Agent-based Modelling and Simulation of Airline Operations Control Decision-Making under Uncertainty

Bouarfa, Soufiane; Blom, H.A.P.; Sharpanskykh, Alexei; Belhadji, K.

DOI
10.2514/6.2021-0654

Publication date
2021

Document Version
Final published version

Published in
AIAA Scitech 2021 Forum

Citation (APA)
Bouarfa, S., Blom, H. A. P., Sharpanskykh, A., & Belhadji, K. (2021). Agent-based Modelling and Simulation of Airline Operations Control Decision-Making under Uncertainty. In *AIAA Scitech 2021 Forum: 11–15 & 19–21 January 2021, Virtual Event* Article AIAA 2021-0654 American Institute of Aeronautics and Astronautics Inc. (AIAA). https://doi.org/10.2514/6.2021-0654

AIAA SciTech Forum
11–15 & 19–21 January 2021, VIRTUAL EVENT
AIAA Scitech 2021 Forum

10.2514/6.2021-0654

Agent-Based Modelling and Simulation of Airline Operations Control Decision-Making under Uncertainty

Soufiane Bouarfa[1]
Abu Dhabi Polytechnic, Al Ain, 66844, United Arab Emirates
Delft Aviation, Delft, The Netherlands
Henk Blom[2], Alexei Sharpanskykh[3]
Delft University of Technology, Delft, 2628 CD, The Netherlands
Kamal Belhadji[4]
Legian Consultancy, The Hague, 2517 JX, The Netherlands

Abstract

Motivated by the need to understand and further optimize AOC decision making processes under uncertainty, this paper implements and evaluates the effects of operational uncertainties using Agent-Based Modelling and Simulation. The specific application concerns a challenging scenario composed of two consecutive disruptions. To evaluate the effects of uncertainties, an agent-based model of AOC processes has been developed using a logic-based ontology. Subsequently, this agent-based model is used to analyze the sensitivities of different model parameters. The simulation results provide novel insights into the effects of operational uncertainties on AOC decision-making and consequently airline performance. For the aircraft breakdown scenario considered, it is shown that adding buffers into the schedule promote a degree of self-recovery. The sensitivity analysis also reveals that transit buffer time and crew duty slack time act as tipping points for the airline operating costs. This demonstrates that ABMS allows to analyze and bring into light various sensitivities, which can be used in the early design phase to increase airline resilience, and train airline controllers for different environment states. The paper concludes that ABMS is a valuable approach that can enable a paradigm shift from reactive recovery to proactive recovery.

Keywords: Decision-Making; Socio-Technical Systems Modelling; Uncertainty; Airline Operations Control; Disruption Management

1. Introduction

In order to deal with disruptive events and reduce their impact, major airlines have established Airline Operational Control (AOC) centers. An AOC center gathers an extensive array of operational information and data, with the purpose of maintaining the safety of operations, and efficiently managing aircraft, crew, and passenger operations. When disruptions occur operators at an AOC center adjust in real-time the flight operations by selecting and implementing the best possible actions. This is known as airline disruption management. AOC's main responsibility as formulated by Bruce [1] is to plan and coordinate the disruption management process to achieve network punctuality and customer service while utilizing assets effectively and minimising cost. Castro et al. [2] has estimated that irregular airline operations can cost between 2% and 3% of the airline annual revenue and a loss of passenger goodwill; for an airline like Air France KLM, this amounts to €521M- €780M annually [3].

During disruption management AOC controllers monitor the progress of operations, identify problems, make decisions and implement solutions [4]. Due to the complexity of the airline operating environment, controllers are confronted with many operational uncertainties. Coupled with an inadequate information supply and time constraints, this may create hazardous situations that could lead to extreme economic consequences for the airline [5]. Furthermore, airlines have become more concerned with optimizing operational schedule by being

[1] Assistant Professor Aviation, Abu Dhabi Polytechnic, AIAA TC member
[2] Professor Air Traffic Management Safety, Delft University of Technology
[3] Assistant Professor, Air Transport Operations, Delft University of Technology
[4] Cyber Security Consultant, Legian Consultancy

reserved in adding robustness into their schedule i.e. slacks, buffers and standby resources [4,6]. This results in the operational schedule being more prone to disruptions and limits the possibilities for recovery, which adds more pressure on Airline Operations Control.

AOC controllers rarely have time to explain their reason for decision-making [1]. Additionally, multiple decision-makers are involved during disruption management resulting in more difficulties to evaluate decision-making processes. Modelling and simulating these decision-making processes is expected to yield novel insights into the effect of robust scheduling and operational uncertainties on disruption management. Earlier ABMS studies of AOC operations have been conducted by Bouarfa et al. [7,8]. In [7] ABMS is used to evaluate and compare the socio-technical and socio-economic effects of four AOC coordination policies. Three of these coordination policies are based on established airline practices, whereas the fourth policy is based on the joint activity coordination theory from the psychology research domain [reference]. The results of [7] provide novel insights on the operational effects of each AOC coordination policy. In [8] ABMS is used to evaluate socio-technical and socio-economic effects of a Multi-Agent System (MAS) that was designed to automate key roles in the AOC center. The findings indicate that implementing a MAS supported AOC policy leads to both better and faster resolutions, though the replacement of human roles also poses novel challenges that remain to be resolved. The main challenges are a potential increase in workload for the remaining human role and a loss of experience in handling exceptional situations.

The above ABMS studies have focused on understanding of AOC managing effects of external disturbances to airline operations. The purpose of this paper is to take an ABMS approach in analyzing effects of internal aircraft maintenance disturbances on AOC decision-making under uncertainty. For the agent-based modelling of a complex socio-technical operation like AOC, Nikolic & Ghorbani [11] have developed a systematic approach in developing an ABMS approach. The first step is to perform an agent-based analysis of the operation considered. The second step is to develop a formal agent-based model, including agent definitions and the agent ontologies. Subsequently this formal model is implemented in a selected simulation environment. Upon evaluation of the proper working of the software implementation, the ABMS is used for the simulation of selected cases of the operation. This systematic approach to ABMS development has also been used to evaluate other air transportat operations, e.g. for runway safety [9] and for airport security [10].

The paper is organized as follows. Section 2 provides an agent-based analysis of airline operations from an AOC and aircraft maintenance perspective. Section 3 presents the development of the ABMS environment for the airline operation considered. Section 4 presents ABMS results for two specific aircraft maintenance cases. Section 5 draws conclusions.

2. Agent-Based Analysis of Airline Operations Control

This section presents an agent-based analysis of AOC in the contexed of the selected disruption scenario. The analysis identifies the main agents involved in managing the disruption, and the uncertainties they face during decision-making.

2.1 Scenario Description

To make the identification of the socio-technical system under investigation concrete, we combine two disruption scenarios from [1] for which qualitative data had been collected from 52 airline controllers. In Bruce's experiments [1], controllers commented on real-life scenarios by expressing their thoughts regarding the uncertainties they face, scheduling parameters they are interested in, and the decision considerations they make. Using a think-aloud protocol, this resulted in a wealth of qualitative data that was used to identify and analyze the socio-technical system. This data has been further combined with findings from meetings with industry experts at three major airlines and AOC literature.

The scenario involves both an aircraft mechanical problem at an outstation and a potential passenger connection problem:

> *The time is 0900 UTC. Flight DL 1945 is about to be operated by crew 'A' from AMS to DLF with aircraft PH-TUA. During the pre-flight check, the technician reports a hydraulic leak such that it may require a hydraulic pump change. The staff at AMS (which is an outstation of DLM) has*

stopped checking in the passengers for the flight. There are transits passengers on board that have a connecting flight at DLF (DLM's home base). Due to company procedures, the crew contacts Flight Dispatch of Airline Operations Control department to communicate their findings.

This scenario combines two scenarios reported in Bruce [1] namely an aircraft mechanical problem and a passenger connection problem. Previously, the aircraft mechanical problem scenario was considered in Bouarfa et al. [7,8]. In this study, we increase the complexity of the scenario by combining two disruptions.

2.2 Identification of agents and their goals

For the identification of the relevant AOC agents we follow [7,8]. The relevant agents are the Operations Controller (OC), Aircraft Controller (AC), Crew Controller (CC), Stations Operations Controller (SC) and Flight Dispatch (FD) who share the same common goal namely recovering from the disruption through collaborating with each other. The goals of the agents in this scenario are as follows:

- **OC:** Coordinate the management of aircraft, crew, and passenger problems to execute the schedule and deliver the customer service level at minimum cost and high efficiency.
- **AC:** Get aircraft TUA back to operations as soon as possible; avoid using reserve aircraft.
- **CC:** Get crew A back to fly operate the flight as soon as possible; avoid using reserve crew.
- **SC:** Prevent passengers from being stranded; avoid rebooking; ensure successful connection for transit passengers.
- **FD:** Plan the flight and monitor flight progress and weather.

2.3 Description of environment and uncertainties

As a follow up to the scenario description step, this step aims at describing the operational environment in which the agents operate in detail. This was achieved through analyzing the controllers comments from Bruce [1] which indicate what controllers focus on when managing disruptions. An example from the considered scenario was the interest of controllers in information related to aircraft maintenance and repair actions. Hence, the environment description includes the availability of spare parts, engineer certification, hangar space, weather, and so forth.

AOC controllers face different uncertainties during disruption management. Two types of uncertainties have been identified namely timing uncertainties and resource and environment uncertainties. These are shown in Table 1a and Table 1b respectively.

Table 1a: Resource uncertainties

#	Resource uncertainty	Description
a	Technical Diagnosis adequateness	adequateness of the technical diagnosis provided by the local technicians at AMS
b	Spare Part availability	availability of spare parts at AMS for solving the mechanical failure of aircraft TUA[5]
c	Weather Pattern favorability	favorability of the weather pattern at AMS for the repair of aircraft TUA at apron
d	Hangar Space availability	availability of hangar space at AMS for the repair of aircraft TUA
e	Organizing Connection possibility	the possibility to hold the (next) connecting flight or to increase flight speed or accelerate turn around for the purpose of a successful connection of passengers
f	Positioning crew possibility	availability of seats from DLF to AMS for either positioning reserve crew , or to position resources like technicians and parts to AMS
g	Reserve crew availability	availability of reserve crew for either positioning from DLF to AMS, or for deployment to dispatch reserve aircraft from DLF to AMS
h	Rebooking possibility	possibility to rebook passengers on other flights that depart from AMS to DLF

[5] Aircraft TUA - the aircraft with tail number PH-TUA that has the mechanical failure

i	Reserve aircraft availability	availability of reserve aircraft to ferry empty from DLF to AMS, to pick up the passengers A at AMS and bring them back to DLF

Table 1b: Timing uncertainties

#	Timing uncertainty	Description
r_t	Repair time	the time that is required to repair aircraft TUA
c_t	Crew duty slack time	the crew duty time slack that is available for crew A to complete the flight back to DLF
d_t	Positioning time	the time before the positioned reserve crew arrives at AMS to take over flight DL 1945
k_t	Ferry time	the time for reserve aircraft to fly from DLF to AMS i.e. the time for the passengers to wait for the reserve aircraft to arrive
b_t	Rebooking time	the time for the rebooking flight to depart from AMS to DLF
p_t	Transit-buffer time	the buffer in time the transit passengers have on flight DL 1945 to make a successful connection

3. ABMS development

3.1 Agent-based model specification steps

Having identified the relevant agents and their behavior, the model design step aims at a specification of the interactions between different agents in the context of the chosen scenario e.g. through using flowcharts. In this phase, various uncertainties that affect the recovery solutions are further elaborated. The purpose of the model is to generate appropriate recovery solutions for the aircraft, crew, and passenger problem while taking the various uncertainties into consideration.

- **Specification of agent's actions.** This step identifies the actions of the agents involved during disruption management and their interactions with other agents in their environments. To achieve this, AOC flowcharts have been used. These charts visualize different phases of disruption management, reasoning processes, and communication flows between the agents.
- **Identification of valid recovery solutions** as function of these uncertainties:
  The first step aims at identifying all possible recovery solutions for each of the three disruption management problems: aircraft, crew, and passenger. This is followed by eliminating invalid combinations using truth tables. For instance, it is not possible that passengers would be both accommodated and connecting to another flight on the same day. Using truth tables and conditional statements, we have identified twenty valid recovery strategies.
- **Environment conceptualization and expressing uncertainties**: In this step, the environment is conceptualized using conditions and parameters. Resources uncertainties in Table 1a are expressed using Boolean valued conditions, while timing uncertainties in Table 1b are expressed using a time parameter. Full explanation of these parameters is in [12].
- **Task analysis of airline controllers:** The tasks of the controllers are abstracted from the systems analysis step which identifies the agent's actions. Table 2 provides a listing of the identified tasks. A model structure is designed to provide a general view of the different phases of the decision-making process. Each phase is associated with tasks being conducted together with specific conditions and parameters. These tasks are translated into processes which represent outgoing or incoming interactions of the controllers and the environment. The decision-making process is initiated by the disruption scenario and is ended with a selection of an integrated recovery solution.

Table 2: Task Analysis of Airline Controllers

Agent	Task
AC	Check adequateness of technical diagnosis Determine spart parts availability Determine time required to repair the mechanical problem Check hangar space availability

	Check reserve aircraft availability
CC	Determine effect of repair on crew duty time Check availability of reserve crew Check crew positioning time
SC	Determine effect of delay on passenger connections Check rebooking possibilities Check poisoning possibilities
FD	Check weather at station where the mechanical problem is reported Check possibility to organize connection measures Check ferry time
OC	Coordinate with controllers through requesting/providing relevant information Select recovery strategy

3.2 Ontology specification using Temporal Trace Language

The details of the agent-based ontology specifications for the AOC operation considered are given in Appendix A. This ontology of the agent-based model formally captures the information flow and interactions between agents during disruption management. For this ontology specification use has been made of Temporal Trace Language (TTL). TTL has been used before in other agent-based modelling studies [13]. TTL uses ordered sort predicate logic that can specify dynamics over time. Description of the behavior of the system component is done using ontologies that are specified by sorts, constants, variables, functions, and predicate. A description of TTL theory can be found in [14, 15]. TTL language is based on the assumption that dynamics can be described as an evolution of states over time by using order-sorted predicate logic [16]. A key difference between normal order-sorted predicate logic and TTL is that the latter is used for properties that change over time i.e. dynamic properties. Dynamic properties are relations in time between states of agents, states of the environment or states between agents and the environment. By using ontologies and logical connectives dynamic properties can be described. There are five types of dynamic properties:

- *Role Property (RP)* **-** the relation between input and output state of a role that is fulfilled by the role
- *Environment Property (EP)* **–** the relation between input and output state of the conceptualized environment
- *Transfer Property (TP)* **-** the relation between output state and input states of agents
- *Environment Interaction Properties (EIP)* **–** the relation between either output to input or input to output states between the conceptualized environment and agents.
- *Interlevel Link Property (ILP)* **-** the relation between a input or output of a composite role and the input or output of one of its subrole.

To understand how a dynamic property is formalized, an example is provided below:

Information Description: When controller A observes that "event x" takes place, he will take action upon this particular event
Semi-Formal Description: In any trace γ, at any point in time t_1 if controller A observes "event x", then at a later point in time t_2, controller A wil take action upon "event x"
Formal Description: $\forall t_1{:}\, TIME, \forall \gamma{:}\, TRACE\ state(\gamma, t_1, input(A)) \Vdash observation(event\_x)\ \wedge \exists t_2 > t_1 \Rightarrow state(\gamma, t_2, output(A)) \Vdash performing\_action(event\_x)$

Following this approach, we formalized all the flowcharts identified in the model design phase. An example of an aircraft controller decision-making process is provided in Figure 1. In this example, the controller needs to determine if the technical diagnosis is adequate (Condition A1) or inadequate (Condition A0).

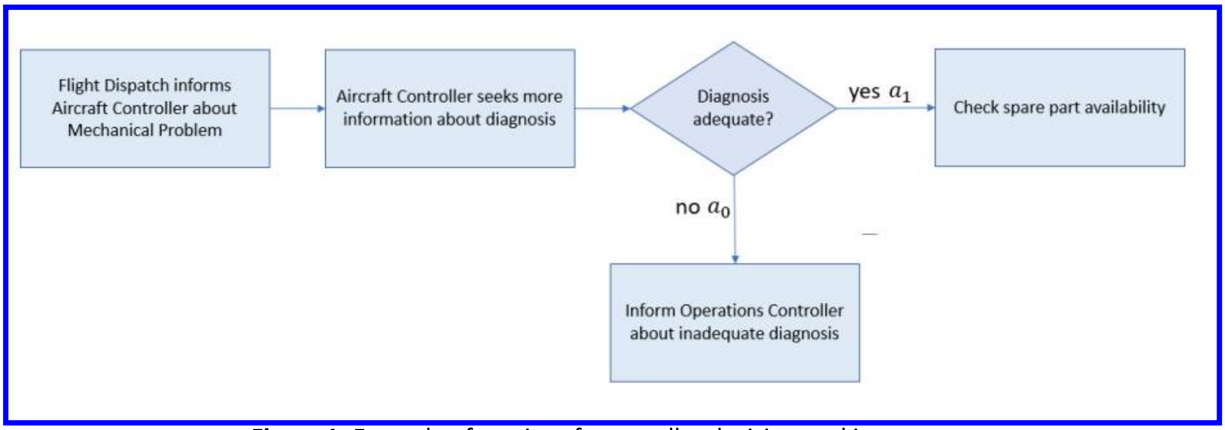

Figure 1: Example of an aircraft controller decision-making process

3.3 Software Implementation

The model has been implemented in LEADSTO, which is an executable sub-language of Trace Temporal Language. Using LEADSTO, one can express qualitative and quantitative aspects and specify dependencies between state properties to simulate dynamic processes [13]. The simulation results are a specification of all the states and state properties referred to as a trace. Verification of these traces is done using the cross-functional flowcharts developed during the model design phase.

The equation $\alpha \twoheadrightarrow_{(e,f,g,h)} \beta$ models dependencies between state properties in LEADSTO. It consists of an antecedent (α), a consequent (β) and time variables (e, f, g, h). The expression states that : if state property α holds for a time interval with duration g, then after a delay between e and f, state property β (consequent) will hold for a time interval length h. This expression is also referred to as a LEADSTO rule. Below is an example of a LEADSTO rule used to model role property 1 in the previous section.

$$\alpha: input(ac)|com(fd, ac, inform, aircraft\_tua\_has\_mechanical\_problem,$$
$$delay(x1, x2, x3, x4), p('1'))$$
$$\beta: output(ac)|com(ac, env, request, technical\_diagnosis\_adequateness,$$
$$delay(x1, x2, x3, x4), p('1'))$$

LEADSTO rules have been implemented for various dynamics properties, and simulations were conducted to assess the impact of uncertainties on recovery solutions and associated operating costs. To quantify the costs, the cost model from (Castro et al 2014) was used. The complete simulation files can be found in [12].

3.4 Evaluation of ABMS implementation

The last step is model evaluation. The amount of combinations of the conditions that can be evaluated is considerable. Because of this, a case by case approach was followed. Each scenario case was then evaluated in relation to various uncertainties through a sensitivity analysis to explore the impact on overall performance. The simulation traces have been used to derive the operating costs using the model of Castro et al. [17].

4. ABMS results

The ABMS environment that has been developed in Section 3 will be applied to the following two cases:

- Case 1: repair time exceeds the transit buffer time but still below the crew duty time.
- Case 2: repair time exceeds the crew duty time but below transit buffer time.

These two cases capture two different transit buffer times, which allows to study the effect on recovery strategy. The experiment variables include repair time r_t; crew duty time buffer c_t; and transit time buffer p_t. Table 3 shows the values used in both cases.

Table 3: r_t denotes the repair time; c_t denotes the buffer in crew duty time; and p_t denotes the buffer in transit time

Case ID	Repair Time r_t	Buffer in crew duty time c_t [min]	Buffer in transit time p_t [min]
Case 1	$p_t < r_t \leq c_t$	240	180
Case 2	$c_t < r_t \leq p_t$	180	240

In addition to the values given in table 3, the following assumptions were made:
- Repair takes at least two hours $r_{t_{min}} = 120$ and four hours at most $r_{t_{max}} = 240$.
- It takes three hours until ferry flight arrives and is ready for departure $k_t = 180$. The minimum and maximum values $k_{t_{min}} = 120$ and 4 hours at most $k_{t_{max}} = 240$.
- It takes three hours until the rebooked flight departs $b_t = 180$.
- It takes three hours until the positioned crew arrive and is ready to operate the flight $d_t = 180$.

4.1 Case 1: repair time exceeds transit buffer time but below crew duty time (pt < rt ≤ ct)

The results corresponding to case 1 are shown in table 4 and figure 2. Table 4 shows the impact of the repair time on recovery solutions for various uncertainties. Figure 2, shows the effect of repair time on operating costs.

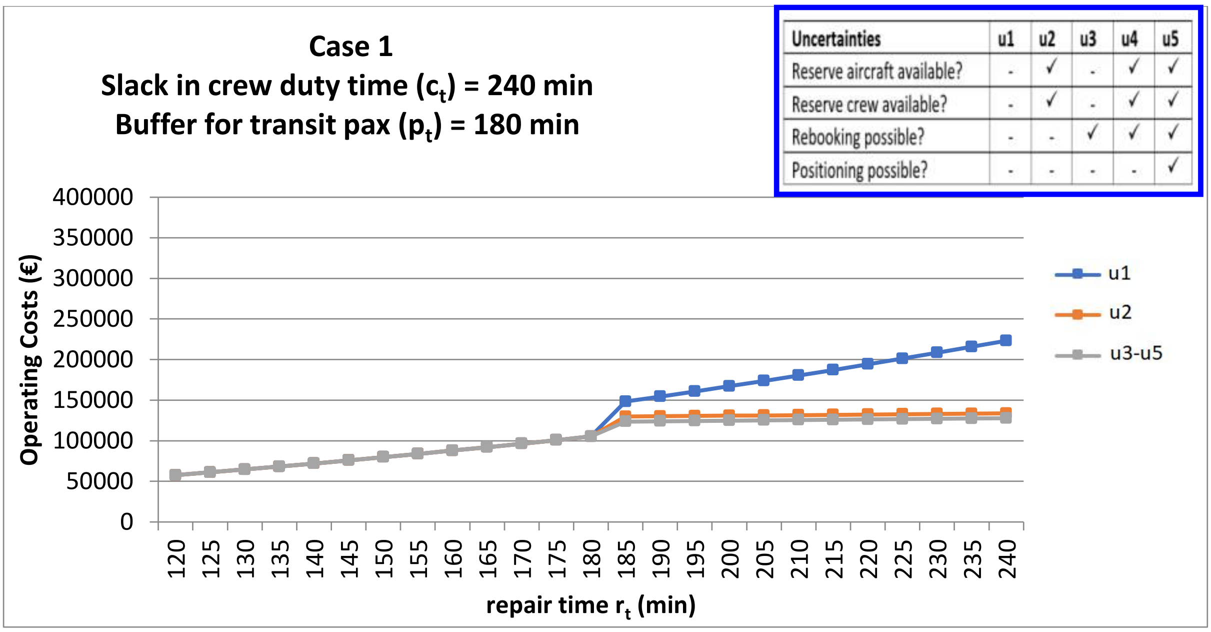

Figure 2: The effect of repair time r_t on operating costs for Case 1(c_t = 240, p_t = 180)

Table 4: The effect of repair time on the recovery solution for aircraft, crew, and passenger for Case 1

Repair time r_t	Uncertainties	Recovery Strategies	Aircraft	Crew	Pax
$120 \leq r_t \leq 180$	$u_1 - u_5$	RS1	fixed	Delayed until aircraft fixed (resolved)	Delayed until aircraft fixed (transit successful)
	u_1	RS2	fixed	Delayed until aircraft fixed (resolved)	Delayed until aircraft fixed (transit not successful)

$180 < r_t \le 240$	u_2	RS8	fixed	Waiting at airport for aircraft to be fixed	Waiting for reserve aircraft to be ferried to DLF (transit successful) delay = 180
	$u_3 - u_5$	RS4	fixed	Waiting at airport for aircraft to be fixed	Rebooked onto other flight (transit successful) delay = 180

The chosen recovery strategies for this case is to either keep the passengers waiting for the aircraft to be fixed (RS1 and RS2); deploy a reserve aircraft and crew to get passengers back to base (RS8); or rebook passengers on another flight (RS4). In all recovery strategies, passengers will make it to their connecting flight except for strategy RS2. In all simulations, both the aircraft and crew problems are resolved. It can be observed that when $120 \le r_t \le 180$, the recovery strategy is independent of the uncertainty. Conversely, when $180 < r_t \le 240$, the choice of recovery strategy depends on the uncertainty. The simulations corresponding to uncertainties u_3, u_4 and u_5 provide the same result. In u_4 and u_5, reserve resources are not utilized even though they are available.

One can conclude that when repair time exceeds the transit buffer time, the operating costs changes significantly. This implies that the transit buffer time acts as tipping point for costs. Furthermore, the results show that during interval $p_t < r_t < c_t$ utilizing reserve resources (u_2) results in lower operating costs compared to when there are no recovery opportunities (u_1). Nevertheless, direct costs increase when using reserve resources. Another remark is that repair time ($r_t \le p_t$ or $p_t < r_t < c_t$) significantly impact the selection of recovery strategy

4.2 Case 2: repair time exceeds crew duty time but below transit buffer time ($c_t < r_t \le p_t$)

The results corresponding to case 2 are shown in table 5 and figure 3. Table 5 shows the impact of the repair time on recovery solutions for various uncertainties. Figure 3, shows the effect of repair time on operating costs.

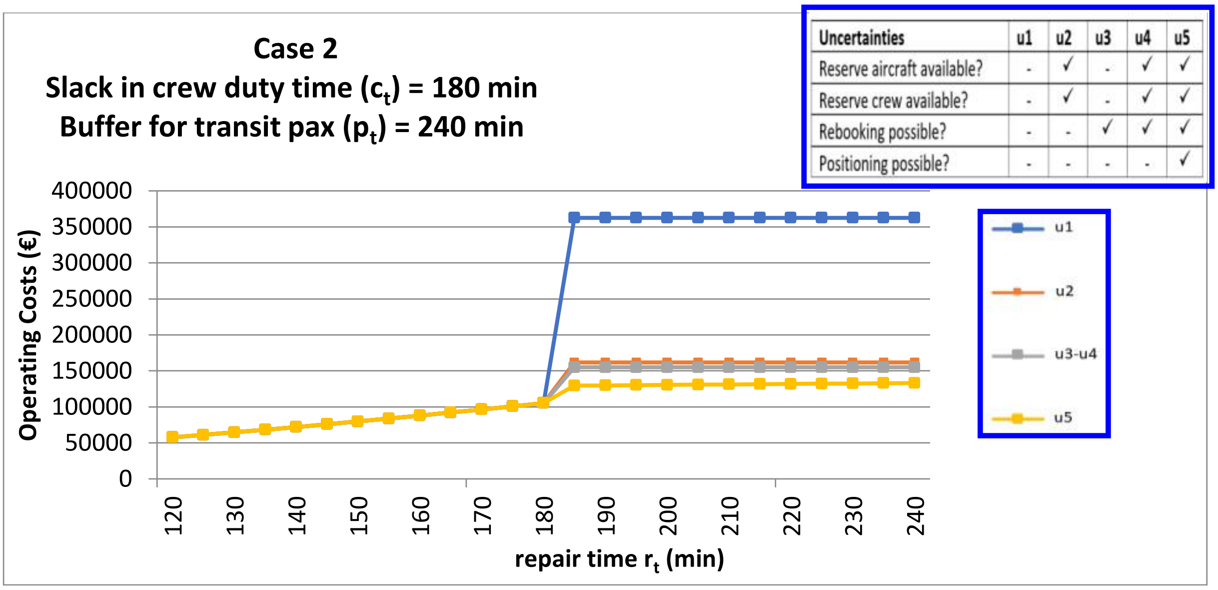

Figure 3: The effect of repair time r_t on operating costs for case 2 (c_t = 180, p_t = 240)

Table 5: The effect of repair time on the recovery solution for aircraft, crew, and passenger for Case 2

Repair time r_t	Uncertainties	Recovery Strategies	Aircraft problem	Crew problem	Pax problem
$120 \leq r_t \leq 180$	$u_1 - u_5$	RS1	fixed	Delayed until aircraft is fixed (resolved)	Delayed until aircraft fixed (transit successful)
$180 < r_t \leq 240$	u_1	RS3	fixed	Accommodated	Accommodated (distressed) (transit not successful)
	u_2	RS10	fixed	Accommodated	Waiting for reserve aircraft to be ferried (transit successful) delay 180 min
	$u_3 - u_4$	RS6	fixed	Accommodated	Rebooked on another flight (transit successful) delay 180 min
	u_5	RS11	fixed	Accommodated. Reserve crew positioned to pick up aircraft	Rebooked on another flight (transit successful) delay 180 min

Like case 1, when $120 \leq r_t \leq 180$ the passengers wait for the aircraft to be fixed. However, when $180 < r_t \leq 240$ different alternatives are available: The passengers and crew are accommodated (RS3); or a reserve aircraft is dispatched (RS10); or passengers are rebooked without positioning the crew (RS6) or with positioning of crew (RS11). The transit passengers will make a successful connection in all recovery strategies except in RS3. In all cases, the disrupted aircraft is recovered after the crew rests. Additionally, it can be seen that p_3 and p_4 result in the same recovery strategy even though in p_4 reserve resources are present, but not utilized. However, in p_5 reserve crew is used and passengers are rebooked, while reserve aircraft is available and retained.

One can conclude that when repair time exceeds the transit buffer time, the operating costs changes significantly. This implies that the transit buffer time acts as tipping point for costs. Furthermore, the results show that during interval $p_t < r_t < c_t$ utilizing reserve resources (u_2) results in lower operating costs compared to when there are no recovery opportunities (u_1). Nevertheless, direct costs increase when using reserve resources. Another remark is that repair time ($r_t \leq p_t$ or $p_t < r_t < c_t$) significantly impacts the selection of recovery strategy. According to figure 3, when repair time exceeds the slack crew duty time, the operating costs increase for all uncertainties. Furthermore, the results corresponding to uncertainty u_1 leads to higher operating costs compared to other uncertainties. This means that having no reserve resources available and no rebooking and repositioning possibilities leads to significant higher costs.

5. Conclusion

AOC controllers rarely have time to explain their decision making actions [1]. Modelling and simulating AOC decision making helps understand and evaluate the effects of both internal and external factors on controller's decision-making and hence on recovery performance.

This paper explored, through a sensitivity analysis, the effects of **robust scheduling** and operational uncertainties on AOC decision-making. The simulation results show that adding buffers into the schedule promote a degree of self-recovery. This means that AOC controllers do not necessarily have to act on every disruption if a delay can be absorbed by the incorporated buffers. Hence, although increasing buffers lead to less profitability, it can also save the airline significant costs during disruptions because less reserve resources such as aircraft and crew will be used. When there are no positioning and rebooking opportunities, reserve resources have been shown to be an asset in terms of delivering customer service.

For the considered scenario, the simulations show that the transit buffer time and crew duty slack time act as tipping point in terms of operating costs. The operating costs could either rise or flatten out after a delay threshold. Delays exceeding crew duty time lead to more “one-off” costs, while delays exceeding transit buffer time lead to much higher operating costs.

The sensitivity analysis show that when repair time exceeds crew duty slack time, the transit buffer time becomes insensitive in certain cases. This can be explained by the fact that when repair time only exceeds transit time, then this would lead to a passenger problem. However, if repair time exceeds crew duty slack time, it would also lead to a crew problem. This also means that since transit buffer time can become insensitive to crew duty time, the controllers could be performing unnecessary tasks. For instance, when a crew controller already identified that repair time exceeds crew duty time, then it is not necessary for the station operations controllers to compare repair time with transit buffer, nor it is necessary for the flight dispatcher to organize favorable connections. Overall, it can be concluded that schedule robustness has a significant impact on AOC decision making processes and operating costs.

The simulation results show that **operational uncertainties** have a significant impact on the selected recovery strategies for the aircraft, crew, and passenger problem. If uncertainties are not overcome, for instance through collecting more information or making assumptions, then recovery solutions become limited and could be costly. On the other hand, when uncertainties are overcome, more recovery opportunities are identified which lead to less operating costs. Surprisingly, not all operational uncertainties need to be overcome as some can be insensitive as shown in this study. Hence, through modelling uncertainties, one can demonstrate which scenario-based parameters are relevant for AOC decision making processes.

In this study, we also explored the impact of AOC decision making on multiple **performance objectives**. These objectives include 1) Schedule execution; 2) Customer service delivery; 3) Effectiveness resource utilization; and 4) Cost minimization. The simulations show that AOC objectives are highly coupled. For instance, it was shown that some decisions that lead to higher customer service level might lead to less effective use of standby resources. Although the operations controller is the main responsible for meeting AOC objectives, this study shows that conflicts of objectives are inevitable. Customer satisfaction might come at the cost of additional costs for the airline and vice versa. It is also important to formulate recovery strategies in a coordinated way especially when there are competing performance objectives.

This study can be extended in different ways by 1) Modelling additional scenarios to identify decision-making patterns in airline disruption management; 2) Analyzing the effect of AOC decisions at the network level and studying the propagation into the entire airline schedule; and 3) Considering additional performance objectives such as sustainability.

Acknowledgements

The authors would like to acknowledge Mr. Arjen Blom from KLM for arranging the visits to KLM’s OCC and conducting the interviews with the first author.

References

1. Bruce, P. J. (2011). *Understanding decision-making processes in airline operations control*. Ashgate Publishing, Ltd.
2. Castro, A. J. M., Rocha, A. P., & Oliveira, E. (2012). Towards an autonomous and intelligent airline operations control. *2012 15th International IEEE Conference on Intelligent Transportation Systems*, 1429–1434.
3. KLM Annual Report 2015. www.airfranceklm.com
4. Kohl, N., Larsen, A., Larsen, J., Ross, A., & Tiourine, S. (2007). Airline disruption management—perspectives, experiences and outlook. *Journal of Air Transport Management*, *13*(3), 149–162.
5. Feigh, K. M. (2008). *Design of cognitive work support systems for airline operations*. Georgia Institute of Technology.
6. Clarke, M. D. D. (1998). Irregular airline operations: a review of the state-of-the-practice in airline operations control centers. *Journal of Air Transport Management*, *4*(2), 67–76.
7. Bouarfa, S., Blom, H. A. P., & Curran, R. (2016). Agent-Based Modeling and Simulation of Coordination by Airline Operations Control. *IEEE Transactions on Emerging Topics in Computing*, *4*(1). https://doi.org/10.1109/TETC.2015.2439633

8. Bouarfa, S., Müller, J., & Blom, H. (2018). Evaluation of a Multi-Agent System approach to airline disruption management. *Journal of Air Transport Management*, *71*. https://doi.org/10.1016/j.jairtraman.2018.05.009
9. Bouarfa, S., Blom, H. A. P., Curran, R., & Everdij, M. H. C. (2013). Agent-based modeling and simulation of emergent behaviour in air transportation. *Complex Adaptive Systems Modeling*, *1*(15). https://doi.org/https://doi.org/10.1186/2194-3206-1-15
10. Knol, A., Sharpanskykh, A., & Janssen, S. (2019). Analyzing airport security checkpoint performance using cognitive agent models. *Journal of Air Transport Management*, *75*, 39–50.
11. Nikolic, I., & Ghorbani, A. (2011). A method for developing agent-based models of socio-technical systems. *2011 International Conference on Networking, Sensing and Control*, 44–49.
12. Modelling and simulation of decision-making processes in Airline Operations Control. MSc thesis. Delft University of Technology. July 7th 2016.
13. Sharpanskykh, A., & Treur, J. (2010). A temporal trace language for formal modelling and analysis of agent systems. In *Specification and verification of multi-agent systems* (pp. 317–352). Springer.
14. Jonker, C. M., Sharpanskykh, A., Treur, J., & Yolum, P. (2007). A framework for formal modeling and analysis of organizations. *Applied Intelligence*, *27*(1), 49–66.
15. Hoogendoorn, M., Jonker, C. M., van Maanen, P.-P., & Sharpanskykh, A. (2008). Formal analysis of empirical traces in incident management. *Reliability Engineering & System Safety*, *93*(10), 1422–1433.
16. Bosse, T., & Mogles, N. M. (2013). Studying aviation incidents by agent-based simulation and analysis. *Proceedings of the Fifth International Conference on Agents and Artificial Intelligence*
17. Castro, António J M, Rocha, A. P., & Oliveira, E. (2014). *A new approach for disruption management in airline operations control* (Vol. 562). Springer.

Appendix A: Agent-based ontology specification

To model the agents and environment ontologies are used. These consist of sorts, predicates, functions and variables [15]. For ontological correspondence it is important to express (1) who is interacting with who (2) what type of message is sent (3) what the content of the message is (4) in which phase do interactions take place (5) and what kind of recovery strategy is chosen (see **Error! Reference source not found.**).

Table A1: Sorts

Sort	Description
CTRL	Controllers which are involved in this scenario
MSG_TYPE	Types of message that is applicable (i.e. interaction)
MSG	Messages of one controller to the other
PHASE	Phases in which the state property takes place
RS	The recovery strategies

The five airline controllers (agents) involved in the scenario are provided in table A2

Table A2: Terms of the sort CTRL

SORT	Terms	Description
CTRL	oc	Operations Control, the main decision-maker in the disruption management process
	ac	Aircraft Control, responsible for aircraft related disruptions and support
	fd	Flight Dispatch, responsible for pre-flight planning, ATC and weather related issues
	cc	Crew Control, responsible for crew related disruptions and support
	sc	Station operations Control, responsible for passenger related disruptions and support

Three types of interactions among the controllers and environment have been identified (Table A3)

Table A3: Terms of the sort MSG_TYPE

SORT	Terms	Description
MSG_TYPE	inform	informing an controller or being informed
	request	request information from the environment or other controllers
	observe	observing the environment

Semi-formal description of role property 1: In any trace γ, at any point in time $t_1$when aircraft control is informed about the mechanical problem, then at a later point in time t_2, aircraft control will request information about the technical diagnosis (*A1*).

Formal description of role property 1

$$\forall t_1: TIME, \forall \gamma: TRACE, state(\gamma, t_1, input(ac)|com(fd, ac, inform, aircraft\_tua\_has\_mechanical\_problem, delay(x1, x2, x3, x4), p('1')) \wedge \exists t_2 > t_1 \Rightarrow state(\gamma, t_2, output(ac)|com(ac, env, request, technical\_diagnosis\_adequateness, delay(x1, x2, x3, x4), p('1'))$$

Semi-formal description of environment interaction property 1: in any trace γ at any point in time t_1 when the aircraft controller requests the adequateness of the technical diagnosis, then at a later point in time t_2 the conceptualized environment will receive this request.

Formal description of environment interaction property 1

$$\forall t_1: TIME, \forall \gamma: TRACE, state(\gamma, t_1, output(ac)|com(ac, env, request, technical\_diagnosis\_adequateness, delay(x1, x2, x3, x4), p('1')) \wedge \exists t_2 > t_1 \Rightarrow state(\gamma, t_2, input(env) \Vdash com(ac, env, request, technical\_diagnosis\_adequateness, delay(x1, x2, x3, x4), p('1'))$$

At this point the aircraft controller requests the adequateness of the environment. Due the fact that this condition is Boolean, there are two possibilities described below.

Semi-formal description of environment property 1: in any trace γ at time point t_1 when the conceptualized environment receives a request for the technical diagnosis adequateness and the condition in this case is that it is adequate (a_1), then at a later point in time t_2 the conceptualized environment will provide an adequate technical diagnosis

Formal description of environment property 1

$$\forall t_1: TIME, \forall \gamma: TRACE, state(\gamma, t_1, input(env) \Vdash com(ac, env, request, technical\_diagnosis\_adequateness, delay(x1, x2, x3, x4), p('1')) \wedge \boldsymbol{a\_1} \wedge \exists t_2 > t_1 \Rightarrow state(\gamma, t_{2,} output(env)) \Vdash com(env, ac, inform, technical\_diagnosis\_adequate, delay(x1, x2, x3, x4), p('1'))$$

Semi-formal description of environment interaction property 2: in any trace γ at any point in time t_1 when the environment provides an adequate technical diagnosis, then at a later point in time t_2 the aircraft controller will observe an adequate technical diagnosis.

Formal description of environment interaction property 2

$$\forall t_1: TIME, \forall \gamma: TRACE, state(\gamma, t_1, ooutput(env)) \Vdash com(env, ac, inform, technical\_diagnosis\_adequate, delay(x1, x2, x3, x4), p('1')) \wedge \exists t_2 > t_1 \Rightarrow state(\gamma, t_{2,} input(ac)) \Vdash com(env, ac, observe, technical\_diagnosis\_adequate, delay(x1, x2, x3, x4), p('1'))$$

Semi-formal description of role property 2: in any trace γ at any point in time t_1 when the aircraft controller observes an adequate technical diagnosis, then at a later point in time t_2 the aircraft controller will request spare parts availability from the environment.

Formal description of role property 2

$$\forall t_1: TIME, \forall \gamma: TRACE, state(\gamma, t_1, input(ac)) \Vdash com(env, ac, observe, technical\_diagnosis\_adequate, delay(x1, x2, x3, x4), p('1')) \wedge \exists t_2 > t_1 \Rightarrow state(\gamma, t_{2,} output(ac)|com(ac, env, request, spare\_parts\_availability, delay(x1, x2, x3, x4), p('1'))$$

Semi-formal description of environment property 2: in any trace γ at time point t_1 when the environment receives a request for the technical diagnosis adequateness and the condition in this case is that it is inadequate

$(\underline{a_0})$, then at a later point in timet_2 the conceptualized environment will provide an inadequate technical diagnosis.

Formal description of environment property 2:
$\forall t_1: TIME, \forall \gamma: TRACE, state(\gamma, t_1, input(env))$
$\Vdash com(ac, env, request, technical\_diagnosis\_adequateness, delay(x1, x2, x3, x4), p('1')) \wedge \boldsymbol{a\_0} \wedge \exists t_2$
$> t_1 \Rightarrow state(\gamma, t_{2,} output(env))$
$\Vdash com(env, ac, inform, technical\_diagnosis\_inadequate, delay(x1, x2, x3, x4), p('1$

Semi-formal description of environment interaction property 3: in any trace γ at any point in time t_1 when the environment provides an inadequate technical diagnosis, then at a later point in time t_2 the aircraft controller will observe an inadequate technical diagnosis.

Formal description of environment interaction property 3
$\forall t_1: TIME, \forall \gamma: TRACE, state(\gamma, t_1, ooutput(env))$
$\Vdash com(env, ac, inform, technical\_diagnosis\_inadequate, delay(x1, x2, x3, x4), p('1'))$
$\wedge \exists t_2 > t_1 \Rightarrow state(\gamma, t_{2,} input(ac))$
$\Vdash com(env, ac, observe, technical\_diagnosis\_inadequate, delay(x1, x2, x3, x4), p('1'))$

Semi-formal: formal description of role property 3: in any trace γ at any point in time t_1 when the aircraft controller observes an inadequate technical diagnosis, then at a later point in time t_2 the aircraft controller will inform operations controller about the inadequate technical diagnosis.

Formal description of role property 3:
$\forall t_1: TIME, \forall \gamma: TRACE, state(\gamma, t_1 input(ac))$
$\Vdash com(env, ac, observe, technical\_diagnosis\_inadequate, delay(x1, x2, x3, x4), p('1'))$
$\wedge \exists t_2 > t_1 \Rightarrow state(\gamma, t_{2,} output(ac))$
$\Vdash com(ac, oc, inform, technical\_diagnosis\_inadequate, delay(x1, x2, x3))$

The terms of the sort MSG are presented in **Error! Reference source not found.**. No description is provided since the aim of the message is to be self-explanatory.

Table A4: Terms of the sort MSG

SORT	Terms	
MSG	aircraft_tua_has_mechanical_problem	positioning_not_possible
	technical_diagnosis_adequateness	positioning_crew_connects_tpax_successful
	technical_diagnosis_adequate	positioning_crew_connects_tpax_unsuccessful
	technical_diagnosis_inadequate	effect_of_kt_on_tpax
	spare_parts_availability	effect_of_dt_on_tpax
	spare_parts_available	effect_of_rt_on_tpax
	spare_parts_unavailable	tpax_unaffected_by_rt
	wx_pattern_favourability	tpax_affected_by_rt
	wx_pattern_favourable	rebooking_possibilities
	wx_pattern_unfavourable	rebooking_possible
	hangar_availability	rebooking_not_possible
	hangar_available	rebooking_connects_tpax_successful
	hangar_unavailable	rebooking_connects_tpax_unsuccessful
	reserve_aircraft_availability	repair_time
	reserve_aircraft_available	rebooking_time
	reserve_aircraft_unavailable	transit_buffer_time
	dispatch_reserve_aircraft_connects_ tpax_successful	reserve_crew_availability

	dispatch_reserve_aircraft_connects_tpax_ unsuccessful	reserve_crew_available
	organizing_cxn_measures_possibilities	reserve_crew_unavailable
	organizing_cxn_measures_possible	crew_duty_slack_time
	organizing_cxn_measures_not_possible	ferry_time
	effect_of_rt_on_crew	positioning_time
	crew_unaffected_by_rt	positioning_resources_possibilities
	positioning_possibilities	positioning_resources_possible
	positioning_possible	positioning_resources_not_possible

From the model description it was clear that there are twenty recovery strategies that could be formulated, which means that there are twenty terms for the sort 'RS' i.e. RS1-RS20. To use the multi-trace application, the conditions will also be SORTS and are described in table A5.

Table A5: Sorts and terms used for the environment

Sort	term	description
DIAG	a_0	Inadequate technical diagnosis
	a_1	Adequate technical diagnosis
PART	b_0	Spare parts unavailable
	b_1	Spare parts available
WX	c_0	weather pattern unfavourable
	c_1	weather pattern favourable
HANG	d_0	hangar space unavailable
	d_1	hangar space available
CONM	e_0	organizing connection not possible
	e_1	organizing connection possible
DEAD	f_0	positioning opportunities unavailable
	f_1	positioning opportunities available
RCREW	g_0	reserve crew unavailable
	g_1	reserve crew available
RBOOK	h_0	rebooking opportunities not present
	h_1	rebooking opportunities present
RAC	i_0	reserve aircraft unavailable
	i_1	reserve aircraft available

The six time parameters will be quantitative variables. This means that these are instantiated with terms of the sort *VALUE* (i.e integers). For the completeness of the formal description these are listed in **Error! Reference source not found.** A6.

Table A6: Time variable in the model

Variable	Description
r_t	The time that is required to repair the aircraft and prepare to fly
d_t	The time the reserve crew is positioned and ready to operate the disrupted flight
k_t	The time that the reserve aircraft is ready to take over flight A
p_t	The available buffer time for the transit passengers
b_t	The time before the rebooking flight is to depart
c_t	The available slack of crew duty time
d_f	The delay of the passengers

Two predicates are used during formalization: (1) communication predicate and (2) recovery predicate. The communication predicate expresses the communication between two controllers (source and destination), the type of message, the actual message, the communicated delay and the phase in which the interaction takes place. The predicate for the recovery strategy that will be formulated consist of the chosen recovery strategy and the associated delays for the passengers. These two predicates can be referred to in Table A7.

Table A7: Model Predicates

Predicate	**Description**
com(r: CTRL, dst: CTRL, t: MESSAGE_TYPE, v: MSG ,delay(rt:integer,dt:integer,bt:integer,kt:integer),p(‘ x: PHASE’)	the message “v” and current time parameters rt, dt, bt, kt are communicated by “r” to “dst” by using messaging type “t”, which takes place in phase ‘x’
Recovery(r: RS,df,rt,dt,bt,kt)	the chosen recovery strategy is “RS” with a passenger delay df of either “rt”, “dt”, “bt” or “kt”