USING QUALITY COSTS IN A MULTI-AGENT SYSTEM FOR AN AIRLINE OPERATIONS CONTROL

Antonio J. M. Castro and Eugenio Oliveira
Informatics Engineering Department and LIACC/NIAD&R, Faculty of Engineering, University of Porto, Portugal

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Abstract: The Airline Operations Control Centre (AOCC) tries to solve unexpected problems that might occur during the airline operation. Problems related to aircrafts, crewmembers and passengers are common and the actions towards the solution of these problems are usually known as operations recovery. Usually, the AOCC tries to minimize the operational costs while satisfying all the required rules. In this paper we present the implementation of a Distributed Multi-Agent System (MAS) representing the existing roles in an AOCC. This MAS has several specialized software agents that implement different algorithms, competing to find the best solution for each problem that include not only operational costs but, also, quality costs so that passenger satisfaction can be considered in the final decision. We present a real case study where a crew recovery problem is solved. We show that it is possible to find valid solutions, with better passenger satisfaction and, in certain conditions, without increasing significantly the operational costs.

1 INTRODUCTION

Operations control is one of the most important areas in an airline company. Through operations control mechanisms the airline company monitors all the flights checking if they follow the schedule that was previously defined by other areas of the company. Unfortunately, some problems arise during this phase (Clausen et al., 2005). Those problems are related to crewmembers, aircrafts and passengers. The Airline Operations Control Centre (AOCC) is composed by teams of people specialized in solving the above problems under the supervision of an operation control manager. Each team has a specific goal contributing to the common and general goal of having the airline operation running with few problems as possible. The process of solving these problems is known as Disruption Management (Kohl et al., 2004) or Operations Recovery. To be able to choose the best solution to a specific problem, it is necessary to include the correct costs on the decision process. It is possible to separate the costs in two groups: *Operational Costs* (easily quantifiable costs) and *Quality Costs* (less easily quantifiable costs). The operational costs are, for example, crew costs (salaries, hotel, extra-crew travel, etc.) and aircraft/flights costs (fuel, approach and route taxes, handling services, line maintenance, etc.). The quality costs that we are interested in calculating in the AOCC domain are, usually, related to passenger satisfaction. Specifically, we want to include in the decision process the cost of delaying or cancelling a flight from the passenger point of view, that is, in terms of the importance that a delay will have to the passenger. In (Castro and Oliveira, 2007) the authors presented a Distributed Multi-Agent System (MAS) to solve airline operations problems that included operational costs but did not take into consideration the quality costs we mentioned before. Starting from this work and based on our observations we have done on an AOCC of a real airline company we hypothesize that the inclusion of quality costs in the decision process will increase the customer satisfaction (a fairly obvious prediction) without increasing significantly (or nothing at all) the operational costs of the solutions in a given period. Basically, we expect to find valid alternate solutions within the same operational cost but with a better impact on the passenger satisfaction.

In this paper we show how we changed the MAS presented in (Castro and Oliveira, 2007) specifically how we improved the specialized agents to include the quality costs on the decision process. The rest of the paper is organized as follows. In section 2 we

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present some work of other authors regarding operations recovery. Section 3 shows how we arrived at the formulas we have used to express the importance of the flight delay, from the passenger point of view. Section 4 shows how we have updated the MAS presented in (Castro and Oliveira, 2007) to include quality costs, including the MAS architecture and the algorithm used to choose the best solution. In section 5 we present the scenario used to evaluate the system as well as the results of the evaluation. Finally, we discuss and conclude our work in section 6.

2 RELATED WORK

Traditionally, the Operations Recovery Problem has been solved through Operations Research (OR) techniques. The paper (Barnhart et al., 2003) gives an overview of OR applications in the air transport industry. We divided the papers in three areas: crew recovery, aircraft recovery and integrated recovery. For a more detailed explanation of the papers as well as for older papers related with each of these subjects, please consult (Clausen et al., 2005).

Aircraft Recovery. The most recent paper considering the case of aircraft recovery is (Rosenberger et al., 2001). They formulate the problem as a Set Partitioning master problem and a route generating procedure. The goal is to minimize the cost of cancellation and retiming, and it is the responsibility of the controllers to define the parameters accordingly. It is included in the paper a testing using SimAir (Rosenberger et al., 2002) simulating 500 days of operations for three fleets ranging in size from 32 to 96 aircraft servicing 139-407 flights. Although the authors do try to minimize the flights delays, nothing is included regarding the use of quality costs.

Crew Recovery. In (Abdelgahny et al., 2004) the flight crew recovery problem for an airline with a hub-and-spoke network structure is addressed. The paper details and sub-divides the recovery problem into four categories: misplacement problems, rest problems, duty problems, and unassigned problems. The proposed model is an assignment model with side constraints. Due to the stepwise approach, the proposed solution is sub-optimal. Results are presented for a situation from a US airline with 18 problems. This work omits the use of quality costs.

Integrated Recovery. In (Bratu and Barnhart, 2006) the author presents two models that considers aircraft and crew recovery and through the objective function focuses on passenger recovery. They include delay costs that capture relevant hotel costs and ticket costs if passengers are recovered by other airlines. According to the authors, it is possible to include, although hard to estimate, estimations of delay costs to passengers and costs of future lost ticket sales. To test the models an AOCC simulator was developed, simulating domestic operations of a major US airline. It involves 302 aircrafts divided into 4 fleets, 74 airports and 3 hubs. Furthermore, 83869 passengers on 9925 different passengers' itineraries per day are used. For all scenarios are generated solutions with reductions in passenger delays and disruptions. The difference regarding our proposal is that we use the opinion of the passengers when calculating the importance of the delay.

Lettovsky's Ph.D. thesis (Lettovsky, 1997) is the first presentation of a truly integrated approach in the literature, although only parts of it are implemented. The thesis presents a linear mixed-integer mathematical problem that maximizes total profit to the airline while capturing availability of the three most important resources: aircraft, crew and passengers. The formulation has three parts corresponding to each of the resources, that is, crew assignment, aircraft routing and passenger flow. In a decomposition scheme these three parts are controlled by a master problem denominated the Schedule Recovery Model. Although the author takes into consideration the passenger, it does so regarding finding the best solution for the disrupted passengers. The difference regarding our approach is that we use the *opinion* of the passengers regarding the delay (expressed through a mathematical formula) to make the best solution regarding delaying the flight. We do not approach the also important issue of finding the best itinerary for disrupted passengers.In (Castro and Oliveira, 2007) the author presents a Multi-Agent System (MAS) to solve airline operations problems, using specialized agents in each of the three usual dimensions of this problem: crew, aircraft and passengers. The MAS represents the Airline Operations Control Centre (AOCC) and is able to deal with different operational bases (geographically distributed) each with its own resources. The architecture and the specialized agents of the crew recovery sub-organization are presented as well as a case study of how the MAS solved several crew related problems during a one-month period. However, in the examples presented, the author ignores the impact that a delay in the flight might have on the decision process and only use operational costs to make the best decision. That is the biggest difference regarding the work we present in this paper. We start from this approach and make the necessary changes on the specialized agents and in the multi-criteria algorithm, so that the quality costs are included. For those interested in agent-oriented methodologies and in how this MAS was developed, please read (Castro and Oliveira, 2008).

3 QUALITY COSTS IN AOC

3.1 How to Quantify

Overview. The Airline Operations Control Centre (AOCC) has the mission of controlling the execution of the airline schedule and, when a disruption happens (aircraft malfunction, crewmember missing, etc.) find the *best solution* to the problem. It is generally accepted that, the *best solution*, is the one that does not delay the flight and has the minimum operational cost. In summary, it is the solution that is nearest to the schedule, assuming that the schedule is the optimal one. Unfortunately, due to several reasons (see (Kohl and Karish, 2004) for several examples), it is very rare to have available solutions that do not delay a flight and/or do not increase the operational cost. From the observations we have done in a real AOCC, most of the times, the team of specialists have to choose between available solutions that delay the flight and increase the operational costs. Reasonable, they choose the one that minimize these two values.

The Perception of Quality Costs. In our observations, we found that some of the teams in the AOCC, used some kind of *rule of thumb* or *hidden knowledge* and, in some cases, they did not choose the solutions that minimize the delays and/or the operational costs. For example, suppose that they have disruptions for flight A and B with similar schedule departure times. The best solution to flight A would cause a delay of 30 minutes and the best solution to flight B would cause a delay of 15 minutes. Sometimes, and when technically possible, they would prefer to delay flight A in 15 minutes and flight B in 30 minutes or more if necessary. We can state that flights with several business passengers, VIP's or for business destinations correspond to the profile of flight A in the above example. In our understanding this means that they are using some kind of quality costs when taking the decisions, although not quantified and based on personal experience. In our opinion this makes the decision less reliable but that knowledge, represents an important part in the decision process and should be included on it.

Quantifying Quality Costs. To be able to use this information in a reliable decision process we need to find a way of quantifying it. What we are interested to know is how the delay time and the importance of that delay to the passenger are related in a specific flight. It is reasonable to assume that, for all passengers in a flight, less delay is good and more is bad. However, when not delaying is not an opinion and the AOCC has to choose between different delays to different flights, which ones should they choose? To be able to quantify this information, we have done a survey to several passengers on flights of an airline company. Besides asking in what class they were seated and the reason for flying in that specific flight, we asked them to evaluate from 1 to 10 (1 – not important, 10 very important) the following delay ranges (in minutes): less that 30, between 30 and 60, between 60 and 120, more than 120 and flight cancellation. From the results we found the passenger profiles in table 1.

Table 1: Passenger profiles.

Profiles	Main Characteristics
Business	Travel in first or business class; VIP's; Frequent Flyer members; Fly to business destinations; More expensive tickets;
Pleasure	Travel in economy class; Less expensive tickets; Fly to vacation destinations;
Family	Usually immigrants; Fly to/from destinations with immigrants communities; Fly to see family and/or to go to funerals; Travel in economy class;
Illness	Stretcher on board; Medical doctor or nurse travelling with the passenger; Personal oxygen on board or other special needs;

The most important information that we want to get from the survey data is the trend of each profile, regarding delay time/importance to the passenger. Plotting the data and the trend we got the graph in figure 1 (x – axis is the delay time and y – axis the importance).

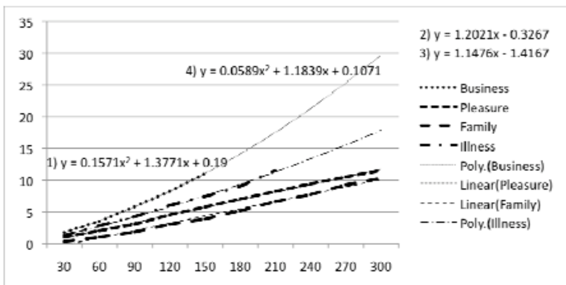

Figure 1: Delay Time vs Importance.

From the graph in figure 1 it is possible to see the equations that define the trend of each profile. If we apply these formulas as is, we would get quality costs for flights that do not delay. Because of that we re-wrote the formulas. The final formulas that express the importance of the delay time for each passenger profile are presented in table 2.

Table 2: Final quality costs formulas.

Profile	**Formula**
Business	$y = 0.16*x^2+1.38*x$
Pleasure	$y = 1.20*x$
Family	$y = 1.15*x$
Illness	$y = 0.06*x^2+1.19*x$

3.2 Using Quality Costs in Operations Recovery

Overview. The MAS we used is a modification of the one used in (Castro and Oliveira, 2007) and represents the Airline Operations Control Centre (AOCC).

In the MAS, each operational base has its own resources that are represented in the environment. For example, *Crew Roster* and *Aircraft Roster* are databases of schedules for the crewmembers and aircrafts, respectively. Other resources represented are the *airport information system*, *legacy systems* and a *knowledge database* for the learning capabilities of the MAS. Each operational base has also software agents that represent roles in the AOCC. The *Crew Recovery Agent*, *Aircraft Recovery Agent* and *Pax Recovery Agent* are dedicated to solve crew, aircraft and passengers problems, respectively, and should be seen as sub-organizations inside the MAS. The *Apply Solution Agent* applies the solution found and authorized in the resources of the operational base.

Architecture and Specialized Agents. The MAS sub-organizations have their own architecture with their specialized agents. Figure 2 shows the architecture for *Crew Recovery* in a UML diagram. The architecture for *Aircraft Recovery* and *Pax Recovery* are very similar. The agent class *OpMonitor* is responsible for monitoring any crew events, for example, crewmembers that did not report for duty or duties with open positions, that is, without any crewmember assigned to a specific role on board (e.g., captain or flight attendant). When an event is detected, the service *MonitorCrewEvents* will initiate the protocol *inform-crew-event* (FIPA Request) informing the *OpCrewFind* agent. The message will include the information necessary to characterize the event. This information is passed as a serializable object of the type *CrewEvent*.

The *OpCrewFind* agent detects the message and will start a CFP (call for proposal) through the *crew-solution-negotiation* protocol (FIPA contractNET) requesting to the specialized agents *HeuristicAlgorithm*, *AlgorithmA* and *AlgorithmB* (or any other that is implemented and deployed in the MAS) of any operational base of the airline company, a list of solutions for the problem. Each agent implements a different algorithm specific for this type of problem. When a solution is found a serializable object of the type *CrewSolutionList* is returned in the message as an answer to the CFP.

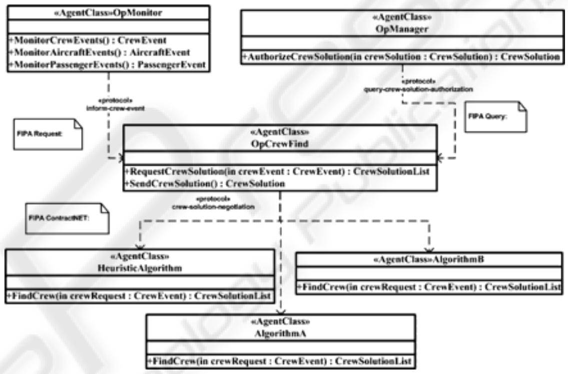

Figure 2: Crew Recovery Architecture.

The *OpCrewFind* agent collects all the proposals received and chooses the best one according to the algorithm in Table 3. This algorithm is implemented in the service *SendCrewSolution* and produces a list ordered by total cost (a multi-criteria cost) that each solution represents. Some of the computed values in the algorithm in Table 3 are the following (see (Castro and Oliveira, 2007) for more information):

oCost: The operational cost of the solution.
pBus: The total of passengers in the *business* profile on the disrupted flight.
pFam: The total of passengers in the *family* profile on the disrupted flight.
pIll: The total of passengers in the *illness* profile on the disrupted flight.
pPleasure: The total of passengers in the *pleasure* profile on the disrupted flight.
bPfCost: The importance of the delay for each passenger of the *business* profile.
iPfCost: The importance of the delay for each passenger of the *illness* profile.
pPfCost: The importance of the delay for each passenger of the *pleasure* profile.
fPfCost: The importance of the delay for each passenger of the *family* profile.

qCost: The quality cost of the solution.

It is important to point out the use of coefficient C1 in the quality cost formula. The goal of this coefficient is to give a value to the quality costs in the same unit of the operational costs. Operational costs are expressed in monetary units (Euros, Dollars, etc.) because they are direct and real costs. On the other hand, quality costs are not real costs and express a level of satisfaction of the passengers. Besides transforming the quality costs into a monetary unit, airline companies can also use this coefficient to express the importance that this type of cost has in the decision process, by increasing its value.

Table 3: Multi-criteria algorithm.

```
foreach item in CrewSolution list
  tDuty = monthDuty+credMins
  if (tDuty-dutyLimit) > 0
    cDuty = tDuty-dutyLimit
  else
    cDuty = 0
  end if
  pDays = (endDateTime-dutyDateTime)+1
  pPay = pDays*perdiemValue
  dPay = cDuty*(hourSalaryValue/60)
  oCost = (dPay+pPay)*bFactor
  pBus = cPax+vipPax+fflyerPax+paxTot*busDest
  pFam = yPax+paxTot*imigDest
  pIll = illPax
  pPleasure = yPax+paxTot*vacDest
  bPfCost = 0.16*fltDelay^2+1.38*fltDelay
  iPfCost = 0.06*fltDelay^2+1.19*fltDelay
  pPfCost = 1.2*fltDelay
  fPfCost = 1.15*fltDelay
  qCost = C1*(bPfCost*pBus+iPfCost*pIll +
pPfCost * pPlea + fPfCost * pFam)
  totalCost = oCost+qCost
end foreach
order all items by totalCost desc
select first item on the list
```

The first solution of the list in descendant order by cost is selected. The *SendCrewSolution* service initiates the protocol *query-crew-solution-authorization* (FIPA Query) querying the *OpManager* agent for authorization. The message includes the serializable object of the type *CrewSolution*.

4 EXPERIMENTS

Scenario. To evaluate our MAS we have setup the same scenario used by the authors in (Castro and Oliveira, 2007) that include 3 operational bases (A, B and C). Each base includes their crewmembers each one with a specific roster. The data used corresponded to the real operation of June 2006 of base A. After setting-up the scenario we found the solutions for each crew event using our Crew Recovery Architecture and Specialized Agents of our MAS. As a final step, the solutions found by our MAS were presented to AOCC users to be validated.

Results. Table 4 presents the results that compare our method (method B) with the one used by the authors in (Castro and Oliveira, 2007), updated with quality costs for a better comparison (method A). We point out that in method A the quality costs were not used to find the best solution. From the results obtained we can see that on average, method B produced solutions that decreased flight delays in 36%.

Table 4: Comparison of the results.

	Method A		Method B		A/B
	Total	**%**	**Total**	**%**	**%**
Delay (avg):	11	100	7	64	-36
Time (avg)	25	100	26	103	3
Total Costs:	11628	100	8912	77	-23
Oper. Costs:	3839	100	4130	108	8
Qual. Costs:	7789	100	4782	61	-39

Regarding the total costs (operational + quality), the method B has a total cost of 8912 and method A a total cost of 11628. Method B is, in average 3% slower than method A in finding a solution and produces solutions that represent a decrease of 23% on the total costs. Regarding operational costs, method A has a cost of 3839 and method B a cost of 4130. Method B is 8% more expensive regarding operational costs. Regarding quality costs, method A has a cost of 7789 and method B a cost of 4782. Method B is 38% less expensive regarding quality costs.

5 CONCLUSIONS

Regarding our first hypothesis we were expecting that the inclusion of quality costs would increase customer satisfaction. This is a fairly obvious conclusion. The quality costs we present here measure the importance of flight delays to the passengers and this is one of the most important quality items in this industry. If we decrease delays we are increasing passenger satisfaction. Regarding hypothesis two we were expecting to increase the passenger satisfaction without increasing significantly (or nothing at all) the operational costs in a given period. From the results in table 4 we can see that operational costs increased 8% when comparing with the method used by (Castro and Oliveira, 2007). If we read this number as is we have to say that our hypothesis is false. An 8% increased on operational costs can represent a lot of money. However, we should read this number together with the flight delay figure. As we can see, although method B increased the operational costs in 8% it was able to choose solutions that decrease, in average, 36% of the flight delays. This means that, when there are multiple solutions to the same problem, our method is able to choose the one with less operational cost, less quality costs (hence, better passenger satisfaction) and, because of the relation between quality costs and flight delays, the solution that produces less flight delays. From this conclusion, one can argue that if we just include the operational costs and the expected flight delay, minimizing both values, the same results can be achieved having all passengers happy. In general, this assumption might be true. However, when we have to choose between two solutions with impact on other flights, which one should we choose? In our opinion, the answer depends on the profile of the passengers of each flight and on the importance they give to the delays, and not only in minimizing the flight delays. Our method takes into consideration this important information when taking decisions.

This paper has presented an improved version of the distributed multi-agent system in (Castro and Oliveira, 2007) as a possible solution to solve airline operations recovery problems, including sub-organizations with specialized agents, dedicated to solve crew, aircraft and passenger recovery problems, which take into consideration the passenger satisfaction in the decision process. We have introduced a process of calculating the quality costs that, in our opinion, represents the importance that passengers give to flight delays. We show how, through a passenger survey, we build four types of passenger profiles and, for each one of these profiles, how we calculate a formula to represent that information. We have introduced an updated multi-criteria algorithm for selecting the solution with less cost from those proposed as part of the negotiation process, taking into consideration the quality costs. A case study, taken from a real scenario in an airline company where we tested our method was presented and we discuss the results obtained. We have shown that our method is able to choose solutions that contribute to a better passenger satisfaction and that produce less flight delays when compared with a method that only minimizes operational costs.

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