Scheduling Airline Reserve Crew to Minimise Crew Related Delay using Simulated Airline Recovery and a Probabilistic Optimisation Model

Chris Bayliss, Geert De Maere, Jason Atkin
Automated Scheduling, Optimisation and Planning (ASAP)
School of Computer Science
University of Nottingham, UK
cwb,gdm,jaa@cs.nott.ac.uk

Marc Paelinck
KLM Decision Support, Information services department
KLM Royal Dutch Airlines
KLM Headquarters, The Netherlands
Marc.paelinck@klm.com

***Abstract*—This paper addresses the problem of airline reserve crew scheduling for a single hub and spoke network. The proposed method involves a simulation parameter generation phase used to derive probabilities of crew related delay and associated expected delay durations. The parameter generation simulation simulates recovery from delays by searching for crew and aircraft swaps that absorb delays, therefore the probabilities of crew related delay are independent of the effects of reserve crew. The parameters generated in the simulation phase are stored in matrices which record the causal relationship of propagating crew related delays. The parameter matrices are then used to search for a reserve crew schedule that minimises the total expected crew related delay. The search method is based on calculating the effect a given reserve schedule has on the probabilities of crew related delays occurring. The experimental results indicate that the proposed model minimises crew related delay in comparison to a variety of alternative methods of reserve crew scheduling for the problem instances considered here.**

***Index Terms*—Probabilistic model, Reserve scheduling, Crew related delay, Simulation**

I. INTRODUCTION

Airline schedules can become infeasible due to the effects of uncertainty in an airline's operating environment. Moreover, delays (including crew delays) can propagate through the schedule due to the presence of resource connections such as dependencies between different aircraft rotations and crew pairings (allocations to aircraft) in the schedule. Even when resource connections are not present, a crew's pairing can become infeasible if the crew is delayed enough so that their maximum flying time would be exceeded. If crews are absent or delayed, reserve crew can be used to restore the schedule's feasibility. Most airlines therefore also schedule reserve crew in addition to their regular crew.

The model introduced here is concerned with crew related delay propagation. The aim of the model is to assign the start times for a fixed number of reserve crew duties such that the total expected crew related delay propagation is minimised.

978-1-4799-0652-9/13/$31.00 ©2013 IEEE

The outline of this paper is as follows. Section II provides an overview of related work in this field. Our approach is introduced in Section III. Section IV sets out an experiment to test the methods put forward and gives the experimental results with interpretations. Section V concludes with a summary of the main findings and future work.

II. RELATED WORK

Previous work on airline reserve crew scheduling includes [2], [3], [7], [8]. In [2], Boissy describes an absenteeism forecast model and a model for minimising the cost of reserves and missing crew. The model balances the risk of crew absence against the cost to determine the appropriate number of reserves. In [8], Paelinck describes a practical approach which was implemented at KLM to optimise cabin crew reserve duties. The approach calculates daily demands for reserves and the expected number of reserve crew remaining each day, and uses a reserve block stacking approach. The aim is to always have standby reserve crew available. In [7], Bailey et al. present an airline reserve crew scheduling model that takes training days and bidline conflicts into account as extra sources of crew unavailability, and observes that they have a dominant influence on reserve demand. Gaballa uses the probabilities of callouts as a guide to reserve sizing in [4]. The author observed that the reserve policy used by Quantas at the time was over conservative. The presented alternative approach was estimated to save $600,000 (1979) a year. Dillon and Kontogiorgis [3] present an approach for pilot reserve crew scheduling that generates reserve pairings which are then subject to crew bidding. They focus on quality of life considerations such as regularity. This work helped in negotiations with pilot unions.

III. THE PROBABILISTIC CREW DELAY MODEL

Our approach for reserve crew scheduling consists of three sequential steps: (1) *input generation* through *simulation*, (2) *probabilistic crew delay optimisation*, and (3) *validation*. Phase one estimates the delay probabilities and expected durations for each individual flight in the schedule using simulation and assumes no reserves are available for recovery. This

978-1-4799-0652-9/13 $31.00 © 2013 IEEE
DOI 10.1109/SMC.2013.334

information is then used as input for the probabilistic crew delay model (Phase 2), which generates a reserve schedule that minimises crew delay for the given inputs. The resulting reserve schedule is validated through simulation in phase three, during which reserves can be used for recovery. The individual components of our approach are described in more detail in Sections III-A, III-B, and III-C, respectively.

Notation

P	:	Probabilities of crew delay
p_{ij}	:	Probability of departure i being delayed by crew related delay propagating from flight j
$p_i = \sum_{j=1}^{ND} p_{ij}$	:	Total probability that departure i is delayed due to crew
Q	:	Hard copy of P after phase 1
L	:	Mean crew delays
l_{ij}	:	Mean crew delay of departure i propagated from flight j
D_j	:	List of departures with non-zero probability of crew delay originating in flight j
E_i	:	List of flights with non-zero probability of propagating crew delay to departure i
NS	:	Number of simulations used for input parameter derivation
ND	:	Number of departures
CT	:	Cancellation threshold
DT	:	Delay threshold
DL	:	Crew duty length
MS	:	Minimum sit period (rest time) for crew between consecutive flights
TT	:	Minimum aircraft turn time between consecutive flights
R	:	Number of reserve crew
X	:	Reserve crew schedule
x_k	:	Duty start time of reserve k
S	:	Schedule
C	:	Set of crew
A	:	Set of aircraft
S_i^{Dep}	:	Scheduled departure time of flight i
S_i^{Arr}	:	Scheduled arrival time of flight i
S_i^A	:	Aircraft scheduled to flight i
S_i^C	:	Crew scheduled on flight i
C_n^{eta}	:	Estimated time of arrival of crew n
C_n^{cst}	:	Duty start time of arrival of crew n
LDN_n	:	Last flight assigned to crew n
A_r^{eta}	:	Estimated time of arrival of aircraft r
a_i	:	Relative importance of flight i in objective function evaluation
cd_i	:	Crew related delay experienced by flight i
lcd_n	:	Crew related delay experienced by the previous flight crew n operated
pd_i	:	Probability a reserve is required to cover crew related delay at flight i
pr_k	:	Probability of reserve k being available to cover crew related delay

A. Phase 1: Input Generation

Simulation is used to generate two matrices P and L that contain the delay probabilities and the expected delay durations for each individual flight in the schedule. The simulation model uses delay distributions derived from historic data and applies aircraft swaps and crew swaps (but no reserves) to recover from disruptions. Crew delay can be divided into two categories: *root delays* where the cause cannot be traced back to preceding flight(s) and *propagated delays* which can be traced back to preceding flights. Each flight i in the schedule has two variables, cd_i and $lcd_{S_i^C}$, associated with it which correspond to the propagated and root crew related delays of flight i, respectively. For any two flight legs j then i which are operated by the same crew, $lcd_{S_i^C} = cd_j$. If cd_i and $lcd_{S_i^C}$ are both positive, at least some of the crew related delay is propagated delay. The exact value of cd_i is defined by Equation 1, and is equal to the delay that can be attributed to connecting crew discounting any delay due to the connecting aircraft and not including delays which are less than the delay threshold. The value of cd_i is equal to the delay that could be avoided/absorbed if a reserve crew were available for flight i. We reiterate that during phase 1 all other recovery actions except for reserve crew are considered and that the calculation of cd_i is performed after all other recovery actions have been considered and applied. This ensures that further reduction in delay is likely to be only achieved through the consideration of reserve crew use.

$$cd_i = max\left(0, C_{S_i^C}^{eta} + MS - max\left(A_{S_i^A}^{eta} + TT, S_i^{dep} + DT\right)\right) \tag{1}$$

If cd_i exceeds zero during simulation the matrices P and L are updated. Each row in P and L corresponds to a flight, and models the delay probability and expected delay duration for that flight. Each column in P and L corresponds to a flight from which crew related delay can propagate. Since crew related delay cannot propagate backwards through time, both matrices have a lower triangular structure (when flights are ordered in earliest scheduled departure time first).

Whenever a crew related delay occurs ($cd_i > 0$), the corresponding entries in P and L are updated using Algorithm 1, in which $a = 1/NS$. Root delays are modelled by the diagonal axis of P and L (i.e., p_{ii} and l_{ii}), and propagated delays are modelled by the off diagonal entries in P and L (i.e. p_{ij} and l_{ij} with $i \neq j$). Each entry in P and L therefore tells us the probability and the expected crew related delay duration propagated from flight j to flight i. Algorithm 1 states that when a crew related delay occurs at flight i, flight i can only be identified as a root cause of crew related delay if the crew related delay of flight i exceeds that of the crew related delay of flight j ($lcd_{S_i^C}$). Otherwise all of the crew related delay is propagated crew related delay.

Algorithm 1 Procedure for populating P during simulation

if $cd_i > 0$ **then**
  if $(cd_i - lcd_{S_i^C}) > 0$ **then**
    $p_{ii} = p_{ii} + a\left(\frac{cd_i - lcd_{S_i^C}}{cd_i}\right)$
    $p_{ij} = p_{ij} + a\left(\frac{lcd_{S_i^C}}{cd_i}\right)$
  else
    $p_{ij} = p_{ij} + a$
  end if
end if

B. Phase 2: Probabilistic Crew Delay Optimisation

The probabilistic crew delay model generates a reserve schedule that minimises the probabilistic crew delay for the delay probabilities and expected delay durations in P and L. It is assumed that: (a) reserves are based at the hub station only, (b) reserves have a zero response time, (c) each reserve crew can cover exactly one disrupted crew per duty, and (d) each flight requires exactly one team of crew. Further, it is assumed that, if a disruption occurs, reserves are allocated in earliest start time order. This maximises the remaining reserve crew duty time and results in an optimal recovery policy when each reserve crew can cover exactly one disruption whilst on duty. We assume reserve crew are used as demand occurs and never held in anticipation of larger crew related delays.

1) Objective Function: The objective function used in our probabilistic crew delay model quantifies the effects that a reserve crew schedule has on a disruption by iteratively calculating the probability that a reserve crew is still available (i.e., that they have not been used to handle previous disruptions) and can be used to cover a given crew disruption. Let p_i denote the probability that departure i ($i \equiv x_k + m$ in Algorithm 2) is delayed, and pr_k denotes the probability that reserve k is available to cover a crew related delay. Let pd_i denote the probability that reserve k is required to cover crew related delay of flight i. The probability that the reserve is still available to cover the next flight is then given by Equation 4.

$$pd_i = p_i \tag{2}$$

$$p_i = p_i(1 - pr_k) \tag{3}$$

$$pr_k = pr_k(1 - pd_i) \tag{4}$$

Equations 3 and 4 underpin Algorithm 2, which calculates the objective value of a reserve schedule (the expected total weighted crew related delay propagation for flights when the reserve schedule is enacted) for the delay probabilities and delay durations given by P and L. Algorithm 2 iterates through the R reserves in the schedule X in start time order, one at a time. For each reserve, the initial probability of availability is initialised to 1 and the probability that the first flight that occurs during the reserve's duty suffers a crew delay is initialised to 0 (a reserve is definitely available, line 2). Lines 3 to 6 iterate through all flights that can be covered by the respective reserve. The probabilities that a departure is still delayed after recovery using reserves is considered; a knock on delay occurs; or that the reserve crew is still available, are updated on lines 7 to 10, respectively. The reduction in future crew-related knock-on delays is calculated on line 9 using the Algorithm 4. The objective value for the entire schedule is calculated on line 17, and is equal to the weighted sum of the expected crew delay durations. The weight a_i denotes the relative importance of flight i and may be derived from factors such as passenger numbers or the availability of alternative flights for rerouting passengers. The $immedEval$ (Algorithm 3) and $knockOnEval$ (Algorithm 4) procedures used in objective function evaluation (Algorithm 2) calculate how the probabilities of crew related delays are reduced for a given reserve crew schedule. These reduced probabilities of crew related delay are used in line 17 to calculate the weighted sum of expected crew related delay which we are trying to minimise by manipulating the reserve schedule (X).

Algorithm 2 Objective function evaluation

1: $P = Q$
2: **for** $k = 1$ to R **do**
3: $pd_{x_k} = 0$, $pr_k = 1$
4: **if** $x_k < ND$ **then**
5: $m = 0$
6: **while** $S^{Dep}_{x_k+m} < S^{Dep}_{x_k} + DL$ **do**
7: **if** $S^{Arr}_{LDN_{S^C_{x_k+m}}} <= S^{Dep}_{x_k} + DL$ **then**
8: $pd_{x_k+m} = p_{x_k+m}$
9: Evaluate the immediate benefit of reserve ($immedEval(pr_k, x_k + m)$)
10: Evaluate knock on effects of reserve ($knockOnEval(pr_k, x_k + m)$)
11: $pr_k = pr_k(1 - pd_{x_k+m})$
12: **end if**
13: $m = m + 1$
14: **end while**
15: **end if**
16: **end for**
17: $objVal = \sum_{i=1}^{ND} \sum_{j=1}^{ND} a_i p_{i,j} (l_{i,j})^b$

The immediate effect that an available reserve has on the probability that the crew related delay of flight i still occurs is evaluated on Line 8. The exact evaluation is stated in Algorithm 3.

Algorithm 3 Procedure for calculating the effect a reserve crew has on the probability that flight i is delayed for crew related reasons

$immedEval(pr_k, i)$
for $j = 1$ to $|E_i|$ **do**
$p_{ij} = p_{ij}(1 - pr_k)$
end for

The purpose of accounting for knock-on delays is to determine the effect that a reserve available for flight j has on future delays. The probability of crew related delay of future flight i originating at flight j is reduced proportionally to the probability that a reserve is available for flight j and to the probability that flight i is delayed due to flight j. We also assume that the probability that flight i is delayed due flight j is proportional to ratio of the expected delay duration of flight j relative to i. This reasoning is applied recursively until all delay is absorbed, as shown in Algorithm 4.

Algorithm 4 Procedure for calculating the effect a reserve crew has on the probabilities of future crew related delays still occurring

$knockOnEval(pr_k, i)$
for $j = 1$ to $|D_i|$ **do**
$knockOnEval\left(pr_k\left(\frac{p_{D_{ij},i} l_{D_{ij},i}}{\sum_{k=1}^{|D_i|}\left(p_{D_{ij},k} l_{D_{ij},k}\right)}\right), D_{ij}\right)$
$p_{D_{ij},i} = p_{D_{ij},i}(1 - pr_k)$
end for

The outer loop in Algorithm 4 considers each flight j ($\in D_i$) that has a non-zero probability of experiencing a delay due to flight i. Within the loop the recursive call of the procedure is made. The probability that a reserve has an effect on the next layer in flight i's probabilistic delay propagation tree (for more delay propagation trees see [1]) is reduced proportionally to the probability that the delay will propagate. The second line in the procedure evaluates the probability that a crew related delay still occurs given that the reserve was available at flight i.

2) Search Algorithm: For this paper the model is solved using a greedy heuristic which proceeds by adding one reserve crew to the schedule at a time, choosing a duty start time (discretised according to scheduled departure times) such that the reduction in the objective value is maximised. The simplicity of this search algorithm and the results which are shown in Table I in Section IV show that this modelling approach outperforms a variety of alternative reserve crew scheduling approaches even without solving the problem to optimality. A local search approach was also considered, where the neighbourhood structures which were used included single swap, cut and insert and power set shift, and the results are shown in Section IV. The "power set shift" neighbourhood is defined as each possible lateral shift of each substring of a binary string solution bounded by 1's such that the shift does not overwrite any surrounding 1's.

C. Phase 3: Validation

Simulation was also used to validate the probabilistic reserve crew scheduling model described above, this time considering reserves as one of the recovery actions. Our simulation model is based on a single hub airline, assumes that all aircraft belong to the same fleet, and that reserves are based at the hub. Each departure from the hub station is modelled as an out-and-back cycle, so from the hubs perspective each departure results in an arrival after visiting a single spoke station. This modelling simplification means that block time distributions for each spoke destination account for the time between leaving the gate at the hub to the time the aircraft arrives at the gate back at the hub. Journey time distributions were provided by [6].

The simulation model consists of a stochastic element and a recovery component. The stochastic element assumes that, when the scheduled departure time of flight i is reached, the expected arrival time of its previous flight is known with sufficient accuracy in order to determine the effectiveness of different recovery actions. It considers each flight in the order of planned departure time and uses the previous arrival time of the crew and aircraft, augmented by the minimum sit time (MS) and minimum turn time (TT) to determine the earliest departure time. If the earliest departure time exceeds a delay threshold (set to 15 minutes) the recovery module is called. The recovery module uses pairwise aircraft and crew swaps, and reserves (as a last resort) to recover from the delays, or to minimise their impact. Swaps are considered feasible if the delay is reduced without delaying other flights involved in the swap. If crew are swapped, the respective crews must be able to finish one another's duty. If no recovery is possible, or if the cancellation threshold (set to 180 minutes) is still exceeded after recovery, the respective flight is cancelled. Once the necessary recovery actions have been implemented, a journey time is selected randomly from the relevant distribution.

IV. Results

A. Data Instances

The schedules considered here cover a time span of 24 hours, contain 300 flights carried out by 37 aircraft and approximately 120 teams of crew. All aircraft are assumed to be of the same fleet type to simplify the analysis of the results. All instances were generated using a custom developed instance generator that is underpinned by real world data.

Airline schedules that contain a risk of crew related delay propagation are required to show the method's effectiveness. Such a risk can be introduced by increasing the number of aircraft changes by crew and by reducing the time available to make those connections. Without either of these characteristics, crew delay will propagate less frequently. In such cases delay is a direct consequence of other uncertain events.

In order to vary the level of risk of crew related delay propagation, our instance generator has two parameters that can be altered. The first $OnTime\%$ chooses the allocated block time (gate to gate) such that the specified % of flights according to journey time distributions are completed on time. Aircraft routings are generated by assuming that each aircraft serves exactly one remote destination and shuttles back and fourth with a ground time equal to the minimum between each flight leg. As a result $OnTime\%$ effectively determines the aircraft routing and all scheduled departure and arrival times. Increasing the $OnTime\%$ has the effect of increasing the chance connecting crew will be able to make the connection without causing a delay to the awaiting aircraft. The second parameter $PofAC$ (probability of aircraft change) is the rate of aircraft changes of crew and controls the risk of crew related delay in an airline schedule.

25 schedules were created using each pairwise combination of the following parameter sets. $PofAC = [0, 0.1, 0.2, 0.3, 0.4]$ and $OnTime\% = [0.55, 0.6, 0.65, 0.7, 0.75]$. These 25 schedules are used in §IV-B and §IV-D1. These parameters were chosen to be representative of real values, to give some degree of confidence that the method will work in a variety of real world situations.

B. Convergence

Since P and L were approximated using simulation in phase 1 (§III-A), it was necessary to ensure that sufficient iterations had been performed to allow these matrices to converge. Here we concentrate on convergence of the rows of P and L, or more specifically the overall probability of crew related delay of each flight and the overall expected delay duration of crew related delays respectively regardless of the root cause of crew related delay. K-fold cross validation was used for this [5]. A partition in this case corresponds to a P or L matrix derived from a number of simulations, the number of simulations defines the sample size. The results are illustrated in Figure 1, showing the average root mean squared errors over

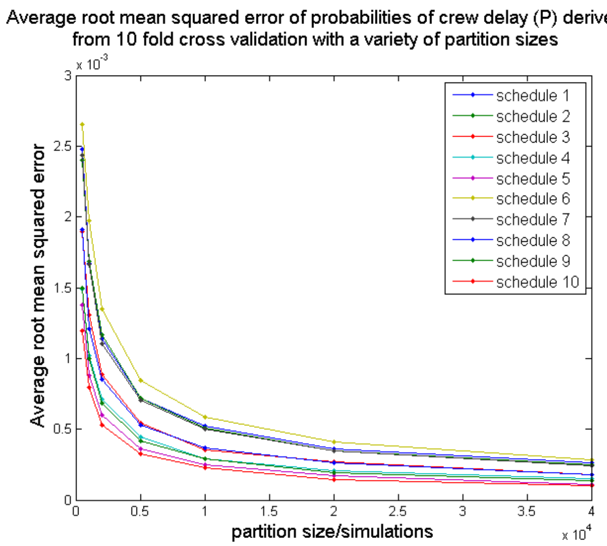

Fig. 1. Average root mean squared error of P parameters derived from simulation using 10-fold cross validation for a variety of sample sizes

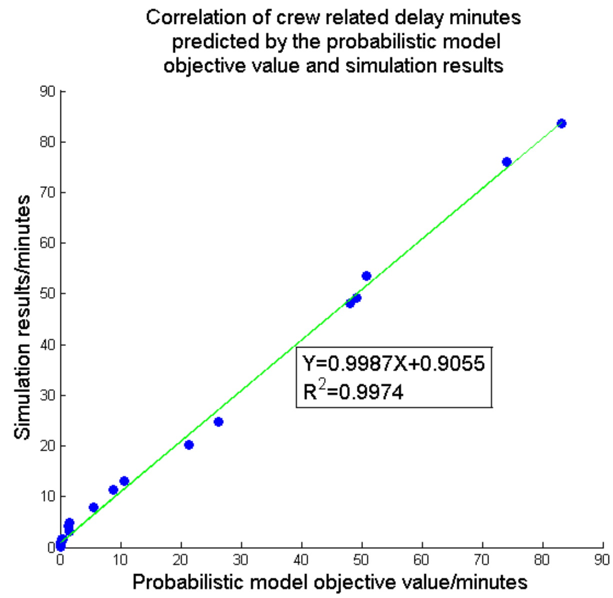

Fig. 2. Probabilistic model predicts crew related delay observed in validation simulations

all departures from a sample of 10 schedule instances. Seven different simulation sample sizes were considered.

It can be observed from Figure 1 that the average root mean squared error for P falls between $0.2e-3$ and $0.5e-3$ depending on the schedule that is considered. Full convergence to zero may require a number of simulations many orders of magnitude larger than the sample sizes considered here. The reason is that the number of reachable simulation configurations or states is excessively large. Based on a trade off between parameter accuracy and the time required to run the simulations, 20000 simulations was considered to be sufficient to derive useful estimates of P and L for any given schedule instance. L has a very similar convergence rate to P.

C. Accuracy of the model

The 25 problem instances generated above were solved using the three-phase approach described in Section III. The resulting objective values, equal to the expected crew related delay propagation, were recorded. The reserve schedules that were generated were simulated to estimate the total expected crew related delay. The values of the simulation model were then compared against the objective function values obtained by the probabilistic crew delay model. The results are shown in Figure 2.

In order to conclude that the probabilistic model accurately predicts the crew related delay, there should be a linear relationship with gradient 1 and intercept 0 between the values obtained by the probabilistic model and the simulation. It can be observed from Figure 2 that a nearly perfect linear relationship with gradient close to 1 and intercept slightly above zero exists between the expected crew delay predicted by the probabilistic model and the crew delay observed during the simulation. This shows that the probabilistic model is consistent and accurately predicts how reserves are used, as well as the impact they have.

D. Comparison with other approaches

To validate the probabilistic model as an effective approach for scheduling airline reserve crew taking into account other recovery actions and operational uncertainty, a comparison was made between the approach presented here and other alternative approaches (briefly introduced below). Simulation was used to validate the reserve crew schedules obtained by each of the individual approaches and to derive performance measures that reflect their quality. The performance measures of interest are the number of cancellations, the reserve utilisation, the crew related delay propagation and total delay propagation. Approaches which required simulation were limited to 20000 runs to determine a reserve schedule for a given planned day of operations. For each schedule, 8 teams of reserve crew were to be scheduled.

1) Models: Various models are evaluated including variants of the probabilistic model and two other types of method that are not probabilistic.

Probabilistic models: Different variations of the probabilistic model were developed and compared against the model introduced above. The first two variations of our approach, denoted by *Prob 1* and *Prob 2*, have a delay exponent equal to 1 (b in Algorithm 2) and 2, respectively. The idea is that having a delay exponent greater than 1 will lead to reserve crew schedules that provide more coverage for departures associated with larger expected delays. *Prob** is the same as *Prob 1* except that (Algorithm 4) is removed from Algorithm 2. This enables us to verify whether this aspect of our model results in improved reserve crew schedules. In our last variation of the probabilistic model, denoted by *Prob LS*, the greedy algorithm used in *Prob 1* was replaced with a local search algorithm, enabling us to verify the influence of the search algorithm on the quality of the resulting reserve crew schedules.

Area under the graph: Area 1. This approach runs a number of simulations and records the total crew related delay associated with each departure. Reserves are then scheduled such that each reserve covers an equal amount of the total crew related delay. The name "area under the graph" comes from the visualisation of how this method works. If you imagine a bar chart of the total crew related delay for each scheduled departure, the reserve schedule is based on dividing the bar chart into R adjacent equal area segments. The reserves are then scheduled to begin duties at the departure times corresponding to the beginning of each equal are section.
Iterative area under the graph: Area 2. This approach is an iterative variant of *Area 1*. The reserves are used in the simulation to iteratively derive when reserves are likely to be needed. This approach is divided into stages where each stage derives a reserve schedule (as in *Area 1*) based on the results from the previous stage. The next stage uses the new reserve schedule to derive more information about when reserves are required. A possible pitfall of this approach is that it may not converge.

The next two approaches try to maintain an equal distribution of reserves in two slightly different ways.
Uniform start rate: Uniform. This solution approach starts reserve crew duties at equal times intervals throughout the scheduled day of operations.
Equal intervals of useful duty time: Useful. This approach calculates for each departure time considered as a possible reserve duty start time the total flight time of flights for which the reserve would be feasible to cover had they started at that time and given a fixed duty length. The cumulative vector of these total feasible duty hours for each departure time considered as a possible reserve duty start time is converted to a reserve schedule by finding the intervals corresponding to integer multiples (up to R) of the total cumulative sum of feasible duty hours corresponding to each possible departure time divided by the number of reserve crew available for scheduling.

2) Observations: The simulation used to validate the approaches described above implements a recovery policy which first considers crew and aircraft swaps, and subsequently reserve crew in conjunction with aircraft swaps. The validation simulation also assumes that once reserves are used they are treated as regular crew and once regular crew are replaced by reserves, the regular crew cannot be used as reserves. However, the simulation is general enough to allow for changes to these assumptions.

Table I shows cancellation rates, reserve utilisation rates average crew delays, average delays, probabilities of crew delays over 30 minutes, and solution times for 8 methods of reserve crew scheduling. The results are based on 20000 repeat simulations for each of the 25 schedule instances for each method. This means that each method is tested on 500,000 days of operations with a total of 150,000,000 simulated departures. The first row *No res* shows the results corresponding to no scheduled reserves. The results show that cancellations due to delays are very rare and that *Prob 1* minimises cancellations and gives the lowest average crew related delay. *Prob LS* gives the highest reserve utilisation rate. The *Useful* heuristic gives the lowest average delay, however this is actually a result of this method also having the highest cancellation rate. Cancellations prevent further delay propagation by giving a single flight the maximum possible delay (a cancellation). This was confirmed by running the same simulation tests without a cancellation threshold, in which probabilistic model 1 had the lowest average delay whilst the *Useful* method had the highest average delay. *Prob 1* and *Prob 2* have the lowest probabilities of crew delays over 30 minutes with *Prob 2* having the lowest, this can be attributed to the delay exponent of 2 used in the objective function. All of the methods that are based on simulation (*Prob 1,*,2,LS* and *Area 1,2*) took over 20 minutes to find reserve schedules for all of the 25 schedule instances, almost all of this time is spent running simulations to derive parameters for the respective models. *Prob 2* took slightly longer than *Prob 1*, the only explanation for this is that the presence of the delay exponent of 2 in the objective function made the objective function computationally more demanding to compute. The *Prob ** results indicate that removing the $knockOnEval$ procedure given in Algorithm 4 from function evaluation (Algorithm 2) results in marginally higher average crew delay and total delay however the cancellation rate is reduced, however cancellations are negligible on the using all methods.
In general the probabilistic model based approaches were most effective. Of the four variants of the probabilistic model the method *Prob 1* dominated the other variants on nearly all performance measures considered including the main objective criterion used in this investigation which is to minimise crew related delay.

TABLE I
SIMULATION DERIVED PERFORMANCE MEASURES FOR A VARIETY OF SOLUTION METHODS

Solution method	Cancel rate	Reserve utilisation	Avg. crew delay	Avg. total delay	Prob. of delay > 30 min	Solution time (sec)
No res	4.18E-6	0.0000	0.3465	2.0846	2.58E-3	0
Prob 1	2.20E-6	0.7890	0.1394	1.5511	7.95E-4	1226
*Prob **	2.40E-6	0.7863	0.1414	1.5735	7.95E-4	1219
Prob 2	2.41E-6	0.7797	0.1407	1.5769	7.83E-4	1232
Prob LS	2.51E-6	0.7894	0.1399	1.5528	8.04E-4	1400
Area 1	2.41E-6	0.7332	0.1542	1.6383	8.22E-4	1215
Area 2	2.43E-6	0.7331	0.1537	1.6376	8.23E-4	1216
uniform	2.35E-6	0.6771	0.1827	1.5420	1.29E-3	1

V. CONCLUSIONS

A probabilistic model for scheduling airline reserve crew in anticipation of delays was presented. The probabilistic model takes schedule uncertainty into account as well as the availability of other recovery actions. Simulation provides the mechanism which makes this possible. The probabilistic model is also able to anticipate the future impact of the reserves it schedules in terms of the absorption of crew delays that are likely to propagate further in a schedule. The method was tested over a range of schedule instances in which the likelihood of crew related delay propagation was controlled with schedule generation parameters. It was shown that the probabilistic approach accurately models the expected crew related delay associated with a given flight schedule and reserve crew schedule combination. In comparison with a range of alternative approaches to reserve crew scheduling the probabilistic model proved most effective overall and using a delay exponent in the objective function greater than 1 leads to reserve crew schedules that minimise the probabilities of longer crew delays. We also found that average delays can be reduced be increasing the number of cancellations (shown by *Useful* in table I. Additionally we provided results suggesting that the recursive procedure (Algorithm 4) for factoring in the effect of knock on crew delays absorbed by reserves scheduled previously appears to reduce average delays at the expense of a marginal increase in cancellation rate. The solution times are also reasonable from a practical point of view.

Future Work

This paper mainly focussed on introducing a probabilistic crew delay model for airline reserve crew scheduling. The results are based on a specific airline simulation implementing a given recovery policy. Future work could investigate the the interaction between the reserve crew schedule and the recovery policy used by the airline. It is expected that the reserve crew schedule will be sensitive to the exact recovery policy used by an airline. The approach introduces above could be used to investigate this interaction.

Acknowledgements

Many thanks are owed to KLM for providing data and perspectives based on first hand experience. Thanks are also owed to the technical support group in the computer science department, the administrative staff at ASAP and the partial funding provided by the LANCS initiative. We would also like to thank the anonymous reviewers for their helpful comments.

References

[1] Shervin AhmadBeygi, Amy Cohn, and Yihan Guan. Analysis of the potential for delay propagation in passenger airline networks. *Journal of air transport management*, 2008.

[2] Alexandre Boissy. Crew reserve sizing. In *Agifors syposium*, 2006.

[3] Jeffrey E. Dillon and Spyros Kontogiorgis. Us airways optimises the scheduling of reserve flight crews. *Interfaces*, 29(5):123, September/October 1999.

[4] Adel Gaballa. Planning callout reserves for aircraft delays. *Interfaces*, 9(2), February 1979.

[5] Hastie and Tibshirani. Cross validation and bootstrap. In *http://www-stat.stanford.edu/ tibs/sta306b/cvwrong.pdf*, 2009.

[6] KLM. Private communication.

[7] T. Glennn Bailey Milind G. Sohoni, Ellis L. Johnson. Operation airlines reserve crew scheduling. *Journal of Scheduling*, 2006.

[8] Marc Paelinck. KLM cabin crew reserve duty optimisation. In *Agifors proceedings*, 2001.