Simulating a Self-Bag-Drop System at an International Airport

S. Jacobs[1] & W.L. Bean[1*]

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Contact details
* Corresponding author
wilna.bean@up.ac.za

Author affiliations
1 Industrial and Systems Engineering, University of Pretoria, Pretoria, South Africa

ORCID® identifiers
S. Jacobs
https://orcid.org/0009-0007-7392-6823

W.L. Bean
https://orcid.org/0000-0003-1965-0081

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ABSTRACT

A low-cost airline is considering implementing a self-bag-drop system, because the current check-in system results in excessive passenger waiting times. The research presented in this paper uses discrete-event simulation to investigate the feasibility of the proposed system. Results from multiple simulation experiments demonstrate that the implementation of self-bag-drop counters could significantly reduce passenger waiting times when appropriately aligned with user adoption levels. This study contributes to the field of airport operations management by illustrating the benefits of self-bag-drop systems in a South African case study and by helping to understand the potential impacts and risks of a self-bag-drop system in a developing country.

OPSOMMING

’n Laekostelugredery oorweeg die implementering van ’n selfdiens-bagasie-afleweringstelsel, aangesien die huidige inboekstelsel tot buitensporige wagtye vir passasiers lei. Die navorsing wat in hierdie artikel aangebied word, gebruik diskrete-gebeurtenissimulasie om die uitvoerbaarheid van die voorgestelde stelsel te ondersoek. Die resultate van verskeie simulasie-eksperimente toon dat die implementering van selfdiens-bagasie-afleweringstoonbanke passasiers se wagtye aansienlik kan verminder, mits dit toepaslik met gebruikersaanvaardingsvlakke belyn word. Hierdie studie lewer ’n bydrae tot die veld van lughawebedryfsbestuur deur die voordele van selfdiens-bagasie-afleweringstelsels aan die hand van ’n Suid-Afrikaanse gevallestudie te illustreer, en deur ’n beter begrip van die moontlike uitwerkings en risiko’s van so ’n stelsel in ’n ontwikkelende land te bevorder.

1. INTRODUCTION

Air travel is one of the most integral aspects of modern life, with passenger numbers steadily rising [1]. Despite this, check-in procedures at airports are often time-consuming and frustrating. In response, airports are embracing technology to enhance the check-in process and to improve operational efficiency. Air travel has become more convenient and accessible thanks to these innovations.

Airports are the primary point of contact for passengers worldwide, since thousands travel by air each year [1]. These facilities offer check-in, passport, and security checks, luggage drop off, and baggage claim, all involving queueing processes and waiting times. In particular, large airports during peak hours are prone to congestion and delays [2], increasing the risk of passengers missing their flights if check-in delays occur [3]. According to estimates from the International Air Transport Association (IATA), passenger numbers will reach 7.8 billion by 2036, growing at an annual rate of 3.6% [1]. To meet this increased demand, airports must adapt and manage their facilities in a way that maintains quality standards and minimises waiting times [3].

An innovative process that has transformed customer service in the aviation industry is self-check-in through self-bag-drop (SBD) stations [4]. In addition to improving efficiency and performance, SBD processes have reduced labour costs considerably [5]. This has resulted in a more streamlined and cost-effective approach to passenger check-in, which is undeniably transforming the air travel landscape.

Oliver Reginald Tambo International Airport (ORTIA) is the primary international gateway to South Africa. Located in Johannesburg, it serves as a major hub for domestic and international flights. Check-in times during peak season were found to be more than twice as long as during off-peak periods [6]. As a result of these increased waiting times, the airline considered the implementation of a SBD system at ORTIA to reduce queue waiting times. This system requires passengers to attach their own baggage tags and drop their bags at the baggage drop belt [7]. To ensure that the system meets the needs of both the airline and its passengers, a thorough assessment of the feasibility and efficiency of an SBD must be conducted prior to implementation.

Simulation models are frequently used in airport terminal design to replicate real-world processes while accounting for variables such as human behaviour and passenger attitudes. These models have been widely applied in analysing passenger flow, queueing procedures, and check-in operations at airports. For example, Lee et al. [8] used simulation software at Singapore Changi Airport to estimate the impact of self-service check-in desks on queueing and processing times. Bevilacqua and Ciarapica [9] examined the use of simulation to determine the optimal number of check-in counters for departing flights and to develop improved service management strategies, while Guizzi et al. [10] developed a discrete-event simulation model to illustrate passenger flow from arrival to boarding at Naples International Airport. Simulation modelling eliminates the need for physical testing, and enables more efficient and effective system optimisation [11].

Several studies have demonstrated that implementing SBD systems could reduce passenger waiting times and improve operational efficiency [5], [7]. The implementation of a SBD system at ORTIA would therefore be expected to reduce queueing times and improve passengers' overall satisfaction, potentially increasing the low-cost airline's attractiveness to passengers and contributing to customer loyalty and revenue growth. In line with these findings, this paper simulates SBD systems at ORTIA to evaluate their feasibility before implementation. Simulation is used to test the current and proposed systems, analyse the resulting operational performance, and identify possible issues and areas for improvement.

This study therefore aims to determine the feasibility of implementing a SBD system at ORTIA by evaluating the operational impact of varying SBD use and passenger acceptance rates on check-in performance. In particular, the study identifies the optimal number of conventional check-in counters that should be converted to SBD counters under different scenarios of usage to minimise passenger waiting times and improve operational efficiency. The findings provide insights for airlines into the operational impacts, infrastructure requirements, and planning considerations associated with SBD implementation.

This study makes a notable contribution to the fields of airport process planning and operations management by confirming past findings about the benefits of SBD systems through a real-world case study conducted in South Africa. The study also highlights how passenger adoption rates influence the operational performance and infrastructure requirements of SBD systems, particularly in environments where varying levels of technology acceptance may affect use of the system. The findings provide decision-makers with a structured approach to evaluate the operational impacts, planning considerations, and potential risks associated with implementing SBD systems, while also supporting improved capacity planning and customer service delivery.

The remainder of this paper is structured as follows. The literature is reviewed in Section 2. A simulation model of the check-in procedure at ORTIA is presented in Section 3. This model helps to understand the issues at hand and guides the design of the proposed check-in procedure using SBD technology. The model is validated using data collected from the current check-in procedure. The results of the study and a risk analysis are presented in Section 4. This provides insights into the potential impact and risks of implementing SBD technology to improve the check-in process at ORTIA. The model should also function as a basis for evaluating the proposed check-in procedure. Finally, conclusions and recommendations on how airlines could proceed with the suggested check-in procedure are presented in Section 5.

2. LITERATURE REVIEW

Through implementing SBD systems, the aviation industry has improved airport operations by allowing passengers to check-in their own luggage, which has gained considerable traction. In addition to reducing queueing times, these systems can free up staff for other tasks and improve operational efficiency [7].

Simulation modelling has evolved into a powerful tool to assess the performance of SBD systems [3]. Simulation modelling enables the identification of bottlenecks in the system and makes it easier to test different scenarios to determine the best-performing scenario. This can be done by simulating passenger behaviour, baggage handling processes, and airport staff operations [12].

2.1. Self-bag-drop systems in the literature

SBD systems offer numerous benefits for airlines, making them a transformative addition to airport operations. Research has shown that SBD systems can shorten check-in times by up to 60%, significantly enhancing efficiency and minimising queueing delays during peak periods [13]. This improvement could enable airlines to handle increasing passenger volumes, optimise throughput, and increase their capacity to accommodate future growth [5]. In addition to time savings, SBD systems streamline staffing requirements, and reduce operational costs by reallocating human resources to other critical tasks. In addition, these systems enhance accuracy and security in the baggage handling process, which reduces errors and improves overall customer satisfaction [14].

The implementation of SBD systems also aligns with growing consumer preferences for self-service technologies, which provide travellers with enhanced control and convenience during their journey [13]. By adopting SBD systems, airlines could deliver an innovative, customer-centric experience that meets evolving expectations and strengthens their market position. However, user acceptance is crucial to the success of SBD systems. While their operational and financial benefits are well documented, passengers must be willing to embrace and adapt to this technology for it to achieve its full potential [15]. Proactive engagement and user-friendly designs could play a pivotal role in facilitating widespread adoption, making SBD systems an essential and effective tool for modernising airport operations.

2.2. User acceptance

User acceptance is crucial to implementing SBD systems successfully at airports. Key determinants of user acceptance include perceived usefulness, ease of use, and trust. Perceived usefulness reflects the system's ability to help users to achieve their goals; ease of use pertains to the effort required to operate the system; and trust influences confidence in the system's reliability [16], [17], [18]. In addition, user experience and personal characteristics, such as age and technological familiarity, play a significant role in determining acceptance. Kamel *et al.* [15] found that African travellers are willing to adopt airport technologies, highlighting the potential for implementing SBD systems in the region.

Understanding and integrating these factors allows airlines to design systems that align with customer preferences and ensure successful adoption. This is especially critical in South Africa, where a diverse population requires tailored approaches and thorough user feedback [16]. Furthermore, adopting SBD systems has broader implications, including improved efficiency, reduced waiting times, and economic benefits through increased tourism [5], [19]. Successful implementation would also depend on infrastructure readiness and regulatory compliance. Airlines must collaborate with airport authorities and governing bodies to address these factors and ensure a seamless transition [13]. Understanding user acceptance would be essential for improving performance and success.

2.3. Simulation modelling

Simulation is the practice of replicating real systems' behaviour to assess or experiment with them [20]. It can be described as a form of indirect experimentation, in which a system analysis is performed without affecting the operational system itself [11]. Researchers can generalise their results through simulation, as it allows them to control a number of variables [21].

Kelton *et al.* [22] argue that there are three key characteristics that distinguish different types of simulations. First, simulations can be static or dynamic. Static models do not depend on time, as an event's validity does not change when performed at different times. When an event is time-sensitive, such as a manufacturing process, dynamic simulations are more common. Second, models can be defined as continuous or discrete. A continuous simulation represents a system that is ever-evolving, such as pressure levels or fluid levels, while a discrete event simulation models a system that changes at specific time intervals. Discrete simulations are effective when modelling parts or people arriving at specific times and undergoing particular processes. Discrete event simulation (DES) could accurately model discrete operations of an SBD system. Third, simulations may be deterministic or stochastic. Deterministic simulations have no random input, which means that events always occur at the same time. In a stochastic simulation, some events occur randomly, such as passenger arrivals at check-in.

According to Kelton *et al.* [22], DES provides the most suitable method for analysing SBD systems. The system is dynamic, and events occur according to a timeline, so that an event may affect another event. An SBD system is characterised by discrete events that occur from the moment a user enters the system until they exit. Last, events in a SBD system are greatly affected by human factors, which result in stochastic or random events. Based on these system descriptions, a DES approach is the best method for simulating the SBD system.

2.3.1. *Discrete event simulation modelling*

DES is widely recognised as an effective tool for evaluating and optimising complex systems, including self-service technologies in airports. It models real-world processes, such as passenger arrivals and baggage handling, by simulating events over time, enabling detailed scenario testing and informed decision-making about system design and implementation [10], [22], [23]. A significant advantage of DES is its ability to replicate system behaviour with precision, allowing for analysis without costly or disruptive real-world experimentation [24]. Its capacity to incorporate randomness and adjust parameters makes it ideal for understanding the implications of different operational strategies. This is particularly relevant for intricate systems such as check-ins and SBD [20].

In aviation, DES has been instrumental in optimising airport operations, such as reducing waiting times [10], [25]. For example, Guizzi *et al.* [10] used DES to develop a model for Naples International Airport, accurately predicting delays and optimising terminal layouts. Similarly, Esteban and Pedro [26] modelled the check-in process at Lisbon Airport, demonstrating that extending check-in periods would significantly reduce wait times and queue lengths. These applications highlight DES's versatility in testing scenarios and configurations that would be difficult in real-life settings [20].

Airports are particularly well-suited for DES modelling because of their dynamic and complex nature. Valid models allow stakeholders to experiment with regulations, procedures, or methodologies digitally, avoiding costly disruptions [23]. At ORTIA, DES could provide valuable insights into the performance of SBD systems, ensuring alignment with passenger and airline needs. While DES proves highly effective for airport operations, exploring alternative approaches such as agent-based simulation (ABS) could complement its capabilities for even more robust analysis [5], [27].

2.3.2. *Agent-based simulation modelling*

ABS models use individual entities, or agents, each with distinct behaviours, traits, and decision-making processes, focusing on their interactions in a system [28]. Unlike DES, which simulates systems holistically, ABS models adapt dynamically as agents adjust their behaviour based on their environment and interactions [22]. This approach has been effectively applied to various airport operations, such as modelling passenger flow policies at Kempegowda International Airport [29], [30].

ABS has been widely used in transportation-related applications, including travel demand forecasting, crowd simulations, and disaster evacuations, demonstrating its versatility in capturing individual-level dynamics [31], [32], [33]. Majid *et al.* [34] found no significant statistical differences between DES and ABS models when assessing reactive behaviour or when comparing simulation outputs with real system performance. These findings indicate that both DES and ABS are viable approaches to simulating the SBD system at ORTIA. Although Dorton and Liu [20] concluded that DES would be the most effective approach to simulating a SBD system, ABS could still be used as an alternative method to validate the initial simulation results. It would be imperative to investigate the risks associated with systems such as these to ensure robust and realistic modelling. A risk matrix can be used to systematically identify and assess potential risks, providing a structured approach to evaluating their likelihood and impact.

2.4. Risk analysis

Risk management is critical to project planning. Risk is defined broadly as the likelihood of undesirable outcomes [4], loss uncertainty [35], or the modification of future outcomes under certain scenarios [36]. Risks are characterised by their objective existence, abrupt nature, potential for harm, uncertainty, and evolving nature as technology advances [4]. To manage risks effectively, a structured tool such as a risk matrix can be used. Defined by Asana [37], a risk matrix assesses risk based on its likelihood and severity. It categorises risks into low, medium, or high impact on a scale from 1 to 25.

Developing a risk matrix involves establishing scales for severity (ranging from negligible to catastrophic) and likelihood (from very unlikely to very likely). The matrix calculates risk impact by multiplying severity and likelihood, enabling risk prioritisation. This process has five key steps: identifying risks, determining their severity and likelihood, calculating risk impact, and prioritising and addressing risks through action plans. Such analysis helps organisations to prevent potential disruptions and respond effectively to identified risks. This makes it a valuable tool for projects such as implementing a SBD system [37], [38].

3. MODELS AND METHOD

Simulation modelling is highlighted as an effective evaluation technique for complex systems such as airport check-in and bag-drop systems. DES allows for accurate system modelling and testing of different scenarios. In this way, simulation models can accurately represent real-world systems and provide insights into their performance. These simulation results can then be used to analyse the feasibility of the proposed SBD system. Two models were developed for this study: a current check-in model representing the existing ORTIA domestic check-in procedure, and a proposed SBD model that iteratively converts check-in counters to SBD counters.

3.1. Methodology

The design research methodology of Manson [39] provides a structured approach to evaluating the feasibility of implementing a SBD system at ORTIA. The process begins with *awareness of the problem*, identifying that check-in times are more than doubled during peak periods. This phase assesses whether the proposed SBD system could effectively reduce these delays.

The *suggestion* phase involves developing conceptual models of both the current and the proposed check-in systems, evaluating variables such as passenger arrival and service rates. A literature review supports this phase by identifying key parameters and performance indicators from similar airport settings.

In the *development* phase, detailed simulation models are created using DES. The DES approach captures the system's overall dynamics and accounts for passenger behaviours' stochastic nature, enabling a comprehensive performance evaluation. An ABS approach was also investigated as an alternative method to validate the DES results. As discussed in Section 2.3.2, both DES and ABS have been shown to produce comparable outputs [34]; however, DES was selected as the primary modelling method, given the system characteristics described by Kelton *et al*. [22].

The *evaluation* phase assesses the system's effectiveness by comparing the simulation results for current and the proposed check-in procedures, analysing changes in queueing times. Model verification (confirming that the model functions as intended) and validation (confirming that outputs align with real-world data) are integral to this phase, and are discussed in Section 4.1. Finally, the *conclusion* phase synthesises the findings into actionable recommendations, enabling informed decision-making about implementing a SBD system. This systematic approach ensures that both feasibility and efficiency are thoroughly examined.

3.2. Simulation model

Two simulation models were developed for this study. The first represents the current domestic check-in procedure at ORTIA, serving as a baseline. The second represents the proposed SBD system. Both models were built in AnyLogic simulation software.

Domestic check-in procedures were identified as critical areas of operations that could benefit from optimisation. For the current model, a scale layout of the ORTIA domestic check-in area was constructed in AnyLogic. The check-in hall contains two banks of counters, each comprising 13 positions. One bank is designated for economy check-in and the other for priority check-in. In the economy bank, one counter displays the flight schedule, one is reserved for closing flights, and one is assigned to the flight controller; the remaining counters are active service points. All the counters in the priority bank are fully used for priority check-in – a paid add-on that passengers may select at the time of booking. It grants access to a dedicated, typically shorter queue, as well as additional benefits such as priority boarding and other service enhancements. Economy passengers who have not purchased this add-on use the standard check-in counters. A scale model of the current check-in layout is shown in Figure 1.

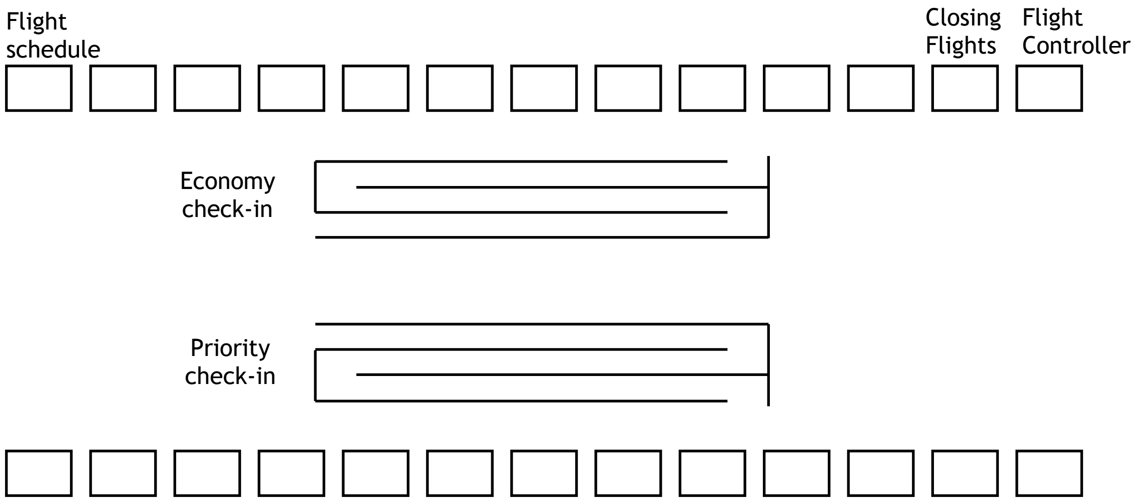

Figure 1: Scale model of current check-in counters

Upon arrival, passengers proceed to the appropriate queue and wait for their turn. Once called, passengers proceed to the counter and complete the check-in process. At the check-in counter, a trained agent assists the passenger by verifying their ID, scanning the boarding pass, checking in the luggage, and printing baggage tags. The involvement of the check-in agent introduces variability in processing time, as agent speed, passenger preparedness, and the complexity of the transaction all contribute to the service time distribution. Once the agent completes the check-in, the passenger's bags are collected, weighed, tagged, and placed on a conveyor belt to be loaded onto the aircraft. This agent-assisted process is the primary source of extended waiting times compared with the proposed self-service alternative. Finally, passengers exit and head to security. The flow logic is illustrated in Figure 2.

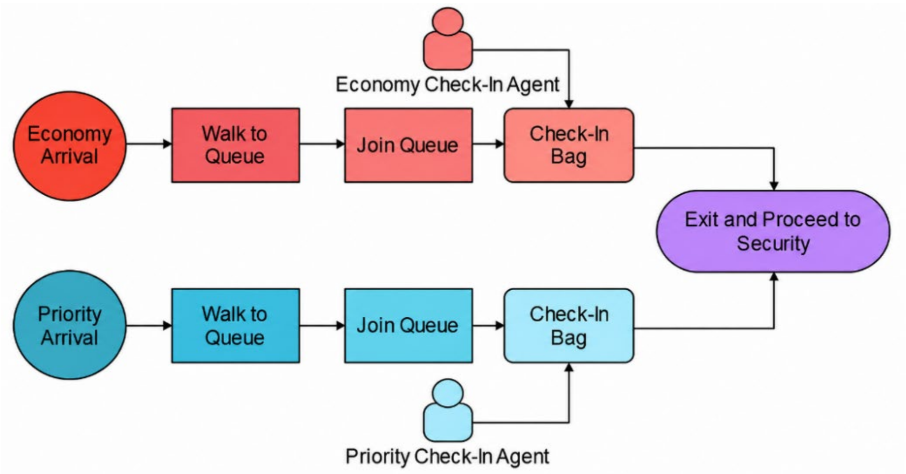

Figure 2: Simulation model logic of current system

For the proposed SBD model, check-in counters are iteratively converted to SBD counters to determine the optimal number of counters to be converted. In the proposed system, passengers choose between the standard agent-assisted queue and the SBD queue on arrival at the check-in area. Economy and priority passengers are modelled as separate streams, each with the option to select the SBD path based on the assumed rate of use. The methodology followed for designing this simulation was similar to that of the current model, with the additions shown in Figure 3.

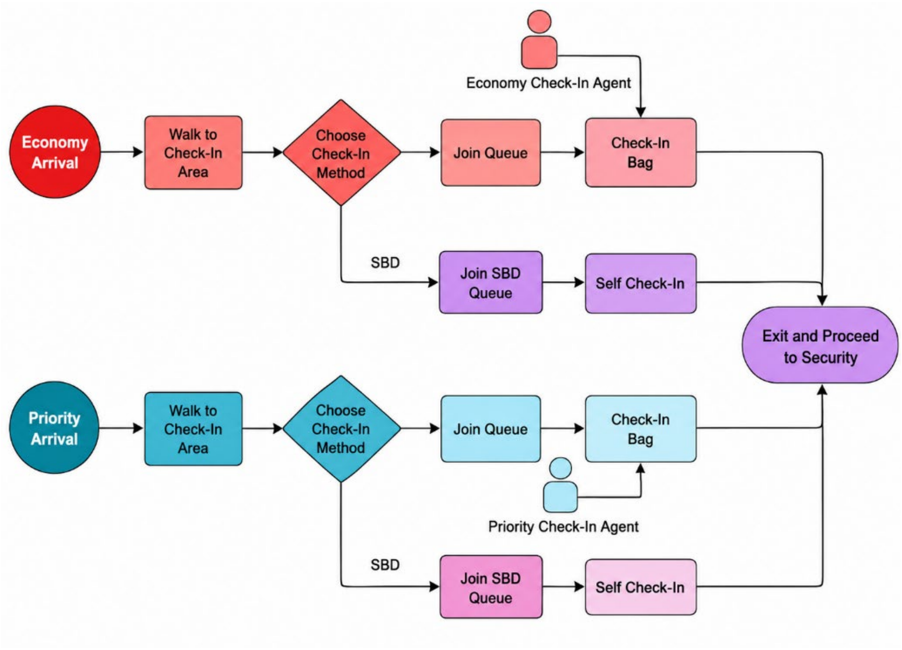

Figure 3: Simulation model logic of proposed system

Data collected for this study included passenger arrival rates and service rates measured during the peak morning hours between 06h30 and 07h30, obtained from previous time studies conducted by Lutwama [6] for August 2022 and December 2022. A third data set for July 2023 was collected through direct time studies at ORTIA using a stopwatch and spreadsheet. Arrival rates were derived from flight bag-check data, filtered for flights departing from ORTIA, and distributed across the check-in window.

An important input assumption for the proposed model concerned the SBD service time. Based on SITA [13], the service time for SBD was assumed to be half the service time of agent-assisted check-in. This assumption is acknowledged as a key limitation, as it directly affects the simulation outputs. The accuracy of this estimate would benefit from empirical testing at a live SBD installation.

In addition, the user acceptance (use) rate was treated as an independent input variable, not estimated from simulation outputs. Based on Kamel *et al.* [15], around 74% of African travellers indicated their willingness to use new airport technology. The model was therefore simulated in use intervals of 10%, from 10% to 70%, for each SBD counter configuration. This would allow decision-makers to identify the required number of SBD counters for each anticipated use scenario.

The simulation was executed 50 times per scenario to account for the stochastic nature of the model. Stochastic components include passenger inter-arrival times, service times, and path selection. Averaging over 50 runs reduces the influence of random variation and produces more stable estimates of mean waiting time. The simulation run duration was set to correspond to the one-hour peak window (06h30–07h30) to maintain consistency between scenarios and to prevent biased comparisons.

3.3. Risk analysis

A detailed risk analysis was not the primary focus of this study; however, several implementation risks associated with SBD systems were identified during the research process. These risks included passenger resistance to new technology, insufficient staff training, technical system failures, and infrastructure readiness constraints.

While a risk matrix was initially developed to identify potential implementation concerns, the primary contribution of this study lies in evaluating operational feasibility through simulation modelling rather than in conducting a comprehensive risk assessment. The identified risks nevertheless provide useful considerations for future implementation planning and operational decision-making.

4. RESULTS

This section presents the simulation results. The current check-in model is first evaluated against the collected data to confirm its credibility, after which the proposed SBD model results are examined to determine the most suitable counter configuration for each passenger use scenario.

4.1. Simulation results

Model verification and validation: Before drawing conclusions from the simulation results, it was necessary to confirm that the model accurately represented the real-world check-in process. Verification ensured that the model logic behaved as intended: passengers arrived at the correct rates, joined the appropriate queues, were served in the expected sequence, and exited the system without error. This was achieved by tracing individual passengers through each stage of the AnyLogic model and confirming that the outputs aligned with the intended process flow illustrated in Figure 2.

Validation was then conducted by comparing the model's average outputs from 50 simulation runs with the empirical data collected by Lutwama [6]. For the December 2022 period, the model deviated from the observed data by only 2.41% for economy check-in and by 3.04% for priority check-in, while the July 2023 results showed similarly small deviations. These close correlations provide strong confidence that the simulation model accurately represents the real system. The August 2022 dataset was excluded from further analysis because it reflected a historical booking policy according to which passengers who pre-booked checked baggage automatically received priority check-in access. Since this policy was no longer in effect, the resulting priority arrival rates were not considered representative of current operations.

With the model successfully validated, the baseline operational picture became clear: during peak periods, both economy and priority check-in queues experienced significant congestion, with passenger waiting times exceeding comfortable service levels. These findings confirm that there is meaningful opportunity for operational improvement, and support further investigation into the implementation of a SBD system.

Identifying the best-performing number of SBD counters: A key contribution of this study is not only demonstrating that SBD systems can reduce passenger waiting times, but also determining how many conventional check-in counters should be converted to SBD counters under different passenger use rates. To evaluate this, the simulation was conducted iteratively, beginning with one SBD counter at 10% use and progressively increasing both the use rate and the number of SBD counters until a stable configuration was identified for each scenario, up to 70% use. For each use scenario, the stopping criterion was reached when the average waiting time in the SBD queue exceeded the average waiting time in the assisted check-in queue, indicating that the current number of SBD counters was no longer sufficient to support passenger demand efficiently.

The results, presented in Table 1, were consistent for both the December 2022 and the July 2023 periods. This consistency suggests that the findings are robust for different demand conditions rather than being specific to a single operational period.

Table 1: Passenger use and optimal number of counters

Passenger use	Number of counters
10%	1
20%	2
30%	2
40%	3
50%	4
60%	5
70%	6
80%	6
90%	7
100%	9

As shown in Table 1, the number of SBD counters required increases in line with passenger use rates. At lower use levels, a single SBD counter is sufficient to maintain acceptable queue performance, while higher use rates require additional counters to accommodate increased demand. By the time 70% of passengers use the SBD system, six SBD counters are required to maintain efficient queue waiting times.

These findings highlight an important operational consideration: accurately estimating passenger use rates is critical when planning SBD implementation. Overestimating passenger uptake and converting too many conventional counters to SBD facilities could reduce capacity in the assisted check-in queue, negatively affecting passengers who prefer or require staff assistance, such as older travellers or those less familiar with self-service technology. Conversely, underestimating use rates could result in underused SBD infrastructure and reduced operational benefit. This demonstrates the importance of conducting a study of passenger willingness or technology acceptance prior to implementation to support more accurate infrastructure planning and counter allocation decisions.

The operational improvements achieved through the implementation of the SBD system are best illustrated by the best-performing configurations identified for each simulation period, as summarised in Table 2. For December 2022, the 60% use scenario with five SBD counters produced the greatest reduction in waiting times, improving assisted check-in queue performance by 34.71% for economy passengers and by 34.45% for priority passengers. Even greater reductions were observed for passengers using the SBD system directly.

For July 2023, the corresponding best-performing scenario also showed meaningful operational improvements, with waiting time reductions of 16.51% for economy passengers and 19.84% for priority passengers. Although these improvements were smaller than those observed during December 2022, they remain significant, given that July 2023 represented a high-demand school holiday travel period with substantially higher baseline congestion levels.

Table 2: Waiting time improvement for December 2022 and July 2023 (best configurations)

Queue type	% improvement (assisted check-in)	% improvement (SBD)
Dec 2022 economy	34.71%	58.22%
Dec 2022 priority	34.45%	57.14%
Jul 2023 economy	16.51%	35.58%
Jul 2023 priority	19.84%	50.72%

These improvements were achieved through a relatively straightforward operational mechanism. By diverting a portion of passengers to self-service counters, the demand placed on the remaining assisted check-in counters decreases. As a result, check-in agents are able to process the shorter assisted queues more efficiently, which benefits even those passengers who choose not to use the SBD system.

A best-case scenario was also evaluated for use rates above 70%, extending to full passenger adoption. The simulation results indicated that, at 100% use, nine SBD counters would be required to maintain acceptable queue performance. Although full use is unlikely in the short term, based on the technology adoption patterns identified in the literature [15], this scenario provides a useful upper limit for long-term infrastructure planning, and demonstrates that the proposed system scales consistently as passenger uptake increases.

4.2. Risk analysis results

While risk considerations remain important when implementing a SBD system, risk analysis was not the primary focus of this study. A generic set of off-the-shelf implementation risks was therefore used to demonstrate the application of a risk matrix in the context of SBD implementation. These risks included factors such as passenger resistance to new technology, staff training requirements, technical failures, and infrastructure readiness. However, the main contribution of this research lies in evaluating the operational feasibility of SBD implementation and determining the best-performing number of conventional check-in counters to convert to SBD counters under varying passenger use rates. Consequently, greater emphasis was placed on the simulation modelling and counter conversion analysis than on conducting a comprehensive risk assessment.

5. CONCLUSION

This paper evaluated the feasibility of implementing a SBD system at ORTIA for a low-cost airline, with specific emphasis on reducing passenger waiting times during peak check-in periods. Previous studies have shown that SBD systems have been implemented successfully at airports worldwide, resulting in improved processing efficiency, lower operational costs, and increased passenger satisfaction [5], [7], [13]. Building on these findings, this study aimed not only to determine whether a SBD system would be feasible in the ORTIA context, but also to establish how such a system should be configured to operate effectively.

To evaluate this, DES models representing both the current and the proposed check-in systems were developed in AnyLogic. The current system model was validated using empirical time-study data collected during the December 2022 and July 2023 peak periods. The simulation outputs differed from the observed operational data by less than 3.5% in both the economy and the priority queues, showing that the model accurately represented the real-world system. An ABS model was also developed as an alternative validation approach. The ABS outputs differed from the DES results by between 3% and 9%, further supporting the reliability of the findings. Although both modelling approaches produced comparable results, DES consistently provided slightly greater accuracy and aligned more closely with the literature on queue-based airport operations [20], [22]. DES was therefore retained as the primary evaluation tool for this study.

A key contribution of this research is that it moves beyond simply assessing the feasibility of SBD implementation and instead addresses a more practical operational question: how many conventional check-in counters should be converted to SBD counters under different passenger use levels? To answer this, simulation experiments were conducted iteratively for use rates ranging from 10% to 70%. The upper limit was informed by Kamel *et al.* [15], whose findings suggested that about 74% of African travellers would be willing to adopt emerging airport self-service technologies.

The results demonstrated a clear relationship between passenger use rates and the number of SBD counters required. At lower use levels, a single SBD counter was sufficient to maintain efficient queue performance. As passenger adoption increased, additional counters were required, with six SBD counters needed at 70% use. A best-case scenario extending to full passenger adoption indicated that nine SBD counters would be required to maintain acceptable queue performance, providing a useful upper limit for future infrastructure planning.

The operational benefits observed during the simulation experiments were substantial. The best-performing configuration for December 2022, consisting of five SBD counters at 60% use, reduced economy passenger waiting times by 34.71% and priority passenger waiting times by 34.45% compared with the current system. The July 2023 period produced smaller but still meaningful improvements of 16.51% and 19.84% for economy and priority passengers respectively, reflecting the higher baseline congestion associated with school holiday travel demand during that period. Importantly, these improvements benefited not only passengers who used the SBD system directly, but also those remaining in the assisted check-in queue because of the reduced pressure placed on staffed counters.

Although a simplified risk analysis was included as part of the study, this was not the primary focus of the research. Generic implementation risks were used mainly to demonstrate the application of a risk matrix in the context of SBD implementation. The primary emphasis remained on evaluating operational feasibility and identifying the best-performing counter conversion strategies through simulation modelling.

Overall, the findings support the conclusion that implementing a SBD system at ORTIA would be both feasible and operationally beneficial. However, the extent of these benefits would depend heavily on passengers' willingness to adopt the system. This highlights the importance of conducting a dedicated passenger use or technology acceptance study before implementation. Overestimating passenger uptake and converting too many counters to SBD facilities could negatively affect passengers who rely on assisted check-in services, while underestimating use could result in underused infrastructure and reduced operational benefit. Accurately estimating use rates would therefore be just as important as the technical implementation itself.

Several opportunities for future research remain. This study focused specifically on peak-hour operations between 06h30 and 07h30, as this period represents one of the busiest operational windows at ORTIA. Expanding the simulation to include a broader operational timeframe would provide a more comprehensive understanding of queue behaviour and system performance during a full day of airport operations, including off-peak periods and disrupted schedules. Finally, future research should investigate the long-term financial implications of SBD implementation, including infrastructure investment costs, staffing impacts, and return on investment, to complement the operational findings presented in this study.

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