent contacts the FC agent over the radio. After the FC agent has interpreted the message from ATC, the FC agent contacts the DM via ACARS. With the information that the DM received, a conference call is started to spread the information to other agents in the AOCC.

Secondly, the predefined solution strategies used in the model have been subject to validation. This entails both the solution strategies representing the human controllers and the solution strategies according to the business rules of the Decision Support Tool. These have been validated through face validation with the airline's operational control experts [30].

Lastly, the output of the decision-making mechanisms and thus results of the model, have been validated through face validation with the airline's operational control experts. Hereby the results of the developed model are verified and validated.

Figure 6: Traces of agent behavior

7 Results

The results that are generated by the developed agent-based model are discussed in this section. In section 7.1 the simulation setup and scenarios for which the results are generated are elaborated. Thereafter, the results of the decision-making per control mode are discussed in section 7.2 through section 7.5.

7.1 Simulation Setup and Scenarios

The purpose of simulation in this research is to analyse the decision-making of the agents' in the AOCC while operating in the different control modes. The simulation is performed on a flight schedule that has been flown by the airline on Monday the 30th of July 2019. This flight schedule has been used since it is representative of a regular summer flight schedule of the airline under consideration. Summer flight schedules are characterised by a high density of flights and do not provide any slack to accommodate for disruptions. One reserve aircraft and one set of reserve crew are present in the schedule. However, the scenarios specify whether the agents are allowed to make use of these reserves in their disruption management strategies.

The scenarios that are evaluated are characterised by the categorical variables that describe the state of the environment. To recall from section 5.1 these variables are: the available holding time of the diversion aircraft, availability of fleet and crew reserves, reopening time of LCY airport and the selected diversion airport. The scenarios that evolve from these variables are shown in Figure 7.

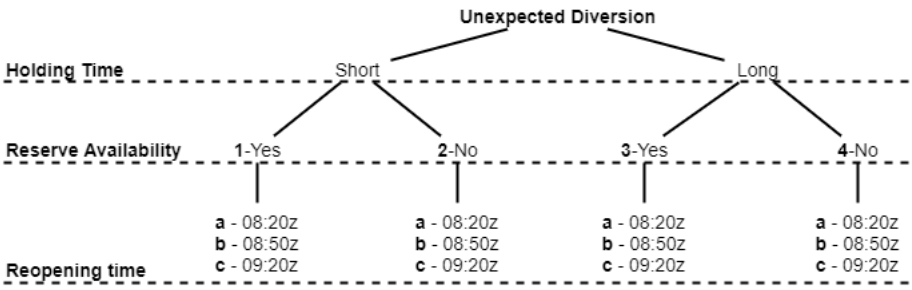


Figure 7: Scenario tree indicating the twelve scenarios

Four main scenarios (1,2,3,4) and three sub scenarios (a,b,c) make that a total of twelve scenarios have been evaluated. The model was run separately for the agents operating in the scrambled, opportunistic, tactical, and strategic control modes. In the strategic control mode, each scenario has been run additionally for four different contexts as per section 5.3.4. Hereby the strategic control mode will be analysed for a total of 12 scenarios and four levels of context, which makes a total of 48 results.

In the following section, the results are presented. These results will be grouped per control mode and based on reserve availability. Hereby scenario 1 and scenario 3 (characterised by reserve availability) are analysed simultaneously and scenario 2 and 4 (characterised by reserve unavailability) are analysed simultaneously.

To increase the understanding of the solution strategies in the following section, the abbreviations of the solution strategies are summarized in Table 7. These solution strategies have been elaborated upon in section 2.2 and are included in more detail in the appendix [24].

Abbreviation	Description
A	Divert to alternative airport - await reopening - continue flight to LCY
B	Divert to alternative airport - bus passenger to alternative airport - return to AMS
C	Divert to alternative airport - bus passengers to LCY - ferry empty to AMS
D	Mid-air return of KL985 to AMS - cancelling the complete LCY rotation
E	Mid-air return of KL985 to AMS - delay the LCY rotation to a later moment on the day
F	Await reopening of LCY in a holding pattern
X_{DST}	Solution strategy X as proposed by the Decision Support Tool

Table 7: Abbreviations of solution strategies

7.2 Results for the scrambled control mode

In this section, the results generated by the model for the agents operating in the scrambled control mode are presented. The agents decide on the solution strategy by using the plurality voting protocol. The resulting decisions of the agents in this control mode are discussed in section 7.2.1 and section 7.2.2.

7.2.1 Scenario 1 & 3

For scenarios 1 and 3, the agents in the scrambled control mode decide on the implementation of solution strategy B. This is unanimously decided since all three decision-makers vote for this solution strategy. This can be explained since solution strategy B induces the least damage on the remainder of the flight operations out of the available set of solution strategies. Solution strategy B involves the use of the reserve aircraft and crew. However, no extra delays are introduced on other flights, no cancellations are necessary, and no passengers need to be rebooked.

Reopening time does not influence the decision-making since the agents are not aware of the reopening time in this control mode. Furthermore, the only diversion airport considered by the agents is SEN which also is a result of the limited situation awareness.

7.2.2 Scenario 2 & 4

In scenarios 2 and 4, the agents decide upon implementation of solution strategy C. This decision was not unanimously. The Commercial Desk votes for solution strategy B, in contrast to Fleet Control and Crew Control, who vote for solution strategy C. Fleet Control and Crew Control vote for C since there are no reserves available and they want to minimise the damage to other scheduled flights. The Commercial Desk votes for the passengers, similar to scenarios 1 and 3, and does not change its vote based on reserve availability.

7.3 Results for the opportunistic control mode

In the opportunistic control mode, the solution strategy is voted upon through the preference relations of the agents. These preference relations are evaluated by the Borda voting protocol to arrive at a decision on solution strategy. The decisions made by the agents in this control mode are discussed in section 7.3.1 and section 7.3.2.

7.3.1 Scenario 1 & 3

In Table 8 the Borda vote results for scenario 1 are given. In this table, it can be seen that solution strategy A is the most preferred solution independent of reopening time. In all sub scenarios, the votes of the agents for solution strategy A and B are close. In scenarios 1a and 1b Fleet Control and Commercial Desk prefer solution strategy A over B. Fleet Control prefers solution strategy A since a reserve aircraft is available and they want to achieve the goal of completing all planned flights. The Commercial Desk votes for solution strategy A to maximise passenger convenience. Hereby this agent aims to minimise the bussing and rebooking of passengers. Crew Control prefers solution strategy B over A. In the crew domain, it is preferred to not fly an extra cycle, since this changes the planned duties of the flight crew due to which they might not be able to execute the remainder of their planned flights.

In scenario 1c Fleet Control prefers solution strategy B over A since bussing the passenger from SEN to LCY takes less time compared to continuing the flight from SEN to LCY. However, for passenger convenience, the Commercial Desk still prefers solution strategy A over B. Crew Control prefers to fly empty back to AMS by means of solution strategy C since this reduces the impact of the diversion on the flight duty period of the crew, which results in the least extra flying time, no extra cycles, and no waiting for passengers to be bussed.

Scenario	A	B	C	D	E
1a	14	13	8	3	7
1b	14	13	8	3	7
1c	13	12	10	3	7

Table 8: Borda vote results - scenario 1

Scenario	A	B	C	D	E	F
3a	14	13	8	3	7	18
3b	14	13	8	3	7	18
3c	14	12	11	3	7	16

Table 9: Borda vote results - scenario 3

The Borda vote results for scenario 3 are given in Table 9. In scenarios 3a and 3b, the agents vote unanimously for solution strategy F. However, in scenario 3c the decision-makers do not agree on their first preferences. Fleet Control prefers F since this solution only involves extra flying time and the use of the reserve aircraft. Crew Control wants to reduce the impact of the disruption and does not want to use the set of reserve crew. Lastly, the Commercial Desk prefers solution strategy A since loitering is usually experienced as unpleasant by the passengers according to the airline's operational control experts and the delayed arrival of either solution strategy A and F in this scenario is approximately equal.

7.3.2 Scenario 2 & 4

In scenario 2 the Borda voting protocol results in the decision on solution strategy C, independent of the reopening time of LCY airport. The exact Borda count is given in Table 10. From these resulting Borda count values, it can be seen that solution strategy C is increasingly preferred with increasing reopening time. This is mainly because solution strategy C is most preferred by Fleet Control and Crew Control. Commercial Desk votes, independent of reopening time, for solution strategy A. Fleet Control and Crew Control want to minimise the damage on other flights by voting for solution strategy C. The Commercial Desk does not mind the lack of fleet and crew reserves and votes for passenger satisfaction.

Scenario	A	B	C	D	E
2a	9	10	12	9	5
2b	7	8	15	12	3
2c	7	8	15	12	3

Table 10: Borda vote results - scenario 2

Scenario	A	B	C	D	E	F
4a	9	10	12	9	5	18
4b	10	10	14	9	5	15
4c	10	10	14	11	5	13

Table 11: Borda vote results - scenario 4

The Borda vote results for scenario 4 can be seen in Table 11. The results are approximately equal to the results of scenario 2. However, the set of available solution strategies is extended with solution strategy F. In scenario 4a and 4b the Borda vote results in solution strategy F. However, in scenario 4c it is determined to implement solution strategy C, which is motivated by the preference of Fleet Control and Crew Control. Due to the lack of reserves, there is no room in the flight schedule to absorb the induced delays by solution strategy F in this scenario. To prevent the cancellation of other flights, it is decided to cancel the return flight from LCY through the implementation of solution strategy C.

7.4 Results for the tactical control mode

In the tactical control mode, the agents decide on their solution preferences based on the cost functions that have been defined in section 5.3. These preferences serve as input for the Clarke Tax Algorithm that is used as decision-making mechanism. Furthermore, the decision-making agents are able to evaluate the solution strategies for all the available alternative airports and are able to use the Decision Support Tool. An overview of the resulting decisions and exact costs and taxes paid by the agents is attached in the appendix [24].

In the Clarke Tax Algorithm, as implemented in this research, a decision is made based on the minimum total utility obtained that results from the implementation of a solution strategy. This total utility is calculated by the sum of the total costs inherent to a solution strategy and taxes paid by the agents. The total cost resulting from the implementation of a solution strategy is calculated by summing the cost functions of Fleet Control, Crew Control, and Commercial Desk. Taxes are paid when agents are influential in the decision-making. A tax is paid to compensate other agents for not implementing their preferred solution strategy. The theoretical background of this algorithm has been given in section 4.1.3 and the details on the implementation in this research are given in section 5.3.3.

The resulting decisions from the application of the Clarke Tax Algorithm in the tactical control mode are discussed in section 7.4.1 and section 7.4.2.

7.4.1 Scenario 1 & 3

Table 12 and Table 13 depicts the chosen solution strategies per diversion airport for scenarios 1 and 3.

For scenario 1 it can be seen that the decision on solution strategy does not vary with reopening time, but is varying with selected diversion airport. For diversion airport SEN, the agents decide on the implementation of solution strategy B_{DST}. In this solution strategy, the agents decide to divert the aircraft to an alternative airport and wait for the passengers to be bussed from LCY, after which the aircraft returns to AMS. For diversion airport SOU the agents decide to implement solution strategy A_{DST}. In this solution strategy, the aircraft is diverted to an alternative airport, where the aircraft awaits the reopening of LCY. Upon reopening the flight continues to LCY. For diversion airport NWI it is decided to implement solution strategy C, which is to divert to an alternative airport and then return empty back to AMS.

Scenario	SEN	SOU	NWI
1a	B_{DST}	A_{DST}	C
1b	B_{DST}	A_{DST}	C
1c	B_{DST}	A_{DST}	C

Table 12: Clarke Tax results - scenario 1

Scenario	SEN	SOU	NWI
3a	F	F	F
3b	F_{DST}	F_{DST}	F_{DST}
3c	F_{DST}	F_{DST}	F_{DST}

Table 13: Clarke Tax results - scenario 3

The analysis of the taxes paid in scenario 1 shows that Fleet Control consistently pays a tax for the implementation of the solution strategies, independent of diversion airport. This indicates that Fleet Control is influential in the decision-making. By paying a tax, Fleet Control is aware that the other decision-makers would prefer the implementation of a different solution strategy.

For diversion airport SEN, the other decision-makers prefer the implementation of solution strategy C. However, Fleet Control pays a tax to prevent the (expensive) cancellation that is inherent to this solution strategy. As a result, the agents agree on the implementation of solution strategy B_{DST}.

In the case that diversion airport SOU is selected, the other decision-makers would prefer the implementation of solution strategy A. Fleet Control pays a tax to prevent the high cost involved by the reserve devaluation that is inherent to this solution strategy. Hereby, Fleet Control influences the other decision-makers to decide for solution strategy A_{DST}.

For diversion airport NWI, Fleet Control pays a tax and influences the other decision-makers to decide on the implementation of solution strategy C. The tax is paid to prevent the additional costs that are involved with flying an extra cycle, additional flying time, and increased reserve devaluation in solution strategy A.

The Commercial Desk only influences the decision-making when SOU is selected as diversion airport. This agent pays a tax to prevent the bussing and rebooking of passengers that are involved with the preference of Fleet Control and Crew Control for solution strategy C.

In Table 13 the resulting solution strategies for scenario 3 are given. In this table, it can be seen that solution strategy F is dominantly preferred. For increasing reopening time the decision-makers decide on the implementation of solution strategy F_{DST}. In solution strategy F the aircraft awaits reopening of LCY airport while flying a holding pattern.

In scenario 3a, independent of diversion airport, the agents unanimously decided on the implementation of solution strategy F. This decision is unanimous since none of the decision-makers pays a tax and therefore the total utility obtained is equal to the total costs inherent to the solution strategy. As a result, all decision-makers are satisfied, since their most preferred solution strategy is decided upon.

In scenario 3b, Fleet Control and the Commercial Desk influence the decision-making. This influence is expressed by the taxes that are paid by these agents. Both agents prefer solution strategy F_{DST} over solution strategy F. The reasoning behind this is that F_{DST} is characterised by a lower reserve devaluation and less induced delays.

The decision in scenario 3c for diversion airport SEN is influenced by the Commercial Desk. This agent pays a tax to minimise the bussing of passengers and reduce the amount of delay introduced in the schedule. As a result, the total obtained utility increases. Hence, there is a disagreement in the preference of the decision-makers. For the diversion airports of SOU and NWI, none of the decision-makers pays a tax. Hereby, it can be stated that the socially most preferred solution is decided upon.

The results described in this section for scenarios 1 and 3 indicate that Fleet Control and the Commercial Desk frequently influence the decision-making. This results in an increase of the total obtained utility, which is undesired. Due to this increase, it is evident that the decisions are not preferred by all decision-makers. Crew Control never pays a tax which means that this agent does not have any influence on the decision-making in the analysed scenarios. This can be an indication that the cost functions from Fleet Control and the Commercial Desk do not anticipate the impact of a decision on the other domains.

In general, it is noticed that the use of reserve aircraft and crew is avoided, which is due to the costs involved. This is also confirmed by the influence of Fleet Control in most decisions. To prevent reserve devaluation, a high number of registration swaps in the late window are applied.

7.4.2 Scenario 2 & 4

Upon analysis of Table 14 and Table 15, it is obvious that the decided solution strategies in scenarios 2 and 4 are not different from scenario 1 and 3. However, there is a difference in the total obtained utilities by the agents, due to different amounts of tax being paid.

Scenario	SEN	SOU	NWI
2a	B_{DST}	A_{DST}	C
2b	B_{DST}	A_{DST}	C
2c	B_{DST}	A_{DST}	C

Table 14: Clarke Tax results - scenario 2

Scenario	SEN	SOU	NWI
4a	F	F	F
4b	F_{DST}	F_{DST}	F_{DST}
4c	F_{DST}	F_{DST}	F_{DST}

Table 15: Clarke Tax results - scenario 4

In scenario 2 for diversion airport SEN, Fleet Control and the Commercial Desk influence the decision-making. Fleet Control has a strong preference for solution strategy B_{DST}, in contrast to the other decision-makers who prefer solution strategy C. This preference is motivated by the cost of a cancelled leg. The Commercial Desk influences the decision-making by preferring solution strategy B_{DST} over solution strategy B. This is motivated by the minimisation of the induced delays.

For diversion airport SOU only the Commercial Desk pays a tax. Without the participation of this agent, the other decision-makers would decide on solution strategy B. However, the Commercial Desk pays a tax to minimise the delay minutes, rebookings, and bussing activities. Hereby, influencing the other decision-makers to decide upon solution strategy A_{DST}.

Lastly, in scenario 2 and diversion airport NWI it is noticed that none of the agents pays a tax and hereby they have a common agreement on the implementation of solution strategy C.

In scenario 4 again solution strategy F is dominating as seen in Table 15. Fleet Control is influential for the decision-making in scenario 4c with diversion airport SEN. Without the participation of Fleet Control, the other decision-makers would decide upon implementation of solution strategy C. Fleet Control pays a tax to prevent the cancellation inherent to this solution strategy.

The Commercial Desk influences the decision-making in scenario 4a, 4b, and 4c. This influence increases with reopening time since the total obtained utility increases with reopening time. The Commercial Desk is motivated to decide on solution strategy F to prevent excessive delays, rebookings, and bussing of passengers.

For diversion airport SOU the Commercial Desk influences the decision-making in scenario 4b and 4c. The other decision-makers would prefer the implementation of solution strategy B. However, the Commercial Desk convinces them to decide on solution strategy F_{DST}. The Commercial Desk is motivated here by the minimisation of bussing and rebooking of passengers. The total obtained utility, in this case, increases with reopening time due to the increasing amount of tax paid with increasing reopening time.

For diversion airport NWI, the decision-making is only influenced by the Commercial Desk. The Commercial Desk pays a tax to minimise the amount of rebooked passengers. Due to the influence of this agent, the other decision-makers agree with the implementation of solution strategy F_{DST} instead of solution strategy F.

The described results for scenario 2 and 4 indicate Fleet Control and Commercial Desk regularly influence the decision-making. Due to this, the total obtained utility is increased. This is an indication that a preferred solution strategy for one domain is not necessarily preferred by the other domains. As a result the decision-making agents regularly disagree in the decision-making. This disagreement shows through the difference between the total costs inherent to a decision and the total obtained utility by the decision-makers.

7.5 Results for the strategic control mode

In the strategic control mode, the agents use MCDM with the AHP decision making-mechanism to make their decisions (section 4.2). Each scenario is analysed for four different contexts to capture the use of the CDM and OrbiFly systems by the decision-makers. These contexts are (section 5.3.4):

1. Regular day of operations.
2. Slot delays at AMS until 10:00z.
3. Slot delays at AMS effective from 10:00z.
4. Critical passenger connections.

For the application of this decision-making method, the goals of the agents have been derived into criteria (section 5.4). These criteria are then subject to a pairwise comparison by the airline's operations controllers for each scenario and context combination. These pairwise comparison matrices capture the expert judgement of the operations controllers in the decision-making and are attached in the appendix [24]. The pairwise comparisons express the relative importance of the criteria and are transformed by means of calculation into criteria weights. These criteria weights ultimately define the solution strategy preference of the decision-makers. This process is summarized as:

Goals ⟶ Criteria ⟶ Pairwise comparisons ⟶ Criteria weights ⟶ Solution strategy preference

In the remainder of this section, the criteria weights that lead to the implementation of a solution strategy will be discussed. Scenarios 1 and 3 are analysed simultaneously for the different contexts as well as scenarios 2 and 4. In Table 16 the definition of each criterion is given, as discussed previously in section 5.4.

Criterion ID	Description	Optimality Condition	Agent
c_1	Extra cycles flown	Minimize	Fleet Control
c_2	Extra minutes of flight	Minimize	Fleet Control
c_3	Leg cancellation count	Minimize	Fleet Control
c_4	Registration swaps in early window	Minimize	Fleet Control
c_5	Registration swaps in late window	Minimize	Fleet Control
c_6	Reserve devaluation minutes	Minimize	Fleet Control
c_7	Crew swap count	Minimize	Crew Control
c_8	Crew reserve usage count	Minimize	Crew Control
c_9	Bussed elite passenger count	Minimize	Commercial Desk
c_{10}	Bussed non-elite passenger count	Minimize	Commercial Desk
c_{11}	Rebooked elite passenger count	Minimize	Commercial Desk
c_{12}	Rebooked non-elite passenger count	Minimize	Commercial Desk
c_{13}	ETD delay minutes	Minimize	Commercial Desk
c_{14}	Collateral delay minutes	Minimize	Commercial Desk

Table 16: Criterion Definition

In section 7.5.1 through section 7.5.5 the decisions made by the agents for the scenarios in the different contexts are evaluated.

7.5.1 Scenario 1 & 3 in the context of a regular day of operations

The decisions of the agents for scenario 1 and 3 in the context of a regular day of operations are given in Table 19 and Table 20. In scenario 1 the decisions are changing with the diversion airport. For diversion airport SEN and NWI the agents decide upon implementation of solution strategy C. In this solution strategy, the aircraft is diverted to an alternative airport and flies empty back to AMS. For diversion airport SOU it is decided to implement solution strategy D. In this solution strategy the aircraft returns mid-air back to AMS and the complete LCY rotation is cancelled.

In scenario 3 the agents decide, independent of diversion airport or reopening time, on the implementation of solution strategy F. In this solution strategy the aircraft awaits reopening of LCY while loitering.

Scenario	SEN	SOU	NWI
1a	C	D	C
1b	C	D	C
1c	C	D	C

Table 17: Results scenario 1 - Context 1

Scenario	SEN	SOU	NWI
3a	F	F	F
3b	F	F	F
3c	F	F	F

Table 18: Results scenario 3 - Context 1

The criteria weights that result in these decisions are shown in Figure 8. In this context, the agents anticipate that no major events will affect the airline's operations in the near future. Each domain is assigned equal importance by the Duty Manager Network since no major events are expected to affect the flight, crew and passenger schedules.

Fleet Control translates this anticipation by assigning a high criterion weight to the leg cancellation count criterion (c_3). This criterion is deemed to be important since no major events are expected to occur and there is a reserve aircraft available, which can be used to absorb delays. Furthermore, the reduction of registration swaps in the early window (c_4) are deemed to be important. This is explained by Fleet Control's goal of executing the flights as planned. The registration swaps in the early window require quick re-scheduling of the gate and turnaround planning at AMS airport. Under the current context, the effort required for this re-scheduling is not deemed to be necessary.

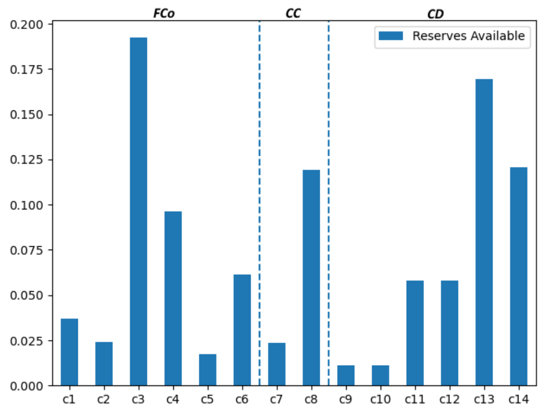


Figure 8: Criteria weights scenario 1 & 3 - Context 1

Crew Control deems the crew reserve usage count (c_8) to be the most important. Hereby, Crew Control anticipates that the crew reserves might be needed at a later moment during the day of operations. To prevent the use of crew reserves, Crew Control is willing to apply crew swaps in the crew schedule.

The Commercial Desk assigns the highest criteria weights to the delay criteria (c_{13}, c_{14}). Due to the early morning time of the unexpected diversion, the Commercial Desk aims to minimise the impact of the solution strategy on the passenger schedule. If a delay is introduced into the schedule at this time in the morning, it is most likely that passenger connections will be broken. Hence, the anticipation of the possible consequences of introduced delays results in these criteria weights.

In scenario 1 the decision-makers decide to implement either solution strategy C or D, depending on the diversion airport. These solution strategies are both limiting the damage to the remainder of the flight schedule. Solution strategy C comes at the cost of a single cancellation and solution strategy D involves two cancellations. However, these strategies do not require any registration swaps, crew reserves to be used, and do not introduce any delays into the schedule. Fleet Control would not prefer these solution strategies due to the cancellations involved. However, the other agents overrule Fleet Control with their priorities. The anticipation of Crew Control and the Commercial Desk is reflected in the solution strategies which results in a compromised decision for Fleet Control.

The decisions made by the agents in scenario 3 are given in Table 18. In this scenario, solution strategy F is decided upon, independent of reopening time or diversion airport. This solution strategy requires no cancellations, no crew reserves to be used, and only comes at the cost of a delayed return flight to AMS. Hereby the KPIs of this solution strategy are in favour of the assigned criteria weights and all decision-makers are satisfied with this decision.

7.5.2 Scenario 1 & 3 in the context of slot delays at AMS until 10:00z

The decisions of the agents for scenario 1 and 3 in the context of slot delays at AMS until 10:00z, are given in Table 19 and Table 20. In scenario 1 the decisions vary with diversion airport. For diversion airport SEN and NWI the agents decide upon implementation of solution strategy C. In this solution strategy, the aircraft is diverted to an alternative airport and flies empty back to AMS. For diversion airport SOU it is decided to implement solution strategy A_{DST}. In this solution strategy, the aircraft is diverted to an alternative airport, where it awaits the reopening of LCY airport. Upon reopening, the flight is continued towards LCY.

In scenario 3 the agents decide, independent of diversion airport or reopening time, on the implementation of solution strategy F. In this solution strategy the aircraft awaits reopening of LCY while loitering.

Scenario	SEN	SOU	NWI
1a	C	A_{DST}	C
1b	C	A_{DST}	C
1c	C	A_{DST}	C

Table 19: Results scenario 1 - Context 2

Scenario	SEN	SOU	NWI
3a	F	F	F
3b	F	F	F
3c	F	F	F

Table 20: Results scenario 3 - Context 2

The criteria weights that result in these decisions are shown in Figure 9. In this context, all flights at AMS are suffering from slot delays due to bad weather. The weather is expected to be clear by around 10:00z. The Duty Manager Network assigns the fleet and crew domains relatively high importance compared to the passenger domain. This is due to the anticipation that sufficient fleet and crew should be available to fly the remainder of the schedule when the slot delays are resolved. Consequently, the decision-making is fleet and crew driven.

Fleet Control deems the leg cancellation count (c_3) to be most important. The slot delays already introduce a lot of stress on the other flights in the flight schedule, due to which Fleet Control wants to protect the LCY rotation from cancellations. However, since there are also other flights suffering from slot delays, it is not preferred to use the reserve aircraft (c_6). It is anticipated that the reserve aircraft will be needed to manage disruptions on other flights. Hereby, Fleet Control is adapting to the current context and still trying to achieve its goals. The low weights assigned to the remaining criteria shows that Fleet Control wants to do everything possible to prevent cancellations and the use of the reserve aircraft.

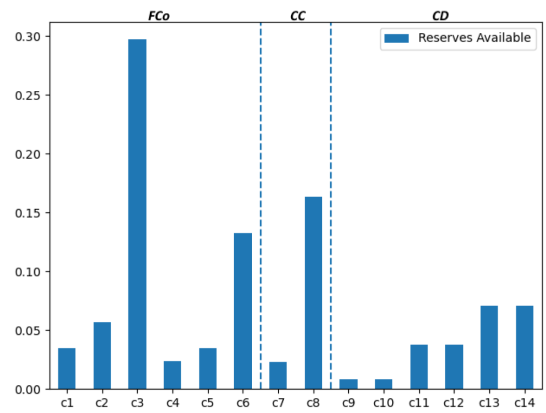


Figure 9: Criteria weights scenario 1 & 3 - Context 2

Crew Control is not eager to use the reserve crew (c_8). This controller anticipates that, due to the other flights that are suffering from the slot delays, the reserve crew will be needed to solve bigger disruptions. To prevent the use of crew reserves, Crew Control is willing to make the necessary crew swaps (c_7).

The Commercial Desk's criteria are assigned relatively low weights compared to the other decision-makers. In this context, the fleet and crew domains are more important, since if the disruption is poorly managed in these domains the passenger domain will also suffer. The most significant weights are assigned to the prevention of delays (c_{13}, c_{14}). Due to the slot delays, there are already a lot of delays in the passenger schedule. Hereby, the aim is to minimize any additional delays and try to ensure timely flight execution of the afternoon flights.

In scenario 1, for diversion airports SEN and NWI, the assigned criteria weights result in the decision on solution strategy C. The decision for this solution is motivated by the protection of the reserve aircraft and crew. However, this is conflicting with the prevention of cancellations. The criterion of the leg cancellation count is overruled by the criteria which capture the use of reserve aircraft, the use of reserve crew, and the minimisation of delays.

For diversion airport SOU the agents decide on the implementation of solution strategy $\mathrm{A}_{\mathrm{DST}}$. The agents do not decide on solution strategy C, since the flight from SOU to AMS takes a relatively longer time than from the other diversion airports. As a result, this strategy would also require a reserve aircraft to be used. Therefore, it is chosen to continue the flight to LCY and make full use of the reserve aircraft and crew and prevent additional delays in the flight schedule by making a high number of registration swaps.

In scenario 3 it is chosen to implement solution strategy F. This solution strategy requires minimal use of reserve aircraft, no cancellations, no reserve crew, and the delays are limited to the LCY rotation. Hereby, this solution strategy satisfies all decision-makers.

7.5.3 Scenario 1 & 3 in the context of slot delays at AMS effective from 10:00z

The decisions of the agents for scenario 1 and 3 in the context of slot delays at AMS effective from 10:00z, are given in Table 21 and Table 22. In scenario 1 the agents' decisions are dependent on the diversion airport. For diversion airports SOU and NWI, the agents decide upon implementation of solution strategy C. In solution strategy C it is decided to divert the aircraft to an alternative airport and return without passengers back to AMS. For diversion airport SOU, the agents decide on the implementation of solution strategy A. In solution strategy A the aircraft is diverted to an alternative airport, where it awaits the reopening of LCY airport. Upon reopening, the flight departs from the diversion airport to LCY.

In scenario 3 the agents decide, independent of diversion airport or reopening time, on the implementation of solution strategy F. In this solution strategy the aircraft awaits reopening of LCY while flying a holding pattern.

Scenario	SEN	SOU	NWI
1a	C	A	C
1b	C	A	C
1c	C	A	C

Table 21: Results scenario 1 - Context 3

Scenario	SEN	SOU	NWI
3a	F	F	F
3b	F	F	F
3c	F	F	F

Table 22: Results scenario 3 - Context 3

The criteria weights that result in these decisions are shown in Figure 10. In this context, all flights at AMS are expected to be suffering from slot delays from 10:00z. The Duty Manager Network assigns the fleet and crew domains the highest importance since the availability of fleet and crew are the limiting factors in the decision-making in this context. They are the limiting factors since fleet and crew are important to be available for the flights that will be suffering from slot delays. Consequently, the decision-making is again fleet and crew driven.

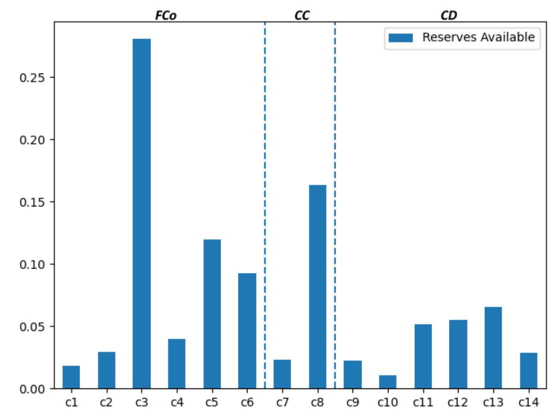


Figure 10: Criteria weights scenario 1 & 3 - Context 3

Fleet Control aims to minimize the leg cancellation count (c_3). Due to the slot delays that are expected to be effective later on the day of operations, it is likely that more disruptions will affect the flight schedule. Due to this anticipation, Fleet Control does not prefer to cancel a flight in solving the unexpected diversion. Furthermore, a high weight is assigned to the registration swaps in the late window (c_5). These registration swaps are likely to involve the flights that are expected to suffer from the slot delays later on, due to which Fleet Control does not want to make the situation more complex by making registration changes on these flights.

Crew Control expects the crew reserves to be needed to solve disruptions that are going to be introduced by the slot delays and therefore does not want to use them to solve the unexpected diversion. This explains the high criterion weight of the crew reserve usage count (c_8).

The Commercial Desk expects difficulties with the rebooking of the passenger as a consequence of the slot delays. As a result of this anticipation, the rebooking criteria (c_{11}, c_{12}) are assigned high weights. Furthermore the (confirmed) ETD delays (c_{13}) are also deemed to be important. If ETDs are set due to the disruption management of the unexpected diversion, these delays are likely to propagate to the flights that are going to suffer from slot delays. This is unwanted since the slot delays will add to these ETDs and the resulting delays will be even bigger.

The decision on solution strategy C for diversion airports SEN and NWI conflicts with the prevention of cancellations and rebookings but is in accordance with the reduction of registration swaps in the late window, the preservation of fleet and crew reserves, and the minimisation of introduced delays. Fleet Control expresses conflicting objectives through the criteria weights and therefore the minimisation of the registration swaps and the preservation of the reserve aircraft, come at the cost of a cancellation.

For diversion airport SOU the agents decided on the implementation of solution strategy A. This solution strategy is characterised by using reserve aircraft and crew, no registration swaps in the late window, and the induced delays being isolated to the LCY rotation. Hereby, the most important criteria of the decision-makers are satisfied.

In scenario 3 the decision-makers decide on solution strategy F, independent of reopening time or diversion airport. This solution strategy requires minimal use of reserve aircraft, no cancellations, no reserve crew, and the delays are limited to the LCY rotation. Due to this, the implementation of this solution strategy will not affect the flights that are expected to suffer from slot delays. Additionally, the reserve aircraft will be available from 10:00z onward to use for the disruption management during the slot delay period.

7.5.4 Scenario 1 & 3 in the context of critical passenger connections

The decisions of the agents for scenario 1 and 3 in the context of critical passenger connections, are given in Table 23 and Table 24. In these tables, it can be seen that for scenario 1 and diversion airports SEN and NWI, the decisions are independent of reopening time. The agents decide on the implementation of solution strategy B, which involves a diversion after which the aircraft waits for the passengers being bussed from LCY to the diversion airport. After the passengers have arrived at the diversion airport, the aircraft departs back to AMS. For diversion airport SOU the agents decide on the implementation of solution strategy B_{DST}.

Scenario	SEN	SOU	NWI
1a	B	B_{DST}	B
1b	B	B_{DST}	B
1c	B	B_{DST}	B

Table 23: Results scenario 1 - Context 4

Scenario	SEN	SOU	NWI
3a	F	F	F
3b	F	F	F
3c	F	F	F

Table 24: Results scenario 3 - Context 4

In scenario 3 the agents decide, independent of diversion airport or reopening time, on the implementation of solution strategy F. In this solution strategy the aircraft awaits reopening of LCY while flying a holding pattern.

The criteria weights that result in these decisions are shown in Figure 11. In this context, the agents observe in CDM that a lot of flights are suffering from unstable slot times. Due to this, the decision-makers focus on flight completion and minimal collateral damage to other flights. The Duty Manager Network determines that the passenger domain is the most important in this context since the disruption management of the passenger schedule is critical. This results in relatively low criteria weights for Fleet Control and Crew Control and the decision-making being passenger driven.

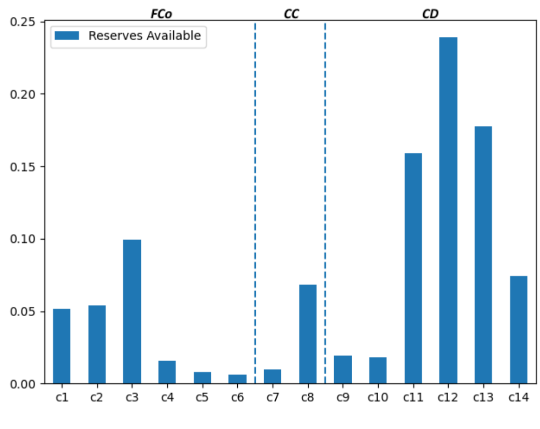


Figure 11: Criteria weights scenario 1 & 3 - Context 4

Fleet Control again focuses on the minimisation of the leg cancellation count (c_3). Furthermore, the minimisation of extra cycles flown (c_1) and extra minutes of flight (c_2) are deemed to be important. The importance of these criteria is motivated by the goal of executing flights as planned. Flying an extra cycle or increased flight time results in changes to the maintenance schedule. This is undesired since Fleet Control anticipates that these changes will endanger the execution of the remainder of the flights.

Crew Control is not changing the priorities based on this context and acts identical to the context of a normal day of operations. Due to this, Crew Control is not keen on already using reserve crew (c_8) at the start of the day.

The decision-making in this context is mainly driven by the Commercial Desk. The minimisation of the rebookings (c_{11}, c_{12}) and the delay minimisation (c_{13}, c_{14}) are assigned the highest criteria weights. The unstable slot times result in uncertainty about the exact departure times of the other flights in the schedule. Due to this, the Commercial Desk wants to minimise the rebookings and does not want to introduce additional delays. The anticipation of uncertain departure times makes it difficult to rebook the passengers as efficiently as possible. Furthermore, additional delays will further increase the damage to the passenger schedule by endangering other flights and passenger connections.

In scenario 1, solution strategies B and $\mathrm{B_{DST}}$ were decided upon. Solution strategy B involves the use of reserve aircraft and crew, the bussing of passengers, and isolates the induced delays to the LCY rotation. In solution strategy $\mathrm{B_{DST}}$ the reserve aircraft is not used, but instead, a tremendous amount of registration swaps is applied. From the criteria weights and the characteristics of the implemented solution strategies, it can be said that Fleet Control and Commercial Desk are satisfied with their decisions. However, Crew Control would have liked to not use the reserve crew already.

In scenario 3 solution strategy F was decided upon. This solution strategy involves extra minutes of flight and the use of a reserve aircraft. Crew Control and Commercial Desk are satisfied with this solution since no reserve crew has to be used and the passengers arrive at their destination with only a relatively small delay.

7.5.5 Scenario 2 & 4 in all contexts

In scenarios 2 & 4, which are characterised by reserve unavailability, the decisions that the agents make are not changing with the contexts. Due to this, the results for the different contexts are analysed simultaneously. The resulting decisions of the agents in scenario 2 are shown in Table 25 and for scenario 4 in Table 26.

In scenario 2 the decisions are independent of reopening time but vary with diversion airport. For diversion airport SEN the agents decide to implement solution strategy B, which involves a diversion after which the aircraft waits for the passenger being bussed from LCY to the diversion airport. As soon as the passengers from LCY have arrived, the aircraft departs back to AMS. For diversion airports SOU and NWI the decision was made to implement solution strategy C. In solution strategy C it is decided to divert the aircraft to an alternative airport and return without passengers back to AMS.

Scenario	SEN	SOU	NWI
2a	B	C	C
2b	B	C	C
2c	B	C	C

Table 25: Results scenario 2 - All Contexts

Scenario	SEN	SOU	NWI
4a	F	F	F
4b	B	F	F
4c	B	C	C

Table 26: Results scenario 4 - All contexts

In scenario 4 the decisions are changing with reopening time. For the earliest reopening time it is decided to implement solution strategy F. In this solution strategy the aircraft awaits reopening of LCY airport in a holding pattern. With increasing reopening time, depending on diversion airport, the agents revert to the decisions as made in scenario 2.

The criteria weights that result in these decisions are shown in Figure 12. Scenario 2 and 4 are characterised by reserves being unavailable. Due to this, the Duty Manager Network determines that the decision-making, independent of context, should be fleet and crew driven. As a result, the criteria weights have a negligible variation over the contexts and do not result in different decisions being made.

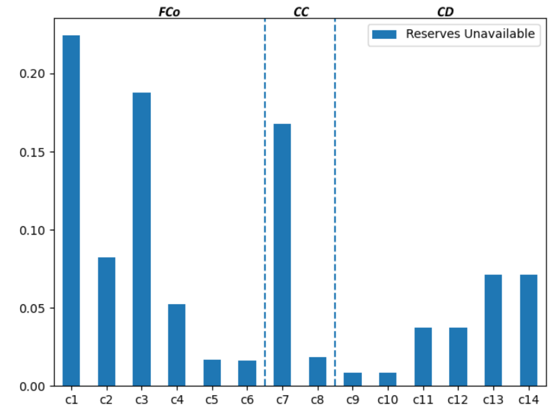


Figure 12: Criteria weights scenario 2 & 4 - All contexts

Fleet Control assigns the highest criterion weight to the minimisation of extra cycles flown (c_1). Due to the unavailability of a reserve aircraft, the absorbing capacity of the flight schedule is reduced to a minimum. Flying an extra cycle can result in additional maintenance activities, for which the flight schedule is not able to accommodate. Additionally, flying an extra cycle is likely to come at the cost of cancelling other flights which is a consequence of the lack of absorbing capacity. The anticipation of these consequences makes that this is one of the focus points of Fleet Control. Furthermore, the minimisation of the leg cancellation count (c_3) is deemed to be important. Since the flight schedule is characterised by reduced absorbing capacity, Fleet Control is willing to do everything possible to minimise the leg cancellation count. This is confirmed by the relatively low criteria weights of the extra flying time (c_2) and registration swaps (c_4, c_5). As a result of the unavailability of a reserve aircraft, the minimisation of the reserve devaluation (c_6) is assigned a negligible criterion weight.

Crew Control aims at the minimisation of the crew swap count (c_7). Due to the unavailability of crew reserves, the only measure available to Crew Control in this scenario is making adjustments to the crew schedule. Crew Control aims to reduce the crew swaps since this induces a lot of extra work. All changes made should be in accordance with the CLA of the crew. The anticipation of the work involved with checking the conformity of these changes with the CLA and the dangers inherent to this makes that Crew Control is not eager to do this.

The Commercial Desk is motivated to minimise the introduction of delays (c_{13}, c_{14}) in the passenger schedule. The awareness about the lack of absorbing capacity in the flight and crew schedules makes that the Commercial Desk anticipates that all delays can endanger other flights. Through these criteria, the agent expresses the anticipation of the damage that can be done to other flights as a result of delays. The bussing of passengers (c_9, c_{10}) and rebookings of passengers (c_{11}, c_{12}) are deemed to be appropriate measures to prevent the introduction of delays in the passenger schedule. Overall, the criteria weights of the Commercial Desk are relatively low compared to Fleet Control and Crew Control. This is due to the decision-making being fleet and crew driven.

In scenario 2, solution strategies B and C were decided upon. For diversion airport SEN, solution strategy B was chosen. Solution strategy B is characterised by a small amount of extra flying time, bussing of passengers and the introduction of delays. This decision shows that the decision-making is fleet and crew driven since the main priorities of the Commercial Desk are overruled by the fleet and crew criteria. Solution strategy C is characterised by a single cancellation and the bussing of passengers. The agents do not decide on solution strategy B for diversion airport SOU and NWI, since waiting for the passengers to be bussed from LCY to these airports takes a significant amount of time and comes at the cost of two cancellations. Therefore, the criteria values of solution strategy C are favoured by the agents for diversion airport SOU or NWI. Overall, these solution strategies are characterised by a minimum amount of cancellations and low impact on other flights.

In scenario 4 the agents decided on solution strategy F for the earlier reopening times. This solution strategy only involves increased flying time and delays. However, with increasing reopening time these criteria increase in value and also require additional cancellations to be made. For diversion airport SEN, solution strategy F is only favourable in scenario 4a. For diversion airport SOU and NWI, solution strategy F is favourable in scenarios 4a and 4b. In the remaining scenarios, the same decisions as in scenario 2 are made, which is compliant with the discussed criteria weights.

8 Discussion

In this section, the obtained results are discussed in relation to resilience (section 8.1), the decision-making of the agents in the different control modes is discussed (section 8.2) and recommendations for the improvement of operational decision-making and further research are given (section 8.3).

8.1 Reflection on Resilience

The goal of this research was to analyse the decision-making in the AOCC by developing a socio-technical agent-based model. More specifically, the resulting decisions from the proposed decision-making mechanisms are analysed. To perform the resilience analysis of the developed model the conceptual framework for resilience by Vert et al. [35] has been used. In this framework, resilience is defined through the use of adaptive capacity by the agents in response to either an unexpected- or an expected unplanned adverse event. Opposing resilience is resistance, which is defined by the use of procedures and plans in response to either an expected planned- or expected unplanned adverse event.

The results for the agents in the scrambled control mode showed that the agents are not able to adapt their decision-making to the sub-scenarios. This is a consequence of a lack of situation awareness and coordination concerning the reopening time of LCY airport. This reduced context comprehension results in the agents having a limited set of available solution strategies. Moreover, the agents vote on the solution strategies based on their interpretation of the airline's working procedures and personal experience, due to which they are not able to make sense of the complications that might occur in the near future as a result of the implementation of a solution strategy. Decisions that are made in this control mode are therefore characterised by a lack of anticipation. The combination of the lack of adaptive responses and lack of anticipation results in the agents not being able to make resilient decisions. To conclude, the scrambled control mode does not allow the agents to make resilient decisions, since the agents do not use any adaptive capacity in their response to the disruption. Hereby the agents can only exercise resistance to expected (un)planned adverse events.

The results of the agents operating in the opportunistic control mode show that increased situation awareness allows the agents to evaluate all scenarios individually. This increased context comprehension enables the agents to determine the importance of the solution strategies relative to each other. Hereby being able to express their goals in a preference relation concerning the solution strategies. This shows that the agents can make sense of the current situation. However, they are still lacking anticipation. The situation awareness is too limited for the agents to be able to adapt their decision-making based on the anticipation of possible future events. Since the preference relations only hold for the scenarios that either are encountered before or are defined in the working procedures of the airline, the agents will not be able to respond to an unexpected adverse event. Therefore, the agents in the opportunistic control mode are only able to manage disruptions that have occurred before and would not be able to make decisions to manage unknown and unexpected disruptions. The decision-making in the opportunistic control mode does not allow for resilient decision-making due to the lack of adaptive capabilities.

From the model variant in which the agents operate in the tactical control mode, it showed that the decisions of the agents were not varying over the scenarios based on reserve (un)availability. The agents decided not to use the reserve aircraft and crew due to the costs inherent to these measures. The ability of the agents to evaluate the costs that are involved with the implementation of a solution strategy is a form of procedural anticipation. These costs are a result of the translation of the airline's working procedures to a cost model. According to the cost model used in this research, the use of a reserve aircraft is highly undesirable, which explains the decisions made in this control mode. Furthermore, the situation awareness and coordination of the agents is increased. The decision-makers coordinate about the selection of the diversion airport and Fleet Control uses the Decision Support Tool to obtain cost-optimal solution strategies and extend the available solution space. Hereby, the decision-makers have greater context comprehension than in the scrambled and opportunistic control modes. Additionally, through the use of the Clarke Tax Algorithm, the agents are aware of their influence in the decision-making. The ability to quantitatively calculate the impact of a solution strategy, allows the agents to increase their sense-making and improve the decision-making. The agents can quantitatively value each solution strategy and select the most preferred solution based on these valuations. This can be considered to be a form of adaptive responding since this holds for both unexpected adverse events and expected unplanned adverse events. To conclude, the tactical control mode allows the agents to apply a combination of procedural anticipation and adaptive responding which is referred to as resilience as rebound [37]. Hereby the decision-making in this control mode is partly characterised by resilience.

The results of the model being run in the strategic control mode show that the contexts result in varying decisions per scenario. In this control mode, the agents have the most extensive situation awareness due to the additional access to CDM and OrbiFly. These systems allow the agents to increase their anticipation and sense-making of events that might affect flight operations in the near future. The anticipation and adaptation of the agents are reflected in the results through the varying criteria weights over the contexts. The decisions resulting from the MCDM decision-making mechanism are dependent on the nature of the event that is disrupting the flight operations and on the sense that the agents make about the context. The reasoning that the agents apply results in criteria weights that are determined based upon the combination of context and scenario. These criteria weights indicate which KPIs of a solution strategy are deemed to be important by the decision-makers. Based on these criteria weights the solutions are evaluated, resulting in a ranking of the different solution strategies relative to each other. The higher this ranking, the more preferred the solution strategy. Therefore the use of the MCDM decision-making mechanism allows the agents to adapt to unexpected and expected unplanned adverse events. Thus, the strategic control mode reflects resilient decision-making of the operations controllers. In this control mode, the decision-makers use both their adaptive responding and adaptive anticipation capacities.

8.2 Reflection on the decision-making

The results generated by the model for the agents operating in the different control modes indicate that the decisions on solution strategies are varying with control mode. These variable decisions are a consequence of the resistance or resilience that is exercised to the unexpected diversion as has been discussed in the previous section.

The disagreement between the decisions of the agents operating in the opportunistic and tactical control modes showed that the experience of the decision-makers does not match the working procedures that are represented by the airline's cost model. The combination of the access to the Decision Support Tool and the use of the Clarke Tax Algorithm as decision-making mechanism in the tactical control mode results in different decisions being made. The preference relations expressed in the opportunistic control mode are representative for the experience and interpretation of the airline's working procedures by the operations controllers. Hence, it is concluded that the experience and interpretation of the working procedures by the operations controllers is not captured in the cost functions and cost model as used in this research.

By a closer examination of the difference between the rationale of the operations controllers and the working procedures, the differences in the decision-making between the tactical and strategic control modes are analysed. In both of these control modes, the agents have the competence to use the Decision Support Tool. In the tactical control mode, the agents frequently decide on the implementation of a proposed solution strategy by the Decision

Support Tool, in contrast to the agents in the strategic control mode. A trend that can be observed in the proposed solution strategies by the Decision Support Tool, is that these solutions are characterised by a lower reserve devaluation (c_6) but an increased number of registration swaps in the late window (c_5) and additional induced delays (c_{13}, c_{14}). The reserve devaluation is minimised by the Decision Support Tool since this is a cost-intensive measure according to the airline's cost model. Opposed to the registration swaps in the late window, which are free of charge in this cost model. There are costs inherent to the delays but these are relatively cheap compared to reserve devaluation. The free of charge registration swaps and the high cost for reserve devaluation represents a lack of procedural anticipation in the cost model. The difference between procedural anticipation in the tactical control mode and adaptive anticipation in the strategic control mode makes that the decision-makers in the strategic control mode are not eager to decide on the implementation of one of the proposed solution strategies by the Decision Support Tool.

Comparing the results of the opportunistic control mode to the results from the strategic control mode, one can observe that the experience of the operations controllers in the opportunistic control mode is not representative for the adaptive responses of the decision-makers in the strategic control mode. This difference can be explained by the reasoning that the agents can express through the criteria weights by the use of the MCDM decision-making mechanism in the strategic control mode. This reasoning allows the agents to focus on specific criteria based on their knowledge about the current and future state of the environment. In the opportunistic control mode, the agents' lack of context comprehension, lack of anticipation, and decision-making mechanism used do not enable the agents to reason at this level of detail.

In the higher control modes, the number of coordinating activities among the agents increased. The coordination of the airline's agents with the agent from the closed destination airport (LCY) about the reopening time proved to be essential. This coordination activity adds solution strategies A and F to the solution space which are frequently decided upon by the agents when available. Due to this, the opportunistic control mode is the lowest control mode that the decision-makers should operate in during operational decision-making. Hereby it is concluded that the coordination about the reopening time of LCY airport is essential for the response to the unexpected diversion. Moreover, the decision-makers should at least operate in the opportunistic control mode to have sufficient awareness for adequate operational decision-making.

Furthermore, the communication between the decision-makers and technical systems in the AOCC showed to be crucial for the anticipation in the decision-making. Especially the use of CDM and OrbiFly in combination with the MCDM decision-making mechanism allows the agents to express their anticipation in the model. These systems contain the information that is required for the decision-makers to make predictions about the future state of the environment. The use of the Decision Support Tool did not prove to be essential which is explained by the mismatch between the procedural anticipation of this tool and the adaptive anticipation of the decision-making agents. In conclusion, the use of CDM and OrbiFly are essential for the adaptive anticipation in the decision-making.

The agents operating in the opportunistic, tactical and strategic control modes unanimously decide on solution strategy F (loiter until reopening of LCY) within scenario 3 (long holding time and fleet and crew reserves available). Due to this, it is concluded that solution strategy F is the preferred solution independent of reopening time, diversion airport and context within this scenario. The AOCC is capable of managing the unexpected diversion without the need for the agents to operate in the higher control modes. The coordination efforts and decision-making mechanism applied in the opportunistic control mode have proven to exercise sufficient resistance. Hereby, there is no need for the agents to waste their time and effort to operate in the tactical or strategic control mode.

The results for scenarios 2 and 4 (characterised by reserve unavailability) showed that the decisions made by the agents in the strategic control mode were fleet and crew driven. This resulted in the criteria of Fleet Control and Crew Control to be prioritised over the criteria of the Commercial Desk. These criteria resulted in identical decisions, independent of context. From this, it is concluded that the anticipation of the agents on the future state of the environment is not required for the decision-making in these scenarios. Due to this, the agents are able to handle these scenarios and contexts in the opportunistic control mode. A prerequisite for the agents operating in this control mode is that the voting preferences of the agents in the opportunistic control mode are updated to match the solution preferences that result from the decision-making in the strategic control mode. This is a prerequisite since the strategic control mode evaluates the impact of the implementation of a solution strategy in more detail and thus results in more representative decision-making. Voting methods are beneficial in these scenarios since it requires less effort from the decision-makers and more time can be spent on other disruptions that might require more adaptation.

8.3 Recommendations

The recommendations that follow from the interpretation of the results are two-fold: recommendations for the improvement of operational decision-making within the airline and recommendations on the developed model. These topics are discussed respectively in section 8.3.1 and section 8.3.2.

8.3.1 Recommendations for operational decision-making

In this research four decision-making mechanisms have been proposed: plurality voting, Borda voting, Clarke Tax Algorithm, and MCDM. The plurality and Borda voting protocols represent the decision-making based on the experience of the operations controllers and therefore are representative for the decision-making in the AOCC. However, they do not expose the exact reasoning behind a decision. From the decisions made based on the Clarke Tax Algorithm, it was concluded that this decision-making mechanism is not representative of human decision-making due to a lack of anticipation of the future state of the environment. The decisions made with the MCDM decision-making method showed that this mechanism is able to fully adapt the decision-making to a specific context and reveals the reasoning of the decision-making. Hereby, this mechanism is representative of the decision-making of the operations controllers in the AOCC. The recommendation that follows from this is explained in Figure 13 and elaborated below.

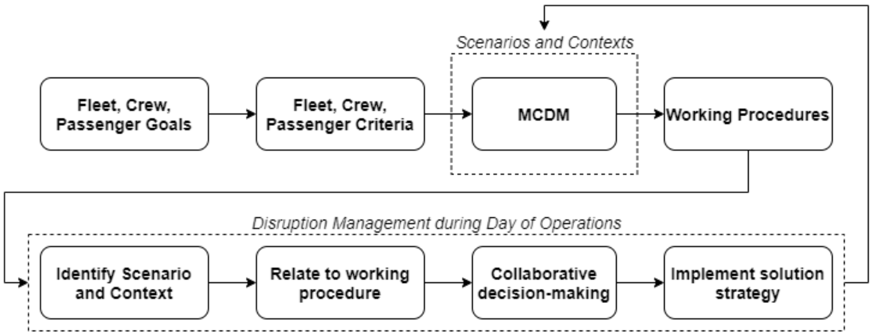


Figure 13: Recommendation for improvement of operational decision-making

The MCDM decision-making mechanism can be used to improve the operational decision-making by deriving the criteria of the fleet, crew, and passenger domains in close cooperation with the responsible operations controllers. It is not recommended to adopt the criteria as used in this research since only a few operations controllers have been involved in identifying these criteria. Involving all operations controllers in the identification of the criteria will increase the understanding, and thus acceptance, of the decisions resulting from the MCDM decision-making mechanism. After the criteria have been identified, the MCDM decision-making mechanism can be used to determine the importance of criteria for scenarios and contexts that suffer from inconsistent decision-making. The insights gained through the use of MCDM can lead to updated or additional working procedures. These working procedures describe for a certain scenario and context, which criteria should drive the decision-making. During a day of operations, the identification of a disruption can be related to a working procedure, from which the operations controllers know which criteria are leading in the disruption management. Based on these criteria the operations controllers can collaboratively decide on a solution strategy. Hereby, the operations controllers are facilitated with guidelines in the decision-making. Ultimately, this will lead to more consistent and efficient decision-making since the operations controllers do not need to use their adaptive capacity in scenarios that are contained in the working procedures. Lastly, a feedback loop should be included. This feedback loop allows the AOCC to learn from scenarios that have been challenging to manage during a day of operations. The goal of this feedback loop is to improve the decision-making, the next time a similar scenario occurs. Ultimately, the goal of this recommendation is to improve the consistency in the decision-making and extend the capability of the AOCC to deal with disruptions through resistance instead of resilience.

The decision-making in the tactical and strategic control modes showed that the decision-makers rarely reach a mutual agreement about a decision on solution strategy. In the scrambled and opportunistic control modes, the vote of the Commercial Desk in scenarios 2 and 4 was different from the votes of Fleet Control and Crew Control. The decision-making in the tactical control mode showed that Fleet Control and the Commercial Desk are influential in the decision-making since they often had to pay a tax. The decision-makers operating in the strategic control mode, could not always be pleased since they express conflicting priorities through the criteria weights. An example of conflicting criteria are the reserve devaluation minutes (c_6) of Fleet Control and the crew reserve usage count (c_8) of Crew Control. In the case study, using a reserve aircraft often implies the use of a reserve crew. For example in the context of a regular day of operations (context 1), Fleet Control deems the reserve devaluation to not be one of the priorities. However, Crew Control's main priority in this context is the prevention of using crew reserves. To prevent these conflicts in the decision-making, it would be recommended to define inter-department criteria instead. In this example, it would be the 'reserve' criteria. To determine the importance of these criteria in the contexts, Fleet Control and Crew Control would have to collaboratively decide on the importance of the inter-department criteria. This is dependent on the scenario and context and can be determined by using the proposed MCDM decision-making mechanism.

Lastly, the solution strategies proposed by the Decision Support Tool are not appreciated by the human decision-makers in the model. To increase the appreciation of the operations controllers of the solution strategies as proposed by the Decision Support Tool, a modification to the cost model should be made. More specifically, the lack of anticipation on the use of the reserve aircraft should be resolved. The results from the tactical control mode showed that the reserve devaluation criterion (c_6) is minimised at the cost of increasing the criterion value of registration swaps in the late window (c_5). To achieve this the costs regarding these criteria should be adjusted in the cost model. Overall, the Decision Support Tool should be more willing to make use of the reserve aircraft instead of making a tremendous amount of registration swaps. The cost parameters, that are required to resolve this behaviour of the Decision Support Tool, can be calibrated by running the developed model in the strategic control mode for scenarios in which anticipation of the use of reserve aircraft is needed. The proposals of the Decision Support Tool will increase in preference by the decision-makers if the cost parameters approach the desired values.

8.3.2 Recommendations for the developed model

The proposed model in this research is subject to improvement with respect to several aspects.

The cost model that is used in this research for the decision-making in the tactical control mode and the Decision Support Tool, is a simplified version of the airline's cost model. Due to the complicated nature and confidentiality of this cost model, not all aspects could be included. As a consequence, some assumptions have been made. Due to the disagreement of the decisions made in the opportunistic and tactical control modes, it would be recommended to reduce the number of assumptions. This disagreement originates from the difference between the experience of the operations controllers and the working procedures represented in the airline's cost model. By reducing the number of assumptions, a more accurate representation of the real cost model and thus working procedures can be included.

The differences in situation awareness of the agents in the different control modes are defined through a small set of global parameters. However, to increase the context comprehension of the agents, especially in the strategic control mode, the situation awareness could be extended with more detailed information. For example, aircraft maintenance status can be included. These details allow for more variety in the contexts and will result in additional insights on the assigned criteria weights of the decision-making agents in the fleet, crew, and passenger domains.

The crew domain is represented by a set of two criteria. The results of the tactical control mode showed that Crew Control is not influential in the decision-making since Crew Control never pays a tax. Therefore it can be questioned whether the defined criteria provide full coverage of the crew domain. Hereby it is recommended to increase the understanding of the complexity of the crew domain in the model by extending these criteria. This will result in the model to be increasingly representative of the AOCC.

Another limitation of the model is that passenger connections are not included in detail. To increase the accuracy of the model with respect to the airline's operations, the passenger connections should be included by loading data that contains the sequence of flights that are based on individual passenger bookings. Based on this information the solution strategies can be based on passenger connections which allow the rebookings to be included in more detail. Hereby the consequences of the implementation of a solution strategy can be assessed more accurately.

It would be interesting to apply the developed model to different use cases within the airline operations control context. The use case covered in this research is fairly simple since it covers a disruption that is isolated to a single rotation and a single type of aircraft. An example would be to analyse a use case in which disruptions occur simultaneously on different rotations and thus different aircraft. Such a use case requires more complex solution strategies for which it would be interesting to see how the different control modes and decision-making mechanisms cope with this complexity.

A more specific recommendation is given on the use of the decision-making method within the application of MCDM in the strategic control mode. The AHP method used requires the operational control experts to make pairwise comparisons for all the criteria. This allows for the expert knowledge of the operations controllers to be captured in the model. However, the downside of this method is that the more criteria are defined, the more lengthy this process becomes. Therefore, it is recommended to explore other decision-making methods and determine how the results of these methods compare to each other.

9 Conclusions

In this research, a socio-technical agent-based model has been developed, that allows the analysis of the decision-making of the AOCC under consideration, in particular in the context of resilience. In this model, the agents' behaviour has been modelled according to the four contextual control modes. For each control mode respectively the plurality voting protocol, Borda voting protocol, Clarke Tax Algorithm and MCDM decision-making mechanisms have been modelled.

The model has been developed based on an unexpected diversion case study that involves an early morning LCY rotation in a high-density flight schedule. In this case study, the holding time of the aircraft, the availability of fleet and crew reserves and the reopening time of LCY airport were the categorical environment variables that resulted in a total of 12 simulated scenarios. For the strategic control mode, each of these scenarios has been simulated for four different contexts to simulate the use of the CDM and OrbiFly systems.

The results showed that the decision-making in the scrambled and opportunistic control modes exercised resistance to the unexpected diversion. The decision-making in the tactical control mode exercised a combination of procedural anticipation and adaptive responding, known as resilience as rebound, to the unexpected diversion. In the strategic control mode, the agents showed the ability to make resilient decisions through adaptive responding and adaptive anticipation.

The comparison of the decisions made in the different control modes enabled the analysis of the decision-making in the AOCC. From this comparison, it was concluded that the decisions made based on the airline's cost model are different compared to the decisions made by human operations controllers. As a result of this, the operations controllers are not eager to implement a proposed solution strategy by the Decision Support Tool. Furthermore, it was found that the operations controllers regularly have to make compromises to arrive at a common agreement in the decision-making.

Coordination about the reopening time of LCY airport proved to be essential for the decision-making since it extends the solution space with socially preferred solution strategies. Due to this, the lowest control mode that enables the decision-makers to make adequate decision is the opportunistic control mode. Moreover, the use of CDM and OrbiFly was found to be essential for the adaptive anticipation of the decision-makers.

Based on the results from the scenarios characterised by reserve unavailability, it is concluded that anticipation of the future state of the environment is not required for the decision-making in these scenarios. The unexpected diversion can be handled in the opportunistic control mode to reduce the time and effort spent on disruption management. A prerequisite for this is that the preference relations are updated once with the MCDM decision-making mechanism. Upon doing this, voting methods can be beneficial for operational decision-making.

Lastly, it is recommended that the MCDM decision-making mechanism can be used to improve the consistency of the operational decision-making of the AOCC under consideration. This decision-making mechanism enables the AOCC to learn from previous occurrences and can help to improve the working procedures. Hereby, the capability of the AOCC to deal with disruptions through resistance instead of resilience can be extended.

Overall, it is concluded that based on the conducted research and inherent analysis of results, human operations controllers are essential for adaptive decision-making in the AOCC.

References

[1] Alireza Afshari, Majid Mojahed, and Rosnah Mohd Yusuff. Simple Additive Weighting approach to Personnel Selection problem. International Journal of Innovation, Management and Technology, 1(5):511–515, 2010.

[2] Yana Ageeva. Approaches to incorporate robustness into airline scheduling. Technical Report ICAT-2000-8, MIT, Cambridge, USA, August 2000.

[3] Schiphol Airport. Schiphol airport cdm operations manual. `https://www.schiphol.nl/nl/operations/pagina/cdm-nieuws/`, 2019. "Accessed: 2020-11-03".

[4] Pietro Amenta, Antonio Lucadamo, and Gabriella Marcarelli. On the transitivity and consistency approximated thresholds of some consistency indices for pairwise comparison matrices. Information Sciences, 507:274–287, 2020.

[5] Eugenio Oliveira Antonio J.M. Castro, Ana Paula Rocha. A New Approach for Disruption Management in Airline Operations Control. Springer, Heidelberg, New York, Dordrecht, London, 2014.

[6] Nor Filianie Aziz, Shahryar Sorooshian, and Fatimah Mahmud. MCDM-AHP Method in Decision Makings. ARPN Journal of Engineering and Applied Sciences, 11(11):7217–7220, 2016.

[7] Soufiane Bouarfa, Reydan Aydogan, and Alexei Sharpanskykh. A multi-agent negotiation approach for airline operation control. Ambient Intelligence and Smart Environments, 26:377–388, 2019.

[8] Soufiane Bouarfa, Henk Blom, Alexei Sharpanskykh, and Kamal Belhadji. Agent-based modelling and simulation of airline operations control decision-making under uncertainty. SciTech Forum, pages 11–15, 2021.

[9] Soufiane Bouarfa, Henk A.P. Blom, Richard Curran, and Koen V. Hendriks. A study into modeling coordination in disruption management by airline operations control. AIAA AVIATION 2014 -14th AIAA Aviation Technology, Integration, and Operations Conference, 2014.

[10] Soufiane Bouarfa, Henk A.P. Blom, and Ricky Curran. Agent-based modeling and simulation of coordination by airline operations control. Transactions on Emerging Topics in Computing, 4:9–20, 2016.

[11] Soufiane Bouarfa, Jasper Müller, and Henk Blom. Evaluation of a multi-agent system approach to airline disruption management. Journal of Air Transport Management, 71:108–118, 2018.

[12] Peter J. Bruce. Understanding Decision-Making Processes in Airline Operations Control. Ashgate, Farnham, UK, 2012.

[13] Pawel Cabala. Using the Analytical Hierarchy Process in Evaluating Decision Alternatives. Operations Research and Decisions, 1(1):1–23, 2010.

[14] A. J.M. Castro and E. Oliveira. A new concept for disruption management in airline operations control. Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering, 225:269–290, 2011.

[15] R. Chow, K. Christoffersen, and D.D. Woods. A model of communication in support of distributed anomaly response and replanning. Human Factors and Ergonomics Society Annual Meeting Proceedings, 44(1), 2000.

[16] Edward H. Clarke. Multipart pricing of public goods. Public Choice, 11:17–33, 1971.

[17] M. Clarke and B. Smith. Impact of operations research on the evolution of the airline industry. Journal of Aircraft, 41(1):62–72, 2004.

[18] Karen Feigh and Amy Pritchet. Design of support systems for dynamic decision making in airline operations. Systems and Information Engineering Design Symposium, 2006.

[19] Michael A. Goodrich. The Clarke Tax Algorithm. Technical report, Brigham Young University, Uta, United States, October 2005.

[20] E. Hollnagel. Context, cognition, and control. Resilient Systems Plus, 1998.

[21] ICAO. Effects of novel coronavirus (covid19) on civil aviation: Economic impact analysis. `https://www.icao.int/sustainability/Pages/Economic-Impacts-of-COVID-19.aspx`, 2021. "Accessed: 2021-02-18".

[22] Matteo Ignaccolo, Giuseppe Inturri, Mónica Garcia-Melón, Nadia Giuffrida, Michela Le Pira, and Vincenza Torrisi. Combining analytic hierarchy process (ahp) with role-playing games for stakeholder engagement in complex transport decisions. Transportation Research Procedia, 27:500–507, 2017.

[23] Gary Klein, Paul J. Feltovich, Jeffrey M. Bradshaw, and David D. Woods. Common Ground and Coordination in Joint Activity, pages 139–184. John Wiley & Sons, Hoboken, New Jersey, 2005.

[24] D.H. Koch. Socio-Technical Agent-Based Modelling of AirlineOperations Control: A Study on Resilient Performance. Technical report, TU Delft, Delft, Netherlands, February 2021. Master's thesis.

[25] Igor Nikolic and Amineh Ghorbani. A method for developing agent-based models of socio-technical systems. 2011 International Conference on Networking, Sensing and Control, ICNSC 2011, pages 44–49, 2011.

[26] KLM ODS. Sentry (eur+klc) user documentation. KLM Royal Dutch Airlines Confluence, 2020. "Accessed: 2020-11-17".

[27] Fariborz Y. Partovi, Jonathan Burton, and Avijit Banerjee. Application of Analytical Hierarchy Process in Operations Management. International Journal of Operations & Production Management, 10(3):5–19, 1990.

[28] M. Pavan and R. Todeschini. Multicriteria Decision-Making Methods. Comprehensive Chemometrics, 1:591–629, 2009.

[29] Mongkut Piantanakulchai and Nattapon Saengkhao. Evaluation of alternatives in transportation planning using multi-stakeholders multi-objectives ahp modeling. Proceedings of the Eastern Asia Society for Transportation Studies, 4:1613–1628, 2003.

[30] R.G. Sargent. Verification and validation of simulation models. Journal of Simulation, 7:12–24, 2013.

[31] Emilio Serrano, Pablo Moncada, Mercedes Garijo, and Carlos A. Iglesias. Evaluating social choice techniques into intelligent environments by agent based social simulation. Information Sciences, 286:102–124, 2014.

[32] O.A. Sharpanskykh. Week 2: Specification of models of multiagent systems. Languages for multiagent systems. Technical report, TU Delft, Delft, Netherlands, September 2020.

[33] O.A. Sharpanskykh. Week 5: Auctions, coalitions and games. Technical report, TU Delft, Delft, Netherlands, September 2020.

[34] Nazanin Vafaei, Rita A. Ribeiro, and Luis M. Camarinha-Matos. Normalization Techniques for Multi-Criteria Decision Making: Analytical Hierarchy Process Case Study. Technological Innovation for Cyber-Physical Systems, 470:261–269, 2016.

[35] Matthieu Vert, Alexei Sharpanskykh, and Richard Curran. Resilience of complex safety-critical sociotechnical systems: Towards a unified conceptual framework and its formalization. Unpublished paper, 2019.

[36] Jiang-Jiang Wang, You-Yin Jing, Chun-Fa Zhang, and Jun-Hong Zhao. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renewable and Sustainable Energy Reviews, 13:2263–2278, 2009.

[37] David D. Woods. Four concepts for resilience and the implications for the future of resilience engineering. Reliability Engineering and System Safety, 141:5–9, 2015.

[38] Nico Zimmer. Socio-technical modeling and simulation of airline operations control. Technical report, TU Braunschweig, Institut für Flugführung, Braunschweig, Germany, August 2020.

II

Literature Study

previously graded under AE4020

1 Introduction

During a day of operations airlines are under a constant threat of disruptions to the flight schedule. Most of these disruptions are occurring frequently and therefore the operations controllers know how they can be dealt with. However when unknown disruptions occur, it takes a mix of collaboration, adaptation, anticipation and operational experience to arrive at the solutions that add to their common goal of minimising the impact on the flight schedule.

At the time of writing this report, the Covid-19 pandemic is spread around the world and has a big impact on everyday life. Travelling restrictions are put in place and social distancing has become the new standard. At the deepest low KLM CityHopper only flew 14 flights a day, which is more or less 300 flights short of normal operations. In the airlines magazine as published by IATA [45] it is stated that the passenger booking numbers for June 2020 are 82% down compared to the booking numbers for June 2019. These numbers show that the impact of the the pandemic on the airline industry can be considered to be significant.

A situation like this pandemic introduces a lot of unknown variables and feels like the operational control center (OCC) is entering new and unexplored territories. To be able to determine the ability of the OCC to handle the consequences of these unknowns for the daily operations, a resilient performance analysis becomes of great relevance. Such an analysis allows the airline to obtain insights into the decision making performance, the adaptive capacities of the OCC and helps to identify pitfalls and shortcomings of the processes in the OCC.

Therefore, the main research goal of this report is to study how KLM CityHopper's OCC can be modelled as a socio-technical system that enables the analysis of the resilience capacity of the decision making. This goal is supported by conducting research into the topics of resilience, socio-technical systems and state of the art airline operations control models. How these topics relate to each other can be seen in Figure 1.1.

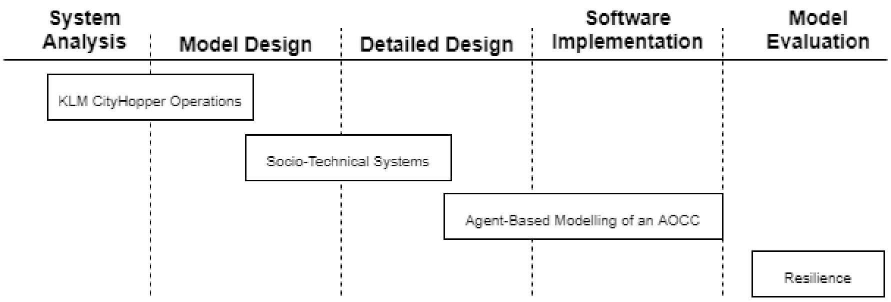


Figure 1.1: Relation between research topics

Originating from the research as conducted from Chapter 2 through Chapter 5 the research proposal, including the research questions, is written in Chapter 6. To conclude the report, the research methodology, the planning and the conclusion will be discussed in respectively Chapter 7, Chapter 8 and Chapter 9.

2
KLM CityHopper Operations

In this chapter an exploratory study of KLM Cityhopper and especially the operational control center is conducted. In Section 2.1 a brief introduction on KLM Cityhopper is given. Section 2.2 elaborates upon the Operations Planning & Control department within KLM Cityhopper and Section 2.3 gives an overview of the actors and common interactions between the actors in KLM Cityhopper's OCC.

2.1. KLM CityHopper Profile

KLM Cityhopper was established in 1991 and originated from a fusion between NLM Cityhopper and Netherlines. KLM Cityhopper is a full subsidiary of KLM Royal Dutch Airlines and executes flights on behalf of KLM. To do so, a fleet of 49 aircraft is used. At the time of writing this report, KLM Cityhopper's fleet is composed of 32 Embraer 190 and 17 Embraer 175 aircraft. These aircraft have a capacity of respectively 100 and 88 passengers. Using this fleet KLM Cityhopper is covering 52% of KLM's European Network, with between 270 and 330 flights a day depending on the day of the week [2]. Together with KLM's fleet of 737s, KLM Cityhopper can be considered to be the feeder for the long-haul flights departing the hub at Amsterdam Schiphol Airport. One of the main characteristics of KLM Cityhopper as an airline are the short flights, with an average flight length of 85 minutes. This enables the fleet to fly between 6-9 legs per day.

The mission of KLM Cityhopper is stated to be:

> *"To carry passengers for KLM in Europe - safe, comfortable and on time - focused on flexible solutions at competitive costs".*

2.2. KLM CityHopper Operations Planning & Control

The Operations Planning & Control department of KLM Cityhopper is responsible for planning, scheduling and operations control of the resources needed to be able to execute flights. The actors involved in the Operations Planning & Control department, can be divided into four categories:

1. Planning & Scheduling
2. Operations Control
3. Crew Control
4. External Parties

Each of these categories and the actors involved in them will be discussed in the upcoming Subsection 2.2.1 through Subsection 2.2.3.

2.2.1. Planning & Scheduling

KLM's network department provides KLM Cityhopper with a yearly schedule, which contains the flights that are expected to be flown by KLM Cityhopper. Next to the flights, also the equipment to be used and the Scheduled Time of Departure (STD) and Schedule Time of Arrival(STA) for each flight leg is specified. The network department generates this schedule based on the expected passenger demand and resources which are expected to be available at the time of execution of the schedule.

When KLM Cityhopper's Planning & Scheduling department receives the schedule from KLM's network department, the planning integrators will start with optimising this schedule and create efficient sequences of flights while taking into account the number of reserve aircraft, minimum turn around times, fleet availability and robustness to be able to cope with disruptions in the schedule execution phase.
Secondly, an estimate of the resources needed to be able to execute the schedule is made. This is mainly about estimating the amount of cockpit and cabin crew FTE's needed while also taking into account possible disruptions during execution of the schedule, which determines the number of reserve crew.
Once the estimate of the amount of FTE's is established, the planning department will start creating anonymous crew pairings. Crew pairings are sequences of flight legs which are to be executed by a single crew member and covers a maximum sequence of five days.

The crew pairings are assigned to actual crew members on every Monday for 4 weeks in advance. This crew roster is published by the scheduling department and allows them to adjust the rosters according to the actual circumstances and crew needs on a relatively short term basis. These crew assignments comply with the requirements as set by the Collective Labour Agreement, which includes amongst others rest and training requirements for flight crew.
Besides the weekly roster publication, there is also the roster maintenance process. This process starts after the crew rosters have been published and ends the day prior to the day of operations (DoO). In this process the changes in availability of the crew due to illness or other reasons, can be managed.

2.2.2. Operations Control

After all the scheduling has been done by the Planning & Control department, the Operations Control department is responsible for the execution of the schedule and managing disruptions during the DoO. The Operations Control department is located in the OCC and is responsible for monitoring and taking preventive or corrective actions to disruptions that affect the execution of the flight schedule.

In the OCC, the Operations Control department is represented by the following group of controllers:

1. Fleet Scheduling (FS)
2. Duty Manager (DMOC) / Fleet Control (FC)
3. Flight Watch (FW)

Fleet Scheduling

The Fleet Scheduler in the OCC is responsible for the tail assignment of flights the day prior to the DoO. Next to that, the fleet scheduler collaborates closely with the Duty Maintenance Controller, to discuss and plan the unplanned and planned maintenance activities that have to take place within the next 2 weeks.
Another responsibility of the Fleet Scheduler is to anticipate the schedule on potential disruptions for the next day or even further. An example of this would be the expectation of a storm on the next day, which will reduce Schiphol's capacity and hence the schedule has to be cut down. The Fleet Scheduler will take the lead in determining which flights are going to be affected by this expected disruption. In other words, the Fleet Scheduler will determine, in collaboration with the other controllers in the OCC, which flights have to be cancelled and which flights can still be kept on the schedule [80].

Duty Manager Operations Control/Fleet Control

The Duty Manager Operations Control/Fleet Control (DMOC/FC) consists of two roles with their specific tasks. Dependent on the duty roster one has to exercise either one of the roles[79].

The DMOC is responsible for the day-to-day management of KLM Cityhopper's Operations Control within the OCC. This also involves the responsibility to manage all involved operational key personnel. To do so, the following list of operational key personnel have direct communication with the DMOC:

- Fleet Scheduling
- Fleet Controller
- Flight Watch
- Crew Control
- Duty Maintenance Controller
- Duty Manager Ground Services
- Duty Manager Passenger Services
- Duty Area Manager
- Duty Manager Network

The Fleet Controller's task is to keep KLM Cityhopper's assets matched with the passenger timetable. This essentially comes down to reaching the agreed quality-parameters, which are amongst others on-time per-

formance and the completion factor.
Furthermore the Fleet Controller has to continuously optimise the use of the resources and anticipate on possible disruptions to keep the passenger timetable as closest to the scheduled timetable.

Flight Watch
Flight Watch is acting as the central point of communication between flight crews, service departments and other relevant departments[78]. In this role they continuously monitor the ground handling of aircraft at Schiphol and the outstations. If some service is missing, for example the fuelling truck, then flight watch has the job to make a call an arrange this.

Next to this, flight watch is responsible for arranging and keeping track of towing operations of KLM Cityhopper's fleet at Schiphol airport. These towings are usually to and from the hangar, or from a parking spot to the gate.
In the end flight watch is a role in which a lot of information is tracked and processed. This enables them to locate possible disruptions in an early stage, which then can be escalated to the DMOC which can take preventive action if needed.

2.2.3. Crew Control
The Crew Control department only consists of the Crew Controllers. The main task of this department is to manage the crew rosters during the execution of the flight schedule. There are usually two Crew Controllers on duty. One of them manages the crew roster from DoO+1 until DoO+3. This Crew Controller basically makes sure that the irregularities occurring due to unforeseen circumstances, like illness or cancellation of flights, are solved in the schedule for the upcoming 3 days.
The second Crew Controller is managing the crew roster during the DoO, which involves coping with delays, cancellations and reserve crew. Together these Crew Controllers have the aim of minimising the effect of disturbances in the crew roster to the flight schedule.

2.2.4. External Parties
This subsection gives an explanation about the external parties that are also involved in the decision making within the KLC Operations Control department and hence are of influence to the disruption management in the OCC.

Duty Maintenance Controller
The Duty Maintenance Controller (DMC), is the one who communicates the status of the ongoing maintenance to the Fleet Scheduler. Updates and changes about planned maintenance activities are directly communicated between the DMC and the Fleet Scheduler, to be able to have a real time view of the fleet availability in the near-future. This enables the Fleet Scheduler to optimise the tail assignments for DoO+1 as best as possible.
Furthermore, the DMC collaborates with the Fleet Controller about when an aircraft has to undergo unplanned maintenance activities during the DoO. The DMC can advise on what the impact is going to be and for how long the aircraft will be grounded. This is essential information for the Fleet Controller, since this translates directly to the execution of the flight schedule.

Duty Manager Ground Services
The Duty Manager Ground Services (DMGS) is constantly monitoring the platform processes. On behalf of KLM Cityhopper, the DMGS is participating in multiple meetings with the different parties (catering, towing, fuelling etc.) involved in the turnaround process. The goal of these meetings is to minimise/remove bottlenecks and keep on optimising the ground handling processes.
Furthermore, the DMGS is monitoring and analysing the delay codes that are originating from the outstations. If the DMGS spots a trend in these delay codes (e.g. structural delays due to a specific reason), then they will communicate this to the outstation manager which will then collaborate with the representative of the outstation to try and break this trend.

Duty Manager Passenger Services
The Duty Manager Passenger Services (DMPS) is leading in the passenger handling processes. The DMPS makes sure all gates are occupied by a sufficient amount of personnel before boarding starts, they count the actual amount of passengers that entered the aircraft and they consult in mismatches between the passenger count and the actual amount of passenger on board. Furthermore, the DMPS is in the lead of monitoring the

connections for transfer passengers.

Duty Area Manager
The Duty Area Manager (DAM) is overseeing the turnarounds of KLM Cityhopper's fleet at Schiphol airport. They have direct contact to all the parties involved in the turnaround process. The DAM will report to the Fleet Controller if a turnaround is delayed due to turnaround related processes. As a result the DAM and Fleet Controller will determine together if the flight is going to be delayed and by how much.

Duty Manager Network
The Duty Manager Network (DMN) is working in close co-operation with the Fleet Controller. The DMN has insights into the passenger connections from KLM Cityhopper's flights to other KLM flights at Schiphol airport. Therefore, the DMN has an overview of the impact on the network if certain flights are delayed/cancelled.
Next to this, the DMN can also advise the fleet controller on which flights have priority in terms of cost. This can impact the decisions made during situations in which disruptions have to be resolved.

Flight Crew
The flight crew are the ones who actually execute the flights. They are important in communicating about the state of the aircraft, the progress on their flights and the special needs per flight. This group generates a lot of information which is of importance for making the right decisions in the OCC.

2.3. KLM CityHopper Operations Control Center actors representation

From the actors in the OCC as discussed in Section 2.2, the interaction between the actors in the OCC is schematically drawn in Figure 2.1. Furthermore, in Subsection 2.3.1 the interaction between the actors in the OCC is described and in Subsection 2.3.2 a description of the used operations control systems is given.
Finally, in Subsection 2.3.3 the operational decision support tools as used by the OCC are elaborated upon.

In Figure 2.1 one can see the interaction scheme of KLM Cityhopper's OCC. In this representation two-way arrows indicate two-way communication. Furthermore, the blue colour indicates actors from KLM CityHopper's Operations Planning & Control department, the orange colour indicates actors from other departments.

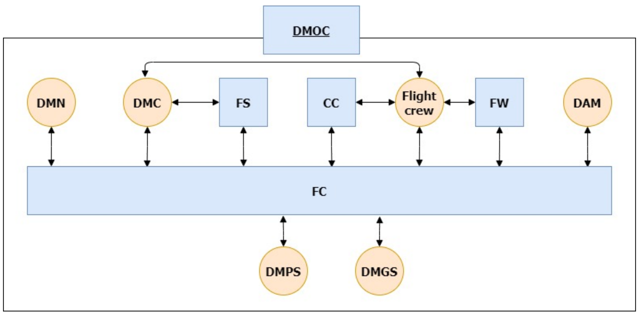


Figure 2.1: Representation of the interaction between actors in the KLC OCC

2.3.1. Interaction

In this subsection an analysis is performed on the interaction between all the actors as indicated in Figure 2.1. The communication that is of influence on the decision making is listed per two actors.

DMN ↔ FC

- Share information on cost prioritisation of flights.
- Share insights in passenger connections.
- Discuss production handovers from KLM Cityhopper's E90/E75 to KLM 737s or vice versa.
- Discuss the delaying of a flight to ensure passenger connections.
- Discuss impact of certain flight cancellations.

DMC ↔ FC

- Share information on daily maintenance progress.

- Discuss impact of unplanned maintenance activities.
- Share information on aircraft's condition (cycle limitations, MEL-items, operational restrictions).
- Discuss technical inspections taking place in-between flights and the possible consequences.

DMC ↔ FS

- Discuss planned maintenance activities.
- Discuss impact of aircraft's condition on the tail assignments.

DMC ↔ Flight Crew

- Share information on aircraft's condition.
- Share flight occurences (lightning strike, overspeed, heavy turbulence).
- Discuss impact of defects on aircraft performance.

FS ↔ FC

- Discuss the safeguarding of night-stops, for maintenance at outstations.
- Discuss the impact of expected disruptions (storm, strikes, airport closures etc.) on the schedule.
- Share information on flight sequences (i.e. do not schedule a short turn around time after a flight which is prone to delays → improvement of schedule robustness).

DMPS ↔ FC

- Discuss mismatches in passenger information.
- Share information on availability of gate personnel.
- Discuss use of Schengen and non-Schengen gates.

CC ↔ FC

- Discuss the progress on crew pairings.
- Discuss crew turnaround times.
- Discuss changes to the schedule.
- Share information on crew reserves.

DMGS ↔ FC

- Discuss information regarding the ground handling of aircraft.

Flight Crew ↔ CC

- Share information on crew roster changes.
- Discuss work-time extensions.
- Discuss physical and mental health.

Flight Crew ↔ FC

- Share information on aircraft defects.
- Discuss on alternate airport in case of diversion.
- Discuss flight information.
- Discuss safety occurrences.
- Share number of cycles flown during training flight.

Flight Crew ↔ FW

- Share information regarding ground handling.
- Share passenger information (unaccompanied minors, disabled people, transfer passengers).
- Share schedule information.

FW ↔ FC

- Share information about towing operations.
- Discuss ATC slot information.
- Discuss delays at outstations.
- Discuss aircraft features (operational limitations due to MEL-items).
- Discuss weather at outstations.

- Discuss alternate airports in case of diversion.

DAM ↔ FC

- Share information on turnaround process at Schiphol airport.
- Discuss the Estimated Off-Blocks Time (EOBT) in case of ATC restrictions.
- Discuss delays induced by turnaround process.

2.3.2. Operational Control Systems

To support the operational decision making in the OCC, KLM Cityhopper makes use of the following systems:

- Netline Ops
- Netline Crew

Netline Ops Netline Ops is an operational control IT system. It is developed and supported by the external IT provider Lufthansa Systems. The system is worldwide in use by approximately 60 airlines.
Netline Ops is the backbone of KLM Cityhopper's operations. The system is used during daily operations to keep track of the most actual status and forecast of all scheduled flights. In addition it shows the activities that are scheduled for each aircraft, including maintenance , towing, standing reserve or flights.
Besides the gantt chart with all the activities in it, also a lot of functionalities are present and a huge amount of information can be extracted (e.g. crew information, number of passengers, callsigns, MEL-items). The information shown in Netline Ops, is received over approximately 15 interfaces and sends data to another 13 interfaces [35]. Therefore, Netline Ops provides essential information that is needed to be able to operate as an airline.
Netline Ops is either functionally used or read-only depending on the actor involved, as discussed in Subsection 2.2.2.

Netline Crew Netline Crew is just like Netline Ops an operational control IT system, as developed and supported by Lufthansa Systems. However, as the name suggests, this system is used to schedule and keep track of the crew pairings. The system is designed and customised to include the business rules conform the KLM Cityhopper cockpit crew's and KLM Cityhopper cabin crew's collective labour agreements. This makes that non-conform changes to the crew pairings by the users of Netline Crew cannot be executed without being notified of the non-conform actions.
Furthermore, the system contains all information that the airline needs about the individual crew members. The location and activities (e.g. simulator, flight, vacation etc.) of the crew member are constantly tracked and updated by the system.
Netline crew is mainly used by the crew controllers. All other actors that need information about crew, are able to access this information through Netline Ops.

2.3.3. Decision Support Tools

In addition to the operational control systems as discussed in the previous subsection, KLM Cityhopper is also innovating by the use of decision support tools. The main goal of these tools, is to advise and help the decision-makers in the OCC to make decisions about operational issues. The decision support tools that are in use at KLM CityHopper are; runway, pathfinder and Sentry.

Runway Runway is a disruption management tool that is able to run scenarios for the next DoO. For example, when a storm is expected to drastically decrease capacity at Schiphol airport during the next DoO, runway can run multiple scenarios based on different expected capacities. Hereby, the tool can be used to determine which flights are the best candidates to cancel and determine what the optimal robust tail assignments are for that scenario.
To do so, Runway is making use of the Netline Ops database through which it is ensured that the solutions provided are taking into account all restrictions that Netline Ops may pose (e.g. planned maintenance).

Pathfinder Pathfinder is an optimization tool, which can determine optimal sequences of flights for DoO+1. Meanwhile taking maintenance activities and night stops into account. This tool is used by the Fleet Scheduler, to aid in the creation of an optimal tail assignment for DoO+1.

Sentry Sentry is a disruption management tool, which aims at assisting the DMOC/FC in finding optimal solutions to disruptions that can occur during the DoO. The ultimate objective of Sentry is to minimise the monetary solving cost of disruptions. This can be decomposed into:

- Minimising Delays
- Minimising Cancellations
- Minimising Swaps/moves

To arrive at these solutions Sentry uses data as in Netline Ops. Next to the aircraft recovery problem, Sentry also takes crew connections into account. The tool is able to present sub solutions to the user, which help the users to decompose a problem into multiple parts.

3
Resilience

During a day of operations in an airline anything can happen. There are disruptions that happen on a frequent basis, but there are also situations in which an unlikely or unique disruption occurs. When such a disruption occurs one would like the environment to be able to adapt quickly and accommodate for the occurrence such that the effects on the flight schedule can be minimised and the environment learns from the occurrence to be able to accommodate better for such disruptions in the future. To do so, the AOCC should have resilient capacities.
In this chapter the definition of resilience is discussed (Section 3.1), adaptive and anticipatory behaviour is researched (Section 3.2) and a literature review is conducted on the state of the art practices of resilience in aviation (Section 3.3). As a basis for resilience, also literature review on robustness in aviation is conducted in Section 3.4. In Section 3.5 the methods to quantify and define resilience through parameter are discussed.

3.1. Defining Resilience

In the dynamic environment of an AOCC, which can be considered to be a sociotiechnical system (STS) since social and technical entities are collaborating, resilience engineering is a highly interesting topic. According to Stroeve and Everdij [74] resilience engineering can be defined in the context of a STS as; *'the ability of a sociotechnical system to adjust its functioning to sustain required operations notwithstanding changes and disturbances and the engineering of the sociotechnical system to achieve such ability'*. Woods and Branlat [30] state a more simplified definition of resilience; *'The organization's adaptive capacity relative to challenges to that capacity'*.

Based on the ever growing developments and the wide areas in which resilience is studied, Woods [81] concludes that resilience can be subdivided into four, most commonly used, perspectives:

1. Resilience as rebound
2. Resilience as robustness
3. Resilience as graceful extensibility
4. Resilience as sustained adaptability

Resilience as rebound This perspective on resilience describes the way in which a system rebounds from the occurrence of surprising events, back to the normal state. The focus in this type of resilience is not on the rebound but on the capabilities and resources that were available in the system before the surprising events occurred.
Resilience as robustness The perspective of robustness is the ability of a system to be able to absorb perturbations. An important aspect of this type of resilience, is that robustness in a system is only valuable when there is a known set of disturbances that possibly can occur. When the robustness of a system is increased, it is meant that the set of disturbances the system can react to effectively is expanded. However, it is unknown how the system will react to perturbations that are not within the known set of disturbances.
Resilience as graceful extensibility This perspective of resilience is described as a systems capability to increase their performance based on disturbances challenging the boundaries of the system. In this context Woods introduces the term 'brittleness' to describe how a system performs near or beyond it's boundaries.

Resilience as sustained adaptability Sustained adaptability focuses on continuous adaptation of the system to new surprises that are introduced to an ever changing environment. A system that is designed with this philosophy should be able to keep adapting to new surprises and hence improving and enlarging the boundaries of the system over it's life cycle.

In the context of an AOC, especially resilience as robustness and sustained adaptability are of interest. Robustness allows the schedule to accommodate beforehand for likely and frequently occurring disruptions. This can be interpreted as the system being able to learn from previous experiences and adapt it's boundaries to be able to better accommodate for a similar event the next time it occurs. The topic of robustness will be further researched in Section 3.4.
Adaptation is a continuously on-going process in the environment of an AOC. Due to the dynamics and variability that airline operations are subject to, an unknown disruption can occur at any moment. The ability to transform these 'unknown' disruption to 'known' disruptions can reduce the impact of these disruptions to the flight schedule.

Based on the above context it seems like resilience and robustness are closely related. The difference however, is in the anticipation aspect. In making ad-hoc decisions in an AOC, anticipation might mean that the chosen solution is not optimal at the moment the decision is made, but will be optimal based on events that are likely to occur after the decision is made. Therefore, the same decision yields different performance KPI's when looking at it either at the moment the decision is made or when looking back at how the day of operations went by after the decision had been made.
This viewpoint is supported by Hollnagel [44], which proposes four abilities that make the analysis of resilient performance of a system possible. These abilities are:

1. Respond
2. Monitor
3. Learn
4. Anticipate

The ability to respond This ability refers to the response of the system to irregular or regular disruptions. The response can be delivered either in a reactive manner by activating prepared actions or by changing the mode of functioning to the new situation.
The ability to monitor Monitoring is about the system being able to identify possible disruptions that can erupt in the environment and that in the very near-future might affect the system's performance.
The ability to learn This ability enables the system to learn from previous experiences and be able to handle the disruptions in an improved manner the next time they occur.
The ability to anticipate Anticipation can be seen as a part of monitoring. However, the difference is that anticipation looks further into the future which enables the system to consider adapting the state of the system in an early stage to disruptions that are likely to happen. To do so, the system does not only interpret the current state but also makes predictions about future events that might influence the functioning of the system. The ability to anticipate is a measure of the level of adaptation of the system to an event beforehand.

Based on the resilience concepts and the four abilities of resilience as discussed in this section and the relation to an AOC environment, it is becoming of interest to study further into adaptivity, anticipation and learning of a system. These topics are further discussed and researched in the subsequent sections.

3.2. Adaptive & Anticipatory Systems Behaviour

For a system to be able to be resilient under adaptation, the system must have the ability to reflect on how well it is adapted, what it has adapted to and what has changed to the environment [82]. When one is able to determine the resilient capability and brittleness of a system and is familiar with the trends, they will have sufficient knowledge to determine where investments can be made to further improve the system.

Resilience captures how well a system can adapt to events that challenge the boundary conditions for its operations. These challenges originate from [82]:

- Fundamental limits of plans and procedures.
- Changing environment.
- The system adapting around successes given changing expectations for performance.

These challenges are likely to be encountered in an AOC environment, where fundamental limits of plans and procedures are introduced by working procedures (e.g. What are the allowed actions to solve a disruption?) and the limited usage of resources (e.g. reserve aircraft or crew). Obviously, an AOC is a continuous changing environment. There are numerous factors that can influence the state of an AOC environment (e.g weather, aircraft defects, strikes, ATC) and therefore introduces challenges to the boundary conditions of the system. Since an AOC is located in an ever changing environment, the boundary conditions are challenged on a regular basis. Adding to this is the cooperation that is going on between human operators, operational control systems and decision support tools. Each human operator has a different interpretation of the environment, which adds to the unpredictability and dynamics of the AOC. In addition, there are also factors like believing in the data that a system presents. Some human operators will trust a system for 99%, but others will not even look at their data since they think they do not need the system's advice or help. Therefore, the environment becomes even more dynamic based on the presence of the human operators.

To be able to study the resilient adaptivity of systems, it is important to be aware of the causes of maladaptation. Maladaptation of a system is one of the main causes for a reduction in resilient capacity. Three basic patterns of maladaptation can be identified:

- Decompensation.
- Working at cross-purposes.
- Getting Stuck in Outdated Behaviours.

Decompensation Decompensation is related to the use of the resilient capacity of the system. Woods and Branlat [82] describe it as 'exhausting the capacity to adapt as disturbances/challenges cascade'. This type of maladaptation occurs when the system is to slow in deploying responses to disturbances, which can result in the exhaustion of the system's capacity to absorb disturbances.
Working at cross-purposes When the different agents in a system work at achieving different goals and they do not coordinate about this with each other their behaviour can be locally adaptive but in view of the overall system the behaviour can be maladaptive. Therefore working at cross-purposes can be of impact to the adaptive capacity and resilience of a system.
Getting stuck in outdated behaviours Over the course of the lifetime of a system the environment tends to change. When the system is not adapting to the changing environment and keeps applying the same adaptive strategies, the system is said to be getting stuck in outdated behaviours. In such a case the adaptive strategies are not adjusted to the changing environment the system is operating in, with as result that the adaptive strategies are no longer valid resilient strategies.

Dalziell and McManus [27] describe resilience as a function of vulnerability and adaptive capacity. The ease with which a system is pushed from one state into another, is regarded to as vulnerability. The adaptive capacity is the ability of the system to adjust to the new situation. The relation between vulnerability and adaptive capacity of a system, as described by Dalziel and McManus can be seen in Figure 3.1. In the graph on the left the system is considered to be highly vulnerable since it is easily pushed from one state to the other. In addition, there is a big envelope of adaptive capacity which indicates that it costs the system a lot of energy to adapt to the new state.
The graph on the right shows a system with low vulnerability and a small envelope of adaptive capacity, which indicates a higher level of resilience to the 'disaster' event.

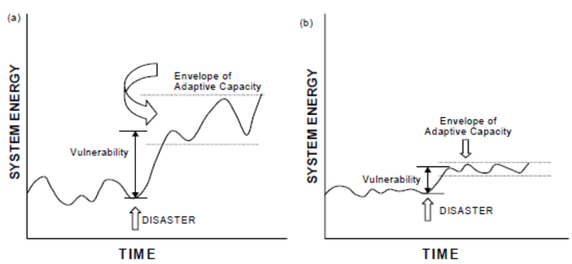


Figure 3.1: Relationship between vulnerability and adaptive capacity of a system [27].

In STS the role of humans is of great influence on the adaptive capacity of a system. Werfs and Baxter [77] define system adaptation in the sociotechnical context as reacting to and anticipation of changes. The value added by humans to a system is mainly in their flexibility, adaptability and anticipation. These are the properties that are often hard to capture in a complex system. Therefore they state that the human input contributes to the resilience of a system, since it can bridge the gap in systems where the used technology is too brittle.

3.3. State of the Art

In this section a state of the art literature review in the air transportation domain, on the application of resilience in STS is conducted.

One of the studies in resilience closest to the application of resilience in an AOC, is the study as performed by Richter et al. [68]. They researched a case study of the re-planning process due to a safety related contingency event in an AOC. In this case only the decision making between the involved human operators (actors) are described. Three decision points are identified, which are analysed for the prioritization of goals and the balancing of different trade-offs. The trade-offs considered originate from Hoffman and Woods [42], who describes five fundamental bounds which relate back to five trade-off mechanisms.

Bounded Ecology This fundamental bound states that a system is never able to match to the environment completely and there will always be a struggle to adapt. This results in the optimality-fragility trade-off. Where fragility is defined as the brittleness near the systems' boundaries.

Bounded Cognizance This fundamental bound states that limited resources and uncertainties will always lead to gaps in the knowledge of the complete system. Which implies an efficiency-thoroughness trade-off. Where efficiency is about going on well-known paths which have proven to be worthy in the past, however they are not adapted to new variations and contingencies in the system. Thoroughness deals with expansion of the scope of the plans and the level of assessment applied and does not allow plans to be changed during execution.

Bounded Perspectives When looking at a problem the system adopts a certain perspective. However when the system is able to consider multiple perspectives, it allows for more knowledge and insights into a problem. Just like most adaptations to a system, the ability to consider multiple perspectives comes at the cost of comparing these perspectives. To do so, a shared language is needed to bridge the gap between the perspectives and be able to identify the differences. Hence, the bounded perspectives fundamental introduces the trade-off between revelation-reflection on perspectives.

Bounded Responsibility In a system one can differentiate between acute goals (e.g. minimize delay for flight X) and chronic goals (e.g. safety). Acute goals can be evaluated in the short-term, however chronic goals can only be evaluated in the long-term. In a system there will always be gaps in authority and responsibility across the various actors and corresponding sub goals. Therefore the acute-chronic goal responsibility trade-off is introduced. This trade-off implies that the interaction and coordination between agents is of great importance since it is undesired that the actors work at cross purposes due to different goals over which no communication has taken place.

Bounded Effectiveness To increase effectiveness in achieving a systems' goal, it can be very help full to divide the goal into multiple sub goals and divide those over multiple agents. However, for an increasing number of agents working on sub problems the synchronising and coherent working to the common overall goal will get of increasing difficulty. To balance task delegation and to ensure the common goal will be achieved the concentrated-distributed trade-off is presented.

The introduced trade-offs were used at each decision point by each stakeholder as a mechanism to safeguard resilient performance. This resulted in an improved situational awareness between actors and broadened the actors' common ground.
In an agent-based model these trade-off mechanisms can be included into the cognitive models that are used to model human agents. However, this research does not include the modelling of technical systems.

In a previous MSc Thesis by Blok [10], in which resilient anticipation is studied in the context of airport security operations, anticipation of a STS is defined as a future-oriented action, decision, or behavior based on a prediction. In this MSc thesis a conceptual anticipation model is proposed, using agent-based modelling techniques. An anticipation agent is modelled which is accessible for all other agents present. Two layers are modelled, an operational and strategic layer.

- Operational Layer
  - Perception and Interpretation Module
  - Action Module
- Strategic Layer
  - Belief Module
  - Reasoning Module

The operational layer is concerned with the interaction of the agents with the environment. The strategical layer is modelling the agents' belief and reasoning. The belief includes the agents' knowledge and awareness in the environment. The reasoning module entails the prediction of possible future events, analysis of the environment and decision making.

Stroeve et al. [73] provide an overview and integration of agent-based modelling constructs that can be used for the analysis of resilience in the sociotechnical Air Traffic Management domain. They provide an integration of model constructs for an human agent, which can be clustered by:

- Sensing
- Sensemaking
- Task Planning
- Functional State
- Deciding
- Actuating

Sensing Processes related to human perception are referred to as sensing. This cluster receives as input the agent's interpretation of the stimuli from the environment and sends as output the sensory interpretation that an agent generates based on the input.
Sensemaking The sensemaking cluster is covering the process in which a human generates beliefs, based on the sensing cluster, about the state of the environment. The output of this cluster are the beliefs that the agent has about the environment.
Task Planning The task planning cluster entails the identification and scheduling of the to be executed tasks. These tasks originate from the sensing or sensemaking cluster.
Functional State This cluster contains model constructs that are of influence to the sense-reasoning-act processes. For example, the operator functional state, cognitive control mode, task load and emotional state are covered by the functional state.
Deciding In the deciding cluster, the agent's beliefs serve as input. These beliefs are then processed in order to generate plans and actions, which are the output.
Actuating The actuating cluster executes the plans that are received as input from the deciding cluster. The output is the effect of the actions on the environment of the system.

Stroeve et al. [73] make the notion that there are model constructs that can potentially play a role in multiple clusters. These model constructs are learning, human error, dynamic variability and stochastic variability.

A conceptual framework for the resilience of complex safety-critical STS is proposed, in a conceptual paper, by Vert et al. [76]. They discuss that to model the adaptive capacity of a resilient STS, the following components have to be considered in a model:

- Situation Awareness
- Sensemaking
- Monitoring
- decision making
- Coordination
- Learning
- Resources

Situation Awareness The perception that an agent has about the environment, or the process of gaining awareness in the environment is referred to as situation awareness. Situation awareness is of great importance for resilient modelling, since it plays one of the main roles in the understanding that the agent has about the environment. Through situation awareness, an agent is able to identify or anticipate on a disruption. In Section 4.3 a more elaborate study into situational awareness is conducted.
Sensemaking This component is defined by Klein et al. [50] as 'a motivated continuous effort to understand connections (which can be among people, places and events) in order to anticipate their trajectories and act effectively'. Therefore, sensemaking enables the model to transform information into knowledge. This adds to resilience, since it enables the model to make predictions.
Monitoring This component is about the system knowing what is going on in the system and it's environment. This can be performed either by a human operator, or the system monitoring KPI's to be able to detect anomalies. Monitoring can take place with a certain perception of the environment, which will determine where the attention of the system or human operator is aimed at.
decision making In case the system detects a disruption, it has to decide whether and what kind of action will be taken. Here the decision making component comes into play. This component is about using the resources available to the system and utilising these resources in an fruitful manner, while having to choose between different solution options. According to Vert et al. [76] Natural decision making is of particular interest with regards to resilient system behaviour. Natural decision making includes the situation awareness

and sensemaking components and describes how people come to decisions under circumstances in which men is under pressure and incomplete information is provided.
Coordination This component describes the method through which the distribution of tasks among the agents in the model is done. These tasks all add to achieving a common goal. Vert et al. [76] describe coordination as a necessity for performing successful adaptations to distributed tasks and therefore it is needed in a STS to be able to exhibit resilient behavior.
Learning Lastly, the learning component improves the resilient behavior of a system since it increases the knowledge of the system. Predictions and anticipation are based on the knowledge of the system, therefore if the system does not learn the system can only react to a disruption and will not be able to pro-actively tackle it.

3.4. Robustness in Aviation

Recent developments and research in the airline industry and especially the operations control domain, shows that resilience is an almost untouched topic. In the contrary to robustness, which is an indicator for the capacity of the schedule to absorb disruptions. Although robustness is passive and only prepares the system for possible disruptions and does not include adapting or reacting capacities to disruptions to the system, it can still be useful to gain insights into it. To be able to obtain a better vision on resilience, a short literature review on robustness in the airline industry is conducted here.

In the operations control domain of an airline, the set of disturbances that can occur to the flight, crew and passenger schedules are known. The typical disturbances in this domain are described by Castro et al. [4] to be:

- En-route air traffic
- En-route weather
- En-route aircraft malfunction
- Flight diversion
- Crew delays
- Cargo/baggage loading delays
- Passenger delays
- No-show crew
- ATC restrictions
- Aircraft malfunctioning
- Airport weather conditions

Kohl et al. [53] describe various commonly used techniques that airlines employ to increase the robustness of the operation.
The first technique they describe, is *adding slack to the schedule*. Adding slack means that not all flights or crew duties are scheduled with the required minimum turnaround time in-between them. Hereby, recovery space is added to the schedules since the schedule is then able to absorb delays without risking conflicting flights or duties. A downside to this technique is that the resources are not used in an optimal manner.
Another technique would be to make crew follow the aircraft they are on, or speaking in KLM CityHopper's terms making flights 'kist-crew'. This reduces the risk of delayed flights due to crew coming in late from other flights. Therefore delays will not propagate to other aircraft in the schedule. In addition, by using kist-crew connections monitoring of the operations is simplified.
Another contributor to the schedule's robustness is the incorporation of reserve aircraft and reserve crew. This is the most valuable addition to the schedule in terms of robustness since these reserves can be used at any moment a disruption occurs, however it comes at great monetary costs. In addition, these reserves are usually located at the hub airport, at which disruptions are most likely to occur. However, when a disruption occurs at an oustation the reserves still have to re-locate to that airport which takes time and comes at great expense. Hence, the effect of having these reserves depends on the location of the disruptions.
The last technique proposed is to increase the cruise speed of aircraft to shorten the flight times which result in a longer turnaround time between two flights. The longer the flights, the bigger the impact of this technique on the robustness. Naturally flying faster comes at the cost of a higher kerosene cost. For airlines, like KLM CityHopper, whose average flight time is relatively low, the impact of this technique is minimal.

Puchkova et al. [67] demonstrate an integrated recovery model that decomposes the disruption recovery problem into a master problem and a sub-problem. This recovery technique focuses on minimizing the impact of delay propagation and keeping crew rosters intact.

Other development put more focus on the forecasting of block times and turnaround times as can be derived from historical data through machine learning and other data analysis methods [69] [7]. In the same direction of research, Kafle and Ergan [47] focus on improving resilience by forecasting maintenance activities and optimising maintenance locations to arrive at an optimal routing. The forecasts generated through these methods can be implemented into the scheduling process, to be able to start the DoO with a more robust schedule.

Ageeva [1] suggest a method for creating more robust airline schedules, which has a high level of adaptability in case of disruptions. In this method the main focus is to maximise the overlap of flights at the hub airport to enable more redundancy in the fleet. To accommodate for this measure of robustness, the maximization of overlapping flights is added to the objective function of the proposed LP schedule optimization program.

Wu [83] developed a sequential optimisation algorithm which aims at improving the operational reliability of airline schedules. In this research it was proven by simulation that implementing 260 minutes of extra buffer time into an airline schedule, containing 20 destinations and 17 narrow-body aircraft, resulted in a reduction in departure delays of 30%.

3.5. Performance-based Quantification of Resilience

For one to be able to determine if a system's performance can be considered to be resilient, it is a prerequisite to express the system in resilient parameters which enable the resilient performance to be quantified. When metrics to measure resilience are in place, it makes it easier for the system's manager to determine and compare the performance of the system in different circumstances. In case of an AOCC, these metrics can be used to improve decision making processes or standard working procedures. In this section a short literature review on the quantification of resilience is conducted.

To measure the resilience of a system to a certain event, Dalziell and McManus [27] propose to use the impact of an event or disruption on the KPI's and the time it takes the KPI to recover from an event. In this measure the numerical change in a KPI indicates the vulnerability of the system and the time it takes the KPI to recover from an event is an indication for the adaptive capacity of the system. This measurement method is shown in Figure 3.2. To measure the total resilience of the system to an event, one has to calculate the total area under the curve.

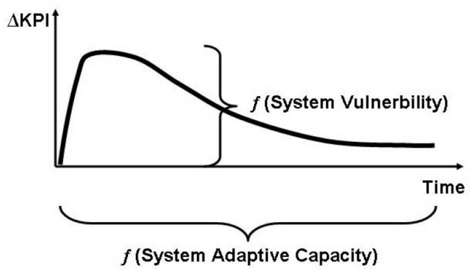


Figure 3.2: Measuring Resilience[27]

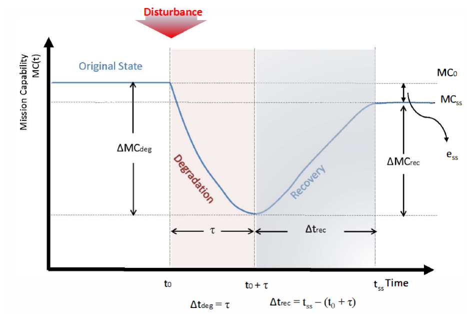


Figure 3.3: Single Disturbance Model [8]

Balchanos et al. [8] defined two metrics which can be used to quantify a systems restoring and absorbing capabilities. To do so, they make use of the single disturbance model as can be seen in Figure 3.3.

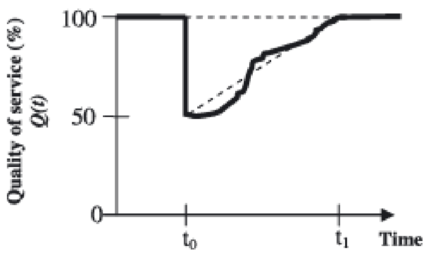
Restoring Capability The restoring capability is defined as the system's ability to partially or entirely return to it's original state after a disturbance was experienced. The first metric defined about the restoring capability is the Average Recovery Rate (ARR). In this equation the total capability recovery (ΔMC_{rec}) that is calculated by subtracting the minimum mission capability (MC_{min}) from the resulting steady state mission capability (MC_{SS}). Lastly, the recovery time (t_{rec}) is calculated by subtracting the time at which the lowest mission capability is achieved (t_{min}) from the time at which the new steady state is reached (t_{SS}). All these equations can be seen in Equation 3.1.

$$\begin{aligned} \Delta MC_{rec} &= MC_{SS} - MC_{min} \\ \Delta t_{rec} &= t_{SS} - t_{min} \\ ARR &= \frac{\Delta MC_{rec}}{\Delta t_{rec}} \end{aligned} \tag{3.1}$$

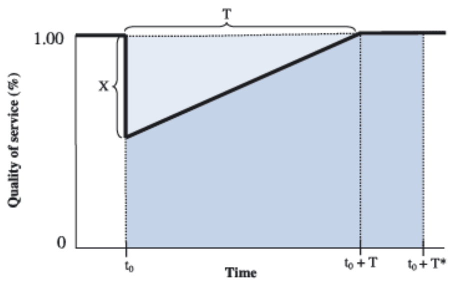
Absorbing Capability When a system is subject to a disturbances and the system does not respond to that disturbance, than the system is absorbing the disturbance. An interesting metric for the absorbing capacity is the Average Degradation Rate (ADR), which can be calculated by dividing the degraded mission capability (ΔMC_{deg}) by the degradation time (t_{deg}). Where ΔMC_{deg} is calculated by subtracting the MC_{min} from the initial mission capability (MC_{init}).

$$\begin{aligned} \Delta MC_{deg} &= MC_{init} - MC_{min} \\ ADR &= \frac{\Delta MC_{deg}}{\Delta t_{deg}} \end{aligned} \tag{3.2}$$

Another approach used in literature to obtain a metric for resilience, is the use of the resilience triangle. Zobel and Khansa [85] mention that the concept of a resilience triangle incorporates both the impact and recovery time of an event to the resilience of a system. They first adapted the idea from Bruneau et al. [17], in which the loss of resilience in a system is calculated by the area above the quality curve ($Q(t)$) as depicted in Figure 3.4a.



(a) Resilience triangle from Bruneau et al. [17]



(b) Predicted resilience triangle from Zobel and Khansa [85]

Figure 3.4: Resilience triangles.

The area above the quality curve R in Figure 3.4a can be calculated by integrating $Q(t)$ for t_0 to t_1, where t_0 is the time at which the disruption occurred and t_1 is the time at which the system has recovered. The mathematical notation of this calculation can be seen in Equation 3.3.

$$R = \int_{t_0}^{t_1} [100 - Q(t)]\,dt \tag{3.3}$$

Zobel and Khansa [85] extended the concept introduced by Bruneau et al. [17] by establishing a concept for the prediction of resilience, which allows one to assess the level of resilience of the system before disruptions occur. To illustrate this, the predicted resilience triangle as in Figure 3.4b is used. Here X is the predicted loss of the quality of service, T is the expected recovery time and T^* is the maximum allowable recovery time. The measure of resilience $R(X,T)$ can now be calculated by the area spanned by X and T expressed as a percentage of the total area. The resulting expression can be seen in Equation 3.4

$$R(X,T) = \frac{XT}{2T^*} \tag{3.4}$$

The resulting measure for the predicted resilience is depending on the value of T^* which can be arbitrarily set by the organization using this metric. If the system is not recovered within the time defined by T^* than the resilience is said to be zero.

This concept can also be extended for the analysis of a system's resilience to a sequence of disruptions. Zobel and Khansa [86] suggest that for a sequence of events, basically the same method can be used to determine the system's level of resilience. As foundation for their proposed method they use a simple example where 2 disruptions occur consequently, this can be seen in Figure 3.5.

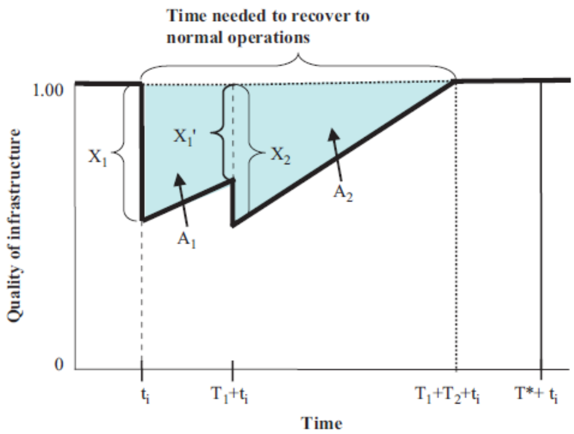


Figure 3.5: Resilience of a system subject to two disruptions [86].

The area covered by the two disruptions can be calculated by Equation 3.5, where $X_2^{'}$ is equal to zero since the system recovers fully after this disruption.

$$Area = \frac{(X_1 + X_1^{'})T_1 + (X_2 + X_2^{'})T_2}{2} \tag{3.5}$$

To transform this into a resilience metric, Equation 3.5 should be divided by the total area T^* and is rewritten to accommodate for i number of events, resulting in Equation 3.6.

$$R = 1 - \frac{\sum_i (X_i + X_i^{'})T_i}{2T^*} \tag{3.6}$$

The metrics as discussed in this section and used in literature to quantify resilience, are applicable to the case of an AOCC. In an AOCC the performance parameters that can be identified are amongst others; delays, cancellations and slack in the schedule. The big difference between the kpi's defined in an AOCC and the metrics as defined in literature, is that the kpi's regarding an AOCC will not always completely recover. For example, when a flight is heavily delayed and the choice of the operations controllers is to absorb this delay and not cancel other flights, the schedule will never be able to recover completely from this delay. Only at the end of the DoO/ the beginning of a new DoO, the schedule is at 100% recovery. Nevertheless, the discussed metrics can still be used to assess the impact of disruptions.

4

Socio-technical Systems

Based on the exploration of KLM CityHopper's OCC in Chapter 2, it is clear that the OCC exists of a combination of humans, operational control systems and decision support tools. These ingredients make that the OCC can be seen and modelled as a socio-technical system (STS), of which the definition and properties are explored in Section 4.1. Thereafter in Section 4.2 a framework for the development of a socio-technical agent-based model is introduced.
The operations controllers that are employed in an AOCC, make decisions based on the elements that they perceive in the dynamic environment. To be able to determine the basis or (in)completeness of information that is used to make decisions, a basic understanding of the level of situational awareness is required. This topic is discussed in Section 4.3. Based on the level of situational awareness one can employ different decision making styles, which are discussed in Section 4.4.

4.1. Defining a Socio-technical System

A STS is characterized by an interdependent relationship between humans (social) and systems (technical). There are different types of STS, from simple to complex. A very simple and recognizable example would be the one of a human using a mobile phone, with just one human operator (the driver) and a single technical system (the mobile phone). One of the more complex examples is the decision making in an AOCC, in which multiple human operators with multiple objectives are making decisions using multiple systems.

Complex systems are known for their subsystems with non-linear interactions, such as feedback loops with delays, that is likely to cause emergent, unpredictable and unexpected behaviour [65]. According to De Bruijn and Herder [31] a STS can be called complex when the system consists of multiple subsystems, has multiple conflicting objectives and there are many dependencies. They divide a STS into two perspectives; the technical perspective and the social perspective.

The technical perspective consists of devices or tools that can transform input into output, to obtain economic gain. The social perspective entails the structure of the organisation, authority structure and the reward system in an organisation. In addition, the social perspective encompasses the skills, attitudes, knowledge, values and needs of the people working in the organisation. A schematic overview of these perspective in a STS in a complex environment is shown in Figure 4.1.

Baxter and Sommerville [9] describe five key-characteristics which are inherent to complex STS:

1. Systems should have inter-dependent parts.
2. Systems should adapt to and pursue goals in external environments.
3. Systems have an internal environment comprising separate but interdependent technical and social subsystems.
4. System goals can be achieved by more than one means.
5. System performance relies on the joint optimisation of the technical and social subsystems.

Relating these characteristics back to KLM CityHopper's operational control center, one can readily conclude that this certainly can be seen as a complex STS. The inter-dependent parts are the different departments that operate with the goal of achieving their own objectives and a goal in the external environment is the passenger satisfaction. The internal environment consists of the social actors (operations controllers) and the operational control systems and decision support tools, which make that the internal environment is comprised of social and technical subsystems. These subsystems have to communicate and collaborate to identify and gain a proper understanding of a problem and come up with the solution which is in the best interest of KLM CityHopper.

It is argued by De Bruijn and Herder [31] that to gain a proper understanding of an STS, one should identify the inter-dependencies between subsystems from both technical and social perspectives. Starting with the classification of dependencies from the technical perspective:

1. Simple-multiple
2. No feedback-feedback
3. Linear-nonlinear
4. Sequential-parallel
5. Synchronous-asynchronous

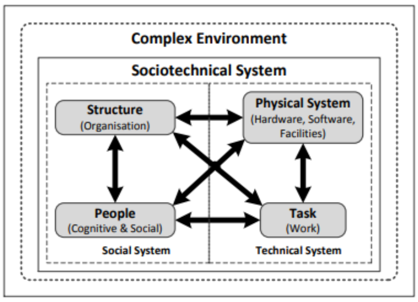


Figure 4.1: Overview of STS [65]

Simple-multiple The inter-dependence between subsystems is considered to be simple when the subsystems are only inter-dependent on one variable. When the subsystems are related to each other through several aspects simultaneously, it is classified as multiple inter-dependencies.
No feedback-feedback Subsystems which employ one-way communication to other subsystem, do not use feedback. However if the output of subsystem A is input for subsystem B and the output from subsystem B is again input for subsystem A, there is a circular relationship between the subsystems and feedback is considered.
Linear-nonlinear In case the subsystem have a linear relationship, the output of the complete system is the sum of the output of the subsystems. In a nonlinear relationship there is no form of proportionality recognizable in the output.
Sequential-parallel In a sequential inter-dependency, subsystem are running in a sequence since they need the output of preceding subsystems to be able to run. In a parallel inter-dependency the subsystems can run at the same time.
Synchronous-asynchronous The synchronization tells something about the way in which subsystems respond to each other. If the subsystems are asynchronous it can pose problems to the overall system and the coordination or control mechanisms should be adapted.

Similar to the inter-dependencies from the technical perspective, the inter-dependencies between the social actors are also worthy to explore. The dependencies between the actors can be classified with four criteria:

1. Simple-multiple
2. Bilateral-multilateral
3. Synchronous-asynchronous
4. Simultaneous-sequential

Simple-multiple In a simple dependency, actors rely one-on-one on each other. In a multiple dependency multiple actors rely on each other for multiple resources, there is no single identifiable relationship.
Bilateral-multilateral In a multilateral dependency, actor A depends on actor B, actor B depends on actor C and actor C depends on actor A. In a bilateral relation, only 2 actors are involved with each other.
Synchronous-asynchronous If actors depend on each other in an asynchronous order, than the times at which they require something from one another is different and there is no two-transaction. In the contrary to a synchronous dependency.
Simultaneous-sequential In a sequential dependency actors have to wait for each others actions to be completed, before their own action can be performed. In a simultaneous dependency, this is not the case.

The above described inter-dependencies enables the ability to gain a proper understanding of the relations between the multiple subsystems, which is knowledge that can be used in the modelling of a STS as will be discussed in the next section.

4.2. Modelling a Socio-technical System

The difficulty in creating a model of a complex STS primarily lies in modelling the human behavior that has to be captured in combination with the usage of technical systems. Human behavior is characterized by emotions and diversity in knowledge and abilities [41]. Hence, to be able to develop a model of a complex STS the modelling approach should allow for the interaction between human behavior, human decision making and technical systems.

The interaction between humans and technical systems in KLM CityHopper's OCC is mainly about the humans using a technical system as a tool that helps them to solve a problem. Hereby it is of importance that the human operator's have trust in the tool, or in other words that they acknowledge the capability of the tools that they are provided with. To achieve this the human operators should be closely involved in the development of such a tool. For this kind of development the agent-based modelling approach seems to be very suitable, since the development of agents in a STS is based on an elaborate description of the behavior that such an agent should exhibit. To develop such a behavioral model of an agent, extensive interviews with the humans should be conducted. Hereby, including the humans in early development stages of the model.

Agent-based modelling is a bottom-up modelling approach that aims at modelling systems that are comprised of autonomous agents, which interact with one another. This makes it suitable for the modelling of a STS. The humans in the system can be modelled by an agent that has cognitive properties and the technical systems can be described by an agent that behaves by the set of rules of the system that is to be represented. The interaction between the different agents are conducted via communication protocols which are selected based on the inter-dependencies between the agents, as described in the previous section.

Macal and North [56] argue that the agent-based modelling approach is a suitable paradigm to be used in models that incorporate elements of human and social behavior and have complex inter-dependencies. In aviation related literature the agent-based modelling approach is used amongst others to model a socio-technical air transportation network [74], decision making in an AOC [13][19] and airport security operations [10].

Nikolic and Ghorbani [60] propose a methodological framework for the development of an agent-based model of a STS. They split the development of such a model in to 5 phases, as can be seen in Figure 4.2.

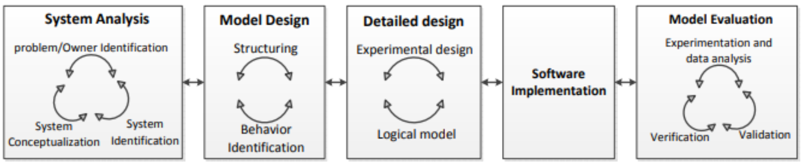


Figure 4.2: A methodological framework for the development of an agent-based model of a STS [60]

System Analysis In this phase the system is studied independently of agent-thinking or software modelling. The main goal of this phase is to identify the internal structure of the system under consideration, such that complex analysis of the respective system can be conducted. To do so, three sub-phases are considered:

- Problem & Problem Owner Identification → The goal is to gain a proper understanding of the problem to be considered in the model.
- System Identification → The goal is to explore the system's components and operating boundaries.
- System Conceptualization → The goal is to setup a structure between the components of the system, for basic understanding.

Model Design In the model design phase the goal is to identify the agents and interactions between the agents in the system. This is divided into two sub-phases:

- Structuring → The systems' components that have been identified in the previous system identification phase, are translated to agents and according to their interactions are ordered in a structured way.
- Behavior Identification → The goal in this phase is to identify the behavior of the defined agents and their environment.

Detailed Model Design Based on the identification of the problem, main systems' components and interaction between components the next step is to go into detailed model design. In this phase the details that are required to build a model of the system under consideration are specified. This is split up into two sub-phases:

- Logical Model Formulation → In this phase the aim is to identify the programming details that are needed to translate the identified system structure, agents, interactions etc. to an agent-based model.
- Experimental Design → Here the desired outcome of the model is defined and a hypothesis is formed.

Software Implementation This is the phase in which the actual programming is performed. With the goal to arrive at a model that is compliant with the previous phases.

Model Evaluation This is a continuous process during the development of a model. It consists of two sub-phases:

- Verification → In this step it is verified whether the model is compliant with the conceptual model and all interactions and components are modelled correctly.
- Validation → In the validation step it is checked whether the outcome of the model matches with the outcome of the real system.
- Experimentation and Data Analysis → In this phase multiple data sets are put into the model to generate outcomes. Based on these outcomes an analysis can be performed to check what the relevant parameters are.

The above described agent-based modelling methodology, can serve as guideline to develop an agent-based model of a STS.

4.3. Situational Awareness

On a daily basis numerous decisions have to be made in an AOCC. A decision can either solve major disruptions, or optimise the usage of resources. To be able to gain an understanding of how decisions are made, first the understanding of when decisions are made should be clear. Therefore some theoretical knowledge about situational awareness is needed, which is provided in this section.

In literature a definition of situational awareness in the context of an AOCC is not readily defined. However, Bruce [16] and Bouarfa et al. [13] adopt the definition of Endsley et al. [37]: 'the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future'.

The controllers in an AOCC use their situational awareness as a foundation for the decisions that are being made. In this context situational awareness can be compared to the availability of information. For a thorough decision, a controller needs just the right amount of information. Having excess information can over-complicate the decision making and a scarcity of information hinders proper decision making. For each disruption the situational awareness to come to a disruption solving solution is different. For example in the case of an aircraft going AOG, the information about the availability of reserve aircraft is critical. However in the case of an ATC delay at an outstation, the information about the involved crew pairings is more relevant [16].

Situational awareness is input for the decision making process. It describes the knowledge of the actors about the environment and the interpretation of this knowledge. Endsley et al. [37] describe situational awareness on 3 levels:

1. Perception of the elements in the environment.
2. Comprehension of the current situation.
3. Projection of the future status.

Perception of the elements in the environment The first level is about the controllers gaining knowledge about the status, attributes and dynamics of the elements that are relevant in their environment. In an AOCC context this includes among others, aircraft availability, crew availability and weather information.

Comprehension of the current situation The level two in situational awareness makes the connection and relates between the elements that are perceived at the first level. The controllers determine whether the elements that are observed differ from the nominal levels. In addition certain combinations of the elements can tell something about the environment. This makes also that situational awareness is dependent on experience levels of controllers.

Projection of future status The last level of situational awareness extrapolates the elements and status of the environment to predictions in the near future. An example of this is projection of consequences by an AOCC controller of a delay of a flight on other flights.

These levels in situational awareness play a big role in the decision making. It determines the perception that the decision-maker has about the problem. In theory, three different solutions to the same disruption are expected when considering the disruption for all three described levels of situational awareness. Especially in the environment of an AOCC this is an important model construct to include when making a model.

At KLM CityHopper the situational awareness of the operations controllers is mainly dependent on the information that is gathered through the use of the operational control systems, which are discussed in Subsection 2.3.2. These systems provide a real time status of the airline's operational environment. The operation control systems that are used provide minor alerting functionality, with as result that the situational awareness is dependent on the scanning for abnormal parameters in the system by the operations controllers. Hence, the context of a disruption is dependent on the interpretation and situational awareness of the operations controllers at duty.
The third level of situational awareness, the projection of future status, is subject to the interpretation of the controllers. There are some minor functionalities in the operational control systems that can show a prediction of the future state based on the current state. An example of this is the delay propagation function in Netline Ops. If the first flight in a sequence of flights is delayed, the system will automatically propagate the successive flights such that the minimum turn around times are ensured between the flights. However, this is only an indication and does not give an accurate projection. Therefore the experience of the controllers plays a big role in the projection of the future state of the system.
The controllers can use the decision support tools to consult the solution that these systems propose for a disruption. This allows the controllers to gain an insight into the possible future state of the system. However, the tools only proposes a single solution. If the ideas of the controllers are not in line with the tool the proposed solution cannot be used to check for the possible future state regarding the decisions that the controller would make. Hereby, the decision support tools become useless to the controllers.

In the next section human decision making is discussed, in which situation awareness determines the context in which the decisions have to be made.

4.4. Decision making in an Airline Operations Control Center

In order to be able to model an AOCC as a STS one should be aware of the decision making styles that are used by the humans controlling the operations. In the dynamic environment of an AOCC, usually decisions have to be taken on a very short notice with incomplete information to minimize the impact of a certain situation or disruption. The decisions are critical for the performance of the airline and involve monetary concerns. Hence, it is important to understand the rationale behind decisions and explore the decision making structures that can be used.

Since the AOCC is characterized by its dynamic environment, the decision making style is dependent on the state of the environment. Feigh and Pritchett [39] argue that the decision making style that is used by the controllers in an AOC is dependent on the context in which the decision have to be made. For example, when only a few small disruptions occur the controllers may discuss several alternatives to solve the disruption and minimise flight delays. Hence, they will make a thorough decision. However when major disruptions occur, which require quick decisions, the controllers do not have the time to discuss alternative solutions and the decisions will be based on previous experiences, gut feeling and the context of the situation.
To capture the influence of the context on human decision making, Hollnagel [43] developed four contextual control modes:

- Scrambled Control → the choice of the next decision is completely random or unpredictable.
- Opportunistic Control → the next decision is purely based on the current context.
- Tactical Control → the next decision is made based on the current context and the extrapolation of that context to the near future.

- Strategic Control → decision are made based on a wider horizon than the current context and the higher level goals are kept in mind.

A human transfers between these control modes based on time limits and information availability in the environment. The characteristics for each of the control modes are elaborately described in Table 4.1.

	Strategic	Tactical	Opportunistic	Scrambled
Number of goals	Several	Several (limited)	One or two	One
Subjectively available time	Adequate	Adequate	Just adequate	Inadequate
Selection of next action	Prediction based	Procedural	Association based	Random
Evaluation of events	Elaborate	Normal details	Concrete	Rudimentary
Event Horizon	Extended	Normal	Narrow	None
Plans Available	Pre-defined/generated	Available and used	Negligible or limited	None
Execution mode	Subsumed and feedback	Feedback	Feedback	Subsumed

Table 4.1: Characteristics of Control Modes [43]

These control modes allow us to understand decisions that are made under a specific context, however these do not describe the decision making styles that are used. To bridge the gap between the above control modes and the decision making styles in an AOCC the work of Bruce [16] is analysed.
A big chunk of research on the topic of decision making in an AOCC has been done by Bruce, hence the majority of information discussed in the upcoming text is based on this work. In his book, Bruce explores 3 decision making styles that are of interest and applicable to the decision making in an AOCC:

- Rational decision making
- Intuitive decision making
- Naturalistic decision making

Rational decision making Rational decision making is referred to as a logical, step-by-step and systematic approach to decision making. It allows the human to follow a certain set of steps to make a decision, without having prior knowledge of the problem. This decision making style is commonly used in situations in which multiple alternative solutions are considered and a weighted trade off has to be made by the human. This makes that it is suited the best for situation in which there is plenty of time to make a decision.
The limitation of this decision making style is the step-by-step approach, which creates a logical order in which a decision has to be made but does not guarantee good outcomes.

Intuitive decision making The intuitive decision making style describes the intuition of a human to make the right decision at the right time, in situations with and without complete information. Humans that make decisions in this style rely on their experience and gut feeling and are able to react quick to complex and confusing situations in which there is no time for the application of an analytical approach to solve the problem.

Naturalistic decision making This decision making style describes the way that humans use their experience to make natural decisions in natural environments. A natural environment is a setting in which time pressure and equivocal information are present. The aim of naturalistic decision making is to obtain decisions with an increased quality by gaining a better understanding of the decision making processes that take place in natural environments. It is developed to bridge the gap between the rational decision making style and the decision making style that is commonly used by humans. Hence a more appropriate representation of the experience of the decision-maker, the complexity of tasks and the demands of the environment is the goal.

The discussed decision making styles can be related to the control modes as defined in Table 4.1. Here the strategic control mode relates closest to the naturalistic decision making style, the tactical control mode relates closest to the rational decision making technique and the opportunistic and scrambled control modes relate the closest to the intuitive decision making style. Depending on the level of situational awareness that a system has about a certain event, the decision making style that suits best to this level can be used by the system.
In a model the levels of situational awareness can be regarded to as different scenarios, or application of Policies. Bouarfa et al. [13] applied four different policies to a case on an agent-based model of an AOC, which

is discussed in detail in Chapter 5. In their study, Bouarfa et al. apply four decision making policies, to one disruption. In which the policies are based on a certain level of situational awareness that is available in each case. Hence, the levels of situational awareness can help to simulate environments with different levels of information.

In addition to the decision making styles, also different decision making structures can be identified. These structures indicate what the order of authority is between the decision making entities. Decisions can be made in either a centralised, decentralised, or distributed manner.

Centralised decision making In the centralised decision making structure all actors provide their input to a problem to the entity with the most authority. The entity with the biggest amount of authority will then make a decision based on the gathered input from the actors with less authority.
The main benefits of this type of decision making structure is that it is easier to implement policies and easier to control the organisation. The drawbacks of this system are, that the actor which makes the decisions is not locally involved so he is fully dependent on the information that is provided by the others.

Decentralised decision making In this type of decision making structure the decisions are made more locally. There are less layers of authority. The advantage of this is that decision are made based on the local environment and therefore there is an increased local problem comprehension. However, the result of this is that all the entities will make locally optimal decision which endangers the global optimum decision.

Distributed decision making In distributed decision making, there are different levels of authority defined. At the highest level is a supervisor. The entities on the lower levels can make local decisions, however they are communicated to the supervisor. The supervisor is the one who has a view of the total problem under consideration and can delegate the lower levels to adjust their local decisions to increase the value of that local decision to the total problem.

In KLM CityHopper's operational control center decisions are made in a distributed structure. The duty manager acts in this case as a supervisor or coordinator and the operations controllers from the fleet, crew and passenger domains will report to the duty manager about how they would locally solve the problems in their dimensions. This way the duty manager is able to steer the airline's operation to a global decision that aims at the improvement of the state of the OCC environment.

5

Agent-Based Modelling of an Airline Operations Control Center

In this chapter a literature review is conducted on the concepts for agent-based modelling of airline operations control centers. There are two prominent agent-based models present in literature that model disruption management in an AOCC. These models are discussed and compared to each other in Section 5.1. From these models a list of agent-based coordination techniques evolves, which will be elaborated upon in Section 5.2. Thereafter the most common problem solving algorithms as used in both agent-based and linear programming models for disruption management and the ones familiar to KLM CityHopper from previous research are discussed in Section 5.3. Several agent learning techniques, which can increase the resilient capacity of agent-based models will be discussed in Section 5.4 and lastly agent-based languages and software will be discussed in Section 5.5.

5.1. Agent-Based Airline Operations Control Models

In this section, an in-depth analysis is performed on two AOC models that have been developed by the use of agent-based modelling approaches. In Subsection 5.1.1, an agent-based AOC model created based on the joint-activity framework by Bouarfa et al. [15] is discussed, in Subsection 5.1.2 a new concept to disruption management by Castro and Oliveira [19] is presented. To complete this section, in Subsection 5.1.3 a comparison between the two presented models is conducted.

5.1.1. Joint-Activity Framework AOC Model

Bouarfa et al. [15] developed an agent-based coordination model of an AOC. They demonstrate the application of a multi-agent coordination framework, the joint-activity model, to the case of an aircraft going AOG at an outstation. The AOCC used in this framework is modelled as a STS with the following agents:

- Airline Operations Supervisor
- Aircraft Controller
- Crew Controller
- Maintenance Services
- Airport Engineer
- Station Supervisor
- Aircraft Movement System
- Crew Tracking System
- Flight Crew

These agents are incorporated into the joint-activity model from Klein et al. [49] which requires three phases for effective coordination:

1. Criteria for joint-activity
2. Requirements for joint-activity
3. Choreography of joint-activity

Criteria for joint-activity This phase is about the intent of the agents to work together and the willingness to carry out their coordination responsibilities. Next to the intent, interdependence is part of this phase. Interdependence describes the way in which a decision from one agent is of influence to the decisions of the other agents.

Requirements for joint-activity This phase incorporates the values of inter-predictability, common ground and directability. Inter-predictability is the ability of agents to predict the actions of other agents with a reasonable accuracy. Common ground is about the agents' mutual knowledge, like roles, skills, assumptions and intentions. When the conditions or priorities in the model change, agents can try to deliberately modify/influence the actions of the other agents, which is referred to as the directability property.

Choreography for joint-activity The phase that enables the model to identify different phases of the activity and models how the agents signal to each other about the transition between the different phases is the choreography of joint-activity phase. Signalling can either be a signal of starting/-completing a task, or a signal of having difficulties and needing help. The signalling is done over coordination devices, which define the way in which the signalling can be performed. For example, the signalling convention used. In addition, the choreography of joint-activity also includes the coordination costs. This is defined as the willingness and ability of an agent to do additional work and help other agents to achieve their goal with less effort.

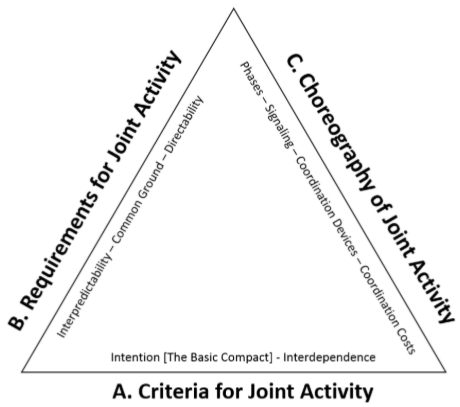


Figure 5.1: Joint-activity model

A schematical view of the joint-activity model and the inherent phases, is presented in Figure 5.1

Bouarfa et al. [13] compared the performance of four disruption management policies applied to an AOG case. In this paper the airline operations control policy P4 that implemented the joint-activity model resulted in the best solution. The AOC policies that were compared here are:

- P1 → Elementary level of performance → operations controllers identify various basic level of considerations.
- P2 → Core level of performance → operation controllers have a greater comprehension of the disruptions.
- P3 → Advanced level of performance → operation controllers are thinking beyond the disruption and find creative ways to solve the disruption.
- P4 → Based on the joint-activity model and the coordination between agents.

These policies can be regarded to as different scenarios in which the agents have different levels of situational awareness. From the P1-policy to the P4-policy agents have increasing levels of situational awareness and thus a better comprehension about the problem and more information available.

In the P4 policy, based on the joint-activity model, the following approaches to coordination were used:

- Master/Slave technique
- Contract Net Protocol
- Multi-agent Planning
- Routines and Protocols
- Mutual adjustment
- Supervision
- Team meetings
- Team Situation Awareness

In [14], Bouarfa et al. expand on the AOC policy P4. The P4 policy is based on the Single Text Mediated Protocol. In this type of protocol there is an unbiased mediator agent searching for an agreement between the agents, without knowing the agents' individual preferences [51]. Applying this protocol to the disruption management context in an AOC, it can be said that the specialised agents propose potential solutions to an supervisor. The supervisor agent then tries to come to a consensus between all specialised agents, which should result in the best overall solution. The Single Text Mediated Protocol consists of a pre-negotiation phase and a negotiation phase.

Pre-negotiation phase In this phase the supervisor agent asks the specialised agents to generate the proposed solutions according to their dimension (crew, aircraft, passengers) of the problem. The specialist agents will then provide their proposals within a set deadline. If one of the specialised agents is unable to propose a solution then the problem is deemed unsolvable.

Negotiation phase In this phase the supervisor agent evaluates the proposals as given by the specialised agents and selects one of these proposals according to the bidding strategy. Hereafter, the supervisor announces the choice to the specialised agents which can then vote for or against the choice of solution. When all agents agree on the solution, then the negotiation is over. If the agents disagree, then the supervisor will reconsider the proposals and will update his solution choice.

From these negotiation phases it becomes clear that the interactions of the agents in the model is based on a supervisory structure which divides the agents into supervisors and specialist. It is stated that a problem cannot be solved when one of the specialist agents cannot come up with a solution to a problem in their dimension. In real operational control centers there is and should always be a solution to every problem. A (very rigorous) solution can even be to cancel all remaining flights of the day. In a real-life airline operational control environment a problem is never unsolvable, but a problem can become unsolvable due to a lack of situational awareness or a solution space that has been left untouched such that the agents do not have knowledge or creativity in their proposals.

The model discussed in this section is regarded to as a socio-technical model, since it includes both operations controllers (social entities) and operational control systems (technical entities). However, there are no decision support tools or algorithms, included that can propose solutions themselves. Also, the coordination techniques employed are all based on social interactions and therefore do not accommodate for decision support tools or algorithms.

5.1.2. A New Concept to Disruption Management

Next to the joint-activity model as discussed in the previous section. there is also an agent-based AOC model, ’a new concept to disruption management’, described by Castro and Oliveira [19]. They developed an agent-based model which also employs a supervisory structure with manager agents and specialised agents. In this agent-based model they modelled an AOCC including the following agents:

- A/C Manager
- Crew Manager
- Pax Manager
- Monitor
- Tracking
- Data Visualization
- Supervisor
- Applier
- Event Information
- Learner

This model is designed as decision support system to be used by the human airline controller and does so by automating the key functions in the OCC using multi-agent negotiation techniques. Each specialist agent has its own utility function which can be for example to minimize delays or to minimize flight cost.

In case of a disruption the monitoring agents sends the observed problem to the supervisor agent. Which in his turn asks the manager agents from the three domains to propose solutions to this problem. The manager agent requests the specialist (aircraft, crew, pax) agents to come up with a solution to the problem as indicated by the monitoring agent. The manager agent then will use an utility function to determine which solution as proposed by a specialist agent, will be taken to the managers negotiation level. At the managers level the local best solution are negotiated into a final proposal, which will be send to the supervisor agent. The supervisor proposes the solution to a human operator, that can either accept or reject the proposed solution. In case the human operator rejects a solution, the whole process starts over again and with the knowledge of the rejected solution a new solution will be proposed. The structure of this process is shown in Figure 5.2.

The software negotiation techniques used in this model are:

- Fipa-request
- Fipa-query
- Fipa-Contract.net
- GQ-negotiation

In the model use is made of two levels of negotiation, *the manager agents level* and *the team level*. At the manager agents level, the negotiation is focused at obtaining a solution that incorporates the impact on aircraft, crew and passengers. To do so, the GQ-negotiation protocol is executed.

At the team level the Fipa protocols are used to negotiate about the solution that the manager of the team will take to the manager’s GQ-negotiation.

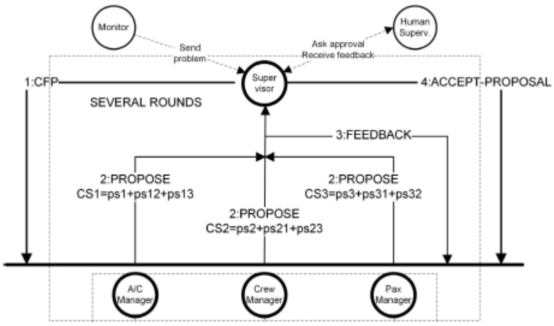


Figure 5.2: Interaction between manager agents [5].

Castro and Oliveira [19] test their model on 3 cases where there is a no show with respect to crew. They differentiate the results obtained between three different methods; *the human method, the agent-no-quality method* and *the agent-quality method.*

Human method In this method an experienced AOC controller solves the problem by using all the tools readily available in the AOC. This can be said to be the calibration test, since the solution that the AOC controller proposes would also be proposed in real problems.
Agent-no-quality method In this method the model generates a solution, without considering the quality cost model behind it. Therefore, this is the method in which the output form the basic model is generated and is later on compared to the outcome of the model with the quality costs behind it.
Quality cost method In this method the quality costs are included in the model, this is an addition to the regular operational costs, based on passenger profile. This cost is introduced to try and simulate the experience and rule-of-thumb usage from experienced AOC controllers. The quality cost-model is able to make choices about delaying flights based on the passenger profiles that are on these flights [20].
In the end the quality-cost model showed the best results for the case considered. Therefore Castro and Oliveira state that it is showed that the proposed MAS is able to generate solutions that have shorter flight delays and contributes to an overall increased passenger satisfaction.

The quality-cost model is implemented to be able to develop rationale behind the software agents to represent experienced human operation controllers. In principal no human agents are modelled. The only human input that is given to the model is the approval or denial of a solution that was proposed by the supervisor agent. It can be doubted whether trying to model human behavior is more efficient than including social agents in the system.
This could also be the reason that a learner agent has been included in the model. This learner agent learns from the interaction with the human supervisor and therefore learns from the input that the human provides. In the end this could result in a model that is able to behave more human-like in the decision making process.

5.1.3. Comparison & Research gap

When one compares the the model from Bouarfa et al. [14] and the model from Castro and Oliveira [19] as discussed in this section, three major differences can be identified:

1. The negotiation techniques used.
2. The use of problem solving algorithms.
3. The presence of a learner agent.

The first noticeable difference between the models are the number and types of negotiation techniques that are used between the agents. This can be explained by the implementation of the joint-activity model by Bouarfa et al.[13] and the more distributed, cooperative and scalable approach as adopted by Castro and Oliveira[19]. Furthermore Castro and Oliveira make use of software agents, which is an explanation for the use of the FIPA protocols.
Bouarfa et al, model human agents. To be able to model the interactions between the human agents, which in general can be considered to be more complicated to model than interactions between technical systems, multiple coordination techniques have to be implemented. the coordination techniques used by Bouarfa et al, are more representative for a STS.
A further elaborate investigation into the coordination techniques used is conducted in Section 5.2.

The second difference is in the use of problem solving algorithms as agents. Castro and Oliveira [19] use problem solving algorithms to represent the specialised agents and only requires human approval or denial as input on the final solution that is proposed. In contrary to the model from Bouarfa et al. [13], in which the solutions from specialised agents are generated by the human specialists behind them. Castro and Oliveira state that humans in a model should not be controllers but managers instead and therefore they have the opinion that repetitive or frequent tasks are better executed by software agents and tasks with higher uncertainty are better performed by humans.

The last major difference is the use of a learner agent. This agent enables the model to learn from past experiences by employing reinforcement learning techniques. The learning agent learns from the acceptance and denial of solutions as proposed by the supervisor agent to the human operator. The presence of a learner agent is beneficial for the resilience of the model and the behavior of the model. Learning enables the model to generate and propose better solutions to the same problem each time it occurs.

From the comparison and the review of the models as discussed in the previous subsections, it can be concluded that the two analysed models are built with a different scope. One is more focused on the modelling of interactions between social agents and simulates a disruption case and the other is more focused on the interaction between technical systems and aims at being a decision support tool to be used by operations controllers. The research gap that can be identified here is that the combination of technical problem solving entities and social agents that both can input solutions to a disruption into the model, have not been researched yet.

5.2. Agent-Based Coordination Techniques

In this section the agent-based coordination techniques that evolve from the AOC models as discussed in the previous section, are elaborated upon in Subsection 5.2.1 through Subsection 5.2.12.

5.2.1. Master/Slave Technique

The master/slave technique is a type of coordination that is typically used in task and resource allocation problems [61]. In this technique the master agent, plans and distributes sub tasks to the slave agents. The slave agents will report the results back to the master agent when the allocated task has been finished. The slave agents are able to communicate amongst each other.

5.2.2. Contract Net Protocol

In the Contract Net Protocol (CNP) coordination technique, there are manager and contractor agents. These roles are not pre-defined and will evolve over time. If an agent is assigned a certain task, but is not able to accomplish the goal of this task by itself, the agent will divide the task into sub-tasks. From that moment on, the agent is referred to as a manager agent and will announce the sub-tasks to the rest of the agents in the network. These are then called the potential contractor agents. The potential contractor agents will evaluate the announced sub-task with respect to their own capabilities. Thereafter each of the potential contractor agents will respond to the manager agent with a bid, which reflects their capability to do the task. Lastly, the manager agent will give the task to the agent whose bid is evaluated to be the most suitable to execute it. The manager and contractor agent will continue to exchange information during the execution of the task.

5.2.3. Multi-agent Planning

In multi-agent planning the agents in the model coordinate about the use of resources and execution of activities. To arrive at a plan, which is an ordered sequence of actions that results in the achievement of the set of goals, the following phases can be identified[32]:

1. Allocate goals to agents.
2. Refine goals into subtasks.
3. Schedule subtasks by adding resource allocation and timing constraints.
4. Communicate planning choices to recognize and resolve conflicts.
5. Execute the plans.

Depending on the nature of the model for each phase different techniques can be used. When the multi-

agent planning approach is used, multiple model types can be defined along three axes [32].
The first axis, defining the relation between individual agents, goes from *independent* to *strongly related*. Independent agents do not share resources and do not depend on each other. In contrary to strongly related agents, which are using shared resources and coordinate joint actions.
The second axis goes from *cooperative* to *self-interested agents*. Cooperative agents, work together to achieve their goals. Self-interested agents are only interested in maximising/optimising their own utility, no matter what the cost or impact is on other agents.
Lastly, there is the axis which goes from *no communication possible* to *reliable communication*. When agents are not able to communicate during the task execution, they have to plan all their actions beforehand. However, when agent have reliable communication they can keep updating the plan during the task execution.

5.2.4. Routines and Protocols

Routines and protocols define rules that constrain the actions of agents in the model. Protocols are a set of pre-defined actions to be applied in a certain situation. Routines capture the lessons-learned from experiences in the past, which enables agents to reproduce a set of actions that have proven to be worked before in a similar situation [40].
An assumption that is made in this type of coordination, is that the set of rules is internally consistent. This assumption requires that the situation which the agents can encounter to be stable, repetitive and few enough to be able to match the rules with the situation [13].

5.2.5. Mutual Adjustment

In the mutual adjustment coordination technique, agents are able to transmit new information during the execution of actions. This is useful in situations which are variable and unpredictable. Mutual adjustment is also referred to as 'coordination by feedback' [13].

5.2.6. Supervision

By Gittel [40], supervisors are referred to as boundary spanners. These are individual agents that have as primary task to integrate the work done by others. Supervisors can increase the performance of interdependent work processes by facilitating the interaction among employees. An example, of a supervisor agent is a project manager.

5.2.7. Team Meetings

Coordination in team meetings, enables the participants in a team to communicate their tasks directly with each other. According to organization design theory, team meetings are beneficial for the performance of interdependent work processes and are increasingly effective under conditions of high uncertainty [40].

5.2.8. Team Situation Awareness

According to Kaber and Endsley [46] situation awareness can be defined as 'the perception of elements in the environment, the comprehension of their meaning in terms of task goals and the projection of their status in the near future'. This definition is in the perception of an individual agent, which has been previously discussed in Section 4.3.
Team situation awareness is the sum of situation awareness of individual agents, independent of any overlap. For example, if two agents need to have knowledge of specific information and one of them has perfect knowledge and the other has no knowledge then the team situational awareness has a deficit. Therefore, a weak link in team situational awareness evolves when an agent needs certain information but is unable to acquire it.
Situation awareness does not only exist between individual agents in a team, but can also exist between multiple teams. However the goals of multiple teams are mostly less interdependent than the goals of the individual agents operating in a single team [46].

5.2.9. Fipa-request

In the fipa-request protocol one agent can request another agent to perform some action. The participant agent that is requested to perform an action, can either accept or refuse the request. When the participant agent accepts the request, then the agent will communicate the status of the action when the action is done. The action status can be one of the following [25]:

- Failure → participant agent failed to fulfill the request.
- Inform-done → the participant agent informs the other agent that the request has been fulfilled.
- Inform-result → the participant agent informs the other agent that the request has been fulfilled and includes the result in the message.

5.2.10. Fipa-query

The fipa-query protocol enables an agent to request to perform an action on another agent. The initiator agent can send either a query-if or a query-ref request. A query-if is used when the initiator agent wants to know whether a certain proposition is true or false. A query-ref is used when the initiator agent wants to query for a specific object. The participant agent can either accept or refuse the query request. Upon successful completion of the query the participant agent either sends the truth or falsehood of a proposition or sends the expression to the objects for which the query was specified [24].

5.2.11. Fipa-Contract.net

In the fipa-contract.net protocol, the initiator agent sends out a call for proposals which specifies the task including conditions under which this task has to be executed. The participant agents respond to this call for proposals with a refuse or a proposal. This response should be prior to the deadline as set by the initiator. If the response is after the deadline, it is automatically rejected. The initiator agent then evaluates all proposals made and selects the agent(s) which have the best ability to execute the task under the specified conditions [23].
Similar to fipa-request (Subsection 5.2.9), the participant agents communicate about the state of the actions by either a failure, inform-done, or inform-result .

5.2.12. GQ-Negotiation

The Generic Q-Negotiation protocol is introduced by Castro et al. [4]. In GQN the agents can assume either the role of Organizer or Respondent. The organizer agent has the responsibility of defining the problem and subdividing it into sub-problems. Thereafter this agent will initiate the negotiations with other agents to solve the sub-problems.
The respondent agents have the expertise to take on one or more of the sub-problems and if needed can negotiate with other respondent agents, this is called the inter-respondent agent negotiation. In the end the respondent agent will be able to present the organizer agent a solution to the whole sub-problem.
An overview of the GQN structure by Castro et al. [4] is given in Figure 5.3.

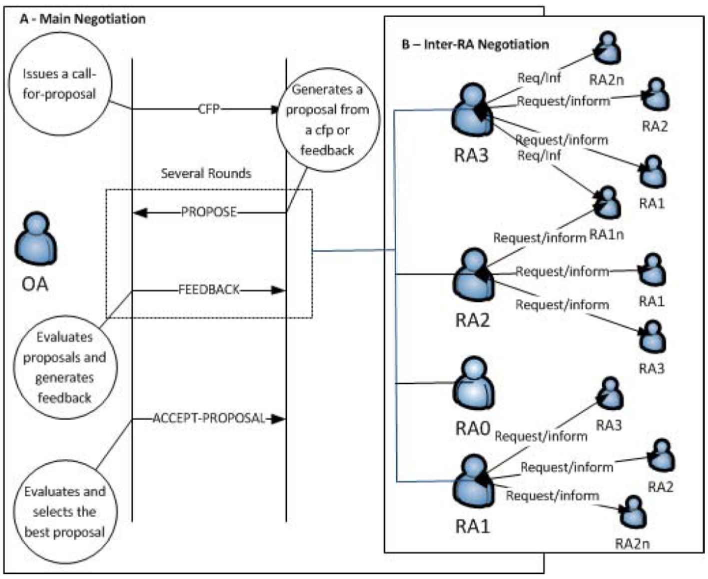


Figure 5.3: GQN structure [4].

5.3. Problem Solving Algorithms

Due the modular nature of agent-based modelling, specialist agents with different goals can be added to the model to increase accuracy or better simulate the environment for which the model is created. Therefore, this section will discuss the algorithms that Castro et al. [4] use for specialised agents. Furthermore, the algorithms that were used in solving the aircraft recovery problem in a disruption management tool as developed by KLM Cityhopper are described [6].

In the MAS by Castro et al.[4] as previously discussed in Section 5.1, the specialised agents that are present in the model employ three different problem solving algorithms; Hill Climbing, Simulated Annealing and the Dijkstra Shortest-Path algorithm. The Hill Climbing and Simulated Annealing algorithms were used for aircraft and crew recovery problems. The Dijkstra Shortest-Path algorithm was used for solving the passenger problem dimension, since this algorithm is suitable for a shortest path problem.

Hill Climbing The hill climbing algorithm starts by generating an arbitrary solution to a problem. Thereafter an iterative cyclus is started in which continuously small single changes are made to the previous solution. If the new solution then is better than the previous one, the next adjustment is done to this solution. This cyclus continues until no further improvements can be found. This algorithm is use full for finding a local optimum, however it cannot be guaranteed that the best possible solution is found out of all the possible solutions.

Simulated Annealing This is a probabilistic method which can find the global minimum of a cost function where there might be several local minima. The algorithm works by emulating the physical process of slow cooling of a solid, such that eventually the solid is frozen or arrives in it's minimum energy configuration [34]. Each step of this algorithm replaces the current proposed solution, with a randomly generated nearby solution. This nearby solution is selected with a probability that is dependent on the values of the solution and the temperature T, which is gradually decreased in the process. If the T is large, the current solution changes almost randomly but is able to gradually improve if T becomes smaller[4].
An advantage of the simulated annealing algorithm is that it is able to do both uphill (worse) and downhill (good) moves, which prevents the algorithm from getting stuck at local optima.

Dijsktra's Shortest Path Algorithm This algorithm is able to find the shortest path given a starting node and a destination node. The shortest path, is the path with the lowest associated costs. When applying this to the passenger dimension of an airline, the nodes can be seen as airports. The starting node is the current location of the passenger and the destination node is the destination airport of the passenger. Dijkstra's algorithm can then find the path with the lowest cost for the passenger to get from the origin to the destination.

In the previous development of a disruption management tool at KLM CityHopper (the Wizard of Ops), a tabu-search algorithm was used in conjunction with a Fisher-Yates shuffle and recursive nested tree build algorithm [6]. The combination of these algorithms was employed to solve the aircraft recovery problem.

Tabu-Search The tabu-search algorithm can be compared to a local search algorithm, which starts with an initial solution and stops when no improvements can be made to that solution anymore. However, in the tabu-search algorithm a tabu-list is introduced. The tabu-list allows the algorithm to temporarily accept worse solutions than the current solution, which helps the algorithm to escape local optima. A set of rules describes whether a solution is allowed and prevents repeated visits to the same solution.
In a tabu-search the size of the tabu-list and the tabu aspiration criterion determine whether the algorithm is going to be successful at finding solutions. The aspiration criterion defines the quality of the solutions that are allowed in the tabu-list [36].

Fisher-Yates Shuffle It is known to be an unbiased algorithm that can shuffle items with an equally likely probability. The Fisher-Yates Shuffle is employed by Aslan [6] to shuffle aircraft pairs and be able to obtain more solutions. These aircraft pairs are used to assign sequences of flights to by the tabu-search.

Recursive Nested Tree Build Algorithm This algorithm is used by Aslan [6], to build aircraft routings which are constrained by minimum turnaround times and origin-departure matches. These routings are fundamental for the solutions as considered by the tabu-search algorithm, as they are input for the Fisher-Yates shuffle.

Sentry, the decision support tool that is available for the operations controllers to consult for generating solutions to disruptions in KLM CityHopper's operational control center, is developed as a mixed-integer programming solver that uses Gurobi as optimizer. In Gurobi two types of algorithms can be used; the barrier algorithm and the simplex method.

Barrier Algorithm Barrier methods are often referred to as Interior Point Methods. This algorithm is designed to solve a constrained problem, by solving a sequence of specially constructed unconstrained problems [57]. The algorithm start with an initial solution point within the feasible region. Every other point that is closer to the edge of the feasible region is penalised heavily. A typical barrier problem can be solved with Newton's method and therefore converges quickly when the initialization point is close to the solution point.

Simplex Method The simplex method can be used to solve linear programming problems. It does so by rewriting all constraints to equality constraints and putting them in a matrix. This matrix is then pivoted on the elements until no increment to the optimal solution can be made anymore. It requires a lot of numerical calculations to come to a solution and therefore can be time intensive to converge to an optimum [66].

5.4. Learning in Agent-Based Modelling

Learning capabilities of a socio-technical model of an AOCC are of big interest in the view of resilient performance. For a system to be able to exhibit resilient performance, being able to learn from previous scenarios is a key characteristic. In this section, learning agent techniques that have been previously used in literature in the context of the dynamic environment of an AOCC are elaborated upon.

Castro et al. [4] used reinforcement learning on the learning agent as discussed in Section 5.1. In this model the learning agent learns from the input of the human supervisor, which can either choose to accept or reject a solution. More specifically, they opt to use two types of Temporal Difference Methods; Q-learning and SARSA. These learning techniques are found to be suitable within the rapidly changing environment in an AOCC.

Reinforcement Learning According to Busoniu et al. [18] a reinforcement learning agent learns by trial-and-error interaction with its environment. A learning agent is able to perceive the state of the environment before and after the state is changed due to actions of other agents that are present in the environment. Based on the change in the environment the learning agent receives a scalar reward signal that enables the agent to evaluate the quality of the change.

Temporal Difference Methods Temporal Difference Methods are a subclass within reinforcement learning. In this method learning occurs based on the difference between successive predictions [75]. A classical example is the weather forecast. If a daily prediction of the amount of rain is made for the weather on next Sunday and the forecast on Thursday says there is a 5% chance of rain on Sunday and the forecast on Friday says there is a 15% chance of rain on Sunday. Then the Temporal Difference Method will increase the forecast on days similar to Thursdays.
Sutton [75] identified two advantages of the Temporal Difference Method over conventional prediction learning techniques:

- The Temporal Difference Method is more incremental and easier to compute.
- The Temporal Difference Method makes more efficient use of their experience; faster convergence and better predictions.

When one is looking for literature in which learning is applied to a system in which the learning goal was to improve future decision making based on results obtained in the past, case-based reasoning is of interest. This technique is used in agent based systems that have a decision support role [84] [72], are aimed at improving quality of a process [64], or negotiation is modelled [38] [55].

Case Based Reasoning Corchado and Laza [26] define case based reasoning in the agent based modelling context. Case based reasoning can be used in a model to solve new problems based on the adaptation of old solutions that were previously implemented on problems of a similar nature.
A case based reasoning system employs a sequantial cyclus of four steps; retrieve, reuse, revise and retain.
In the retrieve phase, the problems that are in the base of previous cases (case base) and are in some way similar to the current problem are retrieved. Thereafter in the reuse and revise stage, the retrieved cases from the case base are adapted to generate a possible solution to the current problem. In the last phase, the generated new solution is reviewed and if deemed to be appropriate stored in the case base.
Due to the retain phase, the system is continuously evolving it's case base and therefore continuously adapts

to the environment.

In literature, case based reasoning has not been applied to the context of an AOCC yet. However an AOCC is a perfect example of an environment in which cases, or in the context of an AOCC; disruptions, are handled with knowledge of previous experiences. These previous experiences can be bundled into a case base, to which the above four phases can be applied. Hence, this would make an AOCC suitable for the application of the case based reasoning technique.

5.5. Agent-Based Modelling Formalization Syntax & Simulation Environments

In this section a high-level analysis is performed on the available formalization syntaxes in the domain of modelling STS in highly dynamical environments. A formalization syntax in the socio-technical domain should be able to accommodate for both quantitative and qualitative aspects of a model. In addition, a state transition of an agent in a STS can either be discrete in time, or based on real-valued state variables that can change continuously over-time, which should also be captured in the formalization syntax [10]. Based on these requirements, a short literature review is conducted on multiple models of STS and specifically the use of formalization syntaxes in these models.

In the model from Bouarfa et al. [13] (Section 5.1) the Temporal Trace Language (TTL) is used as a communication prescript that describes the interaction amongst agents. The interaction rules are then implemented into the LEADSTO simulation environment. In the same context Castro and Oliveira [4] used the Java Agent DEvelopment (JADE) framework in combination with the java programming language. JADE is used, both to develop the agents and to use as runtime environment.
To extend the formalization options for the socio-technical context, formalization syntaxes used in the field of modelling social practices are studied. Social practice theory addresses habits, social intelligence and interconnected behaviour between people [59]. All these aspects are used to increase the understanding and enable social phenomena to be captured in a model, which is relevant in the modelling of a STS. In this field of study the use of the multi-agent programming language 2APL [33] suggested in order to model social practices.
In a study on the anticipation in the context of airport security operations, the Timed Transition Systems (TTS) syntax was proposed [10]. Furthermore, a recent literature review by Larsen [54] on the modelling of social agents in an agent-based model, using Agent-Oriented Programming (AOP), showed that the Agent-0, 3APL, JASON and JACK syntaxes are of interest in this field. Due to their relevance to STS these systems will be described further in this section.

Temporal Trace Language TTL is designed for the formal specification and analysis of the dynamic properties of a system. On the contrary to other modelling languages, TTL is able to capture both quantitative and qualitative aspects of a system [12]. A method which combines these aspects, is also referred to as a hybrid method. Such a hybrid method subsumes formalization approaches based on the simulation of differential equations and discrete qualitative modelling approaches. Hybrid methods are known for their ability to analyse the relations between local and global properties of a system's model [70].

LEADSTO LEADSTO, a Language and Environment for Analysis of Dynamics by SimulaTiOn, can be used as a simulation tool to implement the interaction rules as defined in the TTL communication pre-script. LEADSTO has been developed to enable modelling and simulation of multi-agent systems in dynamic environments, with both quantitative and qualitative aspects. In LEADSTO direct temporal dependencies between state properties in successive states can be modelled [52]. The simulation environment of LEADSTO is used to perform simulations of models that are specified by the LEADSTO language and is able to generate and visualise the simulation traces. These traces are ordered sequences of states, that allow to perform analysis on a process.

JADE The Java Agent DEvelopment (JADE) framework is an agent based modelling framework that enables one to setup a model of a multi-agent system by using the Java programming language. JADE is used in multi-agent systems that are based on software agents and is therefore perfectly suitable to be used in systems that have been set-up in compliance with the FIPA coordination protocols, as described in Section 5.2 [58]. Therefore, JADE is less suitable for the modelling of STS since capturing cognitive behaviour in a programming language is nearly impossible.

2APL 2APL is an agent-oriented programming language that is Belief-Desire-Intention (BDI) based. In 2APL agents can be implemented as an individual or multi-agent concept. In the multi-agent concept, programming constructs can be utilised to create individual agents and external environments, name each individual agent and specify the relation of an individual agent to an external environment. Individual agents can be modelled to have relations to multiple environments. Each environment can execute a set of actions to change it's current state and is implemented as a Java Object. Therefore an environment does not necessarily have to be programmed, but can also be retrieved via an interface over this Java Object [28].
In the individual agent concept, agents are implemented with beliefs, goals, actions, plans and events. These are implemented by using both imperative and declarative programming styles. Declarative programming is used to implement the mechanisms that allow an agent to reason about and update their mental states. Imperative programming is used to implement plans and other mechanisms which allow the agent to interface with already existing imperative programming languages [28].
2APL has already been applied to model different auction types, negotiation mechanisms, cooperative problem solving tasks and to control robots [28].

Timed Transition Syntax TTS is a formal hybrid modelling language, which interprets system dynamics as state transitions. TTS evolved from basic transition system syntax and is different in the way that the notion of real-time is added to allow for representing the temporal-logic/dynamics of the system that is modelled. Through the TTS syntax each agent or subsystem can be represented as a timed transition system. To obtain a view of the overall system, the state of the subsystems can be combined to create the overall state of the system. Therefore, it allows to represent a multi-agent system or concurrent processes in a single-agent system [10].

Agent-0 The Agent-0 syntax only considers the mental categories of belief, commitment (to act, not to pursue a goal) and capability. The mental categories of desires, goals, intentions and plans are not covered by this syntax. Therefore Agent-0 is considered to be a simplified syntax to represent social agents [71].

3APL 3APL is a multi-agent modelling language that can be used to implement organization and coordination in multi-agent systems with cognitive agents. This syntax allows the implementation of sequential or parallel execution of individual agent tasks. Agents constructed with 3APL can either communicate directly to one another, or can communicate through a shared environment. When agents are implemented using the 3APL language, they can observe the environment, reason about their state and execute actions in their shared environment. These properties make that this syntax is suitable to apply in the modelling of a STS [29].

JASON JASON is an agent-based modelling syntax that is based on an extension of the AgentSpeak language. This syntax also adopt the BDI-agent structure and is therefore based on beliefs, desires, intentions, goals and plans. JASON allows for a fully customizable multi-agent system in which individual agents can communicate, perceive the environment, reason and act upon beliefs [11].

JACK JACK is a syntax that allows agents to be written directly by using agent concepts such as beliefs, plans and goals. In contrast to the previously described syntaxes, JACK has the ability to model teams of agents in a hierarchical way. An agent-based platform has been built based on JACK, which includes a platform for executing agents with infrastructure, development tools, a graphical plan editor and debugging views [11].

6
Research Proposal

Following the literature review as done in the preceding chapters, in this chapter the foundation for the remaining steps of this MSc thesis will be built. In Section 6.1 the Research Objective is described, in Section 6.2 the Research Questions are derived and in Section 6.3 the Research Framework is built.

6.1. Research Objective

As a result from the research done in this literature study, the research objective has been formulated as follows:

'To analyse the resilience capacity of the decision making in KLM CityHoppers operational control center, by the development of a socio-technical agent-based model.'

This research objective aims at developing an agent-based airline operation control model, based on the models that have been reviewed in Chapter 5, by putting focus on the coordination between social and technical decision making entities (Chapter 4) and the development of metrics to describe and analyse the resilient performance in an operational control environment (Chapter 3).

6.2. Research Questions

As a follow up from the research objective as described in the previous section, in this section the research questions are derived.

The main research questions that can be derived from the research objective are:

1. What are the components of the use case at KLM CityHopper that describes the problem that is to be analysed?
    (a) What is the problem to be solved?
    (b) Which information flows can be identified?
    (c) Which social actors can be identified?
    (d) Which technical actors can be identified?
    (e) What interactions in-between the different actors can be identified?
    (f) What is the structure in which the interactions take place?
    (g) What are the triggers that initiate the problem solving process?
    (h) What decisions have to be made by the actors?
    (i) What is the structure in which the decisions are made?
    (j) What is the solution space to this case?

(k) What is the effect of the level of situational awareness of the entities on the solution space?

2. How can resilient performance be quantified in the context of KLM CityHoppers operational control center?
    (a) What is resilient performance in the context of KLM CityHopper's operations control center?
        i. How can the absorbing capacity of KLM CityHopper's operational control center be described?
        ii. What are the adaptive capacities of KLM CityHopper's operational control center?
        iii. How does KLM CityHopper's operational control center anticipate on events?
        iv. What learning mechanisms are employed in KLM CityHopper's operational control center?
    (b) What metrics for resilient performance can be developed for the analysis of KLM CityHopper's operational control center?
3. What model constructs are required to develop a model, in the scope of the use case, that represents KLM CityHoppers operational control center?
    (a) Which agents can be identified?
        i. Which social agents can be identified?
        ii. Which technical agents can be identified?
    (b) What coordination techniques can be used to model the interactions between the agents?
        i. What coordination techniques can be used to model the interaction between social agents?
        ii. What coordination techniques can be used to model the interaction between technical agents?
        iii. What coordination techniques can be used to model the interaction between social and technical agents?
    (c) Through what model constructs can resilience be included?
    (d) Which agent-based modelling language is most suitable to model the agents and interactions?
4. What can be learned from the results of the model?
    (a) Is the outcome of the model feasible?
        i. What are the criteria for feasibility?
    (b) What is the delta in the resilience metrics between the outcome of the model and the solution as generated by the operations controllers?
        i. What are the values of the resilience metrics that result from the solution of the operations controllers to the case?
        ii. What are values of the resilience metrics that result from the model for this case?
        iii. What is the delta between these metrics?
        iv. What is the reason for the delta between the metrics?
    (c) Would different decision making yield other (better) resilience metrics?
    (d) Which actors impact the metrics the most?
    (e) Is there room for improvement in the decision making process?

6.3. Research Framework

The research framework that is proposed in this report, can be seen in Figure 6.1. At first the system identification phase will be entered, in which KLM CityHopper's operational control center will be explored. This exploration will be scoped on a case study that is to be determined in the kick-off meeting. This will lead to the answer of the first and third research question.

Thereafter, in the second phase, the resilient capacities of the operational control environment will be analysed. This analysis will then lead to the development of metrics to measure resilience in KLM CityHopper's operational control environment. Hereby providing answers to the second research question.
In the model development phase the third research question is answered and thereby the model is created. During the model creation, the model is continuously verified with the system identification phase to ensure that the model does represent the components and interactions of the system that is modelled.
In the last phase the results as generated by the model are analysed and reflected upon. The results as produced by the model are compared to the results of the system under consideration. Based on this analysis recommendations on both the performance of the system and the model can be made. In addition new metrics for resilience could also be a result of this project. Hereby answering the last research question.

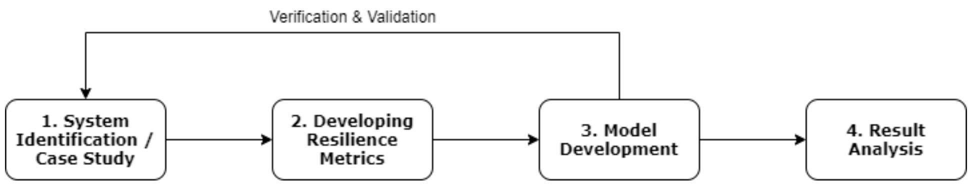


Figure 6.1: Research Framework

7
Research Methodology

7.1. Modelling Approach

Resulting from the extensive literature review as performed in the previous chapters, this is the point at which the modelling approach can be described. From the conducted research it can be concluded that the decision making in an AOC can be captured in a sociotechnical agent-based model. Especially the model from Bouarfa et al. [13] and the model from Castro and Oliveira [4], prove that the agent-based modelling technique is a suitable approach in this domain. Adding to this, agent-based models can be setup in a modular fashion which makes it easy to adapt a model to new use cases or situations that have to be captured. This allows the model to be built from scratch and extended agent-by-agent. Additionally, this enables the model to first be built on a relatively small case with a limited amount of agents. This is perfect for creating a proof-of-concept of a model and enables a more efficient model development.
Recent studies (Section 3.3) have suggested resilient model constructs, that allow an agent-based model to become resilient and exhibit resilient performance. Hereby, the agent-based modelling approach allows the sociotechnical and resilient aspects of KLM CityHopper's OCC to be captured in one modelling approach.

7.2. Research Scope

This study will focus on the development of a sociotechnical agent-based model of KLM Cityhopper's operational control center. The main scope in this model will be on the agent-based modelling of the operations controllers and technical systems as employed in KLM CityHopper's operational control center. The objective of this model is to be able to analyse the resilient performance of the decision making in the operational control center.
The innovation in this research is in the combination of creating an agent-based model of an airline's operations control center that is including both social and technical decision making entities. In similar models by Bouarfa et al. [13] and Castro and Oliveira [4], as reviewed in Section 5.1, the combination of input by both operations controllers and problem solving algorithms has not been modelled yet.

To safeguard the development of the model in this research, the research scope is to start with the a carefully selected case study that has sufficient complexity and frequently arises in KLM CityHopper's OCC. This will limit the amount of data and hereby makes the initial model development more concise, easier to verify, validate and structured.

The following criteria for a case study have been setup:

- The case should be relevant to KLM CityHopper's operational control center.
- The decision making process in the case should include social entities (operations controllers).
- The decision making process in the case should include the use of decision-support systems.
- Measures to solve the case should include aircraft recovery.
- Measures to solve the case should include crew recovery.

- Measures to solve the case should include passenger recovery.
- The case captures multiple decision points with varying levels of information.
- Coordination between stakeholders takes place.
- There is a conflict of objectives (negotiation).

In conclusion it can be said that the scope of this research will be to develop a sociotechnical agent-based model that enables the analysis of resilient performance on a case study that is compliant with the above mentioned criteria for such a case.

7.3. Model Development

The agent-based model development will be done according to the framework as presented by Nikolic and Ghorbani [60] in Section 4.2 (Figure 4.2). Applying this framework to the selected case, the following steps per development phase have been derived:

1. **System Analysis**
   - Description of the problem.
   - Description of the environment that the system is operating in.
   - Description of the boundaries of the system.
   - Identification of the key parameters that describe the environment.
   - Description of the components that are playing an active role in the environment.
   - Description of the relational structure between the system's components.
   - Description of the interactions between the system's components.
2. **Model Design**
   - Translate the identified system components into agents.
   - Structure the agents according to their interactions.
   - Identify the behavior of the agents.
   - Identify the behavior of the environment.
   - Identify communication protocols to be used between agents.
3. **Detailed Model Design**
   - Choose the modelling software to be used.
   - Choose the modelling language to be used.
   - Describe the desired outcome of the model.
   - Define a hypotheses about the model.
4. **Software Implementation**
   - Implement the environment in the modelling software.
   - Implement the identified agents and agents' behavior in the modelling language.
   - Implement the interactions between the agents in the modelling language.
5. **Model Evaluation**
   - Verify the model with the system structure as defined in the system analysis phase.
   - Validate the outcome of the model with the outcome of the system.
   - Create multiple datasets to identify critical model components.

7.4. Simulation, Analysis and Conclusions

Once the model has been developed according to the steps as presented in the previous section, first the model verification and validation has to take place. In the verification phase it will be checked whether the model functions like it was intended to. This entails to verify the models behind the agents with the description given about them in the system identification phase. Furthermore, the calculations which form the basis for the resilient metrics should be verified.
In the validation phase, the outcome of the model to the selected use case will be compared to the outcome that the operations controllers and Decision Support Tools will generate on this case. Since these are input for the model, the metrics can be manually derived and checked with the result of the developed model.

After the model verification and validation has been performed successfully, the model can be run for multiple variants of the presented use case. The results of these runs will be analysed based on the established metrics for resilience. This analysis will provide an indication the level of resilient performance that KLM CityHopper's OCC is performing at in the cases that were run.

The data generated in the analysis phase allows recommendations to be formulated to analyse different cases that are bigger in data size and that might be more interesting for KLM CityHopper's actual operations to analyse. From these recommendations it might also follow that new agents should be added to the model to make it suitable for other cases. Additionally, KLM CityHopper's operations might learn something from this model that they were not aware of yet. This could be in the long-term effect of a certain decision or even in the processes that are considering both social and technical input.

8

Planning

8.1. Work-Breakdown

1. **System Identification / Case Study**

   1.1 *Analysis of the OCC*

   1.1.1 Identify and analyse the KPI's in the OCC.

   1.1.2 Identify and analyse the operations controllers in the OCC.

   1.1.3 Identify and analyse the operational control systems used in the OCC.

   1.1.4 Identify and analyse the decision support tools in use in the OCC.

   1.2 *Analysis of Information Availability*

   1.2.1 Identify and Analyse the information flows in the OCC.

   1.2.2 Identify and Analyse the structure of information flows in the OCC.

   1.3 *Analysis of Operations Controllers*

   1.3.1 Identify and analyse the situational awareness of the operations controllers.

   1.3.2 Identify and analyse the triggers for the operations controllers.

   1.3.3 Identify and analyse the decision making structure.

   1.3.4 Identify the interactions that take place among the operations controllers.

   1.3.5 Identify the interactions that take place between the operations controllers and the operational control systems.

   1.3.6 Identify the interactions that take place between the operations controllers and the decision support tools.

   1.4 *Analysis of Operational Control Systems*

   1.4.1 Identify and analyse the situational awareness of the operational control systems.

   1.4.2 Identify and analyse the tools that operational control systems provide to the operations controllers.

   1.5 *Analysis of Decision Support Tools*

   1.5.1 Identify and analyse the situational awareness of the decision support tools.

   1.5.2 Analyse the triggers to which the tools react.

2. **Developing Resilient Metrics**

- 2.1 *Identification of Resilience in the OCC*
  - 2.1.1 Identify and analyse absorbing capacity of the OCC.
  - 2.1.2 Identify and analyse adaptive capacity of the OCC.
  - 2.1.3 Identify and analyse anticipating mechanisms in the OCC.
  - 2.1.4 Identify the learning mechanisms that are in place in the OCC.
- 2.2 *Develop Metrics*
  - 2.2.1 Develop metrics for absorbing capacity of the OCC.
  - 2.2.2 Develop metrics for adaptive capacity of the OCC.
  - 2.2.3 Develop metrics for anticipation capacity of the OCC.
  - 2.2.4 Develop metrics for learning capacity of the OCC.

3. **Model Development**
   - 3.1 *Model Design*
     - 3.1.1 Translate the identified social entities to agents.
     - 3.1.2 Translate the identified technical entities to agents.
     - 3.1.3 Develop the structure for interactions between agents.
     - 3.1.4 Identify agent behavior.
     - 3.1.5 Determine communication protocols to be used between agents.
   - 3.2 *Detailed Model Design*
     - 3.2.1 Determine the modelling software to be used.
     - 3.2.2 Determine the modelling language to be used.
     - 3.2.3 Describe in detail the desired output of the model.
     - 3.2.4 Formulate a hypotheses about the model.
   - 3.3 *Software Implementation*
     - 3.3.1 Implement the agents in the software.
     - 3.3.2 Implement the interaction between agents in the software.
   - 3.4 *Model Evaluation*
     - 3.4.1 Verify the output of the model.
     - 3.4.2 Validate the output of the model.
     - 3.4.3 Identify the critical model components.

4. **Result Analysis**
   - 4.1 *Feasibility Check*
     - 4.1.1 Develop feasibility criteria for output of the model.
     - 4.1.2 Determine feasibility of the output of the model.
   - 4.2 *Reflection*
     - 4.2.1 Determine if output is according to the hypotheses.
   - 4.3 *Resilient Metrics*
     - 4.3.1 Determine the value of the resilient metrics.

4.3.2 Determine the delta between resilient metrics from the model and the metrics inherent to the solution of the operations controllers.

4.3.3 Determine the delta between resilient metrics from the model and the metrics inherent to the solution of the decision support tools.

4.3.4 Identify the rationale behind the delta.

4.3.5 Identify the lessons than can be learned from the output.

9 Conclusion

Based on the literature review as performed on the topics of resilience (Chapter 3), sociotechnical systems (Chapter 4) and agent-based modelling in airline operations control (Chapter 5), the research objective that is proposed is;

> *'To analyse decision-making of KLM CityHopper's operational control center, by the development of a sociotechnical agent-based model.'*

To be able to achieve this research objective, a set of research question and a research framework are proposed in Chapter 6. These questions and framework evolve around a to be determined use case that is provided by KLM CityHopper. To ensure sufficient complexity and relevance of the use case, a set of criteria has been developed.

As modelling approach the agent-based modelling technique is selected due to the modularity property and the ability to model sociotechnical systems. In addition a modelling framework that is suitable for the development of sociotechnical agent-based models is adopted. During the development phase the model will be verified with the detailed description, that evolves from the case study, about the agents and the interaction among the agents. The validation will take place by running the model on cases that have occurred during KLM CityHopper's real-life operations and are similar to the use case that is used to develop the model. The outcome of the model to such a real-life case can then be validated with KLM CityHopper's operational control center.

As a result of this research project an agent-based model that is composed of both social and technical decision making entities is expected. In addition new metrics for resilient performance of an airline operations control center could be an outcome. The purpose of this model is to be able to analyse the performance of the decision making in KLM CityHopper's operational control center. Hereby, the decision making might be improved or adjusted based on the outcome of the model.

III

Appendices

A

Workflow Diagrams

Based on the working procedures of the airline and the control modes that the agents operate in, workflow diagrams have been constructed. These workflow diagrams capture the interaction among the agents, which is based on the unexpected diversion use case. In Figure A.1 through Figure A.4 the workflow diagrams of the agents operating in the scrambled, opportunistic, tactical, and strategic control mode are shown. To increase the understanding of these diagrams the different phases that can be identified are described.

Trigger - The FC agent is informed by Air Traffic Control that LCY airport has been unexpectedly closed due to a runway blockage. Due to this the FC agent informs the DM agent via ACARS about this information.

Conference Call 1 - Upon receiving the ACARS message from the FC agent, the DM agent setups a conference call to inform all relevant actors in the airline's OCC about this situation. These participating agents are: DMN, FCo, CC, CD, FW, DAM, PS. The DAM and PS agents are not in the workflow scheme due to their reduced participation and for visual representation purposes.

Inform on diversion airport - The FCo agent extracts the list of alternate airports from the OCS technical system and selects an airport from this list. The FC agent is informed via ACARS about the choice of diversion airport, in case a diversion will be part of the solution strategy.

Lookup slot status and TAF - The FCo agent accesses the CDM and OF technical systems to gain awareness about the slot statuses and the weather forecasts.

Conference Call 2 - The FCo agent initiates a conference call to inform the DMN, CC, CD and FW agents on the selected diversion airport, reserve availability, slot status and weather forecasts.

Inform on reopening time - The FW agent calls the DA agent to inform on the reopening time of LCY airport.

Determine set of solution strategies - The DMN, FCo, CC and CD agents discuss the available set of solution strategies based on the context comprehension. The FCo agent uses the DST technical system to increase the solution space with DST variants of the solution strategies.

Provide input for decision mechanism - The FCo, CC and CD agents provide the DMN agent with their requirements and preferences on solution strategy.

Reveal solution strategy - The DMN agent applies a decision making mechanism to arrive at a decision on solution strategy. The decision will be shared in a conference call with the FCo, CC and CD agents.

Implement solution strategy - The FCo and CC agent will implement the selected solution strategy in the OCS technical system. Hereby the solution strategy is published to the rest of the agents that has access to this system. The CD agent will apply the solution strategy in the PCS technical system.

Inform on solution strategy - The FCo agent sends an ACARS to the FC agent. Hereby this agent is aware of the solution strategy and knows what actions are expected by the OCC. Furthermore the FCo agent informs the FW agent on the solution strategy. Upon this information the FW agent informs the DA and AA agents about the solution strategy. Hereby ending the use case.

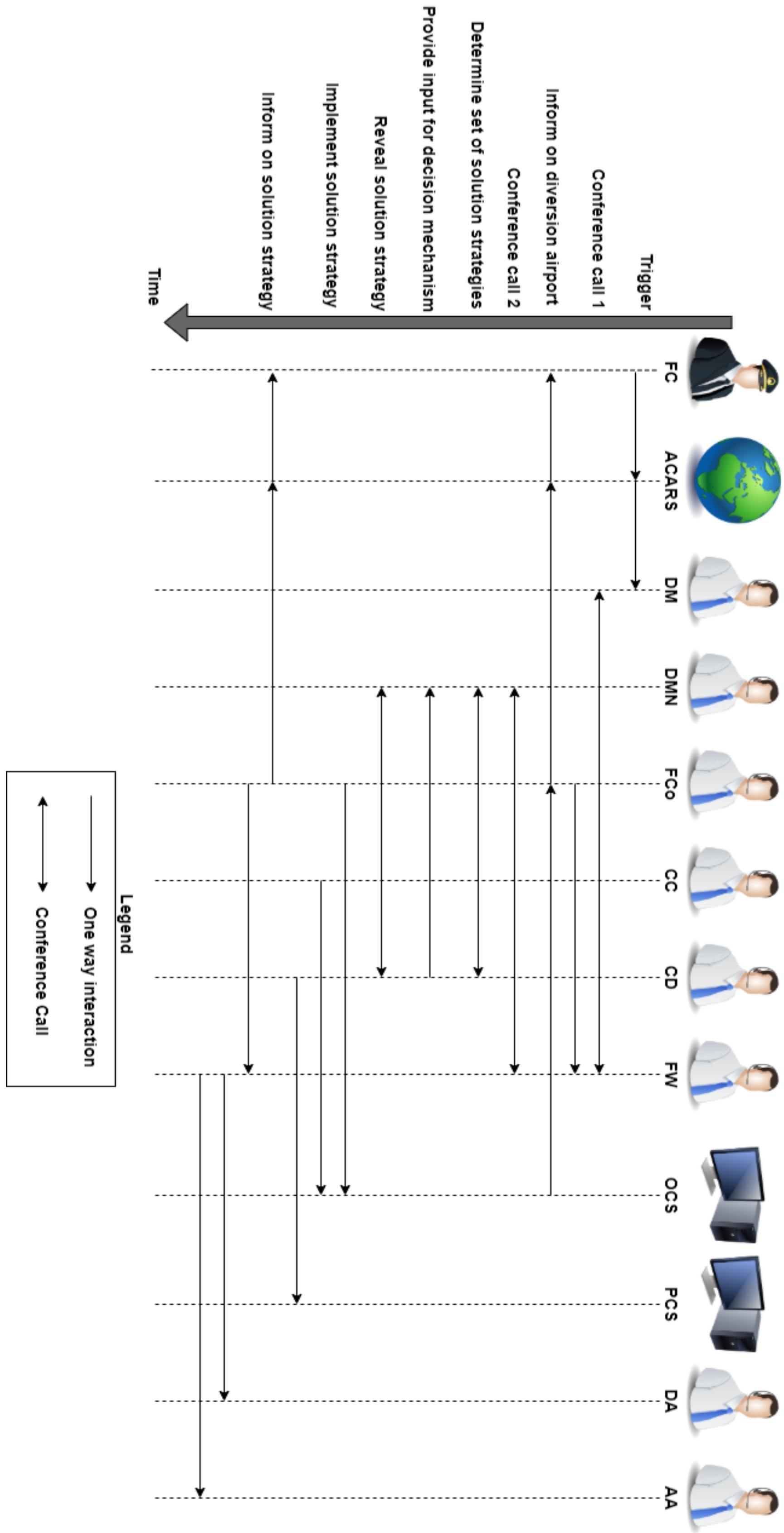


Figure A.1: Workflow diagram Scrambled control mode

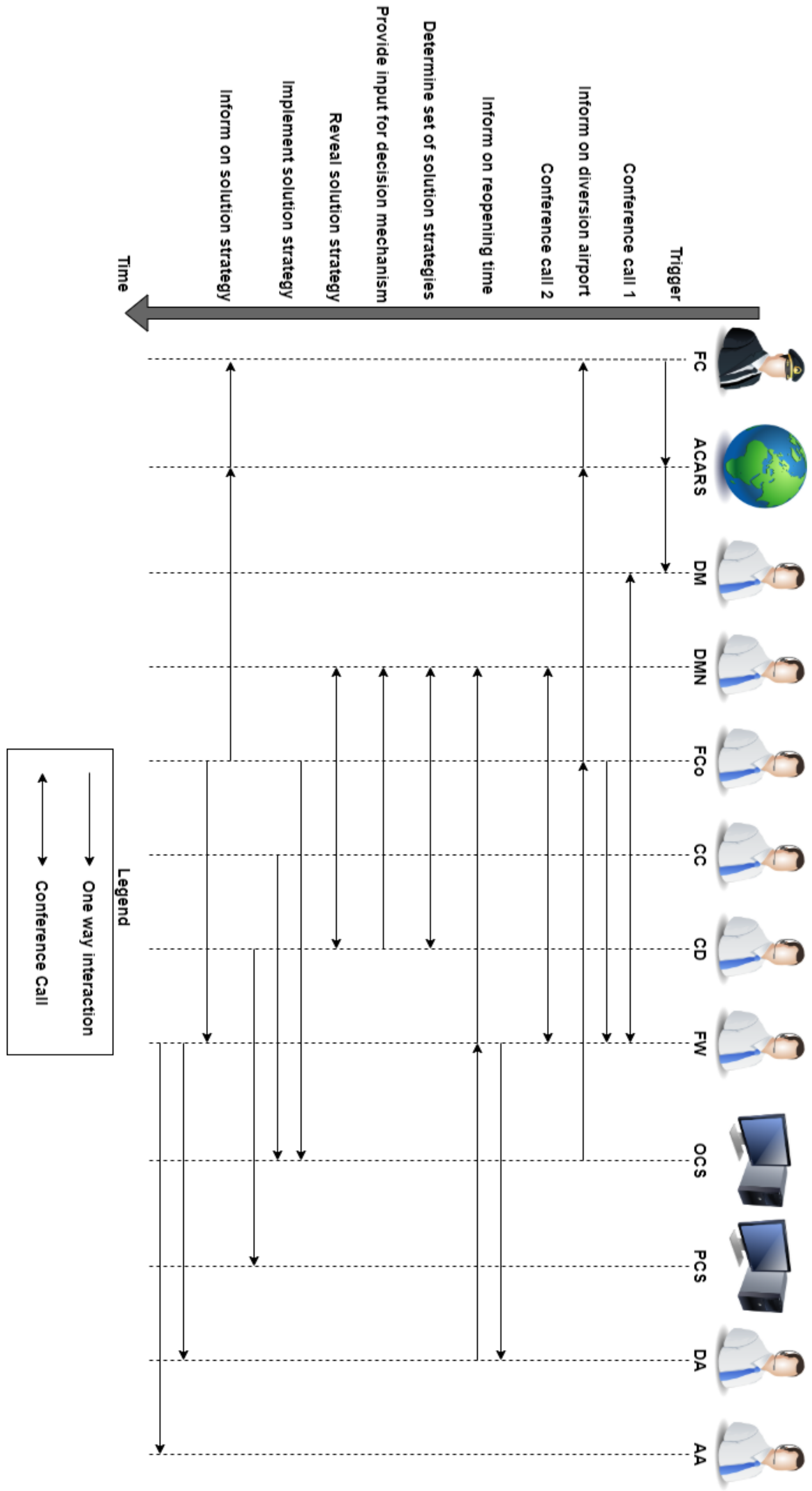


Figure A.2: Workflow diagram Opportunistic control mode

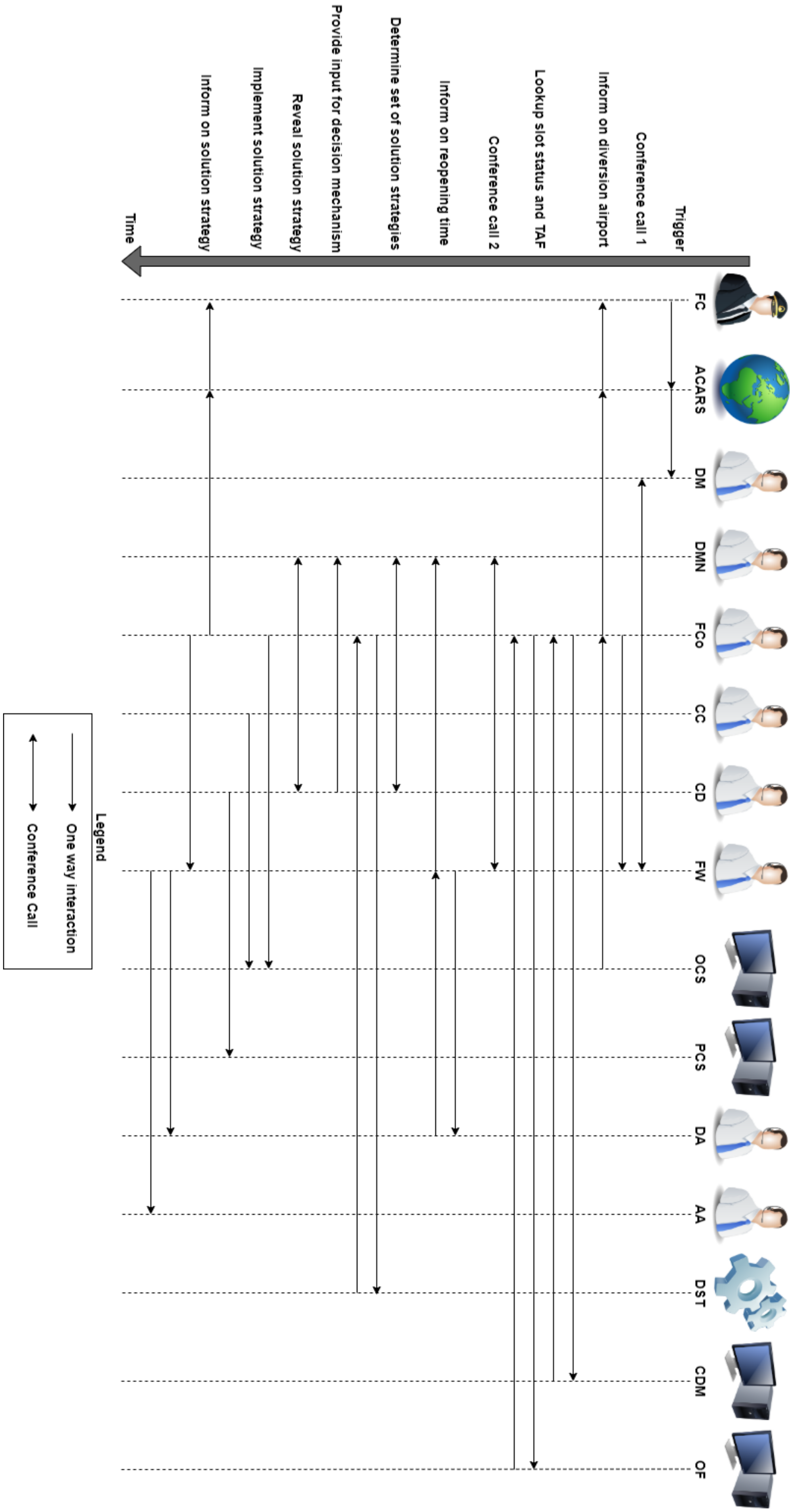


Figure A.3: Workflow diagram Tactical control mode

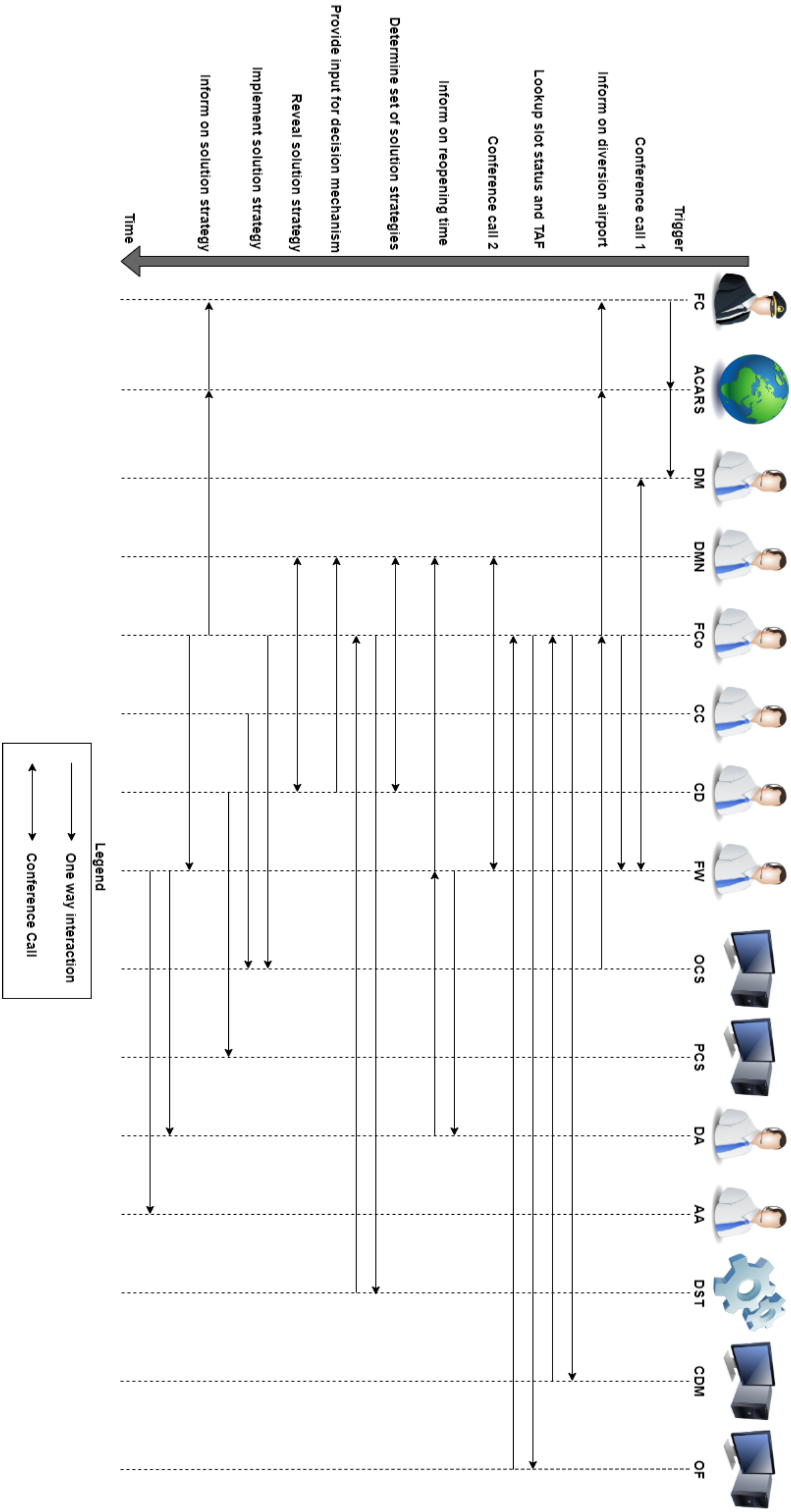


Figure A.4: Workflow diagram Strategic control mode

B

Implementation of Co-Ladder Framework

To define the internal human agent model constructs, the co-ladder framework from Chow et al. [21] is used. This framework aids in defining behavioural rules to enable the modelling of human behaviour. To derive the behavioural rules the co-ladder as depicted in Figure B.1, which is reproduced from the work of Chow et al. [21] by Kaur [48], is used.

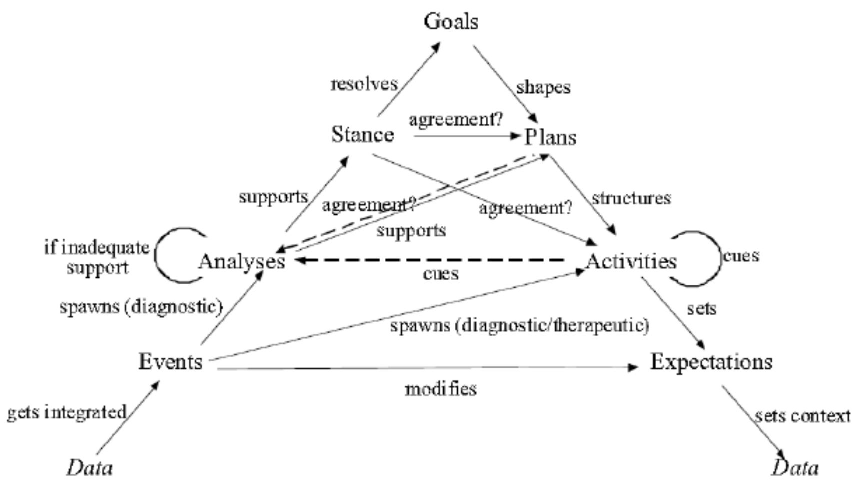


Figure B.1: Co-ladder framework

Using the co-ladder the behavioural rules as in Table B.1 are derived. In this table, Events are regarded as Observations, since the controllers observe data in the environment and integrate this data to Observations upon which they know from experience or working-procedures how to act upon those.

Observation → Expectation	O → E
Observation → Activity → Expectation	O → A → E
Observation → Analysis → Plans → Activity → Expectation	O → AN → P → A → E

Table B.1: Behavioural Rules

All agent behaviour is initiated, similar to humans, with the agent making an *Observation*. An observation can be made through interaction with the environment, or through interaction/coordination with other agents. From an observation either an *Analysis*, *Activity*, or *Expectation* originates.
While performing an *Analysis* the agent is interpreting the observation and performing a task or thought

process based on this observation. An example of analysis would be Fleet Control to determine the diversion airport from the received prioritization lists of the Duty Manager Network and Flight Crew.
Following an analysis, *Plans* are made. A plan is the intention of the agent to execute a certain activity or sequence of activities, which come as a result of an analysis.
Activities are modelled as either communication to other agents, or an agent applying an action in a technical system. In the airline, operational control context communication is either in the form of conference calls, ACARS message, or direct agent to agent communication which can be via phone or face-to-face.
From either an activity or an observation an agent sets an *Expectation*. Expectations are about the result of an applied action, tasks that might be assigned to the agent in the near future, about a change in the environment, and events that might evolve from changes to the environment.

One could argue why these behavioural rules do not include goals in them, since goals are the motivation of agents to take action and strive to achieve them. In the context of an airline operations control center, and especially in the previously discussed diversion scenario, the agents all work towards the higher goals of the airline. In this scenario, the majority of the agents is only passing on information or providing information itself. These actions are defined in the working-procedures of the airline and are not subject to personal agent interpretation, and hereby automatically add to achieving the higher goals of the airline. Next to the majority of the agents, there are the decision-making agents. The decision-making agents are representing the fleet, crew, and passenger domains. Since they represent different domains, naturally they strive to achieve a different set of goals. These goals are not captured in the behavioural rules but are captured in the decision-making mechanisms used by the agents.

The set of *Observations*, *Analyses*, *Plans*, *Actions*, *Expectations*, and the resulting behavioural rules that originate from the diversion scenario are defined in the remainder of this section.

ID	Agent	Type	From	Description
O-1	FC	Message	ATC	Destination airport has runway blockage, need to divert
O-2	DM	ACARS Message	FC	Destination airport closed, due to runway blockage. We have sufficient holding fuel
O-3	FCo	Conference Call	DM	Flight [flightno] needs to divert, has sufficient holding fuel
O-4	DMN	Conference Call	DM	Flight [flightno] needs to divert, has sufficient holding fuel
O-5	CC	Conference Call	DM	Flight [flightno] needs to divert, has sufficient holding fuel
O-6	FW	Conference Call	DM	Flight [flightno] needs to divert, has sufficient holding fuel
O-7	DAM	Conference Call	DM	Flight [flightno] needs to divert, has sufficient holding fuel
O-8	PS	Conference Call	DM	Flight [flightno] needs to divert, has sufficient holding fuel
O-9	FC	ACARS Message	FCo	Diversion airport will be [diversion_airport], stay in holding pattern until notified of solution strategy
O-10	DM	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space is available
O-11	DMN	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space is available
O-12	CC	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space is available
O-13	FW	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space is available
O-14	DAM	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space is available
O-15	PS	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space is available
O-16	AA	Message	FW	Flight [flightno] is diverting to your airport
O-17	DM	ACARS Message	FC	Destination airport closed, due to runway blockage. We are low on holding fuel.
O-18	FCo	Conference Call	DM	Flight [flightno] needs to divert, low on fuel
O-19	DMN	Conference Call	DM	Flight [flightno] needs to divert, low on fuel
O-20	CC	Conference Call	DM	Flight [flightno] needs to divert, low on fuel
O-21	FW	Conference Call	DM	Flight [flightno] needs to divert, low on fuel
O-22	DAM	Conference Call	DM	Flight [flightno] needs to divert, low on fuel
O-23	PS	Conference Call	DM	Flight [flightno] needs to divert, low on fuel
O-24	FC	ACARS Message	FCo	Diversion airport will be [diversion_airport], stay in holding until notified of solution strategy
O-25	FCo	Conference Call	DMN	Negotiate about solution strategies
O-26	CC	Conference Call	DMN	Negotiate about solution strategies
O-27	CD	Conference Call	DMN	Negotiate about solution strategies
O-28	DMN	Message	FCo	Proposal for solution strategy is [fco_proposal]
O-29	DMN	Message	CC	Proposal for solution strategy is [cc_proposal]
O-30	DMN	Message	CD	Proposal for solution strategy is [cd_proposal]
O-31	DMN	Message	FCo, CC, CD	All voting preferences received
O-32	FCo	Conference Call	DMN	The negotiation resulted in [solution_strategy], please implement
O-33	CC	Conference Call	DMN	The negotiation resulted in [solution_strategy], please implement
O-34	CD	Conference Call	DMN	The negotiation resulted in [solution_strategy], please implement
O-35	FC	ACARS Message	FCo	The OCC decided upon [solution_strategy]
O-36	FW	Message	FCo	Inform diversion airport and destination airport on solution strategy
O-37	DA	Message	FW	Flight will be continued according to [solution_strategy]
O-38	AA	Message	FW	Flight will be continued according to [solution_strategy]
O-39	DA	Message	FW	Flight [flightno] is diverting to [diversion_airport], at what time is the runway open again?
O-40	FW	Message	DA	Runway re-opens again at [re-opening time]

Table B.2: Set of Observations - Part I

ID	Agent	Type	From	Description
O-41	DMN	Message	FW	Runway at [destination_airport] re-opens again at [re-opening time]
O-42	FCo	Conference Call	DMN	Runway re-opens again at [re-opening time], negotiate about solution strategies
O-43	CC	Conference Call	DMN	Runway re-opens again at [re-opening time], negotiate about solution strategies
O-44	CD	Conference Call	DMN	Runway re-opens again at [re-opening time], negotiate about solution strategies
O-45	FC	ACARS Message	FCo	Hereby the list of alternates, please prioritise
O-46	DMN	Message	FCo	Hereby the list of alternates, please prioritise
O-47	FCo	ACARS Message	FC	Hereby our preference on the alternate airports
O-48	FCo	Message	DMN	Hereby the prioritised alternate list
O-49	FCo	Message	FCo	Both messages preferences from FC and DMN received
O-50	DM	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
O-51	DMN	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
O-52	CC	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
O-53	FW	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
O-54	DAM	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
O-55	PS	Conference Call	FCo	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]

Table B.3: Set of Observations - Part II

ID	Agent	Description
An-1	FCo	Determine diversion station
An-2	FCo	Determine set of solution strategies from FCo perspective
An-3	CC	Determine set of solution strategies from CC perspective
An-4	CD	Determine set of solution strategies from CD perspective
An-5	DMN	Determine negotiation results
An-6	DA	Determine reopening time
An-7	FCo	Extract list of alternates from Netline
An-8	FC	Determine preference on alternate airports
An-9	DMN	Determine preference on alternate airports
An-10	FCo	Determine diversion station

Table B.4: Set of Analyses

ID	Agent	Description
P-1	FCo	Execute activity A-3, A-4
P-2	FCo	Execute activity A-7, A-4
P-3	FCo	Execute activity A-9
P-4	CC	Execute activity A-10
P-5	CD	Execute activity A-11
P-6	DMN	Execute activity A-12
P-7	DA	Execute activity A-21
P-8	FCo	Execute activity A-24,A-25
P-9	FCo	Execute activity A-28, A-9
P-10	FC	Execute activity A-26
P-11	DMN	Execute activity A-27
P-12	FCo	Execute activity A-7,A-29,A-30,A-31

Table B.5: Set of Plans

ID	Agent	Type	To	Description
A-1	FC	ACARS Message	DM	Destination airport closed, due to runway blockage. We have sufficient holding fuel.
A-2	DM	Conference Call	FCo	Flight [flightno] needs to divert, has sufficient holding fuel
A-2	DM	Conference Call	DMN	Flight [flightno] needs to divert, has sufficient holding fuel
A-2	DM	Conference Call	CC	Flight [flightno] needs to divert, has sufficient holding fuel
A-2	DM	Conference Call	FW	Flight [flightno] needs to divert, has sufficient holding fuel
A-2	DM	Conference Call	DAM	Flight [flightno] needs to divert, has sufficient holding fuel
A-2	DM	Conference Call	PS	Flight [flightno] needs to divert, has sufficient holding fuel
A-3	FCo	ACARS Message	FC	Please stay in holding until notified of the solution strategy
A-4	FCo	Conference Call	DM	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available
A-4	FCo	Conference Call	DMN	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available
A-4	FCo	Conference Call	CC	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available
A-4	FCo	Conference Call	FW	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available
A-4	FCo	Conference Call	DAM	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available
A-4	FCo	Conference Call	PS	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available
A-5	FC	ACARS Message	DM	Destination airport closed, due to runway blockage. We are low on holding fuel.
A-6	DM	Conference Call	FCo	Flight [flightno] needs to divert, low on fuel
A-6	DM	Conference Call	DMN	Flight [flightno] needs to divert, low on fuel
A-6	DM	Conference Call	CC	Flight [flightno] needs to divert, low on fuel
A-6	DM	Conference Call	FW	Flight [flightno] needs to divert, low on fuel
A-6	DM	Conference Call	DAM	Flight [flightno] needs to divert, low on fuel
A-6	DM	Conference Call	PS	Flight [flightno] needs to divert, low on fuel
A-7	FCo	ACARS Message	FC	Diversion airport will be [diversion_airport], stay in holding pattern until notified of solution strategy
A-8	DMN	Conference Call	FCo	Negotiate about solution strategies
A-8	DMN	Conference Call	CC	Negotiate about solution strategies
A-8	DMN	Conference Call	CD	Negotiate about solution strategies
A-9	FCo	Message	DMN	Proposal for solution strategy is [fco_proposal]
A-10	CC	Message	DMN	Proposal for solution strategy is [cc_proposal]
A-11	CD	Message	DMN	Proposal for solution strategy is [cd_proposal]

Table B.6: Set of Actions - Part I

ID	Agent	Type	To	Description
A-12	DMN	Conference Call	FCo	The negotiation resulted in [solution_strategy], please implement
A-12	DMN	Conference Call	CC	The negotiation resulted in [solution_strategy], please implement
A-12	DMN	Conference Call	CD	The negotiation resulted in [solution_strategy], please implement
A-13	FCo	ACARS Message	FC	The OCC decided upon [solution_strategy]
A-14	FCo	Message	FW	Inform diversion airport and destination airport on solution strategy
A-15	FCo	Activity	OCS	Implementation of [solution_strategy] into OCS
A-16	CC	Activity	OCS	Implementation of [solution_strategy] into OCS
A-17	CD	Activity	PCS	Implementation of [solution_strategy] into PCS
A-18	FW	Message	DA	Flight will be continued according to [solution_strategy]
A-19	FW	Message	AA	Flight will be continued according to [solution_strategy]
A-20	FW	Message	DA	Flight [flightno] is diverting to [diversion_airport], at what time is the runway open again?
A-21	DA	Message	FW	Runway re-opens again at [re-opening time]
A-22	FW	Message	DMN	Runway at [destination_airport] re-opens again at [re-opening time]
A-23	DMN	Conference Call	FCo	Runway re-opens again at [re-opening time], negotiate about solution strategies
A-23	DMN	Conference Call	CC	Runway re-opens again at [re-opening time], negotiate about solution strategies
A-23	DMN	Conference Call	CD	Runway re-opens again at [re-opening time], negotiate about solution strategies
A-24	FCo	ACARS Message	FC	Hereby the list of alternates, please prioritise
A-25	FCo	Message	DMN	Hereby the list of alternates, please prioritise
A-26	FC	ACARS Message	FCo	Hereby our preference on the alternate airports
A-27	DMN	Message	FCo	Hereby the prioritised alternate list
A-28	FCo	Activity	DST	Run fleet optimizer and extract proposed solution strategies
A-29	FCo	Activity	CDM	Lookup exact slot information and Schiphol capacity
A-30	FCo	Activity	OF	Lookup weather details
A-31	FCo	Conference Call	DM	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
A-31	FCo	Conference Call	DMN	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
A-31	FCo	Conference Call	CC	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
A-31	FCo	Conference Call	FW	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
A-31	FCo	Conference Call	DAM	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]
A-31	FCo	Conference Call	PS	The alternate station is [diversion_airport], [fleetcrew_space] fleet crew space available, [CDM_status], [Weather]

Table B.7: Set of Actions - Part II

ID	Agent	Description
E-1	FC	Diversion scenario based on long holding time, is initiated in the OCC
E-2	DMN	Controllers are aware of diversion, start procedure for long holding time
E-3	FCo	Aircraft waits in holding for further instructions, and controllers are informed on diversion airport and reserve availability
E-4	DMN	Diversion scenario initiated for long holding time, FCo, CC, and CD will inform on available solution strategies
E-5	CC	Diversion scenario initiated for long holding time, will have to propose solution strategy with respect to crew domain
E-6	FW	Diversion scenario initiated for long holding time, will receive tasks from FCo
E-7	DAM	Diversion scenario initiated for long holding time, turn around planning will be affected
E-8	PS	Diversion scenario initiated for long holding time, gate planning will be affected
E-9	FC	FCo will report back on solution strategy
E-10	DM	In case of diversion, aircraft will go to [diversion_airport]
E-11	DMN	In case of diversion, aircraft will go to [diversion_airport]. [fleetcrew_space] affects set of solution strategies.
E-12	CC	In case of diversion, aircraft will go to [diversion_airport]. [fleetcrew_space] affects set of solution strategies.
E-13	FW	Will need to contact [diversion_airport]
E-14	DAM	Based on [diversion_airport] and [fleetcrew_space], impact is going to be
E-15	PS	Based on [diversion_airport] and [fleetcrew_space], impact is going to be
E-16	AA	Flight [flightno] will divert to my airport
E-17	FC	Diversion scenario based on short holding time, is initiated in the OCC
E-18	DM	Controllers are aware of diversion, start procedure for short holding time
E-19	FCo	FC is aware of [diversion_airport], and controllers are informed on diversion airport and reserve availability
E-20	DMN	Diversion scenario initiated for short holding time, FCo, CC, and CD will inform on available solution strategies
E-21	CC	Diversion scenario initiated for short holding time, will have to propose solution strategy with respect to crew domain
E-22	FW	Diversion scenario initiated for short holding time, will receive tasks from FCo
E-23	DAM	Diversion scenario initiated for short holding time, turn around planning will be affected
E-24	PS	Diversion scenario initiated for short holding time, gate planning will be affected
E-25	FC	FCo will report back on solution strategy
E-26	FCo	DMN will report back on chosen solution strategy
E-27	CC	DMN will report back on chosen solution strategy
E-28	CD	DMN will report back on chosen solution strategy
E-29	DMN	This is the complete set of solution strategies from FCo perspective
E-30	DMN	This is the complete set of solution strategies from CC perspective
E-31	DMN	This is the complete set of solution strategies from CD perspective
E-32	DMN	FCo, CC, and CD will implement the solution strategies
E-33	FCo	FC will respond to the chosen solution strategy. FW will inform AA and DA on the chosen solution strategy, and controllers can observe the solution strategy in Netline Ops.
E-34	CC	Other agents can observe the solution strategy in Netline Crew
E-35	CD	Other agents can observe the solution strategy in Altea
E-36	FC	The solution strategy determined by the OCC has to be executed
E-37	FW	DA and AA are aware of solution strategy
E-38	DA	Depending on solution strategy flight will be continued to my airport
E-39	AA	Depending on solution strategy flight will divert to my airport
E-40	DMN	In case of diversion, aircraft will go to [diversion_airport]. [fleetcrew_space] affects set of solution strategies.
E-41	FW	DA will inform on re-opening time
E-42	DA	FW is aware of re-opening time, will report back if it is chosen to divert or not
E-43	FW	DMN is aware of re-opening time
E-44	DMN	FCo, CC, and CD will adjust their solution strategies with respect to the re-opening time
E-45	FCo	DMN and FC will provide prioritised list of alternates
E-46	FCo	Complete set of solution stragies provided to DMN

Table B.8: Set of Expectations - Part I

ID	Agent	Description
E-47	FC	FCo is aware of our preference on the alternate airports
E-48	DMN	FCo is aware of my preference on the alternate airports
E-49	FCo	This is the honest preference on alternates from FC
E-50	FCo	This is the honest preference on alternates from DMN
E-51	FCo	FC informed on diversion station, will hold until notified. Controllers are aware of complete context
E-52	DM	This is all info regarding the current context
E-53	DMN	This is all info regarding the current context
E-54	CC	This is all info regarding the current context
E-55	DAM	This is all info regarding the current context
E-56	PS	This is all info regarding the current context

Table B.9: Set of Expectations - Part II

Agent	O	An	P	A	E
FC	O-1			A-1	E-1
DM	O-2			A-2	E-2
FCo	O-3	An-1	P-1	A-3,A-4	E-3
DMN	O-4				E-4
CC	O-5				E-5
FW	O-6				E-6
DAM	O-7				E-7
PS	O-8				E-8
FC	O-9				E-9
DM	O-10				E-10
DMN	O-11			A-8	E-4
CC	O-12				E-12
FW	O-13				E-13
DAM	O-14				E-14
PS	O-15				E-15
AA	O-16				E-16
FC	O-1			A-5	E-17
DM	O-17			A-6	E-18
FCo	O-18	An-1	P-2	A-7,A-4	E-19
DMN	O-19				E-20
CC	O-20				E-21
FW	O-21				E-22
DAM	O-22				E-23
PS	O-23				E-24
FC	O-24				E-25
FCo	O-25	An-2	P-3	A-9	E-26
CC	O-26	An-3	P-4	A-10	E-27
CD	O-27	An-4	P-5	A-11	E-28
DMN	O-28				E-29
DMN	O-29				E-30
DMN	O-30				E-31
DMN	O-31	An-5	P-6	A-12	E-32
FCo	O-32			A-13,A-14,A-15	E-33
CC	O-33			A-16	E-34
CD	O-34			A-17	E-35
FC	O-35				E-36
FW	O-36			A-18,A-19	E-37
DA	O-37				E-38
AA	O-38				E-39

Table B.10: Behaviour Rules Scrambled Control Mode

Agent	O	An	P	A	E
FC	O-1			A-1	E-1
DM	O-2			A-2	E-2
FCo	O-3	An-1	P-1	A-3,A-4	E-3
DMN	O-4				E-4
CC	O-5				E-5
FW	O-6				E-6
DAM	O-7				E-7
PS	O-8				E-8
FC	O-9				E-9
DM	O-10				E-10
DMN	O-11				E-40
CC	O-12				E-12
FW	O-13			A-20	E-41
DAM	O-14				E-14
PS	O-15				E-15
AA	O-16				E-16
FC	O-1			A-5	E-17
DM	O-17			A-6	E-18
FCo	O-18	An-1	P-2	A-7,A-4	E-19
DMN	O-19				E-20
CC	O-20				E-21
FW	O-21				E-22
DAM	O-22				E-23
PS	O-23				E-24
FC	O-24				E-25
FCo	O-25	An-2	P-3	A-9	E-26
CC	O-26	An-3	P-4	A-10	E-27
CD	O-27	An-4	P-5	A-11	E-28
DMN	O-28				E-29
DMN	O-29				E-30
DMN	O-30				E-31
DMN	O-31	An-5	P-6	A-12	E-32
FCo	O-32			A-13,A-14,A-15	E-33
CC	O-33			A-16	E-34
CD	O-34			A-17	E-35
FC	O-35				E-36
FW	O-36			A-18,A-19	E-37
DA	O-37				E-38
AA	O-38				E-39
DA	O-39	An-6	P-7	A-21	E-42
FW	O-40			A-22	E-43
DMN	O-41			A-23	E-44
FCo	O-42	An-2	P-3	A-9	E-26
CC	O-43	An-3	P-4	A-10	E-27
CD	O-44	An-4	P-5	A-11	E-28

Table B.11: Behaviour Rules Opportunistic Control Mode

Agent	O	An	P	A	E
FC	O-1			A-1	E-1
DM	O-2			A-2	E-2
FCo	O-3	An-7	P-8	A-24,A-25	E-45
DMN	O-4				E-4
CC	O-5				E-5
FW	O-6				E-6
DAM	O-7				E-7
PS	O-8				E-8
FC	O-9				E-9
DM	O-10				E-10
DMN	O-11				E-40
CC	O-12				E-12
FW	O-13			A-20	E-41
DAM	O-14				E-14
PS	O-15				E-15
AA	O-16				E-16
FC	O-1			A-5	E-17
DM	O-17			A-6	E-18
FCo	O-18	An-1	P-2	A-24,A-25	E-45
DMN	O-19				E-20
CC	O-20				E-21
FW	O-21				E-22
DAM	O-22				E-23
PS	O-23				E-24
FC	O-24				E-25
FCo	O-25	An-2	P-3	A-9	E-26
CC	O-26	An-3	P-4	A-10	E-27
CD	O-27	An-4	P-5	A-11	E-28
DMN	O-28				E-29
DMN	O-29				E-30
DMN	O-30				E-31
DMN	O-31	An-5	P-6	A-12	E-32
FCo	O-32			A-13,A-14,A-15	E-33
CC	O-33			A-16	E-34
CD	O-34			A-17	E-35
FC	O-35				E-36
FW	O-36			A-18,A-19	E-37
DA	O-37				E-38
AA	O-38				E-39
DA	O-39	An-6	P-7	A-21	E-42
FW	O-40			A-22	E-43
DMN	O-41			A-23	E-44
FCo	O-42	An-2	P-3	A-28,A-9	E-46
CC	O-43	An-3	P-4	A-10	E-27
CD	O-44	An-4	P-5	A-11	E-28
FC	O-45	An-8	P-10	A-26	E-47
DMN	O-46	An-9	P-11	A-27	E-48
FCo	O-47				E-49
FCo	O-48				E-50
FCo	O-49	An-10	P-2	A-7,A-4	E-19

Table B.12: Behaviour Rules Tactical Control Mode

Agent	O	An	P	A	E
FC	O-1			A-1	E-1
DM	O-2			A-2	E-2
FCo	O-3	An-7	P-8	A-24,A-25	E-45
DMN	O-4				E-4
CC	O-5				E-5
FW	O-6				E-6
DAM	O-7				E-7
PS	O-8				E-8
FC	O-9				E-9
DM	O-10				E-10
DMN	O-11				E-40
CC	O-12				E-12
FW	O-13			A-20	E-41
DAM	O-14				E-14
PS	O-15				E-15
AA	O-16				E-16
FC	O-1			A-5	E-17
DM	O-17			A-6	E-18
FCo	O-18	An-1	P-2	A-24,A-25	E-45
DMN	O-19				E-20
CC	O-20				E-21
FW	O-21				E-22
DAM	O-22				E-23
PS	O-23				E-24
FC	O-24				E-25
FCo	O-25	An-2	P-3	A-9	E-26
CC	O-26	An-3	P-4	A-10	E-27
CD	O-27	An-4	P-5	A-11	E-28
DMN	O-28				E-29
DMN	O-29				E-30
DMN	O-30				E-31
DMN	O-31	An-5	P-6	A-12	E-32
FCo	O-32			A-13,A-14,A-15	E-33
CC	O-33			A-16	E-34
CD	O-34			A-17	E-35
FC	O-35				E-36
FW	O-36			A-18,A-19	E-37
DA	O-37				E-38
AA	O-38				E-39
DA	O-39	An-6	P-7	A-21	E-42
FW	O-40			A-22	E-43
DMN	O-41			A-23	E-44
FCo	O-42	An-2	P-3	A-28,A-9	E-46
CC	O-43	An-3	P-4	A-10	E-27
CD	O-44	An-4	P-5	A-11	E-28
FC	O-45	An-8	P-10	A-26	E-47
DMN	O-46	An-9	P-11	A-27	E-48
FCo	O-47				E-49
FCo	O-48				E-50
FCo	O-49	An-10	P-12	A-7,A-29,A-30,A-31	E-51
DM	O-50				E-52
DMN	O-51				E-53
CC	O-52				E-54
FW	O-53			A-20	E-41
DAM	O-54				E-55
PS	O-55				E-56

Table B.13: Behaviour Rules Strategic Control Mode

C

Voting preferences

To enable the use of the plurality- and Borda voting protocols in respectively the scrambled- and opportunistic control modes, voting preferences have been developed together with the airline's operational control experts. The resulting preference relations used in the model are given in Section C.1 and Section C.2. The results and reasoning behind the results generated by the agents operating in the scrambled and opportunistic control modes is given in the scientific paper as attached in part I of this report.

C.1. Solution preferences Scrambled control mode

	Fleet Control	**Crew Control**	**Commercial Desk**
Scenario 1	B	B	B
Scenario 2	C	C	B
Scenario 3	B	B	B
Scenario 4	C	C	B

Table C.1: Voting preference scrambled control mode

C.2. Preference relations Opportunistic control mode

FCo	A > B > C > E > D
CC	B > A > C > E > D
CD	A > B > E > C > D

Table C.2: Scenario 1a

FCo	A > B > C > E > D
CC	B > A > C > E > D
CD	A > B > E > C > D

Table C.3: Scenario 1b

FCo	B > A > C > E > D
CC	C > A > B > E > D
CD	A > B > E > C > D

Table C.4: Scenario 1c

FCo	C > D > B > A > E
CC	C > D > B > A > E
CD	A > B > E > C > D

Table C.5: Scenario 2a

FCo	C > D > B > A > E
CC	C > D > B > A > E
CD	A > B > E > C > D

Table C.6: Scenario 2b

FCo	C > D > B > A > E
CC	C > D > B > A > E
CD	A > B > E > C > D

Table C.7: Scenario 2c

FCo	F > A > B > C > E > D
CC	F > B > A > C > E > D
CD	F > A > B > E > C > D

Table C.8: Scenario 3a

FCo	F > A > B > C > E > D
CC	F > B > A > C > E > D
CD	F > A > B > E > C > D

Table C.9: Scenario 3b

FCo	F > B > A > C > E > D
CC	C > F > A > B > E > D
CD	A > F > B > E > C > D

Table C.10: Scenario 3c

FCo	F > C > D > B > A > E
CC	F > C > D > B > A > E
CD	F > A > B > E > C > D

Table C.11: Scenario 4a

FCo	C > F > D > B > A > E
CC	C > F > D > B > A > E
CD	A > F > B > E > C > D

Table C.12: Scenario 4b

FCo	C > D > F > B > A > E
CC	C > D > F > B > A > E
CD	A > F > B > E > C > D

Table C.13: Scenario 4c

D

Pairwise Comparison Matrices

The pairwise comparison matrices in this section have been derived from discussions with the airline's operational control experts. These pairwise comparisons serve as input for the application of the MCDM - AHP method decision-making mechanism that is used in the strategic control mode. These matrices vary with context and reserve (un)availability and result in different criteria weights per context. The use of these matrices is elaborated in the scientific paper as included in part I of this report.

D.1. Context 1 - Reserves Available

CR = 0.0%	*Fleet*	*Crew*	*Passengers*
Fleet	1	3	1
Crew	1/3	1	1/3
Passengers	1	3	1

Table D.1: Context 1 - DMN Pairwise Comparison

CR = 0.0%	c_7	c_8
c_7	1	1/5
c_8	5	1

Table D.2: Context 1 - CC Pairwise Comparison

CR = 9.3%	c_1	c_2	c_3	c_4	c_5	c_6
c_1	1	3	1/5	1/5	3	1/3
c_2	1/3	1	1/9	1/5	3	1/3
c_3	5	9	1	3	5	6
c_4	5	5	1/3	1	7	1
c_5	1/3	1/3	1/5	1/7	1	1
c_6	3	3	1/6	1	1/3	1

Table D.3: Context 1 - FCo Pairwise Comparison

CR = 8.7%	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
c_9	1	1	1/9	1/9	1/9	1/9
c_{10}	1	1	1/9	1/9	1/9	1/9
c_{11}	9	9	1	1	1/5	1/4
c_{12}	9	9	1	1	1/5	1/4
c_{13}	9	9	5	5	1	2
c_{14}	9	9	4	4	1/2	1

Table D.4: Context 1 - CD Pairwise Comparison

D.2. Context 1 - Reserves Unavailable

CR = 3.0%	*Fleet*	*Crew*	*Passengers*
Fleet	1	4	2
Crew	1/4	1	1
Passengers	1/2	1	1

Table D.5: Context 1 - DMN Pairwise Comparison

CR = 0.0%	c_7	c_8
c_7	1	9
c_8	1/9	1

Table D.6: Context 1 - CC Pairwise Comparison

CR = 10.1%	c_1	c_2	c_3	c_4	c_5	c_6
c_1	1	7	1	7	6	9
c_2	1/7	1	1/3	3	3	9
c_3	1	3	1	5	5	9
c_4	1/7	1/3	1/5	1	3	9
c_5	1/6	1/3	1/5	1/3	1	3
c_6	1/9	1/9	1/9	1/9	1/3	1

Table D.7: Context 1 - FCo Pairwise Comparison

CR = 8.7%	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
c_9	1	1	1/9	1/9	1/9	1/9
c_{10}	1	1	1/9	1/9	1/9	1/9
c_{11}	9	9	1	1	1/5	1/4
c_{12}	9	9	1	1	1/5	1/4
c_{13}	9	9	5	5	1	2
c_{14}	9	9	4	4	1/2	1

Table D.8: Context 1 - CD Pairwise Comparison

D.3. Context 2 - Reserves Available

CR = 3.0%	*Fleet*	*Crew*	*Passengers*
Fleet	1	4	2
Crew	1/4	1	1
Passengers	1/2	1	1

Table D.9: Context 2 - DMN Pairwise Comparison

CR = 0.0%	c_7	c_8
c_7	1	7
c_8	1/7	1

Table D.10: Context 2 - CC Pairwise Comparison

CR = 7.8%	c_1	c_2	c_3	c_4	c_5	c_6
c_1	1	1	1/7	1	1	1/5
c_2	1	1	1/5	3	3	1/3
c_3	7	5	1	9	9	6
c_4	1	1/3	1/9	1	1/3	1/5
c_5	1	1/3	1/9	3	1	1/7
c_6	5	3	1/6	5	7	1

Table D.11: Context 2 - FCo Pairwise Comparison

CR = 5.5%	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
c_9	1	1	1/7	1/7	1/6	1/6
c_{10}	1	1	1/7	1/7	1/6	1/6
c_{11}	7	7	1	1	1/3	1/3
c_{12}	7	7	1	1	1/3	1/3
c_{13}	6	6	3	3	1	1
c_{14}	6	6	3	3	1	1

Table D.12: Context 2 - CD Pairwise Comparison

D.4. Context 2 - Reserves Unavailable

CR = 3.0%	*Fleet*	*Crew*	*Passengers*
Fleet	1	4	2
Crew	1/4	1	1
Passengers	1/2	1	1

Table D.13: Context 2 - DMN Pairwise Comparison

CR = 0.0%	c_7	c_8
c_7	1	9
c_8	1/9	1

Table D.14: Context 2 - CC Pairwise Comparison

CR = 9.9%	c_1	c_2	c_3	c_4	c_5	c_6
c_1	1	6	1	9	9	9
c_2	1/6	1	1/3	3	5	9
c_3	1	3	1	7	9	9
c_4	1/9	1/3	1/7	1	7	5
c_5	1/9	1/5	1/9	1/7	1	1
c_6	1/9	1/9	1/9	1/5	1/7	1

Table D.15: Context 2 - FCo Pairwise Comparison

CR = 5.5%	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
c_9	1	1	1/7	1/7	1/6	1/6
c_{10}	1	1	1/7	1/7	1/6	1/6
c_{11}	7	7	1	1	1/3	1/3
c_{12}	7	7	1	1	1/3	1/3
c_{13}	6	6	3	3	1	1
c_{14}	6	6	3	3	1	1

Table D.16: Context 2 - CD Pairwise Comparison

D.5. Context 3 - Reserves Available

CR = 3.0%	*Fleet*	*Crew*	*Passengers*
Fleet	1	4	2
Crew	1/4	1	1
Passengers	1/2	1	1

Table D.17: Context 3 - DMN Pairwise Comparison

CR = 0.0%	c_7	c_8
c_7	1	1/7
c_8	7	1

Table D.18: Context 3 - CC Pairwise Comparison

CR = 8.1%	c_1	c_2	c_3	c_4	c_5	c_6
c_1	1	1/3	1/9	1/3	1/7	1/4
c_2	3	1	1/9	1/3	1/7	1/3
c_3	9	9	1	9	4	4
c_4	3	3	1/9	1	1/5	1/5
c_5	7	7	1/4	5	1	1/7
c_6	4	3	1/4	5	7	1

Table D.19: Context 3 - FCo Pairwise Comparison

CR = 13.2%	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
c_9	1	1	1/5	1/2	1/3	2
c_{10}	1	1	1/7	1/7	1/7	1/2
c_{11}	5	7	1	1	1/2	1
c_{12}	2	7	1	1	1	3
c_{13}	3	7	2	1	1	3
c_{14}	1/2	2	1	1/3	1/3	1

Table D.20: Context 3 - CD Pairwise Comparison

D.6. Context 3 - Reserves Unavailable

CR = 3.0%	*Fleet*	*Crew*	*Passengers*
Fleet	1	4	2
Crew	1/4	1	1
Passengers	1/2	1	1

Table D.21: Context 3 - DMN Pairwise Comparison

CR = 0.0%	c_7	c_8
c_7	1	9
c_8	1/9	1

Table D.22: Context 3 - CC Pairwise Comparison

CR = 7.5%	c_1	c_2	c_3	c_4	c_5	c_6
c_1	1	9	1	9	9	9
c_2	1/9	1	1/3	3	3	9
c_3	1	3	1	9	9	9
c_4	1/9	1/3	1/9	1	1/2	3
c_5	1/9	1/3	1/9	2	1	3
c_6	1/9	1/9	1/9	1/3	1/3	1

Table D.23: Context 3 - FCo Pairwise Comparison

CR = 13.2%	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
c_9	1	1	1/5	1/2	1/3	2
c_{10}	1	1	1/7	1/7	1/7	1/2
c_{11}	5	7	1	1	1/2	1
c_{12}	2	7	1	1	1	3
c_{13}	3	7	2	1	1	3
c_{14}	1/2	2	1	1/3	1/3	1

Table D.24: Context 3 - CD Pairwise Comparison

D.7. Context 4 - Reserves Available

CR = 4.3%	*Fleet*	*Crew*	*Passengers*
Fleet	1	4	1/4
Crew	1/4	1	1/7
Passengers	4	7	1

Table D.25: Context 4 - DMN Pairwise Comparison

CR = 0.0%	c_7	c_8
c_7	1	1/7
c_8	7	1

Table D.26: Context 4 - CC Pairwise Comparison

CR = 8.8%	c_1	c_2	c_3	c_4	c_5	c_6
c_1	1	1	1/3	7	9	7
c_2	1	1	1/3	7	9	9
c_3	3	3	1	9	9	9
c_4	1/7	1/7	1/9	1	5	3
c_5	1/9	1/9	1/9	1/5	1	2
c_6	1/7	1/9	1/9	1/3	1/2	1

Table D.27: Context 4 - FCo Pairwise Comparison

CR = 9.1%	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
c_9	1	1/9	1/9	1/9	1/9	1/3
c_{10}	9	1	1/9	1/9	1/9	1/5
c_{11}	9	9	1	1	1/3	3
c_{12}	9	9	1	1	3	5
c_{13}	9	9	3	1/3	1	2
c_{14}	3	5	1/3	1/5	1/2	1

Table D.28: Context 4 - CD Pairwise Comparison

D.8. Context 4 - Reserves Unavailable

CR = 3.0%	*Fleet*	*Crew*	*Passengers*
Fleet	1	4	2
Crew	1/4	1	1
Passengers	1/2	1	1

Table D.29: Context 4 - DMN Pairwise Comparison

CR = 0.0%	c_7	c_8
c_7	1	9
c_8	1/9	1

Table D.30: Context 4 - CC Pairwise Comparison

CR = 9.9%	c_1	c_2	c_3	c_4	c_5	c_6
c_1	1	6	1	9	9	9
c_2	1/6	1	1/3	3	5	9
c_3	1	3	1	7	9	9
c_4	1/9	1/3	1/7	1	7	5
c_5	1/9	1/5	1/9	1/7	1	1
c_6	1/9	1/9	1/9	1/5	1/7	1

Table D.31: Context 4 - FCo Pairwise Comparison

CR = 9.1%	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
c_9	1	1/9	1/9	1/9	1/9	1/3
c_{10}	9	1	1/9	1/9	1/9	1/5
c_{11}	9	9	1	1	1/3	3
c_{12}	9	9	1	1	3	5
c_{13}	9	9	3	1/3	1	2
c_{14}	3	5	1/3	1/5	1/2	1

Table D.32: Context 4 - CD Pairwise Comparison

E

Cost Modelling - Disruption management

The information in this section is derived from the airline's cost model [62], which has been developed by the airline's operations research department. This cost model is used in the tooling that is used throughout the airline and is developed to enable these tools to quantify the impact of disruption management strategies in a realistic and representative way.

In this section, an approximation of the airline's cost model is made. This approximation is used in the cost functions of the agents in the tactical control mode. Some of the costs that were required for the cost functions of the decision-making agents are confidential and were subject to assumptions based on the input from the airline's operations controllers.

In Section E.1 the cost values for the fleet control department are defined. In Section E.2 the crew control costs are elaborated upon and in Section E.3 the cost values for the commercial desk are discussed.

E.1. Fleet Control Costs

The costs that account for Fleet Control in the cost model are described in Subsection E.1.1 through Subsection E.1.5.

E.1.1. Flying Extra Cycles

The cost of flying an extra cycle could not be derived from the airline's cost model and therefore an assumption has been made. In discussion with operation control experts from the airline, it was decided to assume a cost for flying an extra cycle C_{cycle} of €15.000. This value includes the additional maintenance that is induced, the re-scheduling of technical inspections and cleaning activities. Furthermore, with this cycle, no extra revenue is generated since it is a consequence of the implementation of a solution strategy, which also is included in this cost.

E.1.2. Extended flight

In the solution strategies that opt for staying in the holding for a certain amount of time or an extension of flight time due to delayed decision-making, the cost of the flight is increased due to an increase in fuel burn. In the Decision Support Tool [63], the cost for non-nominal fuel use ($C_{kerosene}$) is calculated according to Equation E.1.

$$C_{kerosene} = \text{Flight Duration (min)} \cdot A_{burn} \cdot \text{Fuel price} \tag{E.1}$$

The fuel price is known to be a very volatile parameter that is subject to change daily, however, for the sake of this project, the price is assumed to be constant at 0.333 €/litres which is in accordance with the value used in the Decision Support Tool [63]. A_{burn} is the fuel use in litres per minute of an Embraer 190.

E.1.3. Leg Cancellation

Cancelling a leg means that the airline loses revenue since fewer flights are flown than expected. Therefore this value represents lost revenue and is assumed through discussions with operational control experts at €12.500.

E.1.4. Aircraft Swaps

Adjusting tail assignments during the execution of the flight schedule is not preferred by the controllers. Changing the tail assignments requires gate planning, ground crew planning, and ground services planning to be adjusted. Within the airline, it is a rule-of-thumb that a flight can be assigned a new registration at the last 60 minutes before STD. It is possible to change tail assignments later on, but that will most likely introduce delays. In the cost model behind the DST [63], a linear swap cost is defined between 0 and 180 minutes before the STD of a flight, starting at €35.000 reducing to €0 at 180 minutes before STD. Hereby indicating that a swap more than 180 minutes before STD does not require much effort. The aircraft swap cost in this project is regarded as C_{swap}.

E.1.5. Fleet Reserves

The cost model for the use of fleet reserves as set up by the airline's operations research department depends on the probabilities of a delay or cancellation, the expected number of delay minutes, and the average costs of delays and cancellations. Since these parameters, especially the probability parameters, are dynamic it is complicated to adopt these. To overcome this a linear or constant cost could be used to simplify this. In the airline's working procedures [79] it is stated that an aircraft is considered to be a reserve when it is not assigned to duties for a period of four or more hours. Hereby it is assumed that four hours of reserve usage costs €40.000 and therefore the reserve use cost per minute ($C_{reservedevaluation}$) is worth €166.67.

E.2. Crew Control Costs

The costs that account for Crew Control in the cost model are described in Subsection E.2.1 and Subsection E.2.2.

E.2.1. Crew Reserves

The cost model used for modelling the use of crew reserves is dependent on the rank of the crew, the amount of reserve crew available and the number of crew reserves that are set as the threshold. Since this data is not available for this research project, the cost of using crew reserves is simplified by setting a fixed cost. For this research it is assumed that crew reserves are always composed of two pilots and two cabin crew, imposing a fixed crew reserve cost ($C_{crewreserve}$) of €10.000 per reserve used.

E.2.2. Crew Swaps

Changing the crew schedule during the day of operations brings many complications. These complications have to do with the CLA that put certain restrictions on working times and the maximum flight duty period. Crew swaps are used as a last resort before calling in reserve crew, and therefore it is assumed that the swap cost ($C_{crewswap}$) is half the cost of the crew reserve use cost and set at €5.000. This assumption is made since there is no detailed crew data available for this research.

E.3. Commercial Desk Costs

The costs that account for the Commercial Desk in the cost model are described in Subsection E.3.1 and Subsection E.3.2.

E.3.1. Delay

The cost of a delayed flight is dependent on the minutes of induced delay. This cost is built up by parameters like; missed passenger connections, possible claims that passengers might impose, rebooking alternatives for passengers that miss their connecting flights, and possible future value loss.

Missed passenger connections due to delays and *claims that passengers might impose* are regulated by the European Parliament Regulation 261/2004 [3], also known as EU-claim compensation. For arrival delay compensation the costs according to this regulation are shown in Table E.1.

Distance (km)	Delay < 2 hours	Delay 2-3 hours	Delay 3-4 hours	Delay > 4 hours
≤ 1500	0	0	€250	€250
> 1500 and ≤ 3500	0	0	€400	€400
> 3500	0	0	€300	€600

Table E.1: Arrival Delay Compensation [3]

Possible future value loss has been introduced to account for the revenue that might be lost in the future, due to passengers being less likely to choose to fly with the airline in the future when they experienced delays due to disruptions in the flight schedule. The airline created a lookup table that shows a value for future value loss per passengers, for delays between 0 and 180 minutes. In this table, differentiation has been made between elite and non-elite passengers and therefore can be used to account for both economy class and business class passengers. A snapshot of this table is given in Table E.2.

Delay (min)	**Elite Future Value Loss (FVL_{elite})**	**Non-Elite Future Value Loss ($FVL_{non\text{-}elite}$)**
0	0	0
20	€28.91	€15.57
40	€60.22	€32.43
60	€91.54	€49.29
80	€119.24	€64.21

Table E.2: Snapshot of future value loss lookup table[62]

E.3.2. Cancellation

When the operations controllers decide to cancel a flight, the passengers have to be rebooked onto other flights. These passengers are also compensated according to Regulation 261/2004 by the European Parliament [3]. The delay compensation in case passengers are rebooked due to a cancellation of their original flight is given in Table E.3. This compensation is defined per passenger and in this project will be regarded as $C_{canxclaim}$.

Distance (km)	**Delay < 2 hours**	**Delay 2-3 hours**	**Delay 3-4 hours**	**Delay > 4 hours**
≤ 1500	0	€250	€250	€250
1500 < and ≤ 3500	0	€200	€400	€400
> 3500	0	€300	€300	€600

Table E.3: Cancellation Rebooking Delay Compensation [3]

Besides the delay compensation due to the cancellation, also future value loss is considered which is calculated identical to the future value loss as discussed in Subsection E.3.1 and shown in Table E.2.

F

Software Implementation of the Agent-Based Model

In this chapter, the rationale and structure of the developed agent-based model are described. An agent-based model is known to be comprised of three main components: the environment, the agents, and the interaction between the agents. How these components are included in the model is discussed in this chapter. The general model structure that will be used to explain the different parts of the model is shown in Figure F.1.

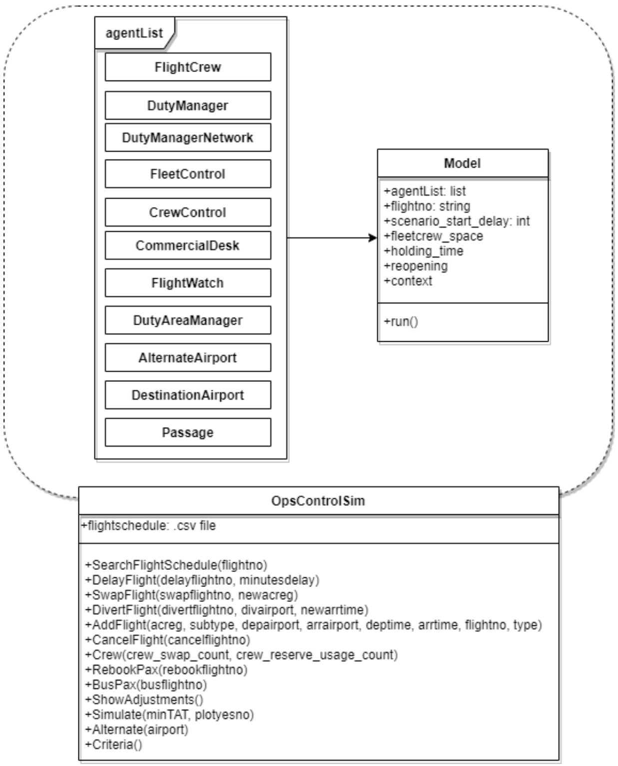


Figure F.1: General Model structure

Naturally, the environment that the agent operate in is the starting point of the model. In the airline's operational control center the environment is comprised of the flight, crew, and passenger schedules. These schedules, and mainly disruptive changes to these schedules, are the triggers for agents to act upon. In the model as developed in this thesis project, the environment is partly captured by the technical systems modelled by the OpsControlSim object and the Model object.

F.1. Model

The *Model* object enables the agent-based model to keep track of time and communicate with one another. The input that is required for the model to run, and is set at the initial model step is described in Table F.1. The user is in control of the agents included in the simulation. Furthermore, the flight, start time, scenario, context, and selected diversion airport can be controlled. These input parameters and their explanation are given in Table F.1.

agentList	The agentList contains the agent objects of all social agents that are included in the model.
flightno	Flight number that is subject to the diversion.
scenario_start_delay	Amount of minutes after STD of the flight number subjected to the diversion, that the scenario is initiated.
fleetcrew_space	'y' - Fleet and crew reserves available. 'n' - No fleet and crew reserves available.
holding_time	'l' - Long holding time available, aircraft able to await reopening in holding pattern. 's' - Short holding time available, aircraft unable to await reopening in holding pattern.
Reopening	Reopening time of the planned destination airport: 30 - Airport reopens 30 minutes after STA 60 - Airport reopens 60 minutes after STA 90 - Airport reopens 90 minutes after STA
Context	Context used within control mode 4: 1 - Regular day of operations 2 - Slot delays at AMS expected to last until 10:00z 3 - Slot delays at AMS expected to be effective from 10:00z onward 4 - Focus on passenger connections of KL985-KL986 rotation
diversion_airport	Selected diversion airport: 'SEN' - London Southend Airport 'SOU' - Southampton Airport 'NWI' - Norwich Airport

Table F.1: Definition of model input parameters

The model object is characterised by a single function, the *run()* function. The *run()* function allows the model to keep track of time and enables the agents to interact with each other and observe/apply changes in the environment. During each step in a run, social agents can make observations in the environment and communicate with other agents. This communication is based on the implementation of the co-ladder framework, as discussed in Appendix B. The components of this framework are used to model the social agent's behaviour and are explained upon in Section F.2. If an agent performs a communicative activity to another agent, this communication is sent as an object to the Model object. This communication object can then be observed in the Model object by the agent which is at the receiving end of the communication. An illustration of the interaction among social agents is given in Figure F.2.

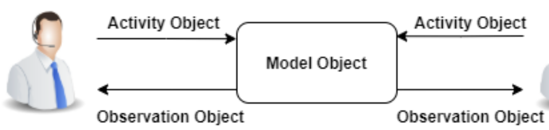


Figure F.2: Interaction between social agents

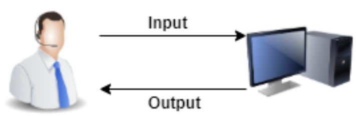


Figure F.3: Input-output interaction between social agents and technical systems

The interaction between a social agent and a technical system is modelled as input-output. Hereby the interaction does not go via the Model object but directly between the agents. This is illustrated in Figure F.3.

F.2. Social Agents

The social agents are developed as an object of their own. Each agent type is developed based on the same object structure which will be elaborated upon in this section. The agent object, and the relation to other objects that each agent is connected with, is illustrated in Figure F.4.

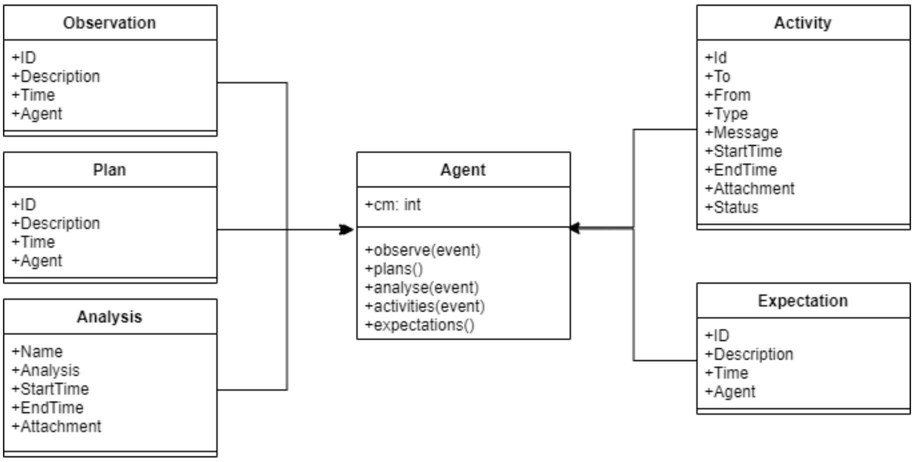


Figure F.4: Agent Object structure

Agent Object

The agent object requires the control mode that the agent should operate in as input. Based on this control mode the agent object knows according to which behavioural rules, derived from the co-ladder framework (Appendix B), they should behave. The control modes are distinguished by integer numbers from 1 to 4.

1 - Scrambled Control Mode
2 - Opportunistic Control Mode
3 - Tactical Control Mode
4 - Strategic Control Mode

The functions contained in the agent objects are directly related to the implementation of the co-ladder framework and are described in Table F.2. When an agent makes an observation in the environment, these functions are activated based on the behavioural rule that is inherent to the observation.

Observe():	Allows the agent to make observations in the environment, and can match the observation to a behavioral rule.
Plans():	Enables the agents to make plans based on the behavioral rule.
Analyse():	Enables the agents to perform analyses based on the behavioral rule, and can extract information from the event (observation) that triggered the analyses to be performed.
Activities():	Enables the agents to perform an activity in the form of interaction with other social agents, or applying an action (input-output) to a technical system.
Expectations():	Enables the agents to set expectation based on observations made or activities performed.

Table F.2: Agent object functions

For each of the above-mentioned functions, depending on the behavioural rule, the agents create an observation, plan, analysis, activity, and expectation object. These objects are used to keep track of the agents' behaviour and contain information about ID, description, time, and agent. These stored objects are used to make the trace plots for the validation of the agents' behaviour. An example, trace plot is given in Figure F.5. In this figure the communication between agents is shown. The

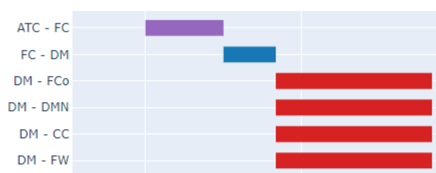


Figure F.5: Traces of agent behavior

ATC agent contacts the FC agent over the radio. After the FC agent has interpreted the message from ATC, the FC agent contacts the DM via ACARS.
With the information that the DM received, a conference call is started to spread the information to other agents in the AOCC.

F.3. Technical Systems

In the developed agent-based model five technical systems are included:

- Operational Control System
- Passenger Control System
- Decision Support Tool
- ACARS
- Collaborative Decision-Making
- OrbiFly

The Operational Control System, Passenger Control System, and Decisions Support Tool are elaborated in Subsection F.3.1. These technical systems are technical agents, since they can perform actions autonomous. The ACARS, Collaborative Decision-Making, and OrbiFly systems are discussed together in Subsection F.3.2, since they are technical resources.

F.3.1. Operational Control System, Passenger Control System & Decision Support Tool

The Operational Control System and Passenger Control Systems are the main operational control systems used. It allows agents to keep track of the exact details of the flight, crew, and passengers schedules. All agents in the AOCC have access to this system, but only Fleet Control, Crew Control, and Commercial Desk can apply changes to this system. To include these systems in the agent-based model, the OpsControlSim object has been developed.

For this project no crew and passenger schedules were available. Therefore, only a flight schedule is used and crew and passengers are not considered in detail.

The input needed for initialization of the OpsControlSim object is the flight schedule in the form of a .csv file. The data contained in this flight schedule is given in Table F.3.

Data	Description	Example Data
ACRegistration	Aircraft registration number	PH-EZA
SubType	Aircraft subtype	E90
DepAirport	IATA code of departure airport	AMS
ArrAirport	IATA code of arrival airport	LCY
DepDateTimeScheduled	Scheduled date and time of departure	2019-07-30 hh:mm:ss
ArrDateTimeScheduled	Scheduled date and time of arrival	2019-07-30 hh:mm:ss
FlightNo	Flight number	KL9999
ElitePassenger	Number of elite passengers on the flight	5
NonElitePassenger	Number of non-elite passengers on the flight	88
Activity	Specifies what type of activity an entry represents	Flight/PM/RES

Table F.3: Flight Schedule Data Specification

To this flight schedule the agents can apply multiple changes. Examples of this are delaying flights, cancelling flights, and making registration swaps. The functions through which these changes can be applied to the flight schedule are elaborated in Table F.4.

The solution strategies are implemented by making changes to the flight schedule through these functions. After implementation of a solution strategy the status of the flight schedule can be saved. These saved solution strategies are used by the decision-making agents to determine their preferred solutions strategy based on the inherent KPIs and values of the cost functions.

The Decision Support Tool is simulated through solution strategies that have been developed based on the business rules of the airline's Decision Support Tool and are stored in the OpsControlSim object [63]. These business rules are quantitatively expressed in Appendix E. The use of the Decision Support Tool is simulated by the development of solution strategies based on these business rules, which are also saved and evaluated by the decision-making agents in the tactical and strategic control modes. The solution strategies, as discussed in Appendix G, are implemented and saved in the OpsControlSim object.

SearchFlightSchedule():	Allows user to extract flight information regarding the inputted flight number.
DelayFlight():	Enables the users to set an ETD based on flight number and minutes of delay.
SwapFlight():	Based on flight number and an aircraft registration, a flight can be moved to another aircraft.
DivertFlight():	Allows the user to divert a flight from it's original destination, to a diversion airport based on inputted diversion airport, new ETA, and flight number.
AddFlight():	Enables the user to add new flights to the flight schedule based on inputted flight details (aircraft details, flight times, and routing).
CancelFlight():	Removes the flight matching the inputted flight number from the flight schedule.
Crew():	Enables the user to keep track of crew reserves used and number of crew swaps.
RebookPax():	Based on the inputted flight number the number of re-booked passengers is counted.
BusPax():	Based on the inputted flight number the bussed passenger count is increased.
ShowAdjustments():	Plots the adjusted flight schedule, based on adjustments made through the above functions.
Simulate():	Takes as input the minimum turnaround time as determined by the user. Based on this the flight schedule is simulated by ensuring the minimum turn around time between flights. If the user requests a gantt chart representation of the flight schedule, this is plotted.
Alternate():	Based on the inputted IATA code, a list of alternate airports and their properties is returned.
Criteria():	This function calculates the criteria values, and costs of the simulated flight schedule based on the criteria and cost functions

Table F.4: OpsControlSim object functions

F.3.2. ACARS, OrbiFly & Collaborative Decision-Making

The ACARS system is a means of communication between the aircraft and the AOCC, when the aircraft is outside of VHF range. Therefore, this system is captured as a type of communication through the behavioural rules.

The OrbiFly and CDM systems are not captured in an object since they are resources used by the social agents. These systems provide the agents in the strategic control mode with information on the context level that they are operating in. This information is captured through the 'Context' input parameter in the Model object. This parameter can take on the following values:

1 - Context 1: Regular day of operations
2 - Context 2: Slot delays at AMS until 10:00z
3 - Context 3: Slot delays at AMS effective from 10:00z
4 - Context 4: Critical passenger connections

G
Criteria in Disruption Management Strategies

In this chapter the criteria values, that are a result of the implementation of a solution strategy, are given. The complete set of solution strategies is given in Figure G.1. These are elaborated upon below this figure.

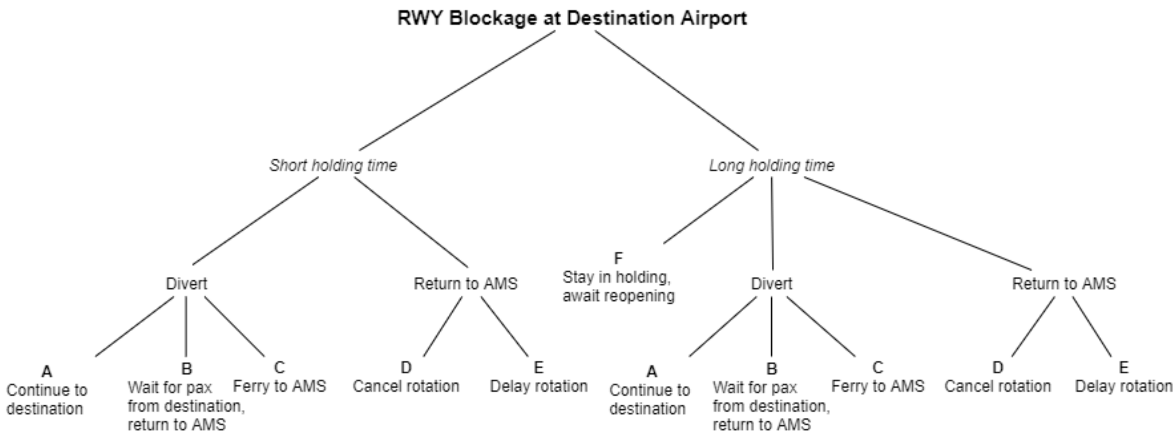


Figure G.1: Disruption Decision Tree

Solution strategy A

In solution strategy A, it is chosen to divert the flight to one of the alternative airports, await reopening of the planned destination airport, and hereafter continuing onward to the planned destination airport.

From a fleet perspective, this solution results in an extra unforeseen cycle of the aircraft and endangers the execution of the remainder of the planned flight schedule. This extra cycle results in additional delays for the LCY rotation.

Looking from a crew perspective this solution strategy has implications for the allowable flight duty period of the flight and cabin crew since an unplanned cycle is flown. Hence, this solution will most likely require an appeal to be made on crew reserves (when available) or adjustments to the crew schedule have to be made by applying crew swaps.

Concerning the passenger domain, the consequences of this solution are limited. The passengers of the diverting flight reach their destination, without needing to rebook or bus them. However, these passengers will be delayed due to the extra landing made. Furthermore, other flights might develop delays due to this solution strategy resulting in more passengers reaching their destination with a delay.

Solution Strategy B

In solution strategy B it is decided to divert to one of the alternative airports and wait at this alternative airport for the passengers to be bussed from the planned destination airport to the diversion airport. When the passengers arrive at the diversion airport, the aircraft will depart for the flight back to AMS. This solution induces delay into the flight schedule since the return flight to AMS is delayed by the time it takes to bus the passengers heading for AMS to the diversion airport.

Difficulties might also arise in the crew schedule since the delay can result in the crew running out of their legal working hours. The delay on other flights might require crew swaps or the use of crew reserves.

For the passengers of the diverted flight and the planned return, flight busses are arranged. This ensures that the flight still can be completed. However, due to changes to the flight schedule delays might be induced on other flights which impact the satisfaction and connections of the passengers on the delayed flights.

Solution Strategy C
This solution strategy opts to divert the flight to one of the alternative airports, drop the passengers, and ferry empty back to AMS. Hereby, having minimal impact on the remainder of the flight and crew schedules.

Since the return flight from the planned destination airport will be cancelled the passengers have to be re-booked to other (partner-airline) flights. Furthermore, the passengers which arrive at the diversion airport will be bussed towards the planned destination airport. The impact on the rest of the passenger schedule is minimal since no delays are induced on other flights due to the aircraft ferrying immediately back to AMS.

Solution Strategy D
In this solution strategy it is decided not to divert to an alternative airport, but to perform a mid-air return back to AMS and cancelling the complete LCY rotation. Due to this decision, the aircraft is available at AMS for the execution of other flights, and therefore not impacting the remainder of the flight and crew schedules.

In the passenger domain, there are consequences based on this decision. The passengers from the cancelled rotation have to be rebooked onto other flight to be able to reach their planned destination. The positive is that no other flights are impacted by this decision, and therefore only the passengers from the cancelled LCY rotation are impacted.

Solution Strategy E
Identical to solution strategy D it is decided to perform a mid-air return back to AMS. The difference is that it is chosen not to cancel the rotation, but to delay the rotation. Due to the delay of the rotation either another rotation has to be cancelled (no reserves available), extensive swaps have to be made in the flight schedule or a reserve aircraft has to be used (if reserves available).

Identically to solution strategy A, looking from the crew perspective this solution strategy has implications for the allowable flight duty period of the flight- and cabin crew since an unplanned cycle is flown. Hence, this solution will most likely require an appeal to be made on crew reserves (when available) or adjustments to the crew schedule have to be made by applying crew swaps.

For passengers, there are also consequences. The passengers from the delayed rotation will naturally arrive with a delay at their planned destination. In case no reserve aircraft is available, there is a chance that legs have to be cancelled which results in the rebooking of passengers and possible delays on other flights.

Solution Strategy F
The prerequisite for this solution strategy is that the aircraft should have sufficient holding fuel and the re-opening time of LCY airport is known by the decision-makers.

Staying in the holding for a longer amount of time, naturally results in extra minutes of flight. The later the reopening time, the more delay will be induced in the schedule and the bigger the impact on the flight and crew schedules. The later the reopening time the more likely it becomes that fleet and crew reserves have to be used.

For the passenger domain, this solution induces some delays but ensure completion of the rotation. Again the amount of delay depends on the reopening time of LCY airport.

An overview of the flight schedule to which these solution strategies are applied is given in Figure G.2. The exact criteria values for the discussed solution strategies per selected diversion airport and reserve (un)availability are given in Table G.1 through Table G.6.

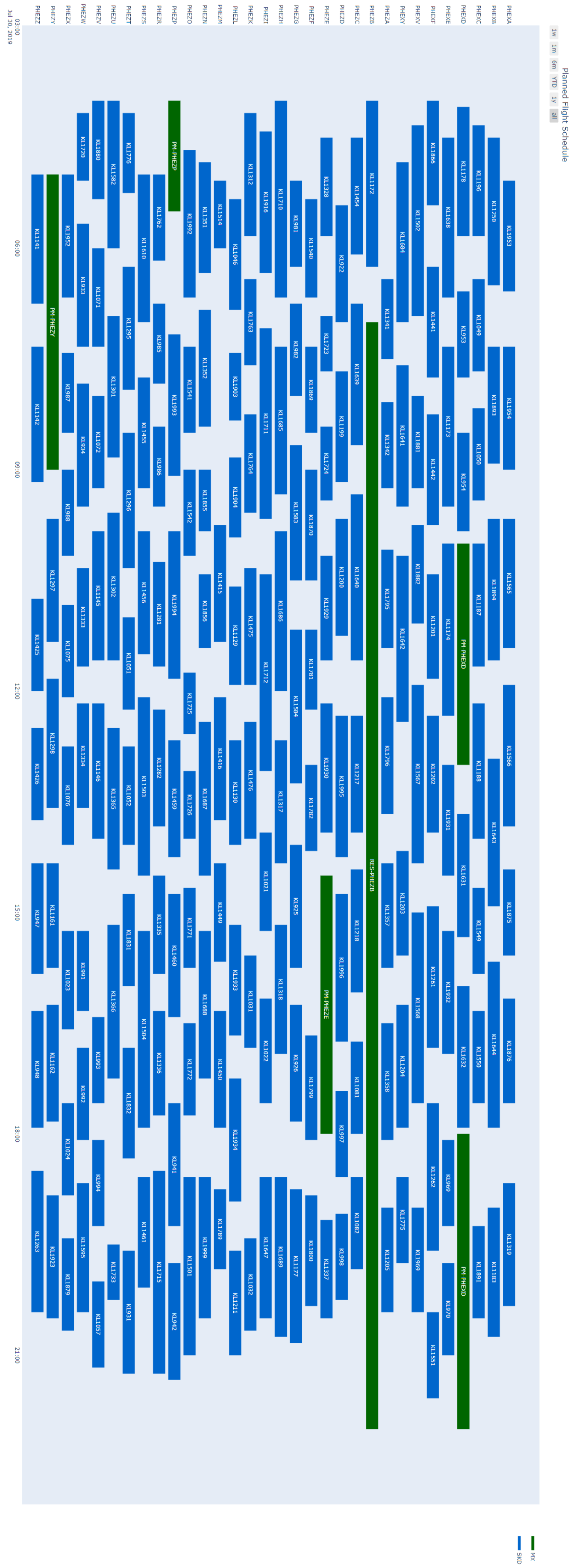


Figure G.2: Flight Schedule 30th July 2019

	Extra cycles flown	Extra minutes of flight	Leg cancellation count	Number of registration swaps in early window	Number of registration swaps in late window	Reserve devaluation minutes	Crew swap count	Crew reserve usage count	Bussed elite passenger count	Bussed non-elite passenger count	Rebooked elite passenger count	Rebooked non-elite passenger count	ETD delay minutes	Collateral delay minutes
SEN 08:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	1	48	0	1	1	420	0	1	0	0	0	0	83	0
A_{DST}	1	48	0	1	5	0	0	1	0	0	0	0	83	25
B	0	15	0	1	1	420	0	1	3	191	0	0	55	0
B_{DST}	0	15	0	1	14	0	0	1	3	191	0	0	55	0
C	0	10	1	0	0	0	0	0	1	95	1	58	0	0
C_{DST}	0	10	1	0	0	0	0	0	1	95	1	58	0	0
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	1	85	0	1	1	420	0	1	0	0	0	0	240	0
E_{DST}	1	85	1	1	4	300	0	1	0	0	0	0	240	0
F	0	30	0	0	0	0	0	0	0	0	0	0	0	60
F_{DST}	0	30	0	0	0	0	0	0	0	0	0	0	0	60
SEN 08:50z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	1	48	0	1	1	420	0	1	0	0	0	0	83	0
A_{DST}	1	48	0	1	5	0	0	1	0	0	0	0	83	25
B	0	15	0	1	1	420	0	1	3	191	0	0	55	0
B_{DST}	0	15	0	1	14	0	0	1	3	191	0	0	55	0
C	0	10	1	0	0	0	0	0	1	95	1	58	0	0
C_{DST}	0	10	1	0	0	0	0	0	1	95	1	58	0	0
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	1	85	0	1	1	420	0	1	0	0	0	0	240	0
E_{DST}	1	85	1	1	4	300	0	1	0	0	0	0	240	0
F	0	60	0	0	3	60	0	0	0	0	0	0	0	150
F_{DST}	0	60	0	1	15	0	0	1	0	0	0	0	0	55
SEN 09:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	1	48	0	1	1	420	0	1	0	0	0	0	90	0
A_{DST}	1	48	0	1	5	0	0	1	0	0	0	0	90	25
B	0	15	0	1	1	420	0	1	3	191	0	0	55	0
B_{DST}	0	15	0	1	14	0	0	1	3	191	0	0	55	0
C	0	10	1	0	0	0	0	0	1	95	1	58	0	0
C_{DST}	0	10	1	0	0	0	0	0	1	95	1	58	0	0
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	1	85	0	1	1	420	0	1	0	0	0	0	240	0
E_{DST}	1	85	1	1	4	300	0	1	0	0	0	0	240	0
F	0	90	0	0	3	90	0	0	0	0	0	0	0	240
F_{DST}	0	90	0	1	14	0	0	1	0	0	0	0	0	85

Table G.1: Criteria specification solution strategies, diversion airport: SEN, Reserves Available

	Extra cycles flown	Extra minutes of flight	Leg cancellation count	Number of registration swaps in early window	Number of registration swaps in late window	Reserve devaluation minutes	Crew swap count	Crew reserve usage count	Bussed elite passenger count	Bussed non-elite passenger count	Rebooked elite passenger count	Rebooked non-elite passenger count	ETD delay minutes	Collateral delay minutes
SEN 08:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	0	0	2	0	0	0	0	0	0	0	4	82	83	141
A_{DST}	1	48	0	0	6	0	1	0	0	0	0	0	83	151
B	0	15	0	0	0	0	0	0	3	191	0	0	55	180
B_{DST}	0	15	0	1	9	0	1	0	3	191	0	0	55	115
C	0	10	1	0	0	0	0	0	1	95	1	58	0	0
C_{DST}	0	10	1	0	0	0	0	0	1	95	1	58	0	0
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	0	0	2	0	0	0	0	0	0	0	6	107	240	0
E_{DST}	0	0	2	0	0	0	0	0	0	0	6	107	240	0
F	0	30	0	0	0	0	0	0	0	0	0	0	0	60
F_{DST}	0	30	0	1	3	0	1	0	0	0	0	0	0	80
SEN 08:50z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	0	0	2	0	0	0	0	0	0	0	4	82	83	141
A_{DST}	1	48	0	0	6	0	1	0	0	0	0	0	83	151
B	0	15	0	0	0	0	0	0	3	191	0	0	55	180
B_{DST}	0	15	0	1	9	0	1	0	3	191	0	0	55	115
C	0	10	1	0	0	0	0	0	1	95	1	58	0	0
C_{DST}	0	10	1	0	0	0	0	0	1	95	1	58	0	0
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	0	0	2	0	0	0	0	0	0	0	6	107	240	0
E_{DST}	0	0	2	0	0	0	0	0	0	0	6	107	240	0
F	0	60	0	0	0	0	0	0	0	0	0	0	0	235
F_{DST}	0	60	0	1	3	0	1	0	0	0	0	0	0	110
SEN 09:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	0	0	2	0	0	0	0	0	0	0	4	82	90	155
A_{DST}	1	48	0	0	6	0	1	0	0	0	0	0	100	185
B	0	15	0	0	0	0	0	0	3	191	0	0	55	180
B_{DST}	0	15	0	1	9	0	1	0	3	191	0	0	55	115
C	0	10	1	0	0	0	0	0	1	95	1	58	0	0
C_{DST}	0	10	1	0	0	0	0	0	1	95	1	58	0	0
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	0	0	2	0	0	0	0	0	0	0	6	107	240	0
E_{DST}	0	0	2	0	0	0	0	0	0	0	6	107	240	0
F	0	0	2	0	0	0	0	0	0	0	4	82	0	230
F_{DST}	0	90	0	0	5	0	1	0	0	0	0	0	0	265

Table G.2: Criteria specification solution strategies, diversion airport: SEN, Reserves Unavailable

	Extra cycles flown	Extra minutes of flight	Leg cancellation count	Number of registration swaps in early window	Number of registration swaps in late window	Reserve devaluation minutes	Crew swap count	Crew reserve usage count	Bussed elite passenger count	Bussed non-elite passenger count	Rebooked elite passenger count	Rebooked non-elite passenger count	ETD delay minutes	Collateral delay minutes
SOU 08:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	1	68	0	1	1	420	0	1	0	0	0	0	103	0
A_{DST}	1	68	0	1	14	0	0	1	0	0	0	0	103	6
B	0	30	0	1	1	420	0	1	3	191	0	0	130	0
B_{DST}	0	30	0	1	4	300	0	1	3	191	0	0	130	0
C	0	45	1	1	1	420	0	1	1	95	1	58	0	0
C_{DST}	0	45	1	1	3	0	0	1	1	95	1	58	0	25
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	1	85	0	1	1	420	0	1	0	0	0	0	240	0
E_{DST}	1	85	1	1	4	300	0	1	0	0	0	0	240	0
F	0	30	0	0	0	0	0	0	0	0	0	0	0	60
F_{DST}	0	30	0	0	0	0	0	0	0	0	0	0	0	60
SOU 08:50z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	1	68	0	1	1	420	0	1	0	0	0	0	103	0
A_{DST}	1	68	0	1	14	0	0	1	0	0	0	0	103	6
B	0	30	0	1	1	420	0	1	3	191	0	0	130	0
B_{DST}	0	30	0	1	4	300	0	1	3	191	0	0	130	0
C	0	45	1	1	1	420	0	1	1	95	1	58	0	0
C_{DST}	0	45	1	1	3	0	0	1	1	95	1	58	0	25
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	1	85	0	1	1	420	0	1	0	0	0	0	240	0
E_{DST}	1	85	1	1	4	300	0	1	0	0	0	0	240	0
F	0	60	0	0	3	60	0	0	0	0	0	0	0	150
F_{DST}	0	60	0	1	15	0	0	1	0	0	0	0	0	55
SOU 09:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	1	68	0	1	1	420	0	1	0	0	0	0	103	0
A_{DST}	1	68	0	1	14	0	0	1	0	0	0	0	103	6
B	0	30	0	1	1	420	0	1	3	191	0	0	130	0
B_{DST}	0	30	0	1	4	300	0	1	3	191	0	0	130	0
C	0	45	1	1	1	420	0	1	1	95	1	58	0	0
C_{DST}	0	45	1	1	3	0	0	1	1	95	1	58	0	25
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	1	85	0	1	1	420	0	1	0	0	0	0	240	0
E_{DST}	1	85	1	1	4	300	0	1	0	0	0	0	240	0
F	0	90	0	0	3	90	0	0	0	0	0	0	0	240
F_{DST}	0	90	0	1	14	0	0	1	0	0	0	0	0	85

Table G.3: Criteria specification solution strategies, diversion airport: SOU, Reserves Available

	Extra cycles flown	Extra minutes of flight	Leg cancellation count	Number of registration swaps in early window	Number of registration swaps in late window	Reserve devaluation minutes	Crew swap count	Crew reserve usage count	Bussed elite passenger count	Bussed non-elite passenger count	Rebooked elite passenger count	Rebooked non-elite passenger count	ETD delay minutes	Collateral delay minutes
SOU 08:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	0	0	2	0	0	0	0	0	0	0	4	82	103	181
A_{DST}	1	68	0	0	6	0	1	0	0	0	0	0	103	191
B	0	0	2	0	0	0	0	0	2	190	4	82	250	115
B_{DST}	0	30	0	0	5	0	1	0	3	191	0	0	250	150
C	0	45	1	0	0	0	0	0	1	95	1	58	0	130
C_{DST}	0	45	1	1	9	0	1	0	1	95	1	58	0	25
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	0	0	2	0	0	0	0	0	0	0	6	107	240	0
E_{DST}	0	0	2	0	0	0	0	0	0	0	6	107	240	0
F	0	30	0	0	0	0	0	0	0	0	0	0	0	60
F_{DST}	0	30	0	1	3	0	1	0	0	0	0	0	0	80
SOU 08:50z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	0	0	2	0	0	0	0	0	0	0	4	82	103	181
A_{DST}	1	68	0	0	6	0	1	0	0	0	0	0	103	191
B	0	0	2	0	0	0	0	0	2	190	4	82	250	115
B_{DST}	0	30	0	0	5	0	1	0	3	191	0	0	250	150
C	0	45	1	0	0	0	0	0	1	95	1	58	0	130
C_{DST}	0	45	1	1	9	0	1	0	1	95	1	58	0	25
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	0	0	2	0	0	0	0	0	0	0	6	107	240	0
E_{DST}	0	0	2	0	0	0	0	0	0	0	6	107	240	0
F	0	60	0	0	0	0	0	0	0	0	0	0	0	235
F_{DST}	0	60	0	1	3	0	1	0	0	0	0	0	0	110
SOU 09:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	0	0	2	0	0	0	0	0	0	0	4	82	103	181
A_{DST}	1	68	0	0	6	0	1	0	0	0	0	0	103	191
B	0	0	2	0	0	0	0	0	2	190	4	82	250	115
B_{DST}	0	30	0	0	5	0	1	0	3	191	0	0	250	150
C	0	45	1	0	0	0	0	0	1	95	1	58	0	130
C_{DST}	0	45	1	1	9	0	1	0	1	95	1	58	0	25
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	0	0	2	0	0	0	0	0	0	0	6	107	240	0
E_{DST}	0	0	2	0	0	0	0	0	0	0	6	107	240	0
F	0	0	2	0	0	0	0	0	0	0	4	82	0	230
F_{DST}	0	90	0	0	5	0	1	0	0	0	0	0	0	265

Table G.4: Criteria specification solution strategies, diversion airport: SOU, Reserves Unavailable

	Extra cycles flown	Extra minutes of flight	Leg cancellation count	Number of registration swaps in early window	Number of registration swaps in late window	Reserve devaluation minutes	Crew swap count	Crew reserve usage count	Bussed elite passenger count	Bussed non-elite passenger count	Rebooked elite passenger count	Rebooked non-elite passenger count	ETD delay minutes	Collateral delay minutes
NWI 08:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	1	80	0	1	1	420	0	1	0	0	0	0	115	0
A$_{\text{DST}}$	1	80	0	1	4	300	0	1	0	0	0	0	115	0
B	0	40	0	1	1	420	0	1	3	191	0	0	150	0
B$_{\text{DST}}$	0	40	0	1	4	330	0	1	3	191	0	0	150	0
C	0	30	1	0	0	0	0	0	1	95	1	58	0	55
C$_{\text{DST}}$	0	30	1	0	0	0	0	0	1	95	1	58	0	55
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D$_{\text{DST}}$	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	1	85	0	1	1	420	0	1	0	0	0	0	240	0
E$_{\text{DST}}$	1	85	1	1	4	300	0	1	0	0	0	0	240	0
F	0	30	0	0	0	0	0	0	0	0	0	0	0	60
F$_{\text{DST}}$	0	30	0	0	0	0	0	0	0	0	0	0	0	60
NWI 08:50z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	1	80	0	1	1	420	0	1	0	0	0	0	115	0
A$_{\text{DST}}$	1	80	0	1	4	300	0	1	0	0	0	0	115	0
B	0	40	0	1	1	420	0	1	3	191	0	0	150	0
B$_{\text{DST}}$	0	40	0	1	4	330	0	1	3	191	0	0	150	0
C	0	30	1	0	0	0	0	0	1	95	1	58	0	55
C$_{\text{DST}}$	0	30	1	0	0	0	0	0	1	95	1	58	0	55
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D$_{\text{DST}}$	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	1	85	0	1	1	420	0	1	0	0	0	0	240	0
E$_{\text{DST}}$	1	85	1	1	4	300	0	1	0	0	0	0	240	0
F	0	60	0	0	3	60	0	0	0	0	0	0	0	150
F$_{\text{DST}}$	0	60	0	1	15	0	0	1	0	0	0	0	0	55
NWI 09:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	1	80	0	1	1	420	0	1	0	0	0	0	115	0
A$_{\text{DST}}$	1	80	0	1	4	300	0	1	0	0	0	0	115	0
B	0	40	0	1	1	420	0	1	3	191	0	0	150	0
B$_{\text{DST}}$	0	40	0	1	4	330	0	1	3	191	0	0	150	0
C	0	30	1	0	0	0	0	0	1	95	1	58	0	55
C$_{\text{DST}}$	0	30	1	0	0	0	0	0	1	95	1	58	0	55
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D$_{\text{DST}}$	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	1	85	0	1	1	420	0	1	0	0	0	0	240	0
E$_{\text{DST}}$	1	85	1	1	4	300	0	1	0	0	0	0	240	0
F	0	90	0	0	3	90	0	0	0	0	0	0	0	240
F$_{\text{DST}}$	0	90	0	1	14	0	0	1	0	0	0	0	0	85

Table G.5: Criteria specification solution strategies, diversion airport: NWI, Reserves Available

	Extra cycles flown	Extra minutes of flight	Leg cancellation count	Number of registration swaps in early window	Number of registration swaps in late window	Reserve devaluation minutes	Crew swap count	Crew reserve usage count	Bussed elite passenger count	Bussed non-elite passenger count	Rebooked elite passenger count	Rebooked non-elite passenger count	ETD delay minutes	Collateral delay minutes
NWI 08:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	0	0	2	0	0	0	0	0	0	0	4	82	220	100
A_{DST}	1	80	0	0	5	0	1	0	0	0	0	0	220	135
B	0	0	2	0	0	0	0	0	3	191	6	107	150	0
B_{DST}	0	0	2	0	0	0	0	0	3	191	6	107	150	0
C	0	30	1	0	0	0	0	0	1	95	1	58	0	55
C_{DST}	0	30	1	1	8	0	1	0	1	95	1	58	0	30
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	0	0	2	0	0	0	0	0	0	0	6	107	240	0
E_{DST}	0	0	2	0	0	0	0	0	0	0	6	107	240	0
F	0	30	0	0	0	0	0	0	0	0	0	0	0	60
F_{DST}	0	30	0	1	3	0	1	0	0	0	0	0	0	80
NWI 08:50z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	0	0	2	0	0	0	0	0	0	0	4	82	220	100
A_{DST}	1	80	0	0	5	0	1	0	0	0	0	0	220	135
B	0	0	2	0	0	0	0	0	3	191	6	107	150	0
B_{DST}	0	0	2	0	0	0	0	0	3	191	6	107	150	0
C	0	30	1	0	0	0	0	0	1	95	1	58	0	55
C_{DST}	0	30	1	1	8	0	1	0	1	95	1	58	0	30
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	0	0	2	0	0	0	0	0	0	0	6	107	240	0
E_{DST}	0	0	2	0	0	0	0	0	0	0	6	107	240	0
F	0	60	0	0	0	0	0	0	0	0	0	0	0	235
F_{DST}	0	60	0	1	3	0	1	0	0	0	0	0	0	110
NWI 09:20z	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}	c_{14}
A	0	0	2	0	0	0	0	0	0	0	4	82	220	100
A_{DST}	1	80	0	0	5	0	1	0	0	0	0	0	220	135
B	0	0	2	0	0	0	0	0	3	191	6	107	150	0
B_{DST}	0	0	2	0	0	0	0	0	3	191	6	107	150	0
C	0	30	1	0	0	0	0	0	1	95	1	58	0	55
C_{DST}	0	30	1	1	8	0	1	0	1	95	1	58	0	30
D	0	0	2	0	0	0	0	0	0	0	2	115	0	0
D_{DST}	0	0	2	0	0	0	0	0	0	0	2	115	0	0
E	0	0	2	0	0	0	0	0	0	0	6	107	240	0
E_{DST}	0	0	2	0	0	0	0	0	0	0	6	107	240	0
F	0	0	2	0	0	0	0	0	0	0	4	82	0	230
F_{DST}	0	90	0	0	5	0	1	0	0	0	0	0	0	265

Table G.6: Criteria specification solution strategies, diversion airport: NWI, Reserves Unavailable

H

Results tactical control mode

The results of the agents operating in the tactical control mode are presented in this chapter. In the tactical control mode, the Clarke Tax Algorithm is used as decision-making mechanism. For this algorithm the costs, taxes paid and resulting total obtained utility inherent to a solution strategy are the important characteristics. These values resulting from the decision made in the tactical control mode are given in Table H.1. For details about the technical implementation of the Clarke Tax Algorithm as decision-making mechanism and the explanation of the results, one is referred to the scientific paper in Part I of this report.

SEN	Decision	FCo Cost	CC Cost	CD Cost	FCo Tax	CC Tax	CD Tax	Total Utility
Scenario 1a	B_{DST}	€1.172	€10.000	€13.451	€8.091	€0	€0	€32.714
Scenario 1b	B_{DST}	€1.172	€10.000	€13.451	€8.091	€0	€0	€32.714
Scenario 1c	B_{DST}	€1.172	€10.000	€13.451	€7.703	€0	€0	€32.326
Scenario 2a	B_{DST}	€200	€5.000	€21.588	€7.641	€0	€26.588	€61.017
Scenario 2b	B_{DST}	€200	€5.000	€21.588	€7.641	€0	€26.588	€61.017
Scenario 2c	B_{DST}	€200	€5.000	€21.588	€7.641	€0	€26.588	€61.017
Scenario 3a	F	€401	€0	€4.515	€0	€0	€0	€4.916
Scenario 3b	F_{DST}	€1.773	€10.000	€4.527	€4.285	€0	€5.498	€26.083
Scenario 3c	F_{DST}	€2.174	€10.000	€6.661	€0	€0	€7.663	€26.498
Scenario 4a	F	€401	€0	€4.515	€0	€0	€4.716	€9.632
Scenario 4b	F_{DST}	€1.773	€5.000	€8.122	€0	€0	€14.695	€29.590
Scenario 4c	F_{DST}	€1.202	€5.000	€20.541	€7.596	€0	€26.543	€60.882
SOU	**Decision**	**FCo Cost**	**CC Cost**	**CD Cost**	**FCo Tax**	**CC Tax**	**CD Tax**	**Total Utility**
Scenario 1a	A_{DST}	€16.880	€10.000	€7.698	€17.206	€0	€10.506	€62.290
Scenario 1b	A_{DST}	€16.880	€10.000	€7.698	€17.206	€0	€10.506	€62.290
Scenario 1c	A_{DST}	€16.880	€10.000	€7.698	€17.206	€0	€10.506	€62.290
Scenario 2a	A_{DST}	€15.909	€5.000	€21.784	€0	€0	€37.292	€79.985
Scenario 2b	A_{DST}	€15.909	€5.000	€21.784	€0	€0	€37.292	€79.985
Scenario 2c	A_{DST}	€15.909	€5.000	€21.784	€0	€0	€37.292	€79.985
Scenario 3a	F	€401	€0	€4.515	€0	€0	€0	€4.916
Scenario 3b	F_{DST}	€1.773	€10.000	€4.527	€4.285	€0	€5.498	€26.083
Scenario 3c	F_{DST}	€2.174	€10.000	€6.661	€0	€0	€0	€18.835
Scenario 4a	F	€401	€0	€4.515	€0	€0	€0	€4.916
Scenario 4b	F_{DST}	€1.773	€5.000	€8.122	€0	€0	€14.093	€28.988
Scenario 4c	F_{DST}	€1.202	€5.000	€20.541	€0	€0	€21.342	€48.085
NWI	**Decision**	**FCo Cost**	**CC Cost**	**CD Cost**	**FCo Tax**	**CC Tax**	**CD Tax**	**Total Utility**
Scenario 1a	C	€12.901	€0	€26.213	€21.547	€0	€0	€60.661
Scenario 1b	C	€12.901	€0	€26.213	€21.547	€0	€0	€60.661
Scenario 1c	C	€12.901	€0	€26.213	€21.547	€0	€0	€60.661
Scenario 2a	C	€12.901	€0	€26.213	€0	€0	€0	€39.114
Scenario 2b	C	€12.901	€0	€26.213	€0	€0	€0	€39.114
Scenario 2c	C	€12.901	€0	€26.213	€0	€0	€0	€39.114
Scenario 3a	F	€401	€0	€4.515	€0	€0	€0	€4.916
Scenario 3b	F_{DST}	€1.773	€10.000	€4.527	€4.285	€0	€5.498	€26.083
Scenario 3c	F_{DST}	€2.174	€10.000	€6.661	€0	€0	€0	€18.835
Scenario 4a	F	€401	€0	€4.515	€0	€0	€0	€4.916
Scenario 4b	F_{DST}	€1.773	€5.000	€8.122	€0	€0	€14.093	€28.988
Scenario 4c	F_{DST}	€1.202	€5.000	€20.541	€0	€0	€0	€26.743

Table H.1: Clarke Tax Results - Diversion airport: SEN/SOU/NWI

I

Results strategic control mode

The results generated by the model for the agents operating in the strategic control mode, and using the MCDM decision-making mechanism, are two-fold. The first part of the results are the criteria weights that are a result of the pairwise comparison matrices from Appendix D. The resulting criteria weights are depicted in Table I.1. The second part of the results are the relative preference values of the agents on the solution strategies that are a consequence of the criteria weights. The resulting preference values are given in Table I.2 through Table I.5. For details about the technical implementation of the MCDM decision-making mechanism and the reasoning behind the results, one is referred to the scientific paper in Part I of this report.

		Reserves Available				Reserves Unavailable			
		Context I	Context II	Context III	Context IV	Context I	Context II	Context III	Context IV
	Fleet	0.429	0.579	0.579	0.234	0.579	0.579	0.579	0.579
	Crew	0.143	0.187	0.187	0.078	0.187	0.187	0.187	0.187
	Pax	0.429	0.234	0.234	0.688	0.234	0.234	0.234	0.234
c_1	Extra cycles flown	0.037	0.034	0.018	0.052	0.223	0.224	0.238	0.223
c_2	Extra minutes of flight	0.024	0.057	0.029	0.054	0.080	0.082	0.074	0.080
c_3	Leg cancellation count	0.193	0.297	0.281	0.099	0.174	0.188	0.196	0.174
c_4	Registration swaps in early window	0.096	0.024	0.040	0.015	0.058	0.052	0.025	0.058
c_5	Registration swaps in late window	0.018	0.035	0.120	0.008	0.030	0.017	0.031	0.030
c_6	Reserve devaluation minutes	0.061	0.133	0.092	0.006	0.014	0.016	0.015	0.014
c_7	Crew swap count	0.024	0.023	0.023	0.010	0.168	0.168	0.168	0.168
c_8	Crew reserve usage count	0.119	0.163	0.163	0.068	0.019	0.019	0.019	0.019
c_9	Bussed elite passenger count	0.011	0.008	0.022	0.019	0.006	0.008	0.022	0.007
c_{10}	Bussed non-elite passenger count	0.011	0.008	0.010	0.018	0.006	0.008	0.010	0.006
c_{11}	Re-booked elite passenger count	0.058	0.038	0.051	0.159	0.032	0.038	0.051	0.054
c_{12}	Re-booked non-elite passenger count	0.058	0.038	0.055	0.239	0.032	0.038	0.055	0.081
c_{13}	ETD delay minutes	0.170	0.071	0.066	0.178	0.093	0.071	0.066	0.061
c_{14}	Collateral delay minutes	0.121	0.071	0.029	0.074	0.066	0.071	0.029	0.025

Table I.1: Criteria Weights per context and reserve availability

SEN	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}
1a-I	0.613	0.548	0.657	0.702	0.833	0.833	0.691	0.691	0.492	0.409
1a-II	0.587	0.639	0.635	0.735	0.800	0.800	0.628	0.628	0.516	0.398
1a-III	0.639	0.668	0.644	0.625	0.790	0.790	0.612	0.612	0.583	0.444
1a-IV	0.766	0.696	0.822	0.821	0.728	0.728	0.502	0.502	0.626	0.577
1b-I	0.613	0.548	0.657	0.702	0.833	0.833	0.691	0.691	0.492	0.409
1b-II	0.587	0.639	0.635	0.735	0.800	0.800	0.628	0.628	0.516	0.398
1b-III	0.639	0.668	0.644	0.625	0.790	0.790	0.612	0.612	0.583	0.444
1b-IV	0.766	0.696	0.822	0.821	0.728	0.728	0.502	0.502	0.626	0.577
1c-I	0.608	0.543	0.657	0.702	0.833	0.833	0.691	0.691	0.492	0.409
1c-II	0.585	0.637	0.635	0.735	0.800	0.800	0.628	0.628	0.516	0.398
1c-III	0.637	0.667	0.644	0.625	0.790	0.790	0.612	0.612	0.583	0.444
1c-IV	0.761	0.691	0.822	0.821	0.728	0.728	0.502	0.502	0.626	0.577
SOU	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}
1a-I	0.593	0.609	0.600	0.613	0.546	0.484	0.691	0.691	0.492	0.409
1a-II	0.568	0.651	0.603	0.633	0.455	0.511	0.628	0.628	0.516	0.398
1a-III	0.627	0.601	0.618	0.619	0.474	0.521	0.612	0.612	0.583	0.444
1a-IV	0.738	0.720	0.757	0.757	0.616	0.547	0.502	0.502	0.626	0.577
1b-I	0.593	0.609	0.600	0.613	0.546	0.484	0.691	0.691	0.492	0.409
1b-II	0.568	0.651	0.603	0.633	0.455	0.511	0.628	0.628	0.516	0.398
1b-III	0.627	0.601	0.618	0.619	0.474	0.521	0.612	0.612	0.583	0.444
1b-IV	0.738	0.720	0.757	0.757	0.616	0.547	0.502	0.502	0.626	0.577
1c-I	0.593	0.609	0.600	0.613	0.546	0.484	0.691	0.691	0.492	0.409
1c-II	0.568	0.651	0.603	0.633	0.455	0.511	0.628	0.628	0.516	0.398
1c-III	0.627	0.601	0.618	0.619	0.474	0.521	0.612	0.612	0.583	0.444
1c-IV	0.738	0.720	0.757	0.757	0.616	0.547	0.502	0.502	0.626	0.577
NWI	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}
1a-I	0.578	0.583	0.580	0.580	0.707	0.707	0.691	0.691	0.489	0.397
1a-II	0.550	0.562	0.584	0.586	0.716	0.716	0.628	0.628	0.510	0.373
1a-III	0.598	0.535	0.588	0.518	0.754	0.754	0.612	0.612	0.562	0.358
1a-IV	0.721	0.717	0.734	0.730	0.641	0.641	0.502	0.502	0.625	0.571
1b-I	0.578	0.583	0.580	0.580	0.707	0.707	0.691	0.691	0.489	0.397
1b-II	0.550	0.562	0.584	0.586	0.716	0.716	0.628	0.628	0.510	0.373
1b-III	0.598	0.535	0.588	0.518	0.754	0.754	0.612	0.612	0.562	0.358
1b-IV	0.721	0.717	0.734	0.730	0.641	0.641	0.502	0.502	0.625	0.571
1c-I	0.578	0.583	0.580	0.580	0.707	0.707	0.691	0.691	0.489	0.397
1c-II	0.550	0.562	0.584	0.586	0.716	0.716	0.628	0.628	0.510	0.373
1c-III	0.598	0.535	0.588	0.518	0.754	0.754	0.612	0.612	0.562	0.358
1c-IV	0.721	0.717	0.734	0.730	0.641	0.641	0.502	0.502	0.625	0.571

Table I.2: Solution preference Scenario 1 - Diversion airport: SEN/SOU/NWI

SEN	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}
2a-I	0.699	0.421	0.876	0.643	0.870	0.870	0.784	0.784	0.672	0.672
2a-II	0.680	0.430	0.870	0.659	0.857	0.857	0.762	0.762	0.669	0.669
2a-III	0.685	0.452	0.900	0.686	0.838	0.838	0.731	0.731	0.635	0.635
2a-IV	0.691	0.466	0.923	0.676	0.841	0.841	0.727	0.727	0.636	0.636
2b-I	0.699	0.421	0.876	0.643	0.870	0.870	0.784	0.784	0.672	0.672
2b-II	0.680	0.430	0.870	0.659	0.857	0.857	0.762	0.762	0.669	0.669
2b-III	0.685	0.452	0.900	0.686	0.838	0.838	0.731	0.731	0.635	0.635
2b-IV	0.691	0.466	0.923	0.676	0.841	0.841	0.727	0.727	0.636	0.636
2c-I	0.699	0.421	0.876	0.643	0.870	0.870	0.784	0.784	0.672	0.672
2c-II	0.680	0.430	0.870	0.659	0.857	0.857	0.762	0.762	0.669	0.669
2c-III	0.685	0.452	0.900	0.686	0.838	0.838	0.731	0.731	0.635	0.635
2c-IV	0.691	0.466	0.923	0.676	0.841	0.841	0.727	0.727	0.636	0.636
SOU	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}
2a-I	0.682	0.404	0.640	0.624	0.789	0.569	0.784	0.784	0.676	0.676
2a-II	0.664	0.414	0.633	0.643	0.771	0.573	0.762	0.762	0.672	0.672
2a-III	0.676	0.443	0.622	0.661	0.785	0.576	0.731	0.731	0.638	0.638
2a-IV	0.683	0.458	0.646	0.687	0.788	0.545	0.727	0.727	0.638	0.638
2b-I	0.682	0.404	0.640	0.624	0.789	0.569	0.784	0.784	0.676	0.676
2b-II	0.664	0.414	0.633	0.643	0.771	0.573	0.762	0.762	0.672	0.672
2b-III	0.676	0.443	0.622	0.661	0.785	0.576	0.731	0.731	0.638	0.638
2b-IV	0.683	0.458	0.646	0.687	0.788	0.545	0.727	0.727	0.638	0.638
2c-I	0.682	0.404	0.640	0.624	0.789	0.569	0.784	0.784	0.676	0.676
2c-II	0.664	0.414	0.633	0.643	0.771	0.573	0.762	0.762	0.672	0.672
2c-III	0.676	0.443	0.622	0.661	0.785	0.576	0.731	0.731	0.638	0.638
2c-IV	0.683	0.458	0.646	0.687	0.788	0.545	0.727	0.727	0.638	0.638
NWI	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}
2a-I	0.649	0.359	0.695	0.695	0.830	0.586	0.784	0.784	0.672	0.672
2a-II	0.643	0.379	0.679	0.679	0.814	0.590	0.762	0.762	0.669	0.669
2a-III	0.648	0.412	0.627	0.627	0.814	0.594	0.731	0.731	0.635	0.635
2a-IV	0.658	0.429	0.646	0.646	0.817	0.566	0.727	0.727	0.636	0.636
2b-I	0.649	0.359	0.695	0.695	0.830	0.586	0.784	0.784	0.672	0.672
2b-II	0.643	0.379	0.679	0.679	0.814	0.590	0.762	0.762	0.669	0.669
2b-III	0.648	0.412	0.627	0.627	0.814	0.594	0.731	0.731	0.635	0.635
2b-IV	0.658	0.429	0.646	0.646	0.817	0.566	0.727	0.727	0.636	0.636
2c-I	0.649	0.359	0.695	0.695	0.830	0.586	0.784	0.784	0.672	0.672
2c-II	0.643	0.379	0.679	0.679	0.814	0.590	0.762	0.762	0.669	0.669
2c-III	0.648	0.412	0.627	0.627	0.814	0.594	0.731	0.731	0.635	0.635
2c-IV	0.658	0.429	0.646	0.646	0.817	0.566	0.727	0.727	0.636	0.636

Table I.3: Solution preference Scenario 2 - Diversion airport: SEN/SOU/NWI

SEN	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}	F	F_{DST}
3a-I	0.613	0.619	0.657	0.702	0.833	0.833	0.691	0.691	0.492	0.409	0.871	0.871
3a-II	0.587	0.680	0.635	0.735	0.800	0.800	0.628	0.628	0.516	0.398	0.909	0.909
3a-III	0.639	0.685	0.644	0.625	0.790	0.790	0.612	0.612	0.583	0.444	0.961	0.961
3a-IV	0.766	0.739	0.822	0.821	0.728	0.728	0.502	0.502	0.626	0.577	0.907	0.907
3b-I	0.613	0.649	0.657	0.703	0.833	0.833	0.691	0.691	0.492	0.410	0.850	0.706
3b-II	0.587	0.699	0.635	0.738	0.800	0.800	0.628	0.628	0.516	0.398	0.863	0.712
3b-III	0.640	0.695	0.644	0.633	0.790	0.790	0.612	0.612	0.584	0.446	0.913	0.647
3b-IV	0.766	0.758	0.822	0.822	0.728	0.728	0.502	0.502	0.626	0.577	0.885	0.843
3c-I	0.609	0.652	0.657	0.702	0.834	0.834	0.691	0.691	0.493	0.411	0.838	0.700
3c-II	0.587	0.702	0.635	0.736	0.800	0.800	0.628	0.628	0.519	0.401	0.836	0.696
3c-III	0.638	0.693	0.644	0.625	0.790	0.790	0.612	0.612	0.585	0.445	0.897	0.638
3c-IV	0.763	0.759	0.822	0.822	0.729	0.729	0.502	0.502	0.629	0.580	0.869	0.828
SOU	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}	F	F_{DST}
3a-I	0.593	0.626	0.600	0.613	0.546	0.554	0.691	0.691	0.492	0.409	0.871	0.871
3a-II	0.568	0.661	0.603	0.633	0.455	0.553	0.628	0.628	0.516	0.398	0.909	0.909
3a-III	0.627	0.605	0.618	0.619	0.474	0.538	0.612	0.612	0.583	0.444	0.961	0.961
3a-IV	0.738	0.730	0.757	0.757	0.616	0.590	0.502	0.502	0.626	0.577	0.907	0.907
3b-I	0.593	0.634	0.600	0.614	0.546	0.584	0.691	0.691	0.492	0.410	0.850	0.706
3b-II	0.568	0.667	0.603	0.634	0.455	0.571	0.628	0.628	0.516	0.398	0.863	0.712
3b-III	0.627	0.615	0.618	0.621	0.475	0.547	0.612	0.612	0.584	0.446	0.913	0.647
3b-IV	0.739	0.735	0.757	0.757	0.616	0.609	0.502	0.502	0.626	0.577	0.885	0.843
3c-I	0.594	0.636	0.600	0.614	0.546	0.592	0.691	0.691	0.493	0.411	0.838	0.700
3c-II	0.570	0.669	0.604	0.634	0.456	0.577	0.628	0.628	0.519	0.401	0.836	0.696
3c-III	0.628	0.609	0.618	0.619	0.475	0.548	0.612	0.612	0.585	0.445	0.897	0.638
3c-IV	0.741	0.738	0.758	0.758	0.617	0.615	0.502	0.502	0.629	0.580	0.869	0.828
NWI	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}	F	F_{DST}
3a-I	0.578	0.583	0.580	0.580	0.717	0.717	0.691	0.691	0.489	0.397	0.871	0.871
3a-II	0.550	0.562	0.584	0.586	0.721	0.721	0.628	0.628	0.510	0.373	0.909	0.909
3a-III	0.598	0.535	0.588	0.518	0.757	0.757	0.612	0.612	0.562	0.358	0.961	0.961
3a-IV	0.721	0.717	0.734	0.730	0.648	0.648	0.502	0.502	0.625	0.571	0.907	0.907
3b-I	0.582	0.595	0.583	0.593	0.783	0.783	0.691	0.691	0.492	0.410	0.850	0.706
3b-II	0.556	0.587	0.590	0.612	0.761	0.761	0.628	0.628	0.516	0.398	0.863	0.712
3b-III	0.620	0.622	0.610	0.605	0.773	0.773	0.612	0.612	0.584	0.446	0.913	0.647
3b-IV	0.722	0.722	0.736	0.735	0.688	0.688	0.502	0.502	0.626	0.577	0.885	0.843
3c-I	0.583	0.596	0.583	0.593	0.801	0.801	0.691	0.691	0.493	0.411	0.838	0.700
3c-II	0.559	0.589	0.592	0.612	0.771	0.771	0.628	0.628	0.519	0.401	0.836	0.696
3c-III	0.621	0.622	0.610	0.604	0.777	0.777	0.612	0.612	0.585	0.445	0.897	0.638
3c-IV	0.725	0.725	0.737	0.737	0.700	0.700	0.502	0.502	0.629	0.580	0.869	0.828

Table I.4: Solution preference Scenario 3 - Diversion airport: SEN/SOU/NWI

SEN	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}	F	F_{DST}
4a-I	0.699	0.421	0.876	0.643	0.870	0.870	0.784	0.784	0.672	0.672	0.928	0.684
4a-II	0.680	0.430	0.870	0.659	0.857	0.857	0.762	0.762	0.669	0.669	0.925	0.691
4a-III	0.685	0.452	0.900	0.686	0.838	0.838	0.731	0.731	0.635	0.635	0.944	0.737
4a-IV	0.691	0.466	0.923	0.676	0.841	0.841	0.727	0.727	0.636	0.636	0.942	0.702
4b-I	0.711	0.450	0.896	0.658	0.874	0.874	0.784	0.784	0.672	0.672	0.854	0.653
4b-II	0.693	0.461	0.892	0.674	0.860	0.860	0.762	0.762	0.669	0.669	0.847	0.659
4b-III	0.690	0.473	0.912	0.695	0.841	0.841	0.731	0.731	0.635	0.635	0.898	0.709
4b-IV	0.696	0.487	0.934	0.685	0.844	0.844	0.727	0.727	0.636	0.636	0.895	0.672
4c-I	0.709	0.461	0.909	0.668	0.878	0.878	0.784	0.784	0.672	0.672	0.725	0.669
4c-II	0.692	0.474	0.905	0.685	0.865	0.865	0.762	0.762	0.669	0.669	0.699	0.670
4c-III	0.689	0.486	0.920	0.703	0.845	0.845	0.731	0.731	0.635	0.635	0.705	0.712
4c-IV	0.695	0.503	0.943	0.693	0.849	0.849	0.727	0.727	0.636	0.636	0.710	0.710
SOU	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}	F	F_{DST}
4a-I	0.682	0.404	0.640	0.624	0.789	0.569	0.784	0.784	0.676	0.676	0.944	0.701
4a-II	0.664	0.414	0.633	0.643	0.771	0.573	0.762	0.762	0.672	0.672	0.941	0.708
4a-III	0.676	0.443	0.622	0.661	0.785	0.576	0.731	0.731	0.638	0.638	0.958	0.752
4a-IV	0.683	0.458	0.646	0.687	0.788	0.545	0.727	0.727	0.638	0.638	0.957	0.718
4b-I	0.694	0.417	0.648	0.633	0.797	0.570	0.784	0.784	0.676	0.676	0.863	0.662
4b-II	0.677	0.428	0.641	0.653	0.780	0.575	0.762	0.762	0.672	0.672	0.856	0.668
4b-III	0.681	0.449	0.625	0.665	0.788	0.576	0.731	0.731	0.638	0.638	0.906	0.718
4b-IV	0.688	0.463	0.649	0.691	0.791	0.546	0.727	0.727	0.638	0.638	0.904	0.681
4c-I	0.699	0.442	0.651	0.647	0.814	0.584	0.784	0.784	0.676	0.676	0.725	0.669
4c-II	0.683	0.454	0.645	0.667	0.798	0.589	0.762	0.762	0.672	0.672	0.699	0.670
4c-III	0.683	0.470	0.627	0.675	0.802	0.589	0.731	0.731	0.638	0.638	0.705	0.712
4c-IV	0.690	0.485	0.650	0.701	0.805	0.559	0.727	0.727	0.638	0.638	0.710	0.710
NWI	A	A_{DST}	B	B_{DST}	C	C_{DST}	D	D_{DST}	E	E_{DST}	F	F_{DST}
4a-I	0.649	0.359	0.695	0.695	0.830	0.586	0.784	0.784	0.672	0.672	0.941	0.693
4a-II	0.643	0.379	0.679	0.679	0.814	0.590	0.762	0.762	0.669	0.669	0.938	0.700
4a-III	0.648	0.412	0.627	0.627	0.814	0.594	0.731	0.731	0.635	0.635	0.960	0.750
4a-IV	0.658	0.429	0.646	0.646	0.817	0.566	0.727	0.727	0.636	0.636	0.959	0.717
4b-I	0.670	0.387	0.695	0.695	0.841	0.592	0.784	0.784	0.672	0.672	0.874	0.672
4b-II	0.665	0.409	0.679	0.679	0.826	0.597	0.762	0.762	0.669	0.669	0.867	0.678
4b-III	0.657	0.424	0.627	0.627	0.819	0.597	0.731	0.731	0.635	0.635	0.916	0.726
4b-IV	0.666	0.440	0.646	0.646	0.822	0.568	0.727	0.727	0.636	0.636	0.915	0.691
4c-I	0.673	0.400	0.695	0.695	0.846	0.596	0.784	0.784	0.672	0.672	0.725	0.667
4c-II	0.669	0.423	0.679	0.679	0.832	0.601	0.762	0.762	0.669	0.669	0.699	0.668
4c-III	0.659	0.434	0.627	0.627	0.822	0.600	0.731	0.731	0.635	0.635	0.705	0.710
4c-IV	0.667	0.450	0.646	0.646	0.826	0.572	0.727	0.727	0.636	0.636	0.710	0.708

Table I.5: Solution preference Scenario 4 - Diversion airport: SEN/SOU/NWI

Bibliography

[1] Yana Ageeva. Approaches to incorporate robustness into airline scheduling. Technical Report ICAT-2000-8, MIT, Cambridge, USA, August 2000.

[2] KLM Royal Dutch Airlines. Annual report. https://www.klm.com/travel/nl_nl/images/KLM-Jaarverslag-2019_tcm541-1063986.pdf, 2019. "Accessed: 2020-05-28".

[3] KLM Royal Dutch Airlines. Assistance and compensation: in case of cancellations, delays, downgrading and denied boarding. klm.com/travel_gb_en/images/Assistance_and_compensation_tcm638-744708.pdf, 2020. "Accessed: 2020-11-17".

[4] Eugenio Oliveira Antonio J.M. Castro, Ana Paula Rocha. *A New Approach for Disruption Management in Airline Operations Control*. Springer, Heidelberg, New York, Dordrecht, London, 2014.

[5] Eugenio Oliveira Antonio J.M. Castro, Ana Paula Rocha. *A New Approach for Disruption Management in Airline Operations Control*. Springer, Heidelberg, New York, Dordrecht, London, 2014.

[6] Kerem Aslan. A decision support system for airline disruption management at klm cityhopper. Technical Report 2016.TEL.8034, TU Delft, Delft, Netherlands, August 2016.

[7] Ece Ay. Block time forecasting, 2018.

[8] Michael G. Balchanos, Jean Charles Domercant, Huy T. Tran, and Dimitri N. Mavris. Metrics-based analysis and evaluation framework for engineering resilient systems. *7th International Symposium on Resilient Control Systems*, 2014.

[9] Gordon Baxter and Ian Sommerville. Socio-technical systems: From design methods to systems engineering. *Interacting with Computers*, 23(1):4–17, 2011.

[10] Anne-Nynke Blok. Towards formalization and operationalization of resilience. Technical report, TU Delft, Delft, Netherlands, March 2018.

[11] Rafael H. Bordini, Mehdi Dastani, Jurgen Dix, and Amal El Fallah Seghrouchini. *Jason and the Golden Fleece of Agent-Oriented Programming*, pages 3–37. Springer, Berlin, Germany, 2009.

[12] Tibor Bosse, Catholijn M Jonker, Lourens Van Der Meij, and Jan Treur. A temporal trace language for the formal analysis of dynamic properties. pages 1–15, 2010.

[13] Soufiane Bouarfa, Henk A.P. Blom, and Ricky Curran. Agent-Based Modeling and Simulation of Coordination by Airline Operations Control. *IEEE Transactions on Emerging Topics in Computing*, 4:9–20, 2016.

[14] Bouarfa, Soufiane and Aydogan, Reydan and Sharpanskykh, Alexei. A Multi-Agent Negotiation Approach for Airline Operation Control. *Ambient Intelligence and Smart Environments*, 26:377–388, 2019.

[15] Bouarfa, Soufiane and Blom, Henk A.P. and Curran, Richard and Hendriks, Koen V. A study into modeling coordination in disruption management by Airline Operations Control. *AIAA AVIATION 2014 -14th AIAA Aviation Technology, Integration, and Operations Conference*, 2014.

[16] Peter J. Bruce. *Understanding Decision-Making Processes in Airline Operations Control*. Ashgate, Farnham, UK, 2012.

[17] Michel Bruneau, Stephanie E. Chang, Ronald T. Eguchi, George C. Lee, Thomas D. O'Rourke, Andrei M. Reinhorn, Masanobu Shinozuka, Kathleen Tierney, William A. Wallace, and Detlof Von Winterfeldt. A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra*, 19:733–752, 2003.

[18] Lucian Buoniu, Robert Babuška, and Bart De Schutter. A comprehensive survey of multiagent reinforcement learning. *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews*, 38 (2):156–172, 2008.

[19] A. J.M. Castro and E. Oliveira. A new concept for disruption management in airline operations control. *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, 225: 269–290, 2011.

[20] António J.M. Castro and Eugénio Oliveira. Quantifying quality operational costs in a multi-agent system for airline operations recovery. *International Review on Computers and Software*, 4:504–516, 2009.

[21] R. Chow, K. Christoffersen, and D.D. Woods. A model of communication in support of distributed anomaly response and replanning. *Human Factors and Ergonomics Society Annual Meeting Proceedings*, 44(1), 2000.

[22] M. Clarke and B. Smith. Impact of operations research on the evolution of the airline industry. *Journal of Aircraft*, 41(1):62–72, 2004.

[23] FIPA TC Communication. Fipa contract net interaction protocol specification. http://www.fipa.org/specs/fipa00029/SC00029H.html, 2002. Accessed: 18.05.2020.

[24] FIPA TC Communication. Fipa query interaction protocol specification. http://www.fipa.org/specs/fipa00027/SC00027H.html, 2002. Accessed: 18.05.2020.

[25] FIPA TC Communication. Fipa request interaction protocol specification. http://www.fipa.org/specs/fipa00026/SC00026H.html, 2002. Accessed: 18.05.2020.

[26] J. M. Corchado and R. Laza. Constructing Deliberative Agents with Case-Based Reasoning Technology. *International Journal of Intelligent Systems*, 18(12):1227–1241, 2003.

[27] E. P. Dalziell and S. T. Mcmanus. Resilience, vulnerability, and adaptive capacity: implications for system performance. *International Forum for Engineering Decision Making*, page 17, 2004.

[28] Mehdi Dastani. 2APL: A practical agent programming language. *Autonomous Agents and Multi-Agent Systems*, 16(3):214–248, 2008.

[29] Mehdi Dastani, M. van Birna Riemsdijk, and John-Jules Ch. Meyer. *Programming Multi-Agent Systems in 3APL*, pages 39–67. Springer, Boston, USA, 2005.

[30] David D. Woods and M.Branlat. *"Chapter 2: Essential characteristics of resilience"*. Resilience Engineering. 2012.

[31] Hans de Bruijn and Paulien M. Herder. System and actor perspectives on sociotechnical systems. *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, 39(5):981–992, 2009.

[32] Mathijs De Weerdt and Brad Clement. Introduction to planning in multiagent systems. *Multiagent and Grid Systems*, 5(4):345–355, 2009.

[33] Virginia Dignum and Frank Dignum. Contextualized planning using social practices. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 9372:36–52, 2015.

[34] Bertsimas Dimitirs and Tsitsiklis John. Simulated Annealing. *Statistical Science*, 8(1):10–15, 1993.

[35] E.Bax. Netline ops++ business architecture | functional scope, 2019.

[36] Stefan Edelkamp and Stefan Schrödl. *Selective Search*, pages 633–669. Elsevier Inc., Amsterdam, Netherlands, 2012.

[37] Mica R. Endsley, Todd C. Farley, William M. Jones, Alan H. Midkiff, and R. John Hansman. Situation awareness information requirements for commercial airline pilots. Technical Report ICAT-98-1, MIT, Cambridge, USA, September 1998.

[38] Fang Fang and T. N. Wong. Applying hybrid case-based reasoning in agent-based negotiations for supply chain management. *Expert Systems with Applications*, 37(12):8322–8332, 2010.

[39] Karen Feigh and Amy Pritchett. Design of support systems for dynamic decision making in airline operations. *Proceedings of the 2006 IEEE Systems and Information Engineering Design Symposium*, pages 136–141, 2006.

[40] Jody Hoffer Gittell. Coordinating mechanisms in care provider groups: Relational coordination as a mediator and input uncertainty as a moderator of performance effects. *Management Science*, 48(11): 1408–1426, 2002.

[41] Alison J.J. Heppenstall, Andrew T. Crooks, Linda M. See, and Michael Batty. *Agent-Based Models of Geographical Systems*. Springer, Berlin, Germany, 2012.

[42] Robert R. Hoffman and David D. Woods. Beyond Simon's slice: Five fundamental trade-offs that bound the performance of macrocognitive work systems. *IEEE Intelligent Systems*, 26(6):67–71, 2011.

[43] E. Hollnagel. *Human reliability analysis: Context and control*. Academic Press, London, UK, 1993.

[44] Erik Hollnagel. How Resilient Is Your Organisation ? An Introduction to the Resilience Analysis Grid (RAG). *Sustainable Transformation: Building a Resilient Organization*, pages 1–6, 2010.

[45] IATA. A hard winter ahead. https://airlines.iata.org/analysis/a-hard-winter-ahead, 2020. Accessed: 2020-06-25.

[46] David B. Kaber and Mica R. Endsley. Team situation awareness for process control safety and performance. *Process Safety Progress*, 17(1):43–48, 1998.

[47] Nabin Kafle and Erghan Hakan. Maintenance and routing improved for operability mario, 2018.

[48] Kaur, M. Common ground in coordination. Technical report, Delft University of Technology, Delft, NL, February 2017.

[49] Gary Klein, Paul J. Feltovich, Jeffrey M. Bradshaw, and David D. Woods. *Common Ground and Coordination in Joint Activity*, pages 139–184. John Wiley & Sons, Hoboken, New Jersey, 2005.

[50] Gary Klein, Brian Moon, and Robert R. Hoffman. Making sense of sensemaking 1: Alternative perspectives. *IEEE Intelligent Systems*, 21(4):70–73, 2006.

[51] Mark Klein, Peyman Faratin, Hiroki Sayama, and Yaneer Bar-Yam. Protocols for Negotiating Complex Contracts. *IEEE Intelligent Systems*, 18:32–38, 2003.

[52] Matthias Klusch, Michal Pechoucek, and Axel Polleres. *Lecture Notes in Artificial Intelligence: Preface*, volume 5180 LNAI. 2008.

[53] Niklas Kohl, Allan Larsen, Jesper Larsen, Alex Ross, and Sergey Tiourine. Airline disruption management-Perspectives, experiences and outlook. *Journal of Air Transport Management*, 13(3):149–162, 2007.

[54] John Bruntse Larsen. Going beyond BDI for agent-based simulation. *Journal of Information and Telecommunication*, 3(4):446–464, 2019.

[55] Kun Chang Lee, Habin Lee, and Namho Lee. Agent based mobile negotiation for personalized pricing of last minute theatre tickets. *Expert Systems with Applications*, 39(10):9255–9263, 2012.

[56] Charles M Macal and Michael J North. Agent-based modeling and simulation. *Proceedings of the 2009 Winter Simulation Conference*, pages 86–98, 2009.

[57] Epelman Marina A. Barrier methods for constrained optimization. http://www-personal.umich.edu/~mepelman/teaching/NLP/Handouts/NLPnotes12_89.pdf, 2020. Accessed: 2020-07-02.

[58] J. Melorose, R. Perroy, and S. Careas. *Inteligent Agent VII Agent Theories and Architectures*, volume 1. 2015.

[59] Rijk Mercuur, Virginia Dignum, and Catholijn M. Jonker. Modelling Agents Endowed with Social Practices: Static Aspects. pages 1–22, 2018.

[60] Igor Nikolic and Amineh Ghorbani. A method for developing agent-based models of socio-technical systems. *2011 International Conference on Networking, Sensing and Control, ICNSC 2011*, pages 44–49, 2011.

[61] Hyacinth Nwana, Lyndon Lee, and Nick Jennings. Coordination in Software. *BT Technol J*, 14(4):79–89, 1996.

[62] KLM ODS. Midas (cost model). KLM Royal Dutch Airlines Confluence, 2020. "Accessed: 2020-11-17".

[63] KLM ODS. Sentry (eur+klc) user documentation. KLM Royal Dutch Airlines Confluence, 2020. "Accessed: 2020-11-17".

[64] Erik Olsson and Peter Funk. Agent-based monitoring using case-based reasoning for experience reuse and improved quality. *Journal of Quality in Maintenance Engineering*, 15(2):179–192, 2009.

[65] Rudolph Oosthuizen and Leon Pretorius. Modelling Methodology for Engineering of Complex Sociotechnical Systems. *INCOSE International Symposium*, 24(s1):268–281, 2014.

[66] Gurobi Optimization. Choosing the right algorithm. https://www.gurobi.com/documentation/9.0/refman/num_choosing_the_right_alg.html, 2020. Accessed: 2020-07-02.

[67] Alena Puchkova, Anna Ledwoch, Goran Stojkovic, Alexandra Brintrup, Duncan McFarlane, and Miguel Vilaplana. Resilient airline operations, 2017.

[68] Floor Richters, Jan Maarten Schraagen, and Hans Heerkens. Balancing Goal Trade-Offs When Developing Resilient Solutions : a Case Study of Re-Planning in Airline Operations Control. *The 6th Symposium on Resilience Engineering*, 2015.

[69] Judith Semar and Marius Radde. Resilient scheduling & operations, 2018.

[70] O.A. Sharpanskykh. Week 2: Languages for multiagent systems. Agent based simulation. Analysis of simulation results. Model validation. Technical report, TU Delft, Delft, Netherlands, september 2019.

[71] Yoav Shoham. Agent0: A simple agent language and its interpreter. *AAAI-91 Proceedings*, pages 704–709, 1991.

[72] S Srinivasan, Jagjit Singh, and Vivek Kumar. Multi-agent based decision Support System using Data Mining and Case Based Reasoning. *International Journal of Computer Science Issues*, 8(4):340–349, 2011.

[73] Sybert H. Stroeve, Tibor Bosse, Henk A.P. Blom, Alexei Sharpanskykh, and Mariken H.C. Everdij. Agent-based modelling for analysis of resilience in ATM. *Third SESAR Innovation Days*, 2013.

[74] Stroeve, Sybert H. and Everdij, Mariken H.C. Agent-based modelling and mental simulation for resilience engineering in air transport. *Safety Science*, 93:29–49, 2017.

[75] Richard S. Sutton and Christopher J. Matheus. Learning to Predict by the Methods of Temporal Differences. *Machine Learning*, 3:9–44, 1988.

[76] Matthieu Vert, Alexei Sharpanskykh, and Richard Curran. Resilience of complex safety-critical sociotechnical systems: Towards a unified conceptual framework and its formalization. 2019.

[77] Marc Werfs and Gordon Baxter. Towards resilient adaptive socio-technical systems. *ACM International Conference Proceeding Series*, (28):1–5, 2013.

[78] A. Willems. Flightwatch, 2012.

[79] A. Willems. Dmoc-fleetcontroller, 2016.

[80] A. Willems. Fleet scheduler, 2017.

[81] David D. Woods. Four concepts for resilience and the implications for the future of resilience engineering. *Reliability Engineering and System Safety*, 141:5–9, 2015.

[82] D.D. Woods and M. Branlat. *Chapter 10 : Basic Patterns in How Adaptive Systems Fail*. Ashgate, Farnham, UK, 2015.

[83] Cheng Lung Wu. Improving airline network robustness and operational reliability by sequential optimisation algorithms. *Networks and Spatial Economics*, 6:235–251, 2006.

[84] Ren Yu, Benoit Iung, and Hervé Panetto. A multi-agents based E-maintenance system with case-based reasoning decision support. *Engineering Applications of Artificial Intelligence*, 16(4):321–333, 2003.

[85] Christopher W. Zobel and Lara Khansa. Quantifying CyberInfrastructure Resilience against Multi-Event Attacks. *Decision Sciences*, 43(4):687–710, 2012.

[86] Christopher W. Zobel and Lara Khansa. Characterizing multi-event disaster resilience. *Computers and Operations Research*, 42:83–94, 2014.