Robust Airline Crew Scheduling

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The airline crew scheduling problem is to find a set of crew itineraries or pairings that minimize the crew cost. The problem is modeled as the set partitioning problem max$\{cx{:}Ax=1, x$ binary$\}$, where c_j is the cost of pairing j and a_{ij} is 1 if pairing j covers flight i. The problem is computationally hard due to the large number of variables, complex pairing feasibility rules and nonlinear costs. All existing approaches to airline crew scheduling use the planned cost of a pairing, which is a nonlinear function of the sequence of legs flown by the pairing. These models assume that any crew schedule may be flown as planned, and that the operational cost of a crew schedule is its planned cost. In fact, delays and disruptions are pervasive, and airlines are rarely able to operate all the flight legs. The operational cost of a crew schedule depends on these stochastic events since a flight delay results in an increased pairing cost and potentially into calling on duty a reserve crew. For large fleets the operational cost may be eight to ten times larger than the planning cost. Current solutions produce low planning cost by using many short connections that are vulnerable to disruptions. This fact clearly calls for solutions in the planning stage that are more robust, i.e. solutions that can produce lower cost in operations. The robust airline crew scheduling problem is to find crew schedules that are not necessarily optimal in planning, but perform well in operations. .

The airline industry is currently under pressure to improve its on-time performance. The number of delayed and cancelled flights has dramatically increased since 1995, e.g. the number of delayed flights has increased by 11%. The situation got even worse during Summer 2000 when no U.S. airline had an on-time performance better than 75%. These facts call for robust solutions and for a divergence from the traditional thinking that an airline will operate as planned. We believe that our research is one of the first attempts in this direction.

Solving the crew scheduling problem in planning is an involved and time consuming process. Finding a crew schedule that minimizes the expected operational cost is even harder, since it would involve solving a multi-stage stochastic optimization problem with an enormous state and action space. We give two, possibly complementary, heuristic approaches for finding robust crew schedules. In the first one [2] we find an approximate expected cost of each pairing, and then we solve the traditional crew scheduling problem by using these costs. The second approach considers crews that can be swapped in operations. This approach also gives the airline flexibility in canceling flights since it produces several crews that can in operations cover the same flight.

In studying robust crew scheduling, it is necessary to evaluate schedules by simulation. We use SimAir [1] to evaluate the operational performance of various crew schedules. Recovery is the procedure in operations that reschedules aircraft and crews, and it reroutes passengers. SimAir takes as input a recovery procedure, a flight schedule, a crew schedule and delay distributions, and simulates many days of airline operations. It calculates the average operational crew cost, average on-time performance, the number of passengers who miss connections, etc.

The first approach relies on the underlying recovery procedure when evaluating the expected cost of a pairing. The recovery procedure affects the operational cost and therefore it should be taken into account in robust crew schedules. In operations crews share resources such as planes, gates, passengers and flight attendants. Furthermore, some recovery techniques allow crews to fly legs to which they were not originally assigned. Such recovery methods create interactions between pairings and therefore it is extremely difficult to compute an exact expected cost of a pairing. We make two assumptions in estimating the expected pairing cost. The first one is that planes, passengers and flight attendants are always available, and the second assumption requires that in response to a disruption, a flight is delayed until the scheduled departure time has passed and the crew is available. In other words, we ignore the crew costs that arise from the interaction among pairings and we also prescribe a recovery method that pushes back the departure of any flight if its scheduled crew is not available. These two assumptions related to the recovery procedure are not satisfied in practice. The expected cost of each pairing under these assumptions is estimated through a simulation. In contrast to SimAir, this simulation considers only the pairing in question. This procedure simulates at least some minimum number of days of daily operations, and terminates when either a maximum number of days is considered or the confidence interval is sufficiently small.

Let c'_j be the expected cost of pairing j from the simulation. Next we solve $\max\{c'x{:}Ax=1, x \text{ binary}\}$ to obtain our crew scheduling solution. For three fleets from a major domestic carrier, we considered the crew schedule obtained using the expected cost of each pairing and the crew schedule found using the planned cost of each pairing, and then we computed their respective operational cost with SimAir. We found that the schedules obtained by using the expected pairing cost have lower operational costs than the crew schedules found using the planned pairing cost. To measure the impact of the two assumptions we determined how much of the operational cost increase was due to the interaction among pairings. For all six crew schedules, the cost due to these interactions ranged from 4% to 11 % of the total operational cost increase. In other words, our assumptions left only a small portion of the operational cost increase unexplained.

In our second approach we present a model that addresses robustness by considering crews that can be swapped in operations. There is a minimum required connection time between any two flights in the same pairing. We add to the traditional crew scheduling model the second objective of maximizing the number of move-up crews. Given a crew $c2$ covering a flight i, a move-up crew $c1$ is a crew that is ready to fly at the departure time of flight i, see Figure 1. Such a crew can, in case of a delay of the inbound flight *i*' of crew *c*2, cover flight *i*. The two crews can be swapped in operations. In addition, move-up crews give the airline the flexibility to choose either to cancel flight *i* or the flight *j*' of the move-up crew since the move-up crew *c*1 can cover either of the two flights. To capture the objective of maximizing the number of move-up crews the traditional set partitioning model has to be extended with additional variables and constraints. Since it is desirable that a move-up crew *c*1 originates from the same crew base as crew *c*2 and that it has the same number of days till the end of the pairing, we must record the crew base of the pairing covering flight *i* and we must have information on the number of days till the end of the pairing. These two facts lead to additional variables and constraints. However a large portion of the model has the same number of nonzeros as the traditional set partitioning model and therefore it should not be substantially more difficult to solve.

The computational results on a small fleet have shown that solutions from such a model yield a much larger number of move-up crews and are more robust. Larger fleets have to be solved with a Lagrangian decomposition or resource decomposition approach. In a Lagrangian decomposition approach we relax the constraints that count the number of move-up crews and the resulting problem is a variant of set partitioning. The resource decomposition approach solves the problem by assuming that the crew base of the pairing covering each leg is known and the number of days till the end of the pairing is known as well. It then iteratively changes this given information in such a way that we get solutions with better objective values. Branch-and-price heuristics are also an alternative since we have developed a column generation scheme that is not more complicated than the one for the traditional crew scheduling problem. These three methodologies are currently under investigation.

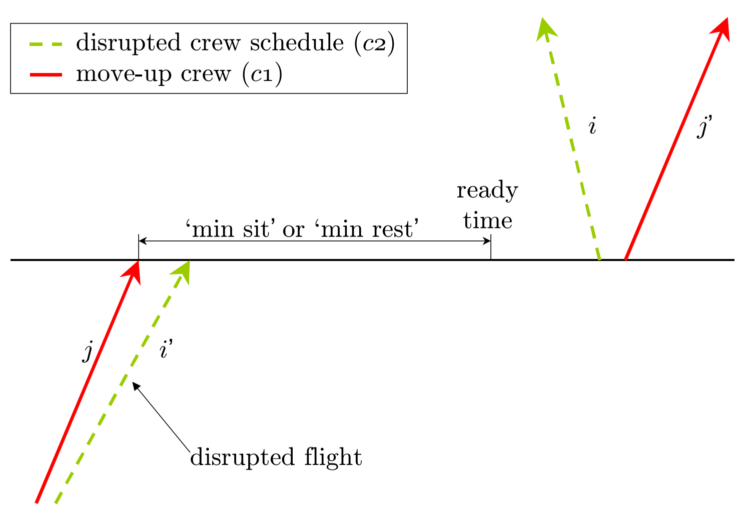

Figure 1

References

1. J.M. Rosenberger, A.J. Schaefer, D. Goldsman, E.L. Johnson, A.J. Kleywegt, and G.L. Nemhauser, *A Stochastic Model for Airline Operations,* Technical report TLI/LEC-00-06, Georgia Institute of Technology (2000).
2. A.J. Schaefer, *Airline Crew Scheduling under Uncertainty*, Ph.D. dissertation, Georgia Institute of Technology (2000).