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# Evaluation of a Multi-Agent System Approach to Airline Disruption Management

S. Bouarfa[1], J. Müller, H.A.P. Blom

***Abstract*— Each day, airlines face disturbances that disrupt their carefully planned operations. Events like adverse weather conditions, sick crew members, or damaged aircraft often result in delays in the airline's schedule. An airline recovers from such disruptions through the role played by its Airline Operations Control (AOC). A Multi-Agent System (MAS) approach to airline disruption management was recently proposed under the acronym MASDIMA (Multi-Agent System for Disruption Management in AOC). The purpose of this paper is to evaluate this MAS supported AOC approach on its performance and its practical introduction. This is done using a scenario-based analysis to compare the MAS supported policy to human-team based AOC policies. A task-based analysis identifies how well AOC is able to cover a set of tasks using the MAS supported policy. The scenario-based analysis shows that the MAS supported AOC is able to find the optimal solution, and to do this significantly faster. The task-based analysis identified two main challenges for implementing the MAS supported AOC policy: i) to overcome the loss of experience that is caused by significantly automating humans roles in AOC, and ii) to reduce the workload for people that remain in AOC after its introduction. The paper concludes that implementing the 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: a potential increase in workload for the remaining human role and loss of experience in handling exceptional situations.**

***Index Terms*—Airline Operations Control, Airline Disruption Management, Coordination, Multi-Agent Systems**

## I. Introduction

Airlines constantly face disturbances that disrupt their carefully planned operations. Events like adverse weather conditions, sick crewmembers, or damaged aircraft often cause delays in the airline's schedule. Each airline has its Airline Operations Control (AOC) monitoring operations worldwide, and managing recovery from disruptions. For an airline such disruptions are very costly because they tend to cause domino effects in the highly optimized air transportation schedule. Over the year 2007 alone, U.S. carriers lost over $8 billion because of delays of some sort (Barnhart, 2009). Reducing the impact of disruptions on the airline schedule could considerably reduce these costs. Most research on the improvement of AOC decision making policy focusses on using optimization techniques for the development of decision support tools. For instance, Bratu & Barnhart (2006) propose two optimization tools that generate recovery plans for aircraft, crews, and passengers by determining which flight leg departures to postpone and which to cancel. Abdelghany et al. (2008) propose a decision-support tool that provides AOC centres with the capability to develop a proactive schedule recovery plan that integrates all flight resources. The optimization tool examines possible resource swapping and flight requoting to generate a schedule recovery that minimizes flight delays and cancellations. Petersen et al. (2012) propose a mixed-integer programming tool to solve the fully integrated airline recovery problem including the schedule, aircraft, crew, and passenger problems. In the same vein, Arikan et al. (2017) propose an optimization tool to solve the fully integrated airline recovery problem using a conic quadratic mixed integer programming formulation. Santos et al. (2017), present an integer linear programming tool to help AOC controllers decide which flights to delay and which flights to make depart on time.

From a combinatorial optimization perspective, these tools have the mathematical capability in minimizing airline operating costs and passenger costs. However, such a combinatorial optimization approach fails in capturing the complex socio-technical nature of AOC (Bruce, 2011a; Feigh 2008; Richters et al. 2017). In order to address these socio-technical challenges, Castro (2013) has taken a Multi-Agent System (MAS) based approach to the development of a novel decision support tool for airline disruption management. The resulting tool is

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referred to as MASDIMA (MAS for Disruption Management in AOC). In order to realize a better handling of the complexity of the airline disruption management problem, Castro (2013) proposes replacing several human roles in AOC by software agents. The latter implies a large change in the established AOC policy that is largely depending on coordination and decision-making by a team of humans. The aim of the current paper is to evaluate the impact of the MAS supported novel AOC policy relative to human-team based AOC policies. To accomplish this, we make use of Agent-Based Modelling and Simulation (ABMS) of various socio-technical AOC policies.

Agent-Based Modelling and Simulation (ABMS) has shown its effective use in analyzing complex socio-technical systems (Macal and North, 2010; van Dam et al. 2013). Recently, Bouarfa et al. (2015) have used ABMS for the evaluation of various AOC policies that were based on coordination and decision-making by human teams. Four policies were evaluated. Three of these were based on current airline practice, whereas the fourth was based on joint activity coordination theory from the psychology research domain. The simulation modeled humans in the AOC team as agents, each of which plays its specified role. The study showed that the fourth policy led to a better outcome compared to the three current airline policies. The aim of the current paper is to evaluate the MAS-supported AOC policy of Castro (2013) and to compare it with the four AOC policies in (Bouarfa et al., 2015).

The evaluation of the MAS supported AOC policy consists of two parts (Muller, 2016): a scenario-based analysis and a task-based analysis. The first part examines how AOC manages an airline disruption using the MAS approach proposed by Castro (2013). It focuses on the same scenario that has been used by Bouarfa et al. (2015). The second part evaluates AOC tasks that were identified in an interview with an AOC expert from a major European airline. It analyzes how work changes for people that remain in AOC after implementing the MAS supported policy. The aim of the evaluation is to understand how AOC performs using the MAS supported policy compared to using the four human team based policies studied in Bouarfa et al. (2017), and to identify potential challenges for introducing the MAS supported policy in AOC.

This paper is organized as follows. Section II provides background on both airline operations control and the agent-based paradigm. Section III provides a summary of multi-agent coordination approaches from literature. Section IV describes the MAS supported AOC policy and its application in AOC. Section V compares the performance of the MAS supported AOC policy and four human coordination policies in the context of an airline disruption scenario. Section VI describes the expert-based evaluation of the MAS supported AOC policy. Finally, Section VII presents the conclusions and recommendations of this research.

## II. Background

### A. *Airline Operations Control*

The idea of monitoring and controlling a transport network in real time is not new. The concept was first established in the 19th century in the railway industry, when the development of the telegraph made it possible for information to travel faster than physical transport (Peters, 2006). This allowed for a central location in which real-time information about the current status of the network could be collected and acted upon. Today, the concept of monitoring operations in real-time is used across industries, with AOC as one example.

Airline disruption management is the last step in the airline scheduling process (Figure 1). The scheduling process start with publishing a preliminary timetable up to 1 year before the day of operations. The timetable provides the basis for the aircraft schedule, which assigns an aircraft type to each flight. With the flights and aircraft types known, crew pairing defines the amount and type of crew per flight. The next step is to assign specific aircraft and individual crewmembers to each flight in the tail assignment and crew rostering phase. After publishing the crew roster, crewmembers can request changes in their schedule in the roster maintenance phase. Disruption management is the last step in the process (Grandeau, 1995; Clarke, 1998; Kohl et al., 2007; Clausen et al., 2010).

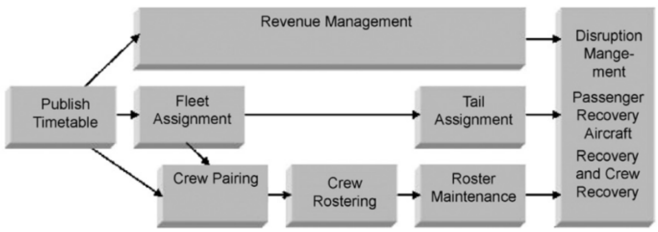


**Figure 1: Disruption management is the last step in the airline scheduling process (Kohl et al., 2007)**

During the day of operations, the airline schedule is subject to many disruptions. The main four airline schedule disruptors are aircraft mechanical problems, severe weather, airport congestion, and industrial action (e.g. strikes). The goal of AOC is to deliver customer promise despite these disruptions. In doing so, it should minimize airline costs incurred during recovery, and return to the original schedule as soon as possible (Kohl et al., 2007).

Disruptions affect the aircraft, crew, and passenger resources of an airline. Managing these resources is the duty of AOC operators. Each AOC operator has his own role. Such roles might vary per airline, but six are common to most airlines: flight dispatch, aircraft control, crew tracking, aircraft engineering, customer service, and Air Traffic Control (ATC) coordination (Kohl et al., 2007). Because the airline operations supervisor is ultimately responsible for AOC operations (Clarke, 1998), he/she has the authority to make changes in the nominal schedule.

An airline controller can manage a disruption in many different ways. To resolve a problem that affects the aircraft resource, a flight can be delayed, cancelled, rerouted, or the aircraft exchanged. Crew related problems can also be resolved by cancelling or delaying the flight, or by calling in new crew or reassigning existing crew. To resolve a passenger problem, an operations controller might change the passenger's flight or delay the passenger (Barnhart, 2009; Castro, 2013).

How well disruptions are managed depends on how AOC is organized. In fact, Kohl et al. (2007) identify organization as one of the main factors affecting an airline's operational stability. According to Castro (2008) and Machado (2010), there are three types of AOC centers. A decision center, a hub control center, and an integrated control center. In a decision center, airline controllers are located in the same space while other functional groups such as maintenance services and crew control are located in a different physical space. A hub control center oversees the activities at the hub, which may include ground and passenger services, but other operations such as aircraft control are monitored from a different location. An integrated airline operational control center integrates all functional groups under the same physical location. The research presented in this paper considers an integrated control center.

Work practice differs from airline to airline and from individual to individual. Smaller airlines tend to use schedule visualization software to easily enable their controllers detect irregularities, while major airlines use software that is able to automatically detect these irregularities. Operators with similar roles sit next to each other to easily communicate and collaborate. Each desk keeps the necessary communication equipment such as phone and telex. Centrally placed screens show live news, as well as weather reports and performance indicators. Clocks indicate the time in different time zones around the world (Feigh, 2008).

### B. *Agent-based paradigm*

There are two main agent-based paradigms in the literature. The first paradigm is Multi-Agent Systems (MAS), and the second paradigm is Agent-based Modelling and Simulation (ABMS) of socio-technical systems. Although there is significant knowledge overlap (e.g. both use distributed autonomous agents) the two are used in complementary ways.

The primary goal in ABMS of socio-technical systems is to search for explanatory insights into the collective behavior of agents obeying specific rules (Nicolic & Kasmire, 2013; Wikipedia 2017). The primary goal of MAS is to exploit the agent-based paradigm as an approach in resolving complex practical or engineering problems (Wikipedia, 2017). Researchers in ABMS of socio-technical systems develop simulations that can reveal system behavior emerging from the agent's collective actions and interactions. In these simulations, the agent entities are used to represent actors in the real world (e.g. individuals or teams as well as (intelligent) technical system agents. They are programmed to react to the computational environment in which they are located, where this environment is a model of the real environment in which the actors operate (Gilbert 2008). So with ABMS comes the need to model human behavior and social interactions.

On the other hand, a technical MAS is a computerized system composed of multiple interacting (intelligent) agents. Here agents can for example conduct some methodical, procedural or algorithmic search. The main difference between ABMS and MAS is that ABMS sets up agents believed to have crucial characteristics of real world analogs to see what happens when they do whatever they do; while in a MAS agents are set up with exactly the characteristics, connections and choices that they need to achieve certain desired emergent states.

## III. Multi-Agent Coordination approaches

This section gives an overview of multi-agent coordination approaches in software agent systems, followed by a review of complementary coordination approaches in human teams.

### *A. Coordination by Software Agents*

One of the classic coordination approaches is the **master/ slave** technique that is typically used for task and resource allocation among slave agents by a master agent (Nwana et al. 1996). The master agent plans and distributes fragments of the plans to the slaves. The slaves may or may not communicate among themselves, but must ultimately report their results to the master agent. Another classic coordination technique is the **contract net protocol** (Bourne et al. 2001). In this approach, agents assume two roles: 1) A manager who breaks a problem into sub-problems and searches for contractors to solve them, as well as to monitor the problem's overall solution, and 2) A contractor who does a sub-task. However, contractors may recursively become managers and further decompose the sub-task and sub-contract them to other agents.

Other coordination approaches include, multi-agent planning (Nwana et al. 1996), negotiation protocols (Sycara 1989, Bussmann & Muller 1992), and voting methods (Bosse & Treur 2006). In **multi-agent planning**, agents build and maintain a multi-agent plan that details all of the future actions and interactions required to achieve their goals, and furthermore interleave execution with more planning and re-planning. Due to the re-planning feature, multi-agent planning is particularly useful in dynamic situations. **Negotiation** is defined by Bussmann and Muller (1992) as the communication process of a group of agents in order to reach a mutually accepted agreement on some matter. Sycara (1989) has explained that to negotiate effectively, agents must reason about beliefs, desires, and other agents. **Voting methods** refer to various techniques that are used to describe decision-making processes involving multiple agents. Although originating from political science, they are currently used within a number of domains such as gaming theory and pattern recognition.

The various coordination approaches presented have their relative advantages and disadvantages and there is no universally best method. In general, the theoretical methods produce good results for narrowly defined coordination problems but many of their underpinning assumptions have limitations in developing real-world systems (Lesser 2014).

### *B. Complementary Approaches in Human Teams*

Various complementary coordination approaches are of use in human teams, ranging from routine and psychological approaches, to ecological, socio-technical and integrative approaches; i.e. a fusion of multiple different approaches (Paris et al. 2000).

Thompson (1967) identified two basic complementary coordination approaches in human teams, namely **routines/protocols** and mutual adjustment. The first approach involves the establishment of rules that constrain the action of each unit or position into paths consistent with those taken by others in the interdependent relationship. An important assumption in coordination by routine is that the set of rules need to be internally consistent, and this requires that the situations to which they apply must be relatively stable, repetitive, and few enough to permit matching of situations with the appropriate rules. The second approach, **mutual adjustment**, involves the transmission of new information during the process of action. March & Simon (1958) refer to this as "coordination by feedback". The more variable and unpredictable the situation, the greater the reliance on coordination by mutual adjustment.

Gittell (2002) identified two other approaches, namely team meetings and supervision. **Team meetings** give participants the opportunity to coordinate tasks directly with one another. According to organization theory, they increase the performance of interdependent work processes by facilitating interaction among participants and are increasingly effective under conditions of high uncertainty. Supervisors, also known as boundary spanners, are individuals whose primary task is to integrate the work of other people.

Socio-technical coordination approaches include the team situation awareness model by Endsley & Jones (1997, 2001), and the joint activity model by Klein et al. (2005). **The team situation awareness** model conceptualizes how teams develop high levels of situation awareness (SA) across members and includes four crucial elements on which team SA is built. These include an understanding of what constitutes SA requirements in team settings, devices, and mechanisms that are important for achieving high levels of shared SA and the processes that effective teams use.

As is pictured in Figure 2, the **joint activity** model (Klein et al. 2005) distinguishes three specific types of process phases that are required for effective coordination namely: 1) Criteria for joint activity, 2) Requirements for joint activity, and 3) Choreography of joint activity. The criteria for joint activity are that participants intend to work together (known as the basic compact) and their work has to be interdependent. The basic compact constitutes a level of commitment for all parties to support the coordination process, e.g. the commitment to some degree of goal alignment, and commitment to try and detect and correct any loss of common ground that might disrupt the joint activity. If these criteria are satisfied, the parties have to fulfill certain requirements such as making their actions predictable, sustaining common ground, and being able to redirect each other. The form for achieving these requirements (the choreography) is a series of activities that are guided by various signals and coordination devices.

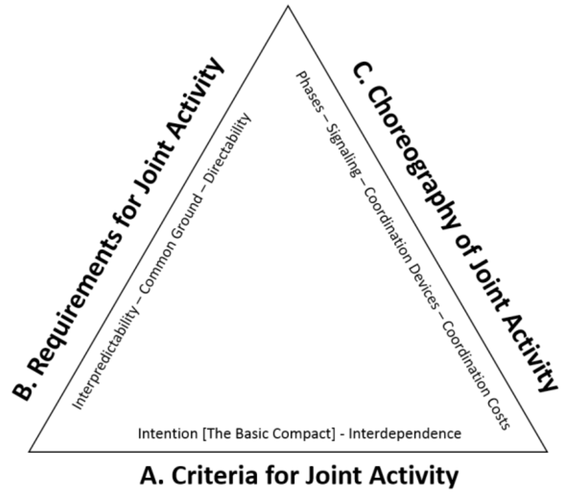


**Figure 2: Joint activity theory of Klein et al. (2005)**

## IV. MAS SUPPORTED AOC POLICY

Castro (2013) developed MASDIMA as a MAS based tool set in support of an AOC policy in which several human roles are automated. This tool set makes use of intelligent software agents that negotiate with each other to manage airline disruptions, but keeps the human in the loop as supervisor. This means that both software agents and humans have to coordinate their actions. Coordination approaches between software agents as well as between human agents are therefore relevant for a MAS supported AOC policy.

Figure 3 compares current AOC with MASDIMA supported AOC. This figure shows how software agents replace the passenger team, aircraft team, and crew team. The roles for humans that remain in AOC are the supervisor, maintenance services, and flight dispatch.

Figure 4 shows how software-agents form MASDIMA's architecture. Rectangles represent software agents and rounded rectangles represent human agents. Solid arrows show interactions between agents, whereas dashed arrows indicate querying of one of the many data sources. Data sources are shown as cylinders in the oval located on the lower side of the figure. The cloud around the supervisor agent and manager agents indicates that these agents negotiate with each other.

MASDIMA manages a disruption as follows. The first step in the disruption management process is to detect disruptive events. This is done by the monitor agent which reads the event database (see dashed arrow between the monitor agent and the data sources in Figure 4). Flight dispatch is responsible for entering information about disruptions in the event database. From the event database, the monitor agent assesses which airlines resources are affected and requests a solution to the disruption problem from the supervisor agent. A problem has three dimensions: the aircraft, the crew, and the passenger dimension. To find a solution the supervisor agent negotiates with an aircraft, crew, and passenger manager. Each manager can solve one dimension of the problem. To get a solution on all three dimensions, the manager agents negotiate with each other. I.e. the aircraft manager solves aircraft related problems, but for problems that also affect the crew it has to negotiate with the crew manager. The crew manager then provides a solution to the crew problem. This negotiation allows manager agents to present an integrated solution, that is, a solution to all dimensions of a disruption problem.

A manager agent has many options to solve a disruption. For instance, to solve an aircraft related problem, the aircraft manager may delay or cancel the flight, or exchange aircraft. To find which of these options is best, each manager defines its utility function. This allows the manager agents to find a solution that is optimal from their perspective. The aircraft manager aims to minimize aircraft delay and aircraft cost, the crew manager minimizes crew delay and crew cost, and the passenger manager minimizes passenger trip time and passenger costs.

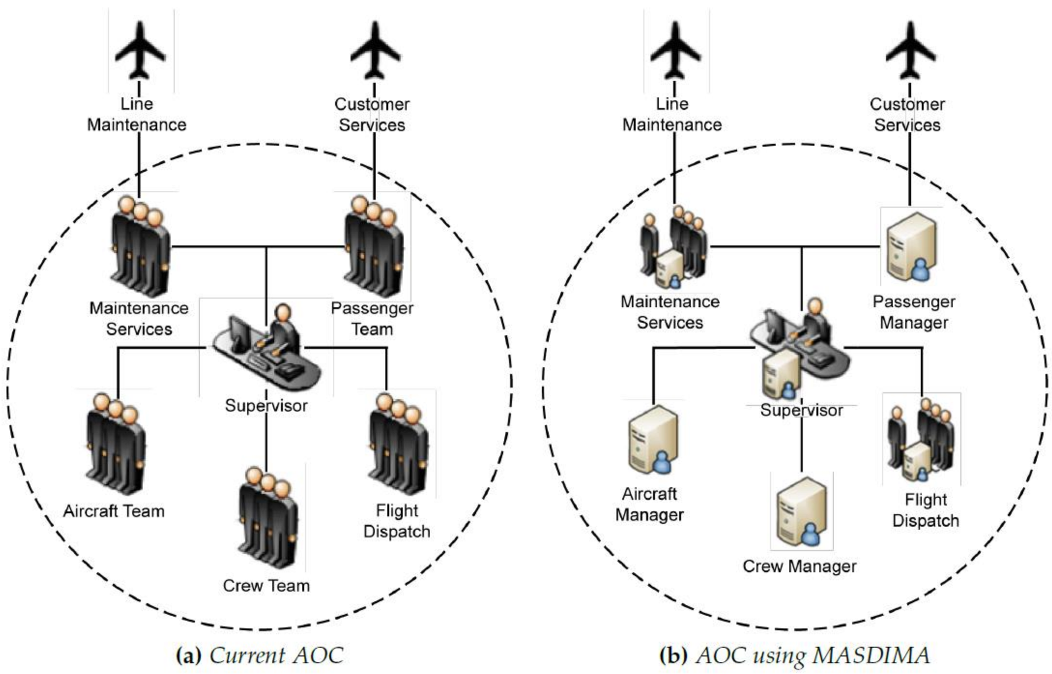


**Figure 3: Castro (2013) proposes to automate several of the roles in AOC**

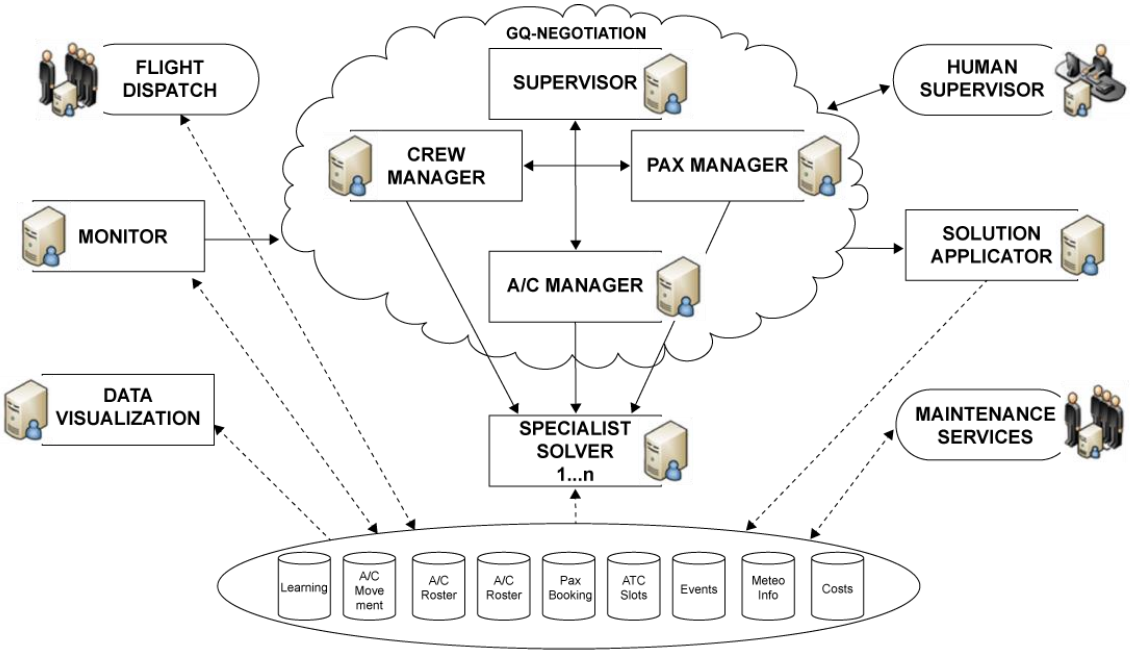


**Figure 4: MASDIMA architecture (Castro, 2013)**

To illustrate this concept, Equation (1) shows the utility function for the aircraft manager. In this equation $t_{ad}$ is the total aircraft delay for all flights in the schedule. The value $max(t_{ad})$ is the total aircraft delay of the solution that results in the maximum delay. Similarly, $C_{a/c}$ is the total aircraft operating cost and $max(C_{a/c})$ the aircraft cost for the solution with the maximum total aircraft operating cost. The weights $\omega_1$ and $\omega_2$ determine the relative importance of aircraft delay versus aircraft cost.

$$U_{a/c} = 1 - \left( \frac{w_1 \left( \frac{t_{ad}}{max(t_{ad})} \right) + w_2 \left( \frac{C_{a/c}}{max(C_{a/c})} \right)}{w_1 + w_2} \right) \quad (1)$$

The software agents in MASDIMA negotiate at two levels. At the first level, the manager agents negotiate with each other to find a solution to all three dimensions of the problem. At the second level, negotiation takes place between the supervisor agent and the manager agents. When the supervisor agent requests a solution from the manager agents, it may receive three different solutions. This is because the manager agents each have their own definition of what is an optimal solution. To determine what solution is best, the supervisor agent defines its utility function. This function covers all three dimensions of the problem. It takes into account aircraft cost and aircraft delay, crew cost and crew delay, passenger compensation cost and passenger travel time.

## V. Evaluating AOC disruption management policies

A scenario-based evaluation was conducted to compare the MAS supported with four human coordination policies in AOC. This section gives an overview of these five policies in relation to the coordination approaches reviewed in Section III. Next, it describes the scenario and performance indicators used in the comparison. This section concludes with the results of the scenario-based evaluation.

### A. Five AOC Disruption Management Policies

We number the five specific AOC disruption management policies to be considered as P1-P5. Policies P1-P3 are based on established AOC practices (Bruce 2011a, 2011b). Policy P4 is based on the joint activity coordination theory of Klein et al. (2005). P5 is the MAS supported AOC policy described in section IV. Policies P1-P4 are summarized below; for a complete description see (Bouarfa et al., 2016).

*1) AOC policy P1 – Elementary level of performance:* Airline controllers identify various basic level considerations such as aircraft patterns and availability, crew commitments and maintenance limitations. For example, when a maintenance problem is reported, controllers at this level appear to acknowledge the information provided and begin considering the basic consequences of the scenario. They also identify opportunities to replace the aircraft or rebook passengers on alternative flights.

*2) AOC policy P2 – Core level of performance:* Airline controllers have a greater comprehension of the problem. They take into account more complex consequences of the problem than those evident at the elementary level. Several constraints such as crew restrictions, slot times, and curfews are identified at this level. Controllers would for instance negotiate maintenance requirements and crew limitations in order to reduce the risk of breaching the curfew.

*3) AOC policy P3 – Advanced level of performance:* Airline controllers demonstrate thinking beyond the immediacy of the problem. They examine creative ways to manage the disruption. For instance, controllers at this level would consider more complex crewing alternatives such as positioning a crew from one airport to another airport where the flight crew is needed. Also, in case of a maintenance problem, controllers at this level would seek alternative information and recheck the reliability of information, e.g. through organizing a conference call with the maintenance watch people.

*4) AOC Policy P4 – Joint activity policy*

The fourth AOC policy P4 is based on the joint activity framework of Klein et al. (2005) that is depicted in Figure 2. In order to apply the joint activity based approach to AOC disruption management, Bouarfa et al. (2016) have identified rules that AOC agents should adhere to in order to comply with Klein's joint activity theory (Klein et al.

2005). These rules are defined for each of the three types of joint activity process phases, and are described in more detail in Bouarfa et al. (2016). Subsequently, Bouarfa et al. (2012) have shown through ABMS the great potential this joint activity theory has for improving current AOC policy.

## *B. Coordination Approaches of P1-P5*

Table 1 gives shows which coordination approaches reviewed in Section III apply for each of the five policies P1-P5. This shows that almost all coordination approaches of Section III (except Voting methods) are used within one or more of the five AOC policies P1-P5.

The AOC policies P1-P4 have several coordination approaches from Section III in common, i.e. master/slave, contract net protocol, multi-agent planning, routines/protocols, mutual adjustment, supervision and criteria for joint activity. This commonality stems from the typical airline manner of flight planning and their AOC organization. Policy P1 has only one coordination approach complementary to this common set, i.e. dedicated routines/protocols in resolving a disruption. Policy P2 also makes use of negotiation protocols between team members as a complementary approach. Policy P3 is similar to Policy P2, though makes use of team meetings instead of negotiation protocols. Policy P4 is an extension of Policy P3 with Team Situation Awareness (Endsley & Jones 1997, 2001) and a replacement of the dedicated routines/protocols of P3 by the rules of joint activity theory (Figure 2). Policy P5 has less commonality with the P1-P4 because human-centred coordination policies play a lesser role.

**Table 1: Approaches from the coordination literature used by AOC policies P1-P5**

| **Coordination Approach** | **Simulated Coordination Policies** | | | | |
|---|---|---|---|---|---|
| | **P1** | **P2** | **P3** | **P4** | **P5** |
| Master/ Slave technique | + | + | + | + | + |
| Contract net protocol | + | + | + | + | + |
| Multi-agent planning | + | + | + | + | + |
| Negotiation protocol | - | + | - | - | + |
| Voting methods | - | - | - | - | - |
| Routines/ protocols | + | + | + | + | - |
| Mutual adjustment | + | + | + | + | - |
| Supervision | + | + | + | + | - |
| Team meetings | - | - | + | + | - |
| Criteria for joint activity | + | + | + | + | - |
| Requirements for joint activity | - | - | - | + | - |
| Choreography of joint activity | - | - | - | + | - |
| Team Situation Awareness | - | - | - | + | |

## *C. Scenario*

The scenario used to evaluate the MAS supported AOC policy P5 originates from Bruce (2011b). Bouarfa et al. (2015) used the same scenario to evaluate human coordination policies P1-P4. The scenario considers an aircraft mechanical failure at an airline's outstation. As a consequence of this failure, the flight is delayed by 3 hours. This may cause crew to exceed their legal duty time. AOC is to find a solution.

Table 2 shows the flight schedule for the two long-haul aircraft that are in Europe around the time of the disruption. $A_{dep}$ and $A_{arr}$ refer to airport of departure and arrival, respectively. Reg. is the aircraft registration, and Day indicates a fictional day of departure. The scheduled time of departure and the scheduled time of arrival are represented by $t_{sd}$ and $t_{sa}$. Furthermore, $t_{flight}$ is the flight time in minutes (excluding taxiing), and $d_{flight}$ the great circle distance in kilometers between departure and arrival airport. The airline's fictional hub Pacific (PCF) is assumed to be located 806km and 90 flight-minutes south of Hong-Kong (Bouarfa et al. 2015).

**Table 2: Flight schedule for the two long-haul aircraft that are in Europe around the time of the disruption. Flight schedule from Bruce (2011b). Flight times and flight distances from Travelmath.com (2015)**

| Flight | $A_{dep}$ | $A_{arr}$ | Reg. | Day | $t_{sd}$ | $t_{sa}$ | $t_{flight}$ | $d_{flight}$ |
|---|---|---|---|---|---|---|---|---|
| 700 | PCF | LHR | LHA | 1 | 09:10 | 22:05 | 771 | 10 453 |
| 706 | PCF | CDG | LHB | 1 | 10:55 | 22:55 | 738 | 10 413 |
| 701 | LHR | PCF | LHA | 2 | 08:35 | 21:30 | 771 | 10 453 |
| 705 | CDG | PCF | LHB | 2 | 09:00 | 21:00 | 738 | 10 413 |
| 761 | PCF | YVR | LHA | 3 | 05:00 | 13:45 | 816 | 11 094 |
| 700 | PCF | LHR | LHB | 3 | 07:00 | 19:55 | 771 | 10 453 |

The scenario chronology is as follows. The disruption is detected at 06:55 UTC. Flight 705 is unserviceable in Paris (CDG). An engineer observed a hydraulic pump leak during routine maintenance. The engineer contacted the ground-supervisor and informed him about the leak. Subsequently, the engineer found out that the hydraulic pump should be changed. Moreover, because of bad weather he believed it is best to do the pump change in a hangar. This would delay the flight by at least 3 hours, such that the crew of flight 705 exceeds their legal duty time.

Flight 705 is not fully booked. It carries 420 passengers on an aircraft with a maximum seat capacity of 450 passengers. There is another long

haul flight from Europe to Pacific around the same time. This is flight 701 from London (LHR) to PCF, carrying 445 out of 450 passengers. Because this flight is almost fully booked, it cannot carry any additional passengers from flight 705. There are no reserve aircraft available at either CDG or LHR.
An expert panel described the optimal solution to fly in reserve crew from PCF to BOM. Subsequently, this reserve crew can fly the aircraft from BOM to PCF without violating their legal duty time Bruce (2011a).

### *D. AOC Performance Indicators*

To assess the solution corresponding to the MAS supported policy, the same performance indicators used by Bouarfa et al. (2015) are considered:

- *Flight:* This performance indicator describes what happens to the flight. For instance, the flight can be cancelled, delayed, or diverted.
- *Integrated solution:* A solution to an airline disruption problem has three dimensions: the aircraft solution, the crew solution, and the passenger solution. For instance, the aircraft solution could be to fix the aircraft mechanical failure.
- *Disruption management time:* The time it takes to solve a disruption problem starts when the disruption is first detected, and ends when a solution is found and implemented by AOC. Implemented here means that the changes are applied to the operational schedules, and all involved parties are informed of the solution.
- *Operational Costs:* The cost model by Bouarfa et al. (2015) is used to compare the solution by policy P5 to the solutions corresponding to policies P1-P4. For the operational costs, Bouarfa et al. (2015) use recent costa data from Air France-KLM (Air France - KLM, 2014).
- *Passenger compensation:* European legislation prescribes that, under certain conditions, passengers can claim compensation from the airline if their flight is cancelled or delayed. When a flight is cancelled without prior notice, passengers flying longer than 3500km can claim €600, or €300 if the airline provides an alternative itinerary (European Parliament, 2004).
- *Passenger delay:* The passenger delay is calculated as the difference in hours between the scheduled time of departure and the estimated time of departure.

### *E. Results for P1-P5*

Table 3 shows the results obtained for the five AOC policies P1-P5. The results for P1-P4 are from Bouarfa et al. (2015). The results for P5 have been obtained as follows.

A scenario-based analysis showed that policy P5 would propose to delay flight 705 to fix the aircraft mechanical problem, to replace the crew from flight 705 by the crew from inbound flight 706, and to keep passengers on the same flight. The airline operating cost was found to be €326,000 and it would take 17 minutes to find and implement the solution.
The solution to the scenario was established as follows: first the ground engineer detects the leak and calls the ground-supervisor. The ground supervisor enters the disruption into the Aircraft Movement System, which can be read from the AOC center. Flight dispatch notices the disruption, and enters the information into MASDIMA's event database.
MASDIMA's monitor agent detects the disruptive event from the database and requests the supervisor agent to solve the problem. As the aircraft, crew, and

**Table 3: Results of the scenario-based analysis. The novel policy P5 finds the same solution as policy P4, which is better than the solutions found by policies P1-P3. Results for policies P1 to P4 originate from Bouarfa et al. (2015).**

| AOC policy | Flight | Aircraft mechanical problem | Crew problem | Passengers problem | Minimum disruption mgmt time | Costs for the airline [Euros] | | Passenger travel delay (hours) |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Operating costs | Legal pax. compensation | |
| P1 | Cancelled | Fixed | Not resolved | Pax. accommodated in hotel (i.e. distressed) | 26 min | 326 kEUR | 168kEUR | 24 |
| P2 | Cancelled | Fixed | Not resolved | Pax. accommodated in hotel (i.e. distressed) | 30 min | 326 kEUR | 168 kEUR | 24 |
| P3 | Diverted | Fixed | Resolved | Pax. significantly delayed due to fixing aircraft and diverting | 33 min | 360 kEUR | 126 kEUR | 8 |
| P4 | Delayed | Fixed | Resolved | Pax. delayed until aircraft is fixed | 20 min | 326 kEUR | 0 kEUR | 3 |
| P5 | Delayed | Fixed | Resolved | Pax delayed until aircraft is fixed | 17 min | 326 kEUR | 0 kEUR | 3 |

passenger dimensions are all affected, all manager agents participate in the negotiation to propose a solution. For the aircraft manager agent, the optimal solution is to delay the flight until the aircraft is fixed. For the crew manager agent, the optimal solution is to exchange the crew from flight 706 with the crew from flight 705. The most optimal solution for the passenger problem is to keep the passengers on the same flight. The manager agents now start negotiating with each other to obtain an integrated solution. In this case, the optimal solutions proposed by the aircraft manager, crew manager, and passenger manager are compatible, and therefore proposed to the supervisor agent. This is also the solution proposed to the human supervisor. If the human supervisor accepts the proposal, the solution is implemented in the operational schedule.
The time to obtain the final solution was determined based on (Machado (2010), Castro and Oliveira (2011)) together with data from developer of policy P5. The timing of the different steps is presented in Table 4.

**Table 4: Timing of steps in disruption management policy P5**

| Step | $t_{solve}$ (min) |
|---|---|
| Ground engineer contacts station supervisor to inform him about the leak | 3.5 |
| Station supervisor enters information on the disruption in the AMS | 4.5 |
| Flight dispatch reads AMS and decides to put the information in the event database | 2.5 |
| Flight dispatch puts disruption in event database | 4.5 |
| MASDIMA solves the disruption | 1 |
| Human supervisor approves solution by MASDIMA | 0.5 |
| MASDIMA applies solution on the operational plan | 0.5 |
| Total time to resolve disruption | 17 |

## VI. Expert-Based Evaluation of P5

Introducing MAS supported policy P5 to AOC might have an impact on the current airline disruption management process. To investigate this, an AOC expert from a major European airline was interviewed. This has led to the identification of several key AOC tasks that could be affected. These tasks have been evaluated from a current AOC perspective.

### *A. AOC Tasks considered*

The AOC tasks have been identified during an interview with an AOC expert. This interview had the form of an open discussion on the operational changes implied by MAS supported policy P5. The list of tasks identified was not exhaustive, but it identified a rough cross-section of AOC tasks affected by policy P5 (See table 5).

**Table 5: AOC tasks affected by MAS supported policy P5**

| AOC Task # | Task Description |
|---|---|
| 1 | Monitoring flight safety |
| 2 | Monitoring whether a flight will make it for its time-slot |
| 3 | Judging the amount of pilots needed on a flight |
| 4 | Checking whether crewmembers reported for a flight |
| 5 | Finding a reserve crewmember |
| 6 | Finding a new itinerary for disrupted passengers |
| 7 | Asking for a crewmember’s permission |

Furthermore, the introduction of MAS supported policy P5 may change the workload for people that remain in AOC. Figure 3 compared AOC under policies P1-P4 (Fig. 3a) to AOC under the MAS supported policy P5 (Fig. 3b). This shows that the passenger team, the aircraft team, and the crew team are replaced by the automated passenger manager, the automated aircraft manager, and the automated crew manager respectively. In order to gain insights into potential effects of these replacements, each task will be evaluated in relation to workload.

### *B. Results of Expert-Based Task Evaluation*

The expert-based evaluation identified for each of the tasks in Table 5 potential problems for the introduction of MAS supported policy P5 in AOC. The details of these potential problems are described for each of these tasks.

1. *Monitoring flight safety*
   Monitoring flight safety is currently the task of flight dispatch. Castro (2015b) proposes to make flight dispatch responsible for entering information on disruptions in the MAS based tool. Unstructured information like weather info is entered manually. The increased workload from this additional task may interfere with the task of monitoring flight safety.

2. *Monitor whether a flight will make it in time for its time-slot*
   In some occasions, airspaces are so crowded that flights are allocated a time-slot to enter it. Flight dispatch is currently responsible for following a flight and noticing when a flight

will not make it in time for the assigned slot. The MAS based tool does not check automatically whether a flight misses its time-slot, and therefore lacks an important functionality.

3. *Judging the amount of pilots needed on a flight*
   Some flights are on the border between requiring two or three pilots. These flights require a third pilot if the flight is expected to take longer than scheduled, for instance due to adverse weather conditions at the arrival airport. Currently flight dispatch monitor flights and judges if an extra pilot is needed . If this role is automated, it might leads to not having enough pilots reporting for a flight.

4. *Checking whether crewmembers reported for a flight*
   Crewmembers generally have to check-in to report for a duty. The Crew Tracking System (CTS) keeps track of whether crewmembers reported for a flight and at what time. Currently flight dispatch monitors the CTS and checks whether all crewmembers reported in time. In order to avoid potential confusion, the MAS supported tool should also read this information from the CTS automatically.

5. *Finding a reserve crewmember*
   Crewmembers do not always report for duty. All kinds of last minute changes in a crewmember's life may result in a no-show. To find a replacement crewmember, AOC currently has a crew reserve list. The crew team is responsible for contacting a crewmember on this list (e.g. by calling or by SMS) and asks if he or she can replace the original crewmember. When an airline would introduce the MAS supported policy P5, this contacting task shifts to the people that remain in AOC after its introduction. This increases their workload and is potentially problematic.

6. *Finding a new itinerary for disrupted passengers*
   When an airline cancels a flight, it is often responsible for providing an alternative itinerary for disrupted passengers. Currently the passenger team is responsible for providing this alternative itinerary. With the introduction of MAS supported policy P5, this tasks shifts towards the automation, but reviewing the solution remains a task for humans. With the passenger team automated by P5, a complaint by a passenger should be handled by the supervisor. As this is an additional task, it increases the supervisor's workload and therefore this task may be potentially problematic to cover.

7. *Asking for a crewmember's permission*
   In some case AOC requires a crewmember that is not officially on stand-by to fulfill a duty. Currently it is up to the crew team to check whether the crewmember is willing to help. Because P5 eliminates the crew team, the AOC supervisor has to call a crewmember to ask permission. This increases the supervisor's workload and is potentially problematic.

### C. *Challenging Scenarios*

In addition to the expert-based evaluation of specific AOC tasks, the expert also identified the following four challenging scenarios.

1. *Finding solutions to exceptional situations*

   There are many examples in which airline employees bypass standard procedures to solve a situation that would otherwise have resulted in a disruption. If an airline were to use MAS supported policy P5 the experience and ability to judge such situations has to be centered in the supervisor. Introducing policy P5 therefore increases the task of the supervisor in handling exceptional situations by for example circumventing standard procedures.

2. *Transporting passengers in the direction of their destination*

   In some cases it is not possible to get passengers to their final destination. As an alternative, an airline may choose to transport passengers as much as possible in the direction of their destination. For instance when passengers cannot directly fly to New York from Amsterdam, the airline may still be able to fly passengers to Houston and transport passengers by another transport mode to their final destination. Currently the passenger team is responsible for finding these types of solutions. Currently there is no feature in policy P5 addressing such solutions.

3. *Protecting the airline's strategic position*

   Some routes are important to an airline for strategic reasons, whilst flights on these routes are relatively easy or cheap to cancel. From literature it appears that no one in AOC is currently explicitly responsible for protecting the airline's strategic position, but it is assumed that this is inherent to AOC tasks. MAS supported policy P5 does not include a feature that protects the airline's strategic position because it replaces several human AOC roles. Such task will shift to the remaining people and increases their workload.

4. *Taking into account political situations*

   Political friction between countries may require attention from an airline, especially when the airline flies to disputed areas. Currently no one in AOC is explicitly responsible for this task, but it is assumed to be inherent to AOC roles. MAS supported policy P5 does not include a feature to check for politically sensitive situations. Ensuring the political neutrality of an airline therefore shifts towards the people that remain in AOC and increases their workload.

## VII. Conclusion

This paper presented a scenario-based and an expert-based analysis of an AOC disruption management policy that makes explicit use of the MAS-based decision support system MASDIMA.

The scenario-based analysis showed that the MAS supported policy P5 identified the best known solution for the challenging disruption considered. This best solution was also found by an advanced human-based AOC resolution policy P4 studied by Bouarfa et al. (2015). However, this best solution was not found by three conventional types of AOC disruption management policies P1-P3.
It was estimated that the MAS based AOC policy P5 takes 17 minutes to identify the best solution. This is significantly faster than any of the other AOC disruption management policies considered.

The expert-based task analysis of the MAS supported AOC policy P5 identified the potential for increasing tasks for the supervisor. Comparing causes for tasks to be problematic, three main categories could be identified.

First, for several tasks the workload increases for human that remain in AOC after the introduction of the MAS supported AOC policy P5. Under policy P5, these tasks can only be performed by the AOC supervisor, which may increase his/her taskload significantly.

Second, eliminating the aircraft team, the crew team, and passenger team asks for centering their experience with the AOC supervisor. The analysis showed that the MAS decision-support tool provides a range of solutions to standard disruption problems, such as finding a reserve crewmember or an alternative itinerary. Because Policy P5 eliminates part of the AOC operators by software agents, AOC loses experience that is key to its flexibility. The effect is that for cases where the pre-programmed solutions are not the best options, the efficiency of AOC decreases and workload increases.

Third, collaboration is key to finding solutions to disruption problems. Automating several human AOC roles also means their contacts and their ability to collaborate are lost. This reduces the resilience of AOC to recover from disruptions and increases the workload for people that remain in AOC.

The scenario-based analysis used in the paper considers one demanding scenario. In order to generalize the findings, it is recommended to also identify and evaluate other demanding scenarios. With respect to the expert-based evaluation, the interview with an AOC expert identified many AOC tasks, but the list was not exhaustive. It is therefore recommended to further extend the list of AOC tasks for expert-based evaluation.

Nevertheless, based on the challenging scenario alone, it can be concluded that MAS-based decision-support has great potential in improving established AOC disruption management policy. Expert-based evaluation showed that there are some remaining issues for which further improvements of MAS supported AOC policy is expected to be beneficial.

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