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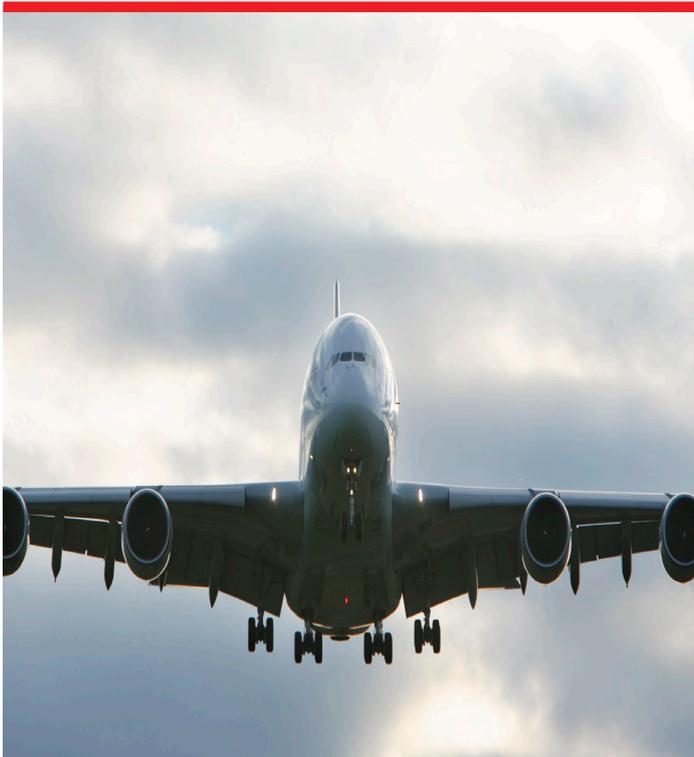
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Optimal assignment of incoming flights to baggage carousels at airports



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Optimal assignment of incoming flights to baggage carousels at airports

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Abstract

The problem considered in this report is an assignment problem occurring at airports. This problem concerns the assignment of baggage carousels in baggage claim halls to arriving aircraft (*baggage carousel assignment problem*). This is a highly dynamic problem since disruptions frequently occur during operations. We introduce a basic static model that can be adapted to the layout of different airports. Afterwards we show how a decision support system based on a MIP-model can be designed in a dynamic real world environment. The system supports the decisions of the dispatcher during daily operations. Computational results for a real world problem at Frankfurt Airport are presented. At Frankfurt Airport the suggested solution method was successfully implemented and is running now for over half an year. The experiences show that the system increases the quality of the dispatching process and in general is a substantial support in decision making.

Keywords: Airport Optimization, Real World Optimization, Multi-Criteria Optimization, Baggage Handling, Robust Optimization

1 Introduction

1.1 General Problem Description

The problem investigated is to assign every incoming passenger flight to the baggage carousels in the baggage claim areas of an airport where passengers pick-up their checked-in bags.

In this paper we look at the dispatching processes in the daily airport operations. The process for steering the inbound baggage may be different from airport to airport since it depends on the airport infrastructure and organizational structure. Moreover the needs of the passengers and the negotiated agreements with baggage handling companies and airlines also influence the decisions.

We consider the following set-up: The baggage infrastructure department of the airport is responsible for the selection of one or more baggage carousels for each flight. There are several hard constraints limiting the freedom of choice given by the terminal building and the laws from the authorities e.g. the need of custom controls or passport checks. If these constraints are applied, there

usually exist different options for assigning each flight to a carousel. Today a human dispatcher decides which flight is assigned to which baggage carousel. The dispatcher is supported by several different IT-systems. He can access different kinds of information and the relevant data are visualized to support his decisions. This set-up represents the situation at Frankfurt Airport.

Each flight can be assigned to no more than three baggage carousels simultaneously. In general, one flight is assigned to one baggage carousel, but for very large flights it can be necessary to use two neighboring baggage carousels at the same time. It is possible to assign an additional baggage carousel to a flight for first class passengers or crew luggage.

The dispatching process starts in general about 30 minutes before the arrival of the aircraft. The dispatcher starts to look at the data and characteristics of the flight and prepares the decision. The decision cannot be seen isolated but as a trade-off between all flights which should be handled in the same area. At the latest when the aircraft arrives at the parking position it is necessary to decide about the baggage carousel assignment. The handling processes start with the arrival of the aircraft. The handling companies need to know the destinations for the bags and the passengers. The destinations are defined by the assignment to baggage carousels. If the parking position is not at the terminal building, the passengers will be transported by buses to the terminal building. The destination for the bus transport depends on the assigned baggage carousel since there can be several entry points in the terminal building depending on the assigned baggage claim area.

The handling process can be described as follows: The bags will be unloaded from the aircraft and then transported to the handling facilities at the terminal building. The bags are stowed in containers, pallets or as loose bags in the aircraft. Loose bags will be transported in dollies. One or more handling facilities belong to each baggage claim hall. We assume that for each baggage carousel there is one belt in a handling facility and that these baggage belts are directly connected to baggage carousels e.g. by conveyor belts. The bags will be unloaded to these baggage belts and then be delivered by conveyor belts to the baggage carousels in the baggage claim hall.

In this article we assume that the scheduling of staff for the unloading from the aircraft and as well the scheduling of the transports are independent problems which are solved independently from the baggage carousel assignment problem. The duration of these processes can be calculated based on past experiences.

When solving the presented problem in a real world environment, there are different challenges to handle. First, often the number of available handling resources is limited. This is especially true in peak hours. Furthermore, the problem is of highly dynamic nature since the input data can alter on very short notice e.g. arrival times, aircraft parking positions. Therefore, the results should be robust to delays and other unforeseen events. It is necessary to satisfy different needs of passengers, airlines, ground handling companies and the airport infrastructure. Furthermore, the solution approach has to be flexible to changes of the business processes and management objectives. The handling

of inbound baggage is one of the critical processes at an airport. Long waiting times, crowded baggage claim halls, reschedulings, missing or wrong displays can be very unsatisfying for passengers and can lead to a bad reputation of the airport. Furthermore, airlines and ground handling companies will complain if agreements are disregarded.

The problem is to assign the flights to baggage carousels in a feasible way. The objective is to get a robust plan, that satisfies the preferences of airlines, passengers and handling companies as much as possible. Furthermore, the flights should be distributed in a balanced way to the baggage carousels.

We present an MIP-model of the static problem and show how the model can be used in a dynamic environment. The model can be solved with a commercial MIP-solver. Computational results are presented for real-life passenger data for one of the world's largest airports. Studying the results from Frankfurt Airport, a theoretical improvement in the achievement of the business objectives was shown. Furthermore, a high acceptance of the suggested solutions was reported.

1.2 Related Work

Since the presented problem is an assignment problem in a dynamic environment, the problem could be modeled as a dynamic assignment problem. The dynamic assignment problem and solution strategies are described in Spivey and Powell (2004). The static problem could also be seen as a resource constrained project scheduling problem. Brucker et al. (1999) give an overview of resource constrained project scheduling problems (RCPSP). In general the RCPSP belongs to the class of the scheduling problems (for an overview see Roberts and Vivien (2010)). The baggage carousel assignment problem is an online scheduling problem (for description of online scheduling problems see Albers (2010)), since the task and the specific times are not known for all flights in advance. Since we try to optimize different objective criteria, the problem can also be seen as a multi-objective scheduling problem.

Most articles in the area of optimization at airports deal either with the gate assignment problem or workforce planning. For the daily airport operations the contribution is quite rare. Examples for research in this field are: Clausen and Pisinger (2010) have examined the dynamic routing of transfer baggage. Barth (2012) presented a successful implementation of a decision support system for the handling of transfer luggage.

Similar to the baggage carousel assignment problem is the handling of outbound flights. This problem was already studied by a few researchers. In Abdelghany et al. (2006) the assignment of handling facilities to outbound flights was studied. The study was made for airports in northern America. These results cannot be compared to the situation at European airports since in northern America the airlines are connected closely to the terminal buildings and the operations are significantly less connected between airlines as in major European airports (Graham (2008)). Different models for the scheduling of outbound baggage to handling facilities were presented by Ascó et al. (2011), Frey et al. (2010) and Barth and Pisinger (2012).

The baggage carousel assignment problem for inbound flights has similarities with the problem but there are some major differences. One difference is that the arrival time of the luggage in the inbound problem is fixed in contrast to the outbound problem where it is possible to store the bags in storage spaces until the handling starts. Furthermore, the objectives of the problems are different with a focus on feasibility for the outbound baggage handling problem and on delivery time for inbound baggage handling problem. Recently, first approaches for the problem were presented by Delonge (2012), Frey et al. (2012) and Barth and Böckmann (2012).

1.3 Outline

The remaining paper is structured as follows: Section 2 presents a basic MIP-model of the static problem and possible extensions of the basic model. The solution method is described in Section 3. The real world application at Frankfurt Airport and the experiences are presented in Section 4. Detailed computational results including a comparison between the decisions of the dispatcher and the developed algorithm are shown in Section 5. This section also includes important issues concerning the calibration of the model. Finally, conclusions and further work are discussed in Section 6.

2 Formal Problem Description

2.1 Basic Model

The baggage carousel assignment problem can be modeled as an extended assignment problem. The solution of the problem consists of an assignment for each flight to one or more baggage carousels. Both, the assignment of the flights to baggage carousels and the overall combination of the chosen assignments have to be feasible.

Given is a set of flights F and a set of baggage carousels B . Each baggage carousel $b \in B$ belongs to one baggage claim hall h in the set of all baggage claim halls H . The set of all baggage carousels in one baggage claim hall h is given by B^h . For each flight $f \in F$ a feasible assignment which optimizes the given goals has to be selected.

It is possible to precalculate all feasible assignments, since the solution space is limited by the available baggage carousels. If a flight is already fixed by the dispatcher, only one assignment — with the chosen baggage carousels — is generated. The set of all assignments is denoted as A and the set of assignments for a specific flight f as A_f .

The model regards only flights in a specific time horizon. The set of all timeslots during the considered time horizon is denoted by T . The length of one timeslot $t \in T$ is l and the planning horizon is thus given by $L = |T| \cdot l$.

The major decision variable for the model is x_a for each $a \in A$. This variable indicates if an assignment is chosen or not. Furthermore, there are several other

Objective	Min / Max	Explanation
Airline preferences	Max	Fulfillment of airline preferences e.g. local proximity to handling agent for missed bags
Transportation time	Min	Time from aircraft parking position to handling area
Continuity of suggestions	Max	No or only small difference between suggestions of two optimization runs
Suitability of baggage carousels	Max	Rating of the suitability of the baggage carousels in general (e.g. operational handling, passenger ways)
Restrictions	Min	Restriction on the handling capacities at one baggage carousel e.g. number of passengers, bags, containers)

Table 1: Examples of soft constraints expressed as direct costs in the objective function

decision variables to calculate the violation of soft constraints. These variables are denoted with "y" as prefix and are explained below.

The objective function of the model consists of two parts of soft constraints. In the first part each criteria can be directly computed as costs on the single assignments. These soft constraints are precalculated and are converted in costs for each assignment (named *direct costs* in the following). The second part of the objective criteria expresses soft constraints which are part of the mathematical model (called *bounding soft constraints* in the following). The decision variables introduced for these constraints depend on the combination of the different assignments and resources. The objective function and the constraints related with these soft constraints are formulated as linear equations. An quadratic formulation is avoided by calculating the sum of the resource usage for the selected assignments at a specific timeslot. Tables 1 and 2 show several examples for soft constraints of direct costs and bounding soft constraints. The concept of soft constraints in the objective function was used by Hansen (2010) for the manpower planning and task scheduling problem. In the model presented in Hansen (2010), the under and over coverage was measured in the objective function. Our model generalizes this approach.

The set of all cost types c is called C . For each each assignment a and cost term c the cost are given by $o_{a,c}$. Furthermore, the sign is defined by n_c (here $n_c = -1$ means minimization and $n_c = 1$ means profit / maximization) and the weight as w_c .

The set of all soft constraints s is called S . For the sign n_s and the weight w_s apply the same rules as seen above for set C . A soft constraint always applies to a set of resources R_s . For each soft constraint s the contribution of each assignment a at a specific timeslot t for the resource $r \in R_s$ is given by $u_{a,s,r,t}$. We assume that there are capacities $CAP_{s,r,t}$ connected with each soft constraint s , resource $r \in R_s$ and timeslot t . These capacities are the relaxed limits of the different resources related with the soft constraints. The bounding soft constraints can be classified in three different categories:

- ordinary soft constraint s_o : aims to minimize the resource usage above a limit, this means the given capacities $CAP_{s_o,r,t}$ are relaxed limits of the resource usage

Objective	Min / Max	Explanation	Type of constraint
Limitations of display	Min	At some airports the number of displayed flights at a baggage carousel is limited	s_o
Avoidance of parallel handling	Min	Two flights at one baggage carousel should not be handled at the same time	s_o
Avoidance of parallel handling at neighboring carousels	Min	The handling of two large flights at neighboring baggage carousel should not be at the same time since the space for the passengers is limited	s_o
Balanced usage of carousels in baggage claim halls	Max	For efficient resource usage a balanced distribution over all baggage carousels is desired for each baggage claim hall.	s_b or s_d
Balanced usage of all baggage claim halls	Max	For efficient resource usage a balanced distribution over all baggage claim halls is desired.	s_b or s_d
Avoid bottlenecks in passenger flow	Min	The passenger ways can depend on the selected baggage carousel or baggage claim area.	s_o
Avoid bottlenecks at bus arrivals	Min	The bus arrivals can depend on the selected baggage carousel or baggage claim area.	s_o
Avoid bottlenecks at passport checks	Min	The distribution of passenger on the passport checks can depend on the selected baggage carousel or baggage claim area.	s_o
Breaks between flights	Max	Delays or early deliveries do not cause immediately handling problems if there are breaks between the different flights	s_o

Table 2: Examples of bounding soft constraints

- box constraint s_b : aims to minimize the positive and negative deviation of the resource usage for each $r \in R_{s_b}$ from the average resource usage of all resources $r \in R_{s_b}$
- distance constraint s_d : aims to minimize the distance between minimum and maximum resource usage of a all resource $r \in R_{s_d}$

The objective function of the model is calculated as follows:

$$\begin{aligned}
\min \sum_{a \in A, c \in C} n_c \cdot w_c \cdot o_{a,c} \cdot x_a + \sum_{s_o \in S_o} n_{s_o} \cdot w_{s_o} \sum_{t \in T, r \in R_{s_o}} y_{s_o, r, t} \quad (1) \\
+ \sum_{s_b \in S_b} n_{s_b} \cdot w_{s_b} \sum_{t \in T, r \in R_{s_b}} y_{s_b, r, t} + \sum_{s_d \in S_d} n_{s_d} \cdot w_{s_d} \sum_{t \in T} y_{s_d, t}
\end{aligned}$$

The first part in (1) calculates the direct costs and the following parts are each related to one category of bounding soft constraints. The problem is formulated as a set partitioning problem with additional constraints. There is one major constraint in the model. Constraint (2) forces that exactly one assignment is selected for each flight.

$$\sum_{a \in A_f} x_a = 1 \quad \forall f \in F \quad (2)$$

All other constraints are part of the representation of the bounding soft constraints.

- Ordinary soft constraint:

In equation (3) the usage of a resource above a certain level is calculated.

$$\sum_{a \in A} u_{a,s_o,r,t} \cdot x_a \leq CAP_{s_o,r,t} + y_{s_o,r,t} \quad \forall s_o \in S_o, \forall r \in R_{s_o}, \forall t \in T \quad (3)$$

- Box constraint:

For the box constraint the average usage is calculated in (5). The positive and negative deviation from the average is calculated in (6) and the absolute value of the deviation is determined in (4) for each resource.

$$y_{s_b,r,t}^+ + y_{s_b,r,t}^- = y_{s_b,r,t} \quad \forall s_b \in S_b, \forall r \in R_{s_b}, \forall t \in T \quad (4)$$

$$y_{s_b,t}^{mean} = \frac{\sum_{a \in A, r \in R_{s_b}} u_{a,s_b,r,t} \cdot x_a}{\sum_{r \in R_{s_b}} CAP_{s_b,r,t}} \quad \forall s_b \in S_b, \forall t \in T \quad (5)$$

$$y_{s_b,t}^{mean} + y_{s_b,r,t}^+ - y_{s_b,r,t}^- = \frac{\sum_{a \in A} u_{a,s_b,r,t} \cdot x_a}{CAP_{s_b,r,t}} \quad \forall s_b \in S_b, \forall r \in R_{s_b}, \forall t \in T \quad (6)$$

- Distance constraint:

The distance between the minimum and maximum usage is calculated in (7). Equation (8) forces that the maximal usage is greater than or equal to every single usage percentage of all resources connected to the constraint. Equation (9) forces that the minimum usage is less than or equal to every single usage percentage of all resources connected to the constraint.

$$y_{s_d,t}^+ - y_{s_d,t}^- = y_{s_d,t} \quad \forall s_d \in S_d, \forall t \in T \quad (7)$$

$$y_{s_d,t}^+ \geq \frac{\sum_{a \in A} u_{a,s_d,r,t} \cdot x_a}{CAP_{s_d,r,t}} \quad \forall s_d \in S_d, \forall r \in R_{s_d}, \forall t \in T \quad (8)$$

$$y_{s_d,t}^- \leq \frac{\sum_{a \in A} u_{a,s_d,r,t} \cdot x_a}{CAP_{s_d,r,t}} \quad \forall s_d \in S_d, \forall r \in R_{s_d}, \forall t \in T \quad (9)$$

The following domains apply for the decision variables:

$$x_a \in \{0; 1\} \quad \forall a \in A \quad (10)$$

$$y_{s_o,r,t} \geq 0 \quad \forall s_o \in S_o, \forall r \in R_{s_o}, \forall t \in T \quad (11)$$

$$y_{s_b,r,t}^+, y_{s_b,r,t}^- \geq 0 \quad \forall s_b \in S_b, \forall r \in R_{s_b}, \forall t \in T \quad (12)$$

$$y_{s_d,t}^+, y_{s_d,t}^- \geq 0 \quad \forall s_d \in S_d, \forall t \in T \quad (13)$$

2.2 Implementation Issues

To solve and apply the in Subsection 2.1 proposed model successfully, it is necessary to take several aspects into account. In the following, we describe the most important points.

- *Symmetry elimination*

To avoid symmetry in the mathematical model which can lead to bad performance, we introduced an objective criterion to measure the suitability of the different baggage carousels, so that there will be no two assignments to carousels with the same objective values. Each baggage carousel should have a different value for suitability. The suitability of a baggage carousel expresses how well the baggage carousel is suited in general for the handling of a flight. The suitability combines the suitability for the passengers (easy to reach; short paths; closeness to exit) and the operational needs (accessibility from the apron for the unloading of bags). If each baggage carousel has an unique suitability value, most symmetry disappears from the model (see Subsection 5.2.1) since all assignments from one flight will be different and it is furthermore very unlikely that two assignments of different flights have the same values (the number of bags or the arrival time will differ in almost all cases).

- *Timeslots*

It can be useful to apply different sets of timeslots for calculating the soft constraints. For some capacity constraints it does not make sense to calculate a balanced distribution for very small timeslots. In this case, larger timeslots can be introduced to calculate these capacity constraints. Furthermore, rolling intervals can help to avoid unpredictable results. Rolling interval means that the resource usage is calculated for different sets of timeslots. The sets of timeslots differ in their shifted start points. If the model is calculated without rolling intervals, it can happen that a flight is favored to another very similar flight if the flights use a scarce resource and flights are close together in time but lie in two different intervals. If the resource usage is calculated with a slightly shifted start point of the intervals, the flights might have been in the same interval and there would be no difference between the flights. Rolling intervals can help to avoid this situation.

It is also possible to calculate the objective criterion without timeslots, e.g. if the capacity usage of the whole planning horizon and not the resource usage at certain timeslot should be regarded.

- *Robustness*

A goal should be to avoid the handling of more than one flight at the same time at the same baggage carousel. This can be modeled with an ordinary soft constraint. Each baggage carousel represents one resource with the capacity of one flight per timeslot. Each assignment uses one

unit of capacity in each timeslot at the assigned baggage carousels during the handling time.

Including breaks between two flights at the same baggage carousel can introduce robustness to the model. Small changes in the handling time are then unlikely to cause problems during operations. This can be modeled in such a way that each flight needs one unit of capacity at the assigned baggage carousels during an extended handling time. The weight for this objective criterion should be less than the weight for the avoidance of parallel handling.

- *Stability*

Since the acceptance is one of the major success factors for a decision support system, it is important that the dispatcher gets similar suggestions every time. In particular, it would be very irritating if the suggestion for one flight is changing in every optimization run. An objective criterion (see cost objective "continuity" in Table 1) was introduced to avoid too many changes between optimization runs. In this objective criterion the model is awarded a bonus if it chooses the same belt for a flight as in the last optimization run.

- *Including data of current situation*

We included the available manpower in the capacity calculation. The model is not only dependent on static technical capacities but also on the assignment of staff to the different baggage claim area. The general assumption is that the staff is only assigned to one baggage claim area and can work at each baggage carousel of the area.

To feed back the deviation from the expected processes during operations, e.g. delays in handling or longer allocation of baggage carousels than calculated, it is necessary to measure the observed values and compare them to the calculated values in the model. We used the calculated deviations to react to the reality and to take these into account for the next decisions. For example, if a baggage carousel is used longer than calculated by one flight.

It is also important to include messages of technical failures in the model. If a technical failure for one of the baggage carousels occurs, this baggage carousel should not be assigned to a flight for a certain period of time.

2.3 Extensions

In the proposed model the assignments are fixed if the dispatcher has made his decision. As an extension all feasible assignments for these flights could be generated. A new objective criterion can be defined and choosing the original assignment will give a large bonus (negative cost). If there is a high gain by choosing one of the other assignments, the model will choose this option. The dispatcher needs then to be informed about the new suggestion, so that he can

	Terminal 1			Terminal 2	
Hall	A	B	C	D	E
Number of baggage carousels	6	12	8	6	6
Delivery duration	2	2.5	2	1	1

Table 3: Overview of baggage claim areas at Frankfurt Airport and average duration of delivery in minutes from handling facilities to baggage carousels

rethink the situation. This option should be limited until a certain point of time, since if the bags are already transported to a baggage carousel or the passengers are waiting at a baggage carousel, a rescheduling can confuse the whole process.

Another possible extension of the model is to include not only static data but to calculate transportation and unloading times dynamically. It is possible to calculate an index from the situation in the last hours and assume the same behavior for the recent optimization run. Systematic delays of unloading or transports caused for example by bad weather conditions or low availability of staff could be integrated in that way.

If the capacity usage of one of the resources is strict, the constraint is modeled as a hard constraint instead of a soft constraint and the related decision variables disappear from the model.

3 Solution Method

The solution method of the developed decision support system consists of two major steps. First, all feasible assignments are determined and afterwards the presented mathematical model is solved for these assignments. The model is formulated as a MIP-model and can be solved with a MIP-solver (see Section 5 for computational results). In the following, we give an overview of the algorithm assuming that only a single baggage carousel can be assigned to a flight.

First, all model parameters (e.g. number of time slots) and all resources and capacities related to the bounding soft constraints are initialized. Afterwards, the algorithm iterates over all baggage carousels for every free flight. If the baggage carousel is a feasible combination with the flight, an assignment is generated. The direct costs and the contribution for each bounding soft constraint is calculated for the generated assignment. Additionally, for every fixed flight one assignment to the assigned baggage carousel is generated and its contribution for each bounding soft constraint is calculated. After generating all assignments, the model (1) - (13) is generated and solved with a solver. Finally, the results are provided to the dispatching system.

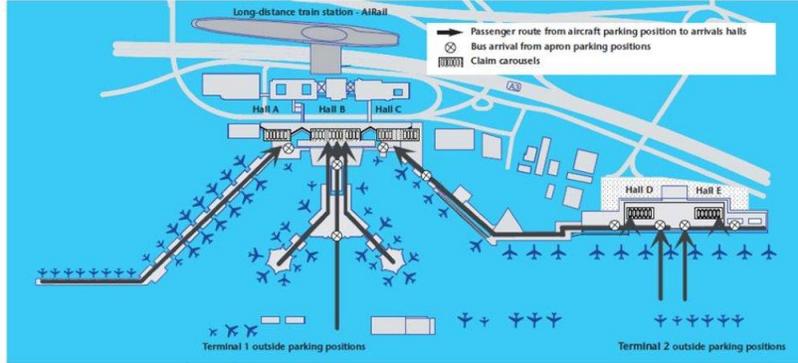


Figure 1: Overview of terminal layout at Frankfurt Airport: connection of aircraft parking positions and handling facilities

4 Real World Application

The presented model was tested in the real world environment at Frankfurt Airport. The developed algorithm has been running since the middle of the year 2010 during daily operations at Frankfurt Airport as a part of an IT-system which supports the dispatcher.

Frankfurt Airport has five baggage claim halls which are named after the concourses in the terminal: A, B, C, D and E. In total, Frankfurt Airport has 38 baggage carousels. Detailed information about the baggage halls and the different baggage carousels can be found in Table 3. Figure 1 shows the layout of the inbound baggage handling facilities at Frankfurt Airport. Baggage claim hall B is assigned to two handling facilities from the ground handling side.

The dispatcher of the baggage handling department assigns the flights to baggage carousels in a predefined baggage claim hall. The aim is to find a feasible solution that maximizes the fulfillment of the airline preferences. The solution should also be operationally well applicable and robust. The agreed standards for baggage return times are depicted in Table 4. In the majority of cases, Frankfurt achieves shorter times than these. The dispatcher is supported by a special IT-system. The presented algorithm delivers a suggestion for each flight to the system. The system then visualizes the suggestions for the dispatcher. The dispatcher has the final decision and does not need to follow the suggestions. Some of the flights are marked as automated, this means that the dispatcher should follow the system, since the suggestion is very important e.g. special agreements with airlines. Furthermore, the suggestions are a backup for the dispatcher. If the dispatcher fails to make a final decision until the aircraft arrives at the airport, the suggestion of the system will be chosen.

The model was adapted at several positions at Frankfurt Airport. Not all optimization possibilities as described in Section 2 are used at Frankfurt Airport at the moment. This has mainly organizational reasons, since the decisions

involve different departments with different responsibilities. At the moment the model only supports the tasks of the baggage infrastructure department.

In the following, the detailed changes and the relevant goals will be presented. One important point is that the assignment to a baggage claim area in general is given by fixed rules and only in a few cases, it is possible to choose between baggage carousels in different baggage claim halls for one flight.

The model at Frankfurt Airport includes all cost terms as shown in Table 1 in Section 2.1 in the objective function. Furthermore, the following soft constraints are calculated in dependency of the combination of the chosen assignments (set of S) in the model:

- A balanced distribution of the usage of the different baggage carousels in each baggage claim hall is calculated as a distance constraint. Rolling intervals are used to calculate this objective criterion.
- Balanced distribution of the usage of the baggage claim halls is calculated as a boxing constraint. Rolling intervals are used to calculate this constraint.
- The limitation of the number of passengers at neighboring baggage carousels is calculated as an ordinary soft constraint. For each pair of neighboring baggage carousels the maximum violation of the capacity in the whole planning horizon is calculated.
- The limitation of the display at the baggage carousels is calculated as an ordinary soft constraint. All flights which are assigned to a baggage carousel will be displayed at the baggage carousel for the orientation of the passengers until the handling is officially finished. The displays are limited to five flights. A flight is officially finished after a fixed duration of time or a manual log-off from the dispatcher.
- The limitation of flights handled at one baggage carousel at the same time is calculated as an ordinary soft constraint. We assume a higher resource consumption for large flights. A flight is defined as large if it contains more than 70 bags or 3 containers. There are different steps defined for the parallel handling of two, three, four normal or two large flights. For each of these scenarios an own objective function part is defined.
- The breaks between flights are calculated as an ordinary soft constraint. There is an extra objective for large flights.
- The limitation of flights to staff availability in baggage handling facilities is calculated as an ordinary soft constraint. In Frankfurt the objective is used to get a balance between the two handling facilities in baggage claim hall B.
- The reservation of baggage carousels with large facilities for large flights is calculated as an ordinary soft constraint. The idea is that these carousels are still available if a flight with many bags comes in the problem.

We assume that a baggage carousel is assigned to a flight from the start until the end of the handling. In reality it could be possible to recognize in the load sheet of the aircraft that there will be breaks in the handling since the bags will be delivered with a temporal delay e.g. if some bags are loaded in the front and the end of the aircraft. For Frankfurt it was decided not to include these breaks since the delivery time of the bags is always connected with some uncertainty.

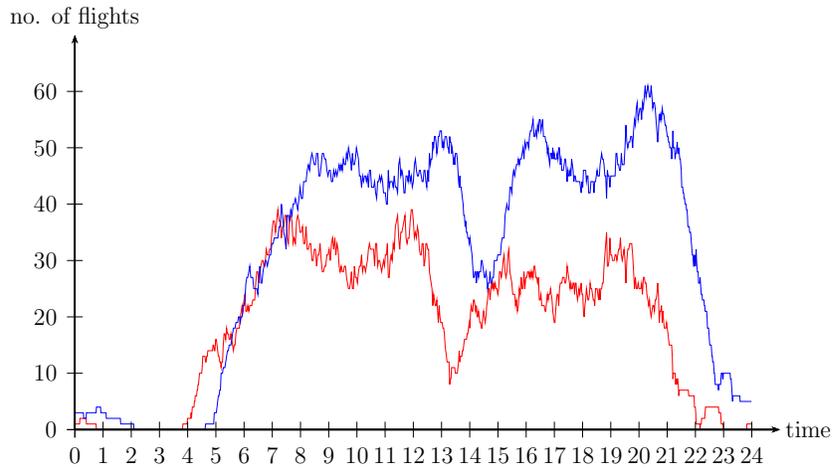


Figure 2: Number of flights in optimization as function of time in day (blue: flights fixed by dispatcher, red: free flights)

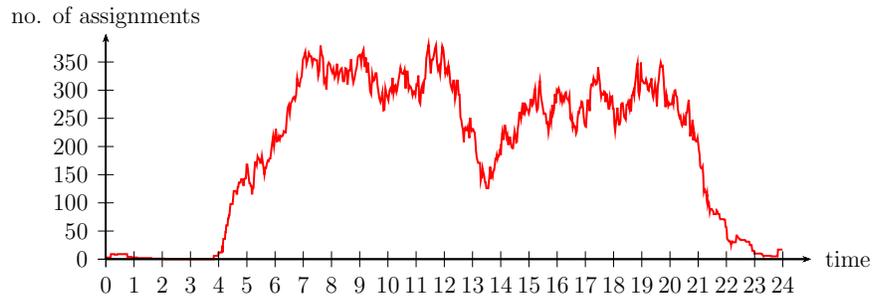


Figure 3: Number of generated assignments as function of time in day

Today, the optimization runs at least every two minutes. The decision for one flight is not made once, but is calculated repeatedly until it is fixed by the dispatcher. In the optimization runs all flights are included where the handling is still in progress or which arrive in the next thirty minutes. In average 40 flights are considered in each optimization run. In the daily peaks up to 90 flights are considered simultaneously. Figure 2 shows the number of flights in the optimization runs during a typical day. The number is split in flights which are already decided by the dispatcher and in flights which are not fixed. Each

Baggage return times for	Building parking position	Remote parking position
Conventional aircraft	15 min. after on-block	20 min. after on Blocks
Wide body aircraft	20 min. after on-block	25 min. after on Blocks

Table 4: Service level for delivery of 1st piece of baggage at Frankfurt Airport

Steps	Avg. duration (s)
Reading data	9.9
Prepare model / generate assignments	2.5
Define and solve optimization problem	0.2
Postprocess	5.0
Writing data	3.8

Table 5: Duration of the solution steps

optimization run includes the most recent data and the suggestions of the last run. The dynamic environment is included by generating robust plans and constantly adjusting the decisions over the time. Figure 3 shows the number of generated assignments at each optimization run during the day.

One side effect of the project was that all process times for unloading, delivery, handling start etc. are calculated in every optimization run. This information — planned and real numbers — were integrated in the IT-system for the dispatchers and give them important additional information about the process status.

5 Computational Results

In this Section we present the results of the operational application at Frankfurt Airport and simulation runs. The calculations are based on a real day at Frankfurt Airport and the most recent adjustment of the weights. The algorithm was implemented using C# .NET and IBM ILOG OPL 12.2. The implementation makes intensive use of IBM ILOG OPL Script. Large parts of the business logic and the generation of the assignments are implemented in IBM ILOG OPL Script.

5.1 Computation Times

The mathematical model was solved for all instances at Frankfurt Airport in a few seconds, which makes the algorithm applicable in the dynamic dispatching scenario. The times for the different solution steps were measured for an average day (see Figure 4). The average values are depicted in Table 5.

Comparing Figures 2 and 4 with Figure 3 shows that run time of the algorithm is depending on the number of flights and assignments. The optimization related steps (generate assignments and solve optimization problems) have the shortest duration of all steps in average (see Table 5).

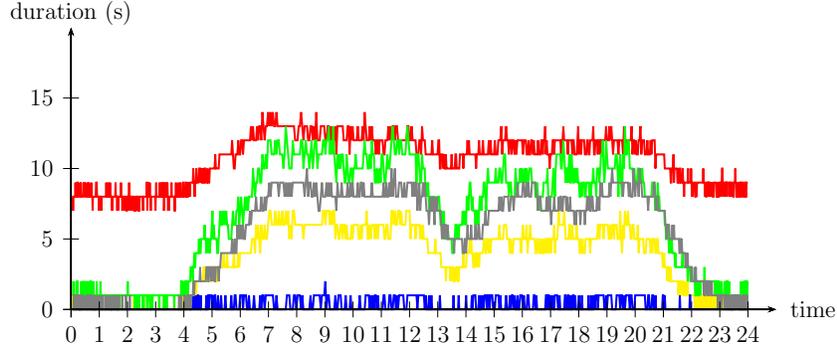


Figure 4: Computational times during a day. red: reading data, yellow: prepare model / generate assignments, blue: solve optimization problem, green: postprocess, gray: writing data

Type of run	weighted objective without suitability	run time (sec)	absolute values of suitability terms
Run without symmetry elimination	42.70944	2.20	44.31667
Run with symmetry elimination	42.57515	0.84	45.61667

Table 6: Changes of objective function, duration of run times and suitability terms for runs with and without symmetry elimination

5.2 Calibration of the model

When implementing the model at Frankfurt Airport, large parts of the project time was spent with the calibration of the model. The most important calibration steps are presented in the following Sections. Furthermore, we did theoretical studies to determine the impact of different elements on the model.

5.2.1 Symmetry

As mentioned in Section 2.2 we recommend the introduction of a cost term to eliminate symmetry from the model. We compared runs with and without symmetry elimination. Computation times could be decreased by a factor of at least two by eliminating symmetry from the model in this way. The results in the case with and without symmetry elimination are summarized in Table 6. The results show that the differences between the optimization runs are small. The weighted objective function for all objective terms except suitability decreases about 1 %, but on the other hand the introduction of the new objective term suitability increases the values for suitability up to 3 %.

5.2.2 Bounding soft constraints versus direct costs

We did several studies to measure the impact of bounding soft constraints and direct cost terms on the model. In the following, we show the impact for the bounding soft constraint "balanced belt usage" and the direct cost "reservation of capacity for large flights" in more detail. Both terms are connected and can be contradicting, since a balanced distribution between the belts does not reserve specific baggage carousels for large flights.

Figure 5 shows the impact of the variation of the weights of the two terms on the objective terms and solution times. Examining the solution time, we can see that a higher weight of the cost term speeds up the optimization slightly and a higher weight of the soft constraint has negative impact. Especially very high weights of the soft constraints lead to long running times. The optimization in the presented runs were aborted after 180 seconds calculation time. The algorithm could find good solutions in this time, but no proof of optimality was given. The bad solution times appear if the weight for the soft constraints is too high. It is interesting to see that the objective term for the soft constraint did not improve very much after this point. After a certain point high weights for the cost term have a strong impact on the objective of the soft constraint.

In general, we observed that the impact on the solution time is much higher for the bounding soft constraints than for the direct cost terms. While calibrating the model the right trade-off between the different weights has to be determined in such a way that the different objective terms are respected in an appropriate way and solution time is acceptable.

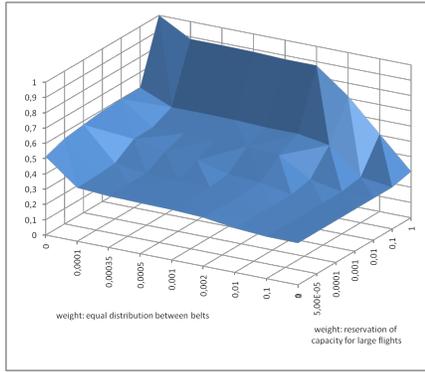
5.2.3 Stability

We did simulation runs for the morning (peak hours of airport operations) of a representative day and compared the results for the optimization with and without stability cost in the objective function (see objective term continuity in Table 1). Stability means that the suggestions for one flight does not change very often between different optimization runs. We measured no impact on the computation time and on the cost values of all other cost in the objective functions. Figure 6 shows the influence of the stability on the different soft constraints implemented at Frankfurt Airport. For most soft constraints no or only small increasings can be seen. For the soft constraint "breaks between large flights" even a decrease can be reported. It is important to note that this decrease is small.

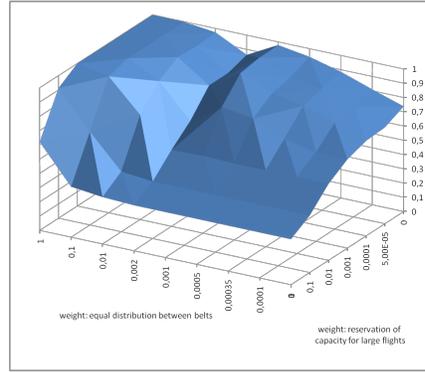
By introducing a cost term for stability it was possible to reduce the number of changes by 15 % (from 8.3 to 7.0 changes per flight). The dispatcher were more satisfied with the suggestions from the stabilized version of the algorithm and the average acceptance rate during a day increased.

5.3 Problem structure

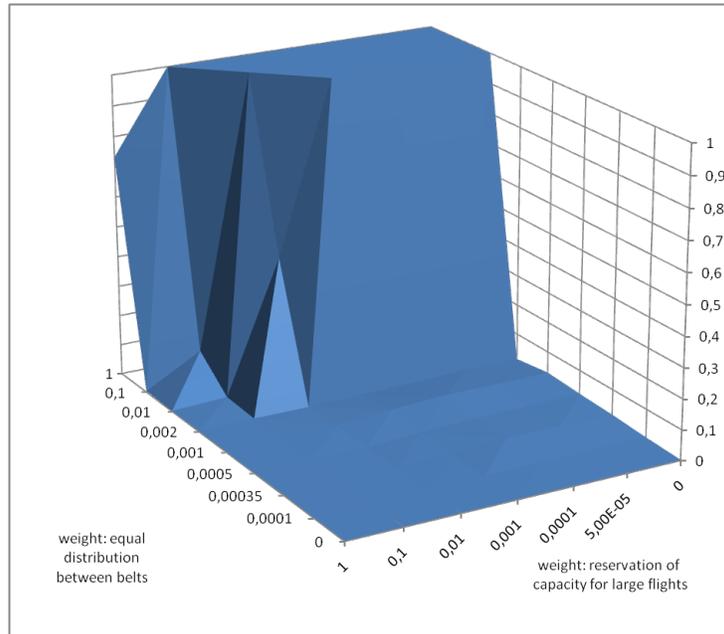
We did several experiments to prove that the model is also applicable at other airports. Two major experiments were conducted to measure the impact of the



(a) Normed objective value: balanced belt usage (minimization)



(b) Normed objective value: reservation of capacity for large flights (minimization)



(c) Normed solution time: duration for solving the optimization problem (runs are aborted after 180 seconds)

Figure 5: Impact of changes in the weights on the objective terms and solution time. Note: The scaling of the weights is not linear.

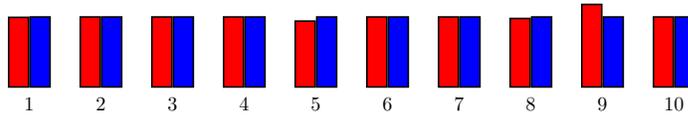


Figure 6: In blue depicted are the average objective values from the runs with stability and in red from runs without stability. The values are normalized by the value from the object criteria from the runs with stabilization. 1: balanced distribution at belts, 2: balanced distribution between handling facilities, 3: limitation of passengers at neighboring carousels, 4: limitation of the display, 5: penalty for parallel handling of two flights, 6: penalty for parallel handling of three flights, 7: penalty for parallel handling of four flights, 8: breaks between handling of flights, 9: breaks between large flights, 10: violation of belt capacities

No. of flights	Total time	Optimization time	Pre- and Postprocess
100	41	2.06	39
150	91	27.00	64
200	697	603.49	94

Table 7: Solution run times in seconds as function of the number of flights

problem size (number of flights in one optimization run) and the layout of the airport on the computation times.

5.3.1 Number of flights

Today (see Figure 2) up to 90 flights are included in one optimization run. In this section we examine how the solution and quality is affected by an increase of the number of flights. We did optimization runs with 100, 150 and 200 flights. Frankfurt Airport has little less than half the movements compared to the world largest airports (Air Transport World (2010)), so doubling the number of flights demonstrates the ability of the algorithm to be used at other large airports.

Table 7 compares the solutions times for the different number of flights. We assume a similar layout of the airport as in Frankfurt. For adding additional flights, we took flights from other hours at the days and adjusted their arrival time in such a way that the arrival time lies within the time horizon of the optimization run. In that way we could include flights with real world data.

The run with 150 flights had a MIP gap below 1 % after one second. The improvement of the objective value was below 0.5 % after 30 seconds for the run with 200 flights. All runs were solved to optimality.

The results show that pre- and postprocess time (generating the assignments and preparing the results) depend almost linearly on the number of flights in the run. The optimization time seems to grow exponentially with the number of flights.

5.3.2 Layout of handling facilities

As described in Section 4, the handling of the luggage is split into several decentral handling facilities at Frankfurt Airport. Other airports have only one central handling facility and all flights can be assigned to all belts. To test our algorithm for such a situation, we assumed that it is possible to assign every incoming flight to every available belt. We included 80 flights and 38 belts in our optimization run.

The total run time of the optimization run with one central baggage handling facility was 229 seconds. The time splits up in 109 seconds for optimization and 110 seconds for pre- and postprocessing. In this case, the generation of the assignments is slower since more assignments are generated per flight. The run with 150 flights had a MIP gap below 1 % after three seconds. Assuming that all characteristics of the belts except the transportation time are still the same, a theoretical improvement of the objective function of 20 % can be shown. This indicates that a more flexible handling of flights could improve quality at Frankfurt Airport.

5.4 Comparison optimization versus dispatcher

In this section we examine the differences between the decisions of the dispatcher and the optimization system. In general, the dispatcher fixes the suggestion earlier than the optimization system would do it. We assume that the decision from the optimization system will be fixed when the aircraft arrives at its parking position.

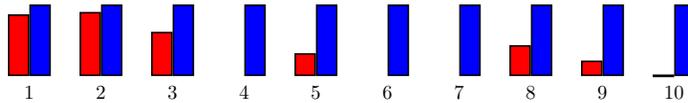


Figure 7: In blue depicted are the objective values from the dispatcher and in red from the optimized solution. The values are normalized by the value from the object criteria from the dispatcher. Note: smaller values are better. 1: balanced distribution at belts, 2: balanced distribution between handling facilities, 3: limitation of passengers at neighboring carousels, 4: limitation of the display, 5: penalty for parallel handling two flights, 6: penalty for parallel handling three flights, 7: penalty for parallel handling four flights, 8: breaks between handling of flights, 9: breaks between large flights, 10: violation of belt capacities

We did compare the results from optimization and the real decisions from the dispatcher over several days. We could examine similar results for every day. For each day we compared the total sums for every objective criteria of type 1 from the chosen assignments. Surprisingly, there was no large difference between the decisions of the dispatcher and the optimization algorithm. For

most criteria the improvements in the optimized case were below 1 %. For the fulfillment of the airline preferences an improvement of 2 % was measured. The general suitability was 20 % improved over a whole day.

For the soft constraints part in the objective function larger benefits can be seen. Figure 7 show the improvement for selected objective criteria. For all objective criteria an improvement was reported.

These results show that the dispatchers concentrate on a good assignment of the single flights and that they lack the consideration of the combination of the different flights. Furthermore, the results show that some situation can be avoided, if they are part of the optimization problem e.g. ensuring that no more than two flights are handled at the same belt.

6 Conclusion and Future Work

6.1 Conclusion

We introduced a general model for solving the inbound luggage handling problem at airports. The model can be adapted to different situations and layouts. Furthermore, we presented important implementation issues. It was shown experimentally that the model represents the reality in an appropriate way and the usage of the solution algorithm can be of a great help for the dispatchers at an airport. The experiments presented in Section 5 show that the model is flexible and can be used for different layouts. The flexibility should allow that the model is used at all types of airports independent of the layout, number of flights, capacities and management objectives. The results showed that it is possible to solve problem sizes of up to 300 flights. To the best knowledge of the authors, there are today no airports with more than 300 flights arriving per hour, so the problem size should not limit the applicability of the model.

The calibration of the model is very important for a successful implementation. A large amount of the project time at Frankfurt Airport was spent with the search of the right adjustment of the different goals and to maintain all parameters e.g. the preferences for the different airlines.

After running the decision support over half a year the following results can be reported:

- A satisfying acceptance rate in total could be reached. The acceptance rate is between 50 % and 90 % depending on the operational situation and the different objectives of the dispatchers.
- The real world time constraints can be fulfilled and no problems with the actuality of the data arise.
- The dispatchers were reported to have more time to concentrate on quality management.
- The algorithm runs stable in different situations e.g. in situations with

many disruptions like gate changes and delays, days with normal operations, delays in unloading due to bad weather.

- For the defined goals like the fulfillment of airline preferences or the balanced distribution, better values for the objective function were achieved (see results in Section 5). Additional to these theoretical proven improvements no negative influence on the processes was reported by the operational staff.
- The introduction of stability has led to an higher satisfaction with the suggestions.

The experiments showed that the model can be adapted to new situations like new guidelines by the authorities very quickly. All changes appearing during the test period could be included with minor efforts and the quality of the solution was not affected.

Furthermore, we can show theoretically that the outcome of the dispatching process can be improved using the optimized solutions. The results demonstrate that the multi criteria problem can be expressed by a linear weighted objective function and almost all criteria can be improved compared to the decisions of the dispatcher.

The results presented in Section 5 show that it is very important to define the objectives in the right way and to have a good understanding of the real world optimization problem. As seen, some situations like the handling of three or more flights at the same time on the same baggage carousel can be avoided in the daily operations with the help of the optimization. It is really important to define these situations in a proper way and identify all situations which should be avoided.

6.2 Future Work

For the usage at Frankfurt Airport, the model will be advanced and adjusted in the future. It showed that changing and developing is a continuous process. In the future we will look at the stability and try to reduce the number of different suggestions for a single flight by tuning of the objective function.

Some extensions of the basic model were described in Section 2.3 but we can think of other extensions. For example the break duration between flights handled at the baggage carousel could be improved. Today only fixed time spans before / after a flight are part of the model. In general, the solution will be more robust with every additional minute of break, so maximizing the duration of breaks could improve the solution. The objective function of the maximization of the breaks should not be linear, since for short breaks it is more important to extend the breaks.

It is possible to use the model not only for operational decisions — the model could be adapted for strategic decision like finding the right management objectives for the process or designing new baggage claim areas. Different operational

business strategies can be tested in an easy way. For the case in Frankfurt it looks promising to have more flexible assignments of flights to baggage halls.

Future fields of work will be the neighboring processes like outbound baggage handling. In a next step, the solution for the inbound, outbound and transfer baggage handling should be integrated in a large scale approach. Furthermore, the inbound handling could be viewed in a broader sense. The unloading of the bags of aircraft and the transport of the bags at the apron could be included in one model. Especially, the dependency to the staff scheduling for the task of baggage handling should be examined in more detail.

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The problem considered in this report is an assignment problem occurring at airports. This problem concerns the assignment of baggage carousels in baggage claim halls to arriving aircraft baggage carousel assignment problem. This is a highly dynamic problem since disruptions frequently occur during operations. We introduce a basic static model that can be adapted to the layout of different airports. Afterwards we show how a decision support system based on a MIP-model can be designed in a dynamic real world environment. The system supports the decisions of the dispatcher during daily operations. Computational results for a real world problem at Frankfurt Airport are presented. At Frankfurt Airport the suggested solution method was successfully implemented and is running now for over half a year. The experiences show that the system increases the quality of the dispatching process and is a substantial support in decision making in general.

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