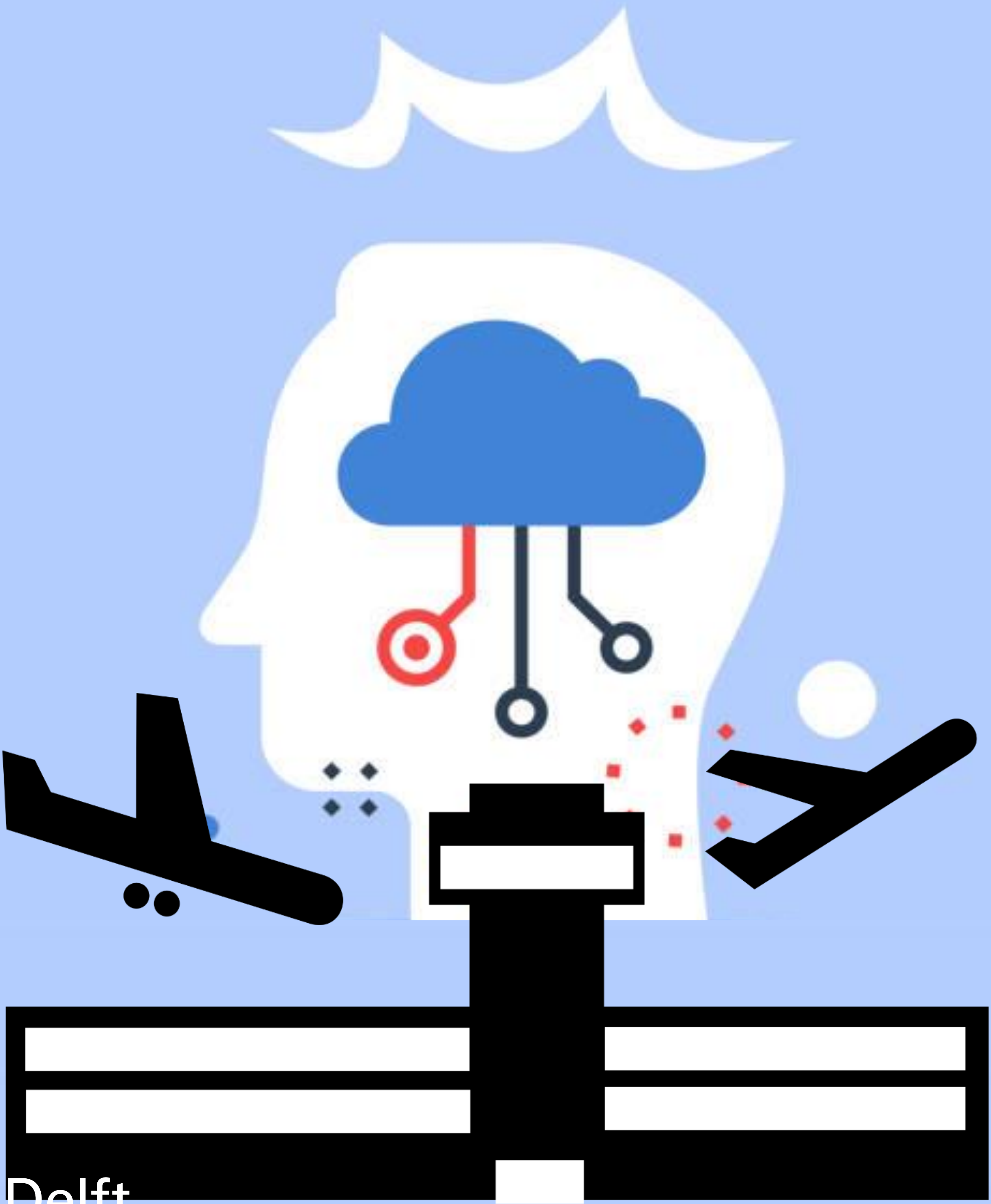
The Effect of Relationship Biases on AOCC Performance

José Maria Soengas

Technische Universiteit Delft



TU Delft

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by

José Maria Soengas

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Thesis committee:	Dr. Henk Blom TU Delft, ATO, Chair
	Dr. O. A. Sharpanskykh TU Delft, ATO, supervisor
	Ir. Olaf Stroosma TU Delft, C&S, external examiner

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Preface

Dear reader,

This thesis reports 16 months of research carried out for obtaining a Master of Science degree in Aerospace Engineering at Delft University of Technology. This work focused on understanding the effect of relationship biases on decision-makers within an Airline Operational Control Center (AOCC). Much of what was needed to conduct this research was perseverance and a thirst for knowledge. It was a long and arduous process and at times, with no end in site. But it was the light at the end of the tunnel that kept calling and I was not going to disappoint it.

I have learnt a considerable amount during the course of this research and have had discussions with more researchers than in all my previous academic life. It has been enlightening. I would like to thank Antonio Castro for giving me that first push toward AOCC disruption management modelling and those final pulls where his domain expertise reassured my approach. I would like to thank Soufiane Bourfa for sitting through my inexplicable models at times and serving as a primary reference for specifying agent properties within the context of the AOCC. Finally, I would like to thank Dr. Sharpanskykh for the incredible amout of support all along the way. Showing no remorse for providing the most constructive feedback at times and engaging in deep and thoughtful discussions in others. I personally reached out and requested that Dr. Sharpanskykh be my supervisor, as agent-based modelling at the time was very appealing to me. To this day, it has never ceased to amaze me.

This thesis will be one of the biggest milestones in an educational journey which has been in the making for decades. If I would have to do it again, I would. However, without the support of my parents, it would not have ever been possible. My father instilled a sense of curiosity and determination in me, which I should bare forever. I am indebted to my mother for the unconditional support and believing in me. It is with these last few words that I would like to thank everyone who helped me get to where I am today.

José Maria Soengas Canteli Ortega y Gasset
Munich, December 2021

Contents

List of Figures

List of Tables

List of Abbreviations

ABMS	Agent Based Modelling and Simulation
ACMI	Aircraft Crew Maintenance Insurance
aocc	Airline Operation Control Center
ARP	Aircraft Recovery Problem
CRP	Crew Recovery Problem
CS	Complex System
IDM	Intuitive decision-making
MAS	Multi-Agent System
NDM	Naturalistic decision-making
PRP	Passenger Recovery Problem
RDM	Rational decision-making
STS	Sociotechnical system
TTL	Temporal Trace Language

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Paper

The Effects of the Relationship Bias on Airlines Operational Control Center Performance

José Maria Soengas Canteli Ortega y Gasset,*

Delft University of Technology, Delft, The Netherlands

Abstract

Passengers are frequently affected by airline disruptions, leading to a poorer than expected passenger experience. Airlines are affected by disruptions in the order of billions of dollars. Managing disruptions effectively is therefore paramount for an airline's long-term commercial success. In spite of decision-support tools being introduced to facilitate Airline Operational Control Center (AOCC) decision-making, their adoption rate is low. For the foreseeable future, humans will unquestionably remain in the loop when it comes to AOCC disruption management and human-factors will continue to come into play in AOCC decision-making. To improve AOCC decision-making, the effects of human factors on decision-making must be well understood. Bias is a human factor that affects decision-making and a relationship bias is a bias where previous negative experiences, between two individuals, will negatively affect future interactions they may have. A lack of trust, unwillingness to concede (in negotiations) or even a reluctance to interact, are a few examples on how a relationship bias may operationally manifest itself. AOCC decision-makers collaborate with one another to arrive at a integrated solution that mitigates an airline's disruption. If a relationship biases exist within the AOCC, this negatively affects collaboration among AOCC decision-makers the development of solutions. The effect of the relationship bias on the solutions selected to mitigate an airline's disruptions motivates the study of the effect of the relationship bias on AOCC performance. The fact that the relationship bias on AOCC decision-making has never been research, further motivates its study. We hope to address this research gap by evaluating the effects of the relationship bias on AOCC performance. More precisely, the research objective is to evaluate the effects of the relationship bias on AOCC performance, by modelling AOCC decision-making through a Naturalistic Decision-making framework using Klein's Extended Recognition-Primed Decision model, and modelling AOCC social decision-making and interactions using Chow's Co-Ladder model. The methodology involves formalizing AOCC goals through a framework [Popova and Sharpanskykh, 2008] which enables us to measure organizational performance. Furthermore, it involves formally integrating Bruce's extension [Bruce, 2011a] of Klein's extended Recognition-primed Decision (RPD) model with Chow's social interaction model [Chow et al., 2000]. The model is finally simulated for a scenario where a scheduled flight suffers a mechanical disruption and the performance is evaluated based on a goal satisfaction and operational costs.

There are three main contributions of this research. Firstly, the individual cognition model developed makes it possible to model AOCC decision-maker's individual cognition within the complex and dynamic AOCC environment. The second contribution is the proposed integrated model, which make it possible to integrate agent individual cognition and agent social decision-making and interactions. The third contribution is the evaluation of various possible relationship biases, which makes it possible evaluate the effect of different relationship types on AOCC performance.

The research conducted led to a few interesting findings. For example, only some relationship biases lead to a significant decreased in AOCC performance, whereas other relationships have a negligible effect. Another interesting finding was that if there is a relationship bais between two agent, they are both not equally affected. The relationship bias only affects the AOCC control agent who requires information from a counterpart in order to develop their partial solution.

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

1 Introduction

EUROCONTROL reports that on average 19.2% of flights in Europe suffered from delays in Q1 of 2019 [Walker, 2019]. In this report, it is also stated that 42% of the total generated delay minutes have a reactionary cause, underlying the cascading effect of disruptions. This shows that disruptions are commonplace and also propagate throughout an airline's schedule. Flight disruptions also cost airlines between $25B and $35B annually, approximating 5% of an airline's revenue [Robyn, 2019]. Therefore, disruptions are not only frequent and an inconvenience to airlines customers, but they also incur detrimental costs to airlines. Currently, decision-support tools are being developed and introduced to facilitate decision-making within Airline Operational Control Centers (AOCCs), however these have not been fully adopted for numerous reasons [Kohl et al., 2007]. It is fair to assume that for the foreseeable future, humans will remain in the loop when it comes to disruption management within the AOCC. Therefore, airlines who understand the effects of human factors on the AOCC disruption management process, will be able to address and mitigate the effects of human factors on AOCC performance.
A human factor extensively studied and well-documented in literature is the cognitive bias [Caputo, 2013, Hannond et al., 1987, Kahneman et al., 1982]. Cognitive biases result in systematic errors and poor decision-making which strongly motivates their study as a means for potentially generating diagnostics. In fact, it has been shown that one-shot de-biasing training can significantly reduce the deleterious influence of cognitive bias on decision making by almost one third [Sellier et al., 2019]. In the research proposed, the effect of the relationship bias on AOCC performance is explored. The relationship bias was selected as the bias to study, among other biases, for two main reasons. Firstly, during AOCC disruption management, controllers collaborate as a means to gain situation awareness about environmental states, to develop partial solutions. Relationship biases may result in limited collaboration, a reduced level of situation awareness as a result the proposal of sub-optimal partial solutions by controllers to the AOCC supervisor. Secondly, relationship biases occur ubiquitously across all types of organizations [Bazerman, 1992] and therefore the outcomes of this study are valuable beyond the AOCC domain.
The relationship biases must be modelled within an individual cognition model that is able to model the relationship bias and is suitable for modelling an AOCC decision-maker's individual cognition. AOCC decision-makers face a highly dynamic and complex operational environment, difficult to predict and with a large number of conflicting goals [Bruce, 2011b].
In the research proposed, the research objective is to evaluate the effects of the relationship bias on AOCC performance, by modelling AOCC individual cognition using Klein's Extended Recognition-Primed Decision (RPD) model, and modelling AOCC social cognition and interactions using Chow's Co-Ladder model. Klein's Recognition-primed Decision-making Model is selected to model individual cognition because it balances intuition and rational analysis, which enables the fast development and evaluation of solutions that are 'good enough' [Klein, 2008]. Chow's Co-Ladder model is chosen to model social cognition and interactions because it introduces flexibly towards modelling different types of social decision-making sequences, applicable at different disruption management phases [Chow et al., 2000].
It is hypothesized that if relationship biases exist within an AOCC, AOCC performance will be reduced as a result of less cost-effective solutions and a decreased number of organizational goals being satisfied. This is because the relationship bias will reduce collaboration among decision-makers and the information needed to develop the best solution is not obtained.
We aim to contribute to this field of research in three ways. Firstly, the individual cognition model developed makes it possible to model AOCC decision-maker's individual cognition within the complex and dynamic AOCC environment. The second contribution is the proposed integrated model, which make it possible to integrate agent individual cognition and agent social decision-making and interactions. The third contribution is the evaluation of various possible relationship biases, which makes it possible evaluate the effect of different relationship types on AOCC performance.
The methodology of this research is based on the following steps. Firstly the research objective and hypothesis are formulated. Secondly, the scope of the model is primarily defined based on the case study selected. Conceptual and formal agent-based models are developed for the organizational structure, the environment, an agent's individual cognition and an agent's social decision-making and interaction. Thirdly, the model is implemented in LEADSTO which is a software that simulates dynamic processes. Fourthly, following the model implementation the AOCC performance in evaluated from a cost-based evaluation and a goal-based evaluation. Finally, verification of the models developed and validation of the results is discussed.
In section 2, related work will be discussed to outline how this paper's research positions itself among the existing literature. In section 3, the research objective and hypothesis are presented. In section 4 the case study will be outlined in detail and the choice for selecting the relationship bias as the bias to research, is motivated. In section 5 the agent-based model is outlined. In section 6 the results are analyzed and in section 7 verification and validation steps are discussed. Lastly, the conclusions and recommendations for future work are presented in section 8.

2 Related Work

In this section, works that is related and greatly contributed towards modelling during this research is presented. Further information regarding what is outlined below can be found in Appendix A, which also discusses other approaches in literature, towards modeling Airline Operational Control Center (AOCC) disruption management in a broader sense.

Decision-making Frameworks
Natural Decision-making (NDM) describes or models the way people use their experience to make decisions in natural settings [Klein et al., 1997]. Settings that are conducive to naturalistic decision-making processes are ones with ill-structured problems, uncertainty, dynamic environments, competing goals, times stress, multiple players, organizational goals and significant consequences for incorrect decisions [Lipshitz et al., 2001]. An AOCC's environment is certainly complex and dynamic, where decisions are made under time constraints.
Klein's Recognition-Primed Decision (RPD) Model
Klein's Recognition-Primed Decision (RPD) model can be used to model the decision-making process of AOCC controllers [Klein, 2008]. The model consists of two main parts, the recognition phase and a mental simulation phase. The recognition phase relies on pattern recognition, where based on cues observed and wished goals, a decision-maker can intuitively generate an action to resolve a problem that is faced. The simulation phase is a phase where the decision-maker quickly evaluates if a solution is good enough to be implemented.
Bruce researched AOCC controller's decision-making and identified that controllers raise decision-considerations while evaluating the feasibility of an action that could be implemented to mitigate an AOCC disruption [Bruce, 2011b]. Identifying decision-considerations refers to identifying possible constraint that could make an action unfeasible to implement. To this end, Bruce has proposed an extension to Klein's RPD model so it can explicitly factor decision considerations as part of the action evaluation process (simulation phase) [Bruce, 2011a].
Chow's Co-Ladder Behavioural Model
The Co-Ladder model models coordinative functions for anomaly response and coordinative functions for dynamic re-planning [Chow et al., 2000]. Coordination among AOCC decision-makers is required for decision-makers to gain situation awareness of a disruption event, to evaluate the feasibility of a potential course of action and finally to integrate various decision-makers proposals into one solution.
Groundwork For Heuristics and Biases
Tversky and Kahneman's seminal paper outlines how heuristics lead to biases that affect people's judgement during decision-making. Biases in turn result in systematic errors and poor decision-making, which strongly motivates their study as a means for potentially generating diagnostics [Tversky and Kahneman, 1974]. There have been no studies on the effect of relationship biases within the context of the AOCC domain. However, Tversky and Kahneman provide the groundwork necessary to research biases in any domain.
Organizational Modelling
Sharpanskykh et al. proposed a formal framework for modelling goals based on performance indicators, thereby explicitly defining their relationship [Popova and Sharpanskykh, 2008]. This enables evaluating the performance of an organization based on the level of goal satisfaction. This research will evaluate AOCC performance based on this framework.

3 Research Objective and Methodology

3.1 Research Objective

In the research proposed, the research objective is to evaluate the effects of the relationship bias on AOCC performance, by modelling AOCC individual cognition using Klein's Extended Recognition-Primed Decision (RPD) model, and modelling AOCC social cognition and interactions using Chow's Co-Ladder model. Klein's Recognition-primed Decision-making Model is selected to model individual cognition because it balances intuition and rational analysis, which enables the fast development and evaluation of solutions that are "good enough" [Klein, 2008]. Chow's Co-Ladder model is chosen to model social cognition and interactions because it introduces flexibly towards modelling social decision-making that occurs at different disruption management phases [Chow et al., 2000].

3.1.1 Hypothesis for Research Conducted

There are three main hypothesis for this theses. The first is tested during the cost-based performance evaluation and the two subsequent ones are tested during the goal-based performance evaluation.

1. It is hypothesized that if two agents have an unfavourable relationship bias, then the solutions implemented to mitigate a disruption, have on average, a higher operational cost.

2. It is hypothesized that if two agents have an unfavourable relationship bias, then the goals both agents wish for will be satisfied to a lesser degree.
3. It is hypothesized that the number of goals not satisfied and wished by agents, is proportional to the number of relationship biases occurring simultaneously.

3.2 Research Methodology

For this research the following research methodology is followed:

1. **Model Scope:** The scope of the model is set by selecting a case study and essential assumptions of the model are specified. The selection of the cognitive bias to research is motivated.
2. **Development of Agent-based Environmental Model:** Informational resources and environment objects are specified by attribute, attribute type and attribute range.
3. **Development of a Formal Agent-based Organizational Model:** The conceptual organizational model defines the type of agents that will be modelled, the AOCC roles these roles assume as well as the hierarchy and relationship type among agents. The formal organizational modelling of goals is performed to specify formal relationship between agents, goals and tasks performed by agents to realize goals.
4. **Development of Conceptual and Formal Agent-based Individual Cognition Model:** The individual cognition of AOCC control agents is modelled based on Klein's extended Recognition-Primed Decision model [Bruce, 2011a].
5. **Development of Formal Agent-based Social decision-making and Interaction Model:** The social decision-making and interaction of AOCC agents is modelled based on Chow's Co-ladder behavioural model [Chow et al., 2000]. The integration between the individual cognition model and the decision-making and interaction model is proposed here.
6. **Model Implementation and Verification:** The agent-based individual cognition model and the social decision-making and interaction model are implemented in integrated form in LEADSTO in the simulator environment.
7. **Results and Analysis:** The simulation results are analyzed and discussed for the case study and scenarios considered. The evaluation of the Airline Operational Control Center performance is evaluated from a cost perspective and a goal-based performance evaluation perspective.
8. **Verification and Validation:** Verification and validation of the model are discussed.

4 Description of the Case Study

The case study chosen for this research is sourced from Bruce's simulation studies of the decision-making processes of 52 controllers from six AOCC centers [Bruce, 2011b]. The reason Bruce's simulation studies are chosen as a source for this research's case study, is two fold. Firstly, Bruce's study collects a considerable amount of data regarding decision-making within the context of AOCC disruption management and more so than any other related work. Secondly, Bruce assumes the most suitable decision-making model for modelling AOCC decision-makers' individual cognition is Klein's Recognition-Primed Decision model. In fact, Bruce identified that decision-makers brought up decision considerations when evaluating potential actions to mitigate disruptions. As a result, Bruce proposed extending Klein's RPD model such that it explicitly includes decision considerations. Bruce's simulations studies enable this research to use the data gathered on AOCC decision-making and apply it to the developed agent-based models.
Bruce conducted simulation studies for six scenarios. Three domestic and three international disruption scenarios. Scenario 2 International from was selected as the case study for this research. This was done for two reasons. Firstly, Scenario 2 international is a scenario that involves the largest number of decision-makers and has the largest number of possible solutions. The larger number of degrees of freedom implies a larger variability of collaboration among decision-makers. This adds value to the research as it allows us to explore the effects of biases on a larger set of possible interactions among decision-makers, enabling a more robust understanding of the effects of biases on AOCC performance. Secondly, Bourfa also considered this scenario during his research on AOCC negotiation. Therefore, the simulation outcomes of this research can be validate against Soufiane's results, on an operational cost basis [Bouarfa et al., 2021].

4.1 Model Assumptions Based on Case Study

In the research proposed, Scenario 2 International from Bruce's study is selected as the case study [Bruce, 2011b]. In this case study, a flight is scheduled from Charles de Gaulle to an undisclosed location in the Pacific. Prior to departure, the flight suffers a mechanical breakdown. A solution is sought to mitigate the effects of the disruption, while giving consideration to the airline's available resources.

Based on Bruce's research and the selected case study we can define: (1) the actions AOCC controllers generate to mitigate the given disruption; (2) decision-considerations raised by controllers that might constrain the implementation of actions generated and (3) AOCC informational resources, that contribute towards evaluating the raised decision considerations. These are shown in Table 1, Table 2 and Table 3.

Crew Actions	Crew Decision Considerations	Informational Resources
Delay flight by repair time	Do crew exceed flight duty period	Repair time
Reroute flight via BOM	Is rerouting possible?	Crew flight duty period buffer
Utilize reserve crew	Is reserve crew available?	Rerouting possibilities
Cancel flight	Are positioning seats available?	Reserve crew availability
		Positioning seats availability

Table 1: Crew controller actions, decision considerations and relevant environmental conditions for the case study under consideration.

Passenger Actions	Passenger Decision Considerations	Informational Resources
Delay flight by repair time	Will transit passenger miss their connection?	Repair time
Connection measures	Are connection measures possible?	Transit passenger transit time limit
		Connection measures possibilities

Table 2: Passenger controller actions, decision considerations and relevant environmental conditions for the case study under consideration.

Aircraft Actions	Aircraft Decision Considerations	Informational Resources
Delay flight by repair time	Is reserve aircraft available?	Repair time
Use reserve aircraft		Reserve aircraft availability

Table 3: Aircraft controller actions, decision considerations and relevant environmental conditions for the case study under consideration.

4.2 Selecting The Relationship Bias

The biases considered for studying the effect of biases on AOCC performance where the ones that follow from Tverksy and Kahneman's seminal paper [Tversky and Kahneman, 1974] and the relationship bias. Tverksy and Kahneman's biases were considered because they are foundational to this domain of research. The relationship bias was considered because collaboration among decision-makers is paramount to AOCC performance and the relationship bias is likely to greatly affect collaboration.
The availability bias, originally researched by [Tversky and Kahneman, 1974], is not chosen as the bias to study for this research, because compared to the two other biases considered, it would require an additional level of assumptions. The assumptions necessary would be related to what is more familiar or of salience (retrievable of instances) to the decision-maker during the decision-making process, of which no data is available. The anchoring bias, originally researched by [Tversky and Kahneman, 1974], would be applicable if for the given case study, decision-makers negotiated with each other. For the given case study, this does not occur. The relationship bias however, does not require an additional set of assumption regarding decision-makers and it is applicable within the context of the case study. It is applicable because it applies when decision-makers collaborate with each other, which take place within the context of the case study.
For the reason mentioned above, the relationship bias is selected as the bias to study for this research and the effects of the relationship bias on AOCC performance will be evaluated.

5 Agent-based Model

5.1 Agent-based Enviromental Model

The high dynamic variability in the AOCC environment is due to variability in aircraft availability, regulations regarding crew flight duty period and the variability of connecting passenger. The environment is 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. Below in Table 4, the informational resources observed by decision-makers to evaluate mitigation actions considered are defined and so are the environmental objects form which they are observed. In Table 5, the attribute each information resource is defined.

Informational Resource	**Agents**	**Environment Object**
Malfunction	All AOCC agents	Aircraft
Repair time	All AOCC agents	Aircraft
Re-routing	CC, AC	Aircraft Management System
Crew duty time	CC	Crew Management System
Reserve crew	CC,	Crew Management System
Positioning seats	CC, PC	Passenger Management System
Transit buffer time	PC	Passenger Management System
Connection measures	PC, AC	Aircraft Management System

Table 4: Environment specification of informational resources from different environmental objects.

Informational Resource	**Attribute**	**Attribute Type**	**Attribute Range**
Malfunction	Identification	Binary	[0,1]
Repair time	Duration	Real number	$[0,\infty]$
Re-routing	Possibilities	Binary	[0,1]
Crew duty time	Duration	Real number	$[0,\infty]$
Reserve crew	Availability	Binary	[0,1]
Positioning seats	Availability	Binary	[0,1]
Transit buffer time	Duration	Real number	[0,1]
Connection measures	Possibilities	Binary	[0,1]

Table 5: The environmental properties under consideration can be classified by attribute, attribute type and range.

5.2 Agent-based Organizational Modelling

Formal goal modelling is performed in this research for two reasons. Firstly, formal goal modelling enables a formal specification of the relationship between organizational roles, agents, goals and tasks. These specifications are necessary to subsequently formally specify individual cognition, social decision-making and social interaction models. Secondly, formal goal modelling also provides a basis for goal-based performance evaluation, as goal structures and goal satisfaction mechanisms can be established.

The meta-model for the performance-oriented view, illustrated in Figure 1, where the first order sorted predicate language is used to express the relationships between goals and other concepts. The concepts formally specified in this research for goal modelling are roles, agents, goals and tasks.

In Appendix B, the conceptual organizational structure is modelled and the AOCC supervisor supporting agents, namely the aircraft control agent, crew control agent and passenger control agent, each assume more than one AOOC role. However, the controller roles and the resource supervisor roles (e.g. crew manager) are committed to different goals in spite of their goals being wished by a single control agent. The performance of the AOCC is however independent of which goals each role is committed to, are directly related to the solutions arrived at (cost-based performance) and the goal satisfied (goal-based performance). Therefore, the specification of the relationship between roles and goals is not formally specified.

The relationship between goals and agents is central to the individual cognition model developed in this research. The relationship between goals, agents and tasks are also central to the social decision-making and interaction

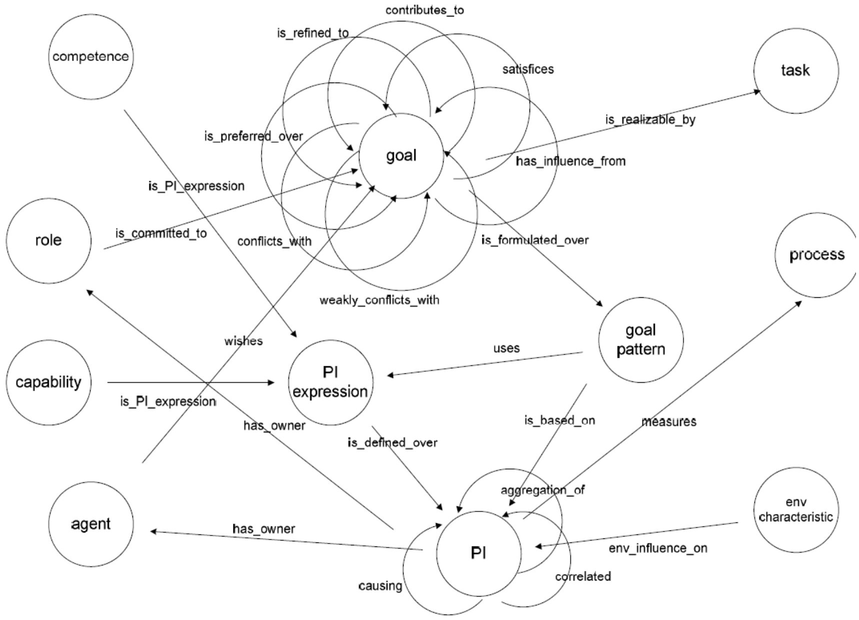

Figure 1: A Meta-model for the performance-oriented view.

model developed in this research.

In section 5.3.2, the individual cognition model is formally specified. The formal specification of goals with respect to agents is required for this. Below, the relationship between agents and goals is specified within the context the case study and individual cognition. The individual cognition model is modelled for a control agents to generate (output) an action (to mitigate a disruption) based on observed (inputs) cues and wished goals. The goals that are relevant for this are the goals related to the generation of actions. In the goal structures developed and presented in Appendix B, the goals that are relevant for the development of a solution are shown. Below, the formal goal specification, in the first-order predicate language, is illustrated for the goals relevant for the development of a solution from an action perspective and relevant for the specification of the individual cognition model. The first order predicate logic used to specify the relationship between the AOCC control agent and goals the agent is committed to is wishes: AGENT X GOAL. Below, the formal specification of the goals the crew, passenger and aircraft control agents wish for, and that are related to the generation of a mitigation action, is presented.

The formal specification of the relationship between Crew Control agent and goals that are relevant during the development of a solution is shown below:

- wishes(CrewControl,G1.3.2)
- wishes(CrewControl,G1.3.3.1)
- wishes(CrewControl,G1.3.3.2)
- wishes(CrewControl,G1.3.4.1)
- wishes(CrewControl,G1.3.4.2)

The formal specification of Passenger Control agent goals, relevant during the development of a solution is shown below:

- wishes(PassengerControl,G1.4.2.1)
- wishes(PassengerControl,G1.4.2.2)
- wishes(PassengerControl,G1.4.3)

The formal specification of Aircraft Control agent goal G1.2.3, relevant during the development of a solution is shown below:

- wishes(AircraftControl,G1.2.3)

In section 5.4.3, the social decision-making and interaction model is formally specified. The formal specification of the relationship between agents, goals and tasks is required for this. Below, the relationship between agents, goals and tasks is specified within the context of the case study and social decision-making and interactions. The first order predicate logic used to specify the relationship between a goal and a task list (where the task in the first argument is within the list of tasks in the second argument) is as follows, s_in_task_list: TASK X TASK_LIST. The first order predicate logic use to specify the relationship between a goal and a task list (where the goal in the first argument is realizable by the list of tasks in the second argument) is as follows: is_realizable_by_by: GOAL X TASK_LIST. The description for the tasks specified below are shown in Appendix B in Table 15, Table 16, Table 17 and Table 18.

The relationships between Crew Control agent, task lists, tasks and Crew Goal G1.3.1.0, which is related to social decision-making and interactions is shown below:

- wishes(CrewControl, G1.3.1.0)
- is_in_task_list(T1.3.1.0.1, TL1310)
- is_in_task_list(T1.3.1.0.2, TL1310)
- is_in_task_list(T1.3.1.0.3, TL1310)
- is_in_task_list(T1.3.1.0.4, TL1310)
- is_realizable_by_by(G1.3.1.0, TL1310)

The relationships between Crew Control agent, task lists, tasks and Crew Goal G1.3.1.1, which is related to social decision-making and interactions is shown below:

- wishes(CrewControl, G1.3.1.1)
- is_in_task_list(T1.3.1.1.1, TL1311)
- is_in_task_list(T1.3.1.1.2, TL1311)
- is_in_task_list(T1.3.1.0.3, TL1311)
- is_in_task_list(T1.3.1.0.4, TL1311)
- is_realized_by(G1.3.1.1, TL1311)

The relationship between Passenger and Aircraft Control agents, task lists, tasks and goals related to social decision-making and interactions are shown in Appendix B.

5.3 Individual Cognition Model

5.3.1 Conceptual Individual Cognition Model

Klein's RPD Model

Klein's originally proposed Recognition-Primed Decision (RPD) model is a decision-making model based on a Naturalistic Decision-making (NDM) framework. The NDM framework is one that models human decision-making in a natural, dynamic and complex environment. Klein's RPD model is frequently acknowledged as a model that is representative of the way in which decisions are made in the real world [Hedlund and Sternberg, 2000, Bruce, 2011b]. For this reason, this research has chosen to model the individual cognition of agents, using Klein's RPD model. Klein's RPD model has two main phases as illustrated in Figure 2 and these two phases are subsequently discussed.

The recognition phase is the pattern matching phase and intuitive part. This is where people use their experience in the form of a collection of patterns. These patterns recognize causal factors such as relevant cues and goals and suggest typical types of actions in a specific situation. This allows decision-makers to quickly match situations to patterns and make quick decisions.

During the simulation phase, decision-makers evaluate a course of action with a mental simulation. In the context of the AOCC, decision-makers would imagine how a generated action would play out within the context of an on-going disruption. If the action generated were to be a working solution, an AOCC decision-makers would select and propose the action as a potential solution to the disruption. Otherwise, they would consider other actions until they found an action that is feasible to implement.

Klein's extended RPD Model

Bruce conducted as study where 52 controllers from six AOCC centers were studied in response to simulations of airline disruptions [Bruce, 2011b]. These simulation studies identified that controllers involved in the disruption management process raise decision considerations regarding possible constraint that would make the implementation of a generated action not feasible. Bruce also identified that the mental simulation process, as originally proposed by Klein in his Recognition-Primed Decision model, does not explicitly account for decision considerations raised by AOCC controllers. Bruce therefore proposed that the RPD model should account for how decision-makers raise decision consideration as they mentally simulate whether generated mitigation actions can be implemented. Bruce proposed raising decision considerations as an interactive component of the mental simulation stage and is highlighted in bold in Figure 2.

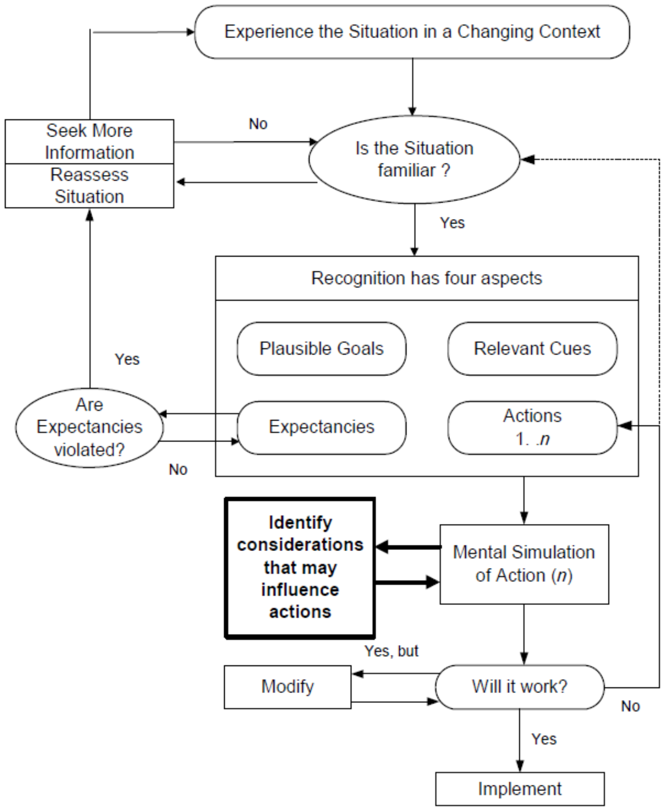

Figure 2: Bruce's proposed revision of Klein's (1993) RPD model [Bruce, 2011a].

Klein's extended RPD Model Concepts

The model components within the recognition phase and the simulation phase are now defined.

The recognition phase is the pattern matching phase where decision-makers use their experience in the form of a collection of patterns that describe causal factors. These causal factors are accounted for in the recognition phase of the model, namely: (1) Plausible Goals, (2) Relevant Cues, (3) Expectancies and (4) Actions. The mental simulation phase is one where the decision-maker imagines how the action generated during the recognition phase would play out in the context of the operational current situation. Klein's extended RPD model, further includes an interactive component to the simulation phase where decision-makers raise decision considerations.

The notions of Plausible Goals, Relevant Cues, Actions, Expectancies and are defined as follows:

- The notion of goals follows from the framework goal modelling framework proposed by Sharpkanskykh et al.'s work [Popova and Sharpanskykh, 2008]. By definition it is an objective to be satisfied describing a desired state or development of the company or an individual.
- Expectancies represent states of what is expected as result of an action. Within the case study's context, when an action is generated, the decision-maker will expect the action to be a solution capable of mitigating the effects of the disruption. The violation of an expectancy will trigger the initialization of a decision-making process to generate a new action. If a decision consideration constraint is evaluated against a

generated action, and it is found the the action is unfeasible (an unworkable solution), the expectancy that this action would mitigate the disruption, is violated.

- Cues are observations of the environment that contribute towards defining the scope of a allowable action for a given disruption problem. In the context of the case study under consideration, there are two types of cues. The first type is related to the source of the disruption. For instance the cue "request solution to mechanical breakdown" is used to generate actions that address this specific type of disruption. The second type of cue is related to the observation of expectancy violations. In the context of this case study, an expectancy is violated when it is found that a generated action is not a working solution. If an expectancy is observed to be violated, this violation becomes a cue in itself, restricting the scope of the solution space to one that excludes previously generated actions.

- An action is a potential solution to an airline disruption, which if feasible and implemented, will mintage the negative effects of the operational disruption. The actions generated follow from the set of cues and goals held by the decision-maker, as further discussed below in the model assumptions. Actions are the output of the recognition phase and are then mentally simulated in the context of the operational disturbance.

An action generated within the recognition phase of Klein's extended RPD model, follows from a set of cues observed and goals an agent wishes. The goals agent's wish for, within the context of the case study and the recognition phase (action generation phase), are specified in section 5.2. The actions and environmental conditions relevant for each decision-maker are outlined in section 4.1 and are derived from Bruce's research [Bruce, 2011b]. For the same set of goals wished for by an agent, different cue observed will lead to different actions generated. The recognition phase of Klein's RPD model is formally specified in section 5.3.2, where the relationship between agents, goals, action and expectancies is formalized.

The role of the mental simulation phase should be regarded as the analytical part of the RPD model. Control agents imagine how actions play out in the context of an on-going disruption. If the action generated is evaluated to be implementable during the simulation phase, the AOCC decision-maker will believe the actions to a working solution. Bruce's proposed the introduction of decision considerations as an interactive part to the mental simulation. The notion of a decision consideration is defined below:

- Notably, decision considerations should not be confused with cues which are referred to variously as sources of information. Within the context of the AOCC, controllers solving disruptions have many considerations such as crew availability, maintenance limitations, airport restrictions, curfews and many others. Decision considerations may influence a decision-maker's choice of whether an action is workable or not. In this research, decision considerations are defined as constraints a decision-maker must take into account to determine whether an action generated is feasible and thus a working solution that can be implemented.

The simulation phase of Klein's extended RPD model is formally specified in section 5.3.2, where the relationship between agents, actions and decision considerations is formalized.

It should be noted that there is an additional component to the RPD model, outside of the recognition and simulation phase, namely the "Will it work" module. Consider a situation where following a mental simulation, an action is considered to be an implementable solution because it is found to be capable of coexisting within the given operational environment. The "Will it work" module models this individual cognition process, which leads a decision-maker to believe whether an action is implementable or not.

Relationship between goals and actions

Each decision-makers' set of possible *actions* for mitigating a disruption within the context of the chosen case study, is defined in section 4.1. *Goals* are also formally modelled in section 5.2, for decision-makers within the assumed organizational structure. The relationship between actions generated by agents and the goals they wish is conceptually modelled below. It is re-emphasized that, cues are observations of the environment that contribute towards defining the scope of actions generated. For instance, a cue may be that a previously generated action is unfeasible. The respective action would therefore not be within the scope of new actions generated, regardless of goals wished by the control agent. The implications of this are that, the relationship between the goals wished and actions generated during Klein's RPD model recognition phase, is subject to cues observed by a control agent. The contribution of cues to the recognition phase become clearer during the formal specification of Klein's RPD model in section 5.3.2.

A conceptual framework is proposed for the relationship between control agent goals and actions. This framework ranks goals based on their relative contribution towards the satisfaction of control agent goals. The framework is illustrated in Table 6 and the ranking defined is numerical, where the number (1) is defined as the most preferred action and the number (4) is the least preferred. Initially each action is ranked with respect to their relative contribution towards a goal, when compared to other alternative actions. Then, for each action, a total average is calculated and this is used to rank the order of preference for actions.

The order of preferred actions defines the order in which actions are generated during the recognition phase. Consider that is the most preferred action action is firstly generated and then found to be unfeasible (simulation phase) to implement, then subsequently the second preferred action is generated and evaluated for.

The criteria used to define the relative rank of each action with respect to one goal is done based on a case by case basis depending on the goal definition. If the goal's goal pattern is of type avoid, then all actions that allow for the satisfaction of the respective goal are equally ranked. If the goal's goal pattern type is to minimize costs, then costs such as resource (crew / aircraft) costs, legal (passenger compensation costs) are considered.

For the crew control agent, there are four goals that drive action generation and these are shown in Table 6. It is observed that Delay is the most preferred action, followed by Re-route. Based on the ranking, Cancel is preferred to Reserve crew because it performs better with respect to the goals the crew control agent is committed to. However, while validating this framework and its outcomes with domain experts, it is concluded that the crew control agent will in practice, prefer to propose the utilization of reserve crew over cancelling the flight. The reason for this is that, cancelling the flight is the least desirable action from an airline's perspective.

	Crew Action			
Crew Goal	**Delay**	**Re-route**	**Reserve crew**	**Cancel**
G1.3.3.1 - Avoid utilizing reserve crew	(1)	(1)	(2)	(1)
G1.3.3.2 - Minimization of crew schedule disturbance	(1)	(3)	(4)	(2)
G1.3.4.1 - Minimize crew ground time	(1)	(2)	(3)	(3)
G1.3.4.2 - Minimize direct crew costs	(1)	(2)	(4)	(3)
Total Average	(1)	(2)	(3.25)	(2.25)

Table 6: Linking crew control agent goals to crew control agent actions.

For the passenger control agent, there are two goals that drive action generation and these are shown in Table 7. It is observed that Delay with passengers connecting is the preferred action over Delay without passengers connecting.

	Delay (pax connect)	**Delay (pax do not connect)**
Minimize Delay	(1)	(2)
Minimize Costs	(1)	(2)

Table 7: Linking passenger control agent actions to passenger control agent goals.

For the aircraft control agent, there is one goals that drive action generation as shown in Table 8.

	Delay Flight	**Utilize reserve aircraft**
G1.2.3 - Avoid utilizing reserve aircraft	(1)	(2)

Table 8: Linking aircraft control agent goals to aircraft control agent actions.

When formalizing individual cognition, it will become apparent how cues and goals jointly contribute towards the generation of actions. Before formalizing the individual cognition model, the conceptualization of the relationship bias within the individual cognition model is discussed.

This relationship between goals and actions is conceptualized above. The role cues take during the recognition phase is reducing the scope of actions generated by excluding actions defined to be unworkable solutions. The relationship between agents, cues, goals, actions and expectancies, during the recognition phase of Klein's RPD model, is formally specified in section 5.3.2.

Integrating the relationship bias
The relationship bias is defined as one where previous experiences between two people affect the selection process of a negotiating or collaborative counterpart [Reb, 2010]. If two people have had unfavourable previous experiences while collaborating or negotiating with one another, then, they are less likely to collaborate or negotiate with each other.

In the research proposed the relationship bias results in control agents' unwillingness to collaborate with each other. It is therefore modelled that, if a control agent identifies it must request information from an agent, with whom it has an unfavourable relationship with, the control agent considers the action to not be a working solution. This will result in the violation of an action's expectancy, triggering the generation of a new action.

The effect of the relationship bias is present within the simulation phase of Klein's extended RPD model. The relationship between agents, the relationship bias and the violation of expectancies is formally specified in section 5.3.2.

5.3.2 Formal Individual Cognition Model

In this research, the Temporal Trace Language (TTL) is employed to specify agent-based model dynamic properties. This language is chosen to model dynamic properties because it allows for combining quantitative and qualitative aspects as well as enabling the analysis of relations between local and global properties of the AOCC model. The fact that this language is widely used in multi-agent systems modelling, further motivates its selection [Sharpanskykh and Treur, 2010].

The formal specification of Klein's extended RPD model will specify AOOC control agent's individual cognition and therefore the local cognitive properties of AOCC control agents. After the ontology of the agent-based model relevant to Klein's RPD model is formalized, the specification of agent's local cognitive properties is divided in two parts. Firstly the local cognitive properties characterized by the recognition phase are specified, and subsequently the local cognitive properties characterized by the simulation phase are specified.

Ontology for the Agent-based Model within the context of individual cognition
An ontology formally defines all the components of the agent-based model and is a set of sorts, sorted variables, constants, functions and predicates.

To describe the agents modelled, the sort AGENT is introduced. The terms of this sort correspond to the agents being modelled namely, the AOOC supervisor agent, and the AOCC aircraft, crew and passenger control agents.

Sort	Terms	Description
AGENT	occs	Operation Control Center Supervisor
	pc	Passenger Control Agent
	cc	Crew Control Agent
	ac	Aircraft Control Agent

Table 9: Terms of the sort AGENT

To describe the concepts within Klein's extended RPD model, the following ontological elements are introduced:

Sort	Description
CUE	Cues used to generate actions
EXPCY	Expectancies regarding actions generated
ACTION	Actions generated based on goals and cues
DECCON	Decision considerations identified to evaluate workability of action
WORKS	Workability of action generated

Table 10: All sorts necessary to conceptualized concepts within Klein's extended RPD model.

The terms of each sort described above are formally specified in Appendix F, where the agent-based models is specified in detail. The predicates used for specifying concepts of a control agent's local cognition within Klein's extended RPD model are outlined below:

- kcue(ob: AGENT, c: CUE)

- kexpectancy(ob: AGENT, exy: EXPCY)
- kaction(ob: AGENT, a: ACTION)
- kdc(ob: AGENT, d: DECCON)
- kworks(ob: AGENT, d:WORKS)

The predicate name (e.g kcue) corresponds to a single concept within Klein's RPD model. The first predicate argument corresponds to a control agent. The second predicate argument corresponds to terms in the sort that corresponds to the respective predicate concept. For instance, the second argument of the predicate kcue, corresponds to terms in the sort CUE which corresponds to the concept of a cue (e.g find_pc_disruption_sol). Agents communicate with each other as a means to collaborate. The following ontological elements are introduced to describe the model communication elements are outlined below:

Sort	Description
MSG_TYPE	The type of message (request, inform)
MSG	Message that is being exchanged among agents

Table 11: Sorts for communication among agents.

The sort MSG_TYPE is used to refer to the type of messages communicated among agents and its terms are described in Table 12. The sort MSG comprises of all messages communicated among agents. The terms for the sort MSG can be found in Appendix F, where the agent-based model is specified in detail. The terms of the sort MSG_TYPE are outlined below:

Sort	Term	Description
MSG_TYPE	Request	When one agent requests information from another agent
	Inform	When one agent informs another about information

Table 12: Terms of the sort MSG_TYPE

Two types of messages are modelled. Message for requesting information and messages for informing about information. This distinction is important as the type of social decision-making that follows from an observe message is dependent on the message type.
The predicates used in agent-based model for specifying the belief internal states, communication activities and environmental states are the following:

Predicate	Description
belief(ob: AGENT, v: MSG)	Agent ob believes that message v is true in the world
communicate(sen: AGENT, ob: AGENT, t: MSG_TYPE, v: MSG)	Agent sen communicates to agent ob message type t with content v
disruption(DT, AC, AP)	describes a disruption of type DT, concerning aircraft with registration code AC, at airport AP

The ontology outlined above is necessary to specify the agent local properties for both the recognition and simulation phase of Klein's RPD model.

Specification of local cognitive properties within the recognition phase of Klein's extended RPD model
An example is used to showcase the specification of the agent local cognitive property that formalizes the recognition phase of Klein's extended RPD model. The concepts from the recognition phase that are formalized are cues, goals, action and expectancy. In this example the crew control agent is requested to find a crew solution, by the AOCC supervisor agent, following a mechanical disruption.

1. **Semi-formal description:** For any time t, if crew control agent observes cue 'find crew solution" and observes cue "repair time is rt" and crew control agent wishes goals G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1 and G1.3.4.2, then there exists a time t', where t' is greater than t, that crew control agent generates action "extend crew duty time" and crew control agent will have expectancy "extending crew duty time will mitigate solution".

- **Formal specification:**
$\forall$t at(kcue(cc, find_cc_disruption_sol), t) & at(kcue(cc, repair_time_(rt)), t) & G1.3.2 == True & G1.3.3.1 == True & G1.3.3.2 == True & G1.3.4.1 == True & G1.3.4.2 == True $\Rightarrow$ $\exists$ t' t' > t & at(kaction(cc, action_extend_crew_duty), t') & at(kexpectancty(cc, extending_crew_duty_time_will_mitigate_disruption), t')

Specification of local cognitive properties within the simulation phase of Klein's extended RPD model

An examples is used to showcase the specification of an agent's local cognitive property that formalizes the simulation phase of Klein's extended RPD model. The concepts from the simulation phase that are formalized are action and decision consideration. In this example, following the generation of action 'extend crew duty', the crew control agent identifies the consideration 'crew flight duty period buffer' which is a constraint on the possible extension of crew.

For local property 2, a decision consideration is identified to evaluate the feasibility of an action generated.

2. **Semi-formal description:** Semi-formal: For any time t, if crew control action is reroute, then there exists a time t', where t' is greater than t, when crew decision consideration is to determine if reroute is possible.

- **Formal specification:**
$\forall$t at(kaction(cc, action_extend_crew_duty), t) $\Rightarrow$ $\exists$ t' t' > t $_& at(kdc(cc, crew_flight_duty_limit), t')

Following the identification of the decision considerations exemplified above, the crew will interact with the environment (crew management system) to gather the remaining time crew has before crew duty time limit is exceeded. An interaction model is required to specify the respective interaction and the social decision-making and interaction model is modelled in the section 5.4. Following the observation of information regarding the crew flight duty period buffer, the simulation phase would continue. Within the context of the example provided, the crew control agent would evaluate whether the repair time exceeds the crew flight duty period buffer, to determine whether crew operation would remain legal by extending crew duty by the repair time. This evaluation part of the simulation is specified below:

3. **Semi-formal description:** For any time t, if crew control agent believes crew duty time limit ct, and crew duty time limit ct exceeds repair time rt, then there exists a time t', where t' is greater than t, where extending crew duty time is a working solution.

- **Formal specification:**
$\forall$t at(belief(cc, crew_duty_time_limit_ct), t) & ct >= rt $\Rightarrow$ $\exists$ t' t' > t $_& at(kworks(cc, extending_crew_duty_time_works), t')

Following the output of the simulation, if the result is as shown above and the action is a working solution, the control agent will propose the action to the AOCC supervisor. This proposal can be specified using an interaction model.

Specification of relationship bias

If an unfavourable relationship bias exist among agents, this is modelled as an agent avoiding collaborating with other agents. More specifically, when an agent identifies it requires information from another agent to evaluate the feasibility of an action, the former agent will not consider the action to be a working solution. Consequently the agent's expectancy that the action will mitigates the disruption is violate and as a result a new action is generated. The expectancy violation is modelled as a cue, used in the recognition phase, to scope actions that are considered non working solution from being generated. The dynamic properties specified bellow illustrate this sequence of actions for a running example. The running example is one where the crew agent identifies the decision-consideration 'determine_if_rerouting_is_possible following the generation of crew action to reroute the flight.

The crew and aircraft control agents have a unfavourable relationship bias. This results in the simulation phase of the crew control agent outputting that the rerouting is not a working solution:

4. **Semi-formal description:** For any time t, if crew control decision consideration is to determine if reroute is possible and a relationship bias between crew and aircraft control agents exists, then there exists a time t', where t' is greater than t, when crew control does not consider rerouting a working solution.

- **Formal specification**

∀t at(kdc(cc, determine_if_reroute_possible), t) & bias_cc_ac_1 ⇒ ∃ t' t' > t & at(kworks(cc, rerouting_does_not_work), t')

If an action is unworkable, then the expectancy that the action is a solution that mitigates the disruption is violated.

5. **Semi-formal description:** For any time t, if crew action rerouting is not a working solution, then there exists a time t', where t' is greater than t, when crew control expectancy that crew action rerouting is a mitigating solution, is violated.

    - **Formal specification:**

    ∀t at(kworks(cc, rerouting_does_not_work), t) ⇒ ∃ t' t' > t & at(kexpectancy(cc, violated_reroute_mitigates_solution), t')

If an expectancy is violated, this violation becomes a cue.

6. **Semi-formal description:** For any time t, if crew control agent's expectancy that rerouting mitigates the disruption is violated, then there exists a time t', where t' is greater than t, when rerouting does not work becomes a crew cue.

    - **Formal specification:**

    ∀t at(kexpectancy(cc, violated_reroute_mitigates_solution), t) ⇒ ∃ t' t' > t & at(kcue(cc, rerouting_does_not_work), t')

If an expectancy is violated, this triggers the generation of a new action by a control agent.

7. **Semi-formal description:** For any time t, if crew control agent observes cue 'violated and observes cue "repair time is rt" and crew control agent wished goals G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1 and G1.3.4.2, then there exists a time t', where t' is greater than t, that crew control agent generates action "extend crew duty time" and crew control agent will have expectancy "extending crew duty time will mitigate solution".

    - **Formal specification:**

    ∀t at(kexpectancy(cc, violated_reroute_mitigates_solution), t) & at(kcue(cc, rerouting_does_not_work), t) & G1.3.2 == True & G1.3.3.1 == True & G1.3.3.2 == True & G1.3.4.1 == True & G1.3.4.2 == True ⇒ ∃ t' t' > t & at(kaction(cc, action_reserve_crew), t') & at(kexpectancty(cc, reserve_crew_mitigates_disruption), t')

In section 5.3, the individual cognition model concepts are defined and the model is specified within the context of the case study. The ontology for the agent-based model within the context of individual cognition is introduced. Many of these ontological elements are also largely relevant for social decision-making and interaction modelling as is shown in section 5.4. Fianlly the specification of the dynamic properties relvant for modelling the effect of the relationship bias on decision-making are formally specified for a running example where the crew and aircraft control agent have an unfavourable relationship bias.

5.4 Social Decision-making and Interaction Model

Social decision-making and interactions will be modelled using a behavioural model. The model that is chosen to model social behaviour and interactions is the Co-Ladder model[Chow et al., 2000]. The Co-ladder model provides the flexibility for modelling social decision-making because different co-ladders can be modelled depending on the forms of collaboration needed during the disruption management phase. This is flexibility is the main reason the Co-Ladder model is selected as the model to model social decision-making and interactions.

Chow's Co-Ladder model is illustrated in Figure 3. Social decision-making is triggered by observations or analysis. Observations within the context of the selected case study, result from incoming communications from other AOCC agents or environmental objects (e.g Crew Management System). Analysis refers to the outputs from the individual cognition model that are relevant for collaboration among agents. Following an observation, plans, activities or expectations may be generated. During analysis, the observation is interpreted and cognitive processes such as problem solving can be performed. From an analysis and a set of goals held by an agent, a plan is being generated which consists of an activity or sequence of activities. An activity in our case study is the communication (informing or requesting) of information. Finally an expectation is set based on the execution of an activity. Within the context of the selected case study, an agent would expect another agent to respond

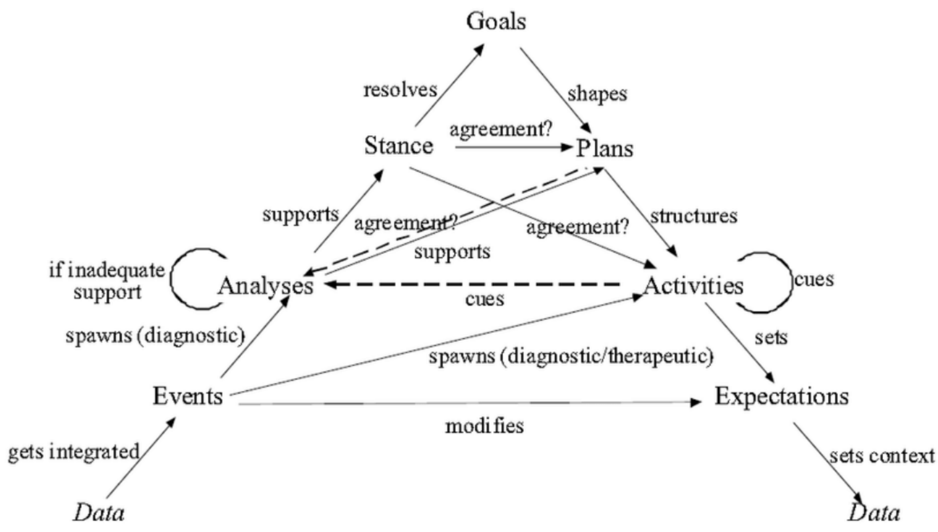

Figure 3: Co-ladder framework [Chow et al., 2000]

to an information request, or expect the supervisor to accept a proposed solution. All social interaction goals are defined within each agent's goal structures and are used for modelling social interactions within Chow's co-ladder model framework.

Social decision-making and interactions are formally specified in section 5.4.3.

5.4.1 Conceptual Modelling of Social Decision-making and Interactions

Social decision-making and interactions are modelled with five co-ladders. The co-ladders modelled in this research are highlighted below the social decision-making associated to each co-ladder model is further elaborated on subsequently:

1. Observation → (Plan + Goals) → Activity → Expectation
2. Analysis → (Plan + Goals) → Activity → Expectation
3. Observation → Activity → Expectation
4. Observation → Activity
5. Observation → Analysis → (Plan + Goals) → Activity

The first co-ladder model applies when the AOCC supervisor agent observes the mechanical disruptions, plans to request a solution form all AOOC control agents based on its goals, requests solutions from all AOOC control agents and expects them to propose a solution to mitigate the disruption.

The second co-ladder applies in two social contexts. The first is when a control agent, following analysis, plans to request another agent about the state of an informational resource relevant towards the contribution of its goals. And subsequently, requests this information to another agent form which the expectation is made that this agent will reply with the information requested. The second case where the second co-ladder applies is when an agent following analysis output that an action should be proposed to the supervisor, the agent plans to propose the action as a solution to the supervisor which is something also relevant to the contribution of its goals. And subsequently, proposes the action as a solution to mitigate the disruption and with the expectation that the AOCC supervisor will accept the proposed action.

The third co-ladder applies when an agent observes the request of another agent regarding the state of an informational resource. As a result, the agent will request this state to an environmental object, and expect the environmental object to inform the agent about the state of the informational resource.

The fourth co-ladder applies when a control agent observes an inform message from the environment regarding the state of an informational resource and communicates this back to the agent who originally requested this information from it.

The fifth co-ladder model applied when the AOCC supervisor agent observed the proposed solutions. When the AOCC supervisor observes the proposed solutions it will analyze them to evaluate their fit. Following this analysis, the supervisor might plan to request a new proposal from one or more control agents which also contributed towards the AOOCS supervisor goals. As a result of this plan, the supervisor will execute one or a sequence of activities depending on the formulated plan. One activity may constitute requesting a new solution from an AOCC control agent. Another activity may constitute in communicating the selected integrated solution to all AOCC control agents.

5.4.2 Conceptual Modelling of Integration Between Individual Cognition Model and Social Decision-making and Interaction Model

This research proposes the integration of a individual cognition model with a social decision-making and interaction model. The individual cognition model is based on Klein's extended RPD [Bruce, 2011a] and the social interaction model is based on Chow's Co-Ladder model [Chow et al., 2000]. The proposal consists on embedding Klein's extended RPD model within the concept of analysis in Chow's analysis module, as illustrated in Figure 4.

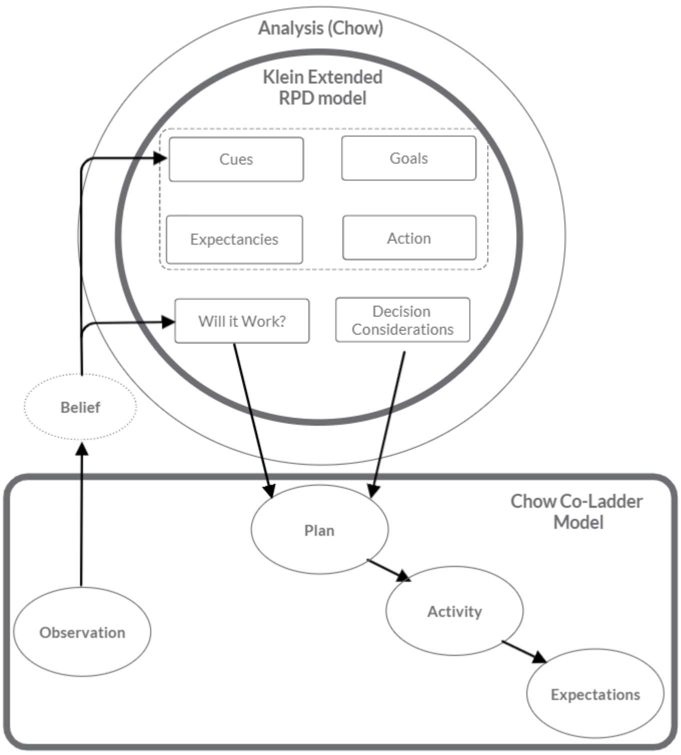

Figure 4: Proposed integrated individual cognition with social interaction model.

The interfaces between concepts within Chow's Co-Ladder model and Klein's extended RPD model are now defined. There are two cases where individual cognition leads to social decision-making and two cases where social interactions lead to individual cognition.

Cases where individual cognition leads to social decision-making:

1. The first case where individual cognition leads to social decision-making is when an control agent observes an inform message regarding the state of an informational resource. If the state of the informational resource means that the action generated (which itself led to the identification of the decision consideration regarding the information resource) is a working solution, then the agent will plan to propose the respective action.

2. The second case where individual cognition leads to social decision-making is when a decision consideration is raised with respect to an action generated, and this consideration requires an agent to request the state of an informational resource to another control agent. If there is no relationship bias between the respective control agents, then the former control agent will plan to request the informational resource from the latter control agent.

Cases where social interaction leads to individual cognition:

1. The first case where social decision-making leads to individual cognition is when a control agent observes an message information about a requested informational resource which is relevant to evaluate the feasibility of an action generated. If the observation is made that the informational resource imposes a constraint of the action that makes it one that is not implementable, then the individual cognition of the control agent will identify the action as a non working solution. If the observation is made that the informational resource does not impose a constraint on the generated action, then the individual cognition of the agent will identify the action to be a working solution.

2. The second case where social decision-making leads to individual cognition is when a control agent observes the inform message from the AOCC supervisor regarding the request of a solution. This observation leads to a cue in the agent's individual cognition model.

5.4.3 Formal Modelling of Social Decision-making and Interactions

Ontology for the Agent-based Model within the context of social decision-making & interactions
To describe the concepts within Chow's Co-Ladder model which are used to model the agent-based model's social decision-making and interactions, the following ontological elements are introduced:

Sort	Description
PLAN	Plans generated following an analysis
EXPECTATION	Expectations following the execution of a given action or sequence of actions

Table 13: All sorts necessary to conceptualized concepts within Chow's co-ladder model

The terms in sort PLAN and sort EXPECTATION are specified in Appendix F, where the agent-based model is specified in more detail.
The predicates used for specifying social decision-making and interaction properties among agents and between agents and the environment, are presented below:

- cobserves(ob: AGENT, sen: AGENT, t: MSG_TYPE, v: MSG)
- cplan(ob: AGENT, p: PLAN)
- cexpectation(ob: AGENT, exp: EXPECTATION)

The predicate name (e.g. cobserves) correspoinds to a single concept within Chow's Co-Ladder model. The first argument of any predicate corresponds to the agent whose social behaviour is being modelled.
Regarding the other arguments within the predicate 'cobserves', the second argument corresponds to the agent from which a message is being sent. The third argument corresponds to the message type that is being sent (inform/request) and the fourth argument corresponds to the message that is being observed.
Regarding the second argument of the predicate 'cplan', this corresponds to agent plans regarding social decisions and interactions.
Regarding the second argument of the predicate 'cexpectation', this corresponds to the expectations regarding social activities executed (e.g. expectation of a response following the request of the state of an informational resource).

Specification of social decision-making and interactions properties
The conceptual modelling of the integration between the individual cognition model and the social decision-making and interaction model was presented in section 5.4.2. In this section, the specification of the social decision-making and interaction model is done in light of the integration between the individual cognition model and the social decision-making and interaction model. Two examples will be used to formally specify social decision-making and one example to specify social interaction.

The first example used to specify agent social decision-making in light of the integration between the individual cognition and social decision-making is based on the second co-ladder model. The first example is specific to when a control agent following the identification of a decision consideration regarding an action it generated, plans to and subsequently requests the state of an informational resource relevant for the evaluation of the action.

8. **Semi-formal description:** For any time t, if crew control agent identifies decision consideration whether reroute is possible, then there exists a time t', where t' is greater than t, when crew control agent plan is to find if reroute is possible.

   - **Formal specification:**
   ∀t at(kdc(cc, determine_if_reroute_possible), t) ⇒ ∃ t' t' > t & at(cplan(cc, find_reroute_possible), t')

9. **Semi-formal description:** For any time t, if the crew control plan is to find if reroute is possible and crew control agent has goal G1.3.1.1, then there exists a time t', where t' is greater than t, when crew control requests if reroute is possible to aircraft control.

   - **Formal specification:**
   ∀t at(cplan(cc, find_reroute_possible), t) & G1.3.1.1 == True ⇒ ∃ t' t' > t & at(communication(cc, ac, request, is_reroute_possible), t')

The second example used to specify agent social decision-making in light of the integration between the individual cognition and social decision-making is also based on the second co-ladder model. The second example is specific to when a control agent finds an action to be a working solution and subsequently plans and proposes the solution to the AOCC supervisor.

10. **Semi-formal description:** For any time t, if crew control agent identifies rerouting to be a working solution, then there exists a time t', where t' is greater than t, when crew control agent plan is to propose reroute as a solution.

    - **Formal specification:**
    ∀t at(kworks(cc, rerouting_works), t) ⇒ ∃ t' t' > t & at(cplan(cc, propose_reroute), t')

11. **Semi-formal description:** For any time t, if the crew control plan is to propose reroute as a solution and crew control agent has goal G1.1.1, then there exists a time t', where t' is greater than t, when crew control agent informs AOCC supervisor agent crew solution is reroute.

    - **Formal specification:**
    ∀t at(cplan(cc, propose_reroute), t) & G1.1.1 == True ⇒ ∃ t' t' > t & at(communication(cc, aoccs, inform, cc_solution_is_reroute), t')

The example used to specify an agent's interaction properties is when an agent observes the inform message from another agent regarding the state of an informational resource and as a result, subsequently believes the action to be a working solution.

12. **Semi-formal description:** For any time t, if the crew control agent observes message from aircraft control agent informing rerouting is possibl, then there exists a time t', where t' is greater than t, when crew control agent believes rerouting is possible.

    - **Formal specification:**
    ∀t at(cobserve(cc, ac, inform, rerouting_is_possible), t) ⇒ ∃ t' t' > t & at(belief(cc,rerouting_is_possible), t')

13. **Semi-formal description:** For any time t, if crew control agent believes rerouting is possible and crew control agent wishes goal G1.1.2, then there exists a time t', where t' is greater than t, when crew control agent identifies rerouting as a working solution.

    - **Formal specification:**
    ∀t at(belief(cc,rerouting_is_possible), t) ⇒ ∃ t' t' > t & at(kworks(cc,rerouting_works), t')

In this section the formal specification of social decision-making and interaction is formally specified in light of the integration that is modelled between the local cognition model and the social decision-making and interaction model.

5.5 Model Implementation

The model is implemented using LEADSTO specification language, allowing us to simulate the agent-based model for the scenario under consideration. LEADSTO is an executable sublanguage of TTL. LEADS allows us to simulate dynamic processes by modelling specific dependencies between state properties. In Figure 5, the LEADSTO architecture is shown. All the dynamic properties are written in a LEADSTO specification file which can be found in section F.2. This specification file will be loaded into the LEADSTO Simulation Tool, which will generate a Trace-file. In the LEADSTO specification file, the following elements are present:

- Sorts and their terms
- Informational resources
- Environmental variables
- Agent local properties (e.g individual cognition)
- Agent social decision-making properties
- Agent interaction properties

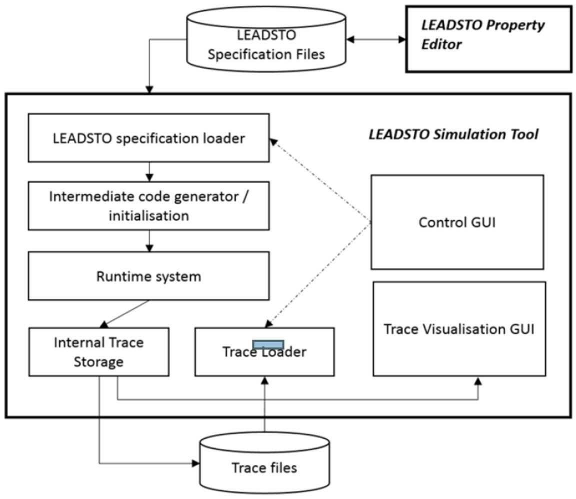

Figure 6: LEADSTO Architecture

Figure 5: LEADSTO architecture

6 Results

The simulation results of the developed agent-based model is now discussed for the selected case study. In section 6.1 the simulation setup and scenarios selected are discussed. Two AOCC performance evaluation approaches are conducted. The first costs-based performance evaluation and and the second is a goal-base performance evaluation. A baseline performance analysis is conducted for both and the baseline results are used as a benchmark for evaluating the decrease in performance as a result of existing relationship biases.

6.1 Simulation Setup

The simulation set up is based on a case study where an aircraft suffers a mechanical break down in Charles de Gaulle (CDG) Airport, Paris, before its departure towards an undisclosed location in the Pacific [Bruce, 2011b]. The flight schedule for this case study can be found in Appendix C. For the simulations conducted in this research, the destination airport assume is Changi (SIN) Airport, where a direct route between CDG and SIN is 10729 km.

The environmental variables that were assumed to be constant were the passenger transit buffer time of 60 minutes and the crew flight duty period buffer of 90 min. The passenger transit buffer time was assumed to be 60 min because is reflective of typical transit times. The crew flight duty period buffer is the additional legal working hours in addition to the scheduled crew flight duty period. The crew flight duty period buffer considered assumed flight time of 12h30m and references existing regulations [EU, 2008].

The informational resources that were assumed to vary were namely, reserve crew availability, positioning seats availability, rerouting possibilities and connection measures possibilities.

Simulations were conducted for 16 scenarios. This is equal to the total number of unique combinations of possible informational resource states. The 16 scenarios are shown in Table 19. For given constant environmental variables, passenger transit buffer time and crew flight duty period buffer, the possible disruption solutions depend on the repair time and information resource states. The solutions that are possible for a give repair time and scenario are outlines in Appendix D.

The simulations were conducted for 9 repair times. Starting at 40 minutes, with 10 minute increments until 120 minutes. The 40 minutes repair time corresponds to when repair time is less than passenger transit buffer time and crew flight duty period buffer. At 60 minutes, the repair time just exceeds the passenger transit buffer time threshold. The 90 minutes repair time is when the repair time has exceeded passenger transit buffer time and just exceeds the crew flight duty period buffer time threshold.

For the cost-based performance evaluation, costs are evaluated at two repair times- The repair times at 60 minutes and 90 minutes are chosen as they mark the threshold were control agents must collaborate to achieve a solution to mitigate the disruption considered. For the goal-based performance evaluation the 90 minute repair time point is the only repair time simulated for. This is because this is the most operationally critical condition, due to high operational costs, that the AOCC will face, for the given disruption considered.

For the goal-based performance evaluation, AOCC performance is only evaluated when the repair time crosses the 90 minute threshold. This threshold is selected as it is one where operational costs are most critical and all possible collaborations are accounted for. For goal-based performance, the same three relationship biases cases considered in the cost-based performance were evaluated. Furthermore, 3 cases were evaluated for when two relationship biases occur simultaneously.

6.2 Cost-based Performance Evaluation

In this section the baseline operational costs for 5 scenarios were no relationship biases exist in the AOCC are discussed. Subsequently, the operational costs for when relationship biases exist, is discussed with respect to the baseline costs, to understand whether there is a decrease in AOCC performance.
The operational costs are equal to the sum of quality and direct costs. The assumptions and costs structure assumed in this research is shown in Appendix D.
Cost distributions were compared using the Varga-Delaney A-test. This is a non-parametric effect magnitude two sample test that measures how probable a sample drawn from one distribution is larger than another distribution is is being compared to. This is a good measure to evaluate if on average the operational costs when relationship biases exist, in larger than when they do not exist [Neumann et al., 2015].

6.2.1 Baseline Operational Costs

Five scenarios were simulated when no relationship biases exist and these scenarios constitute the baseline case. The scenarios simulated were namely, A, B, C, F, G. These scenarios were chosen as they exhaustively cover all possible range of solution outcomes when passenger transit buffer time and crew flight duty period margin were both exceeded. The operational costs associated with the baseline case are shown in Figure 6.
The operational costs, at two relevant time points of interest, for the scenarios considered in the baseline case, are outlined below.

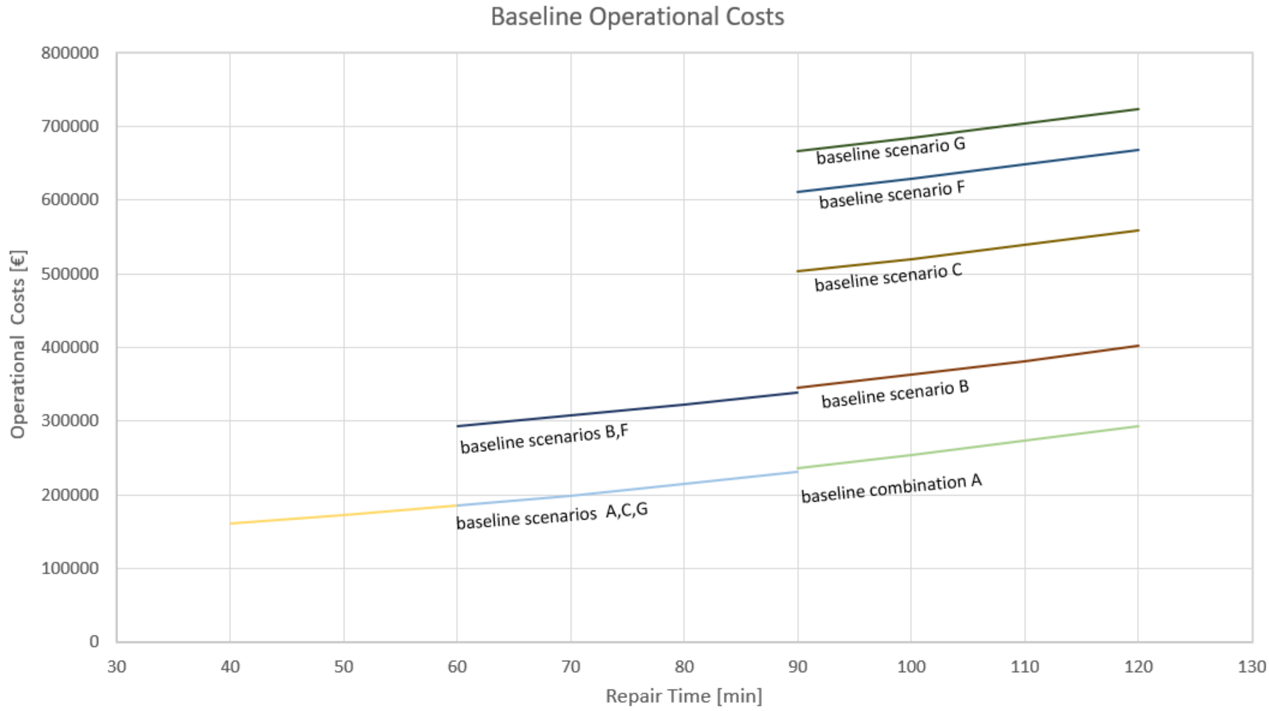

Figure 6: Baseline operational costs for scenarios of environmental conditions: A, B, C, F, G.

When repair time traverses the 60 minute threshold, two solution are possible. The costs associated to each solution are highlighted below:

Scenarios	**Description**	**Costs**
A, C, G	Transit passengers connect	€185,484
B, F	Transit passengers do not connect	€293,868

When repair time traverses the 90 minute threshold, five solution are possible. The costs associated to each solution are highlighted below:

Scenarios	**Description**	**Costs [€]**
A	Connection measures are available and rerouting is possible	236,807
B	Connection connection measures are not available and rerouting is possible	345,191
C	Connection measures are available and reserve crew is utilized	502,932
F	Connection measures are not available and reserve crew is utilized	611,316
G	No resources available to mitigate the disruption and flight is cancelled	667,092

The baseline costs demonstrate the operational cost associated with each solution implemented for each scenario. Baseline costs were then used as a benchmark, to evaluate the decrease in AOCC performance as a result of exiting relationship biases. In the subsequent section, the increase in operational costs compared to the baseline line case, that result from existing relationship biases among agents is explored. Furthermore, to illustrate individual cognition and social decision-making in the baseline case and in the bias cases, traces for the simulations runs are shown. Finally a Vargha-Delaney A-test was performed to evaluate whether relationship biases result in a significant increase in the average operating costs considering all possible scenarios.

6.2.2 Effects of Relationship Bias Between Crew and Aircraft Control Agents

The effects of an unfavourable relationship bias between the crew and aircraft control agents occurs when crew and aircraft control agents collaborate with each other during the development of a solution. The crew and aircraft control agents collaborate when the crew control agent considers rerouting the flight as a potential action to mitigate the disruption. This is because this action requires the crew control agent to request the state of the informational resource 'rerouting possibilities' to the aircraft control agent. The crew control agent will consider rerouting the flight a potential action only if the repair time exceeds the crew flight duty period margin. Therefore, evaluation of costs is performed only when the repair time traverses the 90 minute threshold.

Eight scenarios are simulated for the case when there is an unfavourable bias between the crew and aircraft control agents. The scenarios simulated are namely, A, B, D, E, H, I, K and N. These scenarios are chosen because they are the scenarios where rerouting is possible solution based on environmental conditions. The operational costs associated with the baseline case as well as the operational costs associated with the relationship bias under consideration, are illustrated in Figure 7.

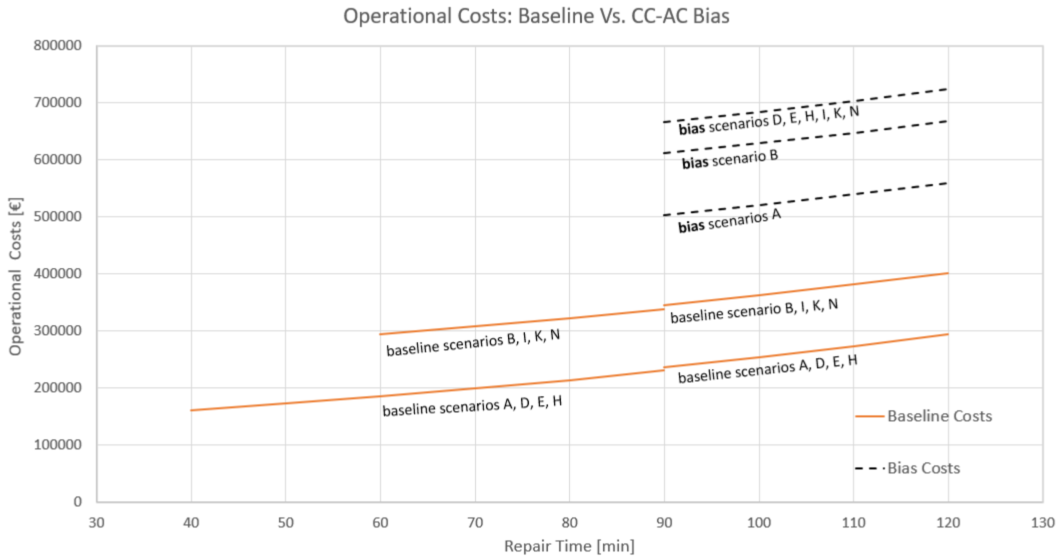

Figure 7: Baseline operational costs versus operational costs for crew control agent relationship bias towards aircraft control agent.

When repair time traverses the 90 minute threshold and the relationship bias between the crew and aircraft control agents exists, three unique solutions are possible. The costs associated to these solutions and cost penalty observed as a result of the relationship bias is shown below:

Scenarios	Description	Costs [€]	Penalty [€]
A	Reserve crew utilized instead of rerouting the flight & connecting pax	502,932	268,663
B	Reserve crew utilized instead of rerouting flight w/ no connecting pax	611,316	268,663
D, E, H	Flight is cancelled instead of rerouting flight &connecting pax	667,092	432,803
I, K, N	Flight is cancelled instead of rerouting flight with no connecting pax	611,316	324,419

Scenarios D, E and H are the ones most affected by the relationship bias, resulting in a 282% operational cost increase. It is also observed that from a pool of 16 scenarios, 12 are affected by this particular relationship bias. This is because the action to re-route the fight is a preferred action due the goals the crew control agent wishes. Therefore, when an agent has a relationship bias that can affect the development of its preferred solution, cost penalties are expected to affect a considerable amount of possible disruption scenarios.

For scenarios A and B, reserve crew is utilized as opposed to rerouting the flight. The difference in individual cognition and social decision-making between the baseline case and when there exists a relationship bias between the crew and aircraft control agents, is illustrated in Figure 8 and Figure 9.

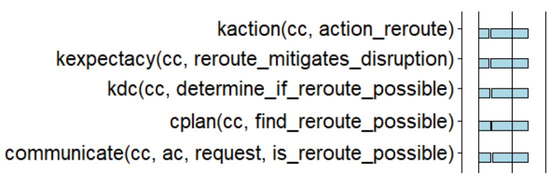

Figure 8: Simulation trace for baseline case when crew control agent explores rerouting the flight.

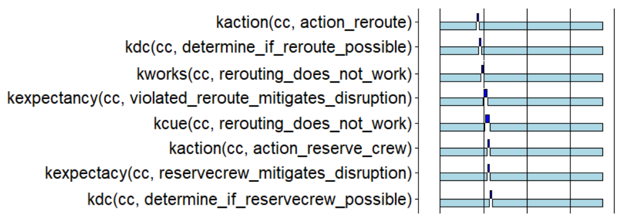

Figure 9: Simulation trace for when crew agent hold relationship bias against aircraft control agent and does not consider rerouting the flight as a workable solution.

The Vargha-Delaney A-test is performed to compared the costs between the baseline case and the relationship bias under consideration. The data used can be found in Table 21 and Table 22. A Vargha-Delaney A-test a value of 0.75 is obtained, indicating that the operational costs for the relationship bias under consideration, is on average, significantly larger than that of the baseline case. As a result, the hypothesis for effect of the crew-aircraft control agents relationship bias on AOCC performance is proven to be true, for this relationship bias. If crew and aircraft control agents have an unfavourable relationship bias, then the solutions implemented to mitigate the case study disruption, considering all possible scenarios, have on average, a higher operational cost.

6.2.3 Effects of Relationship Bias Between Crew and Passenger Control Agents

The effects of an unfavourable relationship bias between the crew and passenger control agents occurs when crew and aircraft control agents collaborate with each other during the development of a solution to mitigate the considered AOCC disruption. The crew and passenger control agents collaborate when the crew control agent considers utilizing reserve crew as a potential action to mitigate the disruption. This is because utilizing reserve crew requires the crew control agent to request the state of the informational resource 'positioning possibilities' to the passenger control agent. The crew control agent will consider utilizing reserve crew a potential action, only if the repair time exceeds the crew flight duty period margin. Therefore, evaluation of costs is performed only when the repair time traverses the 90 minute threshold.

The difference in individual cognition and social decision-making between the baseline case and when there exists a relationship bias between the crew and passenger control agents, is illustrated in Figure 10.

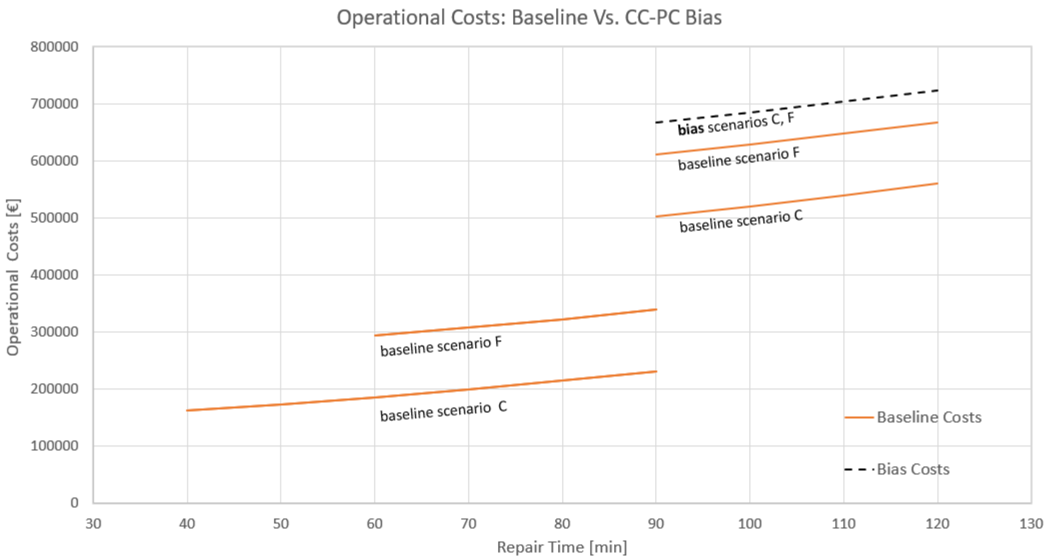

Figure 10: Baseline operational costs versus operational costs for crew control agent relationship bias towards passenger control agent.

When repair time traverses the 90 minute threshold and the relationship bias between the crew and passenger control agents exists, only one solution is possible. The costs associated to this solution and cost penalty observed as a result of the relationship bias is highlighted below:

Scenarios	Description	Costs €	Penalty €
C	Flight cancelled instead of delaying w/ connecting passengers	667,092	151,031
F	Flight cancelled instead of delaying w/ out connecting passengers	667,092	95,256

Scenarios C is the one most affected by the relationship bias, resulting in a 33% operational cost increase. It is also observed that from a pool of 16 scenarios, only 2 are affected by this particular relationship bias. This is because the action to re-route the fight is a preferred action due the goals the crew control agent wishes. Therefore, only when rerouting the flight is not a possibility and both reserve crew and positioning seats are available, does this relationship bias have an effect on operational costs. Furthermore, the incremental cost of the scenario most affected by this relationship is considerably less than the 282% observed for the effect of the relationship bias between the crew and aircraft control agents. This is because, initially the solutions associated with scenarios C and F are already high, as utilizing reserve crew is a relatively costly solution.

The individual cognition and social decision-making between the baseline case and the case where a relationship bias exists between the crew and passenger control agents is illustrated in traces Figure 11 and Figure 12.

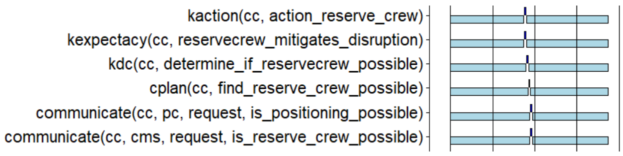

Figure 11: Trace for baseline case when crew control agent explores utilizing reserve crew.

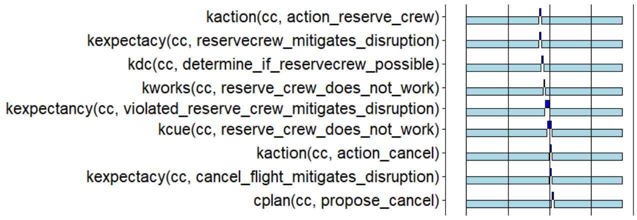

Figure 12: Trace for when crew agent hold relationship bias against passenger control agent and does not consider reserve crew to work as a result.

The Vargha-Delaney A-test is performed to compared the costs between the baseline case and the relationship bias under consideration. The data used can be found in Table 21 and Table 23. A Vargha-Delaney A-test a value of 0.51 is obtained, indicating a negligible difference in the operational costs for the relationship bias under consideration. As a result, the hypothesis for effect of the crew-aircraft control agents relationship bias on AOCC performance is not not proven to be true, for this relationship bias. If crew and passenger control agents have an unfavourable relationship bias, then the solutions implemented to mitigate the case study disruption, considering all possible scenarios, have on average, a similar operational cost.

6.2.4 Effects of Relationship Bias Between Passenger and Aircraft Control Agents

The effects of an unfavourable relationship bias between the passenger and aircraft control agents occurs when passenger and aircraft control agents collaborate with each other during the development of a solution to mitigate the considered AOCC disruption. The passenger and aircraft control agents collaborate when the passenger control agent considers utilizing connection measures as a potential action to mitigate the disruption. This is because utilizing connection measures requires the passenger control agent to request the state of the informational resource 'connection measures possibilities' to the aircraft control agent. The passenger control agent will consider utilizing connection measures a potential action, only if the repair time exceeds the passenger transit buffer time. Therefore, evaluation of costs is performed when the repair time traverses the 60 minute threshold and also when the repair time traverses the 90 minutes threshold. Connection measures in the simulations are assumed to be available and independent from the repair time.

Eight scenarios are simulated for the case when there is an unfavourable bias between the passenger and aircraft control agents. The scenarios simulated are namely, A, C, D, E, G, H, J and M. These scenarios are chosen because they are the scenarios where utilizing connection measures is possible based on environmental conditions. The operational costs associated with the baseline case as well as the operational costs associated with the relationship bias under consideration, are illustrated in Figure 13.

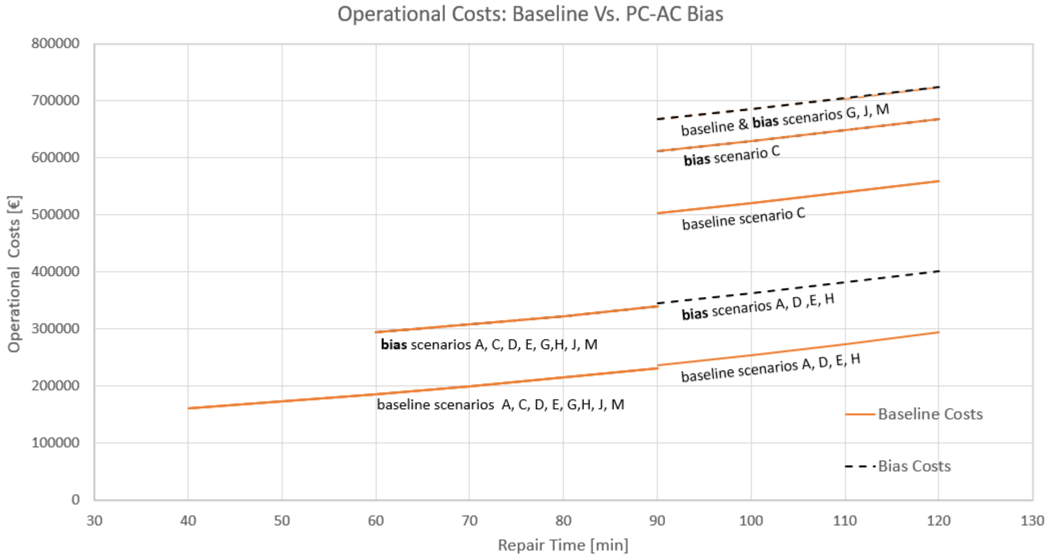

Figure 13: Baseline operational costs versus operational costs for passenger control agent relationship bias towards aircraft control agent.

When repair time traverses the 60 minute threshold and the relationship bias between the passenger and aircraft control agents exists, only one solution is possible. The costs associated to these solutions and cost penalty observed as a result of the relationship bias is highlighted below:

Scenarios	Description	Costs €	Penalty €
A, C, D, E, G, H, J, M	Flight delayed & pax do not connect instead of utilizing connection measures & pax connecting	293,868	108,384

When repair time traverses the 90 minute threshold and the relationship bias between the passenger and crew control agents exists, three solutions are possible. The costs associated to these solutions and cost penalty observed as a result of the relationship bias is highlighted below:

Scenarios	Description	Costs €	Penalty €
A, D, E, H	Flight delayed & pax do not connect instead of utilizing connection measures and connecting pax	345,191	108,384
C	Reserve crew utilized & passengers do not connect instead of utilizing reserve crew and connecting passengers	611,316	108,384
G, J, M	Flight is cancelled, just as in baseline case	667,092	0

With the exception of scenarios G, J and M, for all scenarios considered and all repair time thresholds, the incremental operational costs as a result, for this relationship bias, was the same. This means that the effect of the relationship bias between the passenger and aircraft control agents is independent of an increasing repair time beyond the passenger transit buffer time. Finally for scenarios G, J, the effect of the relationship bias did not emerge if the repair time and environmental conditions for the baseline scenario were already the worst outcome possible, namely a flight cancellation.

For all scenarios considered above, connection measures are not requested for when, in fact, they would have been available. The individual cognition and social decision-making between the baseline case and the case where a relationship bias exists between the passenger and aircraft control agents is illustrated in traces Figure 14 and Figure 15.

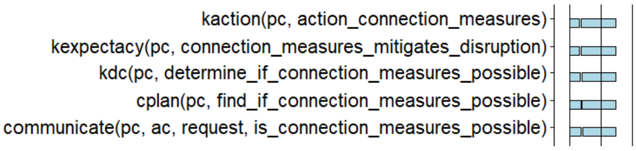

Figure 14: Trace for baseline case when passenger controller explores connection measures.

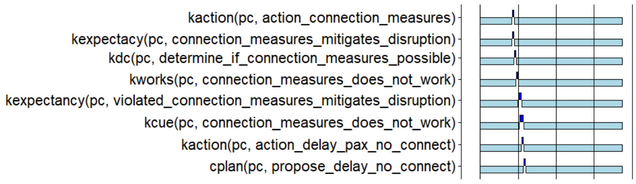

Figure 15: Trace for when passenger control agent holds relationship bias against aircraft control agent and does not consider connection measures to be a working solution.

The Vargha-Delaney A-test is performed on the operational costs for all scenarios in the baseline case and the case were a relationship bias exists between the passenger and aircraft control agents. The data used can be found in the column for minute 90 in Table 21 and Table 24. Vargha-Delaney A-test outputs a value of 0.57 indicating small difference between the distribution of operational costs for the baseline case and the relationship bias case. As a result, the hypothesis for effect of the passenger-aircraft control agents relationship bias on AOCC performance is not proven to be true for this relationship bias. If passenger and aircraft control agents have an unfavourable relationship bias, then the solutions implemented to mitigate the case study disruption, considering all possible scenarios, have on average, a similar operational cost.

6.3 Goal-based Evaluations for AOCC performance

The AOCC performance was measured based on the level of satisfaction of higher level AOCC goals at the top of goal structures. The goal-based AOCC performance evaluation was done based on the level of satisfaction of high level organizational goals. High level AOCC goals are the highest level goal associated with each control agent as well as the highest level organizational goal, G1. In Appendix B, the concepts regarding goal-based performance is explained in more detail.

6.3.1 Baseline Case

For the baseline case, the AOCC performance is evaluted based on the level of satisfaction of high level control agent goals and the key organizational goal G1. Initially the lowest level goals are evaluated and their satisfaction is propagating upwards through the goals structure to determine the level of satisfaction of each agent's high level goal and subsequently the key organizational goal. The lower level goals are evaluated first because they are realized by tasks performed by each individual agent. For a detailed description of which tasks need to be executed to satisfy which goals, refer to Appendix B. For the evaluation of agent lower level goal satisfaction refer to Appendix E.

The goal satisfaction of all control agents' high level goal and the key organizational goal is shown in Table 34. Below, the scenarios for when control agent high level goals and key organizational goal are and are not satisfied is shown:

Scenarios	**Crew G1.3 Satisfaction**	**Passenger G1.4 Satisfaction**	**Aircraft G1.2 Satisfaction**	**Organizational G1 Satisfaction**
A, D, E, G, H, J and M	Satisfied	Satisfied	Satisfied	Satisfied
B, I, K, L, N-P	Satisfied	Not Satisfied	Satisfied	Not Satisfied
C	Not Satisfied	Satisfied	Satisfied	Not Satisfied
F	Not Satisfied	Not Satisfied	Satisfied	Not Satisfied

- **For scenarios A, D, E, G, H, J and M** all high-level agent goals are satisfied. The crew control agent goal G1.3 and the passenger control agent goal G1.4 are satisfied. Because both high-level crew control agent and passenger control agent goals are satisfied, by label propagation, the key organizational goal G1 is also satisfied.
- **For scenarios B, I, K, L, N, O and P** crew control agent goal G1.3 is satisfied and passenger control agent goal G1.4 is not satisfied. The label of the higher level goal G1 is defined by the minimal label propagated from the lower level goals, therefore G1 is not satisfied.

- **For combination C** crew control agent goal G1.3 is not satisfied and passenger control agent goal G1.4 is satisfied. The label of the higher level goal G1 is defined by the minimal label propagated from the lower level goals, therefore G1 is not satisfied.
- **For combination F** crew control agent goal G1.3 is not satisfied and passenger control agent goal G1.4 is also not satisfied. The label of the higher level goal G1 is defined by the minimal label propagated from the lower level goals, therefore G1 is not satisfied.

These results show that the total number of scenarios where the key organizational goal, G1, is not satisfied is 9. This is less than the total number of scenarios where not all crew, passenger and aircraft control agents goals are satisfied, previously observed to be 10. The reason for this is that there is an overlap in scenarios where both for the crew and passenger control agent, not all their goals are satisfied, namely scenario F. Therefore the propagation of goal satisfaction to the key organizational goal is not equal to the sum of goals satisfied per control agent but instead the sum of the unique scenarios where goals were not satisfied.

The level of high level goal satisfaction for control agents and the key organizational goal is used as a benchmark for evaluating the effect of the relationship bias on AOCC performance. The number of goals not satisfied in a case where there is a relationship bias is compared to that in the baseline. The aircraft control agent goal G1.2 is not affected by relationship biases as the development of an aircraft solution does not require collaborating with other agents. For this reason, the level of satisfaction of the aircraft control agent goal G1.2, is not evaluated.

6.3.2 Effects of One Relationship Bias on AOCC Performance

The effects of one active relationship bias between two control agents is shown below:

- When a relationship bias exists between the crew and passenger control agents, scenarios C and F are affected as shown in Table 32. These scenarios are affected because the crew control agent does not request the state of the informational resource 'positioning seats availability' to the passenger control agent, which would have allowed for reserve crew to be utilized. Instead, the solution to the disruption is that the flight is cancelled. When compared to the baseline case there is no difference in the number of goals that are not satisfied as a result of the bias. The total number of high level crew goal G1.4 not satisfied remains at 2 and the total number of key organizational goal G1 not satisfied remains at 9. The passenger level of passenger crew goal satisfaction also remains unchanged.
  Despite the level of high level goal satisfaction remaining unchanged, the result of the relationship bias between the crew and passenger controller leads to the flight being cancelled as opposed to utilizing reserve crew. This worse AOCC performance is not captured by the goal-based performance evaluation.
- When only one relationship bias exists within the AOCC, and this is between the crew and aircraft control agents, the scenarios affected are A, B, D, E, H, I, K and N as shown in Table 31. The reason these scenarios are affected is because the crew control agent does not request the state of the informational resource "rerouting possibilities" to the aircraft control agent, which would have allowed for the flight to be rerouted. Instead the solution for the disruption is utilizing reserve crew or cancelling the flight, depending on each scenarios environmental conditions.
  As result of the relationship bias, for all scenarios considered, there is an increase in the number of goals not satisfied as shown in Table 36. The total number of times the crew control agent goal G1.3 is not satisfied increases by 8 to a total of 10, when compared to the baseline case. The total number of times the key organizational goal G1 is not satisfied increases by 4 to a total of 13. The total number of times the aircraft control agent goal G1.2 is not satisfied remains unchanged.
  When there is a relationship bias between the crew and aircraft control agents, the number of times crew control agent goal G1.4 is not satisfied is not equal to the number of time the key organizational goal G1 is not satisfied. The reason the number of times the key organizational goal is not satisfied does not increase by 8, and only 4, is because in the baseline case passenger control agent goal G1.3 was not satisfied for scenarios B, I, K and N, and therefore the key organizational goal was originally not satisfied.
- When only one relationship bias exists within the AOCC, and this is between the passenger and aircraft control agents all scenarios are affected, as shown in Table 33. The reason all scenarios are affected is because the passenger control agent does not request the informational resource 'connection measures possibilities' to the aircraft control agent, which would have allowed for the flight to be delayed and transit passengers to connect. Instead the solution for the disruption is delaying the flight with transit passengers not connecting.
  As a result of the relationship bias, for all scenarios considered, there is an increase in the number of goals not satisfied as shown in Table 37. The total number of times the passenger control agent goal G1.4 is not satisfied increases by 8 to a total of 16, when compared to the baseline case. The total number of times

the key organizational goal G1 not satisfied increases by 7 to a total of 16. The total number of times the aircraft control agent goal G1.2 is not satisfied remains unchanged.

For the relationship bias between the crew and passenger control agents, there is no change in the number of goals unsatisfied as a result of the relationship bias. For the relationship bias between the crew and aircraft control agents, there is an increase in the number of times the crew control agent goal G1.3 is not satisfied and the number of time the key organizational goal G1 is not satisfied. The hypothesis that if two agents have an unfavourable relationship bias, then the goals both agents wish for will be satisfied to a lesser degree is not validated. Instead, it two things are understood. Firstly it is that, if a relationship bias exists between two agents, the number of goals not satisfied will only increase for scenarios where there is only one possible solution and the bias affects the development of that solutions. Secondly, the an increase in the number of goals not satisfied will only occur for agent(s) that require requesting the state about informational resources to develop a solution.

6.3.3 Effects of Relationship Bias Occurring Simultaneously on AOCC Performance

The effects of multiple relationship biases occurring simultaneously is outlines below:

- When two relationship biases exists within the AOCC, and these are between the crew and passenger control agents as well as between the passenger and aircraft control agents, the scenarios affected are A, C, D, E, F and G as shown in Table 39. These scenarios are affected for the same reasons if these relationships would have occurred independently.
  As a result of both these biases occurring simultaneously, for all scenarios considered, there is an increase in the number of goals not satisfied when compared to the baseline case, as shown in Table 39. The total number of times the crew control agent goal G1.4 remain unchanged. The total number of times the passenger control agent goal is not satisfied increases by 8 to a total of 16. The total number of times the key organizational goal is not satisfied increases by 7, to a total of 16.
  The level of goal satisfaction for either the crew or passenger control agents is the same as it would be, should the relationship biases not occur simultaneously. This is likely due to the fact that the passenger and aircraft control agent's relationship bias will have no effect over whether the crew control agent decided to utilize reserve crew. Similarly, the crew and passenger control agent's relationship bias will have no effect over whether the passenger control agent decides to request connection measures.
- When two relationship biases exist within the AOCC, and these are between the crew and aircraft control agents as well as between the passenger and aircraft control agents, all scenarios are affected. All scenarios are affected because passengers not connect in any scenario.
  As a result of both these relationship biases occurring simultaneously for all scenarios considered, there is an increase in the number of goals not satisfied when compared to the baseline case, as shown in Table 39. The total number of times the crew control agent goal G1.4 is not satisfied increases by 8, to a total of 10. The total number of time the passenger control agent goal G1.3 is not satisfied increases by 6 to a total of 16. The total number of times the the key organizational goal is not satisfied increases by 7, to a total of 16.
  The level of goal satisfaction for either the crew or passenger control agents is the same as it would be, should the relationship biases not occur simultaneously. This is likely due to the fact that the relationship bias between the passenger and aircraft control agent's has no effect over whether the crew control decides to request rerouting possibilities to the aircraft control agent. Similarly, the crew and passenger control agent's relationship bias has no effect over whether the passenger control agent requests connection measure possibilities to the aircraft control agent.

When two relationship biases occur simultaneously, their simultaneous occurrence does not in itself have negative affect on the level of satisfaction of the highest level goals control agents wish for. Therefore, the hypothesis that the number of goals not satisfied and wished by agents, is proportional to the number of relationship biases occurring simultaneously is not proven to be true for the given case study.

7 Verification & Validation

Verification and validation steps were performed to ensure the agent-based model is modelled correctly and also generated the desired and expected results.

Firstly verification was performed during model development by ensuring all errors prompted in the LEADSTO simulation tool were fixed. Secondly, each agent's specification was developed separately at first where hard-coded inputs were introduces, enabling units test for one agent at a time. Thirdly, unit tests were performed once the model was complete to ensure agents states were in line with the expected individual cognition and social decision-making and interaction states. An example of an output trace illustrating expected behaviour is shown in Appendix F. The exemplary trace following the generation of actions by all control agents simultaneously. What is observed is that following the generation of actions, decision-makers identify decision considerations which main constrain the implementation of actions. This subsequently leads to decision makers requesting information from environmental objects that hold the needed information. The sequence of agent individual cognition states and agent social decision-making and interactions states is in line with what is expected from the models developed and case study considered. Unit test were performed several times to validate sequences of states for various agents and various scenarios.

Validation was performed in two steps. Firstly the relationship between agent goals and preferred actions was face validated with an airline operational control expert. This allows us to be reassured regarding the proposed action as a function of agent goals and cues.

Secondly, validation is performed by comparing the solution costs with those of [Bouarfa et al., 2021] who considered the same case study. When considering the cancellation scenario, Soufiane estimates a cost of €168k. The cost of cancellation in this study amounts to €667,092 which is considerably more. The reason for this discrepancy is two fold. One is that in this study, a conservative approach is taken by assuming the the incumbent airline will pay the original crew for the flight cancelled. The second reason is that, the cost of passenger rebooking in Bourfa et al.'s study is set to €120. The values of €120 relates to the cost faced by passengers who look to rebook their flight on an airlines website. In this study, we try and quantify the rebooking costs from the airlines perspective by relating it to the opportunity cost of not being able to sell a seat on another flight from CDG to PCF. The average seat on an airline fomr CDG to SIP averages €740 and this is why we have used the rebooking price of €740 as opposed to 120. When considering other costs such as those when the solution is to re-route the flight or to use reserve crew, the costs in this study surpass those of Bourfa et al.'s study. This is because Bourfa et al. calibrate their baseline aircraft's operational costs to €0k, whereas in this study, the flight's operational cost are always included. This is done so that when a flight is cancelled, this cost is also 0 from total operational costs.

8 Conclusions and Recommendations

In the research proposed, a socio-technical agent-based model has been developed to evaluate the effects of the relationship bias on AOCC performance. In this model, the agent's individual cognition is modelled using Klein's extended Recognition-primed Decision-making model. The agent's social decision-making and interaction dimensions have been modelled using Chow's Co-Ladder model framework. The model has been developed based on a case study where a mechanical failure occurs before flight departure. The independent variables considered in this case study are environmental variables and states of informational resources. The independent environmental variables is repair time. The independent informational resource states are: reserve aircraft availability, reserve crew availability, positioning seats availability, rerouting possibilities and connection measures possibilities. There are are two dependent variables considered in this research. One is used for the cost-based performance evaluation and is namely the operational cost. The other is used for the goal-based performance evaluation and is namely the number of goals satisfied.

It is concluded from the cost-based performance evaluation, that if a relationship bias between the crew and aircraft control agents exists, this will lead to, on average, a higher operational cost. As a result the AOCC performance would decrease. The same conclusion could not be reached for the relationship biases between the crew and passenger control agents or between the passenger and aircraft control agents.

It is concluded from the goal-based performance evaluation, that if two agents have a relationship bias, then only the agent(s) who require the state of informational resources will have a reduction in the number of goals satisfied. From the goal-based performance evaluation, it is also concluded that when two relationship biases occur simultaneously, their simultaneous occurrence in itself, does not additionally affect the level of goal satisfactions.

Based on the results it is concluded that the relationship bias has an effect on AOCC performance when measured from a cost perspective or from a goal-based evaluation perspective. However, the contribution by each relationship greatly differs to the extent that in some cases, the effect of the relationship bias is negligible on costs.

For further research, it is recommended to use a case study that allows for modelling more agents and increasing the number of possible solutions. Particularly if research the effect of the relationship bias on AOCC performance as the extensiveness of agent collaboration is highly dependent on the number agents modelled and number of possible solutions.

Lastly, de-bias training should be focused on relationship where collaboration is frequent since this is likely where most costs could potentially. By enforcing de-bias training, it is possible to raise awareness about relationship bias, and make its effect more transparent. In doing so, it has been shown that decision-makers are able to be de-biased and this will ultimately reduce the negative effects of relationship bias on AOCC performance [Sellier et al., 2019].

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Appendices

A Supporting Material

A.1 Previous Approaches to AOCC Disruption Management

A.1.1 Operations Research Approaches

According to [Bruce, 2011b] and [Castro et al., 2014], most research within the context of disruption management in AOCCs, is focused on OR methods. [Castro et al., 2014] categorized the different OR methods he found in literature and found most research to be (75%) to be Models & Algorithms and are not incorporated into AOCC systems to aid in decision-making. Decision Support Systems that require a human-in-the-loop account for 23% of the OR approaches to disruption management and only 2% are Automatic our Semi-Automatic Systems.

A.1.2 Simulation Approaches

Research on AOCC disruption management with a simulation approach is limited to a set of examples. The impact of organizational structures on airline operations was simulated and researched [Machado, 2010]. An automatic multi-agent simulation of AOCC disruption management was proposed as a Multi-Agent System for Disruption Management (MASDIMA) [Castro et al., 2014]. MASDIMA allows for a distributed and decentralized approach to integrated and dynamic AOCC disruption management. The approach is distributed because it enables a functional, spatial and physical distribution of AOCC roles and the environment and its resources. It is decentralized because it because decisions are taken at different nodes of the agents' network. It is integrated by included different dimensions of an airline disruption problem (aircraft, crew and passengers) and finally it is also dynamic due to the fact that several agents act under a continuously changing environment. MASDIMA is a decision-support tool that explores all possible solution alternatives and optimizes for operational costs. In this research, however, the goal is not to develop a decision-support tool but instead to evaluate the effects of human factors on decision-making, by developing a cognitive model.
Bourfa et al. evaluated the AOCC performance with a focus on multi-agent negotiation techniques [Bouarfa et al., 2021]. They found the Single Text Mediated Protocol to outperform well-established negotiation strategies where the agents involved in the negotiation are experts. Their research considered the same case study considered in this research, allowing us to cross-validate and compare results. Their approach, however, deviates from the research being proposed in that, they do not focus on human factors involved in decision-making, but instead the level of interactions among agents and information exchanged.

A.1.3 Human Factors Approaches

Few studies researched how human factors affect an airline's operational performance. Bruce studied the decision-making processes of 52 controllers from six AOCC centers [Bruce, 2011b]. These controllers were presented with six different types of scenarios in real time simulations, and were asked how they would manage the disruption. Bruce reported on the actions controllers thought could mitigate disruptions and also decision consideration brought as constraints, to evaluate whether actions were feasible. Decision considerations are identified by Bruce as an integral and explicit part of the decision-making process which is unaccounted for in Klein's Recognition-primed Decision (RPD) model. Klein's RPD model is further elaborated on in section A.2 where it is also motivated as the most adequate model to model AOCC decision-makers' individual cognition. As a result the study conducted, Bruce proposed Klein's RPD model be extended to include 'decision considerations' as an explicit concept which is a major contribution of his work. This led to the development of Klein's extended RPD model, which is central to this research.
More recently, Zimmer's researched the effects of human factors, more specifically personality features, on AOCC operational performance [Zimmer, 2020]. The goal was to understand this relationship as a means to design better system acceptance for human factors. Similarly to the research proposed in this paper, human factors are central to Zimmer's research. However, Zimmer chose a Belief-Desire-Intentions (BDI)-agent architecture to model agent behaviour, which simulates rational human beings through agent behavior. This is where the research proposed here, and Zimmer's differentiate themselves. In the research proposed, human decision-making is not modeled assuming a rational decision-making framework, but instead, through a naturalistic decision-making framework.

A.2 Decision-making Frameworks and Models

In this research, human decision-making within the context of the AOCC is modelled. To do so, both individual cognition, social decision-making and social interaction is modelled. Firstly the decision-making frameworks are evaluated and the naturalistic decision-making framework is selected as the most appropriate decision-making framework for modelling decision-making within the AOCC operational context. Secondly it is motivated that Klein's Recognition-primed Decision (RPD) model is adequate for modelling individual cognition within a naturalistic decision-making framework. Finally Chow's behavioural model is motivated as a suitable social decision-making and interaction model for this research.

A.2.1 Decision-making Frameworks

Rational Decision-making (RDM) is defined as a logical, systematic process of analysis that occurs in a series of steps [Beach and Lipshitz, 2017, Dastani et al., 2005]. The rational decision-making process assumes decision-makers have complete knowledge of the situation; Know all the alternative solutions as well as their consequences and probabilities; Objectively follow the decision-making process and have the goal of economic or utility maximization [Bazerman, 1992]. RDM processes are utilized when well-define problems with certain situations are presented. However, in many domains such as, fire-fighting, the military, nuclear power plants, nursing and emergency management, situations are complex and dynamic and as a result, decision-makers do not have time to compare alternatives before making a decision [Klein, 2008]. In these cases, people make decisions quickly and support their decisions afterwards. This is why past research has criticized the inadequacies of a rational decision-making approach for modelling real-world decision-making in natural contexts [Klein et al., 1997], and this has led to the development of the Naturalistic Decision-making (NDM) construct.
NDM describes or models the way people use their experience to make decisions in natural settings. Settings that are conducive to naturalistic decision-making processes are ones with ill-structured problems, uncertainty, dynamic environments, competing goals, times stress, multiple players, organizational goals and significant consequences for incorrect decisions [Lipshitz et al., 2001]. An AOCC's environment is certainly complex and dynamic, where decisions are made under time constraints. Therefore is is motivated that the most appropriate framework for modelling AOCC decision-making is a NDM framework.

A.2.2 Klein's Recognition-Primed Decision (RPD) Model

In previous research, several naturalistic decision-making models are described. Generally, these models rely on recognizing and assessing situations, forming mental pictures, and utilizing intuitive rather than rational approaches in decision-making [Lipshitz, 1993]. Klein's is a key researcher in naturalistic decision-making and proposed a Recognition-primed Decision (RPD) model [Klein, 2008] for modelling human decision-making and is frequently acknowledged as a model that is representative of the way in which decisions are made in the real world [Hedlund and Sternberg, 2000, Bruce, 2011b]. For this reason, this research has chosen to model individual cognition using Klein's RPD model.

Within the context of the AOCC, Klein's RPD model can be used to model the decision-making process of AOCC controllers for the generation of actions to solve an airline operational disruption. The model consists of two main parts, the recognition phase and a mental simulation phase and these are thoroughly discussed in section 5.3.1.

A.2.3 Chow's Co-Ladder Model

Coordination among AOCC decision-makers is required for decision-makers to gain situation awareness of a disruption event, to evaluate the feasibility of a potential course of action and finally to integrate various decision-makers proposals into one solution. The Co-Ladder model is a unified model that models coordinative functions for anomaly response and coordinative functions for dynamic replanning [Chow et al., 2000]. Chow's Co-Ladder model is therefore chosen to model social decision-making and interactions during the disruption management process since it allows for modelling coordination required for anomaly response (from observation of disruption to generation of action) to dynamic replanning (the evaluation of actions are feasible and their proposal if implementable). This framework enables us to model agent's behaviour as a function of defined Co-Ladder rules. In section 5.4 social decision-making and interactions are modelled using the Co-Ladder model framework.

A.2.4 Cognitive Biases

In 1974, Tversky and Kahneman published their seminal paper 'Judgement under Uncertainty: Heuristics and Biases" [Tversky and Kahneman, 1974] regarding systematic biases that influence decision-makers' judgment. They were the first to set the foundations and propose formal definitions for the study of heuristics & biases and their implications. The key takeaway from Tversky and Kahneman's seminal paper is that heuristics lead to biases that affect people's judgement during decision-making. Biases in turn result in systematic errors and poor decision-making, which strongly motivates their study as a means for potentially generating diagnostics.
The heuristics proposed by Tversky and Kahneman, that are relevant within the context of AOCC disruption management are the availability heuristic and the anchoring heuristic.
The availability heuristic is defined as one where the judgement of frequency of an object pertaining to a certain class, is based on how "available" this object is in the judge's mind. This may be due to the the retrievability of instances or the effectiveness of a search set. The retrievability of instances refers to how the familiarity or salience of an event in one's mind, makes one judge this event to occur with a higher frequency than it's base probability. The effectiveness of search set refers to how one judges the probability of an event based on how easily one can search it in one's mind. In practical terms, this leads one to judge words starting with the letter "r" to be occur more frequently then words where "r" is the third letter, because it is much easier to search for words by their first letter than by their third letter.
The anchoring heuristic is defined as one where insufficient adjustments are made to initial estimates of a starting point. In many situations, such as negotiations, people start from an initial value that is adjusted to yield the final answer. Within the context of the AOCC, this could manifest following a decision-maker's proposal to mitigate a disruption. The way it would manifest itself is by the decision-maker being unwilling to deviate significantly from his/hers initially proposed solution, following its rejection by the AOCC supervisor.
Coordination among AOCC decision-makers is observed as central to the AOCC disruption management process. It therefore seems plausible that poor relationships among decision-makers may negatively affect coordination, resulting in worse decision-making. The relationship bias is defined as one where previous experiences between two people affect the selection process of a negotiating or collaborative counter part [Reb, 2010]. If two people have had unfavourable previous experiences while collaborating or negotiating with one another, then, they are less likely to collaborate or negotiate with each.
The choice for which bias or biases should be firstly studied within the context of the AOCC disruption management process is not so evident at first sight. One may be argue that one should begin by studying the biases defined by Tversky and Kahneman, as these were the first and most fundamental ones defined in the relevant literature. However, the case study selected for this research greatly limited the extent to which the availability and anchoring heuristic contributed towards the study of the effects of biases on AOCC performance. In **??**, it will be explained, within the context of the case study selected, why the relationship bias was selected as the bias of study for this research.

A.2.5 Organizational Modelling

Central to this research is the evaluation of an AOCC's performance when cognitive biases exits within the AOCC. Along side evaluating AOCC performance on an operational cost basis, a framework for evaluating an organization's performance based on goal satisfaction would contribute towards the research objective. It is understood that organizations operate for the achievement of one or more goals. However, in practice, performance is not often monitored with respect to goals. Instead, performance is evaluated by estimating performance indicators, where the relation between performance indicators and goals is only implicit. Sharpansky et al. propose a formal framework for modelling goals based on performance indicators, thereby explicitly defining their relationship [Popova and Sharpanskykh, 2008]. Sharpansky et al. also defined mechanisms for establishing goal satisfaction, enabling the evaluation of organizational performance based on the level of goal satisfaction. Sharpansky et al.'s framework is part of a general framework for organizational modelling and analysis.

B Agent-Based Model Supporting Material

B.1 Conceptual Organizational Structure

The AOCC is generally located at an airline's headquarters, which, in turn, is typically located at one of the airline's main hubs [Grandeau, 1995]. The organizational structure is varied and depends on factors such as the airline size, network type (hub vs. spoke), the geographic distribution of services and organizational preference, among others [Castro et al., 2014]. Castro proposed three types of AOCC organizational centers, namely a decision center, a hub control center, and an integrated control center.

In this research, we will assume an Integrated AOCC organizational structure. In an Integrated AOCC, all roles share the same physical space and there is hierarchical dependence [Castro et al., 2014]. The AOCC supervisor takes the final decision that affects all dimensions, after collaborating with other supporting roles. The main advantage is that one person has the final say which likely leads to more rapid decision-making. The reason this organizational structure is chosen is because for this research we will assume an equal hierarchy for AOCC the supervisor supporting roles, namely the passenger, aircraft and crew teams. Secondly, this AOCC structure is chosen as it will be assumed that the AOCC supervisor has the final say in decision-making, which is not the case in an AOCC decision-center structure- where the AOCC is not hierarchically above other support functions, it must cooperate with other support functions to reach decisions.

The selected organizational conceptual model for this research is shown in Figure 16 and is an adaptation to the Integrated AOCC model as proposed by Castro [Castro et al., 2014]. In this research we will assume the supporting teams to the AOCC supervisor are the passenger, aircraft and crew teams. Each of these teams is modelled as an agent, assuming the roles of the team manager and team controllers. Team manager role is ultimately responsible for accepting the developed solution from the team controller role and proposing this to the supervisor. The team controller role is responsible for developing a solution and communicating this to the team supervisor. The choice for modelling three supporting agents for the AOCC supervisor agent is due to the fact that these three agents are modelled as responsible for an airline's main resources which are necessary and sufficient, for the selected case study, to mitigate the faced disruption. It is also true that, most collaboration during the disruption management process occurs among team managers and not between team managers and controllers. Therefore, the scope of the model is exhaustive enough to evaluate the effect of the relationship bias on AOCC performance. The relationship between agents and roles is further defined in the subsequent section on goal modelling, where both these concepts are connected to goals that agent's wish and roles are committed to.

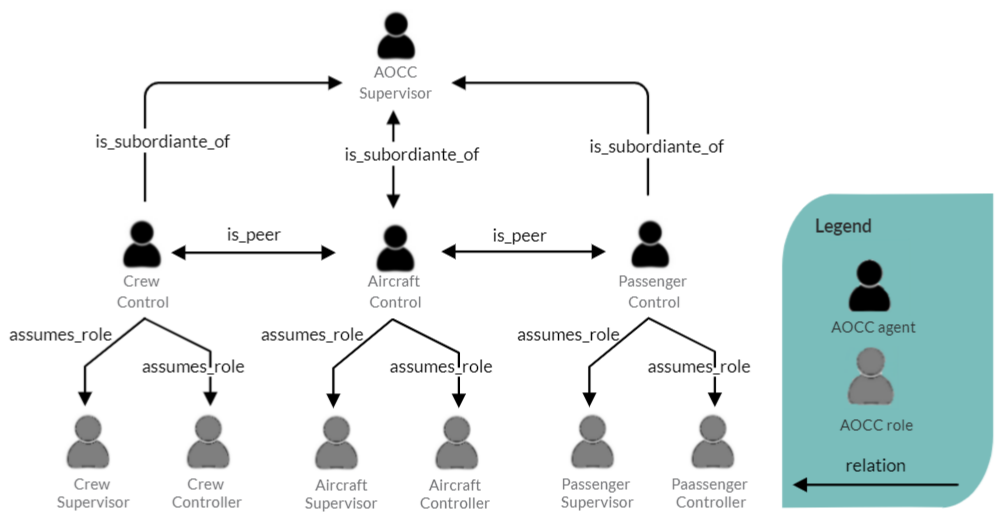

Figure 16: The adapted integrated AOCC conceptual model

B.2 Goal Modeling Concepts

There are three key definitions for goal modelling, namely performance indicator, goal pattern and goal.
The first key definition is regarding the performance indicator. A performance indicator is a measure, quantitative or qualitative, than can be used to give a view on the state or progress of a company or individual within a company (e.g crew ground time). Expressions can be formed over PIs containing $>, = or <$ (e.g PI P1:"crew ground time" is defined as P1 = minimized. The second key definition is a goal pattern, which is a property over one or more PI expressions that can be checked for a given state/time point or interval. A goal pattern is defined by: (1) name; (2) definition; and (3) type. The name is a label attributed to the goal pattern so it is uniquely identified. The type determines how the property will be checked. Below the different goal pattern types are listed:

- achieved - property is checked whether true or false for a specific time point
- maintained (avoided) - property is checked whether true or false for the duration of a specific time interval;
- optimized (maximized/minimized) - checked whether value of the PI expression has increased/decreased for the duration of a given time interval.

Goals are formulated over goal patterns which in turn are formulated over one or more performance indicator expressions. Finally, goals are defined by adding more information to goals patterns. [Popova and Sharpanskykh, 2008] define a goal by characterizing it with 9 properties: (1) name; (2) definition, (3) priority; (4) evaluation type; (5) horizon; (6) ownership; (7) perspective; (8) hardness; and (9) negotiability. Below some goal properties are highlighted:

- Priority is defined by a numerical estimation between 0 and 1 or qualitatively (low, medium, high).
- Evaluation type determines how the goal is evaluated depending on the goal pattern type.
- Horizon specifies the time interval within which, or a which specific time the goal is supposed to be satisfied.
- Ownership can be organizational or individual i.e., belong to an agent. Only organizational goals will be defined in this research.
- Perspective is applicable to organizational goals and defines the point of view (management, customer, etc...).
- Hardness distinguishes hard and soft goals, where the establishment of soft goal requires special attention, as these cannot be clearly established.
- Negotiability refers to whether a goal is negotiable or not. Negotiable goals allow for negotiation in case of conflicts with other goals.

In this research, the 9 goal properties for each individual goal are not laid out. However, some of these properties are further discussed within the context of this research, as they are relevant for discussion.
All goals are assumed to have equal priority as the they are derived from literature without a priority attribute and also because priorities are subjective vary among organizations. The goals that will be formally specified in this research do not have expressions formed over PIs with respect to units of time. Therefore goals horizon property is not irrelevant and all goals are evaluated at the end of the simulation for goal-based performance evaluation purposes. The ownership of the goals will always be organizational as no agent individual (personal) goals will be specified. The perspective of goals will also only be organizational. The hardness of goals is a property that is explored in depth during goal-modelling and is central to the framework that is established for goal-based performance evaluation. For the selected case study, negotiations are not present or modelled for and therefore, the negotiability of goals is not relevant for this research.

B.3 Formal Goal Model Specification

Below, the formal specification of the relationship between Passenger Control agent, task lists, tasks and goals related to social decision-making and interactions.

- wishes(PassengerControl, G1.4.1.1)
- is_in_task_list(T1.4.1.0.1, TL1411)
- is_in_task_list(T1.4.1.0.2, TL1411)

- is_in_task_list(T1.4.1.0.3, TL1411)
- is_realizable_by_by(G1.4.1.1, TL1411)
- wishes(PassengerControl, G1.4.1.2)
- is_realizable_by_by(G1.4.1.1, T1.4.1.1.1)

Below the formal specification of the relationship between Aircraft Control agent, task lists, tasks and goals related to social decision-making and interactions are shown below:

- wishes(AircraftControl, G1.2.1.1)
- is_in_task_list(T1.2.1.1.1, TL1211)
- is_in_task_list(T1.4.1.1.2, TL1211)
- is_in_task_list(T1.4.1.1.3, TL1211)
- is_in_task_list(T1.4.1.1.4, TL1211)
- is_realizable_by_by(G1.2.1.1, TL1211)
- wishes(AircraftControl, G1.2.1.2)
- is_realizable_by_by(G1.2.1.1, T1.2.1.2.1)

B.4 Goal-based Performance Evaluation

In this section the AOCC goal structures are specified are goal satisfaction mechanisms are presented. These are built by refining high level goals and aggregating lower level goals into higher level goals. The refinement of goals may proceed until subgoals are found, which could be realized by lowest-level tasks from the task hierarchy. Goals can be of two types of hardness, namely soft and hard. The type of hardness distinguishes the mechanisms by which goals are satisfied. By establishing goal structures and satisfaction mechanisms, the AOCC performance can be evaluated based on the satisfaction of goals.

Hard goals are refined into an and-list of hard goals. The refinement of a hard goal into a list of hard goals is defined by the expression: is_refined_to: GOAL X AND_GOAL_LIST. This specifies that when all goals in the AND_GOAL_LIST list are satisfied, all goals in the first argument are satisfied. The goal in the first argument will fail to be satisfied if at least one goal in the goal list fails and no other refinement from the first argument goal exists as is satisfied.

The satisfaction state of a hard goal the can be defined by the predicates, satisfied: GOAL and, failed: GOAL. The following axioms are formulated to evaluate whether a hard goal is satisfied or has failed to be satisfied:

∀ I: AND_GOAL_LIST is_refined_to(g, l) & (∀ gi:GOAL is_in_goal_list(gi,l) ⇒ satisfied(gi)) ⇒ satisfied(g)

∀ I: AND_GOAL_LIST is_refined_to(g, l) ⇒ ∃ gi: GOAL is_in_goal_list(gi, l) & failed(gi) ⇒ failed(g)

Where is_in_goal_list(gi,l) expresses that a goal is in a goal list and is_refined_to(g, l) expressed the refinement of a higher level goals into a list of lower level goals.

Soft goals must be given special attention because their satisfaction cannot be established in a clear-cut way and so their refinement differs from that of hard goals. The satisfices relationship expressed below, allows us to define how a soft goal in the second argument strongly contributes in a positive way to the satisficing of a soft/hard goal in the first argument: satisfices: GOAL X GOAL.

This rule is used to determine the degree of satisfaction/satisficing of a higher level goal - specified by a label - based on the satisfaction/satisficing of a lower level goal. The label of a higher level goal is determined by propagating labels of lower level goal in its refinement. In this research we only consider important organization goals, therefore all contributing goals are of label "satisfices", meaning all higher level goals will hold this label too. Then the type of links between higher level goals and lower level goals is shown in Table 14:

Label of contributing goal \ Type of link	**satisfices**
satisficed / satisfied	satisficed
weakly_satisficed	weakly_satisficed
undetermined	undetermined
weakly_denied	weakly_denied
denied / failed	denied

Table 14: The table for determining propagated labels for a higher level goal based on satisfaction/satisficing labels of lower level contributing goals [Popova and Sharpanskykh, 2008].

The AOCC goal structures refinements in this research are of and-list type, which means the label of a higher level goal is defined by the minimal label propagated from the lower level goals, using the defined order between the labels. The implications of this are that, if any goals fails to be satisfied, this will propagate to the highest level organizational goal.
In this research, the goal refinement specification is done illustratively for all goal structures.

The refinement of key organizational goal G1 is illustrated below in Figure 17:

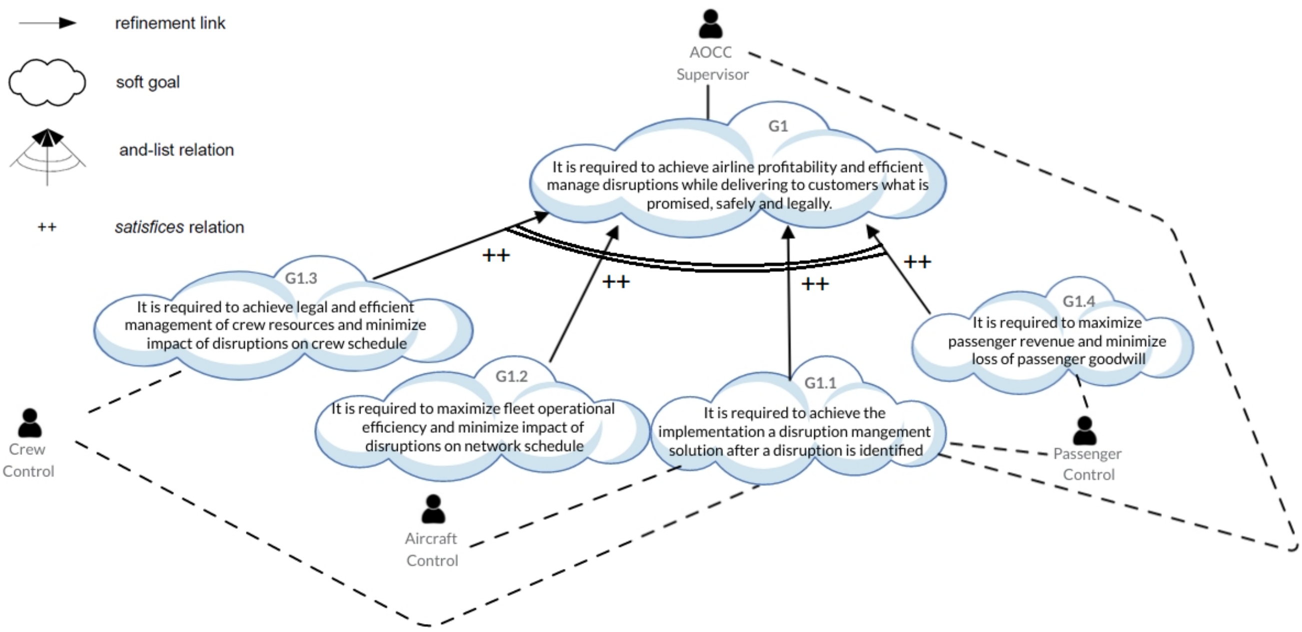

Figure 17: Goal structure for key organizational goals.

The refinement of key organizational goal G1.1 is illustrated below in Figure 18:

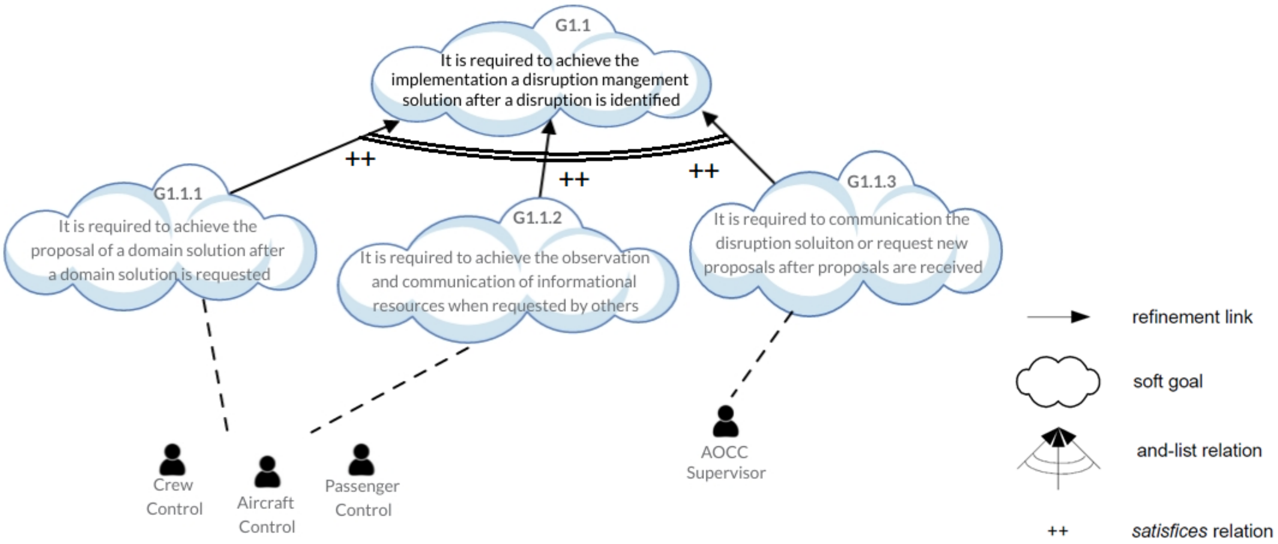

Figure 18: Goal structure for key organizational goal G1.1.

The refinement of crew agent goal, G1.3 is illustrated below in Figure 19.

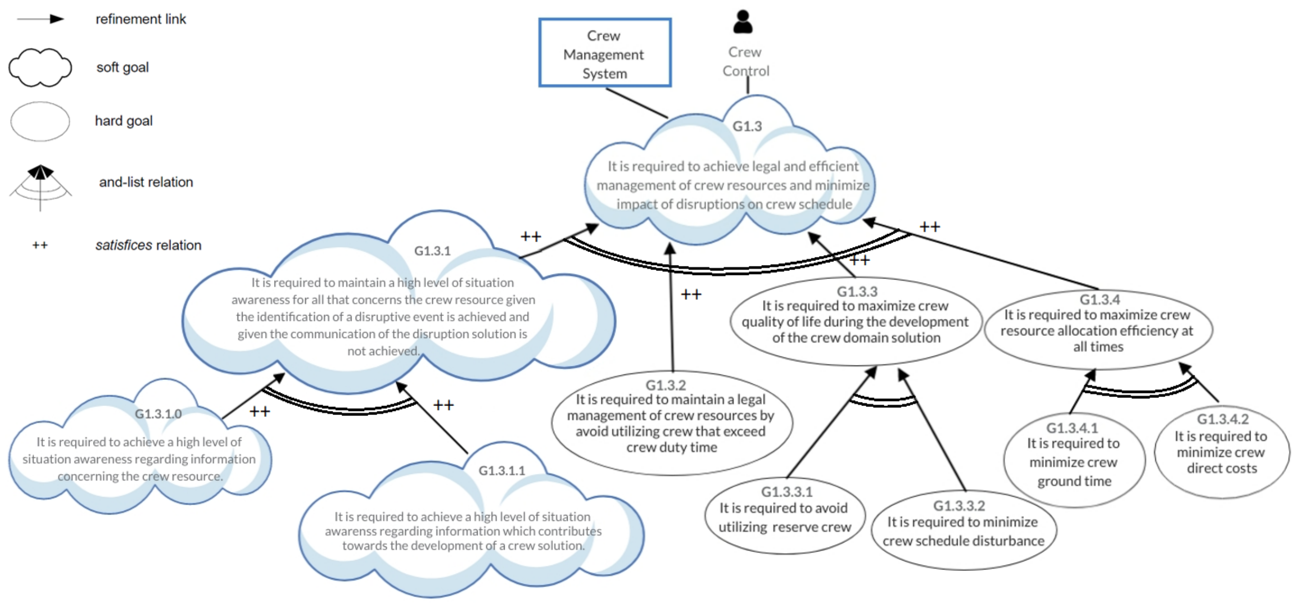

Figure 19: A partial goal structure for the crew control agent. For a detailed description of goals see Appendix B

The refinement of key organizational goal G1.2 is illustrated below in Figure 20:

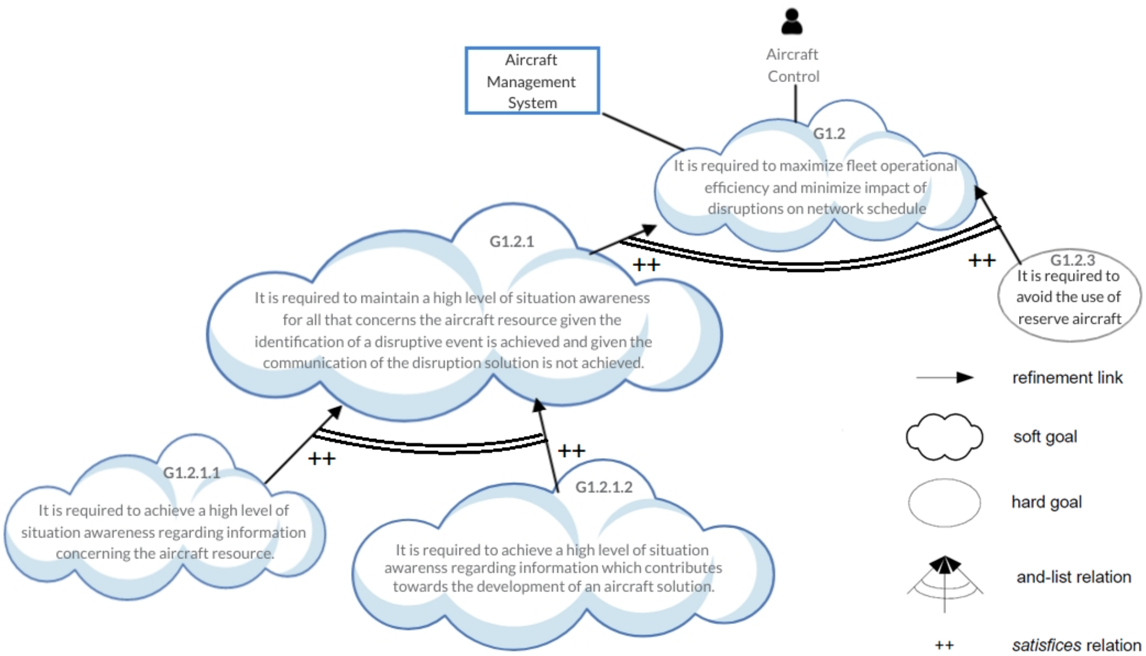

Figure 20: Goal structure for aircraft control agent goal, G1.2.

The refinement of key organizational goal G1.4 is illustrated below in Figure 21:

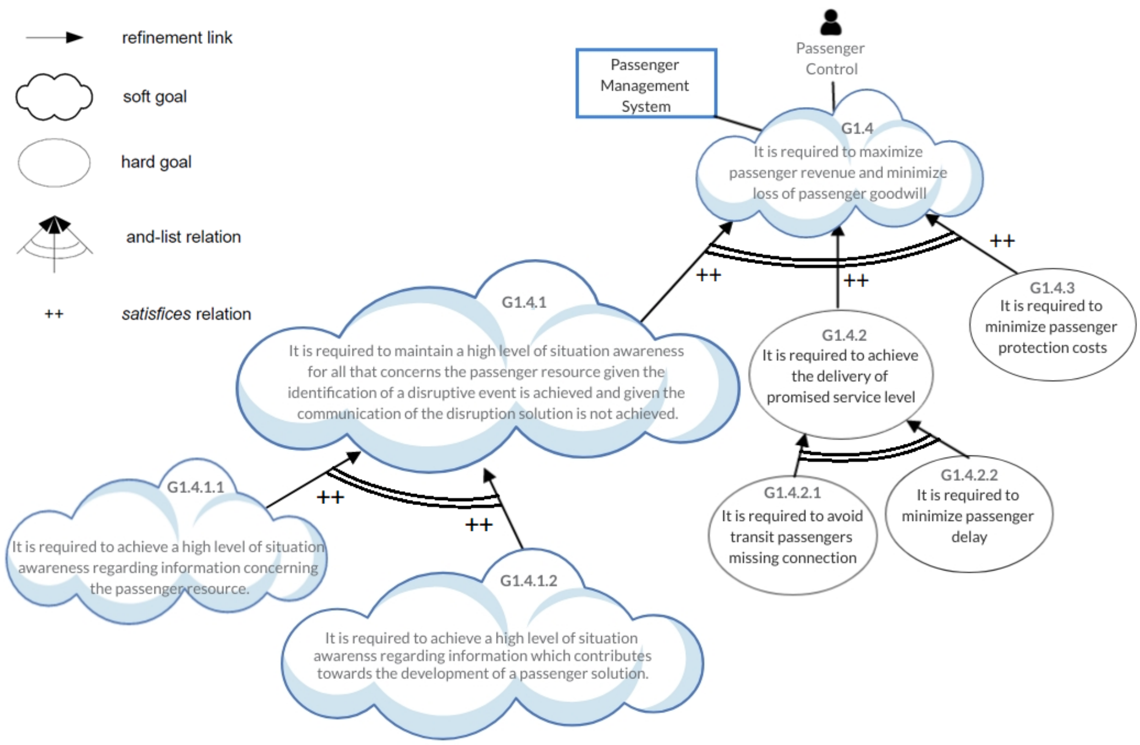

Figure 21: Goal structure for passenger control agent goal, G1.4.

B.4.1 Relationship Between Goals and Tasks

In Table 15 and Table 16, one may observe the relation between goals and tasks, and the level of satisfaction of crew control agent goals, from the considered case study.
In Table 17, one may observe the relation between goals and tasks, and the level of satisfaction of aircraft control agent goals, from the considered case study.
In Table 18, one may observe the relation between goals and tasks, and the level of satisfaction of passenger control agent goals, from the considered case study.

Goal name	Goal Expression	PI	Related Task	Level of goal satisfaction /satisficing
G1.3.1.0 (soft)	It is required to achieve a high level of situation awareness regarding information concerning the crew resource.	The level of situation awareness regarding information concerning the crew resource.	- T1.3.1.0.1: Observe inform message from AOCCS regarding disrupted flight - T1.3.1.0.2: Observe request message from AOCCS requesting crew resource solution - T1.3.1.0.3: Observe inform message from PC regarding positioning seats availability after positioning seats availability has been requested to PC. - T1.3.1.0.4: Observe inform message from AC regarding re-route possibilities after re-routing possibilities has been requested to AC.	satisficed
G1.3.1.1 (soft)	It is required to achieve a high level of situation awareness regarding information that contributes towards the development of a crew solution.	The level of situation awareness regarding information that contributes towards the development of a crew solution.	- T1.3.1.1.1: Observe crew duty time on Crew Management System to evaluate if crew exceed crew flight duty time limit. - T1.3.1.1.2: Observe reserve crew availability on Crew Management System if reserve crew is an plausible crew domain solution	satisficed
G1.3.2 (hard)	It is required to avoid utilizing crew that exceed maximum daily Flight Duty Period	Avoid utilizing crew that exceed maximum daily Flight Duty Period	- T1.3.2.1: Evaluate if repair time exceeds crew flight duty period buffer	satisfied
G1.3.3.1 (hard)	It is required to avoid utilizing reserve crew	Avoid utlizing reserve crew	- T.1.3.3.1.1 Propose CC solution 'Original crew will legally operate repaired aircraft' given that crew duty time limit is not exceeded - T.1.3.3.1.2 Propose CC solution 'Re-route flight from Paris to Mumbai' given that crew flight duty periods is exceeded and re-routing is possible. - T.3.3.1.3 Propose CC solution 'Original crew will be accomodated in Paris and flight will be cancelled' given that crew duty time limit is exceeded and re-routing is not possible.	satisfied

Table 15: The relation between goals and tasks, and the level of satisfaction of crew control agent goals, from the considered case study.

Goal name	Goal Expression	PI	Related Task	Level of goal satisfaction /satisficing
G1.3.3.2 (hard)	It is required to minimize crew schedule disturbance	To minimize crew schedule disturbance	- [1] T.1.3.3.1.1 Propose CC solution 'Original crew will legally operate repaired aircraft' given that crew duty time limit is not exceeded - [2] T.3.3.1.3 Propose CC solution 'Original crew will be accomodated in Paris and flight will be cancelled' given that crew duty time limit is exceeded and re-routing is not possible. - [2] T.1.3.3.1.2 Propose CC solution 'Re-route flight from Paris to Mumbai' given that crew duty time limit is exceeded and re-routing is possible. - [3] T1.3.3.2.4 Propose CC solution 'Reserve crew will be dispatched to legally operate flight from Paris to Mumbai and the original crew will be accommodated' given that original crew cannot legally operate the repaired aircraft and re-routing is not possible.	satisfied
G1.3.4.1 (hard)	It is required to minimize crew ground time	To minimize crew ground time	- [1] T.1.3.3.1.1 Propose CC solution 'Original crew will legally operate repaired aircraft' given that crew duty time limit is not exceeded - [2] T.1.3.3.1.2 Propose CC solution 'Re-route flight from Paris to Mumbai' given that crew duty time limit is exceeded and re-routing is possible. - [3] T1.3.3.2.4 Propose CC solution 'Reserve crew will be dispatched to legally operate flight from Paris to Mumbai and the original crew will be accommodated' given thatoriginal crew cannot legally operate the repaired aircraft and re-routing is not possible. - [3] T.3.3.1.3 Propose CC solution 'Original crew will be accomodated in Paris and flight will be cancelled' given that crew duty time limit is exceeded and re-routing is not possible.	satisfied
G1.3.4.2 (hard)	It is required to minimize crew direct costs	To minimize crew direct costs	- [1] T.1.3.3.1.1 Propose CC solution 'Original crew will legally operate repaired aircraft' given that crew duty time limit is not exceeded - [2] T.1.3.3.1.2 Propose CC solution 'Re-route flight from Paris to Mumbai' given that crew duty time limit is exceeded and re-routing is possible. - [3] T.3.3.1.3 Propose CC solution 'Original crew will be accomodated in Paris and flight will be cancelled' given that crew duty time limit is exceeded and re-routing is not possible. - [4] T1.3.3.2.4 Propose CC solution 'Reserve crew will be dispatched to legally operate flight from Paris to Mumbai and the original crew will be accommodated' given that original crew cannot legally operate the repaired aircraft and re-routing is not possible.	satisfied

Table 16: The relation between goals and tasks, and the level of satisfaction of crew control agent goals, from the considered case study.

Goal name	Goal Expression	PI	Related Task	Level of goal satisfaction/ satisficing
G1.2.1.1 (soft)	It is required to achieve a high level of situation awareness regarding information concerning the aircraft resource.	The level of promptness of observation of incoming messages concerning the aircraft resource.	- T1.2.1.1.1: Observe inform message from AOCCS regarding disrupted flight - T1.2.1.1.2: Observe request message from AOCCS requesting aircraft solution - T1.2.1.1.3: Observe request message from CC regarding re-route possibilities given CC requested re-routing possibilities. - T1.2.1.1.4: Observe request message from PC regarding connection measures, given PC requested connection measures measures.	satisficing
G1.2.1.2 (soft)	It is required to achieve a high level of situation awareness regarding information that contributes towards the development of an aircraft solution.	The level of promptness of observation of information available to the aircraft resource which contributes towards the development of an aircraft solution.	- T1.2.1.2.1: Observe reserve aircraft availability on Aircraft Management System if reserve aircraft is a plausible aircraft resource solution.	satisficing
G1.2.3 (hard)	It is required to avoid the use of reserve aircraft	Avoid the use of reserve aircraft	- T1.2.3.1: Propose AC solution 'Delay flight by repair time and use original aircraft' to AOCCS	satisfied

Table 17: The relation between goals and tasks, and the level of satisfaction of aircraft control agent goals, from the considered case study.

Goal name	Goal Expression	PI	Related Task	Level of goal satisfaction/ satisficing
G1.4.1.1 (soft)	It is required to achieve a high level of situation awareness regarding information concerning the passenger resource.	The level of situation awareness regarding information concerning the passenger resource.	- T1.4.1.1.1: Observe inform message from AOCCS regarding disrupted flight. - T1.4.1.1.2: Observe request msg from AOCCS requesting passenger resource solution. - T1.4.1.1.3: Observe inform msg from AC regarding connection measures possibilities given PC requested connection measures possibilities to AC.	satisficing
G1.4.1.2 (soft)	It is required to achieve a high level of situation awareness regarding information that contributes towards the development of a passenger solution.	The level of situation awareness regarding information that contributes towards the development of a passenger solution.	- T1.4.1.1.1: Observe passenger transit buffer time Passenger Management System	satisficing
G1.4.2.1 (hard)	It is required to avoid transit passengers missing connection	Avoid transit passengers missing connection	- T1.3.2.1 Evaluate if passenger transit buffer time exceeds repair time	satisficing
G1.4.2.2 (hard)	It is required to minimize passenger delay	Minimize passenger delay	- [1] T1.4.2.2.1: Propose PC solution 'Delay flight by repair time and transit passengers will connect' to AOCCS. - [1] T1.4.2.2.2: Propose PC solution 'Connection measures will allow transit passengers to connect' to AOCCS given that delaying flight by repair time will not allow transit passengers to connect and connection measures are possible. - [2] T1.4.2.2.1: Propose PC solution 'Delay flight by repair time and transit passengers will not connect' given that connection measures are not possible.	satisfied
G1.4.3 (hard)	It is required to minimize passenger protection costs	It is required to minimize passenger protection costs	- [1] T1.4.2.2.1: Propose PC solution 'Delay flight by repair time and transit passengers will connect' to AOCCS. - [1] T1.4.2.2.2: Propose PC solution 'Connection measures will allow transit passengers to connect' to AOCCS given that delaying flight by repair time will not allow transit passengers to connect and connection measures are possible. - [2] T1.4.2.2.1: Propose PC solution 'Delay flight by repair time and transit passengers will not connect' given that connection measures are not possible.	satisfied

Table 18: The relation between goals and tasks, and the level of satisfaction of passenger control agent goals, from the considered case study.

C Flight Schedule

Printout of the screen image at the time of disruption 08:35 Coordinated Universal Time (see top horizontal UTC time-scale). A secondary horizontal time-scale showed local time (UTC+ 9 hours). The horizontal blocks (called puks) represent the flights and include relevant information such as the flight number, actual passenger loading, departure and arrival airport, and departure and arrival time. The vertical axis on the left side shows the aircraft registrations that identify each aircraft in the fleet. In this scenario the aircraft with the mechanical problem is designated by registration code LHB 'Lima Hotel Bravo' to the left of the second row.

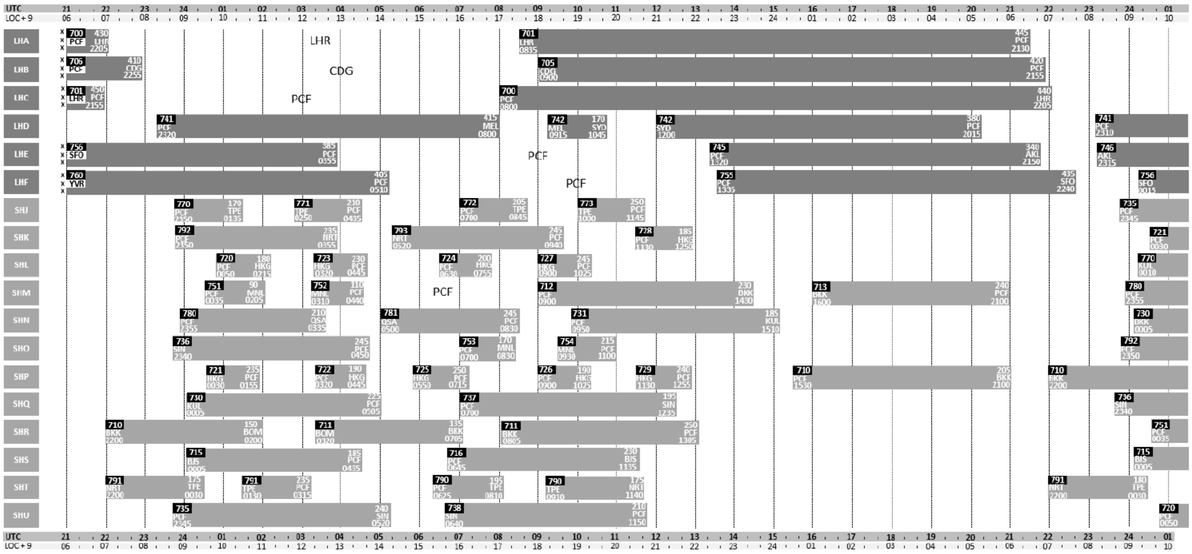

Figure 22: Printout of the screen image of airline controller at the time of disruption

D Simulations

D.1 Scenarios and Solutions

The numbers 1 and 0 refer to the availability/possibility or lack thereof, for a given environmental condition. The reason the aircraft availability is zero is because, in considered case study, no aircraft were available near CDG. This is expected as in the case study referenced, the had airport was in PCF.

Scenario	**reserve aircraft availability**	**reserve crew availability**	**positioning seats availability**	**rerouting possibilities**	**connection measures possibilities**
A	0	1	1	1	1
B	0	1	1	1	0
C	0	1	1	0	1
D	0	1	0	1	1
E	0	0	1	1	1
F	0	1	1	0	0
G	0	1	0	0	1
H	0	0	0	1	1
I	0	1	0	1	0
J	0	0	1	0	1
K	0	0	1	1	0
L	0	1	0	0	0
M	0	0	0	0	1
N	0	0	0	1	0
O	0	0	1	0	0
P	0	0	0	0	0

Table 19: Scenarios of environmental conditions for considered case study.

When repair time does not exceed passenger transit buffer time or crew flight duty period margin, then delaying the flight is the option considered. This solution is unaffected by relationship biases as control agents do not rely on collaboration to arrive at a delay action. Therefore, this solution is not analyzed in this research.

Considering all 16 scenarios, there are 2 unique possible solutions to the case study disruption when repair time exceeds as passenger transit buffer time and does not exceed crew flight duty period margin.

- The flight is delayed and transit passengers connect.
- The flight is delayed and transit passengers do not connect.

Considering all 16 scenarios, there are 5 unique possible solutions to the case study disruption as listed below:

- The flight is re-routed and transit passengers connect
- The flight is re-routed and transit passengers do not connect
- Reserve crew is utilized and transit passengers connect
- Reserve crew is utilized and transit passengers do not connect
- Flight is cancelled

D.2 AOCC Operational Costs

The cost structure for the AOCC can be broken down into two main components. The direct costs and the quality costs jointly contribute to the operating costs.

$$C = D + \beta \cdot Q \tag{1}$$

Where C is the operating cost, D is the direct cost, Q is the quality cost and β is the weight coefficient.
Direct costs are broken down into flight costs, crew costs and passenger costs as shown in Equation 2.

$$D = F + R + P \tag{2}$$

Where F is the flight costs, R is the crew costs and P is the passenger costs. The breakdown of direct costs per resources is shown in Table 20.

Aircraft	
Nominal operating costs	66 [€/h]
Fuel burn	6 [L/km]
Fuel price	2 [€/L]
Landing charges PCF	813 [€]
Landing charges reroute	2293 [€]
Crew	[€/crew]
Original crew nominal cost	25 [/h]
Reserve crew nominal cost	30 [/h]
Per diem crew	80
Hotel original crew	103
Passenger	[€/pax]
Compesation	250
Rebooking costs	740
Hotel	114
Daily meal cost	25

Table 20: Direct costs for operating flight from CDG to PCF broken down by constituent.

The aircraft assumed to be operated is the Boeing 787-9 capable of carrying 300 passengers on a 12h30m flight. The fuel burn rate corresponds to that of a Boeing 787-9 flying at cruise speed of 900 km/h. The fuel price is assumed to be Jet Jet A-1 fuel price including energy tax, which is in line with current market prices at the time of writing. The landing charges for pacific are assumed to be those of Singapore International Airport. The landing charged for the reroute flight are assumed to be those of Singapore International Airport jointly with those of Istanbul International Airport.

The total direct costs for operating the aircraft for the direct or rerouted flight is calculated using a reference direct flight and a reference reroute flight. The direct flight is assumed to be from CDG to SIN and the reroute flight is assumed to stop over IST. The range from CDG to SIN is 10,724 km. The distance from CDG to IST is 2,235 km and from IST to SIN is 8,669 km. Assuming all the above, the direct fight aircraft operating costs are:

$$Fuelburn \cdot Range \cdot Fuelprice + Charges_{landing} \tag{3}$$

$$6 * 10724 * 2 + 813 = 129,501 \tag{4}$$

The reroute flight aircraft operating costs are:

$$6 * (2235 + 8669) * 2 + 2293 = 133,141 \tag{5}$$

The crew costs can be found by factoring the hourly wages for original or reserve crew and considering a flight duration of 12h30.

When considering quality costs, this is quantified heuristically, since it involves passenger satisfaction. The coefficient serves to proportionally increase or decrease the the effect of the quality cost. In our evaluation, we have assume a neutral coefficient of 1. The equation used to calculate the quality cost is derived from Castro's work [Castro et al., 2014] as is shown below in Equation 6:

$$Q = [(\gamma \cdot l_p + t_p) \cdot 1.2 \cdot d_f + (\gamma \cdot l_b + t_b) \cdot (0.16 \cdot d_f^2 + 1.19 \cdot d_f] \tag{6}$$

Where t refers to the number of passengers in a certain class and l refers to the number of transit passengers within a given class. The p subscript refers to economy passengers, the b subscript refers to passengers in business class. d_f refers to delay in minutes. For the aircraft considered, there are 270 economy seats, 30 business class seats. In economy class there are 86 transit passengers and in business class there are 10 transit passengers.

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E Results

E.1 Cost-based Performance Evaluation Results

The operational costs for all possible scenarios of environmental conditions for the baseline case are shown in Table 21:

Repair time [min]	**40**	**50**	**60**	**70**	**80**	**90**	**100**	**110**	**120**
Scenario									
A	132180	132840	133500	134160	134820	141551	142211	142871	143531
B	132180	132840	241884	242544	243204	249935	250595	251255	251915
C	132180	132840	133500	134160	134820	407676	408336	408996	409656
D	132180	132840	133500	134160	134820	141551	142211	142871	143531
E	132180	132840	133500	134160	134820	141551	142211	142871	143531
F	132180	132840	241884	242544	243204	516060	516720	517380	518040
G	132180	132840	133500	134160	134820	571836	572496	573156	573816
H	132180	132840	133500	134160	134820	141551	142211	142871	143531
I	132180	132840	241884	242544	243204	249935	250595	251255	251915
J	132180	132840	133500	134160	134820	571836	572496	573156	573816
K	132180	132840	241884	242544	243204	249935	250595	251255	251915
L	132180	132840	241884	242544	243204	571836	572496	573156	573816
M	132180	132840	133500	134160	134820	571836	572496	573156	573816
N	132180	132840	241884	242544	243204	249935	250595	251255	251915
O	132180	132840	241884	242544	243204	571836	572496	573156	573816
P	132180	132840	241884	242544	243204	571836	572496	573156	573816

Table 21: Baseline operational costs for all environmental conditions scenarios for varying repair time with passenger transit time limit at 60 minutes and maximum flight duty period at 90 minutes.

The operational costs when the crew control agents holds a relationship bias against the aircraft control agent, for all possible scenarios of environmental conditions for the baseline case are shown in Table 22:

Repair time [min]	**40**	**50**	**60**	**70**	**80**	**90**	**100**	**110**	**120**
Scenario									
A	161716	172960	185484	230736	214372	502932	520576	539500	559704
B	185484	172960	293868	339120	322756	611316	628960	647884	668088
C	185484	172960	185484	230736	214372	502932	520576	539500	559704
D	185484	172960	185484	230736	214372	667092	684736	703660	723864
E	185484	172960	185484	230736	214372	667092	684736	703660	723864
F	185484	172960	293868	333180	322756	611316	628960	647884	668088
G	185484	172960	185484	230736	214372	667092	684736	703660	723864
H	185484	172960	185484	230736	214372	667092	684736	703660	723864
I	185484	172960	293868	333180	322756	667092	684736	703660	723864
J	185484	172960	185484	230736	214372	667092	684736	703660	723864
K	185484	172960	293868	333180	322756	667092	684736	703660	723864
L	185484	172960	293868	333180	322756	667092	684736	703660	723864
M	185484	172960	185484	230736	214372	667092	684736	703660	723864
N	185484	172960	293868	339120	322756	667092	684736	703660	723864
O	185484	172960	293868	339120	322756	667092	684736	703660	723864
P	185484	172960	293868	339120	322756	667092	684736	703660	723864

Table 22: Operational costs when relationship bias between crew and aircraft control agents, for all environmental conditions scenarios for varying repair time, with passenger transit time limit at 60 minutes and maximum flight duty period at 90 minutes.

The operational costs when the crew control agents holds a relationship bias against the passenger control agent, for all possible scenarios of environmental conditions for the baseline case are shown in Table 23:

Repair time [min]	40	50	60	70	80	90	100	110	120
Scenario									
A	161716	172960	185484	199288	214372	236807	254451	273375	293579
B	161716	172960	293868	307672	322756	345191	362835	381759	401963
C	161716	172960	185484	199288	214372	502932	520576	539500	559704
D	161716	172960	185484	199288	214372	236807	254451	273375	293579
E	161716	172960	185484	199288	214372	236807	254451	273375	293579
F	161716	172960	293868	307672	322756	611316	628960	647884	668088
G	161716	172960	185484	199288	214372	667092	684736	703660	723864
H	161716	172960	185484	199288	214372	236807	254451	273375	293579
I	161716	172960	293868	307672	322756	345191	362835	381759	401963
J	161716	172960	185484	199288	214372	667092	684736	703660	723864
K	161716	172960	293868	307672	322756	345191	362835	381759	401963
L	161716	172960	293868	307672	322756	667092	684736	703660	723864
M	161716	172960	185484	199288	214372	667092	684736	703660	723864
N	161716	172960	293868	307672	322756	345191	362835	381759	401963
O	161716	172960	293868	307672	322756	667092	684736	703660	723864
P	161716	172960	293868	307672	322756	667092	684736	703660	723864

Table 23: Operational costs when relationship bias between crew and passenger control agents, for all environmental conditions scenarios for varying repair time, with passenger transit time limit at 60 minutes and maximum flight duty period at 90 minutes.

The operational costs when the passenger control agents holds a relationship bias against the aircraft control agent, for all possible scenarios of environmental conditions for the baseline case are shown in Table 24:

Repair time [min]	40	50	60	70	80	90	100	110	120
Scenario									
A	161716	172960	293868	339120	322756	345191	362835	381759	401963
B	161716	172960	293868	339120	322756	345191	362835	381759	401963
C	161716	172960	293868	339120	322756	611316	628960	647884	668088
D	161716	172960	293868	339120	322756	345191	362835	381759	401963
E	161716	172960	293868	339120	322756	345191	362835	381759	401963
F	161716	172960	293868	333180	322756	611316	628960	647884	668088
G	161716	172960	293868	339120	322756	667092	684736	703660	723864
H	161716	172960	293868	339120	322756	345191	362835	381759	401963
I	161716	172960	293868	333180	322756	345191	362835	381759	401963
J	161716	172960	293868	339120	322756	667092	684736	703660	723864
K	161716	172960	293868	333180	322756	345191	362835	381759	401963
L	161716	172960	293868	333180	322756	667092	684736	703660	723864
M	161716	172960	293868	339120	322756	667092	684736	703660	723864
N	161716	172960	293868	339120	322756	345191	362835	381759	401963
O	161716	172960	293868	339120	322756	667092	684736	703660	723864
P	161716	172960	293868	339120	322756	667092	684736	703660	723864

Table 24: Operational costs when relationship bias between passenger and aircraft control agents, for all environmental conditions scenarios for varying repair time, with passenger transit time limit at 60 minutes and maximum flight duty period at 90 minutes.

E.2 Goal-based Evaluation Results

Crew control agent goal satisfaction for baseline case where no relationship bias takes place can be seen in Table 25.

Scenario	Goals satisfied/satificed	Goals not satisfied/satificed
A	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
B	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
C	G1.3.1.0, G1.3.1.2, G1.3.2, G1.3.3.2, G1.3.4.1, G1.3.4.2	G1.3.3.1
D	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
E	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
F	G1.3.1.0, G1.3.1.2, G1.3.2, G1.3.3.2, G1.3.4.1, G1.3.4.2	G1.3.3.1
G	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
H	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.2, G1.3.4.1, G1.3.4.2	
I	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
J	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
K	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
L	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
M	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
N	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
O	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
P	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	

Table 25: Crew control agent goal satisfaction for baseline case for all environmental condition scenarios.

Aircraft control agent goal satisfaction for baseline case wehre no relationship bias takes place can be seen in Table 26.

Scenario	Goals satisfied/satificed	Goals not satisfied/satificed
A	G1.2.1.1, G1.2.1.2, G1.2.3	
B	G1.2.1.1, G1.2.1.2, G1.2.3	
C	G1.2.1.1, G1.2.1.2, G1.2.3	
D	G1.2.1.1, G1.2.1.2, G1.2.3	
E	G1.2.1.1, G1.2.1.2, G1.2.3	
F	G1.2.1.1, G1.2.1.2, G1.2.3	
G	G1.2.1.1, G1.2.1.2, G1.2.3	
H	G1.2.1.1, G1.2.1.2, G1.2.3	
I	G1.2.1.1, G1.2.1.2, G1.2.3	
J	G1.2.1.1, G1.2.1.2, G1.2.3	
K	G1.2.1.1, G1.2.1.2, G1.2.3	
L	G1.2.1.1, G1.2.1.2, G1.2.3	
M	G1.2.1.1, G1.2.1.2, G1.2.3	
N	G1.2.1.1, G1.2.1.2, G1.2.3	
O	G1.2.1.1, G1.2.1.2, G1.2.3	
P	G1.2.1.1, G1.2.1.2, G1.2.3	

Table 26: Aircraft control agent goal satisfaction for baseline case for all environmental condition scenarios.

Passenger control agent goal satisfaction for baseline case where no relationship bias takes place can be seen in ??.

Scenario	Goals satisfied/satificed	Goals not satisfied/satificed
A	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	
B	G1.4.1.1, G1.4.1.2, G1.4.2.2, G1.4.3	G1.4.2.1
C	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	
D	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	
E	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	
F	G1.4.1.1, G1.4.1.2, G1.4.2.2, G1.4.3	G1.4.2.1
G	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	
H	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	
I	G1.4.1.1, G1.4.1.2, G1.4.2.2, G1.4.3	G1.4.2.1
J	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	
K	G1.4.1.1, G1.4.1.2, G1.4.2.2, G1.4.3	G1.4.2.1
L	G1.4.1.1, G1.4.1.2, G1.4.2.2, G1.4.3	G1.4.2.1
M	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	
N	G1.4.1.1, G1.4.1.2, G1.4.2.2, G1.4.3	G1.4.2.1
O	G1.4.1.1, G1.4.1.2, G1.4.2.2, G1.4.3	G1.4.2.1
P	G1.4.1.1, G1.4.1.2, G1.4.2.2, G1.4.3	G1.4.2.1

Table 27: Passenger control agent goal satisfaction for baseline case for all environmental condition scenarios.

E.2.1 Baseline Low Level Goal Satisfaction

For every agent, it is determined for which scenarios all lower level goals are satisfied and for which at least one goal is not satisfied. The satisfaction of lower-level goals for each scenario is shown in Table 25, Table 26 and Table 27, for the crew, aircraft and passenger control agents, respectively. Below, the baseline scenarios for which all agents goals are and are not satisfied are shown.

Scenarios	All Agent Goals
A, B, D, E, G-P	Satisfied
C, F	Not Satisfied

Table 28: Level of satisfaction of crew control agent goals for all baseline scenarios.

- In the baseline case, the crew control agent goal G.1.3.3.1 is not satisfied for the scenarios C and F. Scenarios C and F are scenarios where re-routing is not possible and reserve crew and positioning seats are. As a result goal G.1.3.3.1 is not satisfied. because reserve crew is utilized.

Scenarios	All Agent Goals
A-P	Satisfied
N/A	Not Satisfied

Table 29: Level of satisfaction of aircraft control agent goals for all baseline scenarios.

- In the baseline case, the aircraft control agent goal G1.2.3 is satisfied for all baseline scenarios. In the given case study, it is assumed that reserve crew are unavailable, because the hub airport is too distant from where the mechanical malfunction occurred. As a result goal G1.2.3 is always satisfied because reserve aircraft are never utilized.

Scenarios	All Agent Goals
A, C-E, G, H, J, M	Satisfied
B, F, I, K, L N-P	Not Satisfied

Table 30: Level of satisfaction of passenger control agent goals for all baseline scenarios.

- In the baseline case, the passenger control agent goal G.1.4.2.1 is not satisfied for the scenarios B, F, I, K, L N-P. Scenarios B, F, I, K, L N-P are scenarios where passenger connection measures are not possible. As a result goal G.1.4.2.1 is not satisfied because transit passengers don't connect.

While evaluating the lower level goal satisfaction, it is observed that, the satisfaction of goals is dependent on the scenario considered and hence, environmental conditions. When considering the crew and passenger control agents' goal satisfaction, further observations are made. Crew control agent goals are not all satisfied for two scenarios and passenger control agent goals are not all satisfied for 8 scenarios as seen in Table 34. The crew control agent can choose between two solutions, namely rerouting the flight and utilizing reserve crew, whereas the passenger control agent can only utilize connection measures. Therefore, it is deduced that agents who have a larger set of solutions to choose from, are less affected by environmental conditions. Finally the total number of scenarios where not at lower level goals are satisfied for crew, passenger and aircraft control agents is 10, which is more than half the scenarios considered.

Following the evaluation of goal satisfaction of agent lower level goals, propagation mechanisms are used to determine the level of satisfaction of higher level agent goals and the key organizational goal. The higher level agent goals are G1.2, G1.3 and G1.4 for the aircraft, crew and passenger control agents, respectively. The key organizational goal is goal G1, which is related to achieving airline profitability and efficiently managing disruptions while delivering to the customer what is promised, safely and legally. For the evaluation of key organizational goal G1, only the propagation of agent control goals towards the key organizational goal, is considered. This is done since AOCC performance ultimately relies on the solutions chosen and the agent control goal satisfaction is entirely dependent on the solutions chosen.

Passenger control agent goal satisfaction for case where crew control agent holds relationship bias against aircraft control agent can be seen in Table 31.

Scenario	Goals satisfied/satificed	Goals not satisfied/satificed
A	G1.3.1.0, G1.3.2	**G1.3.1.1, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
B	G1.3.1.0, G1.3.2	**G1.3.1.1, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
C	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	G1.3.3.1
D	G1.3.1.0, G1.3.2, G1.3.3.1	**G1.3.1.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
E	G1.3.1.0, G1.3.2, G1.3.3.1	**G1.3.1.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
F	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.2, G1.3.4.1, G1.3.4.2	G1.3.3.1
G	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
H	G1.3.1.0, G1.3.2, G1.3.3.1	**G1.3.1.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
I	G1.3.1.0, G1.3.2, G1.3.3.1	**G1.3.1.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
J	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
K	G1.3.1.0, G1.3.2, G1.3.3.1	**G1.3.1.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
L	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
M	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
N	G1.3.1.0, G1.3.2, G1.3.3.1	**G1.3.1.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
O	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
P	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	

Table 31: Crew control agent goal satisfaction for case where crew control agent holds relationship bias against aircraft control agent.

Crew control agent goal satisfaction for case where crew control agent holds relationship bias against passenger control agent can be seen in Table 32.

Scenario	Goals satisfied/satificed	Goals not satisfied/satificed
A	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
B	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
C	G1.3.1.0, G1.3.2, G1.3.3.1	**G1.3.1.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
D	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
E	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
F	G1.3.1.0, G1.3.2, G1.3.3.1	**G1.3.1.1, G1.3.3.2, G1.3.4.1, G1.3.4.2**
G	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
H	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.2, G1.3.4.1, G1.3.4.2	
I	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
J	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
K	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
L	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
M	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
N	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
O	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	
P	G1.3.1.0, G1.3.1.1, G1.3.1.2, G1.3.2, G1.3.3.1, G1.3.3.2, G1.3.4.1, G1.3.4.2	

Table 32: Crew control agent goal satisfaction for case where crew control agent holds relationship bias against passenger control agent.

Passenger control agent goal satisfaction for case where passenger control agent holds relationship bias against aircraft control agent can be seen in Table 33.

Scenario	Goals satisfied/satificed	Goals not satisfied/satificed
A	G1.4.1.1	**G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3**
B	G1.4.1.1, G1.4.2.1, G1.4.2.2, G1.4.3	G1.4.1.2
C	G1.4.1.1	**G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3**
D	G1.4.1.1	**G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3**
E	G1.4.1.1	**G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3**
F	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	G1.4.1.2
G	G1.4.1.1	**G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3**
H	G1.4.1.1	**G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3**
I	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	G1.4.1.2
J	G1.4.1.1	**G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3**
K	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	G1.4.1.2
L	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	G1.4.1.2
M	G1.4.1.1	**G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3**
N	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	G1.4.1.2
O	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	G1.4.1.2
P	G1.4.1.1, G1.4.1.2, G1.4.2.1, G1.4.2.2, G1.4.3	G1.4.1.2

Table 33: Passenger control agent goal satisfaction for case where passenger control agent holds relationship bias against aircraft control agent.

Scenario	**Goals**	Crew G1.3		Pax G1.4		Key Org. G1	
	Goal Satisfied	Yes	No	Yes	No	Yes	No
A		X		X		X	
B		X			X		X
C			X	X			X
D		X		X		X	
E		X		X		X	
F			X		X		X
G		X		X		X	
H		X		X		X	
I		X			X		X
J		X		X		X	
K		X			X		X
L		X			X		X
M		X		X		X	
N		X			X		X
O		X			X		X
P		X			X		X
TOTAL		14	2	8	8	7	9

Table 34: Evaluation of goal satisfaction, for key crew control agent goal G1.3, key passenger control agent goal G1.4 and key organizational goal G1, for every environmental condition combination.

Below you will find the effects of the relationship bias on the satisfaction of key organizational goal G1, when only on relationship bias exists among control agents.

		Relationship Bias			
		Crew/ Pax			
Scenario	Goals	Crew G1.3		Key Org. G1	
	Satisfied (Yes/No)	Y	N	Y	N
A		X			
B		X			*X*
C			*X*		*X*
D		X		X	
E		X		X	
F			*X*		*X*
G		X		X	
H		X		X	
I		X			*X*
J		X		X	
K		X			*X*
L		X			*X*
M		X		X	
N		X			*X*
O		X			*X*
P		X			*X*
TOTAL		14	2	6	9

Table 35: Evaluation of goal satisfaction, for key crew control agent goal G1.3 and key organizational goal G1, when the crew control agent holds a relationship bias against the passenger control agent.

		Relationship Bias			
		Crew/ Aircraft			
Scenario	Goals	Crew G1.3		Key Org. G1	
	Satisfied (Yes/No)	Y	N	Y	N
A			X		X
B			X		*X*
C			*X*		*X*
D			X		X
E			X		X
F			*X*		*X*
G		X		X	
H			X		X
I			X		*X*
J		X		X	
K			X		*X*
L		X			*X*
M		X		X	
N			X		*X*
O		X			*X*
P		X			*X*
TOTAL		6	10	3	13

Table 36: Evaluation of goal satisfaction, for key crew control agent goal G1.3 and key organizational goal G1, when the crew control agent holds a relationship bias against the aircraft control agent.

		Relationship Bias			
		Pax/ Aircraft			
Scenario	**Goals**	Pax G1.4		Key Org. G1	
	Satisfied (Yes/No)	Y	N	Y	N
A			X		X
B			*X*		*X*
C			*X*		*X*
D			X		X
E			X		X
F			*X*		*X*
G			X		X
H			X		X
I			*X*		*X*
J			X		X
K			*X*		*X*
L			*X*		*X*
M			X		X
N			*X*		*X*
O			*X*		*X*
P			*X*		*X*
TOTAL		0	16	0	16

Table 37: Evaluation of goal satisfaction, for key passenger control agent goal G1.4 and key organizational goal G1, when the passenger control agent holds a relationship bias against the aircraft control agent.

		Relationship Bias					
		Crew/ Pax		**Pax/ Aircraft**			
Scenario	**Goals**	Crew G1.3		Pax G1.4		Key Org. G1	
	Satisfied (Yes/No)	Y	N	Y	N	Y	N
A		X			X		X
B		X			*X*		*X*
C			*X*		X		*X*
D		X			X		X
E		X			X		X
F			*X*		*X*		*X*
G		X			X		X
H		X			X		X
I		X			*X*		*X*
J		X			X		X
K		X			*X*		*X*
L		X			*X*		*X*
M		X			X		X
N		X			*X*		*X*
O		X			*X*		*X*
P		X			*X*		*X*
TOTAL		14	2	0	16	0	16

Table 38: Evaluation of goal satisfaction, for key crew control agent goal G1.3, key passenger control agent goal G1.4 and key organizational goal G1, given relationship bias between crew and aircraft control agents & passenger and aircraft control agents.

Scenario	Goals	Relationship Bias: Crew/ Aircraft		Pax/ Aircraft			
		Crew G1.3		Pax G1.4		Key Org. G1	
	Satisfied (Yes/No)	Y	N	Y	N	Y	N
A			X		X		X
B			X		X		X
C			X		X		X
D			X		X		X
E			X		X		X
F			X		X		X
G		X			X		X
H			X		X		X
I			X		X		X
J		X			X		X
K			X		X		X
L		X			X		X
M		X			X		X
N			X		X		X
O		X			X		X
P		X			X		X
TOTAL		6	10	0	16	0	16

Table 39: Evaluation of goal satisfaction, for key crew control agent goal G1.3, key passenger control agent goal G1.4 and key organizational goal G1, given relationship bias between crew and passenger control agents & passenger and aircraft control agents.

Scenario	Goals	Relationship Bias: Crew/ Aircraft		Crew/ Pax			
		Crew G1.3		Crew G1.3		Key Org. G1	
	Satisfied (Yes/No)	Y	N	Y	N	Y	N
A			X	X			X
B			X	X			X
C			X		X		X
D			X	X			X
E			X	X			X
F			X		X		X
G		X		X		X	
H			X	X			X
I			X	X			X
J		X		X		X	
K			X	X			X
L		X		X			X
M		X		X		X	
N			X	X			X
O		X		X		X	
P		X		X		X	
TOTAL		6	10	14	2	5	11

Table 40: Evaluation of goal satisfaction, for key crew control agent goal G1.3 and key organizational goal G1, given relationship bias between crew and aircraft control agents & crew and passenger control agents.

		Relationship Bias							
		Crew/ Aircraft		Crew/ Pax		Pax/ Aircraft			
Scenario	**Goals**	Crew G1.3		Crew G1.3		Pax G1.4		Key Org. G1	
	Satisfied (Yes/No)	Y	N	Y	N	Y	N	Y	N
A			X	X			X		X
B			X	X			X		X
C			X		X		X		X
D			X	X			X		X
E			X	X			X		X
F			X		X		X		X
G		X		X			X		X
H			X	X			X		X
I			X	X			X		X
J		X		X			X		X
K			X	X			X		X
L		X		X			X		X
M		X		X			X		X
N			X	X			X		X
O		X		X			X		X
P		X		X			X		X
TOTAL		6	10	14	2	0	16	0	16

Table 41: Evaluation of goal satisfaction, for key crew control agent goal G1.3, key passenger control agent goal G1.4 and key organizational goal G1, given relationship bias between crew and aircraft control agents & passenger and aircraft control agents & crew and passenger control agents.

F Simulation Output Traces

F.1 Exemplary trace output file used for validating sequence of individual cognition into social behaviour.

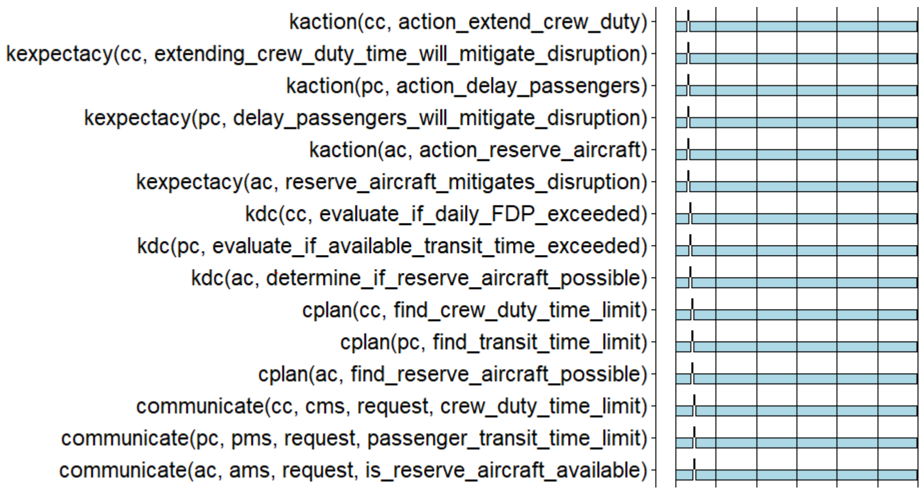

Figure 23: LEADSTO trace that follows the action generation phase of Klein's Extended RPD model. One can observe the decision considerations being raise, a plan being devised and an activity (communication) being carries out. This follows the sequence that is expected based on the integration between Klein's extended RDP model and Chow's Co-Ladder model.

F.2 LEADSTO Specification file for model proposed.

```
content(type(save_lt_editor('c:/Users/Z Soengas/Documents/AE_T/leadsto/
    working_folder/FINAL_scenario_2/
    ontology_specification_ed_w_social_goals_persistent.lt'))).
content(generator(app(leadsto_software, 127, [lteditor:1, psprinting:1]))).
content(run([date('Tue␣Oct␣12␣22:47:56␣2021')])).
qterm(cwa('(_)')).
end_time(k).
sortdef('CTRL', [cc, pc, ac, aoccs]).
constant(k, 75).
interval([], range(0, k), rt_(91)).
interval([], range(0, k), pt_(60)).
interval([], range(0, k), ct_(90)).
interval([], range(0, k), a_1).
interval([], range(0, k), b_1).
interval([], range(0, k), c_1).
interval([], range(0, k), d_1).
interval([], range(0, k), e_0).
interval([], range(0, k), 'G1310').
interval([], range(0, k), 'G1311').
interval([], range(0, k), 'G132').
interval([], range(0, k), 'G1331').
interval([], range(0, k), 'G1332').
interval([], range(0, k), 'G1341').
interval([], range(0, k), 'G1342').
interval([], range(0, k), 'G1311').
interval([], range(0, k), 'G1411').
interval([], range(0, k), 'G1412').
interval([], range(0, k), 'G1421').
interval([], range(0, k), 'G1422').
interval([], range(0, k), 'G1412').
interval([], range(0, k), 'G143').
interval([], range(0, k), 'G1211').
interval([], range(0, k), 'G1212').
interval([], range(0, k), 'G1212').
interval([], range(0, k), 'G123').
interval([], range(0, k), 'G113').
interval([], range(0, k), 'G112').
interval([], range(0, k), 'G111').
interval([], range(0, k), 'G1').
interval([], range(0, k), bias_cc_ac_0).
interval([], range(0, k), bias_cc_pc_0).
interval([], range(0, k), bias_pc_ac_0).
sortdef('CUES', [repairt_time(rt), find_cc_disruption_sol,
    find_pc_disruption_sol, find_cc_disruption_sol,
    extending_crew_duty_time_does_not_work, rerouting_does_not_work,
    reserve_crew_does_not_work, delay_passengers_does_not_work,
    reserve_aircraft_does_not_work, connection_measures_does_not_work,
    cancel_flight_does_not_work]).
sortdef('ACTION', [action_extend_crew_duty, action_delay_passengers,
    action_reroute, action_reserve_crew, action_connection_measures,
    action_reserve_aircraft, action_cancel, action_delay_pax_no_connect,
    use_same_aircraft]).
sortdef('EXPCY', [extending_crew_duty_time_mitigates_disruption,
    violated_extending_crew_duty_time_mitigates_disruption,
    delay_passengers_will_mitigate_disruption,
    violated_delay_passengers_will_mitigate_disruption,
    reroute_mitigates_disruption, violated_reroute_mitigates_disruption,
    reserve_crew_mitigates_disruption, violated_reserve_crew_mitigates_disruption
    , connection_measures_mitigates_disruption,
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    violated_connection_measures_mitigates_disruption ,
    cancel_flight_mitigates_disruption ,
    violated_cancel_flight_mitigates_disruption ,
    delay_pax_no_connect_mitigates_disruption ,
    violated_delay_pax_no_connect_mitigates_disruption ,
    reserve_aircraft_mitigates_disruption ,
    violated_reserve_aircraft_mitigates_disruption ,
    use_same_aircraft_mitigates_disruption ,
    violated_use_same_aircraft_mitigates_disruption]).
sortdef('DECCON', [evaluate_if_daily_FDP_exceeded ,
    evaluate_if_available_transit_time_exceeded , determine_if_reroute_possible ,
    determine_if_reservecrew_possible , determine_if_connection_measures_possible ,
     determine_if_reserve_aircraft_possible]).
sortdef('WORKS', [extending_crew_duty_time_works ,
    extending_crew_duty_time_does_not_work , delaying_passengers_works ,
    delaying_passengers_does_not_work , rerouting_works , rerouting_does_not_work ,
    reserve_crew_works , reserve_crew_does_not_work , reserve_aircraft_works ,
    reserve_aircraft_does_not_work , connection_measures_works ,
    connection_measures_does_not_work]).
sortdef('PLAN', [find_crew_duty_time_limit , find_transit_time_limit ,
    find_reserve_crew_possible , find_if_positioning_is_possible ,
    find_reroute_possible , find_connectionmeasures_possible ,
    find_reserve_aircraft_possible , propose_delay , propose_reroute ,
    propose_reserve_crew , propose_cancel , propose_connection_measures ,
    propose_delay_no_connect , propose_reserve_aircraft , propose_use_same_aircraft
    ]).
sortdef('EXPECTATION', [expectation_cms_informs_crew_time_limit ,
    violated_expectation_cms_informs_crew_time_limit ,
    expectation_pms_informs_passenger_transit_limit ,
    violated_expectation_pms_informs_passenger_transit_limit ,
    expectation_ac_informs_reroute_possibilities ,
    violated_expectation_ac_informs_reroute_possibilities ,
    expectation_ams_informs_reroute_possible ,
    expectation_cms_informs_reservecrew_availability ,
    violated_expectation_cms_informs_reservecrew_availability ,
    expectation_pc_informs_positioning_seats_availability ,
    violated_expectation_pc_informs_positioning_seats_availability ,
    expectation_pms_informs_positioningseats_availability ,
    violated_expectation_pms_informs_positioningseats_availability ,
    expectation_ams_informs_reserveaircraft_availabilty ,
    violated_expectation_ams_informs_reserveaircraft_availabilty ,
    expectation_ac_informs_connectionmeasures_possibility ,
    violated_expectation_ac_informs_connectionmeasures_possibility ,
    expectation_ams_informsconnectionmeasures_possibility ,
    violated_expectation_ams_informsconnectionmeasures_possibility ,
    expectation_aoccs_accepts_delay , violated_expectation_aoccs_accepts_delay ,
    expectation_aoccs_accepts_reroute , violated_expectation_aoccs_accepts_reroute
    , expectation_aoccs_accepts_reserve_crew ,
    violation_expectation_aoccs_accepts_reserve_crew ,
    expectation_aoccs_accepts_cancel , violation_expectation_aoccs_accepts_cancel ,
     expectation_aoccs_accepts_connection_measures ,
    violated_expectation_aoccs_accepts_connection_measures ,
    expectation_aoccs_accepts_delay_pax_no_connect ,
    violated_expectation_aoccs_accepts_delay_pax_no_connect ,
    expectation_aoccs_accepts_delay_pax_no_connect ,
    violated_expectation_aoccs_accepts_delay_pax_no_connect ,
    expectation_aoccs_accepts_same_aircraft ,
    violated_expectation_aoccs_accepts_same_aircraft]).
sortdef('MSG', [aircraft_needs_repair , repair_time_(rt), find_cc_disruption_sol ,
     find_pc_disruption_sol , find_ac_disruption_sol , crew_duty_time_limit ,
    passenger_transit_time_limit , is_reroute_possible , reroute_is_possible ,
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    reroute_is_not_possible, is_reserve_crew_possible, reserve_crew_is_possible,
    reserve_crew_is_not_possible, is_positioning_possible,
    positioning_is_possible, positioning_is_not_possible,
    is_connection_measures_possible, connection_measures_possible,
    connection_measures_not_possible, is_reserve_aircraft_available,
    reserve_aircraft_is_available, reserve_aircraft_is_not_available,
    find_alternative_cc_disruption_sol]).
interval([], range(0, 1), disruption(mechanical_failure, 'LHB', 'CDG')).
leadsto([rt:integer], and(disruption(mechanical_failure, 'LHB', 'CDG'), rt_(rt))
    , and(observes(aoccs, env, inform, aircraft_needs_repair), observes(aoccs,
    env, inform, repair_time_(rt))), standard).
leadsto([], observes(aoccs, env, inform, aircraft_needs_repair), belief(aoccs,
    aircraft_needs_repair), standard).
leadsto([rt:integer], observes(aoccs, env, inform, repair_time_(rt)), belief(
    aoccs, repair_time_(rt)), standard).
leadsto([rt:integer], and(belief(aoccs, aircraft_needs_repair), belief(aoccs,
    repair_time_(rt))), and(communicates(aoccs, cc, inform, aircraft_needs_repair
    ), communicates(aoccs, pc, inform, aircraft_needs_repair), communicates(aoccs
    , ac, inform, aircraft_needs_repair), communicates(aoccs, cc, inform,
    repair_time_(rt)), communicates(aoccs, pc, inform, repair_time_(rt)),
    communicates(aoccs, ac, inform, repair_time_(rt)), communicates(aoccs, cc,
    request, find_cc_disruption_sol), communicates(aoccs, pc, request,
    find_pc_disruption_sol), communicates(aoccs, ac, request,
    find_ac_disruption_sol)), standard).
leadsto([rt:integer], and(communicates(aoccs, cc, inform, aircraft_needs_repair)
    , communicates(aoccs, cc, inform, repair_time_(rt)), communicates(aoccs, cc,
    request, find_cc_disruption_sol), 'G1310'), and(observes(cc, aoccs, inform,
    aircraft_needs_repair), observes(cc, aoccs, inform, repair_time_(rt)),
    observes(cc, aoccs, request, find_cc_disruption_sol)), standard).
leadsto([rt:integer], and(observes(cc, aoccs, inform, aircraft_needs_repair),
    observes(cc, aoccs, inform, repair_time_(rt)), observes(cc, aoccs, request,
    find_cc_disruption_sol)), and(belief(cc, repair_time_(rt)), belief(cc,
    find_cc_disruption_sol)), standard).
leadsto([rt:integer], and(belief(cc, repair_time_(rt)), belief(cc,
    find_cc_disruption_sol)), and(kcue(cc, repair_time_(rt)), kcue(cc,
    find_cc_disruption_sol)), standard).
leadsto([rt:integer], and(kcue(cc, repair_time_(rt)), kcue(cc,
    find_cc_disruption_sol), 'G132', 'G1331', 'G1332', 'G1341'), and(kaction(cc,
    action_extend_crew_duty), kexpectacy(cc,
    extending_crew_duty_time_will_mitigate_disruption)), standard).
leadsto([], and(communicate(aoccs, cc, request,
    find_alternative_cc_disruption_sol), 'G1310'), observes(cc, aoccs,
    find_alternative_cc_disruption_sol), standard).
leadsto([], observes(cc, aoccs, find_alternative_cc_disruption_sol), belief(cc,
    find_alternative_cc_disruption_sol), standard).
leadsto([], belief(cc, find_alternative_cc_disruption_sol), and(cexpectation(cc,
     violated_expectation_aoccs_accepts_cancel), kexpectacy(cc,
    violated_cancel_flight_mitigates_disruption)), standard).
leadsto([], and(cexpectation(cc, violated_expectation_aoccs_accepts_cancel), not
    (kaction(cc, action_extend_crew_duty))), cexpectation(cc,
    violated_expectation_aoccs_accepts_cancel), standard).
leadsto([], kexpectacy(cc, violated_cancel_flight_mitigates_disruption), kcue(cc
    , cancel_flight_does_not_work), standard).
leadsto([], and(cexpectation(cc, violated_expectation_aoccs_accepts_cancel),
    kcue(cc, cancel_flight_does_not_work), 'G132', 'G1331', 'G1332', 'G1341'),
    and(kaction(cc, action_extend_crew_duty), kexpectacy(cc,
    extending_crew_duty_time_will_mitigate_disruption)), standard).
leadsto([], kaction(cc, action_extend_crew_duty), kdc(cc,
    evaluate_if_daily_FDP_exceeded), standard).
leadsto([], kdc(cc, evaluate_if_daily_FDP_exceeded), cplan(cc,
    find_crew_duty_time_limit), standard).
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leadsto([], cplan(cc, find_crew_duty_time_limit), communicate(cc, cms, request,
    crew_duty_time_limit), standard).
leadsto([], communicate(cc, cms, request, crew_duty_time_limit), cexpectation(cc
    , expectation_cms_informs_crew_time_limit), standard).
leadsto([], communicate(cc, cms, request, crew_duty_time_limit), observe(cms, cc
    , request, crew_duty_time_limit), standard).
leadsto([ct:integer], and(observe(cms, cc, request, crew_duty_time_limit), ct_(
    ct)), communicate(cms, cc, inform, crew_duty_time_limit_(ct)), standard).
leadsto([ct:integer], and(communicate(cms, cc, inform, crew_duty_time_limit_(ct)
    ), 'G1310'), observe(cc, cms, inform, crew_duty_time_limit_(ct)), standard).
leadsto([ct:integer], observe(cc, cms, inform, crew_duty_time_limit_(ct)),
    belief(cc, crew_duty_time_limit_(ct)), standard).
leadsto([ct:integer, rt:integer], and(belief(cc, crew_duty_time_limit_(ct)), rt_
    (rt), ct_(ct), <=(rt, ct)), kworks(cc, extending_crew_duty_time_works),
    standard).
leadsto([ct:integer, rt:integer], and(belief(cc, crew_duty_time_limit_(ct)), rt_
    (rt), ct_(ct), rt>ct), kworks(cc, extending_crew_duty_time_does_not_work),
    standard).
leadsto([], kworks(cc, extending_crew_duty_time_does_not_work), kexpectancy(cc,
    violated_extending_crew_duty_time_mitigates_disruption), standard).
leadsto([], and(kexpectancy(cc,
    violated_extending_crew_duty_time_mitigates_disruption), not(kaction(cc,
    action_reroute))), kexpectancy(cc,
    violated_extending_crew_duty_time_mitigates_disruption), standard).
leadsto([], kexpectancy(cc,
    violated_extending_crew_duty_time_mitigates_disruption), kcue(cc,
    extending_crew_duty_time_does_not_work), standard).
leadsto([], and(kexpectancy(cc,
    violated_extending_crew_duty_time_mitigates_disruption), kcue(cc,
    extending_crew_duty_time_does_not_work), 'G132', 'G1331', 'G1332', 'G1341'),
    and(kaction(cc, action_reroute), kexpectacy(cc, reroute_mitigates_disruption)
    ), standard).
leadsto([], kaction(cc, action_reroute), kdc(cc, determine_if_reroute_possible),
     standard).
leadsto([], and(kdc(cc, determine_if_reroute_possible), bias_cc_ac_1), kworks(cc
    , rerouting_does_not_work), standard).
leadsto([], and(kdc(cc, determine_if_reroute_possible), bias_cc_ac_0), cplan(cc,
     find_reroute_possible), standard).
leadsto([], and(cplan(cc, find_reroute_possible), 'G1311'), communicate(cc, ac,
    request, is_reroute_possible), standard).
leadsto([], communicate(cc, ac, request, is_reroute_possible), cexpectation(cc,
    expectation_ac_informs_reroute_possibilities), standard).
leadsto([], and(communicate(cc, ac, request, is_reroute_possible), 'G112'),
    observe(ac, cc, request, is_reroute_possible), standard).
leadsto([], observe(ac, cc, request, is_reroute_possible), belief(ac,
    find_reroute_possible), standard).
leadsto([], belief(ac, find_reroute_possible), cplan(ac, find_reroute_possible),
     standard).
leadsto([], cplan(ac, find_reroute_possible), communicate(ac, ams, request,
    is_reroute_possible), standard).
leadsto([], communicate(ac, ams, request, is_reroute_possible), cexpectation(ac,
     expectation_ams_informs_reroute_possible), standard).
leadsto([], communicate(ac, ams, request, is_reroute_possible), observe(ams, ac,
     request, is_reroute_possible), standard).
leadsto([], and(observe(ams, ac, request, is_reroute_possible), c_1),
    communicate(ams, ac, inform, reroute_is_possible), standard).
leadsto([], and(observe(ams, ac, request, is_reroute_possible), c_0),
    communicate(ams, ac, inform, reroute_is_not_possible), standard).
leadsto([], and(communicate(ams, ac, inform, reroute_is_possible), 'G1211'),
    observe(ac, ams, inform, rerouting_is_possible), standard).
leadsto([], observe(ac, ams, inform, rerouting_is_possible), belief(ac,
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    rerouting_is_possible), standard).
leadsto([], and(belief(ac, rerouting_is_possible), 'G112'), communicate(ac, cc,
    inform, reroute_is_possible), standard).
leadsto([], and(communicate(ac, cc, inform, reroute_is_possible), 'G1310'),
    observe(cc, ac, inform, reroute_is_possible), standard).
leadsto([], observe(cc, ac, inform, reroute_is_possible), belief(cc,
    rerouting_is_possible), standard).
leadsto([], belief(cc, rerouting_is_possible), kworks(cc, rerouting_works),
    standard).
leadsto([], and(communicate(ams, ac, inform, reroute_is_not_possible), 'G1211'),
     observe(ac, ams, inform, rerouting_is_not_possible), standard).
leadsto([], observe(ac, ams, inform, rerouting_is_not_possible), belief(ac,
    rerouting_is_not_possible), standard).
leadsto([], and(belief(ac, rerouting_is_not_possible), 'G112'), communicate(ac,
    cc, inform, reroute_is_not_possible), standard).
leadsto([], and(communicate(ac, cc, inform, reroute_is_not_possible), 'G1310'),
    observe(cc, ac, inform, reroute_is_not_possible), standard).
leadsto([], observe(cc, ac, inform, reroute_is_not_possible), belief(cc,
    rerouting_is_not_possible), standard).
leadsto([], belief(cc, rerouting_is_not_possible), kworks(cc,
    rerouting_does_not_work), standard).
leadsto([], kworks(cc, rerouting_does_not_work), kexpectancy(cc,
    violated_reroute_mitigates_disruption), standard).
leadsto([], and(kexpectancy(cc, violated_reroute_mitigates_disruption), not(
    kaction(cc, action_reserve_crew))), kexpectancy(cc,
    violated_reroute_mitigates_disruption), standard).
leadsto([], kexpectancy(cc, violated_reroute_mitigates_disruption), kcue(cc,
    rerouting_does_not_work), standard).
leadsto([], and(kexpectancy(cc, violated_reroute_mitigates_disruption), kcue(cc,
     rerouting_does_not_work), 'G132', 'G1332'), and(kaction(cc,
    action_reserve_crew), kexpectacy(cc, reservecrew_mitigates_disruption)),
    standard).
leadsto([], kaction(cc, action_reserve_crew), kdc(cc,
    determine_if_reservecrew_possible), standard).
leadsto([], kdc(cc, determine_if_reservecrew_possible), cplan(cc,
    find_reserve_crew_possible), standard).
leadsto([], and(cplan(cc, find_reserve_crew_possible), 'G1311'), communicate(cc,
     cms, request, is_reserve_crew_possible), standard).
leadsto([], communicate(cc, cms, request, is_reserve_crew_possible),
    cexpectation(cc, expectation_cms_informs_reservecrew_availability), standard)
    .
leadsto([], communicate(cc, cms, request, is_reserve_crew_possible), observe(cms
    , cc, request, is_reserve_crew_possible), standard).
leadsto([], and(observe(cms, cc, request, is_reserve_crew_possible), a_1),
    communicate(cms, cc, inform, reserve_crew_is_possible), standard).
leadsto([], and(observe(cms, cc, request, is_reserve_crew_possible), a_0),
    communicate(cms, cc, inform, reserve_crew_is_not_possible), standard).
leadsto([], and(communicate(cms, cc, inform, reserve_crew_is_possible), 'G1310')
    , observe(cc, cms, reserve_crew_is_possible), standard).
leadsto([], observe(cc, cms, reserve_crew_is_possible), belief(cc,
    reserve_crew_is_possible), standard).
leadsto([], and(communicate(cms, cc, inform, reserve_crew_is_not_possible), '
    G1310'), observe(cc, cms, reserve_crew_is_not_possible), standard).
leadsto([], observe(cc, cms, reserve_crew_is_not_possible), belief(cc,
    reserve_crew_does_not_work), standard).
leadsto([], belief(cc, reserve_crew_does_not_work), kworks(cc,
    reserve_crew_does_not_work), standard).
leadsto([], kworks(cc, reserve_crew_does_not_work), kexpectancy(cc,
    violated_reserve_crew_mitigates_disruption), standard).
leadsto([], and(kexpectancy(cc, violated_reserve_crew_mitigates_disruption), not
    (kaction(cc, action_cancel))), kexpectancy(cc,
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    violated_reserve_crew_mitigates_disruption), standard).
leadsto([], kexpectancy(cc, violated_reserve_crew_mitigates_disruption), kcue(cc
    , reserve_crew_does_not_work), standard).
leadsto([], and(kexpectancy(cc, violated_reserve_crew_mitigates_disruption),
    kcue(cc, reserve_crew_does_not_work), 'G132', 'G1331', 'G1332'), and(kaction(
    cc, action_cancel), kexpectacy(cc, cancel_flight_mitigates_disruption)),
    standard).
leadsto([], and(kdc(cc, determine_if_reservecrew_possible), bias_cc_pc_1),
    kworks(cc, reserve_crew_does_not_work), standard).
leadsto([], and(cplan(cc, find_reserve_crew_possible), bias_cc_pc_0, 'G1311'),
    communicate(cc, pc, request, is_positioning_possible), standard).
leadsto([], communicate(cc, pc, request, is_positioning_possible), cexpectation(
    cc, expectation_pc_informs_positioning_seats_availability), standard).
leadsto([], and(communicate(cc, pc, request, is_positioning_possible), 'G112'),
    observe(pc, cc, request, is_positioning_possible), standard).
leadsto([], observe(pc, cc, request, is_positioning_possible), belief(pc,
    is_positioning_possible), standard).
leadsto([], belief(pc, is_positioning_possible), cplan(pc,
    find_if_positioning_is_possible), standard).
leadsto([], cplan(pc, find_if_positioning_is_possible), communicate(pc, pms,
    request, is_positioning_possible), standard).
leadsto([], communicate(pc, pms, request, is_positioning_possible), cexpectation
    (pc, expectation_pms_informs_positioning_seats_availability), standard).
leadsto([], communicate(pc, pms, request, is_positioning_possible), observe(pms,
     pc, request, is_positioning_possible), standard).
leadsto([], and(observe(pms, pc, request, is_positioning_possible), b_1),
    communicate(pms, pc, inform, positioning_is_possible), standard).
leadsto([], and(communicate(pms, pc, inform, positioning_is_possible), 'G1411'),
     observe(pc, pms, inform, positioning_is_possible), standard).
leadsto([], observe(pc, pms, inform, positioning_is_possible), belief(pc,
    positioning_is_possible), standard).
leadsto([], and(belief(pc, positioning_is_possible), 'G112'), communicate(pc, cc
    , inform, positioning_is_possible), standard).
leadsto([], and(communicate(pc, cc, inform, positioning_is_possible), 'G1310'),
    observe(cc, pc, inform, positioning_is_possible), standard).
leadsto([], observe(cc, pc, inform, positioning_is_possible), belief(cc,
    positioning_is_possible), standard).
leadsto([], and(belief(cc, positioning_is_possible), belief(cc,
    reserve_crew_is_possible)), kworks(cc, reserve_crew_works), standard).
leadsto([], and(observe(pms, pc, request, is_positioning_possible), b_0),
    communicate(pms, pc, inform, positioning_is_not_possible), standard).
leadsto([], and(communicate(pms, pc, inform, positioning_is_not_possible), '
    G1411'), observe(pc, pms, positioning_is_not_possible), standard).
leadsto([], observe(pc, pms, inform, positioning_is_not_possible), belief(pc,
    positioning_is_not_possible), standard).
leadsto([], and(belief(pc, positioning_is_not_possible), 'G112'), communicate(pc
    , cc, inform, positioning_is_not_possible), standard).
leadsto([], and(communicate(pc, cc, inform, positioning_is_not_possible), 'G1310
    '), observe(cc, pc, inform, positioning_is_not_possible), standard).
leadsto([], observe(cc, pc, inform, positioning_is_not_possible), belief(cc,
    positioning_is_not_possible), standard).
leadsto([], belief(cc, positioning_is_not_possible), kworks(cc,
    reserve_crew_does_not_work), standard).
leadsto([], kworks(cc, extending_crew_duty_time_works), cplan(cc, propose_delay)
    , standard).
leadsto([], kworks(cc, rerouting_works), cplan(cc, propose_reroute), standard).
leadsto([], kworks(cc, reserve_crew_works), cplan(cc, propose_reserve_crew),
    standard).
leadsto([], kaction(cc, action_cancel), cplan(cc, propose_cancel), standard).
leadsto([], and(cplan(cc, propose_delay), 'G111'), communicate(cc, aoccs, inform
    , cc_solution_delay), standard).
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leadsto([], communicate(cc, aoccs, inform, cc_solution_delay), cexpectation(cc,
    expectation_aoccs_accepts_delay), standard).
leadsto([], and(cexpectation(cc, expectation_aoccs_accepts_delay), not(
    disruption(solved, 'LHB', 'CDG'))), cexpectation(cc,
    expectation_aoccs_accepts_delay), standard).
leadsto([], and(cplan(cc, propose_reroute), 'G111'), communicate(cc, aoccs,
    inform, cc_solution_reroute), standard).
leadsto([], communicate(cc, aoccs, inform, cc_solution_reroute), cexpectation(cc
    , expectation_aoccs_accepts_reroute), standard).
leadsto([], and(cexpectation(cc, expectation_aoccs_accepts_reroute), not(
    disruption(solved, 'LHB', 'CDG'))), cexpectation(cc,
    expectation_aoccs_accepts_reroute), standard).
leadsto([], and(cplan(cc, propose_reserve_crew), 'G111'), communicate(cc, aoccs,
     inform, cc_solution_reserve_crew), standard).
leadsto([], communicate(cc, aoccs, inform, cc_solution_reserve_crew),
    cexpectation(cc, expectation_aoccs_accepts_reserve_crew), standard).
leadsto([], and(cexpectation(cc, expectation_aoccs_accepts_reserve_crew), not(
    disruption(solved, 'LHB', 'CDG'))), cexpectation(cc,
    expectation_aoccs_accepts_reserve_crew), standard).
leadsto([], and(cplan(cc, propose_cancel), 'G111'), communicate(cc, aoccs,
    inform, cc_solution_cancel), standard).
leadsto([], communicate(cc, aoccs, inform, cc_solution_cancel), cexpectation(cc,
     expectation_aoccs_accepts_cancel), standard).
leadsto([], and(cexpectation(cc, expectation_aoccs_accepts_cancel), not(
    disruption(solved, 'LHB', 'CDG'))), cexpectation(cc,
    expectation_aoccs_accepts_cancel), standard).
leadsto([rt:integer], and(communicates(aoccs, pc, inform, aircraft_needs_repair)
    , communicates(aoccs, pc, inform, repair_time_(rt)), communicates(aoccs, pc,
    request, find_pc_disruption_sol), 'G1411'), and(observes(pc, aoccs, inform,
    aircraft_needs_repair), observes(pc, aoccs, inform, repair_time_(rt)),
    observes(pc, aoccs, request, find_pc_disruption_sol)), standard).
leadsto([rt:integer], and(observes(pc, aoccs, inform, aircraft_needs_repair),
    observes(pc, aoccs, inform, repair_time_(rt)), observes(pc, aoccs, request,
    find_pc_disruption_sol)), and(belief(pc, repair_time_(rt)), belief(pc,
    find_pc_disruption_sol)), standard).
leadsto([rt:integer], and(belief(pc, repair_time_(rt)), belief(pc,
    find_pc_disruption_sol)), and(cue(cc, repair_time_(rt)), cue(pc,
    find_pc_disruption_sol)), standard).
leadsto([rt:integer], and(cue(cc, repair_time_(rt)), cue(pc,
    find_pc_disruption_sol), 'G1421', 'G1422', 'G143'), and(kaction(pc,
    action_delay_passengers), kexpectacy(pc,
    delay_passengers_will_mitigate_disruption)), standard).
leadsto([], kaction(pc, action_delay_passengers), kdc(pc,
    evaluate_if_available_transit_time_exceeded), standard).
leadsto([], kdc(pc, evaluate_if_available_transit_time_exceeded), cplan(pc,
    find_transit_time_limit), standard).
leadsto([], and(cplan(pc, find_transit_time_limit), 'G1412'), communicate(pc,
    pms, request, passenger_transit_time_limit), standard).
leadsto([], communicate(pc, pms, request, passenger_transit_time_limit),
    cexpectation(pc, expectation_pms_informs_passenger_transit_limit), standard).
leadsto([], communicate(pc, pms, request, passenger_transit_time_limit), observe
    (pms, pc, request, passenger_transit_time_limit), standard).
leadsto([pt:integer], and(observe(pms, pc, request, passenger_transit_time_limit
    ), pt_(pt)), communicate(pms, pc, inform, passenger_transit_time_limit_(pt)),
     standard).
leadsto([pt:integer], and(communicate(pms, pc, inform,
    passenger_transit_time_limit_(pt)), 'G1411'), observe(pc, pms, inform,
    passenger_transit_time_limit_(pt)), standard).
leadsto([pt:integer], observe(pc, pms, inform, passenger_transit_time_limit_(pt)
    ), belief(pc, passenger_transit_time_limit_(pt)), standard).
leadsto([pt:integer, rt:integer], and(belief(pc, passenger_transit_time_limit_(
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    pt)), rt_(rt), pt_(pt), <=(rt, pt)), kworks(pc, delaying_passengers_works),
    standard).
leadsto([pt:integer, rt:integer], and(belief(pc, passenger_transit_time_limit_(
    pt)), rt_(rt), pt_(pt), rt>pt), kworks(pc, delaying_passengers_does_not_work)
    , standard).
leadsto([], kworks(pc, delaying_passengers_does_not_work), kexpectancy(pc,
    violated_delay_passengers_will_mitigate_disruption), standard).
leadsto([], and(kexpectancy(pc,
    violated_delay_passengers_will_mitigate_disruption), not(kaction(pc,
    action_connection_measures))), kexpectancy(pc,
    violated_delay_passengers_will_mitigate_disruption), standard).
leadsto([], kexpectancy(pc, violated_delay_passengers_will_mitigate_disruption),
     kcue(pc, delay_passengers_does_not_work), standard).
leadsto([], and(kexpectancy(pc,
    violated_delay_passengers_will_mitigate_disruption), kcue(pc,
    delay_passengers_does_not_work), 'G1421', 'G1422', 'G143'), and(kaction(pc,
    action_connection_measures), kexpectacy(pc,
    connection_measures_mitigates_disruption)), standard).
leadsto([], kaction(pc, action_connection_measures), kdc(pc,
    determine_if_connection_measures_possible), standard).
leadsto([], and(kdc(pc, determine_if_connection_measures_possible), bias_pc_ac_1
    ), kworks(pc, connection_measures_does_not_work), standard).
leadsto([], kworks(pc, connection_measures_does_not_work), kexpectancy(pc,
    violated_connection_measures_mitigates_disruption), standard).
leadsto([], and(kexpectancy(pc,
    violated_connection_measures_mitigates_disruption), not(kaction(pc,
    action_delay_pax_no_connect))), kexpectancy(pc,
    violated_connection_measures_mitigates_disruption), standard).
leadsto([], kexpectancy(pc, violated_connection_measures_mitigates_disruption),
    kcue(pc, connection_measures_does_not_work), standard).
leadsto([], and(kexpectancy(pc,
    violated_connection_measures_mitigates_disruption), kcue(pc,
    connection_measures_does_not_work), 'G1422', 'G143'), and(kaction(pc,
    action_delay_pax_no_connect), kexpectacy(cc,
    delay_pax_no_connect_mitigates_disruption)), standard).
leadsto([], and(kdc(pc, determine_if_connection_measures_possible), bias_pc_ac_0
    ), cplan(pc, find_if_connection_measures_possible), standard).
leadsto([], and(cplan(pc, find_if_connection_measures_possible), 'G1412'),
    communicate(pc, ac, request, is_connection_measures_possible), standard).
leadsto([], communicate(pc, ac, request, is_connection_measures_possible),
    cexpectation(cc, expectation_pc_informs_positioning_seats_availability),
    standard).
leadsto([], and(communicate(pc, ac, request, is_connection_measures_possible), '
    G112'), observe(ac, pc, request, is_connection_measures_possible), standard).
leadsto([], observe(ac, pc, request, is_connection_measures_possible), belief(ac
    , is_connection_measures_possible), standard).
leadsto([], belief(ac, is_connection_measures_possible), cplan(ac,
    find_if_connection_measures_possible), standard).
leadsto([], cplan(ac, find_if_connection_measures_possible), communicate(ac, ams
    , request, is_connection_measures_possible), standard).
leadsto([], communicate(ac, ams, request, is_connection_measures_possible),
    expectation(ac, expectation_ams_informs_connection_measures), standard).
leadsto([], communicate(ac, ams, request, is_connection_measures_possible),
    belief(ams, ac, request, is_connection_measures_possible), standard).
leadsto([], and(belief(ams, ac, request, is_connection_measures_possible), d_1),
     communicate(ams, ac, inform, connection_measures_is_possible), standard).
leadsto([], and(communicate(ams, ac, inform, connection_measures_is_possible), '
    G1211'), observe(ac, ams, connection_measures_is_possible), standard).
leadsto([], observe(ac, ams, connection_measures_is_possible), belief(ac,
    connection_measures_possible), standard).
leadsto([], and(belief(ac, connection_measures_possible), 'G112'), communicate(
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    ac, pc, connection_measures_possible), standard).
leadsto([], and(communicate(ac, pc, connection_measures_possible), 'G1411'),
    observe(pc, ac, connection_measures_possible), standard).
leadsto([], observe(pc, ac, connection_measures_possible), belief(pc,
    connection_measures_possible), standard).
leadsto([], belief(pc, connection_measures_possible), kworks(pc,
    connection_measures_works), standard).
leadsto([], and(belief(ams, ac, request, is_connection_measures_possible), d_0),
     communicate(ams, ac, inform, connection_measures_is_not_possible), standard)
    .
leadsto([], and(communicate(ams, ac, inform, connection_measures_is_not_possible
    ), 'G1211'), observe(ac, ams, connection_measures_is_not_possible), standard)
    .
leadsto([], observe(ac, ams, connection_measures_is_not_possible), belief(ac,
    connection_measures_not_possible), standard).
leadsto([], and(belief(ac, connection_measures_not_possible), 'G1211'),
    communicate(ac, pc, connection_measures_not_possible), standard).
leadsto([], and(communicate(ac, pc, connection_measures_not_possible), 'G1411'),
     observe(pc, ac, connection_measures_not_possible), standard).
leadsto([], observe(pc, ac, connection_measures_not_possible), belief(pc,
    connection_measures_not_possible), standard).
leadsto([], belief(pc, connection_measures_not_possible), kworks(pc,
    connection_measures_does_not_work), standard).
leadsto([], kworks(pc, delaying_passengers_works), cplan(pc,
    propose_delay_passengers), standard).
leadsto([], kworks(pc, connection_measures_works), cplan(pc,
    propose_connection_measures), standard).
leadsto([], kaction(pc, action_delay_pax_no_connect), cplan(pc,
    propose_delay_no_connect), standard).
leadsto([], and(cplan(pc, propose_delay_passengers), 'G111'), communicate(pc,
    aoccs, inform, pc_solution_delay), standard).
leadsto([], communicate(pc, aoccs, inform, pc_solution_delay), cexpectation(pc,
    expectation_aoccs_accepts_delay), standard).
leadsto([], cplan(pc, propose_connection_measures), communicate(pc, aoccs,
    inform, pc_solution_connection_measures), standard).
leadsto([], communicate(pc, aoccs, inform, pc_solution_connection_measures),
    cexpectation(pc, expectation_aoccs_accepts_connection_measures), standard).
leadsto([], and(cplan(pc, propose_delay_no_connect), 'G111'), communicate(pc,
    aoccs, inform, pc_solution_delay_no_connect), standard).
leadsto([], communicate(pc, aoccs, inform, pc_solution_delay_no_connect),
    cexpectation(pc, expectation_aoccs_accepts_delay_pax_no_connect), standard).
leadsto([rt:integer], and(communicates(aoccs, ac, inform, aircraft_needs_repair)
    , communicates(aoccs, ac, inform, repair_time_(rt)), communicates(aoccs, ac,
    request, find_ac_disruption_sol), 'G1211'), and(observes(ac, aoccs, inform,
    aircraft_needs_repair), observes(ac, aoccs, inform, repair_time_(rt)),
    observes(ac, aoccs, request, find_ac_disruption_sol)), standard).
leadsto([rt:integer], and(observes(ac, aoccs, inform, aircraft_needs_repair),
    observes(ac, aoccs, inform, repair_time_(rt)), observes(ac, aoccs, request,
    find_ac_disruption_sol)), and(belief(ac, repair_time_(rt)), belief(ac,
    find_ac_disruption_sol)), standard).
leadsto([rt:integer], and(belief(ac, repair_time_(rt)), belief(ac,
    find_ac_disruption_sol)), and(cue(ac, repair_time_(rt)), cue(ac,
    find_ac_disruption_sol)), standard).
leadsto([rt:integer], and(cue(ac, repair_time_(rt)), cue(ac,
    find_ac_disruption_sol), 'G123'), and(kaction(ac, action_reserve_aircraft),
    kexpectacy(ac, reserve_aircraft_mitigates_disruption)), standard).
leadsto([], kaction(ac, action_reserve_aircraft), kdc(ac,
    determine_if_reserve_aircraft_possible), standard).
leadsto([], kdc(ac, determine_if_reserve_aircraft_possible), cplan(ac,
    find_reserve_aircraft_possible), standard).
leadsto([], and(cplan(ac, find_reserve_aircraft_possible), 'G1212'), communicate
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    (ac, ams, request, is_reserve_aircraft_available), standard).
leadsto([], communicate(ac, ams, request, is_reserve_aircraft_available),
    cexpectation(ac, expectation_ams_informs_reserveaircraft_availabilty),
    standard).
leadsto([], communicate(ac, ams, request, is_reserve_aircraft_available),
    observe(ams, ac, request, is_reserve_aircraft_available), standard).
leadsto([], and(observe(ams, ac, request, is_reserve_aircraft_available), e_1),
    communicate(ams, ac, inform, reserve_aircraft_is_available), standard).
leadsto([], communicate(ams, ac, inform, reserve_aircraft_is_available), observe
    (ac, ams, reserve_aircraft_is_available), standard).
leadsto([], observe(ac, ams, reserve_aircraft_is_available), belief(ac,
    reserve_aircraft_is_available), standard).
leadsto([], belief(ac, reserve_aircraft_is_available), kworks(ac,
    reserve_aircraft_works), standard).
leadsto([], and(observe(ams, ac, request, is_reserve_aircraft_available), e_0),
    communicate(ams, ac, inform, reserve_aircraft_is_not_available), standard).
leadsto([], communicate(ams, ac, inform, reserve_aircraft_is_not_available),
    observe(ac, ams, reserve_aircraft_is_not_available), standard).
leadsto([], observe(ac, ams, reserve_aircraft_is_not_available), belief(ac,
    reserve_aircraft_is_not_available), standard).
leadsto([], belief(ac, reserve_aircraft_is_not_available), kworks(ac,
    reserve_aircraft_does_not_work), standard).
leadsto([], kworks(ac, reserve_aircraft_does_not_work), kexpectancy(ac,
    violated_reserve_aircraft_mitigates_disruption), standard).
leadsto([], and(kexpectancy(ac, violated_reserve_aircraft_mitigates_disruption),
     not(kaction(ac, action_delay_flight))), kexpectancy(ac,
    violated_reserve_aircraft_mitigates_disruption), standard).
leadsto([], kexpectancy(ac, violated_reserve_aircraft_mitigates_disruption),
    kcue(ac, reserve_aircraft_does_not_work), standard).
leadsto([], and(kexpectancy(ac, violated_reserve_aircraft_mitigates_disruption),
     kcue(ac, reserve_aircraft_does_not_work)), and(kaction(ac,
    action_delay_flight), kexpectacy(ac, use_same_aircraft_mitigates_disruption))
    , standard).
leadsto([], kworks(ac, reserve_aircraft_works), cplan(ac,
    propose_reserve_aircraft), standard).
leadsto([], kaction(ac, action_delay_flight), cplan(ac,
    propose_use_same_aircraft), standard).
leadsto([], and(cplan(ac, propose_reserve_aircraft), 'G111'), communicate(ac,
    aoccs, inform, ac_solution_reserve_aircraft), standard).
leadsto([], and(cplan(ac, propose_use_same_aircraft), 'G111'), communicate(ac,
    aoccs, inform, ac_solution_same_aircraft), standard).
leadsto([], communicate(ac, aoccs, inform, ac_solution_reserve_aircraft),
    cexpectation(ac, expectation_aoccs_accepts_delay_pax_no_connect), standard).
leadsto([], communicate(ac, aoccs, inform, ac_solution_same_aircraft),
    cexpectation(ac, expectation_aoccs_accepts_same_aircraft), standard).
leadsto([], communicate(pc, aoccs, inform, pc_solution_delay), observe(aoccs, pc
    , pc_solution_delay), standard).
leadsto([], observe(aoccs, pc, pc_solution_delay), belief(aoccs,
    pc_solution_delay), standard).
leadsto([], and(belief(aoccs, pc_solution_delay), not(disruption(solved, 'LHB',
    'CDG'))), belief(aoccs, pc_solution_delay), standard).
leadsto([], communicate(pc, aoccs, inform, pc_solution_connection_measures),
    observe(aoccs, pc, pc_solution_connection_measures), standard).
leadsto([], observe(aoccs, pc, pc_solution_connection_measures), belief(aoccs,
    pc_solution_connection_measures), standard).
leadsto([], and(belief(aoccs, pc_solution_connection_measures), not(disruption(
    solved, 'LHB', 'CDG'))), belief(aoccs, pc_solution_connection_measures),
    standard).
leadsto([], communicate(pc, aoccs, inform, pc_solution_delay_no_connect),
    observe(aoccs, pc, pc_solution_delay_no_connect), standard).
leadsto([], observe(aoccs, pc, pc_solution_delay_no_connect), belief(aoccs,
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    pc_solution_delay_no_connect), standard).
leadsto([], and(belief(aoccs, pc_solution_delay_no_connect), not(disruption(
    solved, 'LHB', 'CDG'))), belief(aoccs, pc_solution_delay_no_connect),
    standard).
leadsto([], communicate(cc, aoccs, inform, cc_solution_delay), observe(aoccs, cc
    , cc_solution_delay), standard).
leadsto([], observe(aoccs, cc, cc_solution_delay), belief(aoccs,
    cc_solution_delay), standard).
leadsto([], and(belief(aoccs, cc_solution_delay), not(disruption(solved, 'LHB',
    'CDG'))), belief(aoccs, cc_solution_delay), standard).
leadsto([], communicate(cc, aoccs, inform, cc_solution_reroute), observe(aoccs,
    cc, cc_solution_reroute), standard).
leadsto([], observe(aoccs, cc, cc_solution_reroute), belief(aoccs,
    cc_solution_reroute), standard).
leadsto([], and(belief(aoccs, cc_solution_reroute), not(disruption(solved, 'LHB'
    , 'CDG'))), belief(aoccs, cc_solution_reroute), standard).
leadsto([], communicate(cc, aoccs, inform, cc_solution_reserve_crew), observe(
    aoccs, cc, cc_solution_reserve_crew), standard).
leadsto([], observe(aoccs, cc, cc_solution_reserve_crew), belief(aoccs,
    cc_solution_reserve_crew), standard).
leadsto([], and(belief(aoccs, cc_solution_reserve_crew), not(disruption(solved,
    'LHB', 'CDG'))), belief(aoccs, cc_solution_reserve_crew), standard).
leadsto([], communicate(cc, aoccs, inform, cc_solution_cancel), observe(aoccs,
    cc, cc_solution_cancel), standard).
leadsto([], observe(aoccs, cc, cc_solution_cancel), belief(aoccs,
    cc_solution_cancel), standard).
leadsto([], and(belief(aoccs, cc_solution_cancel), not(disruption(solved, 'LHB',
     'CDG'))), belief(aoccs, cc_solution_cancel), standard).
leadsto([], communicate(ac, aoccs, inform, ac_solution_reserve_aircraft),
    observe(aoccs, ac, ac_solution_reserve_aircraft), standard).
leadsto([], observe(aoccs, ac, ac_solution_reserve_aircraft), belief(aoccs,
    ac_solution_reserve_aircraft), standard).
leadsto([], and(belief(aoccs, ac_solution_reserve_aircraft), not(disruption(
    solved, 'LHB', 'CDG'))), belief(aoccs, ac_solution_reserve_aircraft),
    standard).
leadsto([], communicate(ac, aoccs, inform, ac_solution_same_aircraft), observe(
    aoccs, ac, ac_solution_same_aircraft), standard).
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II

Literature Study
previously graded under AE4020

1

Airline Operation Control Centers

Airline strategies precede measures performed by an aocc, as presented in section 1.1. The historical context leading up to the monitoring and controlling of transportation networks is shown in section 1.2. Here, the likelihood and financial impact of disruptions is also discussed and the need for an AOCC, responsible for disruption management is motivated. A categorization of disruptions, by chronological order is presented in section 1.3 and other categorizations found in literature are also discussed. In section 1.4, disruptive events are categorized by aircraft and crew categories, as done by Castro. Finally. the AOCC system is categorized as a sociotechnical system in section 1.5.

1.1. Preceding the AOCC

Airline scheduling will determine when and which airline resources are used to accommodate passenger demand well in advance to the day of operations. The main airline resources are the airline's aircraft, crew and passengers [14, 17, 33]. Airline scheduling is a multi-step sequential process. Initially, a timetable is published many months in advance. After this is set, both revenue management and scheduling of the aircraft and crew resources is done. The objective of revenue management is to maximize the revenue generated from seats sold [17, 54] with a few exceptional cases such as when an airline is looking to enter a new market [33]. Fleet assignment assigns a particular aircraft type to a particular flight. This will set the number of seats available for a specific flight. Given the fleet assignment, crew pairing is done to define the amount and type of crew per flight as well as the crew duty periods that will be necessary. For example, long haul aircraft require different technical certifications for aircraft operation than short haul aircraft and also more crew. Crew rostering follows crew pairing and assigns specific crew members to crew pairings which becomes visible to crew members on the crew roster. The crew roster may change up to the day of operations to account for any necessary changes (Clarke [19], Clausen et al. [20], Grandeau [33], Kohl et al. [55]).

The multi-step sequential process described above is called the sap. The SAP will typically deal with scheduled operations, up to one or several days before the day of operation. The SAP optimizes for maximizing profits, given the expected demands and airlines resources available. During the day of operations, events that negatively affect an airline's operational performance often manifest. **The airline disruption management process is concerned with disruptive events.** This way, systematic decisions mitigate the negative effects of operational disturbances, which introduce operational inefficiencies. In Figure 1.1 two illustrations, at different levels of granularity, show the airline scheduling assignment problem followed by the disruption management process.

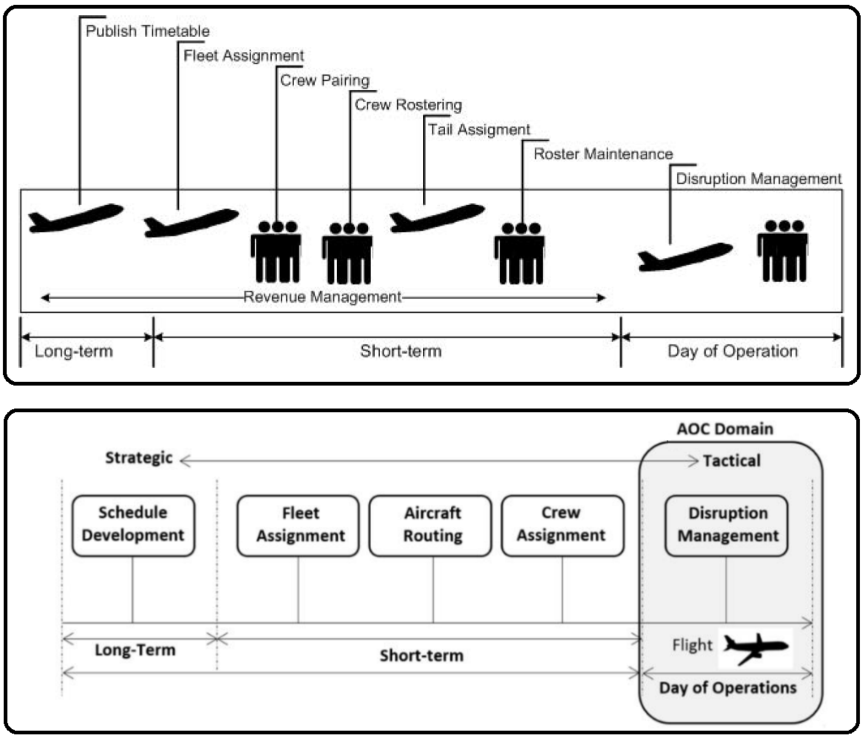

Figure 1.1: The airline scheduling process [14, 17]

1.2. Past, present and future

The notion of monitoring and controlling a transport network in real time is relatively old. In the 19th century, the railway industry made use of telegraphs to communicate faster than physical transport [71]. This enabled them to monitor and act upon real-time operations from a centralized location. Today, this centralized monitoring and control is ubiquitous and present across multiple industries, including the airline industry where the AOCC may act as a centralized location, for monitoring and control.

The external or internal events that disrupt an airline's day-to-day operations introduce additional costs for fuel, crew, aircraft, maintenance and passenger goodwill [8, 17]. EUROCONTROL reports that on average 19.2% of flights in Europe suffered from delays in Q1 of 2019 [26]. The cascading effect of disruptions is also evident as they also report that 42% of the total generated delay minutes have a reactionary cause. In Table 1.1, the impact of disruptive events over the past nine years, on delays, cancellations and diversions, towards North American airlines, is shown. One may observe that, on average 20% of flights have arrival delays, 2% are cancelled (approximately 1 in every 50 people get their flight cancelled at the airport). As shown in Table 1.2, eight billion dollars is the estimated annual direct aircraft operating costs of schedule delays For airlines operating in the US in 2007. This figure excludes the and additional estimated annual passenger delay costs of four billion dollars. [4].

Disruptions may have an immediate adverse effect and also potentially propagate deeper into airline planning. The highly probable large impact of disruptive events on airlines, strongly motivate an organizational body, within an airline, responsible for disruption management, namely the AOCC.

[1]URL https://www.transtats.bts.gov/HomeDrillChart.asp [cited 29 October 2020].

Year	Flight Ops.	Arriv. Delays	Delayed (%)	Cancelled	Cancelled(%)	Diverted
2011	3,580,046	732,617	20.46%	87,423	2.44%	9,341
2012	3,568,292	576,543	16.16%	40,111	1.12%	7,838
2013	3,740,376	775,845	20.74%	62,971	1.68%	9,026
2014	3,412,583	766,539	22.46%	98,017	2.87%	9,489
2015	3,410,230	681,843	19.99%	67,641	1.98%	9,652
2016	3,279,920	571,198	17.41%	44,130	1.35%	8,794
2017	3,307,279	660,224	19.96%	46,298	1.40%	8,142
2018	4,186,903	792,748	18.93%	78,608	1.88%	10,608
2019	4,293,367	854,765	19.91%	98,200	2.29%	12,358
2020*	2,900,462	282,315	9.73%	267,567	9.22%	4,828

Table 1.1: United State Bureau of Transportation Statistics: On-Time Performance - Flight Delays at a Glance[1].
* In 2020 Covid-19 lead to lockdowns and restricter travel.

Direct (aircraft) operating costs	$/ block·minute	Annual delay costs ($ millions)
Fuel	27.86	3727
Crew – pilots/flight attendants	12.71	1 700
Maintenance	9.57	1 281
Aircraft ownership	7.70	1031
Other	2.62	350
Total DOCs	60.46	8089

Table 1.2: Air Transport Association direct operating cost estimates, July 2007 [8].

The AOCC's is responsible for identifying when disruptive events occur, generate potential solutions to mitigate its effects and execute a solution into the operational plan. This id done in accordance with the AOCC's top-level objectives. may have a top-level underlying objective. For instance, this may be to return to the original plan as soon as possible; by next morning, or simply ensure all flights are executed as promised to customers [54]. High-level underlying objectives will generally be decided upon by upper management and it is decision-makers' responsibility to align these with disruption management solutions.

A broad scope of operational disturbances affect airlines. In section section 1.3, these are categorized by phase of operation to obtain a chronological overview. The three phases of operation are, namely en-route, turn around and departure. The three phases and their corresponding operational disturbances are shown in Figure 1.2. Subsequently, events are categorized by aircraft, and crew type in section 1.4. This is done to identify cause-effect relationships that attribute a disruptive event to a particular airline resource and hence an associated disruption management responsibility.

1.3. Disruption Sources by Phase of Operation

1.3.1. En-route Disruption Sources

En-route disruptions occur after flight departure and before landing at a destination airport. Four events that may occur during en-route operations and potentially introduce a flight arrival delay, are described below:

- **En-route traffic delay** will result from congestion in airways. If too many aircraft are occupying predefined flight routes, aircraft separation rules will require that aircraft maintain a safety distance from each other. En-route Traffic Delay may require aircraft to reduce cruise speeds to maintain separation requirements, leading to flight arrival delays.
- **En-route aircraft malfunctions** occur when unplanned technical or mechanical issues arise that have a compromising effect on the performance or safety of an aircraft. Depending on the severity of the situation, further in-flight checks or safety landing preparations (by pilots and/or ground services), may lead to flight arrival delays.

- **Flight diversions** occur when a flight plan is altered after take-off. Flight arrival delays may result from aircraft taking longer routes without cruise speed adjustments.

- **En-route weather** can have an effect on flight operational safety. It may require an original flight plan to be adapted, as a means to adjust cruise altitude or circumvent particularly hazardous geographical regions. Strong runway cross-winds and low visibility are also meteorological factors that can delay flight arrival.

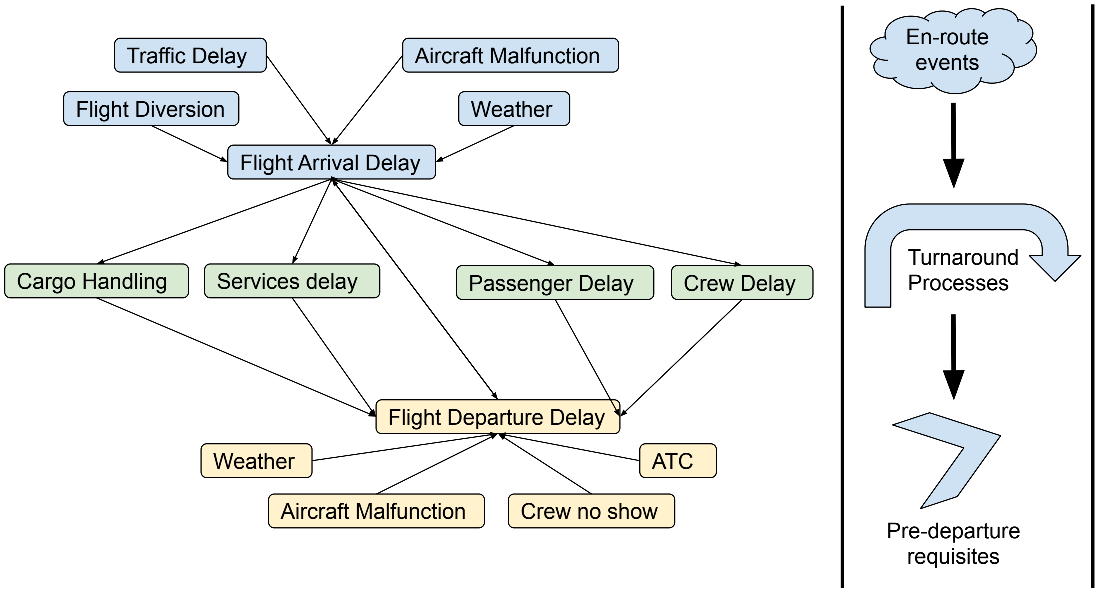

Figure 1.2: Operational disturbances in the three operational phases.

According to Grandeau [33], weather, however mild or severe, is the reason for most irregular operations airlines face. However, severe weather can consequentially lead to aircraft malfunctions and so these are not mutually exclusive. The same goes for weather, flight diversions and en-route traffic delay. It may be conjectured that a snowball effects ensue, such that convective weather leads to flight diversions which in turn increases en-route traffic delay and additional ATC requirements, resulting in a substantial arrival delay. In snowball effect situations an airline will assign one category as the disruption's root cause. That could explain why, in part, TAP Air Portugal reports meteorological conditions as their least frequent disruption as show in Figure 1.3. Another reason why TAP Air Portugal may report infrequent meteorological disruptions, is due to their hub locations. Lisbon airport is situated in a relatively mild weather geographic region, when compared extreme examples such as Boston Massachusetts, where Grandeau [33] performed her research. **From the literature, one may draw the conclusion that the frequency distribution of disruptive sources is a function of hub location as whether and other hub related constraints apply.**

1.3.2. Turnaround Disruption Sources

After landing and before take-off procedures, a turnaround process is initiated. Four disruption sources that may affect turnaround process and lead to delays, are described below:

- **Cargo handling** is a logistical process where payload inside an aircraft is unloaded and distributed inside an airport or to other aircraft, and new payload is loaded onto the respective aircraft. In principle, personnel will know what to expect during the unloading (or loading) of payload as it is the airline's responsibility to communicate this, beforehand. Lack of personnel or training are generic reasons for why cargo handling could take longer than expected. In addition, it could take longer than expected to remove and transport items if these are fragile items or if the number of payload items far exceeds the typical volume handled. Transit times for airport vehicles at the airport could increase as a result of low visibility. This may have an impact on transferring

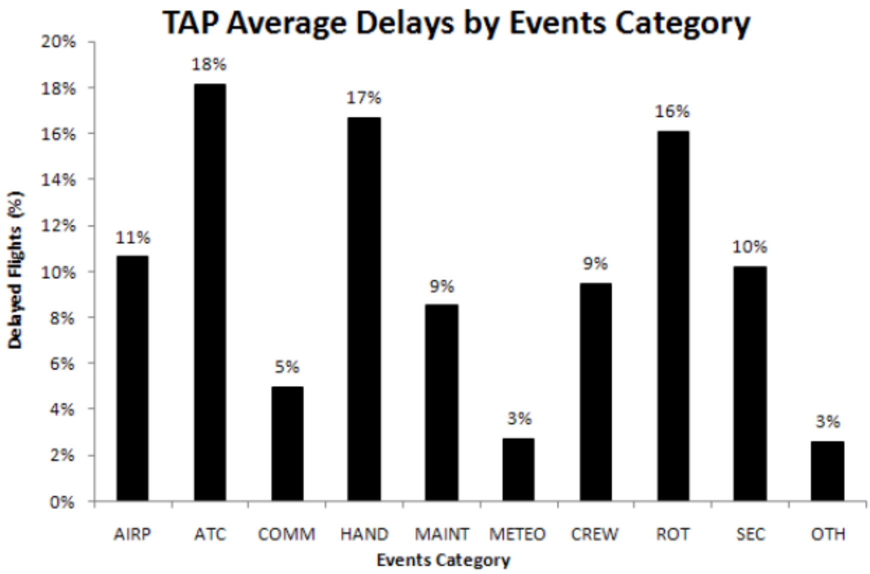

Figure 1.3: TAP Air Portugal delay by event category [17].

payload times. When factoring all variables involved in cargo handling, it is understood that many factors may potentially lead to a turnaround delay.

- Aircraft require refueling and cleaning **services** during turnaround. Both services may be provided by either the airport operator and/or third party partners. Typically, these services will involve some required interaction between airline crew and service personnel. If initial contact is delayed, the completion of the provided services may delay turnaround. In addition, external factors may influence the punctuality or execution time of the provided services by airport operator of third party partners.
- **Passenger delays** that have an effect on turnaround delay result for two main reasons. Firstly from connecting passengers whose previous flight leg arrived late. Secondly, due to skewed gate arrival distribution times. Long security checks or gate changes may result in gate arrival time distributions skewed towards the latter end of boarding windows. As a result, there is insufficient time, before scheduled departure, to seat all passengers. In addition, large events outside the airport may delay large batches of passengers and airlines are willing to delay a flight in such situations. This latter reason is not a written rule, varies by airline policy and is very circumstantial.
- **Turnaround crew delay** refers to events that occur between flight legs that affect crew availability. Events that may lead to situations where the minimum required number of crew for flight is not available are crew falling sick, or delayed for a scheduled flight connection. When a crew member exceeded any labor/law rules like duty time between flights, this is also categorized as a Turnaround Crew delay. An exhaustive list of crew delay reasons will be further presented in this chapter.

In regards to events that may delay operations during turnaround, there are factors that are within the AOCC's control. These are factors such as the communication of cargo type and volume to personnel; airline crew promptness and prompt interactions with 3rd party partners. However, there are situations where delay may occur due to things out of the AOCC's control such as third party promptness or third party execution time.

1.3.3. Departure Disruption Sources

After an aircraft lands and all required unloading, loading and necessary air-side services are complete, an aircraft requires conditions for take-off.

- The meteorological conditions at the departure or destination airport must be favourable for a safe departure and landing. Flights may be delayed if improved **weather** conditions are a requirement for operational safety.
- Hard aircraft landings could lead to mechanical **aircraft malfunctions** which requires additional unplanned inspections and maintenance, not typically included in turnaround processes. Inspections and maintenance are done to ensure aircraft meet regulatory safety requirements before departure. Depending on the seriousness of the issue at hand or the availability of maintenance personnel, the former can be done in parallel to the turnaround process or may require the aircraft's displacement to a maintenance hangar.
- Where **turnaround crew dela** was associated to in-between flight legs events, Crew Departure Delays are all other events that may affect crew availability. Crew Departure Delays are cause by events such as crew not reporting for duty at home base. A exhaustive tabulation of all crew disruptive events will be further shown in this chapter.
- When a flight is scheduled to take-off at a particular time, they are assigned a slot to take-off. If a flight is not ready for take-off at the scheduled time of departure, it will request clearance for take-off at a delayed time (relative to scheduled slot time). **ATC** has the authority to waive take-off clearance rights, until a new ATC slot opens, after flights who requested clearance for take-off at the scheduled slot times, departed.

Concerning departure delays, the event an airline has most control over is 'crew no show'. An in principle should be able to manage crew resources in a resilient way, such that if one crew member's services are unavailable for a scheduled flight, a substitute may be found and allocated promptly. Similarly to the comparison done in the first disruption phase, weather and ATC delay are not mutually exclusive in the third and final phase of operation.

1.4. Formalizing Delays

In this section, formal categorizations of delays are introduced and one thought to be the best reference for researchers.

Airlines record flight delay events following the International Air Transport Association (IATA) numeric delay codes. There 99 hundred delay codes, 5 of which (00-05) are available for airline internal codes. Below a select few from this list are listed for illustrative purposes:

- **Passenger and Baggage:** 15 (PH) BOARDING, discrepancies and paging, missing checked-in passenger.
  This delay that is associated to the passenger resource and may result in a turnaround delay.
- **Aircraft and Ramp Handling:** 39 (GT) TECHNICAL EQUIPMENT, lack of or breakdown, lack of staff, e.g. pushback.
  This delay that is associated to the aircraft resource and may result in a turnaround delay.
- **Flight Operations and Crewing:** 67 (FC) CABIN CREW SHORTAGE, sickness, awaiting standby, flight time limitations, crew meals, valid visa, health documents, etc.
  This delay is associated to the crew resource and may be either a turnaround or departure delay.

Contrastingly to IATA's codification, Grandeau [33] brakes down the effect of operational disturbances into deviations of two groups. Deviations that do not cause rescheduling are called time deviations and those that cause rescheduling and rerouting are irregular operations. Fundamentally, this categorization differentiates between disruptive events that may or may not, require AOCC intervention. This view makes observing a flight that arrived 10 minutes late as an irregular operation because at face value, it would seem trivial to spend resources on this event. The pitfall of this categorization is that it may lead to operational oversight for events that do not require immediate rescheduling or rerouting and may have cascading effects due to operations' reactionary nature.

IATA codes are exclusive and exhaustive and therefore useful to classify delays at a granular level that allows for their thorough study, after disruption. The categorization done by Grandeau [33] however is not granular enough for performing studies and is not insightful with respect resources affected in real-time. To this end, Castro [17] subdivided airline operational disruptive events into aircraft and crew categories. These categories allow for real-time cause-effect information associating disruptive events with affected airline resources, paramount to the disruption management process. This dual categorization is useful insofar as an AOCC is equipped with managers and experts whose primary focus is solving aircraft or crew problems. It should be noted that, the passenger resource has been factored into the aircraft category. Castro's categorization also provides insightful real-time information to be used in a proactive way, to avoid or minimize delay before they happen. Illutrated in Table 1.3 and Table 1.4, **Castro's categorization is argued to be the best reference for disruptive event categorization for research into decision-making within the AOCC domain.**

Event Category	Event Description	Operational Phase
AIRP	Airport infrastructure causes: SEF, Stands, Airport Capacity, ULDs, RX machines, etc.	[T], [D]
ATC	En-route and destination ATC restrictions as well as en-route and destination meteorological conditions.	[A], [D]
COMM	Protection of passengers due to cancellation of another flight or passengers missing after check-in.	[T],[D]
HAND	Problems boarding passengers and/or loading cargo, problemsdue to taxing/runway officer	[T]
MAINT	Problems due to some kind of malfunction and/or maintenance related.	[A],[D]
METEO	Adverse meteorological conditions at departure airport impairing landing or handling.	[A],[T],[D]
CREW	Missing crew members and other crew related problems.	[T],[D]
ROT	Problems related to the rotation of the aircraft. For example, late arrival of the incoming aircraft	[T],[D]
SEC	Baggage identification, search and retrieve of baggage after boarding.	[D]
OTH	All other problems not related to any of the previous.	[A],[T],[D]

Table 1.3: Aircraft Delay Event Categories [17] and their association to arrival [A], turnaround [T] and departure [D].

Event Category	Event Description	Operational Phase
SIGN	Crew member not reporting for duty at home base	[D]
RULES	Crew member has exceeded any labor/law rules like duty time	[T]
INDUTY	Crew member unavailable after sign-on. For instance, accident or illness during flight	[T]
ROT	Crew member miss a flight due to the delay of a previous flight or other causes related to crew rotation	[T]
METEO	Adverse meteorological conditions at departure airport impairing landing or handling	[D]
OTH	Other reasons not included in the previous.	[T],[D]

Table 1.4: Crew Delay Event Categories [17] and their association to turnaround [T] and departure [D].

1.5. The AOCC as a Sociotechnical System

Sociotechnical system attributes are defined below, to motivate its suitableness to categorize the AOCC.

CS are comprised of numerous heterogeneous components, at different scales, with non-linear interactions among components, and also with the environment [92]. An AOCC is comprised of numerous decision-makers in differently resource groups. Non-linear decisions are driven by objectives and limiting constraints and non-linear interactions occur due to human behaviour which may produce chaoticity

[46]. The scale of operation will vary throughout the day with peaks toward the middle of the day, when most passengers travel. For these reasons, it is fair to assume the AOCC as a CS.

A CAS will have components that learn to adapt and modify their local and potentially global behaviour [38]. A STS in an example of a CAS and its main characteristics are identified below [78]:

- A large number of dynamically interacting elements
- Wide diversity of elements i.e., hierarchical structures, task distributions and specializations.
- Unanticipated variability due to uncertain decision-making and due to the fact that the system is open to the environment
- Resilience due to the system's ability to cope with the uncertain and dynamic environment [23]

In an AOCC, aircraft, crew and passenger need to get from A to B which requires dynamic interactions among airline resources. The AOCC organizational structure introduces a hierarchical structure and different roles are responsible for coordinating or executing specialized tasks as means for dealing with disruptions. For reasons within or beyond an airline's control, disruptions occur and decisions are made without clear certainty over their consequences.

Furthermore, due to the large number of interacting elements within an AOCC, a multi-level structure emerges and three levels can be distinguished, namely: individual, social and organisational [92]. At the individual level we have the cognition of specialists and managers. At the social level, interactions occur through direct of indirect communication and coordination among AOCC constituents. At the organizational level we consider more abstract factors such as organizational goals, rules, norms, procedures, and strategy. **For reasons mentioned above, the AOCC may be categorized as a sociotechnical system.**

In this chapter, the Scheduling Assignment Problem is described as a profit maximizing exercise that defines the planned arrangement of resources on the day of operations. Given the percentage of delayed flights and their financial impact, it is imperative that airlines manage these disruptions effectively to control the costs of irregular operations. Inevitable operational disruptions can be managed through a disruption management process. The Airline Operational Control Center is responsible for the disruption management process and disruptions that occur en-route, during the turnaround process or impede an aircraft from departing. Formal categorizations for airline disturbances are found in literature, and Castro appears to provide the most extensive and suitable one, providing real-time time information regarding disruptive event and affected airline resource. Managerial underlying objectives drive the disruption management process. Functions within the AOCC are ultimately responsible for identifying disruptions and generating potential solutions to mitigate a disruptive event and ensure these are aligned with the airline's underlying disruption management goal. The roles and function within an airline AOCC are further described in chapter 2. Finally a categorization of the AOCC as a system is done based on its attributes. Given its large number of dynamically interacting elements, in a hierarchical structure that copes with uncertain events, it is found that the AOCC is highly aligned with sociotechnical system as therefore, it is classified as such.

2
AOCC Features

In this chapter there are four main sections. In section 2.1, there is a natural continuation to the information presented in chapter 1. Here, essential roles required to have a fully functioning AOCC are presented and their responsibilities are described. Furthermore, three types of AOCC organizational structures are presented where the hierarchical order is explained and collaborative elements are discussed. In section 2.2, all possible alternative solutions for disruption events are discussed. These are split into the three main resources, namely aircraft, crew and passengers. In section 2.3, the objectives that drive the disruption management solution are laid out. Finally, constraints that limit the decision space, such that the final solution is an acceptable one for all decision-maker, are elaborated on in section 2.4.

2.1. Responsibilities, hierarchies and sources of information

After the airline planning process and during the Schedule Assignment Problem, where optimizations for operational costs are performed well in advance to the 2 operations, deviations from airline planning are inevitable. Deviations from airline planning require a disruption management process to identify problem sources and also generate, propose and select efficient solutions. During the day of operations, AOCC human resources understand the nature of operational disruptions and find operational solutions compliant with multiple problem domains. In this section roles and responsibilities within an AOCC, organizational structures and sources of information are outlined.

2.1.1. Roles and Functions

The names of the functions most common in an AOCC, their alternative names as well as resources where they have been found, is shown in Table 2.1. Depending on the organization's size and how distributed the airline's operations are across geographic regions, airline organizational structures differ. Regardless of whether an airline has a centralized AOCC or a decentralized Station AOCC, all airlines have the same duties to fulfill [33]. Below, a concise description of the responsibilities for each role is given:

The **flight dispatch role** is responsible for flight planning and flight dispatch. In North America, flight following will also be part of the flight dispatcher's responsibilities, whereas in Europe, it is part of the aircraft controller's responsibilities [54]. Flight planning consists of computing and filing of the flight plan and also calculating the flight's fuel requirements. Flight dispatch will consider the loading scenario to compute take-off and landing performances and request flight slots to Air Traffic Control (ATC) entities [17]. Flight following monitors the flight's progress after take-off and may require the flight dispatcher to act as an intermediary between pilots and ATC during emergencies or off-nominal events [33].

The **aircraft controller** role is responsible for managing the aircraft resource. This role can be subdivided into smaller groups such as long/short haul flights (EU) or even geographical regions (US) [17]. Visual software tools will likely be used to monitor the operation and decision support tools to support

AOCC role	Alternate names	Ascribed to
Flight Dispatch	Flight Dispatcher, Aircraft Dispatcher, Flight dispatch and following Flight follower;	Castro, Bouarfa et al., Kohl
Aircraft Control	Air Traffic Control Coordinator, Aircraft routers	Kohl, Berry and Pace
Crew Control	Crew Scheduler, Crew Tracking, Crew Operations	Castro, Berry and Pace , Kohl, Grandeau
Maintenance Services	Maintenance Watch, Maintenance Control, Aircraft engineering, Aircraft Maintenance	Castro, Bouarfa et al., Kohl, Grandeau
Passenger Services	Customer service, Passenger Handling	Castro, Bouarfa et al., Kohl, Grandeau
AOCC manager	Duty manager, Airline Operation Supervisor, Operations Manager, Duty Director, Sector manager, SOC director	Bouarfa et al., Berry and Pace, Kohl,

Table 2.1: The roles and alternative names used for these roles within airline operations literature.

decision-making. Should any disruptive event emerge, it is the aircraft controller's responsibility to minimize delays through actions such as exchanging aircraft or joining flight, among other things discussed in subsection 2.2.1. It is important to note that, besides managing the aircraft resource, often, the aircraft control plays a central role in the disruption management process. This is because it is a scarce resource and therefore one that is typically solved for first. [54].

The **crew controller** has two main responsibilities which are crew monitoring and crew rescheduling. By monitoring crew check-ins and check-outs, crew control determines if crew rescheduling is necessary. If so, crew rosters are changed according to the disruption, current operational constraints and the available stand-by crew or, in necessary, reserve crew. If there are crew scheduling issues, that do not necessarily stem from an operational disruption, they are responsible to resolve these issues by working with the flight crews [10]. Similarly to the aircraft controller, the crew controller may use decision support tools to aid decision-making.

Maintenance services will act as a liaison between line maintenance and the AOCC. If any unplanned malfunctions emerge, they update maintenance on maintenance issues. They are also responsible for ensuring that aircraft are sent to maintenance for planned scheduled maintenance. Typically, A check and B checks take a considerable amount of time [33], so these are not maintenance checks that can be done only over night. Since maintenance for these requires a substantial amount of resources, it is harder to negotiate their scheduling.

Passenger services are responsible for ensuring that, if any deviation (delay or cancellation) from the original flight plan affects passengers, they will be considered in decision-making and informed about conclusions. It is in the airline's best interest passengers do not suffer great inconveniences from a marketing point of view but also from a cost perspective, in the form of vouchers, meal provisions and accommodation stays. This role may be part of services provided at the airport or, for bigger airlines, a role within the Hub Control Center (HCC) [17].

The **AOCC supervisor** role, as the name suggests, is responsible for the overall coordination (negotiation and collaboration) of operations within the AOCC. The AOCC supervisor role assists with unexpected delays and other issues impacting success. He or she will ensure the disruption management outcomes are aligned with upper management's underlying top-level disruption management goals such as safety, efficiency and economics of operations [10]. Considering all the above, most airlines leave it up to the AOCC supervisor to decide how he or she should perform the task [54].

In light of the above, it is understood how human decision-makers share different roles to achieve a common goal, that is to come up with a solution that mitigates the adverse effects of a disruptive event. In this chapter consideration will also be given towards how the hierarchical structures, individual objectives and constraints guide the disruption management process. Nevertheless, it must be understood that ultimately, humans, in spite of their aiding decision support tools, are ultimately collaborating and negotiating towards their interests during this process. Gaining a solid understanding for what drives human behaviour will likely provide valuable insights towards their effects on the AOCC disruption management process. **Furthermore, studying human factors affecting decision-making in the AOCC domain, may shed light on factors inherent to the human condition, that apply ubiquitously across industries.**

2.1.2. AOCC Organization Structure

The AOCC is generally located at an airline's headquarters, which, in turn, is typically located at one of the airline's main hubs [33]. The organizational structure is varied and depends on factors such as the airline size, network type (hub vs. spoke), the geographic distribution of services and organizational preference, among others [17]. Castro [17] and Machado et al. [64] have proposed three types of AOCC organizational centers, namely a **decision center**, a **hub control center**, and an **integrated control center**.

In an airline's **AOCC Decision Center**, the aircraft controller and the AOCC supervisor share the same physical space and other roles operate remotely. In this center type, the AOCC has autonomy for flight related decisions i.e., delay, cancellation, etc... Since the AOCC is not hierarchically above other support functions, it must cooperate with other support functions to reach decisions affecting other domains. A figure for the organizational structure and horizontal hierarchy is shown below in Figure 2.1.

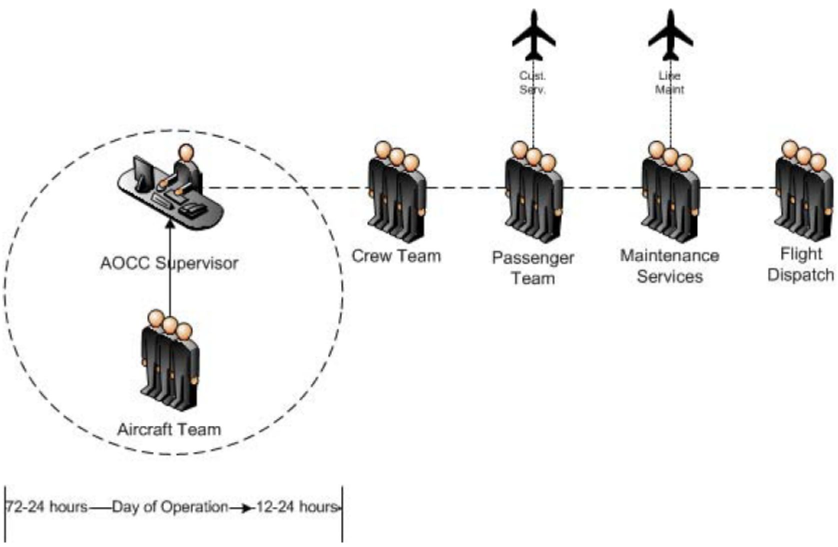

Figure 2.1: AOCC Decision Center [17]

In an **Integrated AOCC**, all roles share the same physical space and there is hierarchical dependence. The AOCC supervisor takes the final decision that affects all dimensions, after collaborating with other supporting roles. The main advantage is that one person has the final say which likely leads to more rapid decision-making. A figure that is illustrative of the integrated AOCC is shown in Figure 2.2.

A **HUB Control Center (HCC)** is a distributed control center where roles are physically separated at the location where airlines operate a hub. In this center type, the HUB supervisor will coordinate passenger services and maintenance services among other local services. If crew and passenger services are located at the hub, they will collaborate with the HUB supervisor, under AOCC coordination. In this situation, the aircraft controller is outside the hub and we have an AOCC Decision Center with a HUB as shown in Figure 2.3.

If crew and passenger services are not located at the hub, and share the same physical location and the AOCC, then we have an **Integrated AOCC with a hub** as shown in Figure 2.4.

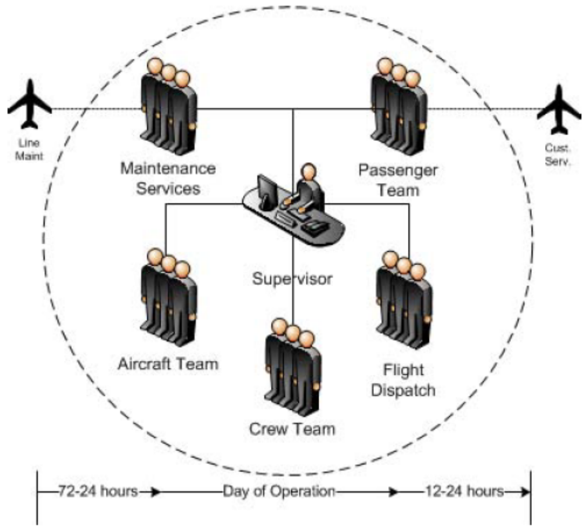

Figure 2.2: Integrated AOCC [17]

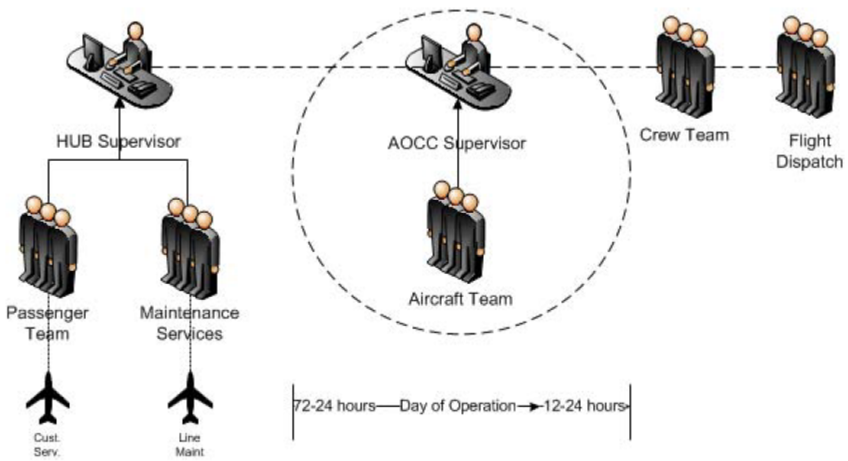

Figure 2.3: Decision Center with a HUB [17].

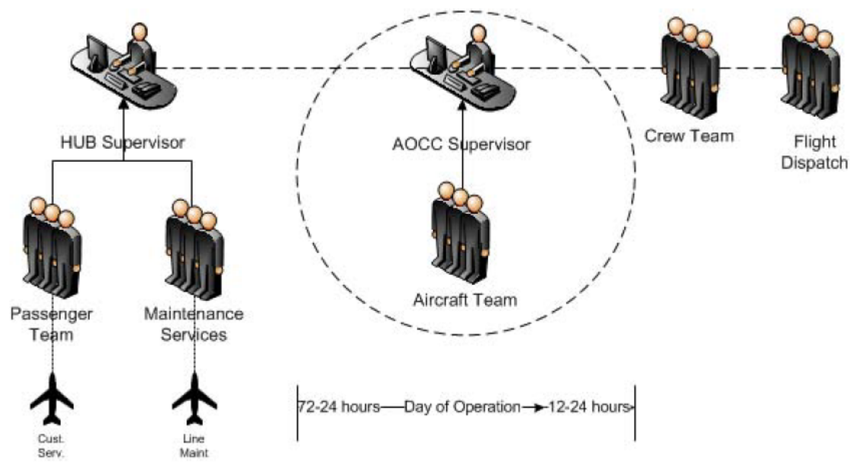

Figure 2.4: Integrated AOCC with a HUB [17].

In this subsection AOCC roles are described. The responsibilities per role may slightly vary per region or airline type however, underlying functions persist. The organizational structure of an AOCC will result in a communication flow structure and hierarchical structure that may have an effect on the final decision reached. Nevertheless, the roles will exercise their functions based on their individual objectives and respective constraints. What precedes the problem solving aspect of disruption management is the identification of a disruption problem. For a problem to be detected, it must be identified by decision-makers. To this end, various sources of information are made available to decision-makers and is shown in subsection 2.1.3.

2.1.3. Sources of information

Sources of information will enable decision-makers within the AOCC to identify disruptive events, triggering the disruption management process. In addition to the identification of disruptive events, information sources also provide two other benefits. **Firstly if the operational environmental is understood, available resources to solve the problem can be identified. Secondly, information sources show decision-makers, constraints that restrict the solution space.** These constraints may be related to temporarily unavailable resources, or rules and regulations that forbid certain solution alternatives i.e., maximum crew duty hours. In Table 2.2 one finds the relationship between information sources and the respective AOCC resource managers that stand to gain actionable insights [10, 17]:

Information Source	Knowledge gained	AOCC Constituents
Flight and aircraft movement (updated through MVT messages and Datalink (ACARS) messages) and flight reports from crew)	Estimated/actual flight arrival/departure times Aircraft type Cancelations and aircraft exchanges (to execute) Passenger connection times	AOCC, ,aircraft, crew, passenger, flight dispatch
Passenger booking	Itinerary of passengers Number of passengers on each flight Boarding status Passenger type (executive, home residence)	AOCC, passenger
Laws and regulations (Airline agreements, EASA FTL, National law)	Crew working hours	Crew
Crew roster	Each crew assigned to each flight Days off Vacation Training	Crew
Aircraft roster	Aircraft tails assigned to each flight Maintenance activities scheduled for each aircraft.	AOCC, flight dispatch, maintenance, aircraft controller
ATC slots (Central Flow Management Unit)	Landing and taking-off times at airports. Available time to overfly particular waypoints.	AOCC, flight dispatch, aircraft controller
Meteorological Information (NOTAM)	Information about airport and en-route weather.	AOCC, flight dispatch, aircraft controller
Aircraft Operational Information	Operational cost Passenger capacity Most optimal routes Medical passenger facilities Pressurized cargo bays (live animals)	AOCC, flight dispatch, aircraft controller
Flight Information	Airport costs Service costs ATC en-route charges Aeronautical Information Publication (night curfew and noise restrictions) Fuel consumption	AOCC, aircraft controller
Crew Costs	Hourly Additional hours Pedriem Hotel Extra-crew travel	Crew
Passenger costs	Airport meals Passenger hotel Compensations	Passenger

Table 2.2: Information sources provide knowledge to AOCC constituents such as resource managers and supervisor.

2.2. Solving AOCC Disruption Problems

When it comes to negotiating alternative solutions or choosing a solution for implementation, there is a defined solution space. Solutions that could ultimately be considered for any disruption problem are presented below. Subsequently, the traditional approach for collaboratively solving disruption problems is discussed. Decision support tools used to guide decision-makers are presented and the solutions respectively considered are stated.

2.2.1. Solution Space for Disruptions

Considering the main airline resources, solutions spaces should, correspondingly, be divided in three, namely aircraft, crew and passenger solution spaces.

The **aircraft solution space** allows for six actions that affect the aircraft resource. These are:

- **Exchange** the disrupted aircraft with a spare aircraft or one that has a later scheduled time of departure.
- **Delay** the disrupted flight.
- **Reroute** the disrupted flight by adapting a flight plan to one with available ATC slots.
- **Join** flights together such that another aircaft will also perform the disrupted flight.
- **ACMI** is the leasing of aircraft, crew, maintenance services and insurance.
- **Cancel** the flight

Action/Source	**AIRP**	**ATC**	**COMM**	**HAND**	**MAINT**	**METEO**	**CREW**	**ROT**	**SEC**	**OTH**	**Av**
Exchange	0%	0%	0%	0%	80%	0%	0%	80%	0%	60%	22
Rerouting	0%	50%	0%	0%	0%	0%	0%	0%	0%	7%	6%
Join	0%	0%	0%	0%	2%	0%	0%	0%	0%	4%	1%
Delay	95%	45%	90%	98%	15%	98%	95%	19%	100%	25%	68
Acmi	0%	0%	0%	0%	1%	0%	0%	0%	0%	1%	0%
Cancel	5%	5%	10%	2%	2%	2%	5%	1%	0%	3%	4%

Table 2.3: Percentage distribution for actions chosen by aircraft controller, given disruption source category [17].

The association between the disruption source and corresponding action taken by an AOCC has been studied in a major European airline [17] and is illustrated in Table 2.3. Event source categories are previously defined in Table 1.3 and Table 1.4. In this figure strong correlations can be identified between disruption source and management action. It is observed that 80% of the time there is a maintenance issue, the disrupted aircraft will be exchanged with another aircraft. It is also observed that when there are unfavourable meteorological conditions, 98% of the time, the only action to be taken is delaying the disrupted aircraft. The values presented are likely influenced by factors that vary across different airlines. **Nevertheless, the conclusion drawn is that aircraft controller actions are highly dependent on the type of disruption source category they are faced with.**

The **crew solution space** allows for ten actions that affect the crew resource. These are shown below and some are self explanatory to the point where a further description is redundant:

- **Use Reserve at Airport**
- **Use Nearest Reserve at Home**
- **Exchange with crew from another flight** is typically done when the schedule time of departure for another flight does not coincide with the disrupted flight.
- **Use crew with Free Time** that does is not assigned to a flight or another activity at the present time.

- **Use Day-Off Crew**
- **Use Crew on Vacation**
- **Propose an Aircraft Change** occurs when available crew is unqualified to operate disrupted flight. Most likely to involve the pilot and this crew type requires highly specialized qualifications.
- **Proceed without Crew**
- **Cancel flight** occurs when there is insufficient crew available to operate the flight, as required by law.
- **Delay flight** occurs when it is decided that it is best to wait for the disrupted crew member.

Action/Source	**SIGN**	**RULES**	**INDUTY**	**ROT**	**METEO**	**Avg**
Use reserve at airport	10%	5%	0%	20%	0%	7%
Use Nearest Reserve at Home	40%	20%	0%	40%	0%	20%
Exchange with crew from another flight	10%	10%	0%	10%	0%	6%
Use crew with Free Time	10%	10%	0%	5%	0%	5%
Use Day-Off Crew	10%	10%	0%	10%	0%	6%
Use Crew on Vacation	5%	10%	0%	5%	0%	4%
Propose an Aircraft Change	1%	0%	0%	0%	0%	0%
Proceed without Crew	2%	5%	90%	5%	0%	20%
Cancel flight	2%	10%	10%	0%	2%	5%
Delay flight	10%	20%	0%	5%	98%	27%

Table 2.4: Percentage distribution for actions chosen by crew controller, given disruption source category. [17]

The association between crew disruption sources and selected action, taken by crew controllers have also studied in a major European airline, can be seen in Table 2.3. Similarly, strong correlations are identified between crew disruption source and AOCC action taken. In particular, its is observed that similarly to when dealing with the aircraft resource, 98% of the time, unfavourable meteorological conditions lead to accepting a delay. Unique to this resource, when a crew member has not signed in for duty, the crew controller typically opts for using crew that are nearest to the airport 40% of the time. The most important conclusion that may be drawn from this table is that crew controller actions are highly dependent on the type of disruption source category they are faced with.

The **passenger solution space** allows for three actions that affect the passenger resource and are shown below:

- **Change passenger to another flight** within the same airline.
- **Change passenger to another flight** within another company.
- **Keep passenger** in delayed flight.

Furthermore, the type of disruptive event is not a driver for actions taken by the passenger controller and so a probabilistic source-action table cannot be generated. What drives the decision is mostly dependent on the solutions that can be applied by the aircraft and crew team. If after a disruption, an aircraft and crew are available to operate a disrupted flight, then passengers are not disturbed or at most, their departure is delayed. If these resources cannot be made available, an airline can serve and aggregate most of its passengers onto its remaining flights and/or those of other airlines. The latter option may be drastic, but often minimizes both lost revenue and the loss of good will from unsatisfied customers. [33].
Beyond Castro's survey, the literature lacks an understanding for the relationship between disruptive source categories and actions taken by the AOCC constituents. The connection between source and action is likely influenced by human factors, and therefore **a better understanding for factors affecting human decision-making may lead to better predictability regarding actions taken by AOCCs.**

2.2.2. Resource Recovery Problem

Using manual approaches for resource recovery due to a disruption, often means only very few solutions are considered. This introduces a real risk that the chosen final solution is far from optimal, across all the key areas [54]. Furthermore, most airlines solve disruptions sequentially by first considering the aircraft resource, then the crew resource and finally with passenger considerations [15, 17]. As a result of the sequential process, decisions implemented for one resource may have a profound impact on other resources. It can therefore be argued that, the traditional sequential approach to disruption management is inefficient as its sequential nature leads to global sub-optimal solutions. Nevertheless, airlines have hierarchical structures that favor sequential problem solving and have also come to adopt decision support tools to optimize each problem domain solution [8]. For this reason, it is motivated that **research on decision-making within AOCCs should consider decision-making as part of a sequential disruption management process because it most reassembles how a real AOCC operates.** It is also important on a validation perspective, as research outcomes can then be compared with real AOCC decision-making.

As stated above, using a manual approach for resource recovery leads to sub-optimal solutions. For this reason, the trend in recent years within the airline industry has been to further introduce recovery models as decision support tools and reduce the number of AOCC personnel [8]. **As decision support tools become an integral part of decision-making, understanding the solutions proposed by these tools to human decision-makers is fundamental towards the study of decision making within the AOCC.**

A literature study has been conducted on the research directed towards the **ARP**. The findings of this research are summarized in Table 2.5, showing aircraft recovery model types and respective solutions considered.

Aircraft Recovery Model	Solutions Considered	Ascribed to
Network-model	Cancellations, retimings and swaps	Teodorovic and Guberinic
Network flow model	Cancellations and retiming	Jarrah et al.
Heuristic based on local search	Cancellations, delaying or reassignment of aircraft	Løve et al.
Connection network: a mixed integer multi-commodity flow model with side constraints	Cancellation, retiming and reassignment	Andersson
Metaheuristic GRASP (Greedy Randomized Adaptive Search Procedure)	Canceling, retiming and swaps	Argüello et al.
Network flow (with side constraints)	Cancellation, retiming and ferrying	Yan and Yang
Minimum cost flow problem with side constraints	Swaps within same fleet	Yan and Young
Algorithmically in polynomial time	Swaps for single flight	Talluri
Two-Stage Heuristic Algorithm	Cancellations and delaying	Zhang
Integer linear programming with heuristics	Delay, cancellations or swaps	Hassan
Column generation-based heuristic	Delay and swaps	Liang et al.

Table 2.5: Aircraft recovery models and solutions considered.

Teodorovic and Guberinic [88] were among the first to address the ARP, and based their approach on Operations Research (OR). Approaches that followed were mainly done so based on OR or meta-heuristics. Besides Teodorovic and Guberinic, researchers that research the ARP using a OR based approach were: Jarrah et al. [42], Andersson [1], Yan and Young [96] and Yan and Yang [95]. In contrast, Argüello et al. [2] Løve et al. [62], Talluri [87], Zhang [97], Hassan [35] and Liang et al. [60] used a meta-heuristics based approach.

The findings of research directed towards the **CRP** are summarized in Table 2.6:
For the CRP, there are also two main approaches that are employed. One approach is based on finding a recovery solution based on a fixed flight schedule and the other is capable of dealing with cancellations and delays. Medard and Sawhney [67] approaches the CRP using a fixed flight schedule approach, whereas Stojkovic and Soumis [84] and Lettovský et al. [59] CRP models can deal with cancelled and

Crew Recovery Model	Solutions Considered	Ascribed to
Generalised set partitioning model	Use crew from available pools i.e., reserve crews and cancellations (no delays)	Stojkovic and Soumis
Relaxed integer programming	Use crew from available pools i.e., reserve crews (no cancellation of delays)	Lettovský et al.
Set covering problem	Use crew from available pools i.e., reserve crews (no cancellation, delays or swapping individual crew members)	Medard and Sawhney
Heuristics, OR and artificial intelligence algorithms	Crew from different airlines, delaying, swapping, deadheading (extra crew) and the use of standby crew	Chaw
Delay	Delay, cancel, swap, use of standby crew.	Hoeben et al.

Table 2.6: Crew recovery models and solutions considered.

delayed flights.

In search for literature on the **PRP**, there is only one source found [58]. Here the PRP is broken down into three steps: Passenger aggregation based on itineraries; feasible paths determined and optimization of model. The type of action considered is changing a passengers to other flights within the same airline.

In view of the recovery problems described above, aircraft recovery is noticeably, by far, where most work has been focused. It is understandably so, seeing that aircraft are the hardest and scarcest resource considering that one aircraft fits several crew and passengers. In the ARP literature, it is observed that aircraft exchanges, flight delays and cancellations are considered as potential solutions to disruptive events. The research lacks the inclusion of rerouting, joining and ACMI of flights. Joining is an action that should be possible solely based on AOCC decision-making. Rerouting is an option that involved collaboration with ATC services, and thus a solution that cannot be granted by a ARP decision- upport tool. The same applies for ACMI, which involves coordinating with other airlines. ACMI is especially difficult to proposed as a soltution by ARP decision support tools since knowledge of other airline's resources is required and this is usually not openly available. However, despite the involvement of ATC rerouting should be among the solutions proposed by ARP decision support tools since data can be used to compute new routes and historical data can be used to determine their likelihood of acceptance by ATC.

In light of the CRP literature tabulated above , it is observed that using crews from reserve pools, flight cancellations and delays, crew exchanges are considered as potential solutions to disruptive events. However, what the literature presented lacks is the possibility for proposing aircraft changes or proceeding without crew. Aircraft changes are a highly unlikely events that may occur when the crew available is not certified to operate the initially planned aircraft type and therefore their absence is acceptable. However, proceeding without a crew member is an event that is highly likely when a crew member is unavailable after sign-on, due to an accident or illness during flight. Given the likelihood of occurrence and accepted practice, proceeding without crew should be an option to consider among the range of possibilities for solving the CRP.

Bearing in mind passengers as part of the problem solving approach, typically it is a problem that at a minimum is integrated with the aircraft recovery and at a maximum with aircraft and crew recovery. Partial-integrated recovery process refers to when only two dimensions are recovered together and (fully) integrated recovery process considers all three dimensions together. Both former and latter approaches are still prone to sub-optimal solutions due to their inherent sequential recovery approach. It is only the simultaneous-integrated recovery process that abstracts itself from prioritizing one domain over another. The the details surrounding integrated recovery process are beyond the scope of this literature study as **the single-domain recovery problem approach is sufficient to gain an**

understanding for the scope of solutions proposed by recovery decision support tools to decision makers within AOCC. The question that however remains is whether humans are actually using these tools in aiding their decision-making or whether the solutions proposed are operationally viable.

To validate the applicability of recovery models using the approaches previously described, it is necessary to understand whether these are operationally viable. To understand the viability of proposed solutions, experts must be consulted to determine whether they would reach the same disruption management solution. Should this be the case, it would be fair to assume human decision-makers will in part, incorporate solutions proposed by recovery decision support tools into the disruption management process. Based on how AOCC decision-makers are organizationally divided, in addition to the solutions proposed for each problem domain, human coordination, collaboration and negotiation is still required for a final decision. **Researching human characteristics that affect coordination, negotiation and collaboration will contributed to the understanding of decision-making within the AOCC disruption management process.**

Validating Recovery Models with Experience Professionals:
To validate recovery modelling techniques with real human decision-making, the Decision Support for integrated Crew and Aircraft recovery (Descartes) research project is studied and reflected on. This is a project that ran over 3 years and between British Airways (BA), Carmen Systems and the Technical University of Denmark. A detailed description about the project and its insightful results can be found in a final project report to the European Union [21]. The prototypes for each dimension recovery are tested using “business experiments”. These experiments were based on Operation Controllers’ experience and knowledge and were solved both by controller and each model, side-by-side. This was done to measure how the quality of the model’s proposed solutions, compares to that of an experienced controller. Realistic scenarios were used with varying degrees of disruption complexity.

- The Disruptive Passenger Recovery (DPR) model outputs were directly compared with the outputs of BA’s Customer Service Recovery Manager (CSRM). It was agreed that the solutions proposed by the DPR were considerably better than those proposed by the CSRM. **Therefore, it can be drawn that since the Descartes DPR is validated, passenger recovery model outputs are likely to be used by passenger controllers/services, since operationally viable solutions are obtainable.**
- The Disruptive Aircraft Recovery (DAR) model outputs were directly compared to experienced aircraft controllers at BA. Before doing so however, the model parameters were calibrated until the DAR returned acceptable and expected solutions. What is meant by above is that, constraints and costs i.e. cost of delay & cost of cancellation were calibrated to reflect decision-making policies within BA’s Operations Control Centre. After parameter tuning, when proposed solutions were compared for different experiments, it was identified that the DAR was able to produce the same solution as the aircraft controller. The Descartes DAR model is therefore validated for being capable of outputting solutions like a human decision-maker would.**Therefore, it can be drawn that aircraft recovery model outputs are likely to be used by passenger controllers/services, as long as parameters are appropriately calibrated.**
- The Dedicated Crew Recovery solver (DCR) model outputs were directly compared to experienced crew controllers at BA. During this process, one main drawback of the DCR was identified. This was that the solutions proposed involved a large set of crew to suggest a solution. BA however, values the quality of life of crew and therefore minimize the number of crew members involved in a disruption solution. Therefore the Descartes crew recovery model was not validated against human decision-making, but the possibility for it’s adaptation with the intent to reflect human decision-making was suggested. From a modelling point of view this requires either considering less crew as part of ’available’ resources or introducing on objective that penalizes large crew involvements in a solution. The latter consideration is something that has been included in one of the models [84] reported in the crew recovery section. **It can be drawn that crew recovery model outputs are likely to be used by crew controllers, if solutions proposed do not involve too many crew members.**

This final part on validation serves to show that, it is possible to design decision support tools that propose operationally viable solutions. Tuning of models can be required such that the costs involved are reflective of those of the airline. In addition, the consideration for human resources' quality of life must be considered when tools decide on the amount of crew resources involved in a crew recovery solution.

In subsection 2.2.2, the recovery problem is studied as the trend is to further introduce resource recovery decision support tools within the AOCC was identified. Two main shortfalls to the research done in the recovery field are identified.The diversity of disruption problems considered is restricted and the degree to which these models are validated is very limited. The conclusions drawn are that parameter calibration is likely necessary to align recovery tool outputs with operationally viable outputs, and the number of crew involved in a solution should be minimal. For these reasons it is motivated that **research studying disruption management within the AOCC should consider a diverse set of disruptive events and also validate model solutions with experience professionals.**
In section 2.2, an exhaustive list of solutions for aircraft, crew and passenger disruptions is reported on. Probabilistic action tables for the aircraft and crew resource are given to illustrate the cause-effect relationship between disruption source and action taken by an AOCC to mitigate its cascading effects. Furthermore, a literature on the the resource recovery problems associate with each resource type is presented. The limitations of the literature found and suggestions for recovery model completeness are provided. Finally, a validation outcome of recovery models developed by a joint research group is given. This validation serves to show that indeed the solutions provided by a recovery model can be operationally viable and this can be achieved through calibrating parameters and incorporating human quality of life into decision making.

2.3. Objectives

American Airlines (NASDAQ: AAL) and Delta Airlines (NYSE: DAL) are publicly traded companies and their board members have the fiduciary responsibility of prioritizing the maximization of shareholder value. For that matter, profit maximization is a key driver in top-level decision-making for publicly traded airlines. Profit maximization is also a likely key driver for private companies. Despite this underlying drive for profit, at an operational level, objectives drive decision-making. Disruption management operational objectives fall into three major categories [54]:

- Ensuring what is initially promised to the passenger is delivered. To that end, passengers and their luggage get to their respective destination as originally planned.
- Seeking cost minimizing solutions during disruptive events. These costs include items such as cost of compensations or accommodations costs to disruptive passengers and crew.
- Be willing to sacrifice passenger satisfaction and cost minimization to get back to the plan as soon as possible.

Two examples for first and last items on the list above are provided to the reader:

- United Airlines disruption management strategy is one that reassembles the first listed objective. The main operational objective of United Airlines is to fly as many of its scheduled flights as possible [33]. This is aligned with ensuring that what is initially promised is delivered to passengers.
- American Airlines' operational objective is to get the airline back on schedule [33] which is aligned with the third objective.

Both objectives laid out above lead to different outcomes. In American Airlines' case, flights can be cancelled or passenger transferred, such that next morning, all flights can depart according to the original flight schedule. In Delta's case, they are willing to accept irregular operations carrying over into the following day as long as flights promised are delivered [33].

In principle, costs minimization my be implicit to either objective. Delta Airlines will minimize deviations from the original plan and so therefore, costs associated with compensations and accommodations are also minimized. Secondly, flights are originally scheduled for profit maximization and hence by operating as closely as possible to the original plan, operations implicitly minimize cost. In American Airlines case, the decision to start next day with the original plan will ensure that costs that could originate from events cascading into coming days, are prevented.

Despite the variation in drivers behind an airline's disruption management strategy, individual roles, focusing on specific domains have objectives specific to their domain. The objectives associated with each individual role are defined below and reflect utility maximization with respect to each problem domain.

2.3.1. AOCC Resource Objectives

Objectives driving AOCC resource decision-making are gathered from literature and categorized in Table 2.7.

AOCC Domain Resource	Objectives	**Ascribed to**
	Complete as many flights as possible	Peters
Aircraft	Utilize assests effectively (minimize costs)	Bruce
	Minimizing spare aircaft used	Belobaba et al.
	Achieve successful transit connections	Peters
Crew	Minimize utilization of reserve resources	Feigh and Pritchett
	Minimizing the cost of reserve crews	Belobaba et al.
	Achieve successful transit connections	Peters
	Achieve customer service level	Bruce
	Minimize protections costs	Castro
Passenger	Achieve punctuality	Peters
	Minimizing passenger recovery costs	Belobaba et al.
	Minimizing loss of passenger goodwill	Belobaba et al.

Table 2.7: Driving objectives behind airline resource decision-making.

The objectives tabulated in Table 2.7 are clearly sub-objectives to top-level AOCC objectives and do not seem exhaustive enough for all matters considered. For this reason, researchers should interview AOCC decision-makers, to better understand driving objectives. In the absence of interviews, it is suggested that researchers rely on recovery model literature, which covers modelled objectives. The remaining part of section 2.3 is dedicated to identifying and evaluating modeled objectives, according to their suitableness for modeling human AOCC decision-maker objectives.

2.3.2. Aircraft Controller Decision-making Objectives

Firstly we will consider the objectives accounted for in aircraft recovery problem literature modelling aircraft controller objectives.
When compiling the literature review for aircraft recovery some obvious trends are observed:

- In most aircraft recovery models, the aircraft controller's main objective is minimizing costs associated with recovery. These costs are delay costs, cancellation costs, aircraft swap costs and ferry costs. In a minority of cases, monetary costs are excluded. Examples of this are when the aircraft recovery model's objective is to minimize (total) passenger delay or the number of cancellations. These are proportional to costs and also one could argue that they are easier for a human decision-maker to bear in mind when making a decisions. The reason being that, given the complexity and therefore vast number of information available, judging and comparing costs is vastly more difficult that judging by the delay time or number of cancellations.
- Talluri [87] considers changes in demand and attempts to minimizing the number of overnight aircraft swaps give potential aircraft type changes. This consideration is one that seems reasonable

Objectives	**Disruption type**	**Ascribed to**
Minimizing passenger delay	Aircraft shortage.	Teodorovic and Guberinic
1st: Minimize the number of cancellations 2nd: Minimize total passenger delay	Aircraft shortage	Stojkovic and Soumis
1st: Minimize swap and ferry costs 2nd: Minimize delay costs or minimize cancelation costs	Aircraft shortage	Jarrah et al.
Maximize flight revenue and minimize swap and delay costs	Aircraft shortage	Jarrah et al.
Minimize costs of delays, cancellations and swaps	Aircraft lines of work in schedule (availability)	Løve et al.
1st: Restoring the original schedule by the following day.	Aircraft shortage	Argüello et al.
Minimize the cost of schedule repair which also considers passenger revenue	Temporary unavailability of one single aircraft	Yan and Young
Maximize profit and and minimize the cost of cancellation and/or delay	Dynamic market demand	Yan and Yang
1st: Maximizing passenger revenues while reducing the cost of re-timings 2nd: Penalize schedule deviations	Dynamic market demand	Thengvall et al.
Minimize the cost of cancellations and delays	Real aircraft transportation dynamics simulated	Rosenberger et al.
Minimize number of overnight swaps due to maintenance reasons	Demand changes therefore aircraft type swap required	Talluri
Minimize the total recovery cost	Airport closures and unplanned maintenance	Zhang
Minimize direct operating costs, costs of delay, cancellation costs and ground-arc costs	Aircraft shortage	Hassan
Minimize recovery cost	Airport capacity and flexible maintenance	Liang et al.

Table 2.8: The objectives for aircraft recovery problems, given selected disruption types.

for a human decision-maker though it would be over simplistic to assume that this is the only consideration when considering changes in demand.

- Maximizing flight revenue is considered as an objective for multiple models. At first it seems like an objective an aircraft controller may have but considering that the schedule is originally optimized for revenue, it is unlikely that any recovery solution will be able to provide more revenue. On that note, instead of searching for opportunities to maximize revenue, it seems more natural that an aircraft controller would be considering the alternative that incurs less costs, which is a proxy for cost minimization.
- Restoring the original schedule by the following day or penalizing deviations from the original flight plan are objectives that at first don't seem to approach the recovery problem in the most optimal way. However, it is highly plausible that as an aircraft controller and human decision-maker, such an objective is sought for individual goal reasons or because this is the airline's objective when it comes to disruption management.

One strong component of the literature reviewed is that an aircraft shortage disruption scenario is often considered. This is great for two reasons:

1. Primarily because an aircraft shortage is the worst possible scenario an aircraft controller may be faced as it imposes a hard constraint.
2. Secondly, this scenario is highly representative of what happens in the field as aircraft frequently require unplanned maintenance.

One shortcoming of the literature review is that little emphasis is given to disruptions that occur purely due to arrival delays. For instance, consider the situation where an aircraft will arrive at 11h00, 30 minutes after its scheduled arrival time. The implications on the subsequent flight leg are a 30 min delay and therefore will depart at 11h30. At the airport there is an aircraft available that has been assigned to a flight that will depart at 11h45. It would be wise to at least consider that the second aircraft be assigned to execute the first flight at no delay, and have the late arriving flight's aircraft execute the 11h45 flight with a 15 min delay. The trivial and sub-optimal solution would have been to delay the first departing flight by 30 min. This is a simplistic example but it exemplifies why only considering aircraft shortages is limiting since other disruption types are highly frequent too.

2.3.3. Crew Controller Decision-making Objectives

Taking a step back, refocusing on the crew recovery problem and assessing the respective literature, the high complexity of the problem becomes immediately obvious. This increase in complexity is due to the large number of cabin crew to consider and the complex rules and regulations for crew.

- In the crew recovery model developed by Wei et al. [94] the main objective is to assign crew to flights that have broken pairings while minimizing the number of uncovered flights. Assigning crew to flights that only have broken pairings is a realistic decision-making because one would expect a crew controller to focus on solving disruptions by focusing on the disruptive flights as opposed to focusing on the disruptive flights and all other flights as a single problem. Minimizing the number of uncovered flights is a decision that is likely to depend on higher level objectives. If management seeks to ensure promises are delivered then one would expect all flights to be covered. If management prioritizes cost minimizing solutions during disruptive events, then it is acceptable to have some uncovered flights if that means less incurred costs.

- Stojkovic and Soumis [84] model the main crew controller objective, as desiring that all flights be covered and at minimum cost. With this objective in mind, they try to also minimize crew disturbance. This approach is representative of a higher level objective where management seeks to ensure promises are delivered and therefore all flights must be covered. The minimum cost objective appears to be representative of a crew controller's domain-level driver and comes as a second priority that would not compromise all flights being covered. Lettovsky [58] similarly, attempts minimizing disturbing the current schedule ,while not considering delays as a problem.

- In more recent research, Chaw Chaw [18], developed a crew recovery model that minimizes crew cost and crew disturbance while ensuring that every flight has all the necessary crew members to operate.

- Hoeben et al. [36], merely considers the minimization of the cost of cancellation and the cost of crew pairing. Attention is not given to crew displacement and this is likely to be because there is a higher focus on implementing learning into the model as opposed to implementing the right optimization model.

Minimizing crew disturbance reflects the pragmatism involved in the crew controller's decision-making. It would seem odd to re-optimize the entire crew roster for a single disruptive problem should the optimal solution require it. If that were the case, then, one would allow for a situation where crew are constantly being shifted around and told to fly to different destinations and different times. Excessive crew disturbance was observed to be the main drawback in the development of a crew recovery model through a collaboration with British Airways [21]. A better approach would be to focus on the disruptions locally, and try to find cost minimizing solutions that would minimize global crew disturbances. This is reflective of the approaches above and seems like a realistic and reasonable approach. Finally, the lack of consideration for delays is a plausible characteristic of a crew controller's decision-making process. This is for multiple reasons one being that the airline's passenger demand (revenue generating source) will not be explicitly affected if a crew's return home is delayed.

Crew's quality of life is appreciated and solutions should minimize the amount of crew involved in a recovery solution. Chaw's research reflects this need which is representative of an airline's need. Ensuring all flights have the necessary crew members to operate is likely to be a fundamental requirement among airlines as it would be difficult to assume a situation where an incremental crew operational expenditure would outweigh the operational revenue from a flight.

2.3.4. Passenger Controller Decision-making Objectives

When looking at the passenger recovery problem Lettovský et al. [59] design a passenger recovery model with the main objective of maximizing the recovered passenger revenue by reassigning disrupted passengers to available seats. The model assesses the financial impact of schedule changes without considering passenger re-accommodation explicitly. It seems reasonable that passenger services would attempt assess disruption solutions by their associated cost. For instance, consider two flights that are to depart at a secondary airport that is not home base and due to a maintenance problem, only one aircraft is available. Corroborating the previous objective, it makes sense that passenger services would rather have passengers board for flight A, if passengers in flight A have a disproportionately larger number of passengers that are connecting and not from Paris. Passengers. The reason being that offering procession to this passenger group through hotel accommodation would be more expensive. Cost reduction due to protection therefore seems like an appropriate driver for passenger services decision-making.

In light of the literature review presented in section 2.3 with focus on recovery problems, is intended to generate ideas for factors considered by human decision-makers, within an AOCC, during disruption management.

- The factors identified in the aircraft recovery literature are mostly quantitative such as costs of delay, cancellations, swaps, and ferry cost, to name a few. There are two exceptions to the rule. One potential exception is the objective of penalizing deviations from the original schedule by Thengvall et al. [89]. It would be possible to classify a set of alternatives based on the degree to which they deviate from the original plan and subsequently, qualitatively select the alternative that deviates the least. The second exception is in Talluri [87] aircraft recovery model, where overnight aircraft swaps should be avoided for maintenance purposes. **Both quantitative and qualitative objectives drive decision-making in recovery models and it seems highly plausible human AOCC decision makers share this property.**
- When assessing the crew recovery literature, the objective to minimize the number of covered flights or ensure no uncovered flights, is a quantitatively based decision that reflects a higher level managerial decision. A qualitative objective identified in the crew recovery literature is that of finding a solution with minimal effect on the current schedule, so as to minimize the amount of crew involved in disruption solutions.
- Bearing the passenger recovery literature, the main points to draw on are the fact that some flight cancellations may require more passenger protection than others. Due to a general understanding of passenger demographics, this decision may be a qualitative one based on hisotric patterns and destination-origin pairs.

2.4. Constraints

The constraints considered during disruption management are discussed below. Firstly constraints pertaining to the aircraft resource are discussed followed by the crew resource and lastly by the passenger resource.

2.4.1. Aircraft Constraints

It is conjectured that given the aircraft is a material resource, constraints found in aircraft recovery models literature is highly representative of those that limit human AOCC solution space. In the literature, a trend for increasing the number of constraints is observed, as would be expected given technological developments. Nevertheless, it is identified that models generally consider three types of constraints, namely time-space continuity constraints, airline constraints and disruption constraints. In addition, other literature regarding AOCC operations is gathered.

- Time-space continuity constraints can either be flight coverage and node continuity constraints. The flight coverage constraint will ensure that all flights will fly the scheduled flight, be canceled or delayed. This constraint also ensures that the lowest cost solution is to fly all scheduled flights which prevents the trivial low-cost solution which would be to ground all the aircraft. The node continuity constraint ensure that an aircraft that arrives at an airport can either, stay at that airport of depart from that airport. This constraint would prevent a solution that would require an aircraft to depart from and airport where it has not landed. It is generally observed that all models contain both time-space constraints.

- The airline constraints considered are the following. When airlines consider exchanging aircraft, some models will include a tail swap time limit constraint within the airline constraints. This takes into consideration that fact that it would physically take so much time to get another aircraft ready for a flight it is not initially scheduled for. Furthermore, later aircraft recovery model developments introduced different fleets and thus an airline with different aircraft types with varying range and seat capacity. For this reason, two other airline constraints are considered. These are the airline seat capacity and aircraft range constraints as it would be unacceptable to assign a group of passengers to an aircraft that is not large enough to accommodate them of fly far enough to reach their destination. A constraint that can also be categorized as an airline constraint is the requirement for ACT clearance given a reroute proposal. If this proposal is not accepted, then the reroute solution is not viable and therefore this bureaucratic process acts as a constraint towards the aircraft resource [17]. Maintenance checks (A and B) are required at certain time intervals and therefore will act as a constraint. It is possible that aviation authorities will grant some leeway under irregular operations to delay these procedures until the aircraft can be returned to a maintenance base [33].

- Disruption constraint that are mention worthy are aircraft and airport unavailability (airport curfew [88]). As can be observed in Table 2.8, most aircraft recovery models assume an aircraft shortage, or airport closure. It is worth modelling for aircraft shortages given that flight delays generally lead to a trivial solution - perform the subsequent flight with the same aircraft and simply delay its departure. On the contrary, a shortage is representative of a situation where there is a disturbance that forbids the operation of a particular aircraft and therefore another aircraft must be used to perform the disturbed flight. One would expect this to be the case for a unplanned aircraft mechanical failure. An airport closure will be representative of situation where flight departures and arrivals have been canceled due to extreme weather conditions at a specific airport.

2.4.2. Crew Constraints

Constraints to solve crew disruptions are far more complex due to the numbers of cabin crew and the more complex rules and regulations for crew [54]. When reviewing the crew recovery literature, a less homogeneous approach regarding the applied constraints is observed with respect to the aircraft recovery literature. Often, it is a constraint that non-canceled flights should have a flight crew assigned and the number of assigned meets a minimum standard to legally operate the aircraft type. One model [35] goes so far to constrain non-reserve crew, that were originally assigned, to be assigned to flights or deadheaded back home. In some instances, to reduce complexity, often a crew resource is only qualified to fly one particular type of aircraft type. In a few models, the number of crew resources affected by a solution is constrained to reflect a desire crew quality of life.
In AOCC literature, is identified that crew controllers must consider the qualification of crew members when considering crew exchanges [17]. Furthermore, in some cases, an acceptance in part of a crew member is required if the respective crew member is on a day-off. Finally, in [17], the constraint to have all crew on board is relaxed, and if possible, a flight may also depart with all initially assigned crew as long as the minimum number of crew required by law is met.

There are **no constraints pertaining to the passenger resource** per se. Most decisions regarding the passenger resource will be solely based on objectives which includes cost minimization.

In section 2.4, constraints limiting the solution space are exhaustively covered. It should also be noted that besides hard constraints like those expressed above for crew of aircraft, airlines may also include soft rules that exist in pratice and further limit their solution space [54].

In chapter 2, roles, AOCC organizational structures and information sources to each AOCC role, are outlined. The solutions that can be considered to solve disruptions related to the aircraft, crew and passenger resources are presented. Recovery literature is exhaustively studied due to the current trend reducing human resources through the adoption of recovery tools and its increasing central role in AOCC decision-making. A study on the Descartes recovery problem is done to explore how the development of decision support tool can be done such that these are representative of real decision-making. The higher level and lower level objective of decision-makers are outlined by AOCC resource responsibility. Finally, constraints identified and found to limit resource controllers' decision space.

3

Resilient Decision-making

A literature review on how different researchers define resilience over the years is presented in section 3.1. Subsequently it is motivated that a resilience framework proposed by Vert et al. [92] should be used to studying decision-making within the AOCC, as resilience is central to the AOCC and Vert et al.'s framework provides structure and meaning to the complex and multifaceted concept of sociotechnical resilience. Decision-making is central to the latter part of this chapter, where rational, naturalistic and intuitive decision-making approaches are described in section 3.2. Finally, the decision-making process most suitable to model AOCC decision-making is further explored in section 3.3, where common heuristics and cognitive biases leading to sub-optimal decision-making, are contextualized within AOCC operations.

3.1. Resilience

Resilience is a concept that has been defined in many scientific fields. It has been studied in the field of physics by Gordon [32], social sciences by Luthans et al. [63], economics by Rose [75] and in computer science by Ghiasvand and Ciorba [31]. Depending on the field of study, one may find varying and even conflicting definitions for resilience. Nevertheless. most literature understands resilience as the capacity for:

- The ability to maintain a desirable state or desirable functions while undergoing adversity.
- The ability to return to a desirable state as quickly as possible after being impacted by adversity.

The existing AOCC decision-making research, focuses on decision-making that drives resilience of a safety-critical sociotechnical system (STS). By definition, safety-critical STS are systems with interacting humans and environments where safety is a critical aspect [92]. Airports, hospitals, nuclear plants, and offshore platforms are examples of such systems [3] and so therefore so is the AOCC.

Numerous literature reviews have been conducted on the subject of resilience, however most lack a systematically structured coherent framework [92]. Francis and Bekera [29] for instance, have broken down resilience into what they categorize as its three main resilience capacities, namely: absorptive capacity, adaptive capacity and recovery/restorative capacity. Vugrin et al. [93] have defined each of those terms as:

- Absorptive capacity is "the degree to which a system can absorb the impact of system perturbations and minimize consequences with little effort".
- Adaptive capacity is the "ability of a system to adjust to undesirable situations by undergoing some changes".
- Recovery/restorative is "the rapidity of return to normal or improved operations and system reliability".

There are clear similarities between these defined resilience capacities and the previously defined generic definition for resilience. In fact, both absorptive capacity and adaptive capacity relate to maintaining a desirable state, whereas the latter recovery/restorative capacity are related to returning to a desirable state. However, Vert et al. argue that, as opposed to adaptive capacity, absorptive capacity does not belong to the concept of resilience and recovery/restorative capacity only partially. The reasons for this are further elaborated on below, after both the taxonomy of adverse events, as shown in Table 3.1, as well as the resistance-resilience dichotomy as clarified in subsection 3.1.1.

Unplanned events and unexpected events can be distinguished as shown in Table 3.1.

Nature/Time	**Known**	**Unkown**
Known	Expected planned adverse event	Expected unplanned adverse event
Unknown	Ø	Unexpected adverse event

Table 3.1: Taxonomy of adverse events [92].

Vert et al. make a clear distinction between resilience and resistance which is why they believe absorptive capacity does not belong to the concept of resilience and recovery/restorative capacity only partially. Before examining this dichotomy and since resilience is a particular relationship between between a system and adverse events, the categorization of adverse events is done first. In particular, the taxonomy of planned, unplanned, expected and unexpected adverse events is defined in Table 3.1.

An expected adverse event is one who's nature is known and understood and therefore impact we can predict. These are typically events that have occurred in the past and we have learnt from. An unexpected adverse event, is an event who's nature in unknown, and thus who's impact we cannot predict. An example of such an event could be hijacking of September 11 in New York City. It is fair to assume that the disturbance created by the nature of such an adverse event - grounding of all aircraft flying in an airspace within the United States of America and the introduction of stricter and permanent security protocols in response - was unpredictable. Expected planned adverse events and expected unplanned adverse events, are both events who's nature will be known. The distinguishing feature between these events is the certainty around the time of occurrence of event. An example of an expected planned adverse event is the first weekend of summer holidays where airport capacity is saturated. An example of an expected unplanned adverse event would be a volcanic eruption. We would know its location and likely severity, therefore being able to deduce the level of disruption without precisely knowing when this adverse event could take place.

3.1.1. Resilience versus Resistance Dichotomy

Robustness is defined as the ability to maintain a level of performance for a given particular adverse event. Robustness is comprised of an active and a passive component. The passive component is related to the the absorptive capacity of the system Vugrin et al., through buffers i.e., redundancies. The active component results from procedures, protocols or rules in place to deal with adverse events. The active component is related to both absorptive capacity and recovery capacity. A resistant system is one that is robust to a large set of adverse events. When there are no buffers, procedures, protocols or plans, there is a need to adapt which cannot be achieved with resistance, but with resilience. The adaptation can be anticipatory or by responding during the event with the goal to maintain a desired level of performance. If the system is capable of maintaining a desired level of performance through adaptation as a result of its adaptive capacity, then it is said to exhibit resilient behaviour. Since absorptive capacity does not require adaptation, and the recovery/restoration may be either a function of robustness or adaptation, then absorptive capacity does not pertain to resilience, and recovery/restoration only partially.

3.1.2. Adaptive capacity and adaptation

The adaptive capacity of a system enables it to perform an adaptation to an adverse event. Adaptation refers to both the process of adaptation and its outcome (which is why recovery/restoration is partially resilience). The adaptive capacity is composed of several mechanism that will be further described below. By definition an adaptation is a modification to any level (individual, social or organizational)

of "plans, schedules, human behaviour, skills, knowledge, goals, use of resources, tasks, roles, ways and means of coordination, relations, norms" as a reaction to adversity. Finally a system is considered adaptive if it is capable of modifying its functions as a means to positively react to an unplanned adverse event.
As mentioned above, there are several mechanisms for a system to have adaptive capacity. These are listed and elaborated on below.

- **Situation Awareness (SA)** may refer to either level awareness of an agent or the process to gaining awareness. These levels are executed interconnected and executed simultaneously. Situation awareness is related to other adaptive capacity mechanisms, namely sensemaking, monitoring and observation.
- **Sensemaking SM** is very closely related to situation awareness (SA). It's distinct in that, as opposed to merely being in a state of knowledge, SM is a "motivated, continuous effort to understand connections, which can be among people, places, and events, to anticipate their trajectories and act effectively" [50].
- **Monitoring** is when a system knows what is happening within the system's environment [92] and refers to intentionally observing something and assessing it, enabling threat detection. It may have humans in the loop or not, depending on whether an automated monitoring system i.e., radar is implemented into the system. If humans are in the loop, monitoring also includes the adaptive capacity mechanisms of situation awareness and sensemaking. As attention is largely related to monitoring, the works of Bosse et al. [12] will be further explored in this research, as they've formalized the process of a human's state of attention.
- **Decision-making** is the process of choosing an option among several options and is present at the individual, social and organizational levels. The process of decision-making can be modelled in three steps, namely: Options to deal with adversity are generated; generated options are evaluated based on their desirability; depending on the valuation, and option is selected.
- **Coordination** is defined as the management of interdependencies to achieve common goals [11]. These are interdependencies between tasks, activities and resources, such as equipment and tools [65]. Interdependencies between agents acting in coordination may be defined with respect to goals, tasks, roles information and resources [92]. To deal with adverse events through adaptation, distributed tasks are required to exhibit resilient behaviour. Coordination requirements for adaptive coordinated resolutions, shows just how central social aspects are for resilient behaviour that emerges from coordination. There are two dimensions to coordination: time and explicitness of coordination. When considering the time dimension, there is coordination done prior (feed-forward control) to or during (feedback control) the actual interactions among agents. When considering the explicitness of coordination, we find that implicit coordination is realized through group cognition (based on shared knowledge) whereas explicit coordination is achieved through task programming mechanisms (e.g., schedules, plans procedures) [11].
- **Learning capacity** Learning occurs at all system levels: individual, social, and organizational. Knowledge is acquired before and after a disruptive events to improve future behaviour. If a system learns from unexpected events, then it may transform unknown unknown events into known unknowns events. This means that the system at least knows about the existence of an unexpected event, without knowing how to deal with it yet. Learning can also transform known unknowns into know events which would be the case when an unexpected event becomes understood and therefore is an expected event for there on-wards.

3.1.3. Adaptive responding

Adaptive responding can be dichotomised into procedural responding and adaptive responding. Adaptive responding is an adaptation performed during or after the system undergoes adversity. The adaptive responding process, can be enumerated as shown below:

1. Observation of the system and its environment

2. Currently acting adversity is identified
3. Potential solutions for final decision are generated
4. Generated options are evaluated
5. A decision is made
6. The chosen decision is executed

The processes to perform an adaptation and their relationships with the defined adaptive capacity's components in subsection 3.1.2, are illustrated in Figure 3.1.

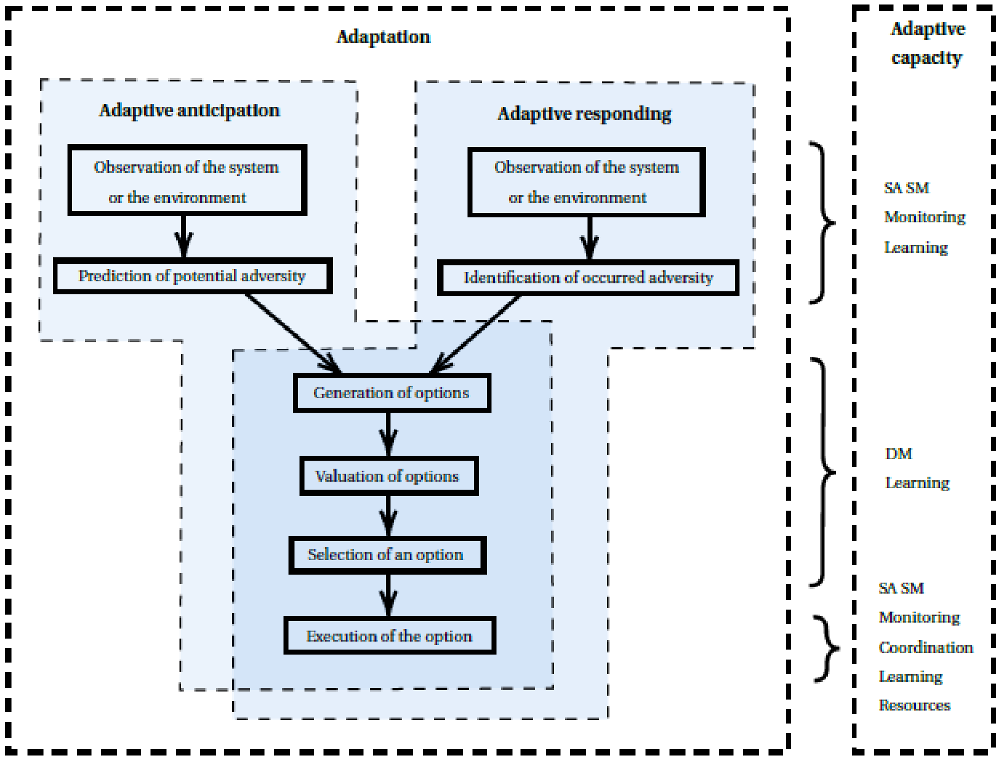

Figure 3.1: The processes to perform an adaptation and their relationships with the adaptive capacity's components [92].

In Figure 3.1, it is observed that the generation and valuation of options and selection of a final solution are part of the decision-making adaptive capacity. Therefore, a thorough understanding on elements that drive or distort human decision-making will provide invaluable insights towards critical steps in an AOCC's adaptive responding to adverse disruptive events. AOCC decision-making research does not explore the influence of human factors on decision-making following the concepts proposed by Tversky and Kahneman [91] and others who built on their work. **The relevance of decision-making towards effective adaptive responding; large influence of human factors on the former, and lack of research to this end, should motivate research that focuses on human factors influencing decision-making within an AOCC environment.**

3.2. Decision-making

Decision-making is central to an AOCC's adaptive capacity and therefore, its understanding is paramount to improve the AOCC disruption management process. The first part of this section will focus on decision-making approaches and the latter part will focus on the implications of human factors have on decision-making, namely the errors cognitive biases introduce to the decision-making process.

3.2.1. Rational Decision-making

RDM is defined as a logical, systematic process of analysis that occurs in a series of steps [6, 22]. The rational decision-making process assumes decision-makers have [5]:

- Complete knowledge of the situation
- Know all the alternative solutions as well as their consequences and probabilities.
- Objectively follow the decision-making process and have the goal of economic or utility maximization.

The above points essentially outline the fact that a RDM process assumes suitable alternatives can be identified, and there is sufficient capacity to combine the information objectively. Traditional RDM models identify a series of steps taken by decision-makers to arrive at the best solution, given a set of alternative solutions. Several RDM models are shown in Figure 3.2

<table>
<tr><th>Beach and Mitchell (1978)</th><th>Hogarth (1987)</th><th>Janis and Mann (1977)</th><th>Mullin and Roth (1991)</th><th>Nutt (1999)</th><th>Simon (1960)</th></tr>
<tr><td>Recognising problem</td><td>Structuring problem</td><td>Appraising</td><td>Recognising problem</td><td rowspan="3">Diagnosis – Signals, Information gathering, Determining need for action</td><td rowspan="2">Intelligence – identifying problem and collecting information</td></tr>
<tr><td>Evaluating task</td><td>Assessing consequences</td><td rowspan="2">Surveying alternatives</td><td rowspan="2">Generating alternative choices</td></tr>
<tr><td>Selecting strategy</td><td>Assessing uncertainties</td><td rowspan="3">Design – planning for alternatives</td></tr>
<tr><td rowspan="2">Processing information</td><td>Evaluating alternatives</td><td rowspan="2">Weighing alternatives</td><td rowspan="2">Evaluating choices</td><td rowspan="4">Action – Establishing direction, Identifying options, Developing plan, Evaluating, Implementing, Review</td></tr>
<tr><td>Conducting sensitivity analysis</td></tr>
<tr><td>Implementing strategy</td><td>Gathering information</td><td>Deliberating decision</td><td>Assessing and modifying decision</td><td rowspan="2">Choice – selecting and monitoring solution</td></tr>
<tr><td>Choosing</td><td>Choosing an alternative</td><td>Adhering to decision</td><td></td></tr>
</table>

Figure 3.2: Rational decision-making models and steps [15].

Generally, rational decision-making models will consist of three stages:

1. Problem recognition stage
2. Generation stage
3. An analysis of alternatives stage (which calls for the provision of information)

It has been brought to the research community's attention [15] that the considerations of factors that decision-makers take into account when evaluating alternative courses of action, is not explicit in the models presented and necessary to optimize solutions. This is an interesting observation that deserves some attention because it may be argued that this step in fact is already implicit to the philosophy behind the RDM process. This is because a RDM process, in the most theoretical sense, in principle, already considers all mutually exclusive factors influencing the outcome - otherwise it would not be rational. In fact, that is precisely one of the assumptions for the rational decision-maker, as itemized above [5]. Therefore, there is no degree of freedom concerning the factors that are to be considered in a RDM approach and these should merely be identified in the process. This does not apply to other decision-making processes and is a fundamental reason that distinguishes each approach.

There are three main advantages of RDM. One is related to the outcome and the other two, to the process [5, 15, 77]:
The reason it is predictable is that given the same problem, the process will inevitably lead to the same conclusion, should all else be equal. Put differently, a rational model will always make the same decisions with the same inputs [5]. This is useful since there will be less uncertainty regarding the outcome of a decision from a rational decision-maker which makes the process stable and brings security to those who may be led by rational decision makers. The reason it is possible to generalize is that the process is independent of the decision-maker's traits and purely dependent on the defined problem, objectives and constraints. Another great advantage from the RDM approach is the fact that the approach is independent of the level of experience of the decision-maker. For a role that requires a RDM approach, organizations can afford to hire less experienced professionals, which in turn are less costly. Finally, RDM only considers data empirically known to have predictive power, disregarding its salience or representativeness.

Since RDM ultimately leads a decision-maker to the most optimal solution, no disadvantage can be attributed to the ultimate outcome of the decision-making style unless an optimal outcome is undesirable. It is perfectly plausible that a decision-maker weighs the advantages of a rational decision against the reality of what a RDM process entails and decides against this style. **To elaborate further on this, it may be more beneficial for a decision-maker to arrive at a decision promptly, than to arrive at an optimal solution eventually. With increasing problem complexity, an inflexion point will likely be reached, where figuring out the consequences of each alternative solution, will not improve the solution sufficiently to justify the time required.**

3.2.2. Naturalistic Decision-making

Prior to the emergence of NDM in 1989, decision researchers conducted experiments and developed models that identified optimal ways of making decisions. This RDM approach would assure alternatives, preferences, and outcomes are known and evaluated in advance, in well-structured and controlled settings. The heuristics and biases paradigm eventually demonstrated that people did not rely on rational strategies but instead on heuristic strategies [45]. A research gap was identified in decision-making research and this inadequacy to account for real-world decision-making, led to the development of NDM. By 1989 the consequential emergence of NDM greatly contributed to the description of how people actually make decisions in the real world [49].

NDM research does not focus on the sub-optimal human decision-making, but on the way people make difficult decisions. Difficult decisions are those that must be made with limited time, uncertainty, high stakes, vague goals, and unstable conditions [49]. At the first NDM conference, in 1989, Hammond's cognitive continuum theory [34] proposed that there is a balance between the reliance on intuitive and analytical processes in human decision-making. Furthermore, the degree to which decisions rely on either is dependent on conditions such as the time available and the amount of information. During the same conference, Klein presented his Recognition-Primed Decision Model (RPD) model which is understood as the dominant NDM model and has received a fair amount of attention.

The RPD model, illustrated in Figure 3.3, describes how people use their experience in the form of patterns that will:

- Identify plausible goals
- Provide expectancy
- Know the primary causal factors in a given situation
- Identify the most relevant cues
- Suggest actions for given situation

In practice, based on patterns learnt, the problem is both identified as a deviation from expectations and the most typical reaction for the problem confronted is considered as a potential solution. This way, **it is possible to make good decisions without comparing options as the decision maker**

uses a mental simulation to imagine how it would play out. If the mental simulation shows the course of action works then it is chosen. If the mental simulation shows the course of action almost works, adaptations are made and otherwise, other courses of action, that are less typical, are considered. This process of looking for the first workable option rather than trying to find the best possible option exemplifies Herbert Simon's notion of "satisficing" [81].

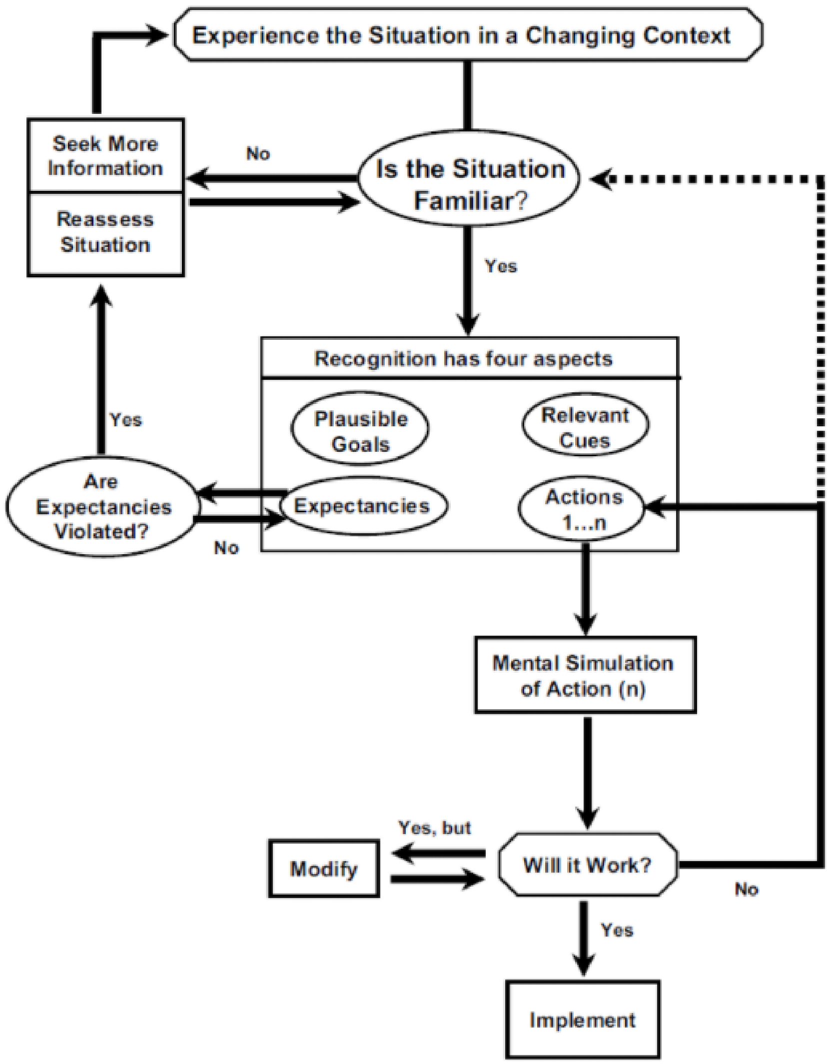

Figure 3.3: Klein's Recognition Primed Decision model. [49]

The RPD model therefore is a conjunction of intuition and analysis. The former due to pattern matching and latter due to mental simulations that are conscious, deliberate and analytical [49]. The intuitive part adds speed to the process by generating a course of action and the analytical part acts to filter out unacceptable solutions. However, if the first option considered is generally poor, the effectiveness of the NDM process is reduced. Klein et al., studied chess players and found the first moves that occurred to them were substantially better than would be expected purely by chance. These results were later replicated [43], and support the RPD hypothesis that the first option considered is generally satisfactory.

Preceding the emergence of NDM, these kinds of issues had already been studied in fields such as medicine [25] and business [40]. Following an incident in 1988, where a U.S. Navy Aegis cruise mistakenly destroyed an Iranian commercial airliner, both the Army and the Navy began funding NDM research. This initiative aimed at improving critical decisions in dynamic and uncertain conditions under extreme time pressure. Researchers have also studied the applicability of NDM in domains such as:

"Navy commanders, jurors, nuclear power plant operators, Army small unit leaders, anesthesiologists, airline pilots, nurses" (Klein [49], p. 457).

The main advantage of NDM is saving decision-making time while allowing a good solution to be reached. As a result of the intuitive part of NDM, experience quickly proposes courses of action from problem solving that leads to extremely rapid decision-making. The quality of the decision is guaranteed by the analytical part which verified the considered course of action works. The NDM decision-making style is valuable in domains where the faster the reaction, the easier the job at hand. For instance, consider the exponential spread of a highly infectious virus, the faster government agencies act, the easier it will be to contain the spread. There would be drawbacks to using natural decision-making in environments where the optimal solution is of the essence, and another solution is insufficient.

3.2.3. Intuitive decision-making

There is some overlap between NDM and IDM as both views approach the study of decision-making with the same mind set: Studying decision-making by studying how people make decisions proves more insightful than studying decision-making by studying how people ought to make decisions. It is valid that, occasionally RDM is employed by decision-makers, but most often, this is not occurring. System 1 and System 2 cognitive functioning descriptions have been proposed to describe the differences between IDM and RDM, respectively [82]. System 1 cognitive functioning is representative of implicit, fast, automatic and effortless decision-making and refers to our intuitive system. Most decisions in life are done using System 1 thinking as we interpret verbal language and visual information automatically and unconsciously [5]. Logical, explicit, conscious and slower reasoning is explained by System 2 cognitive functioning [44].

Consider both illustrated tables below in Figure 3.4:

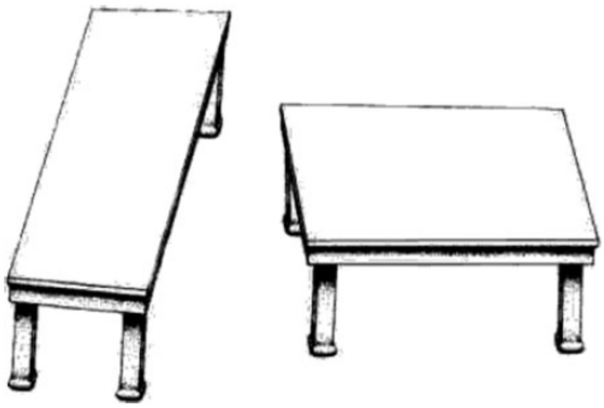

Figure 3.4: Considering two tables with System 1 (intuition) [80]

If one observes the table on the right as being more square, then one has fall victim to System 1's errors. With a System 2 strategy, one can trace either table onto a sheet of paper and place it over the other, to find that the tables have the same length and width. System 1 fails more often than System 2 and even the brightest people regularly make judgemental errors using System 1 [5]. There are several reasons beyond one's own will and effort that influence or promote the high use of IDM:

- Firstly, due to costs or time requirements, decision-makers may not have all the information needed or at sufficient quality standards to perform System 2 cognitive functioning.
- Even if enough information were made available, decision-makers may only retain a small amount of information in their usable memory relative to the information available and needed for a System 2 decision.

These limitations prevent decision-makers from taking rational decisions because they overlook the full range of possible consequences, forgoing the best solution for one that is

reasonably acceptable. This has given the rise to the term coined "satisfice" which formerly means that instead of examining all alternative solutions, a search is done until a satisfactory solution if found that will suffice [81].

In Nobel Prize-winning work, Simon [81], suggests that individual judgement is bounded in its rationality and that by describing and explaining actual decision-making, we can better understand decision-making. In light of this, to better understand IDM and its potential impact towards decision-making within the AOCC, the heuristics employed by intuitive decision makers is studied and reported on and their manifestation as cognitive biases as well.

RDM processes are utilized when relatively structured problems with certain situations are presented, and intuitive decision-making takes place during uncertain and ill-structured problems [56]. A major strength of the RDM approach is the ability of the decision-maker to use a process that follows a number of steps, without having prior knowledge or experience upon which to draw. This seems appropriate for circumstances in which there is abundant time for decision-making and low complexity or inter-dependencies. In many domains such as, medicine, emergency services, fire-fighting and offshore gas installations, decision-making does not follow a step-by-step approach as situations are complex and dynamic [15]. Therefore, in a sociotechnical domains, such as the AOCC, RDM models are unrepresentative of decision-making, and for that reason, several researchers have criticized its approach in such domains [6, 24, 48]. In fact, empirical studies have generally shown that RDM approaches are seldom realized in practice [66, 68] and an intuitive approach is more representative of the way decisions are made in practice [83].

AOCC decision-makers will generally not face well defined problems, due to the inherent highly dynamic and complex operational environment, that is difficult to predict and with a large number of conflicting goals [15]. Surely enough, one can find many reasons and concepts for why decision-makers do not act rationally. These will help in identifying situation in which rational decisions are unlikely to be made, however this approach does not improve our understanding on how judgements may be biased. Fifteen years after Simon's work [81], in the seminal paper by Tversky and Kahneman [91]: "Judgment under uncertainty: Heuristics and biases" , critical information about systematic biases that influence decision-maker's judgment was published. They have set the foundations to our modern understanding of judgement. Furthermore, Tversky and Kahneman and those who have followed suit and built on their work, have find that **people rely on simplifying strategies when making decisions called heuristics**. Heuristics serve as mechanisms to deal with the complex environment surrounding our decisions and implicitly direct our judgement [5]. In section section 3.3 is devoted to identifying heuristics that may apply in the AOCC domain, as a result of the collaborative problem solving setting.

3.3. Heuristics and Cognitive Biases

When reading through Tversky and Kahneman's (1974) seminal paper: 'Judgement under Uncertainty: Heuristics and Biases", the main point brought forth is that heuristics lead to biases that affect people's judgement during decision-making. **Biases in turn result in systematic errors and poor decision-making which strongly motivates their study as a means for potentially generating diagnostics.**

3.3.1. Representativeness Heuristic

Tversky and Kahneman define the representative heuristic as one where the assessment of the probability of a class occurrence, is based on how well it is represented. This representation can take several forms. The ones found to be most relevant for AOCC domain research are: Insensitivity to prior probability of outcomes; insensitivity to sample size; insensitivity to predictability; misconception of chance; Illusion of validity and misconception of regression. Each of these biases that result from the representative heuristic is defined and one or a couple of examples are given as an attempt to match these with where they could take effect during AOCC decision-making.

1. **Insensitivity to prior probability of outcomes**: A situation where descriptions of the features of an object create the illusion that the object pertains to one class, when in reality, it pertains to another. Because people are misled by objects' descriptions (representative of class B), they fail

to use a base-rate probability that would correctly judge the frequency of an object pertaining to class A.

(a) Example 1: A delayed crew member communicates "I'm near landmark Y, on Z street, it is really close to the airport". This description leads one to believe that the crew member can arrive in 10 min, when in fact, a person will typically take 25min to arrive from that location.

(b) Example 2: Aircraft maintenance provides a favourable description of the maintenance problem and the intonation of voice supports this description. This leads the aircraft controller to believe that the maintenance problem will be fixed soon. However, the base-rate probability that this maintenance problem (oil leak) is fixed in the next hour substantially lower than perceived by the aircraft controller.

2. **Insensitivity to sample size**: When one draws from a sample and don't consider sample size.

   (a) Example 1: During the last 7 days, the average number of delayed flights for TAP was 30 % for 2500 flights. For KLM the average delay was 20% for 16,000 flights. Let's assume that 20% is the mean percentage of delayed flight for both airlines. TAP controllers are likely to avoid solutions that will delay flights (due to their higher deviation from the mean) whereas KLM controllers are willing to delay a flight significantly as long as this proves to be the best option (due to their low deviation from the mean). Due to a small sample size of TAP's flights, their average delay will frequently deviate from the mean, and this will frequently affect controller decision-making due to insensitivity to sample size.

   (b) Example 2: Not related to crew, passengers and aircraft resources, but nonetheless an interesting observation that results from understanding sample sizes. For boarding, people must be present to assist passengers. Assuming that boarding can start as soon as the first assistant is present. If one assigns 5 people to a gate, then it is more likely that at least one will arrive at the scheduled boarding time, than if one assigns 2 assistants to a gate despite their mean arrival time being equal and independent of crew size.

3. **Misconception of chance**: People tend to think that independent probabilities will always be expressed globally and locally. Therefore, if a local sequence is skewed, they tend to misjudge the likelihood of the upcoming outcome.

   (a) Example: There are 3 weekly flights from Lisbon to New York. This week, the first two flights have departed exactly on time. A controller must make a decision regarding connecting passengers that are influenced by the last up-and-coming flight. These passengers must catch a connecting flight in New York towards Los Angeles and if the aircraft is delayed on arrival to New York, the passengers will miss the connecting flight. The controller considers that, because the flight has departed exactly on time twice this week already, he doubts this flight will depart exactly on time, since three on time departures in one week is very rare. He therefore chooses that these passengers, wait in Lisbon a few hours and then catch a flight to Boston, and subsequently one to Los Angeles.

4. **Insensitivity to predictability**: When the description of an object is favourable leading to an optimistic outlook for that object, when in fact, the degree to which the description is favourable is unaffected by the degree to which it permits accurate prediction.

   (a) Example: The performance indicators on a monitoring dashboard are indicative of seamless operations. It is known that the reliability of some of these performance indicators is questionable and therefore, in reality, the likelihood that operations are undergoing as seamlessly as they appear, is lower than perceived by controllers.

5. **Illusion of validity**: This occurs when one uses two variables thinking they are dependent of each other as a basis to support a decision, when in fact they are independent therefore providing insufficient evidence to support one's conclusion. Illusion of validity: When a person is overly confident on the relationship between between two variables despite the possibility of there being contradicting evidence of such relationship.

(a) Example: Operations have run smoothly the last couple of days, therefore this is likely to be a trend and major disruptions are unlikely over the coming days.

6. **Misconception of regression**: There is a mean and outcomes are distributed around this mean. Typically, when an outcome fairs away from the mean, people will justify this result using some sort of self-conceived explanation. In reality results will deviate around the mean regardless of what one may think to be affecting this deviation.

   (a) Example: A resource manager has been rejected for his proposed solutions to a problem (by a supervisor) more frequently than he is accustomed to. He therefore adjusts his way of assessing partial solutions generated from specialist as an attempt to better match, what he thinks are, the supervisor's preferences. In reality, the supervisor's preferences haven't changed at all. If the resource manager adjusts his assessment (utility function), therefore is a chance that as a consequence, his proposed solutions actually become less acceptable from thereon outwards.

3.3.2. Availability Heuristic

Tversky and Kahneman define the availability heuristic as one where the judgement of frequency of an object pertaining to a certain class is based on how available this object is in the judge's mind. This availability can take many forms, namely the retrievability of instances; effectiveness of a search set and imaginability.

1. **Retrievability of instances**: This may be due to familiarity or salience. If one commonly witnesses an object, or if in recent history, the manifestation of an object had a great impact, then a person will likely deem that object to occur at a higher frequency.

   (a) Example 1: During the past weeks, since a novice aircraft controller has been hired, he has witnessed disruptions due to oil leaks being dealt with by waiting for the aircraft to be fixed, and thus introducing a delay in operation. Today, when there is an oil leak issue communicated by maintenance, an aircraft controller will believe that the most likely way this problem will be dealt with, in this new case, will be by waiting for the aircraft to be fixed. In reality, this type of problem has been dealt with in various other ways too. Due to the short professional experience of the novice controller, a delay is most familiar to him and therefore he will misjudge this as the way to solve the problem and as a result proposed this as a solution without considering other alternatives.

   (b) Example 2: The last 5 times a resource manager proposed a delay greater than 30 min to the supervisor, this proposal got rejected. Despite the supervisor having accepted proposals with delays greater than 30min in the past, the resource manager does not retrieve these as easily, and consequently, will disregard solutions with a delay greater than 30 min in upcoming proposals.

2. **Effectiveness of a search set** When a person can generate some ideas easily, she will judge these ideas as occurring more frequently than others harder to generate.

   (a) Example: Depending on a controller's level of experience, he or she will be able to imagine solutions to a problem with different levels of complexity. Similarly to above, because a solution is more easily imaginable, the controller will believe that that solution is most often chosen. Because they believe that solution is most often chosen, they will choose it themselves. In Bouarfa et al. [14] research is done into the policies used by AOCC controllers and three levels of performance are distinguished. Each level of performance limits the breadth of complexity of a controller's search set. This can be used to determine the considerations taken by a controller, how this affects the controller's likelihood to imagine the best solution to a problem and therefore its selection.

3.3.3. Anchoring Heuristic

Finally, Tversky and Kahneman define the Anchoring heuristic as one where insufficient adjustments are made to initial estimates of a starting point, suggested by the formulation of the problem or due to a partial computation. The anchoring heuristic may result in: insufficient adjustments, overestimating probability of conjunctive events and the over-optimism regarding compounding events.

1. **Insufficient adjustments**: This results from initial values being presented at the beginning of a problem or from partial computation.
    (a) Example: The direct implications this has on negotiations within an AOCC could be a situation as follows: The first solutions proposed by a resource manager will 'set the tone' for what values are deemed suitable to solve the problem. Any large deviations from this in further negotiations will be penalized by the AOCC supervisor. One should therefore investigate the effect this has on managers and supervisors regarding how far they are willing to deviate from these anchors when communicating their feedback for the next negotiation step.
2. **Evaluation of compound events**: People overestimate the degree to which a series of events is reflective of the probabilities of each event.
    (a) Example: A maintenance procedure has 5 steps and there is a 90% certainty that each step will take less than 30min to complete. Despite this being true, the probability that all steps are executed within 30min is vastly inferior to 90%. Therefore, controllers are left being overly optimistic about the completion time of this procedure.

3.3.4. Framing Bias

1. Framing results from the effect something has on the perceiver, based on how it is (positively or negatively) presented. Tversky and Kahneman found that if something is negatively framed one is more likely to be less risk averse. The prospects of losses are perceived differently than those of gains, influencing a decision-makers risk propensity [5]. Additionally, bargainers who are positively framed are likely to be more cooperative [69]. In disruption management, one is inherently dealing with negative issues that must be solved. However, there is probably a calibration for this with experience. Perhaps novices are mostly influenced. If a calibration is eventually done, then one can expect a normalized distribution around a mean.
    (a) Example 1: On a given day, a substantial amount of flights are delayed introducing pressure on controllers. A new disruption occurs and this further exacerbates the pressure. A controller is given the choice between a smaller than average connection time for a group of passengers or one that is less risky, but decided to go for the riskier option as a measured gamble.
    (b) Example 2: Relating to the roles within the AOCC, feedback from managers may be viewed as negative. Either because they have rejected a proposal or because they are asking for a substantial increase or decrease in some specific solution attribute i.e., delay or cost. This may have an effect on the risk taken by specialists or managers in new proposals. These risks may include small time margins for connections for instance.

Hitherto, heuristics and biases first introduced by Tversky and Kahneman are described and an attempt is made to capture their conceptual implications in an AOCC envirionment. Through interviews and observation, one is likely to develop a better understanding on how these biases holistically affect decision-making during the disruption management process within an AOCC.

3.3.5. Biases Specific to Decision-making Process

Departing from [91] and considering research that builds on their early work, common biases in three phases of the decision-making process are identified by Hogarth [37]. The three phases of decision-making are: the information gathering phase, decision-processing phase and the information response phase.

- During the first phase of the decision-making process, namely **information-gathering phase**, decision-makers tens to be biased towards overestimate the importance of information that is highly visible and acquired early in the process. The consequence of this bias in an AOCC disruption management process would be reflected by controller's giving more importance to information that is visible to them on their flight information display as opposed to information that has been received over email, or communicated via telephone. Furthermore, the consequence of giving more importance to information presented earlier in the process is that controller's could potentially fail to adapt considerations such as constraints during the disruption management process as these constraints may be dynamics throughout the process.

- Hogarth [37] points out that during the **information-processing phase**, decision-makers tend to hold preconceived notions and solutions. This shares some resemblance to the availability heuristic where a one solution is considered to be the most likely successful one, based on the decision-maker's prior experience. The implications of this is that new information that leads to a different alternative better solutions, are not considered in the disruption management process. Consider a scenario where passengers are originally planned to catch a connecting flight but their flight leg is delayed and they miss their connection. A passenger specialist has the preconceived notion that when passengers lose a connection between two flights they should be accommodated with a hotel at the intermediate airport. An aircraft specialist may have the preconceived notion that, these passengers should not board this flight and can take another flight somewhere else, that will allow them to connect with another flight leg and reach their final destination on the same day. It would be interesting to research and build an understanding for how preconceived notions are formed and whether they are affected by domain knowledge, and how they affect the final solution.

- Lastly, during the **information-response phase**, decision-makers fall victims to wishful thinking, and frequently overestimate their control over their decision outcomes [37]. One very practical example within AOCC decision-making where this may manifest is when passenger services believes they will be able to connect so many passenger in a short period of time, when it turns out that the respective passengers take longer than expected, and miss their connecting flight.

3.3.6. Biases Specific to Negotiation

Part of the disruption management process consists on negotiation, where parties with individual objectives go back and forth over what is an acceptable outcome. This section will revolve around decision-making that can alter negotiation dynamics and hence have an effect on the ultimate outcome of a disruption management process. The biases found to further affect negotiations, are described below:

- Researchers have studied the **fixed-pie error** to develop an understanding for why my negotiators fail to reach integrative agreements, or win-win situations [73**?**]. The fixed-pie error bias results from one negotiating party believing the other party has the same priorities as the self on the key negotiating issues [90]. It is defined as "the tendency to assume that the other party places the same importance – or has the same priorities as the self – on the to-be-negotiated issues when the potential for mutually beneficial trades exists" [90]. The reasons this bias leads to an error is because most situations provide an opportunity for joint gain [57, 72]. Within the AOCC domain, the fixed-pie error is likely to manifest when controllers seek to maximize their own objectives and lose sight that everyone stands to gain from a decision that will mitigate a disruptive event's consequences. The AOCC supervisor, with the greatest overview during the disruption management process, will likely play a major role in minimizing the fixed-pie error by finding how one controller can accommodate another controller's goals or constraints and vice-versa.

- **Self-serving bias** results from a judgemental error that skew an individuals perception of a situation in a self-serving way [16]. Self-serving bias can lead to delays in the negotiation process as a result of one party rejecting a counterpart's offer, as they are perceived as unfair [4, 30, 61]. As different teams within the AOCC will have different objectives i.e., passenger services hopes to minimize disrupted passengers and crew controllers hope to minimize disrupted crew, there are bound to be situations in which a solution proposed by one teams will not be a solution that maximizes another team's objectives. In such situations, one team may have to compromise. The level of compromise accepted will vary depending on the self interest of each team in reaching their goals.

- The **relationship bias** is related with the selection process of a negotiating counterpart. One study found a positive correlation between how favourable a past negotiated agreement was and the preference to negotiate with the counterpart in the future [74]. Considering how negotiations within the AOCC take place, an obvious impact this bias may have is by the AOCC supervisor preferring to approach one resource manager first, over another. Choosing to begin negotiations with one domain over another due to their prior experience, as opposed to which domain should be approach first due to the nature of the problem will will to sub-optimal decision-making for the same reason a sequential approach leads to sub-optimal decision making that is because decisions made in one domain will have an impact on the potential decision that can follow from another domain.

Since Kahneman's seminal paper on cognitive biases, the trend has been to further expand on the categorization of cognitive biases affecting decision-making. In Benson's cognitive bias codex, 188 cognitive biases affecting decision-making are presented in a radial dendrogram [9]. **Since there is no research regarding the effect of cognitive biases on AOCC constituents' decision-making, it will be motivated that, research in this direction should begin by exploring the most fundamental biases as presented by Kahneman and those most widely known to affect negotiations central to AOCC decision-making.**

In this chapter on resilient decision-making, the framework of Vert et al. is presented as a reference to a systematically structured coherent framework to conceptualized resilience in safety critical sociotechnical systems. The main goal of an AOCC it to mitigate the effects of (un)expected (un)planned disruptive events by adaptively responding or anticipating using its adaptive capacities. Decision-making is an integral part to an AOCC's adaptive capacity and involved human factors. **Because decision-making is critical for a successful AOCC operation and there is a research gap regarding the effect of human factors on decision-making within the AOCC domain, it is motivated that modelling human factors in decision-making, specifically cognitive biases, will contribute towards a better understanding for how human factors affect the overall outcomes in an AOCC disruption management process.** To this end, literature on decision-making and more specifically, heuristics and cognitive biases that decision-maker behold, is studied. One conclusion drawn is that an intuitive decision-making process is most suitable to model decision-making within the AOCC, as it is a sociotechnical organization dealing with timely, interconnected and complex problems. Furthermore, representative, availability and anchoring heuristics, as originally researched by Tversky and Kahneman, are likely to occur in the minds of AOCC decision-makers. Cognitive biases are also found to be specific to each phase of decision-making and inclusively, may occur as a result of negotiations. **By modelling, simulating and analyzing the effects of cognitive biases of decision-makers with an AOCC, diagnostics for particular biases may potentially be developed to improve decision-making.**

4

Modelling and Simulating the AOCC

In section 4.1 a the Multi-Agent System (MAS) paradigm is described and reasons why elements of a MAS are a natural metaphor for the AOCC is motivated. In section 4.2, the ABMS paradigm is presented and the advantages and disadvantages to model development and implementation are discussed. In section 4.3 the suitability for modelling the AOCC as an ABM is motivated and subsequently, a qualitative modelling approach is presented as as first approach to modelling AOCC decision-making. Following the qualitative approach, the TTL language is suggested as a language appropriate for formally specifying AOCC system properties. In subsection 4.3.4, the description of elements required to formally specify the organizational structure of the AOC is laid out. Finally, the reasons for why validating an ABM is an arduous task and the solution to address this are presented in section 4.4.

4.1. The Multi-Agent System Paradigm

A MAS paradigm enables the modeling of a system comprised of software agents (including interactions amongst agents) that represent roles or functions and account for the surrounding environment [17]. Castro finds the MAS paradigm to have characteristics suitable for proposing a "Distributed and Decentralized approach to Integrated and Dynamic disruption management in airline operations control".

- It is Distributed because it permits the functional, spatial and physical distribution of roles and environment. Distribute roles of agents according to the dimension (aircraft, crew and passenger) of the problem and required expertise (functional distribution). Spatial distribution as data is distributed across different databases and physical distribution as agents and data are distributed by different computers and locations.

- The MAS paradigm enables a Decentralized approach because some decisions are taken at different nodes of the agents' network.

- An Integrated disruption management is possible as all problem dimension may be considered simultaneously and not sequentially.

- A MAS permits Dynamic disruption management, as agents may perform in the environment reacting to constant change, in real-time.

A Multi-Agent System models problems in terms of components interacting autonomously, which is a more natural way of representing task allocation, team planning and user preferences [17]. Agents in a MAS are a metaphor for modelling AOCC human operators as a society of agents reacting and cooperating with each other to solve problems. **Modelling the AOCC through an MAS Paradigm is suitable and in doing so, researchers will contribute to a new trend set by Castro [17] and Bouarfa et al. [14] - the only researchers to adopted the MAS paradigm for AOCC domain research.**

4.2. ABMS Paradigm

In the ABMS, decision-makers are conceptualized as agents. The fundamental idea behind ABMS is that emergent behavior or global phenomenon can be generated from interactions within a MAS. Emergent behavior are patterns that are not immediately derivable from a system's constituents properties and results from these constituents acting and interacting with one another. In ABM these interacting constituents can be naturally viewed as agents. This bottom up nature is the greatest feature of ABMS. Being able to generate phenomenon or emergent behaviour from low-level interacting agents, helps understanding the cause-effect relationships between what drives actions and interactions and the system's high-level performance.

Three elements that must be explicitly dealt with in an ABM are described below and these are further explore in section 4.3:

- Agents must be autonomous with respect to other entities within the simulated environment.
- Agent specifications define interaction among agents and with the shared environment. Since these interactions will define upper level system behavior, their design is central. Furthermore, AOCC organizational structures can be modelled, such that the order of information flow and decision-making is reflective of real AOCC disruption management process.
- The simulated environment contains all other elements such as resources and global properties. The above elements are necessary for modelling an ABM, though, for execution, a simulation infrastructure (not environment) must be defined. This environment should not influence the outcome like a programming language does not affect the result of a calculation. With infrastructure, the order in which agents are updated in a simulation platform are central.

ABM is more of a mindset than a technology. It consists on modelling a system based on its individual constituents and interactions as opposed to modelling a system as a whole. Microscopic modelling would be a synonym to ABM, and macroscopic modelling would be an alternative. If a set of differential equations are used to describe the behaviour of each constituent of a system then, this should also be considered an ABM. The main advantages for using ABM techniques and their relevance for modelling the AOCC domain will be discussed following the research of Kennedy [47] and Klügl [53].

- ABM captures emergent phenomena. What this means is that, through the interactions of individual agents behaviour will emerge than cannot be explicitly derived from the rules that are used to model the constituents or their interactions. For instance, consider a traffic jam which may actually be moving in the opposite direction to the driver's who created it. In the AOCC domain, the collective behaviour of the decision-makers which includes individual problem solving skills, and their ability to collaborate, negotiate and coordinate will determine the overall disruption management solution and thus emergent behaviour. **Particularly considering individual decision-making within the AOCC domain, it is much easier to model threshold and if-then decision-making using agent rules than using differential equations to describe these discontinuities and non-linear decision-making.** An example of a threshold behavior would be when deciding whether connecting passengers have sufficient time to connect to another flight or will need to be accommodated: Typically, a threshold of 1 hour would seem acceptable for this kind of decision threshold. An example of a if-then decision would be to consider if the disrupted passenger can be accommodated to another scheduled flight. If all passengers can be accommodated, then this would be a solution. If they cannot be accommodated, then further decision-making is required to accommodate the remaining passengers.
- Conventionally, probability distributions are introduced to proxy human behaviour. So typically, one way human behavior is modeled in a manufacturing process, is by assign a probability distribution to model the delay that may be introduced by a human actor. In ABM, agents and interactions can be modelled to represent human agents and real-life interactions, respectively. In the manufacturing process example, that would constitute modelling agents that can cause random delays and have intelligent strategies to cope with unforeseen situations. From an AOCC domain viewpoint, it is also more natural to describe the system using activities of individual

decision-makers than system processes, as this way one can model what people actually do. Because ABM is a more natural way of modelling systems that depend on individual behaviour the representation gap between the original system and the model is reduced (when compared to conventional modelling) making it a suitable paradigm to model an AOCC. **Within the scope of the AOCC domain, through the ABMS paradigm it becomes possible to apply rules to model complex human behaviour i.e., cognitive biases, as opposed to arbitrarily adding a noise term an aggregate equation to account for this human behaviour.**

- Due to the inherent architecture of and ABM, observations and analysis of the model are possible on at least two levels. One level is at the local agent level and the other at the system or macroscopic level. Within the AOCC scope, the local agent level refers to the decision-makers involved in the disruption management process. Examples of these would be the aircraft, crew, passenger managers as well as the AOCC supervisor. Analysis of these decision-makers would allow to determine which solutions are proposed, or to what extent concessions are made. At the system level, it would be interesting to analyze if the solutions selected are close to the optimal, or how long it takes to arrive to these solutions.

- ABM also provides more flexibility to modelling as it provides the framework to adjust the number of agents, adjust a gent, environmental or interaction complexity. This is particularly useful for researchers when the appropriate level of complexity to a model is not known in advance and finding it requires adjustments. Specific to studying the effect of cognitive biases on AOCC decision-making, once a reliable model has been established, it would be possible to study how changing the degree to which these biases take effect, influences the solution quality.

- As an ABM architecture splits agent internal rules, from interaction rules, to rules that specify the dynamics of the external environment, this introduces a lot of freedom in the design. The greatest advantage of this is probably that the level of complexity of each agent is arbitrary. The implications of this are that interactions between agents can also be observed and studied during early development when agents haven't been developed to their full extent. Specific to the AOCC scope, the freedom for arbitrary agent is critical as it allows for modelling of a human agent by itself, or augmented by a decision support tool. Therefore, models would be able to be representative of either scenario and to that extent, analyze what the differences are.

Despite the various advantages drawn from the ABM paradigm, and its suitableness for modelling the AOCC domain, it has its pitfalls when it comes to model development and implementation [53]. There are listed below:

- For inexperienced modelers, the high degree of freedom poses a serious challenge as the level of detail and which elements must be included are unclear. For this reason, researchers should avoid using to many details in a model otherwise too many assumptions will require validation. Also, regarding model implementation, the fewer parameters a model has, the easier it will be to calibrate the model. This is particularly useful for the validation of an AOCC ABM as, the proposed solutions will be compared to solutions provided by experienced professionals and calibrate parameters will be a great part of aligning the model outputs with those of the professionals.

- "Knife-edge" parameters are parameters can have a significant effect on the overall results of the simulation [41]. This is a pitfall as, for example in the natural world, one would not expect a huge variations in system behavior from small adjustments to one parameter that defines human agent behavior.

- Specific to model development, one may have to trade-off model complexity with model representatives. Specific to model implementation, the number of agents and size of the environment should be limited to the performance and distributed computing capacities made available to the researcher. Otherwise, simulating the model may require to much computing power and impede the sufficient frequency of analysis required for analyzing the impact of varying parameters. **Within the AOCC decision-making research scope, a model complexity trade-off will entail deciding on which set of AOCC roles must be modelled, to meet the research objectives.**

- Finally, the validation process poses problem for ABMS in general. Particularly when modelling human behaviour, it is hard to find empirical evidence data available for full validation. Validation will be further discussed in section 4.4, however a brief reflection on the approach taken by the Descartes will be reiterated. When determining whether the developed recovery (aircraft, crew and passenger) models, proposed reasonable and operationally viable solutions to disruption problems, proposed solutions were compared to those found by experienced professionals. Particularly in the case of aircraft recovery, parameters i.e., operating costs, where calibrated until the proposed solutions reflected those of experience aircraft controllers.

4.3. ABM Modelling Approaches for AOCC decision-making domain.

When modelling AOCC decision-making one may choose to include all the agents involved in the decision-making process. However, the extent to which introducing this complexity is necessary depends on one's research objectives. If the objective is to study how cognitive biases affect AOCC decision-making, then it would make sense to only model human agents that are sufficient to present all resources available and have most impact on decision-making.

Human agents sufficient to model all resources affected, are those responsible for each airline resource. This includes human agents required to compute solutions for each main resource (i.e., aircraft, crew, passenger, ect. . .) and their respective managers to negotiate these solutions with the AOCC supervisor. It is also possible to model the computation and negotiation into one agent to reduce problem complexity. This decision would lie on understanding the added benefit to including independent computational agents. **It seems appropriate that researchers who focus on AOCC decision-making, or more specifically cognitive biases, may limit agents modelled, to those that are likely highly affected by cognitive biases.**

Through the knowledge gain studying the literature on errors introduced by cognitive biases, it may be drawn that, the subset of biases affecting decision-makers involved in negotiation, collaboration and coordination is larger than the subset affecting a decision-maker involved in purely independent computation. Independent computation is referred to when a human operator can arrive at a conclusion by himself. On such example of this would be a specialist human operator who computes the most optimal solution for a problem with respect to his resource of interest. The subset of biases affecting decision-makers involved in negotiation, collaboration and coordination is larger because these agents will be involved in both independent computation as well as decisions that are affected due to interacting with other agents. Additionally, problems solved by specialist decision makers are driven by specific and tangible objectives and constraints. Therefore, specialist decisions can be easily facilitated by rational decision support tools, unaffected by cognitive bias error, which is not true for all aspects of managerial decision-making. **Based on conclusions drawn from the literature reviewed thus far, research studying the effects of cognitive biases within the AOCC domain will likelier gain more insights through the study of managerial decision-making and for this reason, modelling managerial agents is more important than modelling non-managerial agents. Therefore, to reduce model complexity, it is motivated that when studying effects of cognitive biases on decision-making, researchers should merge problem solving computational agents within resource manager agents, as most valuable insights are likely to be gained through the study of agents that collaborate, negotiate and coordinate.**

4.3.1. A Qualitative Approach for ABMS of AOCC Domain

Before embarking on the quantitative ABMS phase and developing a quantitative model for the AOCC, a qualitative ABMS phase should be done through the development of a qualitative model of the AOCC. A qualitative model is developed using model constructs which represent key aspects of agents' states and interactions [85]. Mental simulations are also a key part to model qualitative development as they are used to arrive at narratives on ways agents behave and interact. These narratives can be used to analyze and asses whether all essential entities and types of performance are represented in the qualitative model developed. **Mental simulation therefore serve as a interim validation phase, where feedback can be used to further improve model representations for the purposed of the**

research question posed.

When attempting to develop an understanding for decision-making within the AOCC, resilience engineering practices can be drawn from, seeing as resilience is quite central to AOCC decision-making. There is a substantial amount of research on resilience engineering and inclusively so, towards the air transport operations domain. Stroeve and Everdij [85] provide an methodological approach to resilience engineering as shown in Figure 4.1, which can be applied to the AOOC domain.

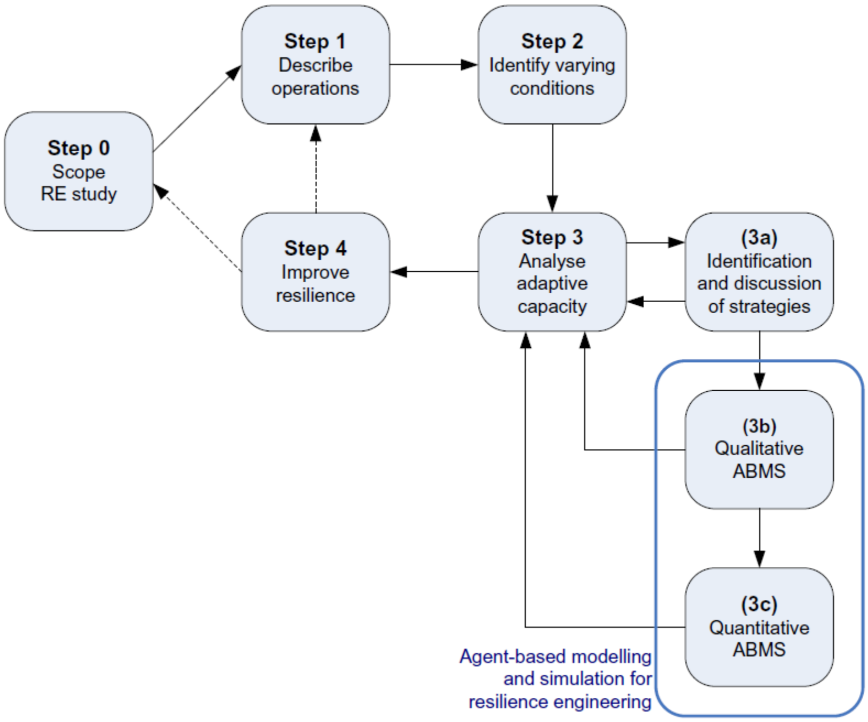

Figure 4.1: Steps in an ABMS supported resilience engineering cycle [85].

As described in chapter 3, adaptive capacities are required for adaptation to disruptive events. Decision-making is an adaptive capacity and its analysis would refer to step 3 in the resilience engineering approach as shown in Figure 4.1. Stroeve and Everdij. Identification and discussion of strategy (3a) is a step that would suffice, if this alone would provide sufficient insight towards answering a research objective. In the case of a sociotechnical system such as the AOCC, where interactions are complex and drive emergent behaviour, further modelling and simulation of these interactions is necessary. This process of modelling begins with a qualitative phase which is central to this section.

The steps to develop a qualitative model and simulation can be broken down into 5 steps:

1. Development of a qualitative model. In the scope of decision-making within the AOCC, this means a focus on the decision-making aspects with the varying conditions that affect decision-making. Agents in the model and their interactions are determined in this step as well as the constructs needed to describe the states and behaviour of agents.

2. Mental simulation focus on building narratives for agent's interactions and understanding the performance variables the model may develop. This step provides a sanity check for the model and it would be great to validate these simulations with domain experts.

3. The development of a formal model to arrive at a mathematical expression where quantitative inputs can be inserted. This step and the one that follow are further elaborated on in subsequent sections.

4. Software implementation by developing code to run a simulation of the model.

5. Computer simulation will run the simulation to ensure that results can be analyzed and conclusions can be drawn based on model performance.

During qualitative model development (step 1) four steps are identified and described in detail [85]:

1. Scoping of the qualitative agent-based modelling:

   During the scoping phase of qualitative ABM, the types of decision-makers involved should be specified. Within the AOCC scope, this would comprise: At the very least an AOCC supervisor and subset of resource managers and at most a subset specialist agents responsible for specific resource computations. The distribution of the airline's main resources (aircraft, crew, passengers) should be defined such that their availability for disruption management is clear. Rules, regulations, airline policies and any constraints should be defined such that viable solutions can be reached using the model. The varying condition for research towards AOCC decision-making should be factors affecting the decision-making approach. This allows for a comparison between different decision-making approaches. Considering decision-makers within an AOCC, the spectrum of solutions that can be considered for the caste study should be defined. Any constraints that narrow down the solution space should also be specified i.e., crew duty time..

2. Identification of agents and interactions:

   The identification of agent and interactions is a step to decide what the agents of the studied sociotechnical system are, and which inter-agent interactions exist. This is useful to identify communication channels across an AOCC. Furthermore, this is the step where model complexity is weighed in, and a modeller decided whether joining agents can further simplify model development without compromising the quality of the answer towards the research question.

3. Identification of model constructs:

   The identification of model constructs that define the way agents behave and evolve based on interactions with other agents or conditions in the environment. Thirty-eight model constructs are defined in Stroeve et al. [86] including constructs such as: Multi-agent situation awareness (observation, communication and reasoning processes that drive such state development); Task identification; Task execution; Decision making and Dynamic variability among others. For the selection of model constructs, the researcher should understand the key aspects of system constituents that drive their behaviour and constitute to the uncertainty in the model performance within the scope of the study.

4. Qualitative description of model details:

   After the model constructs are identified, the specific details required for each model construct are determined at a qualitative level for all agents in the use case researched. Within the AOCC scope, state variables such as the observation of a disruptive event by an agent, are specified. Model variables such as aircraft malfunction resolution process are specified. The type of tasks an agent can perform, such as the AOCC supervisor coordinating a negotiation, or a resource manager proposing their solution to a problem, is specified. The type of behaviour an agent may show such as a bias towards self interests is specified. The way a model construct influences, or is influenced by another model construct (within the same agent or of other agents) is specified. For instance, if an aircraft controller's situation awareness construct believes there is an aircraft malfunction, this would influence its task identification construct, such that the state of problem solving is activated.

During mental simulation (step 2) model development, two sequential steps are identified: [86]

1. Analysis of Interactions

   During the analysis of interactions, the qualitative ABM can be used for structured reasoning about the interactions between agents given the contextual condition of the operations. Within the AOCC scope, that consists on performing mental simulations for the interactions among human operators given a specific disruption scenario. It should be noted that this can be done for a

baseline condition or for a varying conditions. Researching AOCC decision-making would consist on simulating the interactions for varying factors that affect the decision-making process.
A good starting point for the analysis of interactions is the formulation of agents' states given an initial condition. For an AOCC disruption scenario, these initial states would be the environment agent state of 'disruption active' or for agent involved in decision-making, initial states would be the observation of a disruptive event. After defining initial conditions and initial states, a structured list of sequences of triggers and resulting action should be specified. These triggers-action pairs can be internal to the agent or impose an interaction between agents. Within the AOCC scope, this would entail that for instance one if an agent observes there is an aircraft malfunction, then it will believe there is an aircraft malfunction (internal trigger-action pair) and subsequently inform one or more agents about the aircraft malfunction (external trigger-action pair). **When studying decision-making with an AOCC, it would be necessary to define the initial conditions and trigger-action pairs for varying factors that affect decision-making.** For instance, one agent may or may not decide to communicate with another agent depending on a relationship bias that may be in place.

2. Analysis of Dynamics

   The analysis of dynamics is done as a follow up to the previous step of analysis of interactions since the types of interactions need to be understood, to reason about the dynamic effects. This step begins by defining what states are actually useful for the study on the research objective. To that end, an within an AOCC decision-making research scope, some states will be affected by factors that affect decision-making while others will not. For instance, considering the a relationship bias, one agent may decide to that it will prefer to first establish a communicate with a preferred agent as opposed to another. The focus on this part is on motivating how the relevant states change over time due to interactions. The reasoning for such changes can be described in narratives. If one were to vary conditions such as factors affecting human decision-making, state changes can be illustrated by graphs as function of time providing qualitative indicators of the variation.

This subsection motivates a qualitative approach for ABMS in AOCC research domain before a quantitative approach is led, as it can provide significant performance insights through qualitative model development and mental simulation. Validation with experts for the simulations should be done as the simulations can support the identification of missing aspects in the ABM such as particular agents, behavioural aspects or agent interactions.

4.3.2. The Temporal Trace Language

Modelling dynamic systems from the real world is a challenging endeavor. Attempting to do this through differential equations is overly complex due to the great number of equations and parameters needed. Continuous approaches such as Dynamical Systems are unsuitable for defining high level system qualities of qualitative character [79]. Finally, modelling timing relations using logic-based methods will be prove frivolous, as most methods lack quantitative expressivity. When modelling the AOCC, reasoning, coordination and cognitive biases should be accounted for. The AOCC in particular is characterized by both qualitative and quantitative aspects, so their representation is required. The AOCC's environment is excessively dynamic and the solution space during a disruption management process, will consequently change. To address the the limitations for modelling the AOCC using traditional modelling techniques, the TTL is proposed by Bosse et al. [13], Hoogendoorn et al. [39] and Sharpanskykh and Treur [79].

The TTL is used for both, the formal specification of dynamic properties of multi-agent systems as well as its analysis. **A great advantage of the TTL is that it supports the specification of quantitative and qualitative aspects and encompasses other languages based on differential equations or temporal logics.** Furthermore, TTL is a modelling language capable of expressing logical relationships between parts of a system allowing for modelling of a system at different aggregation levels. This would be necessary to model AOCC human decision-makers as well at the collaboration and negotiation taking place, which in turn is coordinated by an AOCC supervisor. A software environment consisting of two closely integrated tools: the Property Editor and the Checker Tool, is built to support the process of specification and automated verification of dynamic properties [13]. Further for the purposed of simulation verification, LEADSTO has been developed. Aspects for modelling the AOCC using the TTL are further explained in this section.

Temporal Trace Language is a variant of an order-sorted predicate logic. TTL has explicit facilities that enable it to represent dynamics properties of systems. A state is referred to as condition where a set of properties hold. Focusing on the technical aspects of the language, a state is characterized based on ontologies which define a set of physical and/or mental (state) properties [13]. The ontologies mentioned are specified by a number of sorts, sorted constants, variables, functions and predicates.

The ontologies that can be used to specify state properties are described below:

- The Internal Ontology, IntOnt(A) is used to express internal state properties of the agent A such as belief(A,aircraft_malfunction).
- The External Ontology, ExtOnt(A) is used to express state properties of the external world (for agent A) such at the temperature around it i.e., has_temperature(environment,7).
- The Input Ontology, InOnt(A) is used to express state properties of the input of agent A such as an observation that was made i.e., observed(A,aircraft_malfunction).
- The Output Ontology, OutOnt(A), to express state properties of the output of the agent such as when an agent acts or communicated with another agent i.e., aircraft_exchange(A,B747).

As a side note, the ontologies described above can reside inside modal constructs mentioned in the previous section on qualitative model development. For instance, the input and internal ontologies: observation and belief, can reside inside model construct: situation awareness.

Input and output states are exemplified in an example provided by Bosse et al. [13] as is later shown. To describe dynamics, the notion of state is important and dynamic properties, with special sorts, can be specified. The special sorts in TTL are: TIME, STATE, TRACE, STATPROP and VALUE.

1. TIME is special sort of assumed linearly ordered time points.
2. A state for a given ontology Ont is an assignment of true, false values to the set of ground atoms At(Ont). It makes sense to consider ground atoms as the most fundamental components of a state. Special sort STATE is a set of all state names of a system. For example, for an agent, STATES(IntOnt) will be a set of all its possible internal states. Similarly, for an agent, STATES(InteractionOnt) denote the set of all interaction states it has with other agents and/or the environment.

   The infix predicate $|=$ is used to relate A state to its state properties. Therefore $state(\gamma, t)| = p$ denotes that state property p holds in trace γ at time point t. STATEPROP then is a set of all state property names. To further explore the aspects of the special sorts STATES and STATEPROP, an example given in "A Temporal Trace Language for the Formal Analysis of Dynamic Properties" [13] is discussed. In this example an agent is supposed to interact with its environment where the interactions take the form of an extensive reciprocal interplay. After attempting to open a door three times, the agent should learn that rotating the door handle is not the correct strategy for opening the door. For this example, a specific ontology was created with the relevant state properties:

   - Property o1: the agent observes being at the door.
   - Property a1(p): the agent turns the key with rotating pressure p.
   - Property o2(r): the agent observes resistance r of the lock.
   - Property c: the agent has learnt that turning the key is not the right strategy.

   Note that these state properties will belong to special sort STATPROP, which included all possible state properties in the system. The dynamic properties for the example presented above are further elaborated on in the description for the TRACE special sort, defined next.

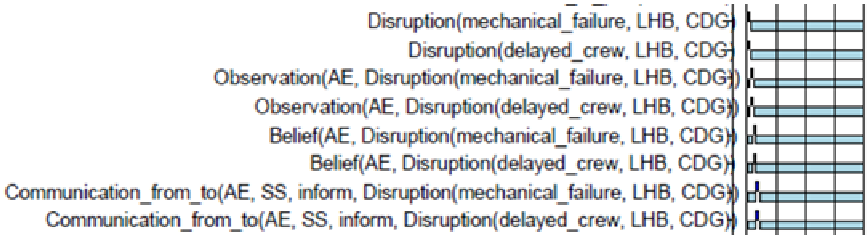

Figure 4.2: Simulation Traces for an AOCC disruption strategy [14].

3. TRACE is a set of all trace names. An example of a TRACE is shown below in Figure 4.2 . Each row represent as state and the sequence in which states appear is related to the dynamical properties defined among states.
   A trace γ over an ontology Ont and time frame T is a time-indexed set of states $\gamma_t(t \in T)$ in STATES(Ont), i.e., a mapping γ: T $\rightarrow$ STATES(Ont).

   For further clarity, the dynamics taking place due to the disrupted event in Figure 4.2, can be more thoroughly described as follows:

   (a) A disruption of a mechanical failure of a flight from London Heathrow to Charles de Gaulle.
   (b) The crew of the disrupted flight is delayed.
   (c) The aircraft engineer observes the mechanical failure disruption.
   (d) The aircraft engineer observes that the crew of the disrupted flight is delayed.
   (e) The aircraft engineer believes the mechanical failure disruption.
   (f) The aircraft engineer believes the crew from the disrupted flight is delayed.
   (g) The aircraft engineer communicates to the Station Supervisor the mechanical failure of the disrupted flight.
   (h) The aircraft engineer communicates to the Station Supervisor the crew delay of the disrupted flight.

   The relationship between the state and state properties is defined by the infix predicate $\models$. Explicit references to time points and traces are necessary to express dynamic properties in a precise manner. Input and output states are exemplified through an example shown in Figure 4.3 [13], which shall illustrate the dynamic properties that tie together the previously specified state properties for the door opening strategy problem.

Representational Content of c

'Internal state **c** occurs iff in the past once **o1** occurred, then **a1(1)**, then **o2(1)**, then **a1(2)**, then **o2(2)**, then **a1(3)**, and finally **o2(3)**'.

∀t1,t2,t3,t4,t5,t6,t7 [t1≤t2≤t3≤t4≤t5≤t6≤t7
& state(γ, t1, input) ⊨ o1
& state(γ, t2, output) ⊨ a1(1) & state(γ, t3, input) ⊨ o2(1)
& state(γ, t4, output) ⊨ a1(2) & state(γ, t5, input) ⊨ o2(2)
& state(γ, t6, output) ⊨ a1(3) & state(γ, t7, input) ⊨ o2(3)
⇒ ∃t8 ≥ t7 state(γ, t8, internal) ⊨ c]
& ∀t8 [state(γ, t8, internal) ⊨ c ⇒

Figure 4.3: Representational content of agent internal and external states and state properties held, when an agent turns a key to find out, turning the key is not a working strategy. [13]

.

The relationship between states and state properties follows as such:

- In trace γ, at time t2 output state property a1(1) holds. This translates to the agent applied a force of pressure p=1 a time = t2.
- Similarly, for trace γ at t3, the output state property o2(1) holds. This translates to the agent observes a resistance of r=1 on the rotating key at time t = 3.

The dynamic property is that is the agent observes the door, and attempt to open is, with increasing pressure three time and this does not succeed, then the agent is led to believe that this strategy does not work - which is denoted by holding internal state c.

4. Finally, the special sort VALUE is an ordered set of numbers. This numbers can be constant variables that are used in during the simulation. Consider entries in VALUE to be variables such as: Time required to repair aircraft and prepare to fly; available buffer time for the transit passengers and passenger delay [7].

4.3.3. Multi-level Modelling the AOCC Using the TTL

Within the AOCC scope, not only will the objectives that drive decision-makers vary, but so will the responsibilities of each decision-maker. When modelling, these differences between agents should be accounted for. Components an ABMS interact with each other and the environment according to input and output ontologies. The input ontologies will enable components to receive information via input ontologies that specify interactions in the form of observations and communication from other components. Similarly, a component generates outputs in the form of communication, observation requests, and actions performed. Bearing in mind the communications that may occur within an AOCC, it seems plausible that resource managers will share similar ontologies, and these will be slightly different to those that specify the behavior of an AOCC supervisor.
An aspect of a state of a component is explicitly indicated by the sorts $ASPECT\_COMPONENT$ (input, output, internal...). The set $COMPONENT$ is a set of all component names and the set $COMPOMENT\_STATE$
$\_ASPECT$ is a set of all names of aspects of all component states. For the reader these sorts are associated to elements within the AOCC domain. The COMPONENT sort can be thought of including one component as an umbrella for all resource managers i.e., aircraft, crew and passenger and another for the AOCC supervisor, who must coordinate the process. $ASPECT\_COMPONENT$ can be thought of as related to a state property. For the AOC supervisor COMPONENT, the $ASPECT\_COMPONENT$ set will hold elements such as inputs, output, and internal. $COMPOMENT\_STATE\_ASPECT$ will hold all items in the $ASPECT\_COMPONENT$ for the AOC supervisor as well as for other components modelled. A functional symbol for $COMPONENT\_STATE\_ASPECT$ is shown in Equation 4.1.

$$comp\_aspect : ASPECT\_COMPONENT \times COMPONENT \rightarrow COMPONENT\_STATE\_ASPECT \tag{4.1}$$

For a specification of agents an indication of the comopnent's aspects is needed. This can be defined through the state function symbol:

$$state : TRACE \times TIME \times COMPONENT\_STATE\_ASPECT \rightarrow STATE \tag{4.2}$$

In the AOCC, an example of this would be:

$$state(\gamma_1, t_1, Input(AOC\_manager))| = Observation(AOC\_manager, Disruption(aircraft\_malfunction))) \tag{4.3}$$

4.3.4. Specifying the AOCC Organizational Structure

Organizational research has identified the advantages of agent-based models for the analysis of dynamics of real organizations like the AOCC [28]. Below, elements required for the specification of organizational structures are laid out.

At the most fundamental level and organizational structure can be described by the relationships between roles at various aggregation levels and between parts of a conceptualized environment and the defined roles within the environment. The specification of an organizational structure is comprised on the following elements as found in [79]:

1. A role represents a subset of functionalities that are performed by an organization that may involve multiple agents to fulfill. A role that is composed of subroles is called a composite role. Each role

has input and output interface used for interaction with other roles or the environment. These interactions are described in terms of input/output ontologies. At the highest aggregation level, an AOCC could be represented as one role; at the lowest aggregation level, a resource manager is a role.

2. An interaction link represents an information channel between two roles at the same aggregation level.

3. The conceptualized environment has input and output interfaces for interaction with roles within the organization. The interfaces are conceptualized by the environment input and output ontologies.

4. An interlevel link for a link between a composite role and its subroles and essential represents information transfer between distinct aggregation levels.

In Figure 4.4 multiple roles, levels of aggregation and the interlink betweeen them is shown.

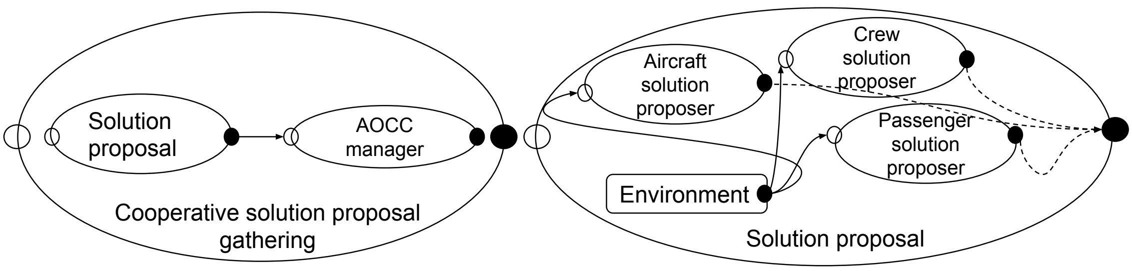

Figure 4.4: A simplified AOCC organizational structure for co-operative disruptive management solution proposal gathering at aggregation level 2 (left) and at aggregation level 3 (right).

At each aggregation level within an organization the dynamics of each structural element may be defined by specification of five types of dynamic properties:

- A role property (RP) describes the relationship between an role's input and output states, over time. For the example shown in Figure 4.4, and the cooperative solution proposal gathering role, where the input may be the requirement to receive solution proposals from AOCC resource managers, and the output may be whether the solutions meet the requirements.

- A transfer property (TP) describes the relationship between an output state of one role, with the input state of another role. In the example illustrated in Figure 4.4, this could be the output communication state of the solution proposal role, which are the three proposed solutions, and the input observation state of the AOCC supervisor role. The AOCC manager would then have subroles to determine whether the solutions are valid.

- An interlevel link property (ILP) described the relationship between input or output state and an input or output state at a different aggregation level for a composite role. This is instantaneous and doesn't represent a temporal process. An example of this for the example shown in Figure 4.4, would be the output of the solution proposal role, where solutions proposed by all managers is found, links to the AOCC manager role input.

- An environment property (EP) described the temporal relationship between environmental state. If a disruption would occur this would be relfected in the environment.
- An environment interaction property (EIP) described the relationship between the output state of a role and the input state of the environment, or the output state of the environment and the input state of a role. This can be seen in Figure 4.4, as the proposers to problem domain have access to the possibilities to solve the problem due to the resources that are made available to them through the environment.

4.4. Validating an AOCC ABS

Arguably, the most important property of a model is its validity, as this essentially means the right model is used and is able to produce reliable results within its experimental frame. When a model is validated the outputs of the simulation can be used to appropriately answer questions about the system.

For ABS, validation is quite problematic for various reasons, as discussed below [52]:

- Firstly, empirical or statistical validation is only possible if characteristic numbers can be found that are able to describe the system appropriately. For the AOCC domain example, it would make sense to output the solution attributes. For instance, the cost of operating a flight; delay in a solution; aircraft type used; number of crew used and passenger load, to name a few. These attributes could be compared to existing ones that result from decision-making in the field.
- The second issue for validation is the non-linearity involved in decision-making and brittleness of solutions. When modelling negotiation among decision-makers within the AOCC, a feedback loop is involved. Feedback loops lead to non-linear effects of parameters changes which in turn may lead to unexpected chaotic effects. For this reason, the simulation outcomes may be quite brittle with respect to parameter change and this behaviour might be hard to validate. In the AOCC domain, this would translate to an AOCC manager accepting different solutions for the same disruptions source based on negotiation dynamics.
- Thirdly, the effort necessary to produce the required simulation data for validation should not be underestimated. This is because validation must be performed at multiple levels of aggregation. Within the AOCC scope, this is at the airline performance level and at the agent level. At the agent-level, it should be possible to perform simulations, that have been face validated by experts, and assess the decision-making and how cognitive biases may have an effect. At the airline level, validation can be done to confirm that the outputs are reasonable and would be accepted by experienced professionals.
- Lastly, the number of parameters involved in ABM is typically large. This introduces a large number of degrees of freedom, introducing the systematic problem of impossibility of falsification. In other words, the amount of available data becomes insufficient to validate a model with a substantially high level of detail. For this reason, it is motivated that researchers should reduce the number of parameters involved in a model to the ones essential to answer their research questions.

To address the above, Klügl [52] proposed a validation framework for ABMs, as illustrated in Figure 4.5:

- The first step is to perform face validation, which subsumes all tests based on reviews and audits used during the presentation and justification of assumptions and the model structure used. Two methodological elements that lead to face validation are discussed. The first one is immersive assessment. To that end, expert humans assess agents' perceptions and corresponding reactions within a simulation and then determine whether the behaviour simulated is appropriate. Cognitive biases have been validated by cognitive bias research, so therefore their translation into the AOCC domain would have to be validated. The effect cognitive biases have on AOCC decision-makers' perception and reactions must be assumed based on the respective literature. Subsequently, the decision-making that follows as a result of such will be assessed by an expert to determine if it is within the realm of decisions.

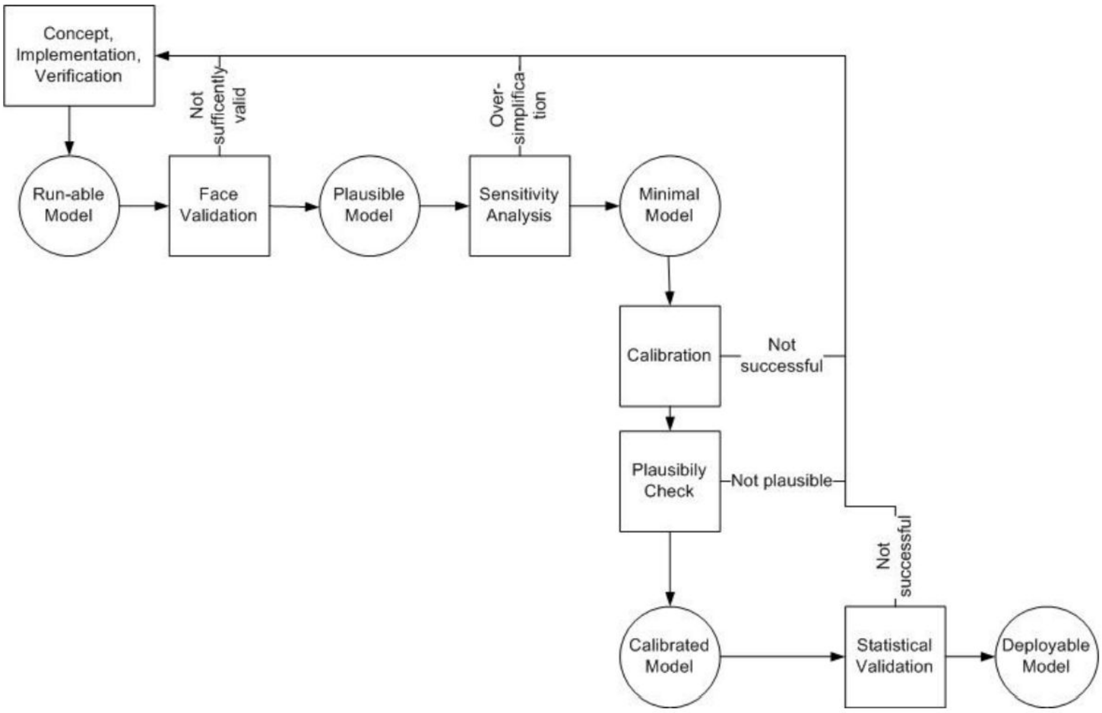

Figure 4.5: Klügl's sketch of a general procedure for validating an agent-based simulation. [52]

- The second step performs a sensitivity analysis with the intent to explore the effect of the different parameters (and their values) at the agent and system level. For some parameters calibration determines the appropriate values. Such parameters might be something such as the maximum acceptable delay by the AOCC supervisor. This will certainly have an effect on the solutions reached. Prior to starting the validation process, it would be difficult for the researcher to determine which values have to be calibrated, or if any need to be, for that matter. The benefit of performing a sensitivity analysis is that a set of parameters found to have minimal effect can be deleted, to leave the researcher with a model using a minimal set of parameters.

- The third validation step proposed is a calibration. This consists of adjusting model parameters based on a given input and output, such that the simulated output reassembles the given output as much as possible. This is basically an optimization problem. This type of validation was performed during the already mentioned, Descartes project, when researchers calibrated the costs in their model such that the aircraft recovery model simulated output reassembled that of the experienced professionals. It seems appropriate that for AOC decision-making researcher, the simulated final proposed solution (which constitutes the sum of individual resource manager solutions) is compared to the final solution experienced AOCC decision-making arrives at - given the same disruption problem.

- The plausibility check is similar to face validation though less intense as only limited changes are to be expected in the simulation outcomes.

- The third validation step that is proposed is calibration. This consists of adjusting the model parameters based on a given input and given output such that the simulated output reassembled the given output as much as possible. This is basically an optimization problem. This type of validation was performed during the Descartes project when researchers calibrated the costs in their model such that the aircraft recovery model simulated output reassembled that of the experienced professionals. The same approach can be taken when researching the effects of cognitive biases on AOCC decision-making, where the proposed solution from resource manager agents is compared to resource manager decision-making at an airline and AOCC agent decision-making is compared to AOCC decision-making at an airlines.

- The final validation step proposed is statistical validation. The proposed approach for this validation technique is to use disruption scenarios that have not been simulated during model development, and compare the proposed solutions (and decision-making at agent level) with those proposed by experts.

In this chapter, the Multi-Agent System Paradigm is introduced by stating its inherent characteristics. The Agent-Based Modelling and Simulation Paradigm is explored by describing the elements that must be explicitly dealt with and the advantages and disadvantages for adopting it. Some discussion is presented surrounding the topic of complexity trade-off based on the research objective and it is concluded that modelling managerial agents will provide most insights when considering the effects of cognitive biases in AOCC decision-making. A qualitative approach to agent-based modelling of a AOCC is motivated as a reasonable way to draw insights towards the effects of human factors on decision-making (and ultimately AOCC resilience) through qualitative model development and mental simulation. Temporal Trace Language can formally specify quantitative, qualitative and dynamic properties of the AOCC system which motivates its adoption for research that models the AOCC using the ABMS paradigm. The ontologies that categorize different aspects on the system is discussed using examples. Furthermore, specifications for modelling the aggregate levels within the multi-level AOCC system are presented as well as the elements required to specify its organizational structure. Finally some thoughts are given to the reader on why validating and Agent-Based Simulation is an arduous task and a subsequent framework to address this is presented and discussed.

5

Research Proposal

In this chapter, the research objective is defined in section 5.1. The research questions sought to meet the research objective are laid out in section 5.2. Finally, the three case studies chosen to study the effect of cognitive biases on decision-making within the AOCC are presented in section 5.3.

5.1. Research Objective

Considering the current state of research regarding cognitive bias effects on AOCC decision-making the main research objective for the research proposed is:

> To contribute to the relatively unexplored research field of evaluating human factor effects on decision-making in complex sociotechnical systems by modelling cognitive bias in decision-making in a simulation study of Airline Operations Control Centers, in the face of an operational disruption by applying an agent-based modelling approach.

Through the formalization of cognitive biases following the concepts of Tversky and Kahneman and those that built a upon their work, this research aims at contributing to the formalization of human factors in decision-making. A series of case studies that typify operational disruptions are proposed to ensure the feasibility of the research objective. The identification of cognitive biases affecting decision-making within the AOCC domain is made possible through data gathering by means of observation at TAP Air Portugal's AOCC as well as interviews with AOCC decision-makers.

5.2. Research Questions

To reach the research objective, answers to the following research questions and corresponding sub-questions are sought:

1. What affects the final AOCC decision?
   (a) Which goals drive AOCC decision-makers?
   (b) Which solution spaces are considered by AOCC decision-makers?
   (c) Which constraints limit AOCC decision-makers' solution space?
2. What are the effects of cognitive biases in AOCC decision-making?
   (a) Which cognitive biases are present in AOCC decision-making?
   (b) How are cognitive biases affecting AOCC decision-making solution space?
   (c) How are cognitive biases affecting AOCC decision-making goals?
   (d) How are cognitive biases affecting AOCC decision-making constraints?
3. How is the AOCC system performance affected by cognitive bias?
   (a) How do cognitive biases affect AOCC direct operating costs?
   (b) How do cognitive biases affect AOCC time to reach a decision?

5.3. Case Study

The combination of disruption scenarios that may have to be dealt with by the AOCC are numerous and their exhaustive study is not required, to answer the research questions proposed. As a result, only a select few scenarios will be investigated in the research proposed. The cognitive biases that will be used for all scenarios will be motivates. Then, a description of the scenario will be presented, followed by the decision-makers involved in resolving each scenario, and finally the possible solutions that could hypothetically be applied to each scenario are presented.

The cognitive biases chosen for study to meet the research proposed are: The **effectiveness of a search set bias** (availability heuristic), the **insufficient adjustments bias** (anchoring heuristic) the and the **relationship bias**. The effectiveness of a search set bias is chosen to research how one's ability to easily generate ideas based on one's experience, effects decision-making. The insufficient adjustments bias is proposed to research how ignoring new information reduces the potential for optimal decision-making. Finally, the relationship bias is chosen to gain a better understanding for how human relationships affects the performance of a sociotechnical system..

Assuming actions proposed by human agents reflect the disruption source-action pair probabilities (as show in Table 2.3 and Table 2.4) the effectiveness of a search set bias will be modelled assuming the most likely action to be chosen from a decision-maker's search set, is the action most likely given a disruption source category. The insufficient adjustment bias can be implemented by introducing new information to a disruption scenario and varying its use for further problem solving relative to the degree of anchoring. The relationship bias can be modelled by introducing preferred agent interactions. This way, should one agent prefer to start problem solving with another, the extent to which this affects the solution space and ultimate proposed solution can be studied.
Measuring quality of disruption management solution, by varying the cognitive biases included in the AOCC decision-making model, is one way to measure their system level effects and also compare their relative effects.

Three requirements for the selection of each scenario are to be met:

1. The scenario characterizes a disruption that a real AOCC could potentially face.
2. The alternative solutions considered by each decision-maker to mitigate the adverse disruption effects are derivable from literature.
3. The scenario is sufficiently complex to include a disruptive event at the gate-to-gate level, affecting multiple airline resources to the point where aircraft, crew and passenger managers and AOCC supervisor must be involved.

The scenarios chosen are based on ones explored by Bruce [15] and Belhadji [7] and are disruptive events associated with (scenario 1) international passenger connection problem, (scenario 2) in-flight mechanical failure, (scenario 3) airport inclement weather situation:

Scenario 1: There is an incoming international flight from GRU to LIS that is delayed. Twenty-five passengers are connecting to another flight to PDL.
The time is 0030 UTC and Flight TP 88 (aircraft type A-330-900 with tail number CS-TUI) operating from São Paulo (GRU) to Lisbon (LIS) has been unserviceable in GRU. The aircraft has eventually departed two hours late and is picking up time into LIS. The ETA to LIS is 1200 UTC. There is no crewing problem. All Tranships are OK, except a Ministerial Delegation of 55 connecting with Flight TP 1859 to Ponta Delgada (PDL). Flight TP 1859 is scheduled to depart at 1245 UTC. So far the decision has been to hold Flight TP 1859 to get it away at 1300 UTC. Subsequently, the inbound flight was delayed further and further decision-making is required.

Scenario 1 considerations:

- Whether and how long they might hold flight.
- Commercial impact (especially the Ministerial delegation of 55 passengers).
- Crew hours.

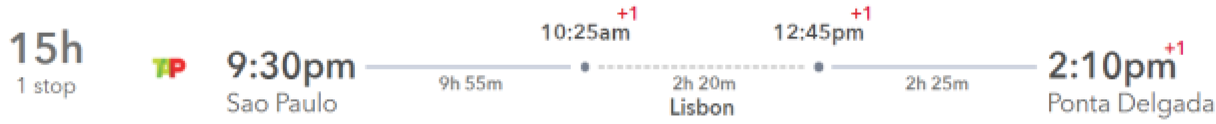

Figure 5.1: Scenario 1: A flight delayed due to unserviceability.

- Clear the 55 connecting passengers through Customs and Immigration and then transport them all by bus to the domestic terminal.

Scenario 2: The time is 1250 UTC. The aircraft with tail number CS-TVA (A320-251N) operating Flight TP 674 Lisbon (LIS) to Amsterdam (AMS) has radio'd back to Lisbon. It has been communicated that there is an instrumental indication problem. The captain has further elaborated that this problem had previously occurred in LIS and that, if the problem re-occured, the aircraft would be grounded until the problem is fixed. The captain would like to know whether he is supposed to return to LIS of keep on going to AMS.

Figure 5.2: Scenario 2: A flight has an instrumental indication problem while in flight.

Scenario 2 considerations:

- Consequences of enabling the aircraft to continue to its destination.
- Consequences of returning to the departure airport.
- Changing aircraft patterns.
- Carrying passengers on alternative flights.
- Delaying, adding, and cancelling flights.

Scenario 3: The time is 0500 UTC. Aircraft with tail number CS-TTL (A319-111) operating Flight TP 1869 Lisbon (LIS) to Ponta Delgada (PDL), is scheduled to depart at 0705 UTC. The wind at PDL the last 24 hours has been on average, below 15 kts. From 0400 UTC to 0500 UTC, the wind has been steadily increasing and at 0500 UTC the wind in PDL is registered as 30 kts. A decision regarding the operation of the flight is made at 0600 UTC as the registered wind speed is 35 kts and it is decided that the flight will be delayed for 3 hours until 1005 UTC. It is 0900 UTC and a decision has to be made regarding the operation of the flight. The wind at 0900 UTC is 34 kts at PDL which is beyond the acceptable threshold. We are told that Ryanair will be boarding passengers on Flight FR 2623 with tail number EI-EVT with a scheduled departure time for 0955 UTC. Is Flight TP 1869 Lisbon (LIS) to Ponta Delgada (PDL) operated?

Scenario 3 considerations:

- Wind threshold for Madeira is 32 kts.
- Hold baggage drop-off counter opening time 6 hours.
- Having to return to LIS or diverted to alternate airport (if possible).
- Competition airline will attempt to fly to same destination - commercial impact.

6

Research Methodology

To develop a MAS model of the AOCC decision-making process that models cognitive bias, the research proposed will make use of the modelling methodology proposed by Nikolic and Ghorbani [70] which comprises of five step: System analysis, model design, detailed design, software implementation.

1. **System analysis:** Knowledge of AOCC disruption management process regarding the roles involved must be gained, the responsibilities of each role as well as their respective objectives and constraints must also be understood. The range of possible disruption sources and the range of solutions that can be considered to deal with them must be recognized. Furthermore, the theory on decision-making and the decision-making process that is applied within the AOCC must be studied. Particularly, the research on heuristics and cognitives biases and their effects on the decision-making process must known. Through expert interviews, information pertaining to the roles involved in the disruption management process within an AOCC, in a mid-sized airline, will be obtained. The modelling paradigm most suited for modelling the AOCC as socio-technical system will be chosen along with the language to formalize the organization, its constituents and cognitive biases.
   A selection of disruption scenarios for a large airline are chosen for a significant amount of resources to be affected. This way, the research hopes to gain knowledge across all domains within the AOCC and validate itself against common disruptions that affect all resources.

2. **Model design:** Conceptual models in an ABM paradigm framework, will be developed before the development of formal models with formal implementation languages.

   - Firstly, conceptual models for decision-making rules based on cognitive biases must be developed. Similarities, differences, quantitative and qualitative relationships must be well defined.
   - Secondly, conceptrual models for decision-making within the AOCC must be developed that characterize the difference and similarities between decision-making approaches, based on AOCC responsibilities. These model should be able to merge with models developed to model decision-making based on cognitive bias effects.
   - An integrated conceptual model, that merges all the above models will also be developed to model the whole AOCC as an organization with it constituents and their biases. This latter model should define organizational rules and the AOCC interfaces with information in the environment.
   - A qualitative model will be developed for research scoping, to identifying agents that need to be modelled as well as model constructs to model human or system behaviour and finally to qualitatively describe of model details.
   - A selection of a language for the formal modelling and analysis of the AOCC as an agent-based system is chosen.

3. **Detailed design:** The formal specification of conceptual models developed must be done in a language that allows for various aggregation levels and relating static and dynamic properties of the a system's constituently. The language selected in the Temporal Trace Language.
   - The specification of the integrated conceptual model is done through the design of ontologies able to explicitly specify input, output, internal and external states specifying all related to a human's overall cognitive behaviour within a sociotechnical system.
4. **Software implementation:** The implementation of the models will be done in Python.
5. **Model evaluation:** The results of the simulations run will be be traces of states executed as the AOCC and its constituents are faced with a disruption problem. A solution is also expects and will hold attributes such as costs and resources, which can then be used for performance analysis and validation purposes.

By applying Nikolic and Ghorbani's modelling methodology, a systematic approach will be followed to model and analyse the effects of cognitive biases in decision-making within the AOCC.

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