Stochastic Modelling of an Airport Baggage Handling System

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Abstract

The main task of air transport is to safely transport both passengers and their baggage to their destinations. Nowadays, one of the most crucial tasks airports have to take on is baggage handling, since a failure of a Baggage Handling System (BHS) often causes a blockage in the airport, which greatly impacts its quality of service. The main goal of this dissertation is to model a BHS, capable of withstanding changes in the pattern of arrivals and unforeseen machine breakdowns, and describe improvement proposals based on the removal of certain system components. The analysis of the BHS was developed in a more generalised approach, to ensure that its takeaways can be applicable to airports with similar characteristics, including the size, features and equipment. The baggage handling model was described on a Discrete Event Simulation (DES) tool, SIMUL8, where the bottlenecks could be identified and the system performance could be evaluated for particular scenarios. Modifications to the system can be suggested after analysing the simulation results. For an increase in the baggage injection rate, results reveal that additional conveyor belts are necessary before the first security stage; whereas in the event of a decline in checked baggage volume, it was demonstrated that certain security stages resources could be excluded from the system and still report low queueing times.
Keywords: Baggage Handling System, Discrete Event Simulation, Stochastic Process

1. Introduction

1.1. Motivation

Air travel is a mode of transportation with many advantages which makes it a popular choice among its alternatives. As of 2019, more than 30 million passengers arrived in Portugal, a number that has almost doubled since 2010 [14], mainly as a result of the rise in popularity of low-cost airlines. This increase in passenger traffic was not only common to Portugal but also to most countries in the world and is directly correlated with an increase in the quantity of checked-in luggage [6]. In fact, it was reported that 4.54 billion passengers and their luggage boarded a flight in 2019 [16].

Despite the overall increase in the number of passengers in the last years, in the second quarter of 2020 only 434 thousand passengers were transported at national airports, representing a decrease of 97.4%, as a result of the impact of the COVID-19 pandemic and the restrictive measures adopted in airspace [10]. However, the passenger volume in 2022 is already approaching the levels recorded in the pre-pandemic period (2019) and, by the end of 2023, it is expected that most regions will have reached or surpassed pre-pandemic levels of demand [11].

Nowadays, airports use modern BHSs to transport baggage through the terminals. Baggage handling consists of numerous subtasks involving the collection, sorting and distribution of luggage, and can be distinguished in three main processes related to the departures, transfers and arrivals to airports. The number of baggage items, passenger arrival rate, barcode misreads, early and late bags, and security checks are all factors that contribute to the performance of a BHS [8]. The management of baggage systems has become a more and more challenging task in the past years and its efficiency directly impacts the airport's performance as well as passenger and airline satisfaction, since misdirected and lost baggage influences the airport's public image [13].

With the recent increase in automation and smart technology, airlines are able to not only improve baggage handling capabilities but also lower the bag mishandling rate. An overall decrease in the number of mishandled bags is reported from 2007 until 2019 [16]. Despite this decrease, airports and airlines are still subjected to substantial costs which greatly impact their operations.

Due to the growth of passenger traffic, BHSs occasionally operate at system capacity and need improvements and/or expansions [6]. However, before applying any improvement strategy to a given BHS, an extensive analysis of the whole process should be done, since implementing changes in the physical system can be very costly. This analysis, which may include the testing and evaluation of various scenarios, requires suitable modelling and simulation tools in order to model and simulate the real system with the utmost rigour, and test and evaluate the performance of the possible modifications to the physical system.

1.2. Objectives and Contributions

The main goal of this dissertation is to model a BHS that is capable of withstanding changes in the pattern of arrivals, unforeseen machine breakdowns and other relevant scenarios. Any of these modifications will always have effects on the performance of the system. Using simulation, it is possible to quantify these effects and explore potential solutions that can lessen them without intervening directly in the actual system.

The following steps have to be established in order to achieve the main objective of the thesis:

- Build a simulation model of the system using a simulation software.
- Identify bottlenecks and describe their impact on the system.
- Create scenarios that improve the overall performance of the system.

This dissertation produced the following contributions: the analysis of a BHS in a generalised approach to facilitate the study of other similar systems; the detection of bottlenecks; and the suggestion of improvement strategies.

2. Background

Air transport requires a separation between passengers and their luggage, which sets it apart from the vast majority of other modes of transportation.

2.1. Airport Environment

Every airport can be divided in two parts: landside and airside (Figure 1). The BHS allows the flow of baggage between the airside and landside.

Figure 1 shows the several baggage inflow and outflow streams at an airport, where it is possible to see that both check-in baggage and transfer baggage are forwarded to a departing flight by the outbound baggage handling, while inbound baggage is forwarded to the baggage claim area.

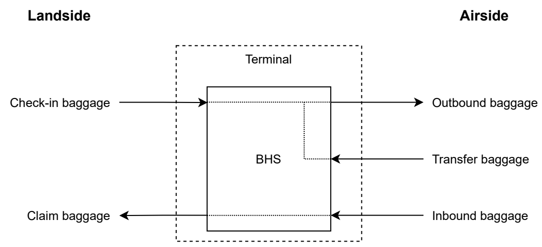

Figure 1: Baggage inflow and outflow streams.

A BHS has three fundamental tasks: transport bags from the check-in counters to the departure gate; from the arrival gate to the baggage claim area; and from one gate to another during transfers. These three jobs can also be referred to as departures, arrivals and transfers, respectively.

The components of a BHS include check-in counters, baggage screening, baggage sorting, baggage carousels, storage systems, handling facilities and baggage claim.

There are four levels of security inspection for the departing flights [7]:

1. Bags go through a Explosive Detection System (EDS) machine that captures an X-ray scan of their content and sends it to the security operators to be analysed.
2. Operators have access to the image captured in the previous level of security and decide if the contents of the bag are explosives or any other forbidden objects that can compromise the security of the airplane.
3. The bag is sent through another EDS machine, this time manually controlled by a operator, allowing for a more precise analysis of the bag.
4. The bag is sent to an isolated place to be checked by a security operator. In the extreme case that the bag is deemed a threat, it is removed from the BHS and handled by the authorities.

2.2. Queueing Theory

Queueing models are used to predict queue lengths and queueing time. A queueing system can be described with the following characteristics [15]:

- Arrival pattern of jobs: since the process of arrivals is typically stochastic, a probability distribution describing the times between successive arrivals is needed to model the arrival pattern of jobs.
- Service pattern of servers: modelled using a probability distribution describing the sequence of service times.

- Number of servers: the numbers of servers available to process a job.
- Queue discipline: the priority in which the jobs in the queue are served.
- System capacity: the maximum number of jobs allowed in the queue.

2.3. Simulation

A simulation is the imitation of the operation of a real-world process or system over time [3]. Simulation can help to get a better understanding of the system, compare different system designs as well as aid in improving the system's efficiency by resolving their problems.

A model is an abstract representation of a system, generally consisting of structural, logical, or mathematical relationships which describe a system in terms of state, entities and their attributes, sets, processes, events and activities. The main components of a system are entities, attributes, activities, states and events.

This dissertation will follow a DES approach since the BHS can be characterised by:

- being a discrete system, where the state variables (number of bags in the system) change at a discrete set of points in time, contrary to a continuous system, where the state variables change continuously (for example, the amount of water flow over a dam);
- being stochastic, opposed to deterministic, incorporating random variables, for instance the interarrival times and the service times.
- being a dynamic system that changes through time in contrast to a static system which represents a system at a particular point in time.

The authors in [1] attempt to identify answers for numerous logically raised and thought out questions that are stumbled upon when using any given simulations package, including the use of spreadsheets as reporting tools, simulation approaches, programming languages and *what if* scenarios. The work developed argues that SIMUL8 is a simulation software suitable to deal with bottlenecks as well as *what if* scenarios. A simulation model in SIMUL8 revolves around processing *Work Items* and is comprised of objects and the routes between them, modelled as a directed graph.

3. Model Implementation

3.1. Problem description

Four key modules compose the BHS simulation model, as illustrated in Figure 2: baggage injection, baggage transportation, security screening stages and baggage unloading.

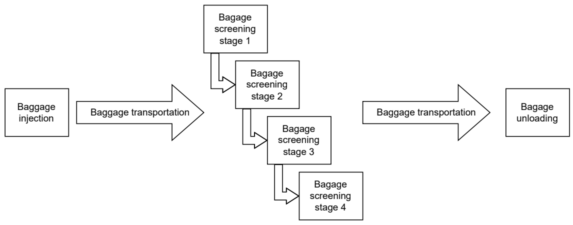

Figure 2: Main processes in the BHS simulation model.

The arrival of entities to a BHS is composed by the check-in baggage as well as the baggage coming from arriving flights (*transfer baggage*). Transfer baggage can be divided in two types: the bags that went through the security in the previous airport and need no further screening (*Screened transfer baggage*) and the ones that need another security screening in the current airport (*Unscreened transfer baggage*).

Taking into account that the majority of airports have their earliest flight of the day at 6:00 and their latest flight near midnight, the operating hours of the BHS were set to start at 5:00 and end at midnight. Hence, based on the input received from *Siemens Logistics*, bags start arriving to check-in counters at 5:00 with a mean arrival rate of 3600 bags per hour.

The outbound baggage volume throughout the day is influenced by the originating passenger arrival profile combined with a flight schedule [2].

Time slots of 30 min were used and the data obtained from [2] had to be adjusted in order to match the average 3600 per hour during the day. The resulting mean arrival rates for outbound baggage are displayed in Figure 3.

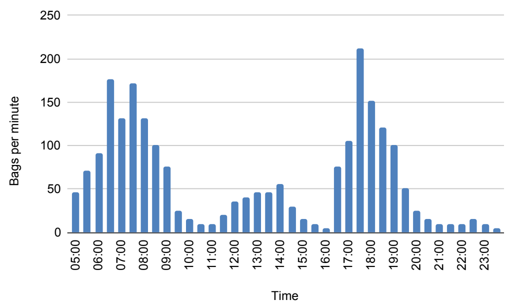

Figure 3: Outbound bag volume in bags per minute.

According to a case study performed in Dusseldorf airport [12], the calculated transfer rate is 12.6%, which corresponds to 454 bags per hour. The same approach was used for the calculation of the arrival rates for the transfer baggage.

EDSs have a mean processing time of 3 s, while Automatic Tag Reader (ATR) machines take 40 s to process a bag. Operators have 15 s to review one image and to decide whether an X-ray image of baggage contains a target or not by clicking on an *OK* button (target absent) or *NOT OK* button (target present) [9]. Additionally, it was defined a mean processing time of 5 min for the fourth stage of security screening and a mean processing time of 1 min for the Manual Tag Reader (MTR) activity.

The Gamma distribution is a typical distribution used to describe processing times, lead time and time to failure. The Probability Density Function (PDF) of the random variable X and the Gamma function $\Gamma(x)$ are represented in equation 1.

$$f(s) = \frac{s^{\alpha-1}e^{-(\frac{s}{\beta})}}{\beta^{\alpha}\Gamma(\alpha)} \quad \text{for} \quad s \geq 0, \qquad \text{where} \quad \Gamma(x) = \int_0^{\infty} s^{x-1}e^{-s}ds \tag{1}$$

If an activity has a known mean ($E[X]$ or μ) and variance ($V[X]$ or σ^2), using equation 2, the shape α and scale β factors for a Gamma distribution can be calculated.

$$\alpha = \frac{E[X]^2}{V[X]} \quad \text{and} \quad \beta = \frac{E[X]}{\alpha} \tag{2}$$

For the conveyors responsible for the baggage transportation in the system, a fixed length of 50 m and speed 0.5 m/s were defined. On the other hand, as the Carousel moves faster than regular conveyors, it was characterized with a length of 50 m and speed 2 m/s. Table 1 summarizes the processing times.

Activity	**Distribution**	**Processing Time**		**Parameters**	
		Mean	Variance	α	β
First Stage	Gamma	3 s	1 s	0.15	0.333
Second Stage	Gamma	15 s	5 s	0.75	0.333
Third Stage	Gamma	30 s	10 s	1.5	0.333
Fourth Stage	Gamma	5 min	5 min	5	1
ATR	Gamma	40 s	5 s	5.333	0.125
MTR	Gamma	1 min	15 s	4	0.25
Conveyors	Fixed	1.67 min		-	
Carousel	Fixed	0.42 min		-	

Table 1: Processing times characterisation.

The Key Performance Indicators (KPI) were the last feature of the framework that needed to be set to verify and validate the behaviour of the system (Table 2). The first step was to establish two high-level metrics to measure the total number of jobs entering the system as well as their average time in the system (CT). Later, for each Workstation (WS), the number of completed jobs and their utilization (u) was set. For each label, the number of completed jobs, the Average Waiting Time (AWT) and the Maximum Waiting Time (MWT) were defined as KPIs.

The performance of the new scenarios could be quickly evaluated and contrasted with the current performance by capturing and gathering all these metrics. To do this, it would first be necessary to analyse the variation of the pertinent KPIs. A desirable scenario would see the AWT decrease and the number of completed jobs, or the throughput, increase.

Scope of the metric	**Performance Measure**	**Terminology in SIMUL8**
System	Number of completed jobs	Work completed
	Average time in system	Average time in system
Workstation	Number of completed jobs	Completed jobs
	Utilization	Utilization
Baggage per level of security	Number of completed jobs	Completed jobs
	Average waiting time	Average queueing time
	Maximum waiting time	Maximum queueing time

Table 2: Metrics defined to record the performance of the simulation model.

3.2. Implementation in SIMUL8

The simulation model constructed in this dissertation is illustrated in Figure 4. In order to thoroughly explain the construction of the simulation model, it can be divided in 5 sections: baggage injection, baggage transportation, security screening stages, baggage identification and baggage unloading.

3.2.1 Security screening stages

After entering the system, bags are subject to security checks, here illustrated as security stages 1 through 4. Every time a Work Item goes through a security stage, the label *Security* is populated with the number corresponding to the that specific security stage, so that at the end of the simulation, one can know how many Work Items went through each security stage.

The first stage of security screening is composed of EDS machines that capture a X-ray scan of the content of the bag. There are 5 WSs in this first stage of security, each one of them succeeding a conveyor belt and a First In First Out (FIFO) queue and include 3 EDS machines, which makes for a total of 15 EDS machines in this stage.

A SIMUL8 *Resource* was created for the second stage of security and populated with 10 available resources, to represent the security operators analysing the X-ray images. After each period of 20 min continuously reviewing X-ray images, operators have to take a break of at least 10 min. To implement this mandatory break, the resource availability was set to 0.7.

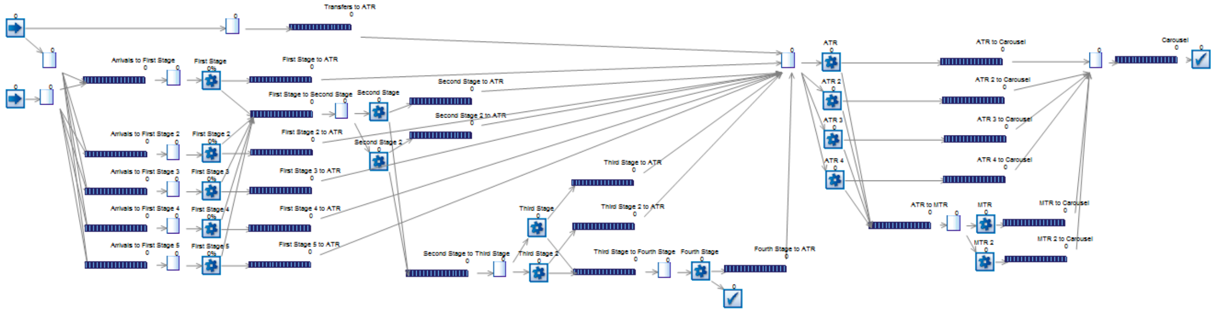

Figure 4: BHS simulation model.

In the third stage of security screening, there are 8 EDS machines controlled by operators, whereas for the fourth stage there are 8 resources available.

3.2.2 Baggage identification

After going through security and being authorized to board the aircraft, bags move to the baggage identification phase. This process in a BHS is responsible for the scanning of the unique tag attached to each bag and can be performed by an ATR machine or by a MTR. There are 48 ATR machines available and 6 operators are available to perform the manual scanning of the tag.

3.3. Verification and validation of the model

This section covers a crucial phase in the construction of a simulation model. Despite its simplicity, using a simplified version of the real model also yields findings that approximate reality. The model cannot be simplified in a way that makes it portray a situation other than what is experienced in the real system. It is essential to validate and verify the developed model in order for these results to be coherent and reflect the actual operation of the system. The primary goal of verification is to make sure the implementation of the model is faultless. Validation ensures that the model presents the rigour required to mimic reality.

3.3.1 Baggage injection in the system

Making sure the baggage is properly entered into the system is one of the important model checks. It was possible to verify that bags enter the system correctly by analysing the results of the first conveyors that receive Work Items from the corresponding *Start Points*. Entities with different values of the label *Origin* could be observed, confirming that both *Start Points* are feeding entities into the system.

3.3.2 Probability of baggage approval in the security stages

The performance of the different security stages is portrayed through baggage approval rates. After each bag is processed in a security stage, the bag's next step is dependent on the *Routing Out* parameter, that allows for the definition of a probability for the bag to be appointed as *clear* on that security stage.

This data was provided by Aeroportos e Navegação Aérea (ANA) and retrieved from [5] regarding a case study performed in a Portuguese airport. These probabilities are calculated based on statistical data collected on the BHS along the years. It is safe to assume that there is not a significant change between these rates and other airport's baggage approval rates, as long as the security screening stages are equipped with the same machines.

Stage	**Percentage of approval**
First	60.04%
Second	97.78%
Third	98.61%
Fourth	99.99%

Table 3: Baggage approval percentages [5].

3.3.3 Probability of baggage not being correctly scanned

Immediately after the security screening stages, bags are forwarded to the baggage identification area. Now, it is crucial to assess the probability that there would be errors with the automatic reading of a bag's destination code, or the probability that a bag would need to be scanned by a MTR.

A probability value for the manual scanning of the bags common to every piece of baggage could be admitted (5.99%) [5] and this probability value was defined in the simulation model through the *Routing Out* parameter in *ATR* activity.

3.3.4 Labels *origin*, *security* and *tag*

The success of the developed model depends on the proper operation of the labels since faulty label use can produce inaccurate results.

In order to verify this, the simulation was paused and the *Current contents* of one of the security stage activities was analysed, confirming the correct functioning of the labels.

3.3.5 Simulation time and *warm-up* period

In order to avoid running lengthy simulations, it was chosen to define a simulation period of one day. The daily start time was set to 5:00 and the end time was set to 24:00. Nevertheless, numerous simulations were run for the same period, through the *Run Trial* feature, and averages of these different runs were derived when collecting the results. The *Warm-up* is the period of time during which the software does not collect any performance metrics. Since, in reality, airports' BHSs begin their operation without any bags in the system from the previous day, it was decided not to define a *Warm-up* period.

3.3.6 Number of runs

In order to ensure results with narrower confidence intervals, it is important to conduct an experiment with multiple runs, adopting a series of pseudo random numbers and independent of one another. A trial is a collection of simulation runs that are all done with the same parameter values, with the exception of the *random numbers* used. It is crucial to run a simulation multiple times in order to mimic the variability of real-world systems.

Trials Calculator is a SIMUL8 feature that recommends a number of runs to use for trials, based on required precision of the confidence limits around the estimate of the mean for the KPIs. Adopting a confidence interval of 5%, the recommended number of runs is 4.

3.3.7 Validation of the simulation model

In this section, it will be determined whether the values obtained from the simulation model developed are accurate and whether there are any visible bottlenecks in the system. The simulation model is currently implemented and already has the necessary data inserted. An important aspect to note is that bags cannot stay in the system after the simulation stops running or, in other words, the Work-in-progress (WIP) has to be zero, since all baggage has to be dispatched to the respective airplane during the work day. That is why it was decided to have a simulation time of one day.

While the model was running, it was possible to identify the periods in which the system was working beyond its capacity. For instance at 7:30 the system was already experiencing significant queueing times in the first and second stages and in the ATR. It was noticeable the decrease in the queue size from around 10:00 until 16:30, since that is when the baggage arrival rate is at its lowest during the day. During that period, the queues in the system were essentially empty and there were no bottlenecks visible. Table 4 shows the average and maximum queueing time for each security stage in addition to the number of completed jobs.

Security stages	**Queueing Time (min)**		**Completed jobs**
	Average	Maximum	
1	59.06	127.83	43442
2	142.22	275.11	28259
3	140.94	270.26	651
4	169.45	256.45	9
No screening	59.27	113.46	3107

Table 4: Queueing times segregated by security stage.

Hereafter, the number of servers currently available in those three critical activities need to increase in order to decrease the queueing time in the system. Another simulation was run with 30 servers available in first stage, 16 in the second and 80 in the ATR. Following this modification, queue times significantly decreased, as displayed in Table 5.

Security stages	**Queueing Time (min)**		**Completed jobs**
	Average	Maximum	
1	21.35	58.82	43231
2	25.96	71.47	28282
3	26.16	69.62	645
4	29.69	64.02	13
No screening	9.49	32.82	3060

Table 5: Queueing times segregated by security stage, after increasing the number of servers.

This simulation yielded an average CT of 29.83 minutes, while the maximum CT was 85.40 minutes. The throughput of the system was 65.9 bags per minute and the WIP recorded at the end of the simulation was 28 jobs. To address the fact that the WIP is not zero, a constraint was set on Check-in *Start Point* to impose a time limit on the arrival time of work items. This way, the injection of baggage into the system ceases at 23:45.

3.4. Scenarios

Passenger data was collected with the goal of predicting the mean arrival rate for the upcoming years in order to determine whether the model can withstand variations in the input, namely an increase in the arrival of baggage, while maintaining the levels of throughput and average time in system. These predictions used data from Instituto Nacional de Estatística (INE), International Air Transport Association (IATA) and Eurocontrol.

Scenario	Description
Baggage injection rate	INE, IATA and Eurocontrol predictions in combination with bag to passenger ratios
Machine breakdown	Carousel breaks down at the peak time of day
Resource availability variation	Second stage available resources change to 14 and 16

Table 6: Overview of the proposed scenarios.

4. Results

4.1. Future baggage volume

Initially, six scenarios were performed to model the number of expected bags entering a BHS in the year 2032. In Table 7, an overview of the scenarios is presented, where it is possible to note that the number of expected bags per day in scenario 1 is higher than the current bag volume used in the simulation model. The remaining scenarios project that there will be less checked baggage in ten years, which is very likely given the rise of Low Cost Carriers (LCCs) and the costs they charge for checked baggage.

Scenario	Month	Expected bags per day
Scenario 1	February	79 915 (H)
	August	76 373
Scenario 2	February	56 847
	August	54 327
Scenario 3	February	43 045
	August	64 273
Scenario 4	February	30 620
	August	45 720
Scenario 5	February	35 812
	August	53 472
Scenario 6	February	25 475 (L)
	August	38 037

Table 7: Future baggage volume scenarios.

Subsequently, the most pertinent scenarios are analysed in more detail.

4.1.1 First scenario

The first scenario simulates the highest baggage injection rate into the BHS and the respective simulation results are displayed in Table 8.

Although this simulation reported a throughput rate of 76.28 bags per minute, the queueing times significantly increased, reaching levels that were not actually feasible for the system to operate at on a regular basis. Given that passengers typically drop off their baggage between 1.5 h and 2 h prior to the departure of their flight, BHSs need to report cycle times under 1.5 h to guarantee that all bags board the respective airplane.

KPI	Total	No screening	1	2	3	4
Completed jobs	87338	3474	50286	32831	735	12
Minimum CT	3.84	3.84	5.46	7.20	9.33	14.76
Average CT	43.16	17.35	36.73	55.39	58.55	52.82
Maximum CT	139.10	43.00	90.67	139.10	136.71	131.54
AWT	36.01	12.72	30.29	46.97	48.03	36.59
MWT	127.81	35.83	80.82	127.81	125.77	115.65

Table 8: KPI results for scenario 1 (February).

In this scenario, only bags that do not undergo security screening and bags that go through stage 1 report CTs within 1.5 h, suggesting that the system is operating beyond its maximum capacity due to the high rate of baggage injection.

The bottlenecks detected during model validation still persist, observed in the first and second stages of security and the ATR, with the queue for second stage being the most problematic, reporting a MWT of 51.87 min. Additionally, the queue immediately after the check-in also reports a considerable MWT of 29.85 min.

When examining the resources available for the activities in the system, it becomes clear that the maximum use of the first stage resources does not even approach the 30 threshold that was established during model validation. The resources available for the third and fourth stages of security were similarly overestimated, since their maximum use was 4 and 1, respectively. The ATR and MTR, on the other hand, make full use of all resources despite having slightly lower average use.

4.1.2 Third scenario

The forecasts derived from the annual growth rate provided by IATA are used in the current scenario. In regard to the month of February, the results displayed in Table 9 reveal a significant drop in the average and maximum CTs, while also reporting minor queueing times. In this case, the system experiences bottlenecks in the second stage and in the ATR, since the queues for those activities are the only ones showing pertinent MWTs.

KPI	Total	No screening	1	2	3	4
Completed jobs	45265	1859	25979	17027	394	6
Minimum CT	3.85	3.85	5.47	7.25	9.05	14.23
Average CT	7.67	4.83	6.66	9.43	11.62	19.43
Maximum CT	24.08	11.74	14.21	22.78	21.94	24.08
AWT	0.64	0.26	0.34	1.15	1.27	1.11
MWT	10.72	4.80	5.05	10.72	9.39	6.64

Table 9: KPI results for scenario 3 (February).

4.1.3 Sixth scenario

Using the predictions derived from annual growth rate reported by Eurocontrol for Portugal in combination with a baggage to passenger rate of 0.69, this scenario was created. The simulation results for the lowest baggage injection rate, corresponding to the month of February from scenario 6 are depicted in Table 10.

KPI	Total	No screening	1	2	3	4
Completed jobs	28505	1113	16371	10772	246	3
Minimum CT	3.85	3.85	5.49	7.22	9.23	17.97
Average CT	7.01	4.59	6.31	8.25	10.46	18.10
Maximum CT	18.28	9.15	11.20	12.86	14.33	18.28
AWT	0.008	0.004	0.003	0.015	0.012	0.005
MWT	0.91	0.54	0.97	0.91	0.53	0.008

Table 10: KPI results for scenario 6 (February).

The lowest injection rate simulated in the system generated an average CT of 7.01 min, a maximum CT of 18.28 min and a throughput rate of 25.01 bags per minute. This is the first instance that the ATR does not utilize the total number of available resources (80); in this scenario, the activity uses 71.

4.2. Simulating a machine breakdown

Afterwards, a scenario was created to model a machine breakdown in a component that directly impacts the normal functioning of the system. Two simulations are run for this scenario, one for the highest number of bags per day and the other for the lowest number of bags per day, which are identified with H and L in Table 7, respectively.

KPI	Total	No screening	1	2	3	4
Completed jobs	28306	1122	16329	10627	226	2
Minimum CT	3.78	3.78	5.51	7.23	9.22	16.30
Average CT	13.66	10.33	12.97	14.99	17.93	36.90
Maximum CT	61.75	56.81	61.58	60.77	61.75	57.51
AWT	6.64	5.79	6.63	6.74	7.38	19.70
MWT	51.99	51.67	51.99	51.94	50.86	39.40

Table 11: KPI results for scenario 7 (Low rate).

In contrast to the simulation of February from scenario 6, which produced a throughput rate of 25.01 bags per minute, this simulation yielded a throughput rate of 24.84 bags per minute, indicating a slight decline. Yet, a significant increase in the maximum CT can be observed in the present simulation, as well as in the AWTs and MWTs for all security stages. In addition, all queues recorded negligible wait times with the exception of the queue preceding the carousel, reporting an AWT of 2.51 min and a MWT of 30.21 min.

KPI	Total	No screening	1	2	3	4
Completed jobs	86933	3530	49747	32925	724	7
Minimum CT	3.85	3.85	5.52	7.19	9.29	32.26
Average CT	47.39	19.94	40.87	59.86	61.72	82.21
Maximum CT	139.49	43.38	89.78	139.37	139.49	128.73
AWT	40.22	15.33	34.42	51.41	51.22	65.25
MWT	128.07	36.26	80.22	128.07	126.92	113.32

Table 12: KPI results for scenario 7 (High rate).

Due to the high baggage injection rate, there are small differences between KPIs from the simulation of February from scenario 1 and the current one, since the system is already working beyong its capabilities. Even though the MWT of the carousel's queue increased from 0 to 41.08 min, the majority of the KPIs remained similar, with the exception of the average CT and the AWT that increased by 4 min.

It is undeniable that a carousel breakdown significantly affects the normal behaviour of a BHS. Due to its dimension and cost, the majority of BHS only has one carousel, making it impossible to route the bags to an alternate component in the event of a breakdown. However, for other components of the system, having an alternate component becomes a clear solution to bypass possible malfunctions.

4.3. Changing the availability of the second stage resources

The second stage resources are required to take a 10 min break after every 20 min of continuous labour. This aspect substantially increases the average queueing times and can create a bottleneck for the BHS. It was chosen to simulate the model by varying the number of available resources in order to reduce this waiting time. The *Low rate* (L) and *High rate* (H) simulations depicted in Table 7 are used in this scenario.

KPI	Resources 12		14		16	
	L	*H*	*L*	*H*	*L*	*H*
Average CT	7.01	43.16	7.02	42.09	6.99	42.44
Maximum CT	18.28	139.10	18.01	118.50	15.84	111.01
AWT	0.008	36.01	0.005	34.95	0.004	35.29
MWT	0.91	127.81	0.99	106.15	1.42	96.44

Table 13: KPI results for scenario 8.

Observing Table 13, it is visible that, for the *High rate* simulations, an increase in the available resources to 14 leads to an overall reduction in the KPIs, especially in the maximum CTs and MWT. It can be noted that only the maximum CTs and MWT decreased significantly when 16 resources are available, while the other KPIs remained unchanged. For the *Low rate* simulations, it becomes clear that the second stage activity does not represent a bottleneck in the system, since an increase in the resources did not affect the KPIs.

Combining the simulation results, Figure 5 illustrates the variation in the AWT and MWT regarding the queue for the second stage. As predicted, the AWT and MWT decrease as the number of available resources increase. The average and maximum CTs experience the same behaviour for both the *High rate* and *Low rate* simulations.

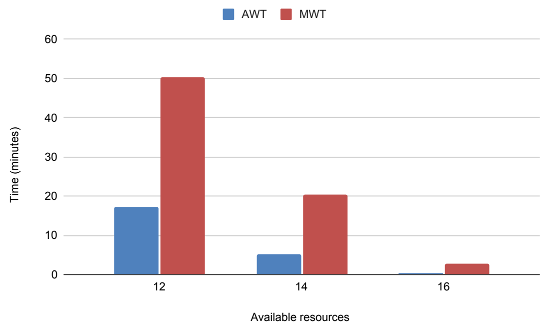

Figure 5: Queue for the second stage: AWT and MWT variation (*High rate*).

Even though the implementation of this scenario in a BHS would benefit its KPIs, it might not be possible to implement due to the European regulation requirements that airports and baggage handlers have to comply [4].

4.4. Discussion

One aspect that was shared by every scenario was the fact that the number of available resources for the third and fourth stages was overestimated. A system improvement would be to set a restriction on the amount of available resources, with 5 for the third stage and 1 for the fourth.

On a similar note, the first stage resources were also slightly overestimated during the model validation phase. The simulation results from the scenarios recorded that the maximum number of resources used was 22, even though the number of available resources was 30. Nonetheless, it becomes clear that for high baggage arrival rates, the system operates beyond its capacity which results in bigger queueing times and CT of the system. To prevent the first queue after the check-in from storing too many bags, more conveyors would need to be placed before the first security screening stage. Additionally, increasing the resource availability in the second stage would highly improve the overall performance of the system.

5. Conclusions

The proposed objectives for this dissertation consisted on performing an analysis of a BHS and elaborating improvement suggestions that would lower waiting times and incur in future cost savings, related to less machinery requirements and operating time. In addition, future predictions for the baggage volume in airports were calculated, using data from INE, IATA and Eurocontrol.

By creating and performing studies for each scenario, the impact of variations in baggage injection volume and its effects on the airport's performance metrics could be demonstrated. On the one hand, a 16 % increase in bag volume was predicted for the year 2032, resulting in a congestion in critical components of the system, which suggests that modifications to the infrastructure of the airport are needed. On the other hand, other projections imply a lower baggage injection rate for the same period, mainly due the rise of LCCs and their respective hold baggage additional costs. This analysis confirmed that certain resources had been overestimated during the design phase and could be excluded from the system, resulting in staff reductions while maintaining the same waiting times.

Furthermore, given that the work was developed in a more generalised approach, its takeaways can be applicable to airports with similar characteristics, including the size, features and equipment.

This work's contributions are focused on the baggage handling processing up to the carousel and do not include the baggage unloading of the system, as it does not significantly impact the queueing times experienced in the system. However, the baggage unloading process can produce queues if the airport experiences delays in the arrival of airplanes. A possible expansion of this work would be to incorporate flight delays in the modelling of the system through the adoption of a stochastic approach.

Lastly, baggage injection to the system could be modelled by using the airport flight schedule. For every flight, the policy for passenger arrival time is selected dependent on the airline and relevant distributions can be determined for each time interval before departure time. Lastly, the aggregate number of passengers arriving per time interval is obtained to estimate the volume of passengers arriving at the airport [17].

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