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A workforce planning and allocation model for the outbound baggage loading area at Santiago International Airport

Juan Pablo Cavada[a], Cristián E. Cortés[a] and Pablo A. Rey[b]

[a]Department of Civil Engineering, FCFM, Universidad de Chile and Instituto Sistemas Complejos de Ingeniería (ISCI), Santiago, Chile [b]Department of Industry and Programa Institucional de Fomento a la Investigación, Desarrollo e Innovación, Universidad Tecnológica Metropolitana, Santiago, Chile

ABSTRACT
A methodology is presented that determines the staff requirements for a baggage handling operation at an international airport facing high demand. It consists of two sequentially solved integer linear programming models. The first model determines the handler requirement using historical demand data and incorporates the operation's spatial constraints. The second model, taking as input the results of the first model, defines each handler's shift and task assignments. This formulation can be considered as the solution of a set covering problem using feasible shift structures pre-defined by an algorithm. The proposed approach is validated in an application to a real-world case, demonstrating significant improvements over the baggage handling operator's own staff planning decisions.

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Ground handling; personnel scheduling; integer programming

1. Introduction

Arturo Merino Benítez International Airport (hereafter AMB) is the only international airport in the Santiago region of Chile. Use of the facility has grown rapidly in recent years, which has motivated the construction of a new terminal that will double its current capacity. In 2016 the total number of passengers observed was over 19 millions, representing an 11.4% increase with respect to the previous year. As shown in Figure 1, a rising tendency has been observed over the last decade, which has strained the whole baggage system pushing it to an operation close to the physical limits of the different devices.

The main ground service provider at AMB is Andes Airport Services (hereafter also "the company"). Andes has had to maintain a high level of efficiency to ensure it can carry out many processes involved in flight preparation amid a collapsed system. One of the most important of these processes is loading the carts that transport outbound baggage to the aircraft. The critical element in this process is a sufficient number of staff to cope with the level of operation at all times. On a single day in the

CONTACT Cristián E. Cortés ccortes@ing.uchile.cl Department of Civil Engineering, FCFM, Universidad de Chile and Instituto Sistemas Complejos de Ingeniería (ISCI), Santiago, Chile

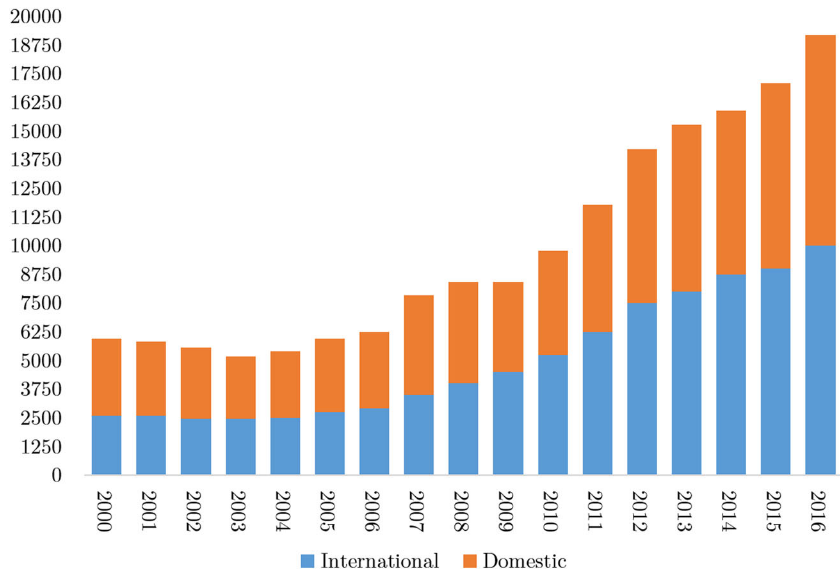

Figure 1. AMB Annual Passengers Evolution from 2000 to 2016 (source: AMB website).

high season, the company may handle more than 20,000 pieces of luggage for some 160 flights, or 80% of terminal traffic.

Airlines generally design their schedules according to standard commercial criteria based on satisfying customer wants, with relatively little regard for airport operating conditions. As a consequence, activity at the airport terminal fluctuates widely, with high demand periods when the baggage handling system (BHS) is overwhelmed alternating with low demand periods when the system is underused. This wide variation in the system's spare capacity levels raises obvious challenges for BHS personnel planning.

The present study proposes an approach for efficiently determining baggage handler requirements in the context of Andes' operations at AMB. The problem the company faces consists in deciding the number of necessary staff and their job assignment in such a way so as to meet applicable service standards. More specifically, we develop a methodology that includes a task generation and a shift assignment model for daily staffing baggage handlers who operate the loading carrousels at the airport's baggage loading area. The design challenge is to come up with a model that can be easily adopted both by personnel planners and on-site work coordinators. Not only must it be fast but also simple to parameterize, solve and implement.

The approach we chose was aimed at achieving a design that would be practical for use by the coordinators. Thus, the methodology consists of two stages that can be run independently. The first or tactical stage determines the number of handlers required for each work position using an integer linear programming formulation whose input is the expected baggage demand. This model does not require luggage to be handled immediately. Instead, bags can spend a short period in the carrousels. This flexibility, resembling actual operation, allows reducing the number of handlers required in some periods of the day. The second or operational stage then attempts to organize the handler shifts for the day. To improve the model's execution speed and ensure its results can be directly applied to the baggage handling operation, the tasks to be assigned are selected from a set of predefined shift patterns or structures. Each of these structures is a possible combination of tasks to be carried out by a handler. They are generated a priori by an algorithm and must comply with the prevailing workplace rules.

The remainder of this article is organized in six sections. Section 2 surveys the literature on shift and task assignment in a general context as well as in the more specific area of airport personnel planning. Section 3 then introduces the shift scheduling problem for an airport baggage handling operation and proposes a solution approach using two sequentially executed models. This is followed by Section 4, which formulates the task generation model, and Section 5, which develops the second or shift scheduling model. Section 6 sets out some illustrative results of the application of the proposed approach to an actual baggage handling operation and compares the model's results to the real planning used by the operator. Finally, Section 7 presents our conclusions.

2. Literature review

Personnel planning issues arise in every industry and have been extensively studied. Many different techniques have been developed to deal with them, for although the basic problem is always the same —assigning staff to tasks— each case has its own characteristics and no single unified theory can address all of them.

The planning and assignment of personnel over a given time horizon, generally known as staff scheduling, has been systematically treated in the literature since Dantzig (1954) first proposed an integer programming model for this class of problems. Determining how many employees to assign and the start time of each work shift in order to maximize coverage of an activity's requirements is referred to as the workforce allocation problem. Together with rostering problems, workforce allocation comes up in almost every industry, including airlines and airports, railway and bus transport, hospitals, telephony, emergency services, banking, etc.

One of the earliest classifications of these problems is due to Baker (1976), who proposed two basic categories. One is *shift scheduling*, which assigns each employee their shift start and end times and corresponding duties, and the other is *day-off scheduling*, which determines each employee's cycle of working days and days off. In the latter case, as well as satisfying demand, the problem typically includes constraints on the number of weekends and consecutive days off.

The abundant literature on workforce allocation and staffing has been surveyed by Ernst et al. (2004), Alfares (2004) and Van den Bergh et al. (2013), who classify the studies covered by solution method, area of application and type of problem. Van der Bergh et al. also include classifications for such characteristics as employee category (full or part-time), type of decision (by task, shift sequence, time, etc.), type of coverage constraint (soft or hard) and type of skills. In general terms, skill is defined as the ability of an employee to carry out a task. A comprehensive survey of works in this area may be found in De Bruecker et al. (2015), which reviews publications in terms of their managerial impact as well as their technical aspects.

Since staffing problems in a given organization typically involve various actors and elements, many solution approaches tackle them in stages. Ernst et al. (2004) divide the process into six modules: (i) demand modelling, (ii) days-off scheduling, (iii) shift scheduling, (iv) line-of-work construction, (v) task assignment, and (vi) staff assignment. The combination used in any given case will depend on the problem's particular characteristics.

The range of techniques that have been employed to address these problems is also very extensive. There are mathematical programming studies proposing the use of integer programming, linear programming, dynamic programming, and constraint programming, among others Van den Bergh et al. (2013).

One of the most common approaches is based on the generalized set-covering formulation suggested by Dantzig (1954). The incorporation of additional constraints such as breaks, employee preferences or skills has resulted in large numbers of variables, greatly complicating the solution process and prompting a search for more sophisticated methods. One of these methods is due to Brusco and Jacobs (2000), who model tours implicitly to add break periods and flexible start times, enabling them to solve real-world 24/7 scenarios.

The large number of variables in scheduling problems has led a number of authors to turn to decomposition techniques (Bard and Wan 2008; Detienne et al. 2009), especially column generation and branch and price (Beliën and Demeulemeester 2007, 2008; Ni and Abeledo 2007).

Despite many existing studies of staff planning, relatively few have treated the case of airport ground personnel, and fewer still have focussed on baggage handling systems. The baggage handler problem has various interesting peculiarities distinguishing it from other scheduling contexts that have received more attention. One such characteristic is that the staff requirements are determined by the combined effect of the flight schedules and the pattern of passenger arrivals at the airport, with the result that achieving an accurate determination of the requirements is far from trivial.

Scheduling problems in the area of air transport generally have been the subject of much investigation. What sets the problems in this industry apart is that staff requirements are always determined by the airport's flight schedules. Historically, research has concentrated on flight planning (Qi et al. 2004; Bianco et al. 2006) or airline crews (Gamache et al. 1999; Schaefer et al. 2005); relatively little work has so far been done, however, on landside personnel.

Brusco et al. (1995) develop column generation and simulated annealing algorithms to improve shift scheduling for United Airline's ground personnel at Denver International Airport in the United States. The study covers staff working in maintenance, check-in, departure lounges, baggage handling, etc. They estimate that the potential savings obtainable by applying their model would be more than USD 8 million. Dowling et al. (1997) use a similar approach to determine the monthly shifts of the approximately 500 employees at a large international airport and distribute the workload evenly among them. The authors use a two-stage methodology in which the first stage estimates total demand for staff and plans a monthly roster for meeting it while the second stage assigns specific tasks to each staff member required.

Mason et al. (1998) describe the development of a planning system for customs personnel at Auckland Airport in New Zealand. The method proposed by the authors iterates an assignment heuristic and the simulation of passenger arrivals to determine the required staff for each period. An optimization model is then used to build rosters for covering this demand using full-time and part-time employees. Alvarez-Valdes et al. (1999) approach the personnel planning problem for a refuelling installation using a tabu search heuristic. Atkins et al. (2003) use a combined simulation and optimization approach to develop a shift schedule for the Vancouver's airport security screening. Begen et al. (2018) analyse the provision of transportation assistance for travellers with special needs at a Canadian airport and the planning of the necessary resources. They consider a centralized system not existing in practice. They develop a queueing and a simulation models to determine operational strategies and resource levels. In a highly stochastic system, simulation allows to build a very detailed model, even though it could be difficult to update and maintain. A simpler queueing model with an user interface would be easier to maintain and usually enough to support decision making.

A methodology proposed by Chu (2007) for ground services staff planning applies an algorithm consisting of three sequentially solved stages based on goal programming. It begins with a duties generating stage that calculates the hourly demand for each location. This is followed by a model that calculates each location and the number of staff starting their shifts at each moment, taking into account breaks and the use of overtime. The approach was applied at Hong Kong International Airport. A similar decomposition was suggested by Rodič and Baggia (2010), who develop heuristic algorithms for estimating work load and personnel assignments. The authors constructed groups of workers who are assigned to areas and allow a single group to work at various tasks simultaneously.

The planning of check-in counter staff has also been studied. Linear integer programming models for application to real cases of counter personnel are taken up in Stolletz (2010), who uses a single matrix for all feasible shifts and models the tours as constraints. The approach is extended in (Brunner and Stolletz 2014) to a branch and price algorithm incorporating break periods.

Kuo et al. (2014) present a mixed integer formulation for the problem of assigning airline customer service agents. The model accommodates different skill types and staff levels for each location in each period as well as staff heterogeneity, transfer time between locations, and break planning.

Finally, two interesting studies are worth to be cited in this review as they consider other resources, different from personnel, which have to be scheduled in the context of the outbound baggage process in airport operations. Frey et al. (2010) proposed an approach for assigning flights to carrousels along with start processing times, resulting in a high-complex problem which has to be solved through a decomposition heuristic. Barth and Pisinger (2012) compared a GRASP heuristic approach with a decomposition method to solve the same problem as Frey et al. (2010) testing their methods on real world data from Frankfurt Airport.

Lin et al. (2015) developed a simulation model for the BHS in Taiwan Taoyuan International Airport. One of their analyses was the evaluation of time windows for a buffer area, in which the bags that arrive too early can wait so that they do not crowd the handling carrousels. In the present work, although we studied a system with no

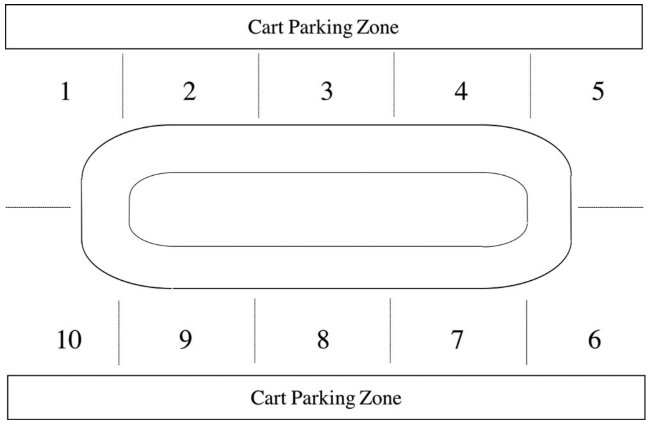

Figure 2. Carrousel layout scheme.

buffer section, we seek to capitalize the idea of allowing bags to wait at the carrousels to serve first the most urgent ones. The idea of prioritizing bags is also studied in Kim et al. (2017) at check-in area and in Johnstone et al. (2015) at conveyors merge points. Frey et al. (2017) use a column generation for planning the outbound baggage handling, that is deciding for each flight the preparations starting time and the carrousel where it would be handled. In our case these decisions are already taken by the company.

3. The shift planning problem and the proposed solution structure

One of the fundamental resources in the baggage handling process is the baggage handling area (BHA) personnel. For certain BHA tasks, the required staff is easily determined and relatively constant but for others, especially flight preparation, staff requirements vary greatly depending on the workload at any given moment.

3.1. The baggage handling area

The baggage handling area at AMB consists of 8 carrousels that receive the luggage items through a system of conveyor belts connecting the BHA to the check-in counters. The counters are located on a different level where passengers deposit their baggage and pick up their boarding passes. Upon arriving at the carrousels, the bags are removed and inspected by baggage handlers who then place them in carts for transfer to the aircraft. A special area in the BHA is reserved for items requiring special security checks.

Each flight is prepared from a single loading carrousel to which the bags for that departure are carried from the check-in sector by the conveyor system. The handlers for a given flight are deployed along the carrousel assigned to it, transferring the bags as they arrive to a cart and recording them on a loading sheet. Figure 2 illustrates the physical layout of a carrousel showing the separation of the working space around it; in this example, ten *working areas* for handlers are illustrated.

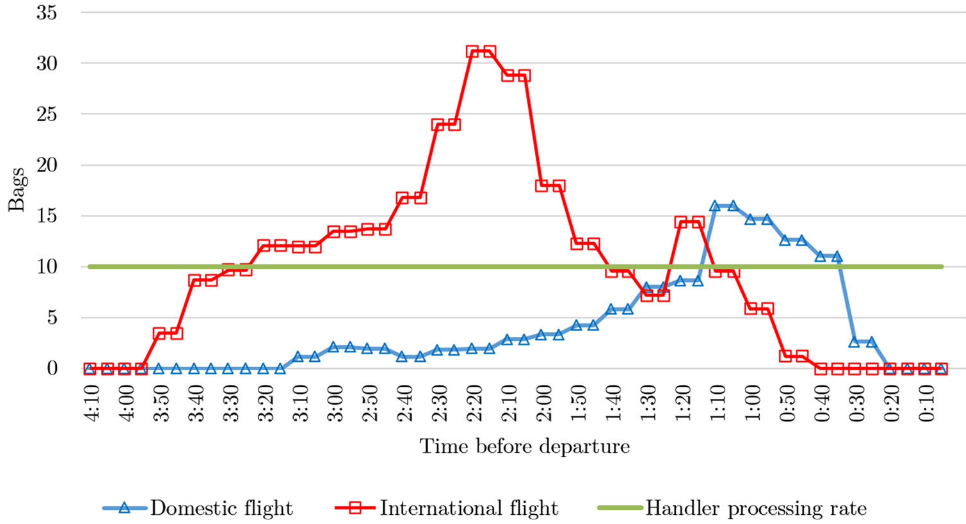

Figure 3. Examples of distribution of bag arrivals during the flight preparation period preceding departure for a domestic and an international flight.

At times when there are relatively few bags to be loaded, a single handler may handle more than one flight. Except for certain critical periods, the bag processing rate of an individual handler is generally well above the level necessary to manage a single departure. However, for more complex cases or at moments of high demand, various staff may be needed for a single flight to prevent departure delays and ensure no bags are left behind. A parameter whose importance has been identified in previous studies done by the airport is the relationship between flight departure times and the pattern of bag arrivals at the carrousels. Data on bag arrival distributions are available for all flights. An example is given in Figure 3, showing the bag arrival flows in 5-minute intervals over the 4 hours preceding the departure times for a domestic and an international flight. Also plotted is the handler processing rate, which at certain moments is significantly exceeded by the rate of bag arrivals.

In addition to the "regular" loading carrousels for flight preparation, there is a special zone in the BHA known as M9 where bags flagged for higher level security checks are sent. Baggage items from the entire airport arrive at the M9 carrousel. In our modelling we assumed that for each flight a certain proportion of checked bags, estimated from the flight's historical data, would be redirected here.

3.2. Definition of the problem

The problem is to plan the staffing of the baggage handling area for 24-hour intervals in three shifts: Opening, from 4 a.m. to 12 noon; Afternoon, from 12 noon to 8 p.m.; and Night, from 8 p.m. to 4 a.m. the following morning. Although these shift start and end times apply to the majority of personnel, some handlers will be assigned to begin their shifts before or after these official times in order to produce shift overlaps. If well planned, such overlaps will provide staff reinforcements at high demand periods and reduce their idle time when demand is low.

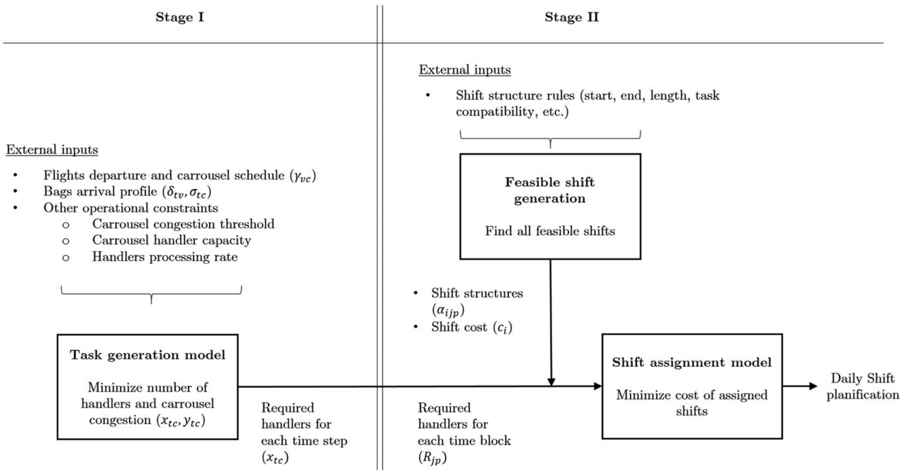

Figure 4. The two stages of the solution structure.

The solution generated by the proposed model determines the required staff level for BHA flight preparation. More specifically, it determines the number of handlers needed to prepare flights over the course of the day, indicating for each handler the shift start and end times and the various tasks they are to perform during the shift such that all flights will be prepared in time for takeoff. Our approach assumes that the handlers are able to prioritize baggage and flights depending on the carrousel load state at any given moment.

To obtain useful solutions for a real-world baggage handling operation, the model restricts the times when handlers can begin or end a shift and change tasks. It also must limit the number of employees entering or leaving service at the same time, as incoming and leaving employees must pass security screening and have to move between the baggage handling area and the company's base. Finally, the model allows handlers to work together on multiple flights simultaneously at each assigned carrousel, takes advantage of the handlers' ability to prioritize baggage, and has the flexibility to reduce idle periods that may arise over the course of a day.

3.3. Solution structure

Our proposed two-stage methodology consists of two integer linear programming models that are solved sequentially (see Figure 4). The first model determines the need for handlers at each carrousel based on the schedules of the flights to be prepared while the second model minimizes the number of required shift assignments.

In more specific terms, the first or task generation model defines the number of handling staff needed to deal with the demand arising from the bags arriving at the loading carrousel. Time in this model is discretized into five-minute periods, the minimum allowable between flight departures. Spatial constraints on the times at which the number of handlers can be changed are also included in the formulation.

The second or shift assignment model uses the results generated by the first model on the staff required for each task, grouped into half-hour intervals, to determine for a given day the total number of handlers needed, the shift start and end times, break times and each task to be carried out.

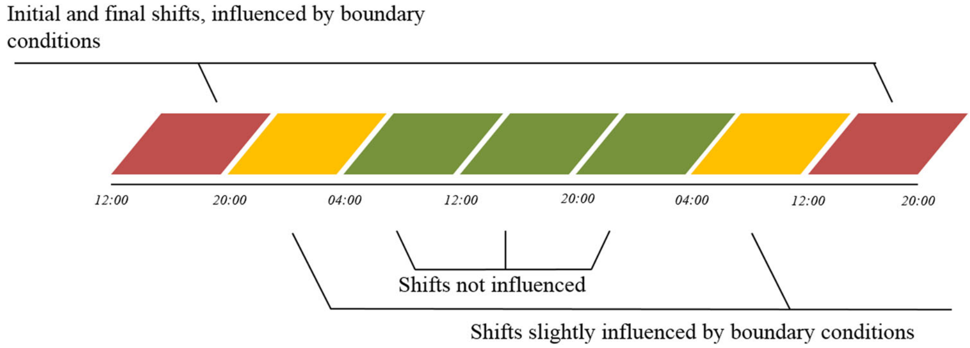

Figure 5. Extended planning horizon and influence of boundary conditions.

We choose this two-stage structure because the objectives for each one are different. In the task generation step, the main concern is minimizing the number of workers while achieving a smooth enough operation ("low congestion"). In the shift assignment step, priorities turn to select a set of "good" shifts that meet the demand determined in the first step.

Before presenting a detailed description of the two models in Sections 4 and 5 below, some further description of the modelling of the planning horizon is in order. The goal of our approach is to build daily operational plans (24-hours), and be able to plan each day separately. However, we must also take into account the above-mentioned shift overlaps, particularly the overlap between the night shift and the following morning shift. Thus, some night shift handlers continue working alongside the first handlers coming in the next morning. This implies that the boundary conditions at these shift transitions, that is, the initial and final system states, will have a major impact on the solution. To take account of this effect we extend the planning horizon by at least 16 hours (two shifts) before and after the moment being planned.

This concept of an extended horizon with shift overlaps is depicted in Figure 5. The horizon's initial and final shifts, shown in red, are strongly influenced by the boundary conditions whereas the shifts in yellow are influenced by the initial conditions only in the early hours. The shifts coloured green are preceded and followed by shifts that have been optimized, suggesting that in these cases we may assume the boundary conditions are too distant to exert any influence.

Although the use of this extended horizon technique allows us to formulate each day's shift plan separately, this comes at the cost of increasing the size of the problem since the planning horizon now stretches over 56 hours. In the solution we implemented, the initial condition is that the airport is empty at 6 a.m. the day previous to the day being planned while the final condition is that no departures are scheduled beyond 12 noon the day following.

4. Task generation model

The task generation model determines the handler staff requirements for each time interval. The model's main consideration is the expected number of bags arriving at each loading carrousel from the check-in counters. When a bag arrives at a carrousel, the handlers decide what priority to assign it, that is, whether to process it immediately or leave it for a later period. This results in the formation of an inventory of bags at the carrousel for each flight to be prepared. However, all bags for a given flight must be processed before it is closed to further loading.

Another factor to be taken into account is that as the number of bags on a carrousel increases, so do the chances of a handling error. To model this consideration we defined a "congestion threshold" above which the efficiency of the operation is considered to be negatively affected. Exceeding this threshold is penalized in the objective function.

In addition to the regular carrousel job positions, the model also includes those at the M9 carrousel zone where bags that have cleared high-level security checks are sent to the appropriate regular carrousel for processing in the following period.

The presence at the airport of flight preparation companies other than Andes, which together account for about 20% of daily flights, is also included in the model. This factor is significant given that it increases the number of bags in the BHS and the practical limits on the number of handlers that can work at a carrousel at any time.

In the following model the planning horizon is discretized into T periods of equal length. We use the following sets

Index sets

$v \in V$	Flights
$c \in C$	Carrousels
$t \in T$	Time periods.

Parameters

γ_{vc}	Equal to 1 if flight v is prepared at a regular carrousel c, otherwise 0.
δ_{tv}	Expected number of bags of flight v arriving at the assigned carrousel in period t.
σ_{tc}	Bags of companies other than Andes on carrousel c at the end of period t.
λ	Bags per period processed by a handler at a carrousel (the handler processing rate).
M_c	Maximum number of bags on carrousel c at the end of a period.
L_c	Bag congestion threshold for carrousel c.
θ_{tc}	Number of handlers from companies other than Andes working at carrousel c in period t.
H_c	Maximum number of handlers that can work simultaneously at carrousel c.
Δ_t	Limit on variation in personnel in period t; equal to 0 for periods where the staff level cannot be varied.

For greater notational clarity we define the following parameters separately for security carrousel M9:

$\tilde{\delta}_{tv}$	Expected number of bags of flight v redirected to M9 arriving to this carrousel in period t.
$\tilde{\lambda}$	Processing rate of bags at M9.

Variables

x_{tc}	Required number of handlers in period t at each carrousel c.
f_{tv}	Number of bags for flight v processed at the carrousel associated with it in period t.
s_{tv}	Number of bags for flight v remaining to be processed at the end of period t (inventory).
y_{tc}	Number of bags above the congestion threshold at the end of period t at each carrousel c.

Again, to formulate the M9 dynamic we define two analogous variable sets:

$\tilde{f}_{tv}$	Number of bags for flight v processed at the carrousel M9 it in period t
$\tilde{s}_{tv}$	Number of bags for flight v remaining at the carrousel M9 to be processed at the end of period t.

Having now defined all the necessary notation, we specify the task generation model as follows:

Model

$$\min\ \beta_1 \sum_{t\in T}\sum_{c\in C} x_{tc} + \beta_2 \sum_{t\in T}\sum_{c\in C} y_{tc}$$

subject to:

$$s_{(t+1)v} = s_{tv} - f_{tv} + \delta_{tv} + \tilde{f}_{(t-1)v} \qquad \forall v, \forall t : 1 \le t \le T-1 \qquad (1a)$$

$$\tilde{s}_{(t+1)v} = \tilde{s}_{tv} - \tilde{f}_{tv} + \tilde{\delta}_{tv} \qquad \forall v, \forall t : t \le T-1 \qquad (1b)$$

$$s_{tv} = 0 \qquad \forall v, t \in \{0, T\} \qquad (2a)$$

$$\tilde{s}_{tv} = 0 \qquad \forall v, t \in \{0, T\} \qquad (2b)$$

$$\sigma_{tc} + \sum_{v\in V} \gamma_{vc} s_{tv} \le M_c \qquad \forall t, \forall c \ne \mathrm{M9} \qquad (3a)$$

$$\sigma_{tc} + \sum_{v\in V} \tilde{s}_{tv} \le M_c \qquad \forall t, c = \mathrm{M9} \qquad (3b)$$

$$y_{tc} \ge \sum_{v\in V} \gamma_{vc} s_{tv} - L_c \qquad \forall t, \forall c \qquad (4)$$

$$\lambda x_{tc} \ge \sum_{v\in V} \gamma_{vc} f_{tv} \qquad \forall c : c \ne \mathrm{M9}, \forall t \qquad (5a)$$

$$\tilde{\lambda} x_{tc} \ge \sum_{v\in V} \tilde{f}_{tv} \qquad c = \mathrm{M9}, \forall t \qquad (5b)$$

$$x_{tc} + \theta_{tc} \le H_c \qquad \forall t, \forall c \qquad (6)$$

$$-\Delta_t \le x_{tc} - x_{(t-1)c} \le \Delta_t \qquad \forall c, \forall t \ge 1 \qquad (7)$$

$$x_{tc} \in \mathbb{Z}^+ \qquad \forall t, \forall c \qquad (9)$$

$$y_{tc} \ge 0 \qquad \forall t, \forall c \qquad (10)$$

$$f_{tv}, \tilde{f}_{tv}, s_{tv}, \tilde{s}_{tv} \ge 0 \qquad \forall t, \forall v \qquad (11)$$

The objective function is the weighted sum of two terms. The first term minimizes the number of handlers used in each period at each carrousel while the second term penalizes carrousel congestion. The penalty itself is assumed to be a linear function of excess bags. Parameters β_1 and β_2 define the relative weights of the two objectives. This objective function represents the tradeoff between number of operators and congestion on carrousels. Even though carrousels can be operated above the congestion threshold for short periods, this kind of operation cannot be sustained for long.

For each of the three first pairs of constraints: (1a)–(1b), (2a)–(2b) and (3a)–(3b), the first constraint models the operation of the regular carrousels while the second one models the special case of M9. Constraints (1a) and (1 b) model the dynamic of the bags on the regular and M9 carrousels, respectively. The former term includes both the bags arriving directly from check-in and those that cleared M9 in the previous period. Constraints (2a) and (2 b) set the initial and final conditions for the number of bags on the carrousels for any flight. The combination of these restrictions with constraints (1a) and (1 b) forces the processing of all bags to be performed in time for their respective flights. The extended planning horizon in our approach makes it possible to define simple boundary conditions for this model.

The number of bags allowed on a carrousel at the end of each period is constrained by (3a) and (3 b). The left-hand side of the two inequalities gives the total number of bags on the carrousel, the first term representing bags of other companies and the second term those of Andes. Constraint (4) together with the non-negativity condition of variables y_{tc} (9) defines the number of bags by which the congestion threshold is exceeded.

The processing capacity of each carrousel is defined by (5a) and (5 b) as a function of the number of handlers present. The left-hand side of the two expressions is the maximum processing rate given the number of assigned handlers.

Constraint (6) sets the upper bound for the number of handlers working simultaneously at each carrousel. Inequalities (7) limit the variation in handler staff levels from one period to the next, the purpose of these restrictions is twofold: first to smooth the ups and downs in staff requirements, thus avoiding abrupt changes and second we allow $\Delta_t \neq 0$ only in the periods where staff changing is possible. Constraint (8) imposes that the number of handlers be an integer while (9) and (10) require the remaining variables to be non-negative.

Finally, note that the problem is not separable by carrousel given that bags for any flight may flow to carrousel M9 from where they are subsequently distributed to the regular carrousel assigned to their respective flights.

5. Shift assignment model

5.1. Description

The objective of the shift assignment model is to find the combination of shifts that allows the handlers to carry out all of the tasks generated by the task generation model. Each shift is defined by its start and end times, break times, what tasks are to be carried out and their duration. Conditioning these definitions are a number of restrictions governing factors such as shift length, eligible break periods and break length, minimum assignable working time, the maximum assignable number of different tasks, and allowable task combinations.

5.2. Mathematical formulation

The model solves a generalized set covering problem in which there is a set I of feasible shift structures that can be chosen from to cover the requirements for the carrousel jobs during a given full shift. This set is generated previous to solving the model using the algorithm described below in Section 5.3.

The sets, parameters and variables and their notation are defined below.

Index sets

$i \in I$	Feasible shifts.
$j \in J$	Carrousel jobs.
$p \in P$	Half-hour time blocks.

Parameters

R_{jp}	Staff requirement for job j in block p.
a_{ijp}	Equals to 1 if shift i covers job j during block p, otherwise 0.
c_i	Penalty for using shift type i.

For carrousel jobs, parameter R_{jp} is the output of variable x_{tc} of the task generation model expressed in terms of half-hour blocks. To build this parameter we took the maximum value of x_{tc} for each block.

Variables

$z_i \in \mathbb{Z}^+$	number of type i shifts used.

Model

$$\min \sum_{i \in I} c_i z_i$$

subject to

$$\sum_i a_{ijp} z_i \geq R_{jp} \qquad \forall j, \forall p \qquad (12)$$

$$z_i \in \mathbb{Z}^+ \qquad \forall i \qquad (13)$$

The only set of constraints for this model ensures that handler staff demand is satisfied. The objective function is the weighted sum of the assigned shifts. The penalty associated with each shift creates preferences for certain shifts over others and can thus be used to represent the planner's criteria and company policy.

The policy at Andes is to have relatively few changes in handler job assignments. Thus, the rule adopted for the model is that *the fewer the changes in handlers' tasks, the better is the shift, but a bad shift is preferable to an additional handler*. To represent this criterion, the penalty associated with a given shift is specified as $c_i = \omega_0 + \omega_1 N_i$, where ω_0 is the fixed cost of a shift, ω_1 is the cost of an operator switching tasks during a shift and N_i is the number of different tasks in shift i. Thus, searching for the lowest-cost combination of shifts will induce the model to choose preferred shifts.

5.3. Feasible shift structure generation

A feasible shift structure is defined as a combination of tasks that can be performed by a handler during a single shift. The simplest task considered in the model is handling bags in a carrousel. Nevertheless, the model can be easily extended to any job associated with a carrousel. Since the set of feasible shift structures generally stays constant, the algorithm only needs to generate them once unless a change occurs in the general operational conditions. This means that shift generation can normally be done "offline."

To ensure the shift structures are operationally viable and comply with labour regulations, the following set of shift structure generation rules were adopted:

1. Shift length is always 8 hours, divided into half-hour blocks.
2. Handler tasks may have a duration of 1.5, 2, 3, 3.5 or 4 hours.
3. A break is defined as a special task that is 1 hour long (2 blocks). It cannot start before the 7th block or after the 9th, that is, no earlier than 3 hours into the shift but no later than 4.5 hours into it.
4. Shift start times are restricted to relatively narrow bands around the "official" start times of 4 a.m., 12 noon and 8 p.m. (see 3.2 above).
5. A handler can perform no more than two different tasks before the break and no more than two after it. Thus, no more than four tasks per shift can be performed.

To build the shift structures the algorithm uses only two task-duration alternatives: 1.5 hours (3 blocks) and 2 hours (4 blocks). Combinations of them are used to construct all other durations. Thus, a 3-hour task is generated as two tasks of 1.5 hours each. The six possible shift structures that satisfy the above conditions combining blocks into tasks and breaks are diagrammed in Figure 6.

A simple way to generate all feasible shift structures is to first enumerate all possible structures and then to filter the infeasible ones. The time required to generate the shift structures grows rapidly with the number of tasks, but never to the point where the process is too slow to be practical for use during daily operations (see Table 1). Since the overall work patterns in a real application tend not to change

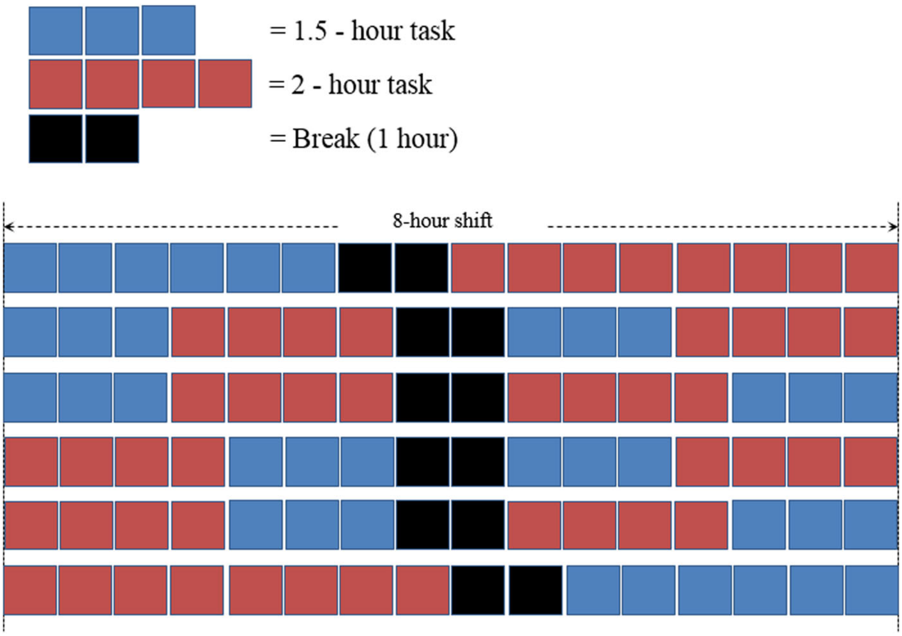

Figure 6. Possible shift structures.

Table 1. Shifts generated by number of tasks.

No. of tasks	Shifts generated	Shifts accepted	% accepted	Time (s)
7	374556	340158	90.8	38
8	638976	587392	91.9	64
9	1023516	949806	92.8	157
10	1560000	1458600	93.5	397

significantly on a frequent basis, the construction of feasible shift structures should not need to be repeated often.

6. Computational experiments

To test our proposed two-stage approach, experiments were conducted using real data from Andes' daily operations at the AMB baggage handling area between December 2011 and February 2012. The main input data for the models is the *flight schedule* of each day. Most of the parameters are calculated from this schedule.

Testing was confined to the eight regular carrousels used by the company, which include M2, M3 and M4 for international (high complexity) flights, M5 and M6 for domestic (low complexity) flights, M7 and M8 mostly for other companies, as well as security zone carrousel M9.

To construct the instances, a number of values had first to be defined. We estimated carrousel bag arrival (δ_{tv}) from the actual number of passengers over the course of the day. This was done using a baggage handling simulator (Cavada et al. 2017) to obtain realizations of the bag arrival process for each flight.

As regards the parameters we chose a conservative demand level, defining δ_{tv} in the first (task generation) model as the 80% quantile of bag flow for each period in the

Table 2. Computational results summary (61 instances).

Period	Avg. daily number of flights	Avg. shifts assigned		Difference		
		Model	Benchmark	Min.	Max.	Avg.
December	204	55	69	10.3%	35.2%	20.9%
January	287	93	98	1.0%	11.5%	5.5%
February	297	95	103	2.9%	16.0%	7.5%

simulation. The bag processing rates (λ, $\tilde{\lambda}$) were those recommended for a safe operation according to the company's operating procedures, they were both set at 2 bags per minute. The values for other companies' handlers and bags (σ_{tc} and θ_{tc}) were defined using data provided by Andes. Specifically, the number of handlers is estimated using the amount of space that other companies have assigned to prepare their flights in each carrousel. Finally, in order to prioritize the quality of the carrousel operation over staff size, greater relative weight was given to the second term in the objective function over the first in the task generation model ($\beta_1 = 10, \beta_2 = 1$). A standard strategy to find relative weights of a bi-objective optimization problem is to solve the problem several times iterating over the values of β_1, β_2 and to build a Pareto frontier (number of handlers versus time over congestion in our case), then choose an acceptable point in the frontier to use. In this case, we choose a point where the congestion level was comfortable for the company.

The parameter values for δ_{tv}, $\tilde{\delta}_{tv}$, and γ_{tv} were derived directly from the flight schedules for each day. The maximum number of handlers (H_c), maximum number of bags (M_c) and bag congestion threshold (L_c) were determined by the available physical space for handler maneuvers and cart storage. Assuming the carrousels were identical, the values for the latter three parameters were set at 8 handlers, 80 bags and 30 bags, respectively. Lastly, the parameters for other companies were estimated on the basis of the schedules for the flights they handled.

In Table 2, a summary of the experiments results is presented, averaged by month. The first column shows the month from which the instances were obtained. In total, 61 instances were run: 17 corresponding to the month of December, 19 for January and 25 for February. These months represent the peak season in the airport, being January and February the busiest months of the year. The table refers to the staff level determined by the stage 2 model. Column "Avg. shifts assigned Model" reports the total number of handlers scheduled by the model. Column "Avg. shifts assigned Benchmark" reports the total number of handlers scheduled by the company as benchmark. The last three columns show the minimum, maximum and average percentage reduction in the staff obtained by the model with respect to the benchmark. From this summary, it can be seen that the models outperform the company assignment. The difference is however less significant when the airport is operating near capacity during January and February. The detail of all instances is reported in Appendix.

The results of an illustrative case based on the operating situation for December 19, 2011 at AMB are discussed below. As an aid in understanding the analysis, a graphical representation of the model's solution output showing the daily operating plan for each Andes handler (y-axis) in each time block (x-axis) on the aforementioned date is given in Figure 7. The number in each block indicates the carrousel the handler is assigned to while the blocks shown in black and labelled -1 are the handler's shift break.

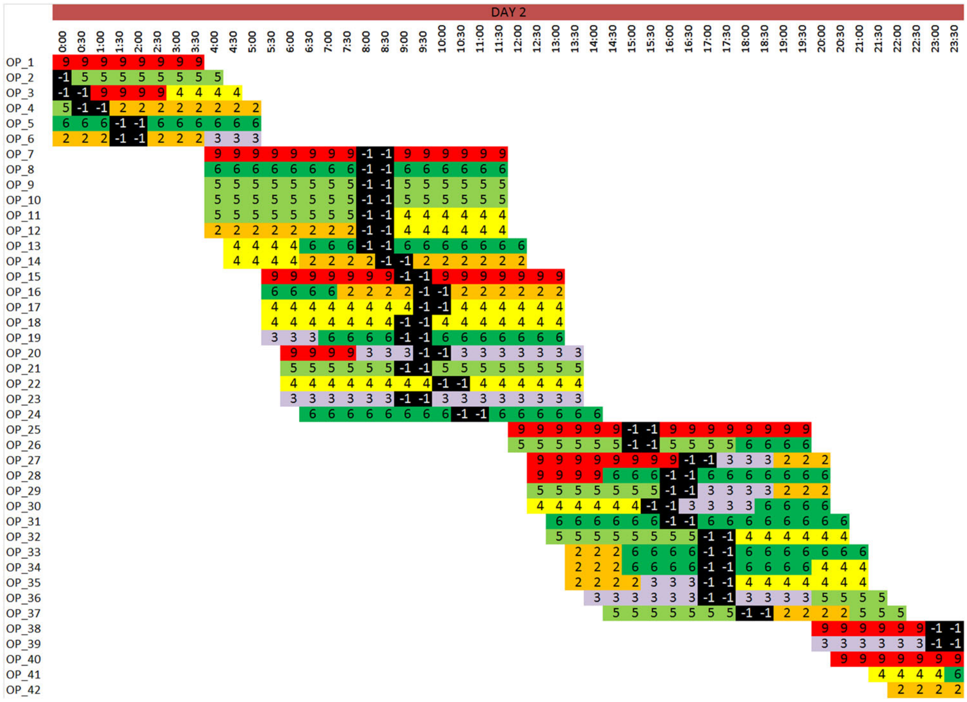

Figure 7. Daily operating plan generated by model.

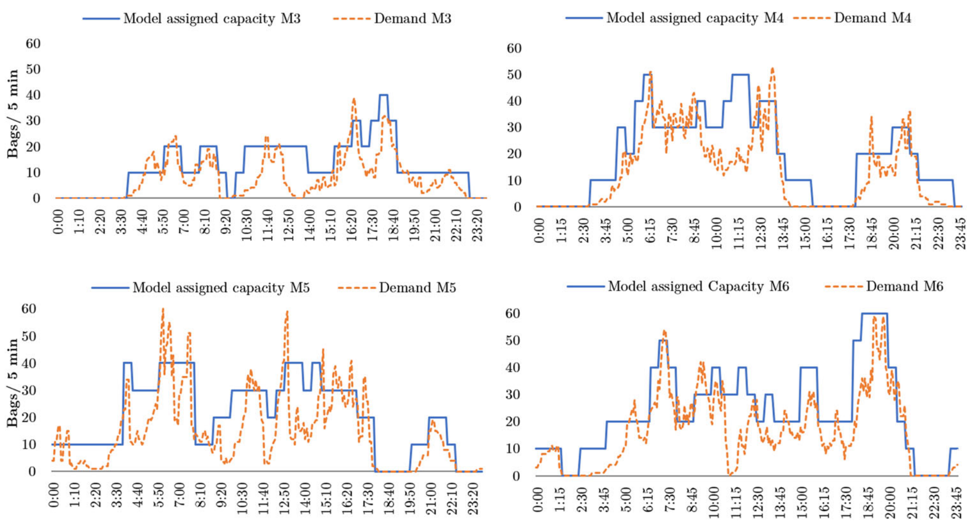

Figure 8. Demand vs. Processing capacity assigned by model. Carrousels M3-M6 during a representative day.

6.1. Comparison of model and real company staff assignments

The first objective of the model is to assign staff efficiently to the various jobs. A comparison of the staff numbers in the model-generated plan with the numbers for the real company plan shows that on average with the model 42 handlers are required instead of 47.

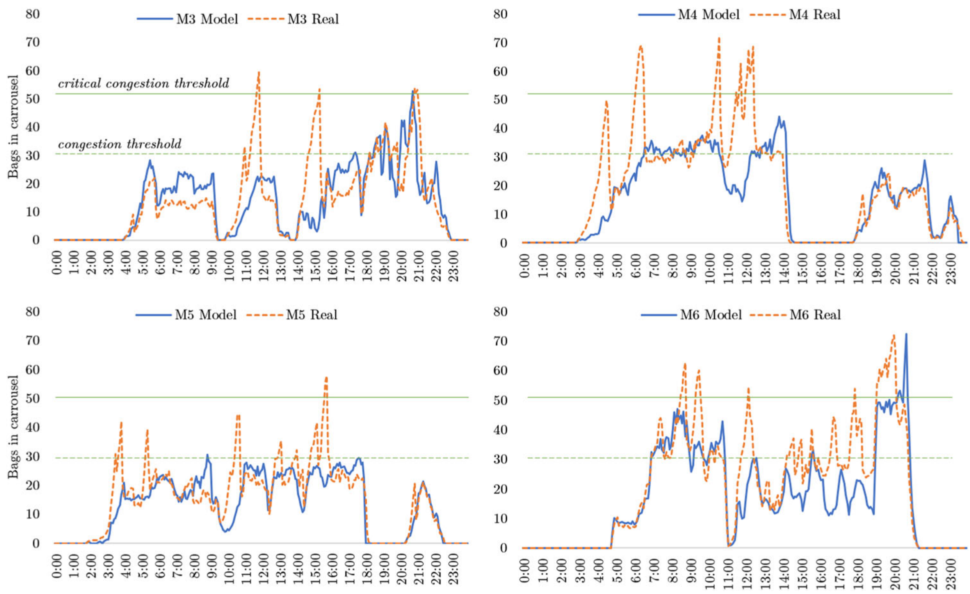

Figure 9. Bag congestion on carrousels – model versus real. Carrousels M3-M6 during a representative day.

In Figure 8 the total assigned processing capacity specified by the model for each time block, shown in red and calculated as the product of the number of assigned handlers and the individual handler processing rate, is plotted against the bag arrival rate, shown in blue, for the four largest of the six carrousels (M3 to M6). As can be seen, the model tended to increase the staff level before high demand periods and assign handlers to process the bags as they arrive, effectively anticipating demand increases. The model did not overreact to certain demand peaks, however, but rather managed them deftly by allowing bag inventories to form on the carrousels. This is visible in the graph of M5 between 6 a.m. and 8 a.m. and again from 12 noon to 1 p.m. Note that, there is an overlapping between morning and evening shifts during the time ranges from 10 a.m. to 12 p.m. and from 5:30 p.m. to 7:30 p.m., which could produce unavoidable overcapacity as observed in some cases shown in Figure 8.

6.2. Bag congestion on carrousels

The second objective of the model is to manage the amount of baggage on each carrousel so that the bag congestion threshold (30 bags) is not exceeded for extended periods. The model solutions are considerably more efficient in achieving this than the company planning. To evaluate this indicator we simulated both the model and real operating plans for the same four carrousels and plotted the results in Figure 9. We run these simulations using the simulator described in Cavada et al. (2017). As the graphs show, with the model the threshold was exceeded only for short periods, and only twice did the number of bags reach the critical level (50). By contrast, under company planning the congestion threshold was exceeded for much of the day and the operation reached critical levels on more than 12 occasions. This implies that the redistribution of handlers generated by the model has a strongly positive impact on system performance.

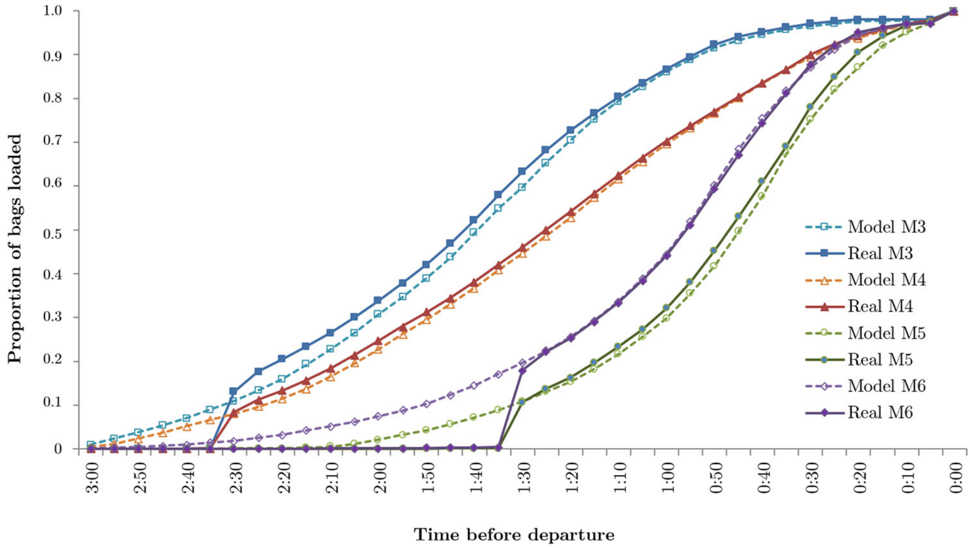

Figure 10. Evolution of the average proportion of loaded bags for each carrousel before departure.

The superior results of the model solutions on this criterion is due primarily to the fact that they assign staff to the carrousels earlier than the company planning, thereby avoiding baggage buildup at the start of each flight preparation process. The same phenomenon can also be observed in the evolution of bag removals from the carrousels for loading. This is illustrated in Figure 10, where the curves represent the accumulated proportion of bags loaded onto the aircraft as a function of time left to flight closure. The graph reveals that for all four carrousels, the model gives a different result from the company planning only for the early bag loadings, after which the curves more or less coincide. This result is particularly important for Andes because it ensures the staff level defined by the model has not negatively affected the quality of the flight preparation operation.

7. Conclusions

This article presented an approach to personnel shift planning for an airport baggage handling operation using two sequentially executed integer programming models. The models are developed and solved over an extended time horizon to address the shift boundary conditions. The first model determines the staff requirements for each carrousel in the baggage handling area as a function of the number of bags that must be handled, attempting to find the optimum balance between the required number of handlers and bag congestion on the carrousels. The second model takes the staff requirements determined by the first model as input to construct the daily shifts for handler staff. This formulation is a generalized set covering model that seeks to cover the staff requirement from among a predetermined set of feasible shift structures. These structures are generated offline in a matter of minutes by an algorithm that takes account of various operating conditions and operator-defined handling policies.

The assignments obtained by this proposed methodology were compared with the real-world personnel planning used by a handler operation at Santiago International

Airport in Chile during a Southern Hemisphere Summer. The model solutions reduce the requirement for handlers; most importantly, the model reduces bag congestion on the carrousels, which results in a more orderly baggage handling operation.

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Disclosure statement

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ORCID

Juan Pablo Cavada http://orcid.org/0000-0002-6103-1930
Cristián E. Cortés http://orcid.org/0000-0001-7041-4602
Pablo A. Rey http://orcid.org/0000-0002-1337-4701

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Table A1. Features of solved instances.

	Flights									Shifts assigned		
Instance	Andes	Other	Constraints	Variables	z_{LP}	z_{MIP}	Nodes	Time (s)	gap	Model	Benchmark	Diff
Dec02	215	181	663860	1036283	31410.9	35853.2	23523	1800	0.8%	60	72	16.7%
Dec03	240	197	727200	1142375	30902.5	35224.5	26734	1800	0.6%	46	71	35.2%
Dec04	190	181	631560	971583	29829.0	34020.2	8481	659	0.5%	57	70	18.6%
Dec05	210	181	657400	1023043	31965.1	36375.5	12079	1227	0.5%	55	72	23.6%
Dec06	211	180	656752	1023344	31296.4	35514.5	27	189	0.5%	62	73	15.1%
Dec07	204	179	645768	1002641	30627.3	34831.6	1337	385	0.5%	56	73	23.3%
Dec08	200	177	635428	984527	30138.8	34599.3	25802	1800	0.6%	57	67	14.9%
Dec09	203	176	638656	992292	30002.0	34719.5	21775	1800	0.9%	55	69	20.3%
Dec10	190	179	627680	966409	29148.2	33567.6	32282	1800	0.8%	53	68	22.1%
Dec11	192	182	636084	979346	30001.4	34512.2	27184	1800	0.7%	54	72	25.0%
Dec14	213	185	669036	1040807	29991.4	34516.6	7825	946	0.5%	55	70	21.4%
Dec15	217	186	674852	1051158	30552.6	35091.2	20877	1800	0.8%	55	69	20.3%
Dec16	204	176	639948	994880	29178.6	33581.2	20919	1800	1.1%	49	65	24.6%
Dec17	196	184	645132	994872	29863.7	34317.3	27007	1800	0.8%	56	70	20.0%
Dec18	196	184	643840	992284	29993.2	34409.2	33676	1800	0.9%	61	68	10.3%
Dec19	216	187	675500	1051505	32224.6	36592.1	22914	1800	0.7%	59	74	20.3%
Dec20	179	155	566908	875853	25304.2	29095.1	601	193	0.4%	39	51	23.5%
Jan13	273	144	667016	1090668	40477.8	45265.4	152	246	0.5%	84	87	3.4%
Jan14	253	146	645056	1044082	39934.5	44673.0	4217	446	0.5%	83	85	2.4%
Jan15	255	141	637940	1036323	41547.5	46452.7	619	265	0.5%	84	89	5.6%
Jan16	266	130	630812	1036334	42615.7	47252.3	970	334	0.5%	85	89	4.5%
Jan17	284	134	661828	1093266	43665.3	48831.7	271	185	0.5%	84	91	7.7%
Jan18	282	136	663124	1093264	42726.2	47699.9	54	238	0.5%	84	86	2.3%
Jan19	279	139	665068	1093261	41598.5	46322.3	1448	554	0.5%	82	87	5.7%
Jan20	273	144	667016	1090668	41510.7	46254.8	9232	971	0.5%	85	85	0.0%
Jan21	287	112	623024	1044116	46366.7	51863.1	974	399	0.5%	99	105	5.7%
Jan22	284	112	619148	1036352	46378.1	52096.5	722	322	0.5%	97	103	5.8%
Jan23	303	112	643696	1085524	49145.3	54645.6	187	230	0.5%	103	107	3.7%
Jan24	306	112	647572	1093288	48038.7	53912.9	25	198	0.4%	97	108	10.2%
Jan25	306	112	647572	1093288	47665.8	53124.2	0	193	0.2%	100	101	1.0%
Jan26	306	112	647572	1093288	47337.7	53067.1	620	327	0.5%	100	108	7.4%
Jan27	305	112	646280	1090700	47778.9	53338.9	45	240	0.5%	98	109	10.1%
Jan28	287	112	623024	1044116	46599.0	52250.2	715	324	0.5%	98	107	8.4%
Jan29	284	112	619148	1036352	46550.5	52380.2	2362	435	0.5%	100	103	2.9%
Jan30	304	112	644988	1088112	49466.3	55219.8	7	208	0.4%	103	108	4.6%
Jan31	306	112	647572	1093288	48098.6	53806.5	2	199	0.5%	92	104	11.5%
Feb01	305	112	646280	1090700	47599.5	53153.1	27	212	0.2%	101	104	2.9%
Feb02	306	112	647572	1093336	47612.1	53467.4	70	232	0.5%	101	106	4.7%
Feb03	306	112	647572	1093336	48505.6	54010.7	0	196	0.5%	103	114	9.6%
Feb04	284	112	619148	1036400	46165.7	51632.7	27	243	0.4%	98	107	8.4%
Feb05	282	112	616564	1031224	46429.1	51827.7	618	266	0.5%	93	103	9.7%
Feb06	300	112	639820	1077808	48330.6	53568.5	497	233	0.5%	102	106	3.8%
Feb07	301	112	641112	1080396	46215.7	51778.9	0	204	0.3%	90	96	6.3%
Feb08	301	112	641112	1080396	45533.7	50750.6	15	203	0.4%	95	100	5.0%
Feb09	304	112	644988	1088160	46030.7	52169.4	27	227	0.5%	97	105	7.6%
Feb10	304	112	644988	1088160	46892.7	52797.4	735	322	0.5%	99	105	5.7%
Feb11	282	112	616564	1031224	44352.4	49925.6	44	192	0.5%	89	98	9.2%
Feb12	280	112	613980	1026048	44510.9	50122.1	606	200	0.5%	95	98	3.1%
Feb13	299	112	638528	1075220	47305.7	52502.8	9	185	0.5%	100	105	4.8%
Feb14	300	112	639820	1077808	45750.5	50900.5	0	182	0.5%	88	98	10.2%
Feb15	300	112	639820	1077808	45138.8	50264.0	27	209	0.3%	94	104	9.6%
Feb16	305	112	646280	1090748	45979.8	52033.1	330	237	0.5%	97	105	7.6%
Feb17	305	112	646280	1090748	47039.1	52742.1	452	237	0.5%	95	106	10.4%
Feb18	285	112	620440	1038988	44924.4	50498.6	359	214	0.5%	92	101	8.9%
Feb19	281	112	615272	1028636	44849.3	50369.1	619	235	0.5%	92	99	7.1%
Feb20	299	112	638528	1075220	47660.9	53160.8	0	208	0.4%	101	105	3.8%
Feb21	301	112	641112	1080396	46218.0	52501.8	0	193	0.5%	89	96	7.3%
Feb22	301	112	641112	1080396	44925.6	51063.8	19	205	0.3%	92	102	9.8%
Feb23	308	108	642396	1088164	45593.1	51842.4	159	247	0.4%	98	102	3.9%
Feb27	294	112	632068	1062280	46910.1	52070.7	94	252	0.5%	92	106	13.2%
Feb28	290	112	626900	1051928	44890.3	49965.5	397	244	0.5%	84	100	16.0%

Appendix: Computational experiments

Table A1 reports the features and indicators of instances and solutions, and each instance is labelled by the corresponding date. The two following columns represent the number of flights served by the company handlers and flights of other companies, respectively. The fourth and fifth columns report the number of constraints and variables in the stage 1 model. The two following columns show the optimal value of the linear relaxation and the value of the best integer solution found. The next two columns display the number of branch-and-bound nodes and total time in seconds required by CPLEX to solve the instance. The following column reports the relative gap between the best integer solution and the best known lower bound at the stopping time. Experiments were performed with the stopping criteria of a gap less o equal to 0.5% or 1800 seconds of computational time.

The last three columns in Table A1 refer to the final staff levels determined by the stage 2 model. Column "Shifts model" reports the total number of handlers scheduled by model 2 using as input the requirements defined as output of the stage 1 model. Column "Shifts benchmark" reports the total number of handlers scheduled by model 2 using as input, the requirements constructed by the simplified procedure used by the company as benchmark. The last column of the table shows the percentage reduction in the staff obtained by the model with respect to this benchmark. Stage 2 performance indicators are not explicitly shown because all the instances had the same number of feasible shifts (949806 columns), and they were all solved to optimality in less than ten seconds.