Alleviating airport terminal congestion through dynamic space reallocation

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Abstract

This paper addresses the problem of congestion prevalent in most airports around the world, especially at security screening and check-in areas of departure terminals due to rapid growth in civil aviation demand. Addressing this problem is often limited by space and financial constraints, making layout optimization the most feasible option available. However, misestimating space needs due to a common misuse of international standards for space requirements at different levels of service (LOS) renders many re-layout projects ineffective. This factor coupled with an inefficient initial layout are found to be the main reasons behind the high congestion experienced at Beirut-Rafic Hariri International Airport (BEY) departure terminal during peak season demand, making it an ideal candidate for a case study on terminal layout optimization. Therefore, this paper presents a macroscopic system dynamics model to depict the overall flow of departing passengers at the BEY passenger terminal and uses dwell time as a variable in the model to assess and re-allocate existing space needs in the departure terminal for minor investment costs. The value of this research is in providing a decision support tool for airport operators to improve passenger flow in the terminal within existing space constraints and for minimum investment costs.

Keywords
Airport planning, System dynamics, Dwell time, Dwell area, Passenger flow

1. Introduction

The problem of congestion in passenger terminals is a common occurrence in many airports around the world, especially at security screening and check-in areas of departure terminals due to rapid growth in civil aviation demand. This is compounded by a number of factors such as small waiting areas, inadequate number of opened counters, slow rate of service, or errors in processing steps. Airport owners and operators often try to address terminal congestion by expansion projects if additional space for expansion is available, but these typically incur large investment costs and require long implementation times. In many cases, such expansion is not possible due to limited space constraints and/or limited financing, which usually narrows down improvement options to the optimization of the existing facility layout and the introduction of automation technologies for some processes such as the use of self-check-in and self-baggage-drop. However, expansion planning and re-layout efforts at many airports are often sub-optimal due to a common misuse of the International Air Transport Association (IATA) standards that define space requirements per passenger for different levels of service (LOS) (Belobaba et al., 2015; de Neufville & Odoni, 2013).

A common mistake done by terminal planners is to scale up the IATA space standards per passenger by the maximum number of passengers that flow into the space on an average peak day, disregarding the fact that the same area will cater to different batches of passengers depending on the average waiting time in the area, and thereby allocating unnecessary additional space. This average waiting time is known as "dwell time" and defined as the typical length of time passengers stay in an area waiting for service (Ashford et al., 2012; de Neufville & Odoni, 2013). Dwell time is important because it indicates how fast a space can be reused by another batch of passengers, and it's implicitly incorporated in the IATA space standards. However, this fact is not always made obvious in some terminal design processes, especially in re-layout initiatives where the focus is most urgently on relieving

congestion in a bottlenecked space by increasing its area without necessarily paying attention to dwell time considerations. This can lead to numerous design errors as reported in the literature (Belobaba et al., 2015; de Neufville & Odoni, 2013), most notably in oversizing one area at the expense of another. This is why there is a need for a holistic and easy to use decision support tool that can assist airport planners and operators in estimating dwell time accurately for a new terminal, or evaluating it and improving it for an existing one as is the objective in this research. In fact, state of the art and state of practice reviews show that existing models and tools are either too high level, falling short of capturing important details of airport terminal processes and passenger flows, or too complex and data-intensive, requiring technical expertise and user familiarity with advanced tools.

Misestimating space needs coupled with an inefficient departure terminal layout were found to be the main reasons behind the high congestion experienced at Beirut-Rafic Hariri International Airport (BEY) during peak season demand prior to the COVID-19 pandemic. The waiting time in queues at different stages of the departure process exceeded 3 hours in peak seasons, making this airport a good candidate for a case study on assessing and improving passenger flow through a re-layout of the existing terminal facility, which is the subject of this paper. To this end, a macroscopic system dynamic (SD) model is developed to depict the overall flow of departing passengers in BEY, while using dwell time and IATA space standards in order to assess and re-allocate space needs in the departure terminal at minor investment costs. SD models can be large and sophisticated but usually require less data, effort and computing resources than discrete-event simulation models (DES) typically used for this purpose. SD models can be easily adapted to serve as comprehensive decision support tools that airport owners/operators can easily use in the planning and continuous improvement of space needs and layout design for a passenger terminal. Dwell time is used as a variable in the model to realistically assess the performance of currently allocated space for different areas in the terminal within existing constraints for resources and passenger processing rates, in order to recommend re-layout alternatives in an optimal and cost-effective way.

The rest of the paper is organized as follows: the following section gives a review of the literature about the use of SD modeling for capacity and layout planning of airport terminals. Section 3 presents the methodological steps followed in developing the SD model and the local data and assumptions used in the modeling. Section 4 presents the case study for BEY airport, and section 5 present the modeling results for the current and future states in terms of their impacts on dwell time and dwell area. Recommendations are provided for managing terminal performance by altering dwell time and speeding up service through the use of new technology or additional resources, and thus to further reduce space requirements. Final remarks and future work are discussed in the conclusion section.

2. Review of the Literature

Countless simulation models have been developed to represent and understand congestion at airport passenger terminals using discrete-event simulation (Čerić, 1989; Guizzi et al., 2009) and a variety of other simulation tools (Andreatta et al., 2007) and simulation-optimization methods (Bruno et al., 2018) in order to support decision makers in improving airport efficiency while providing the required level of service. However, the body of literature using dynamic modelling to assess the performance of airport terminals remains relatively small. An extensive review of SD modeling studies in transportation by (Shepherd, 2014) classified a total of only ten publications using SD to model airline and airport systems. This was further validated by another review of SD modeling in civil aviation management (Feng & Luan, 2019), which found that only a small subset of SD studies tackles airport terminals, as reviewed in this section.

(Manataki & Zografos, 2009, 2010) developed an SD-based decision support tool to analyze airport terminal performance at a mesoscopic-level, meaning between macroscopic models which fail to capture the complex interactions between different parts and processes of an airport terminal, and microscopic models which are focused on a single process and are too resource intensive. The SD model captures the different service facilities in the airport terminal and their associated processes, with the purpose of testing different operational policies in terms of the required resources to meet desirable service levels. Since the model is generic, it is useful as a starting point for modeling passenger flow in different airport terminals with different service facilities, as well as for extending it with different performance metrics such as dwell time and dwell area.

(Suryani et al., 2010) propose an SD model to forecast air passenger demand and evaluate expansion of runway and passenger terminal capacity to meet future demand. The model is the first to measure passenger flow in terms of dwell time, but fixed values are assumed rather than calculated for arrival and departure dwell times. The research

confirmed that dwell time has a significant impact on passenger required space in the terminal, and consequently on the terminal capacity expansion needs.

(Barbeito et al., 2016) present a macroscopic SD model of the overall workings of a generic airport, including both aircraft and passenger dynamics, with the latter consisting of the flow of passengers through the terminal to the gates (and appears to be based on a simple indicator of passenger counts per minute at different terminal locations). The model can be used to optimize the use of the airport's resources, and is demonstrated for different emergency and security events as they impact passenger queuing at security checks, serving to illustrate the relationship between landside and airside parts of the airport.

(Biesslich et al., 2014) propose a comprehensive SD model covering aircraft movement, passenger flows as well as cash flows in order to model airport infrastructure planning and development over the long-term. The focus of the model is not however on terminal layout planning. Similarly, (He & Wang, 2019) built an SD model to assess the impact of different modes of economic growth on airport capacity and congestion in terms of passenger flow along the airport transport corridor. The model does not however tackle passenger flow inside the terminal.

Using lessons learned from the reviewed literature, particularly in terms of best practices for dynamic modeling of airport terminal processes and associated passenger flows, a comprehensive SD model for the departure terminal in BEY airport was developed in this research. The methodology for building the model is detailed in the next section.

3. Methodology

The model developed in this research is based on the SD approach since it provides the ability to capture the complex behavior of passenger flow through an airport system. The model was built using the software tool Vensim Professional version 7.3 (Ventana Systems Inc., 2013). The building blocks of SD modeling consist of stocks where quantities accumulate, such as passengers in a queue at airport security, flows between different parts of the system such as passengers moving between security and check-in; auxiliary variables to represent calculated model parameters such as passenger dwell time; constants to capture fixed model parameters such as the numbers of self-baggage-drop counters; and, information links to capture interdependencies in the system, such as the relationship between the baggage claim and passport check processes. By convention (Forrester, 1969), stocks are represented by a rectangular shape, flows by double arrows, auxiliary variables and constants by the name of the variable or constant, information links by single arrows; and, model boundaries are represented by cloud symbols.

The SD model depicting passenger flow through the various processes of the departure terminal in BEY airport is presented in Figure 1. The model consists of modules for "Check-in and Baggage drop", "Passport Check", "Security Screening" and "Gates". The modules are developed along similar lines of previously published models as reviewed in Section 2, but adapted to the particularities of the BEY airport departure terminal as detailed in the following section. As a result, the model captures the flow and processing of passengers through all of a departure terminal's functional areas as described in each of the model's four modules, and can in turn be adapted to any other airport passenger terminal.

However, unlike previous SD models which either did not make use of dwell time (Manataki & Zografos, 2010), or only included it as a predetermined constant (Suryani et al., 2010) which limits its usefulness, the current model uses dwell time as a strategic parameter for determining area requirements. The importance of this difference is illustrated in Equation (1) which shows the calculation for estimating area requirements based on IATA standards and dwell time (de Neufville & Odoni, 2013):

$$\begin{aligned} &Required\ dwell\ area \\ &\quad = (number\ of\ pax\ in\ queue/hour) \times (standard\ space/pax) \\ &\quad \times (dwell\ time\ in\ hours) \end{aligned} \tag{1}$$

This shows that the required space for a service area is directly proportional to the dwell time for any given standard. The shorter the dwell time, the sooner a passenger will leave the space, making it available again for another one. This means that space requirements can be less than when estimated for a total passenger count assumed to occupy the space over an entire average peak hour of demand without considering their actual dwell time during this period.

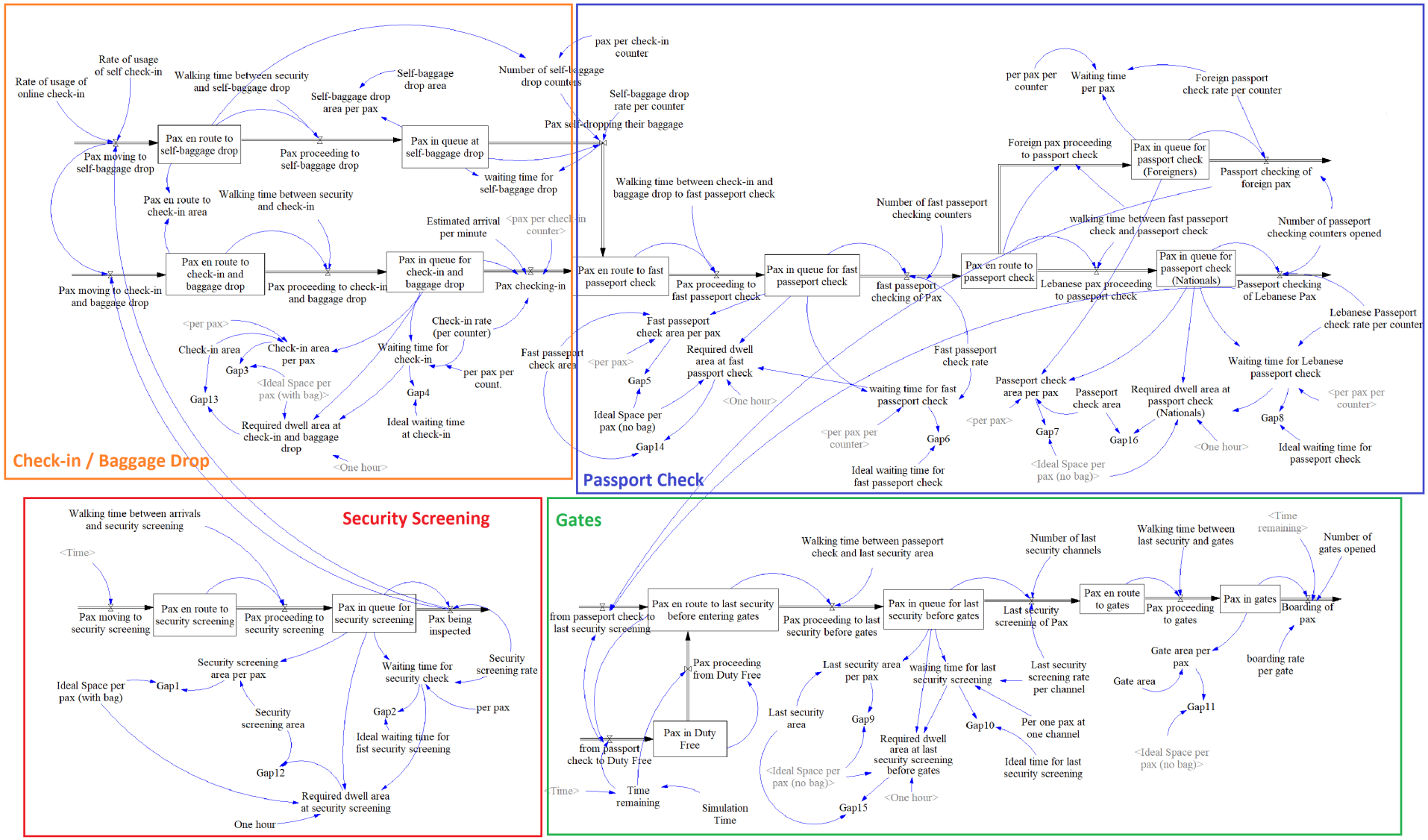

Figure 1. SD Model of passenger flow through departure processes at BEY airport terminal

Thus, the use of dwell time as a variable in the model serves a strategic purpose of assisting planners to evaluate current and projected space requirements for each functional area at a desired LOS within overall space and resource constraints. This is particularly important for re-layout projects where space and costs are constrained, making it crucial to know how dwell time changes over time during peak hours of demand.

In contrast, setting the dwell time in Equation (1) a priori to some constant value according to a desired LOS standard limits its usefulness to the case of designing a new facility, whereby the space requirement for a given area would only depend on the forecasted demand at some average peak hour in the future, with the assumption that all passengers in that area would have a dwell time at or below the predetermined value. Typically, the estimated space would initially be larger than necessary, until the actual demand exceeds the forecasted demand at some point in the long-term.

Table 1 presents the IATA space standards used in Equation (1) corresponding to different LOS for functional and service areas in the terminal. A category "C" LOS (equivalent to "stable and steady" passenger flow with "acceptable" delays and "good" comfort level) is considered as an overall "good" LOS and is used in this research.

Table 1. IATA Standards (IATA, 1995)

Activity	**Situation**	**Level of Service Standard (m^2)**					
		A	**B**	**C**	**D**	**E**	**F**
Waiting, circulating	Moving about freely	2.7	2.3	1.9	1.5	1	Less
Bag claim area	Moving with bags	2.0	1.8	1.6	1.4	1.2	Less
Check-in queue	Queued with bags	1.8	1.6	1.4	1.2	1	Less
Hold rooms	Queued without bags	1.4	1.2	1	0.8	0.6	Less

The model's four modules are each made up of two types of stocks, one capturing the number of passengers "en route to" the next area and the other describing those in queue awaiting service, as shown in Figure 1. The outflow from a queue is equivalent to the rate at which passengers get serviced at the corresponding process. For example, the outflow of "Pax self-dropping their baggage" is a function of the processing rate of the baggage drop counter, the number of counters opened for self-baggage drop, and the number of passengers in the queue. For clarity, two types of auxiliary variables were used in each module, one representing the waiting time a passenger will spend in queue at each process, and the other representing the area available per passenger in queue. Finally, "Required dwell area" was introduced as auxiliary variable in the model to evaluate the current and future required space for the security screening and check-in areas, as discussed in the simulation results in section 5.

Sample model equations are summarized in Table 2.

Table 2. Sample SD model equations

Variable	**Equation**	**Units**
Check in area per pax	IF THEN ELSE (Pax in queue for check in and baggage drop <=1, Check in area * Per pax, Check in area / Pax in queue for check in and baggage drop)	m2/pax
Check in area	350	m2
Check in rate (per counter)	1/(RANDOM UNIFORM (7, 12 , 1))	1/(minute*counter)
Dwell area required for first security screening	Ideal Space per pax (with bag) * Pax in queue for security screening * (Waiting time for security check / One hour)	m2
Fast passport checking of Pax	Fast passport check rate* Number of fast passport checking counters * Pax in queue for fast passport check	pax/minute
Gap1	Ideal Space per pax (with bag) – Security screening area per pax	m2/pax
Last security screening rate per channel	RANDOM UNIFORM (1, 3 , 1)	1/(minute*channel)
Foreign pax proceeding to passport check	(0.4 * Pax en route to passport check) / Walking time between fast passport check and passport check	pax/minute

Lebanese Passport check rate per counter	ABS (1/(RANDOM UNIFORM (2, 3 , 1)))	1/(minute*counter)
Number of self baggage drop counters	Pax en route to self baggage drop / Pax per check in counter	counter
Pax in Duty Free	INTEG (From passport check to Duty Free – Pax proceeding from Duty Free, 1)	pax
Prevalence in year 2035	0.5	dimensionless
Security screening area per pax	Security screening area / Pax in queue for security screening	m2/pax
Security screening rate	(2/(RANDOM UNIFORM (3,6,1)))*0.7*3	1/minute
Waiting time for check in	Pax in queue for check in and baggage drop*(1/Check in rate (per counter)) * Per pax per count	minute

The SD model was validated against the current state of the airport terminal and was able to reproduce the observed delays and queue lengths, as discussed in the next section. In addition, a dimensional consistency test was done to check the validity of the equations used and the correctness of all units. A sensitivity test was also done to ensure that small or large parameter changes do not affect the validity of the results (Barlas, 1996).

4. Case Study

The departure terminal at BEY airport consists of two identical wings with 12 gates each, and passengers proceed to their gate through the following process steps: self check-in (6 kiosks), first security screening, check-in (23 counters), fast passport check, passport check, duty free, last security screening and gates, as shown in Figure 2.

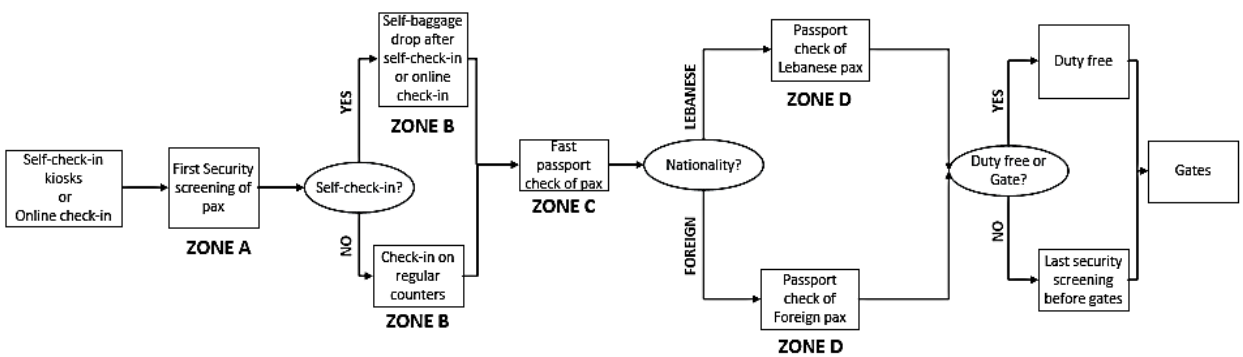

Figure 2. Passenger flow map at BEY airport departure terminal

Between the years 2007 and 2017, BEY airport experienced major growth in passenger traffic averaging over 7.8% per year, and exceeding by over one third the existing annual terminal capacity of 6 million passengers. This rapid growth alongside poor layout planning have drastically affected terminal performance, resulting in excessively long wait times (over 3 hours total wait time on average) and very poor passenger experience, especially at the security screening and check-in areas during peak periods. To alleviate congestion, an emergency re-layout project was launched within the current terminal building at an estimated cost of $18M (Lewis, 2019).

The SD model of BEY airport is simulated for a 3-hour peak period during an average day of the busiest month (August) in the year. On average, 35 passengers arrive each minute to the departure terminal during this peak period. The arrival process is assumed to follow a Poisson distribution with an arrival rate of 35 passengers per minute and is modeled in Vensim using the LOOKUP function.

Time and motion studies were conducted over multiple visits to the airport and included timing of passenger flow through the terminal. The time needed to go from the last security screening to the proper gate was assumed to follow a random uniform distribution since passengers are equally likely to go to any gate, with the nearest and farthest gates being respectively 5 and 16 minutes walking from the last security screening area. Table 3 presents the average walking times between different areas of the airport terminal.

Table 3. Average walking times between different areas at the airport terminal

Route	Average Walking Time (minutes)
From arrival to first security screening	3
From first security screening to check-in/self-baggage drop	5
From check-in/self-baggage drop to fast passport check	4
From fast passport check to passport check/Duty Free	3
From passport check to last security screening before gates	5
From last security screening to gates	RANDOM UNIFORM between 5 and 16

Processing times at different stages of the departure process are listed in Table 4 below. Minimum and maximum values were collected during multiple airport visits. A random normal distribution is used between the extreme values since the time durations for servicing passengers is random and depends on multiple variables such as passenger and operator behavior, paper errors, varying numbers of baggage per passengers and others.

Table 4. Time distribution for processes at different steps

Time Distribution	Average Servicing Times (minutes)
At first security screening	Random normal (3,6)
At check-in	Random normal (7,12)

The SD model was validated by comparing the simulation results for dwell time at different steps of the departure process against the actual values observed during data collection. Figure 3 shows the simulation results for the waiting time in queue at security screening. The average waiting time in queue per passenger marked by the red line in the figure below is around 3 hours which concurs with our observations of the current state. A 3-hour waiting time is way beyond the limits of "acceptable" delays under a category "C" LOS, and therefore needs to be addressed and improved

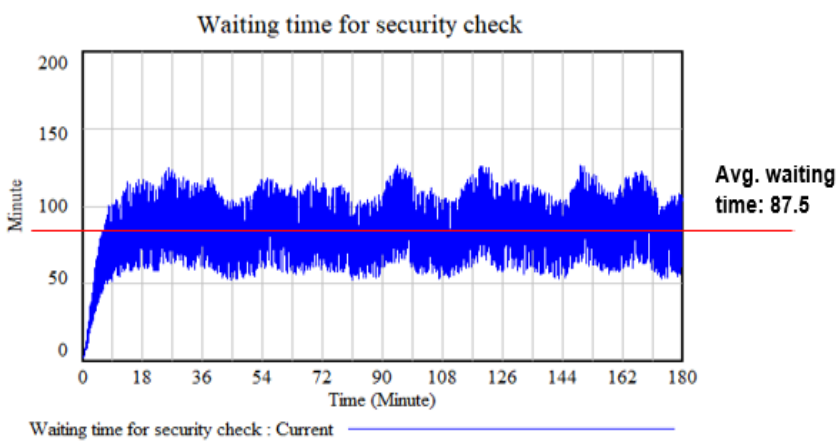

Figure 3. Waiting time in queue at security screening

And while the simulation results obtained for the dwell time in the check-in/baggage drop area showed that the average waiting time in queue per passenger at that process step is less than at security screening, it's still too high for a "good" LOS averaging 50 minutes per passenger (see Figure 4). This value was also validated through site visits and observation of the current state during peak demand periods.

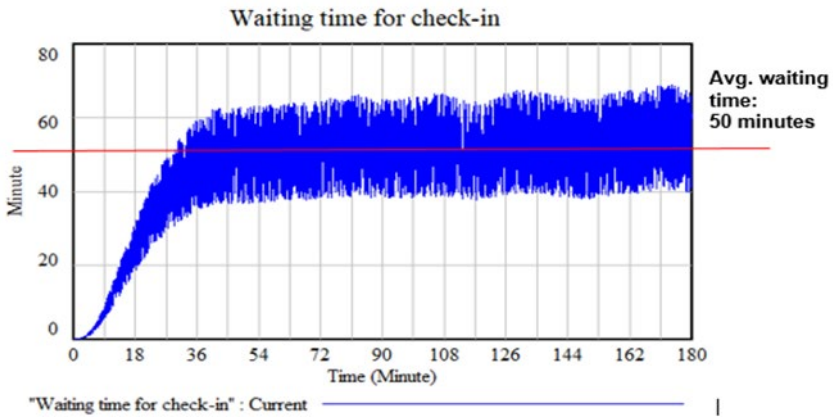

Figure 4. Waiting time in queue at check-in/baggage drop

5. Results and Recommendations

The SD model is used to track two strategic metrics to alleviate the congestion problem: the area occupied per passenger waiting in queue at different steps of the departure process, and the required dwell area at each step to comply with IATA standards for a category "C" LOS. Figures 5 and 6 show the simulation results for the area per passenger at the security screening and the check-in/baggage drop processes, respectively, in the current state of terminal operations at BEY.

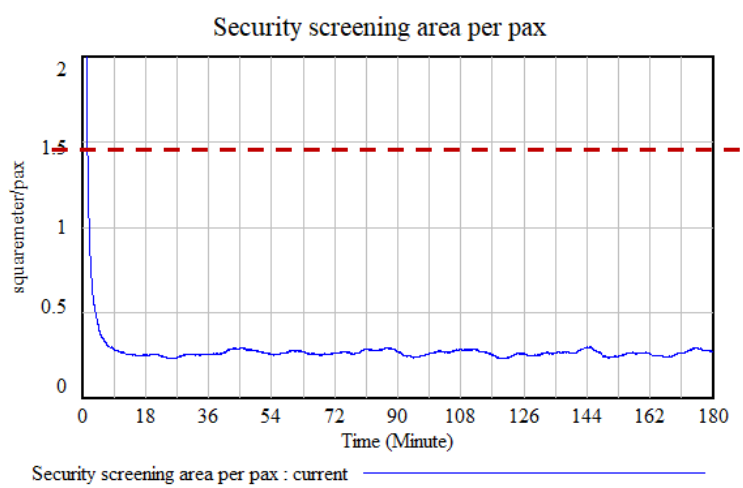

Figure 5. Area available per passenger at security screening in the current state

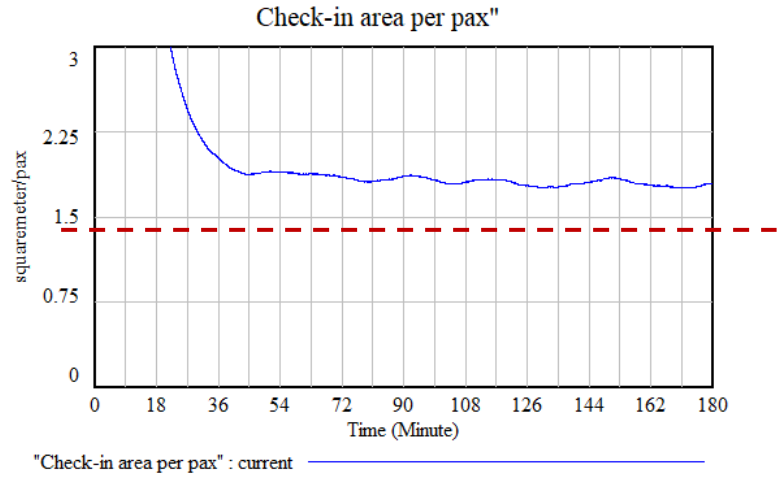

Figure 6. Area available per passenger at check-in/baggage drop in the current state

The simulation results show that the area available per passenger at security screening is below 0.5 m^2 per passenger, falling way below IATA standards of 1.4 m^2 indicated by the dashed red line representing the required area per passenger with baggage for a category "C" LOS. In contrast, the results shown in Figure 6 indicate that the area occupied per passenger at the check-in/baggage drop is at least 1.9 m^2, which exceeds the same IATA standards and are considered therefore considered satisfactory for a "good" LOS.

The SD model also calculates the dwell area required at every step of the departure process to comply with IATA standards at the C-LOS. The simulation results for this strategic indicator are shown in Figures 7 and 8 for security screening and check-in/baggage drop respectively.

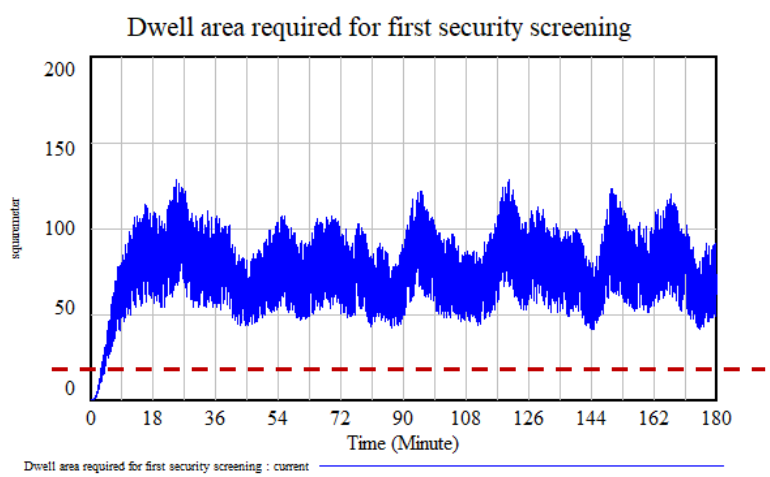

Figure 7. Required Dwell area for first security screening graph

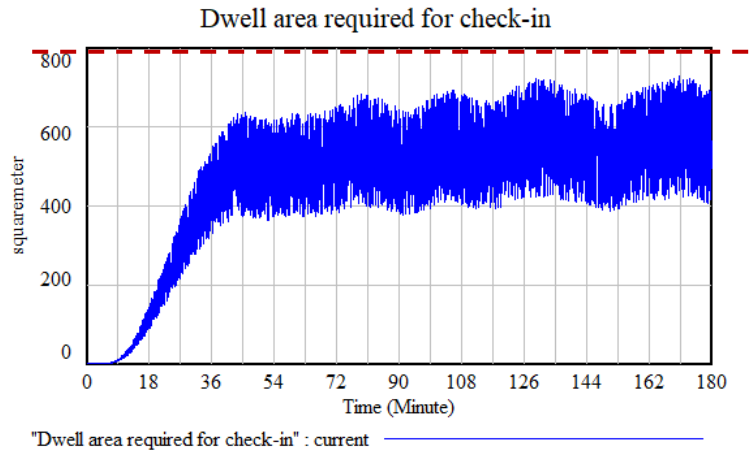

Figure 8. Required Dwell area for check-in graph

Comparing the simulation results against the currently assigned dwell areas in BEY as marked by the dashed red lines in the two figures above, reveals that the 10 m^2 dwell area currently allocated for queueing at security screening falls way below the required dwell area if a category "C" LOS is to be maintained within the same constraints for resources and passenger processing rates. However, this is not the case for the check-in/baggage drop area which is well within the currently allocated space for queueing in the current layout.

Table 5 summarizes the results detailed above and compares the current state of allocated space at security screening and check-in/self-baggage drop in BEY to the required dwell areas and required areas per passenger for compliance with IATA category "C" LOS.

Table 5: Summary of current state simulation results and benchmark with IATA standards for C-LOS

Process Step	**IATA area/pax for C-LOS (m^2/pax)**	**Maximum area/pax in current layout (m^2/pax)**	**Dwell area in current layout (m2)**	**Max required Dwell Area per IATA standards (m2)**
Security screening	1.4	0.4	10	variable see Fig 6 with max value equal 120
Check-in/Self-Baggage drop	1.4	1.9	800	variable see Fig 7 with max value equal 700

The current state assessment pointed to an opportunity for reallocating space between the security screening area and the check-in/baggage drop area as an initial quick fix that would alleviate congestion at minimal to no capital investment. The additional area needed for security screening is around 110 m^2, whereas the current queueing area at check-in exceeds the required dwell area by 100 m^2. The reallocation of space between the two functional areas is feasible since they are adjacent and since the physical boundaries separating them consist only of drywalls that can be easily dismantled and pushed back.

The reallocation of space alleviates the problem but does not ensure a sustained "good" level of service as defined by IATA C-LOS. Additional measures should be taken and the SD model can be easily adapted and used to conduct scenario analysis to evaluate the effectiveness of some changes prior to adopting them. One such change is derived from the relationship between dwell time and the required dwell area. It is clear from Equation (1) that reducing dwell time by increasing the service rate of passengers leads to a reduction in the required dwell area. Improving the service rate can be achieved by either optimizing the current operation or by introducing automation such as the use of automated security screening lanes, as well as encouraging and/or incentivizing passengers to use the self-check-in kiosks or to do online check-in prior to airport arrival.

6. Conclusion

In this paper we present a proof of concept on the importance of using two strategic metrics, dwell area and dwell time, coupled with SD modelling to re-plan the layout of airport passenger terminals as a way to alleviate congestion caused by the rapid increase in passenger demand versus the slow expansion of airport capacity. Our modelling results focused on the check-in/baggage drop and security screening functional areas of the departure terminal at Beirut-Rafic Hariri International Airport (BEY) airport as the most typical of problematic areas.

The presented SD model provides a holistic and easy decision support tool that can assist airport planners and operators in more accurately and efficiently evaluating dwell time and required dwell area for an existing terminal for the purpose of improving it. The model was used to demonstrate how misestimating space needs due to a common misuse of IATA standards leads to oversizing some areas at the expense of others, which was found to be one of the main reasons behind high congestion experienced at BEY airport.

The proposed changes to the current layout consisted of a simple reallocation of space among functional areas coupled with low cost, high impact operational improvements that would "immediately" alleviate heavy congestion in the security screening area and improve passenger experience and comfort without compromising standards and resource utilization, while saving the need for costly physical expansion.

Future research should focus on developing additional quantitative standards to complement standards on the area per passenger for each LOS defined by IATA. Such standards would include ranges for dwell time to be used in determining required dwell areas.

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