A System Dynamics Model of the Airport-Airline Financial Interactions

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Abstract

After the deregulation process, both airports and airlines have become capital intensive businesses. In order to sustain the whole air transport structure, airports must engage in highly complex relationships with the airlines. The mainstream literature, drops much of its attention either on the airport or on the airline industries, however, there is still few research regarding the dynamic and interconnected airport-airline financial relationship. This research aims to explore how the financial interactions between the airport and the airlines, particularly the airport managers’ strategic decisions towards airlines and their respective feedback, reflect on the airports’ revenues over time. For that purpose, a System Dynamics (SD) model, using Anylogic simulation software, was developed. The employed SD simulation method has the capability to model, generate scenarios and analyze the simulation performance based on information feedback that are continuously transformed into decisions and actions. Altogether, a generic and easily customizable SD based framework has been constructed to assess Lisbon International Airport revenue performance regarding three distinct scenarios of Airport Charge Variation due to airport LOS variation, FSC and LCC share at the airport and Airline Elasticity Coefficients. It was found that the more sensitive the airport manager, the more reactive the airlines will be, and hence the more irregular the revenue outcome. Moreover, concerning the short/medium-term, a hyper sensitive to airport LOS type of airport manager induces a much stronger growth on the total airport revenues, than an unresponsive to LOS type of airport manager. Considering the long-term perspective, the latter leads to higher total airport revenues, as well as higher annual flights frequency.

Keywords: System Dynamics, Airport-Airlines Interactions, Airport Revenues.

1. Introduction

The air transport system comprises the relationship among three main agents: the airport, the airline and the passenger (Ashford, 1997). Whilst airlines only consider passengers as their customer group and consider themselves as customers of the airports, airports, on the other hand, regard both airlines and passengers as their key buyers (D’Alfonso, 2012). As a result, airports are confronted with a two-sided market, in which both sides may influence the airport strategy and operations (Struyf, 2016).

Until now, much of the attention was dropped into the airlines’ relationships, however both airlines and airports are capital intensive businesses (Starkie, 2012). Then, not only airports do matter, but more importantly the airport-airline relationship and its consequences may define the success of the air transport. Following the airport-airline relationship it is essential to identify which key factors (endogenous and exogenous) may be crucial to understand the dynamics of the system and its relationships over time (Allroggen, Malina, & Lenz, 2013; Fichert & Klophaus, 2011; Jones, Budd, & Pitfield, 2013).

Concerning the state of the art literature, it either focuses on the airport or on the airline. However, there is still few research on the operational airport-airline interaction and its potential financial consequences, challenging the air transport community to develop new and innovative tools regarding these two entities’ relationship, as a feedback of one another’s’ decisions and actions. As a result, there is a need to evaluate the financial benefits of such airport-airline interactions on a case-by-case basis (Fu, Homombat, & Oum, 2011). The aim of this work is, then, to simulate and illustrate how the financial interactions between the airport and the airlines, particularly the airport managers’ strategic decisions towards airlines and their respective feedback, reflect on the airports’ revenues over time.

For that purpose, a System Dynamics (SD) model, using Anylogic simulation software, was designed to simulate and analyze the airport-airline financial interactions and respective implications on each other’s behaviour. The employed SD simulation method has the capability to model, generate scenarios and analyze the simulation performance based on information feedback that are
continuously transformed into decisions and actions. Altogether, a generic and easily customizable SD based framework has been constructed to assess Lisbon International Airport – Humberto Delgado Airport (LIS) – revenue performance, concerning distinct scenarios of airport charge variation due to airport LOS variation, level of service and airline elasticities. The major contributions of the developed model consist of providing a generic and flexible decision support tool that will facilitate high-level airport decision-making, as it predicts the airport’s revenue impacts, as well as the airlines’ reaction, as a feedback of the airport manager’s decisions and actions.

The present paper is structured as follows. Section 2 provides a literature review concerning the airport business and the airport-airline relationships. Section 3 describes the research methodology. Section 4 defines the base model development, as well as its base assumptions. Section 5 evidences the model validation and scenario setting. Section 6 shows and discusses the simulation model results. Section 7 summarizes the major findings and elucidates about future research.

2. Literature Review

After the deregulation process, airports have become complex two-sided enterprises that require a wide range of competencies and skills, offering both aeronautical and non-aeronautical services (Gillen & Mantin, 2014). Concerning the operational income produced by an airport, a distinction may be made between aeronautical (or aviation) and non-aeronautical (or commercial or concession) revenues (Graham, 2008; Peneda, 2010; Struyf, 2016; Zhang & Zhang, 2010). Aeronautical revenues (AR) are directly related to the activity of the aviation, as in the usage of the infrastructure, arising directly from the operation of landing/takeoff of aircraft, passengers and freight (Graham, 2008; Peneda, 2010; Struyf, 2016; Zhang & Czerny, 2012; Zhang & Zhang, 1997, 2003). Non-aeronautical revenues (NAR) are those generated by activities that are not directly related to the aircraft’s operation, namely income from commercial activities within the terminals and on airport land (Graham, 2008; Peneda, 2010; Zhang & Czerny, 2012; Zhang & Zhang, 1997, 2010).

In order to sustain the whole airport structure by generating adequate amounts of AR and NAR, airports must engage in highly complex relationships within the airlines. Therefore, it was found essential to unveil the core factors affecting the airports and airlines interaction. Suryani, Chou, & Chen (2010), Fichert & Klophaus (2011) and Alloggen et al. (2013) added that the airport-airline relationship and, then, the airport’s development regarding revenues, passengers and aircraft movements may be influenced by two types of factors, the endogenous or internal – airport charges, airport-airline incentives, level of service (LOS) and runway capacity – and exogenous or external factors – only the Gross Domestic Product, impacted on the model. Figure 1 lists the factors that were established as paramount on the airport-airline interactions.

In order to approach the airport-airline dynamic and intertwined behaviour it was suggested to adopt, first of all, a conceptual method consisting of feedback loops, which aims to identify the variables and its relationships as a whole. As a result, a holistic feedback loop diagram was achieved (Figure 2), so that the dynamic interactions of the previously presented variables in the airport-airline context could be envisaged. According to Faboya & Siebers (2015) a feedback loop diagram provides a way of expressing the understanding of the dynamic, interconnected nature of the real world.

2.1. Aeronautical Charges

The aeronautical charges play a key role in shaping the airport-airline financial interaction and, hence, the airports’ market structure (Gillen & Mantin, 2014).

Gillen & Mantin (2014) enlightened that an increase on the aeronautical charges would stimulate the airlines to reduce their flight frequency. By doing it so, the authors’ stressed that it would have a positive impact concerning both terminal and runway congestion, which would be more relaxed, despite reducing the AR share. Apart from the AR decline, Zhang & Czerny (2012) added that an increase in the aeronautical charges and consequent reduction of the passenger quantity, also impacts the demand for concession revenues, since the less time passengers spend at the airport, the less likely they are to spend on concession services.

On the other hand, Zhang & Zhang (2010) found that, generally, the aeronautical charge becomes lower when an airport has concession operations – cross-subsidy. Regardless the airport ownership, the cross-subsidy may happen when the airport shares its concession revenues with the airlines by charging lower aeronautical fees and, thereby, incentivizing airlines to supply more flights and hence, deliver more passengers (Gillen & Mantin, 2014).
Moreover, following Zhang & Zhang (2010) and Alcobendas (2014), the reduction of the aeronautical charges certainly intensifies both the terminal and runway congestion at the airport, which in turn will reflect on the concession revenues.

2.2. Airport-Airline Incentive Schemes

Regarding the airport-airline incentives, Albers et al. (2005) and (D’Alfonso, 2012) stated that the primary benefit for the formation of airport-airline alliances is the reduction of the uncertainty for both partners. Alloroggen et al. (2013) advocated the airport manager could offer targeted incentives through rebates on aeronautical fees based on two categories of airport incentive schemes (AIS): “incentives for volume growth”, which may be provided whether the airline increases passenger throughput, raises flight frequency or, even whether it broadens aircraft capacity; “incentives for route growth” only applicable if new routes or destinations are introduced.

On the other hand, Fichert & Klophaus (2011) classified the airport incentives as “incentives within the established charging system” and “separate incentives”. According to the authors the former refers to incentives that might be applicable on the already designed charging system and whose purpose would be shifting parts of the risk caused by demand fluctuation from the airlines to the airport. Concerning the latter, it might be related either to the annual traffic values or to the development (growth) of traffic over time. Moreover, these traffic volume incentives, similarly to Alloroggen et al. (2013), are typically based on the airline’s total number of passengers, flight frequency, load factor or maximum takeoff weight. Furthermore, Jones et al. (2013) also supported Fichert & Klophaus’s (2011) airport incentives classification.

2.3. Level of Service

The concept of level of service (LOS) may be applied to the planning, design and monitoring of the airport terminal infrastructures. According to the Airports Council International (2014) the notion of level of service has been applied in various ways for the design of new facilities, the expansion and monitoring of existing ones and as a metric that determines whether contractual obligations of airport managers are being fulfilled. Moreover, IATA (2015) added that the LOS concept is typically used for the following two purposes: assessing the current service level of the airport operations and planning the future service levels of the airport facilities.

Regarding the airport-airline interaction, the level of service play a crucial role as it may measure the airport services performance in terms of quality or adequacy of the infrastructure and the effectiveness of the overall logistics management (Ashford, Martin Stanton, Moore, Coutu, & Beasley, 2013), more specifically the utilization ratio (λ) of the most important processing areas. According to Neufville et al. (2013), as well as Miller & Clarke (2007), the utilization ratio is possibly the most fundamental measure of LOS, as it determines all the other measures of queuing systems’ performance.

2.4. Runway Capacity

According to Miller & Clarke (2007) and Suryani et al. (2010), runway capacity is the limiting factor that leads to congestion. As demand for air travel increases, the average number of aircrafts requiring service on this runway also increases, i.e. the runway utilization increases. The authors added that whether the runway capacity is held constant, the increase in demand would lead to congestion, which raises the airlines’ congestion cost. In addition, the higher the airline cost, the greater the airfare impact will be. In addition, the runway capacity is directly related to the LOS. In Graham’s (2008) analysis, the author found that the level of delays and, hence, congestion is a crucial measure of airport performance, since maximum runway throughput may only be achieved with queuing aircraft, either on the ground for the departing flights or through speed control and holding in the air for the arriving flights.

2.5. GDP’s Growth Rate

Concerning The GDP factor, according to KfW IPEX-Bank (2016), it is widely acknowledged that the number of passengers at airports around the world have a strong correlation with the worldwide GDP. In addition, Ishutkina & Hansman (2008) also recognized the air transport services and the economic development interaction with each other through a series of mutual causality feedback relationships. Similarly to the conclusions drawn by KfW IPEX-Bank (2016), Ishutkina & Hansman (2008) argues that a general correlation between the amount of air travel and GDP is achieved. Following KfW IPEX-Bank (2016), the reasons for this vigorous passenger growth along with either the national or global GDP are the worldwide population increase, the expanding networks, the expansion of the middle class in the emerging nations, the increase of tourism and the growing of the low-cost market.

2.6. Summary

Considering all the previously stated key factors affecting the airport-airline financial interactions, it was found indispensable to demonstrate the influence of these key factors together and its consequences on airport’s and airlines’ dynamics (Figure 2). Sterman (2000) added that the dynamics of all systems may arise from the interactions of
these networks of feedbacks; when multiple loops interact, it is not so easy to determine what the dynamics will be. As mentioned at the beginning of section 2, the feedback loop became an essential tool regarding a primary and conceptual phase of the model’s construction. Therefore, the feedback loop on Figure 2 represents a holistic and conceptual draft of the core components of the model presented in sections 4 and 5 and its main relationships.

3. Methodological Approach

A System Dynamics model composed by seven distinct modules – infrastructures’ demand; aeronautical revenues; non-aeronautical revenues; airport’s level of service; airport’s discounts; airlines’ operating costs; and GDP – was designed from the feedback loop diagram on Figure 2. Thus, it intends to simulate and analyze the airport-airline financial interactions and respective implications on each other’s behaviour. As a result, a generic and easily customizable SD based framework has been constructed to assess Lisbon International Airport – Humberto Delgado Airport – revenue performance, concerning distinct scenarios of airport charges, level of service and incentives and airline elasticities.

This SD framework has been implemented in the form of a stock-and-flow diagram in Anylogic 7.0.2 Professional Edition. According to Manataki & Zografos (2009), Suryani et al. (2010) and Qin & Olaru (2016) the SD’s suitability to the airport-airline financial interactions is confirmed, as it consists of interacting multiple feedback loops. Then, it adapts easily to a wide spectrum of airport strategic configuration, enabling a holistic assessment of the system performance, as it provides the capability of examining the impact of all interactions between the system’s elements. Moreover, SD’s fundamental variables vary in time, which is crucial, since a financial assessment of the airport revenues over the year is being carried out. Finally, SD supports model assumptions and “what-if” scenarios, as well as, time delays, as for instance time lags between the airport charge change and the flight frequency adjustment.

4. Base Model Development

4.1. Model Structure

The present SD model applied to Humberto Delgado Airport (LIS) has been based on five main assumptions, as well as on the feedback loop of Figure 2. Bearing in mind the objective of this model, the following assumptions have been presumed:

- The considered model time step is the day and the delay to respond to any model change is the season (IATA). One change in season n, will present its reaction in season n+2;
- The airport manager considers three decision variables that affect the next IATA season’s airport charges: the airport LOS, AIS and GDP growth rate;
- The airport charges will reflect the airlines’ flight frequency as a reaction/feedback of the previous IATA’s season airport LOS;
- The airlines’ flight frequency (DFF) generates the air passengers;

![Figure 2 – Feedback Loop Representation of the Endogenous and Exogenous Key Factors Influencing the Airport-Airline Financial Interactions (qualitative approach)](image-url)
Three main periods throughout the year were considered in which air ticket prices and passengers shares may vary: January and December (medium season); from February to May and from September to November (low season); and June to August (high season).

Considering the previous assumptions, the model consists of seven distinct modules, in which each module’s feedback influences the others and allows the model to achieve a general output result of the interdependencies and interrelations among the modules. Figure 3 is a schematic representation of the real Anylogic SD model.

4.1.1. Main Basic Elements

Before start explaining how each module operates, it was found extremely important to highlight some transversal concepts that will be used throughout the whole model.

Daily Flight Frequency (DFF): it defines the daily number of flights that depart from and arrive to the airport. According to ANA Aeroportos de Portugal (2017a) the admitted DFF corresponds to one landing plus one take-off. In the first two IATA seasons the DFF is scheduled and given as an input by the airport manager (from historical data), however, from the third season onwards the model calculates the DFF as a feedback of the previous season’s airport LOS (Module 4), AIS (Module 5) and the GDP growth rate trend (Module 7), which is converted in the following equation:

\[
DFF_n = \text{WinterDFF}_{n-2} + (\text{WinterDFF}_{n-2} \times DFF_{\text{FSCWinterVariation}} \times FSC_{\text{Share}}) + (\text{WinterDFF}_{n-2} \times DFF_{\text{LCCWinterVariation}} \times LCC_{\text{Share}}) + (\text{WinterDFF}_{n-2} \times DFF_{\text{DiscountFSCWinterVariation}} \times FSC_{\text{Share}}) + (\text{WinterDFF}_{n-2} \times DFF_{\text{DiscountLCCWinterVariation}} \times LCC_{\text{Share}}) + \text{WinterDFF}_{n-2} \times GDP_{\text{Influence}}
\]

(1)

Seat Capacity per Flight: it designates the average number of seats provided by one aircraft per day and it was admitted, as a simplification, that in one day all of the aircrafts provide the same number of seats. As a result, the number of seats varies on a daily basis according to a PERT distribution.

PERT distribution was found the most suitable distribution to accommodate this simplification as an airport, in this case LIS, may have a wide range of type of aircrafts landing and taking-off along the day, nevertheless having a most used type of aircraft (most likely).

4.1.2. Module 1

Module 1 presents itself as the generator of the number of flights per day – Daily Flight Frequency – and, consequently, the number of air passengers per day – Initial Daily Demand.

\[
\text{Initial Daily Demand} = \text{Daily Flight Frequency} \times \text{Seat Capacity Per Flight} \times \text{Average Load Factor}
\]

Thus, among the generated air passengers different types of travelers are also considered in module. Similarly to Czerny & Zhang (2011), Graham (2008), Miller & Clarke (2007) and Suryani et al. (2010), in this paper they were considered two types of travelers – leisure and business – considering their different perspectives and behaviours concerning price and time values. Furthermore, module 1 considers the possible congestion that the total demand of aircrafts will induce on the airport’s runway taking into account its capacity. Miller & Clarke (2007), Suryani et al. (2010) and Neufville et al. (2013) define congestion \((Wq)\) as waiting time (per peak hour of traffic) for each aircraft that intends to land on the runway. In addition, the authors stress that the waiting time is obtained by modeling this situation queuing system as a M/G/1 queuing system¹:

¹ M/G/1 queuing system is a system with Poisson demand (M), any type of service time (G) and one server (1) and infinite capacity.

(Suryani et al., 2010). For detailed information see Neufville et al. (2013).
\[ W_q = \frac{\lambda + \frac{1}{2} \sigma^2 + \sigma^2}{2 \cdot (1 - \rho)} \]  
(3)

\[ \rho = \frac{\lambda}{\mu} \]  
(4)

In which \( \lambda \) represents the average number of flights for a specific period of time determined by the Poisson distribution; \( \mu \) stands for the runway capacity; \( \sigma \) denotes the standard deviation of service times and \( \rho \) characterizes the already described runway utilization. According to the congestion values, it will prompt a reaction on the airlines’ airfares, as a growth of congestion will increase the congestion costs and, hence the airfares (Qin, 2016), which in turn will slightly affect the air passengers initial demand. In addition, this module considers another relevant factor affecting the initial passengers’ demand which is the check-in and security level of service.

\[ \text{Airfare Effect}_{\text{Congestion}} = \text{Price Elasticity} \]  
(5)

\[ \text{CheckIn and Security LOS}_{\text{los}} = \text{Time Elasticity} \]  
(6)

Altogether, its main outputs to the system regard the Actual Daily Demand, which consists of the Initial Daily Demand affected of the airfare congestion effect and the effect of the LOS.

\[ \text{Actual Daily Demand} = \text{Initial Daily Demand} \times (1 + \text{Airfare Effect}_{\text{Congestion}} + \text{CheckIn And Security LOS}_{\text{los}}) \]  
(7)

4.1.3. Module 2

Aeronautical revenues are directly related to the aviation activity. Its direct output concerns the airport’s daily aeronautical revenues based on the main aeronautical charges airports levy to the airlines. Therefore, its output comprises the yearly \( i \) value of the aeronautical revenues resulting from the daily summation \( j \) of various variables, which are directly or indirectly (through air passengers) imputed to airlines.

\[ \text{Daily Aeronautical Revenues}_j = \sum_{j=1}^{365} f(\text{Parking, Landing, Terminal, GPS}, \text{Baggage Handling, PRM, Security, Passenger Handling, Air bridge, Airline Handling, Airline Catering}) \]  
(8)

\[ \text{Aeronautical Revenues}_i = \sum_{j=1}^{365} (\text{Daily Aeronautical Revenues}_j) \]  
(9)

4.1.4. Module 3

Module 3 is the product of the model’s non-core activities levied per passenger, whose output consists of the non-aeronautical revenues. Therefore, it comprises the yearly \( i \) value of the non-aeronautical revenues resulting from the daily summation \( j \) of the several non-aeronautical variables, mainly imputed to the air passengers. Regarding the different categories of passengers – departing, arriving and transit or transfer passengers – they were allocated to different non-core activities.

\[ \text{Daily Non Aeronautical Revenues}_j = \sum_{j=1}^{365} f(\text{Advertisement, Car Rental, Car Parking, Real Estate, Retail}) \]  
(10)

\[ \text{Non Aeronautical Revenues}_i = \sum_{j=1}^{365} (\text{Daily Non Aeronautical Revenues}_j) \]  
(11)

4.1.5. Module 4

Considering the airport LOS as an influencing factor of the DFF, four distinct LOS quantitative queueing lengths were developed in the present model. In order to reflect the DFF of a certain season and to calculate what will be the airlines’ behaviour to the next one, the model uses Runway LOS and Ground Handling LOS, based on the feedback loop previously exposed. Altogether, in a determined winter/summer season \( n \), the number of flights will induce a certain runway and ground handling LOS, in which the aggregation of both of them (Table 1) will represent an Airport Attractiveness to the airlines. The Airport Attractiveness – Table 1 – is a variable that comprehends 11 levels (in which the 1\textsuperscript{st} represents the best and 11\textsuperscript{th} denotes the worst performance) and measures the attractiveness of an airport from the airlines’ perspective.

<table>
<thead>
<tr>
<th>Runway/Ground Handling</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
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<tr>
<td>B</td>
<td>2</td>
<td>3</td>
<td>4</td>
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<td>6</td>
<td>7</td>
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<tr>
<td>C</td>
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<td>D</td>
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<td>9</td>
<td>10</td>
</tr>
<tr>
<td>F</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>10</td>
<td>11</td>
<td>12</td>
</tr>
</tbody>
</table>

Table 1 – Airport Attractiveness Level according to the Runway and Ground Handling LOS

Therefore, for each one of the Airport Attractiveness levels it is associated a certain delta percentage change of the DFF (\( \Delta \text{DFF} \)) concerning the Airport Charge. Furthermore, it was also considered that a full service carrier (FSC) and a low cost carrier (LCC) have different business models and, then different reactions (elasticities) to a certain increase or
decrease in the Airport Charges. As a result, this sensitivity was considered through two distinct coefficients based on the concept of Elasticity, regarding each type of carrier. Through the following equation it is possible to estimate the delta percentage of flights (\(\text{\(\Delta\)}\text{DFF}\)) of each type of air carrier in response to a certain season’s Airport Attractiveness (based on the airport LOS).

\[
\text{Airline Elasticity} = \frac{\text{\(\Delta\)}\text{DFF}}{\text{\(\Delta\)}\text{Airport Charges}} \quad (12)
\]

\[
\text{\(\Delta\)}\text{DFF} = \text{Airline Elasticity} \times \text{\(\Delta\)}\text{Airport Charges} \quad (13)
\]

Based on the delta percentage change of the number of flights (\(\text{\(\Delta\)}\text{DFF}\)) of the FSC and LCC regarding the previous season, it is possible to calculate the subsequent season’s DFF affected by the runway and ground handling LOS through Equation (1).

**4.1.6. Module 5**

Module 5 was designed to encourage airlines to increase their traffic services, at the assessed airport. In other words, module 5’s output is a positive delta percentage change (\(\text{\(\Delta\)}\text{DFF}\)) of the airlines’ DFF motivated by the following modeled AIS: departing passengers’ charge discount, transfer passengers charge discount and long-haul flights discounts. As a result, these incentives will be translated into a seasonally (positive) variation concerning the daily number of flights departing from and arriving to LIS. In order to estimate the impact these incentive schemes or discounts have on the airlines’ DFF, the model considers what have been the impact of the total discounts on the total airlines’ operating costs (module 6) on the previous season, converting it, again, in a positive delta percentage change of the DFF (\(\text{\(\Delta\)}\text{DFF}\)). Therefore, considering that SD models have a high level of aggregation, it is assumed that the summation of the airport discounts represent a share of the airlines’ total operating costs.

\[
\text{\(\Delta\)}\text{Airport Discount} = (\text{Passenger Fees}_{\text{Discount}} + \text{Transfer Fees}_{\text{Discount}} + \text{Airbridge and GPS}_{\text{Discount}}) / \text{Airlines’ Total Operating Costs} \quad (14)
\]

Then, bearing in mind that the FSCs and LCCs may react differently to the AIS as they have different elasticity coefficients and knowing the share of airport discounts regarding the airlines’ total operating costs, it is possible to estimate the delta percentage change (\(\text{\(\Delta\)}\text{DFF}\)) for each type of air carrier.

\[
\text{\(\Delta\)}\text{DFF} = \text{Airline Elasticity} \times \text{\(\Delta\)}\text{Airport Discount} \quad (15)
\]

Moreover, considering the model’s delay of a season, a change in the total airport discounts concerning its share of the airlines’ total operating costs in season \(n\), will motivate a change (increase) on the DFF (\(\text{\(\Delta\)}\text{DFF}\)) in season \(n+2\). The DFF is calculated according Equation (1).

**4.1.7. Module 6**

Considering the previous module, it may be perceived that modules 5 and 6 are not only connected, but module 5’s output depends on module 6’s one. This being said, module 6 output regards the Airlines’ Operating Costs, which stands for the summation of the total airlines’ operating costs, i.e. the total costs that an airline incur whilst on the LIS from the moment the aircraft lands until the moment it takes off. Altogether, module 6’s product consists of the yearly \(i\) value of the airlines’ operating costs resulting from the daily summation \(j\) of the variables which represent the airlines’ costs.

\[
\text{Daily Airlines’ Operating Costs}_{ij} = \sum_{j=1}^{365} \text{(Maintenance, Airport Fee, Handling, Passenger, Lease)} \quad (16)
\]

\[
\text{Airlines’ Operating Costs}_{i} = \sum_{j=1}^{365} \text{(Daily Airlines’ Operating Costs)}_{ij} \quad (17)
\]

**4.1.8. Module 7**

Along with the already addressed airport LOS and AIS, the GDP entails the last of the three factors affecting the DFF (Equation 1) and, hence, the airport-airline financial interaction. In order to add the GDP to the model, correlations between the European Union (EU) 28’s GDP and the total air passengers at LIS have been drawn. Based on data from the European Comission (2017), INE (2017) and Pordata (2017), similarly to Steer Davies Gleave (2014) a correlation between the EU 28’s GDP growth rate and the LIS’ passenger growth rate from 2006 to 2015 have been achieved. Reaching a correlation coefficient (\(R^2\)) of approximately 0.70, it means that a strong statistical dependence between these two variables does exist. As a result, through this correlation equation it made possible to induce the delta percentage change of the DFF (\(\text{\(\Delta\)}\text{DFF}\)) regarding a determined GDP growth rate, which will be a yearly variable input from the airport manager. The DFF is calculated according Equation (1).

\[
\text{GDP}_{\text{Influence}} = 1.1088 \times \text{GDP}_{\text{GrowthRate}} + 0.0356 \quad (18)
\]

5. **Case Study: Humberto Delgado Airport**

5.1. The Humberto Delgado Airport

Lisbon International Airport (ICAO code LPPT; IATA code LIS) represents the larger and the most productive airport of ANA Group. In 2015, it accounted for approximately 20.1 million commercial passengers, representing a business
volume of approximately 57.5% of the ANA Group’s\textsuperscript{2} total revenue. As a result, in 2015, LIS attained 213 million euros in AR (ANA Aeroportos de Portugal, 2015b) and approximately 84.8 million euros in NAR.

5.2. Model Validation

The validation process comprised the two steps, previously argued by Barlas (1996): structure validation and output behaviour validation. First of all, a structure validation was carried out by using Face Validity technique (Sargent, 2005), which consisted in asking individuals knowledgeable about the system whether the logic of the conceptual model and its input-output relationship were assumed reasonable. Regarding the output behaviour validation, a Historical Data Validation technique (Sargent, 2005) was conducted, which consisted of using part of the historical data from 2015 to build the model and the remaining 2015 data was used to determine whether the model behaves as the system does. In order to set some degree of accuracy when comparing the model output with the real value, it was adopted an error rate of less than 5% as Barlas (1994, 1996) and Suryani et al. (2010) suggested in the following equation to establish its validity.

\[
\text{Error Rate} = \frac{\hat{S} - \hat{A}}{\hat{A}} \leq 0.05 \tag{19}
\]

It is noteworthy that \(\hat{S}\) stands for Simulation and \(\hat{A}\) for Actual values. As a result, Table 2 verify the output behaviour validation.

<table>
<thead>
<tr>
<th>Model Validation (year 2015)</th>
<th>(\hat{S}) (Euros)</th>
<th>(\hat{A}) (Euros)</th>
<th>Error Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total AR</td>
<td>241987310</td>
<td>239677341</td>
<td>-0,01</td>
</tr>
<tr>
<td>Total NAR</td>
<td>84801920</td>
<td>83984277</td>
<td>-0,01</td>
</tr>
<tr>
<td>Total APD</td>
<td>20096994</td>
<td>20370796</td>
<td>0,01</td>
</tr>
</tbody>
</table>

Table 2 – Main Output Validation (based on the model outputs and (ANA Aeroportos de Portugal, 2015a))

5.3. Scenario setting

According to Suryani et al. (2010), scenario development is a prognosis method in which the present data is used to investigate a myriad of possibilities, often characterized as feasible future alternatives. In order to accomplish the model’s purpose, twenty four different parameter scenarios distributed over three main cases, were evaluated. Each case assessed the impact of three distinct parameters – Airport Manager LOS sensitiveness, FSC and LCC share at LIS, Airline Elasticity Coefficients – on the model’s core outputs: Aeronautical Revenues (AR), Non-aeronautical Revenues (NAR), Air Passengers’ Demand (APD) and the Annual Number of Flights (ANF).

Case 1: evaluates the impact of a highly sensitive type of airport manager, varying the FSC and LCC shares and Elasticity Coefficients, on the model’s core outputs. Case 2: assesses the impact of a moderately sensitive type of airport manager, also varying the FSC and LCC shares and Elasticity Coefficients, on the model’s core outputs. Case 3: estimates the impact of an unresponsive to airport LOS type of airport manager, also varying the FSC and LCC shares and Elasticity Coefficients, on the model’s core outputs.

6. Results Analysis

Aiming to assess the twenty four different parameter scenarios distributed over the three main cases, 120 runs of the model were performed. Each subcase of the model was run five times in order to eliminate the possible variability that results from the already mentioned and studied PERT distribution. The results and further discussion evaluate the impact that each case’s characteristics have on the model’s primary outputs. To begin with, the scenarios in which the FSC and LCC share of 70/30 at LIS and regarding the distinction among the Airlines’ Elasticity Coefficients, by analyzing the total aeronautical and non-aeronautical revenues at LIS in a five year period, it was found that case 1 induces the largest aggregated growth rate when compared to the other two cases. However, given that in case 1 a more responsive to airport LOS variations type of airport manager has been represented, it is logical that once it becomes closer to the airport LOS capacity, the airport manager tries to discourage the airlines to add more traffic, as it is perceived by the decrease in the ANF on Graphic 2. In this case, a high increase in charges (8%) will lead to a significant decrease on the airlines’ flight frequency and, consequently, the airport’s revenues are also expected to decrease. In contrast, cases 2 and 3 present smoother and more regular curves, which tend to an almost linear increase along the considered five years, with steadier growth rates. Given that in cases 2 and 3 a more unresponsive to airport LOS variations type of airport managers have been represented, it is evident that until it becomes closer to the airport full capacity, the airport manager tries to incentivize the airlines to add more traffic, as it is perceived in Graphic 2, by lowering their aeronautical charges. In this case, a high decrease in charges will lead to a high increase of the airline flight frequency reaching, after the five year period, 185 thousand annual flights regarding case 2 and 200 thousand annual flights concerning case’s 3. Consequently, on a long-term period, higher than case 1’s airport revenues are expected.

\textsuperscript{2} The ANA Group fully owned by VINCI Airports International, S.A. in 2013, comprises the management of the airport infrastructures and aviation-related services in ten Portuguese airports.
On the other hand, considering the FSC/LCC share 100/0 at LIS, by analyzing Graphic 3 regarding the total airport revenues, it is noticeable that, again, case 1’s type of airport manager induces a much stronger growth than the other two cases. Moreover, after the five year period, it was found that a less reactive type of FSC (0.90) led to higher airport revenues of 440 million euros, whereas a more reactive to airport decisions FSC would induce slightly lower results, of about 430 million euros. Nevertheless, case 1’s wilder growth is predicted to lower on the next seasons as Graphic 4 displays, once the lower responsiveness of both the airport managers to the airport LOS variation, maintain the airport charges low and, then, encourages the airlines to increase their flight frequency.

Summing up, regardless the type of airport manager (case 1, 2 or 3), the FSC/LCC share 100/0 remains approximately 10 million euros more profitable than the 70/30 share. Secondly, the more sensitive the airport manager, the more reactive the airlines will be towards it. Regarding the Airlines’ Elasticity Coefficients, higher total airport revenues tend to occur when the LCCs are more reactive (-
1.70) to airport LOS variations and the FSCs are typically reactive (-1.23) to the same airport LOS variation.

Concerning the short/medium-term of five years, case 1, induces a much stronger growth on the total airport revenues, than the other two cases. However, the first case’s robust growth is predicted to lower after the five year period becoming irregular and not tending to any type of smooth equilibrium, as the hyper sensitivity to control and preserve the designed airport LOS induce higher airport charges, as the airport becomes close to its full capacity.

Considering the long-term perspective (more than five years), cases 2 and 3 lead to higher total airport revenues, as well as higher annual flights frequency. Thus, it is predicted that both cases gradually tend to an asymptotic maximum according to the airport’s runway and terminal capacities, although case 3 is able to lead to the highest revenues and the lowest level of service, result of the unresponsiveness of the airport manager.

7. Conclusions and Future Research

This paper presents a System Dynamics (SD) model to explore, simulate and analyze how the financial interactions between the airport and the airlines, particularly the airport managers’ strategic decisions towards airlines, reflect on the airports’ aeronautical and non-aeronautical revenues and on the airlines’ behaviour. Altogether, a generic and easily customizable SD based framework has been constructed to assess Lisbon’s International Airport – Humberto Delgado Airport (LIS) – revenue performance, concerning distinct scenarios of airport charges, level of service and airline elasticities.

Aiming to accomplish the model’s purpose, twenty four different parameter scenarios distributed over three main cases were evaluated. Each case represented one type of airport manager regarding its sensitivity to the airport LOS variation. Concerning each one of the three types of airport managers, from the hyper sensitive (case 1) to the almost unresponsive to airport LOS variation type of airport manager (case 3), three distinct parameters were assessed – Airport Manager LOS sensitivity, FSC and LCC share at LIS, Airline Elasticity Coefficients – on the model’s core outputs: Aeronautical Revenues, Non-aeronautical Revenues, Air Passengers’ Demand and the Annual Number of Flights.

The attained results demonstrate, first of all, that regardless the type of airport manager, the FSC/LCC share 100/0 remains always more profitable than the 70/30 share. Then, the more sensitive the airport manager is, the more reactive the airlines will be, hence the more irregular the model’s outputs will be. In addition, it was found that, as the LCCs have higher Elasticity Coefficients than the FSCs, when the airport capacity allows it, they shall inject much more flights than the FSCs. This implies that an identical increase of the airport charges will influence differently the FSCs and the LCCs (Qin & Olaru, 2016), as they present different reactions to airport charges variations. Concerning the short/medium-term of five years, case 1, a hyper sensitive to airport LOS type of airport manager induces a much stronger growth on the total airport revenues, than the other two cases. On the other hand, considering the long-term perspective (more than five years), cases 2 and 3 lead to higher total airport revenues, as well as higher annual flight frequency.

This research may be an important contribute for the future of the aviation sector, once after the deregulation of the air transport, the rise of competition between airports and the increase of the bargaining power among airlines (Barbot & D’Alfonso, 2014) is putting airports under growing pressure to increase their revenue and reduce their costs (Fu et al., 2011). Consequently, airports need to keep and preserve strategic airlines by having acceptable aeronautical charges and, at the same time, without compromising the airport’s level of service, as they wish to be protected from demand risk, financial support and secure business volume (Barbot & D’Alfonso, 2014). Therefore, the developed model provides methodological and practical contributions as it presents itself as a generic and flexible decision support tool that will facilitate high-level airport decision-making. Moreover, it provides an expandable and valid modeling structure, which creates the possibility to explore a myriad of distinct conditions and variables – costs, revenues, annual number of passengers and flights.

The challenges regarding the airport-airline interactions still have much potential for further investigation. According to Sterman (2000) “modeling is part of a learning process, is iterative, a continual process of formulating hypothesis, testing and revision, of both formal and mental models”. This being said, three main future work topics were suggested:

- To eliminate the variability arising from the Seat Capacity per Flight parameter, so that more realistic results could be achieved.
- To distinguish both FSCs and LCCs passengers’ spending patterns at the airport terminal.
- Further structure the airline operating costs.
8. References


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