Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

ENHANCING OPERATIONAL EFFICIENCY IN MUMBAI'S AIRPORT DEPARTURE TERMINAL: A HYBRID SIMULATION MODELING APPROACH

Armin Kashefi[1], Faris Alwzinani[1], Noaman Malek[2],

[1]Department of Computer Science, Brunel University of London, Uxbridge, UK
[2]Bestway Wholesale LTD, London, UK

ABSTRACT

Airports function as complex systems comprising interrelated entities, resources, and processes. Inefficiencies within these systems, particularly long waiting times, contribute to passenger dissatisfaction. This study examines operational improvements at Mumbai International Airport, one of India's busiest hubs, focusing on identifying bottlenecks and reducing congestion for departing passengers. Discrete event simulation served as the core methodological framework. Through hybrid simulation, AS-IS models were developed to analyze operational processes and evaluate bottlenecks. BPMN was used for conceptual modeling, followed by Simul8 for dynamic modeling. TO-BE system configurations for check-in, security screening and boarding were then remodeled. Simulation experiments were conducted to determine the optimal setup that minimizes queuing time while maximizing passenger throughput. The findings highlight an ideal system configuration that significantly reduces waiting times and overall passenger processing time, resulting in improved operational efficiency. These insights provide data-driven recommendations for optimizing airport processes, ultimately enhancing passenger experience and improving airport performance.

1 INTRODUCTION

As air travel continues to grow, airports, being a complex system, face the challenge of scaling up their operations to meet the rising number of passengers without compromising service quality. This involves managing waiting times in queues, reducing overcrowding, and minimizing delays. In certain cases, delays in terminal operations can lead to interruptions in related activities, such as baggage handling, air traffic coordination, and overall air travel. Service optimization is therefore inevitable to create a delicate balance between efficiency and comfort, where passengers experience a smooth and timely journey through the airport, from check-in to boarding. System optimization may involve implementing effective system configurations and integrations, streamlining processes, investing in new technologies, and developing employee skills, among other measures. Airports that successfully maintain this balance will not only meet the increasing demand for passengers but also enhance their reputation and competitiveness in the global aviation industry.

Chhatrapati Shivaji Maharaj International Airport (CSMIA), also known as Mumbai International Airport (MIA), situated in Mumbai, is one of the busiest airports in India, handling a diverse range of domestic and international flights. MIA's yearly passenger throughput has increased significantly over the years, reaching millions. In 2024, the airport handled 54.8 million passengers, representing a 6.3% increase from 2023, when it served approximately 51.58 million passengers (Indian Express 2025; Moodie Davitt Report 2025; Travel Daily Media 2025). However, this surge has led to significant congestion, long waiting times, process inefficiencies, and suboptimal resource utilization. In February 2024, the Ministry of Civil Aviation intervened, directing MIA to reduce daily flight operations by approximately 40 flights to ease congestion and improve punctuality. This decision was prompted by the airport's consistently poor on-time performance and excessive slot distribution without adequate time margins. Additionally, in December 2024, MIA handled 5.05 million passengers, marking its busiest month with a 3.4% increase compared to

December 2023 (Indian Express 2025; Travel Daily Media 2025). These developments underscore the urgent need for MIA to enhance its infrastructure and operational strategies to effectively and efficiently manage the growing passenger demand.

The aim of this paper is to develop a hybrid simulation model for assessing bottlenecks for crowd management at MIA, with a focus on enhancing operational efficiency for departing passengers. This includes reducing passenger waiting times and inconvenience, minimizing the average time a passenger spends in the departure terminal, and increasing passenger throughput.

This paper is structured as follows: Section 2 offers a detailed exploration of the problem. Section 3 outlines the research methodology. The results of the AS-IS model are presented in Section 4, followed by the development of the TO-BE model in Section 5. Section 6 discusses the findings, and Section 7 concludes the paper.

2 LITERATURE REVIEW

The Indian aviation sector significantly contributes to India's economy, supporting approximately 7.5 million jobs and generating roughly $30 billion annually towards the nation's GDP (IATA 2024a). The industry's economic influence predominantly arises from its promotion of tourism and increased air travel accessibility, facilitated largely by more affordable airfares (IATA 2024a). According to forecasts by the International Air Transport Association, India is expected to surpass the United Kingdom by 2024, becoming the third-largest air passenger market globally, further highlighted by predictions that India's aircraft fleet will exceed 2,000 aircraft by 2034 (IATA 2024b).

Recent data highlights the robust recovery of India's aviation sector in the aftermath of the COVID-19 pandemic, with domestic air passenger traffic reaching a record high of approximately 152 million passengers in the year 2023, which reflects a remarkable growth of 23% compared to the 123 million passengers recorded in 2022 (AAI 2024). Additionally, data from the Airports Data from the Airports Authority of India (AAI) indicates that domestic and international passenger traffic collectively reached approximately 340 million between April and December 2023, reflecting a significant resurgence in air travel following the pandemic (AAI 2024).

MIA serves as a major aviation hub in India, facilitating approximately 52.8 million passenger movements during the fiscal year 2023–2024. Its passenger throughput is second only to that of Indira Gandhi International Airport in Delhi, which handled almost 65 million passengers in the corresponding period (AAI 2024). Mumbai's status as India's financial and entertainment capital underscores its strategic significance as a pivotal aviation hub, considerably facilitating both business and tourism travel. The noticeable increase in passenger volumes necessitates a comprehensive reassessment of terminal operations at MIA. Meticulous assessment and enhancement of key operational aspects, including passenger flow management, boarding efficiency, and security protocols, are necessary to accommodate rising passenger volumes. For instance, optimizing passenger flow can mitigate congestion, streamlining boarding procedures can diminish delays, and enhancing security measures is imperative to guarantee passenger safety without compromising efficiency.

Research into airport operational efficiency has frequently employed simulation techniques, notably Discrete Event Simulation (DES), Agent-Based Simulation (ABS) and System Dynamics (SD). DES has proven effective in modeling discrete operational processes within airports, such as passenger check-in, security screenings, and baggage handling (Munasingha and Adikariwattage 2020; Guizzi et al. 2009; Groot 2018; Orhan and Orhan 2020; Wu and Mengersen 2013; Dorton and Liu 2016; Malandri et al. 2018). ABS, on the other hand, offers insights into complex interactions and behavioral dynamics within airport terminals, flight planning and scheduling (Ma et al. 2023), passengers' shopping behavior (Chen et al. 2022), implications of policy changes on passenger services (Verma et al. 2020), airport capacity assessments (Peng et al. 2014), and security risk management (Janssen et al. 2019). Finally, SD offers a flexible decision support system, enabling effective high-level decision-making for substantial changes to the airport terminal system's structure and operation (Manataki and Zografos 2010).

Despite the extensive application of various simulation techniques, including DES within airport contexts, existing research has largely focused on dynamic modeling and the experimentation phase. Relatively limited attention has been devoted to the critical stages that precede and follow model development. As a result, there exists a significant research gap concerning the broader simulation lifecycle, particularly in relation to hybrid simulation modeling. This study seeks to address this gap by adopting a tailored methodological framework that integrates key simulation stages into a unified, holistic approach. Specifically, it employs a comprehensive mapping process that bridges static (conceptual) modeling and dynamic (simulation) modeling, encompassing both AS-IS (current state) and TO-BE (future state) business processes (Robinson 2004; Taylor et al. 2014). The proposed methodology is adaptable to diverse operational environments and business scenarios. Moreover, this paper contributes methodologically to a context that remains under-explored. Accordingly, this research offers a preliminary investigation into the applicability and effectiveness of hybrid modeling within this domain, contributing to the literature by addressing this critical gap in the understanding and operationalization of the complete simulation lifecycle.

3 METHODOLOGY

As noted, this paper aims to enhance the operational efficiency of MIA's international departure terminal by employing a hybrid modeling approach that integrates static (Business Process Model and Notation - BPMN) and dynamic (DES via Simul8) modeling techniques. Robinson's four-phase simulation study (Figure 1) guided our overarching methodological approach. The process begins with developing an understanding of the problem situation. Following this, the model to be built is described in the conceptual modeling phase. A computer simulation model is then constructed. Once created, experiments are conducted with the simulation model to gain a deeper understanding of the real world and/or to find solutions to real-world problems. This involves a process of "what-if" analysis, which entails making changes to the model's inputs, running the model, examining the results, learning from those results, making adjustments to the inputs, and repeating this cycle. Last, the solution or understanding phase is derived from the experimental results. Implementation can be perceived in different ways. It can refer to applying the findings from a simulation study in the real world, or it can signify learning where the study has led to an enhanced understanding that will influence future decision-making.

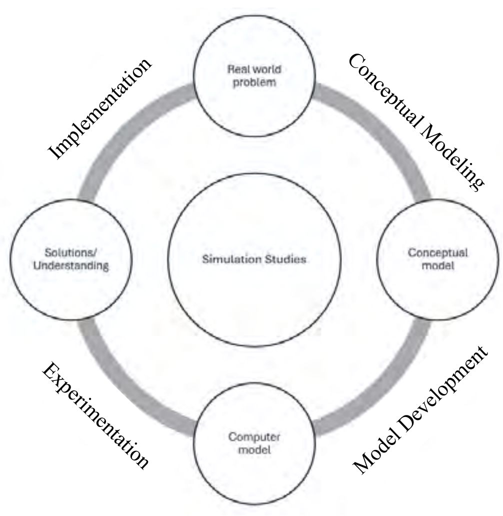

Figure 1: Stages of simulation studies (adapted from Robinson, 2004)

A more fine-grained, tailored approach was then adapted to suit the context of this study (Figure 2). Figure 2 illustrates this approach by first identifying and defining the operational problem (including objectives, constraints, and performance indicators). It then creates a conceptual BPMN model of the current (AS-IS) process to establish a high-level view. Next, a corresponding dynamic simulation is built to capture timing, queues, and probabilistic elements, followed by an assessment of performance to pinpoint inefficiencies and bottlenecks. Informed by these findings, process improvements are proposed and integrated into a revised (TO‑BE) conceptual model, which is then realized through an updated simulation that is validated to ensure logical consistency and data accuracy. 'What-if' scenarios are subsequently run to test different demand or resource configurations before key performance indicators are analyzed and final recommendations are drawn. Using the collected data, an AS-IS (i.e., current state) model was developed to identify operational challenges within the terminal, from check-in to boarding. This model was then analyzed to inform the development of a TO-BE (i.e., optimized future state) model, proposing solutions to mitigate bottlenecks and enhance overall efficiency. The TO-BE model focuses on improving key process metrics for better crowd management, including passenger throughput, waiting times, and total time within the system. The illustrations below present the adopted process flow, which guided the development of models and simulations for MIA's departure terminal.

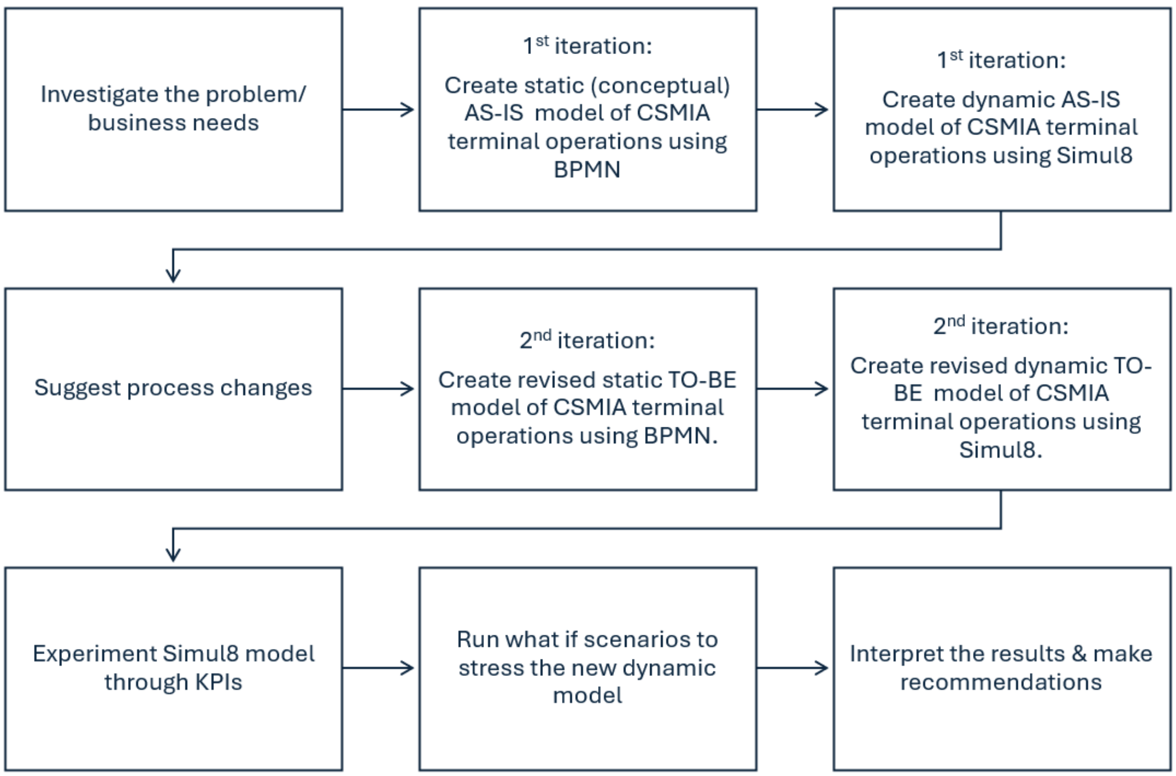

Figure 2: Tailored approach (adapted from Taylor et al., 2014)

Regarding data collection, we employed a mixed-methods approach, integrating both qualitative and quantitative research methodologies to strengthen our investigation and enhance the robustness of our findings. One of the authors, a citizen of India, traveled to the city of Mumbai to gather the necessary data. The involvement of a local citizen facilitated greater cultural sensitivity and improved access to participants, thereby enhancing the authenticity and contextual relevance of the data collected. All authors participated in data triangulation, analysis, and visualization. Data collection took place over a two-month period, from December 2023 to January 2024.

The initial phase of our research was qualitative, aimed at gaining in-depth insight into the operational mechanisms of the departure terminal. We employed techniques such as semi-structured interviews and document analysis (for historical data) to develop a comprehensive understanding of terminal processes, which were subsequently represented using BPMN diagrams. Creating these diagrams was a crucial step, as it enabled us to conceptualize complex workflows in a structured and coherent manner, thereby facilitating further analysis.

To gather qualitative data, we conducted semi-structured interviews with five staff members, including one senior officer and four experienced officers from different sections of the departure terminal, namely check-in, security screening, immigration, and boarding. Each interview lasted approximately 30 minutes. The data collected provided essential input for constructing the BPMN diagrams. Interview questions focused on staff roles and responsibilities, procedural bottlenecks, interdepartmental coordination, and everyday operational challenges. This enabled us to identify both standard practices and context-specific variations in the terminal's workflow.

Building on the contextual insights gained during the qualitative phase, we then transitioned to the quantitative phase. Key numerical inputs were required to configure the simulation model across various components. These input parameters were collected through interviews, structured surveys, and document reviews. During the interviews, in addition to qualitative discussions aimed at developing the conceptual model, quantitative questions were also posed to support the development and calibration of the simulation model. These included estimations of the daily number of departing passengers, average working hours for various resource types in the four terminal sections, total processing time from entry to boarding, and average queuing times per section.

In addition to the interviews, we designed and administered structured surveys to gather numerical data relevant to the identified processes and model inputs. A broader group of officers from each section was invited to complete the survey, thereby improving the accuracy of the simulation model's parameters and estimations. Document reviews constituted the third technique employed. Access to these operational documents was granted by the senior officer. Quantitative data were instrumental in both developing dynamic simulation models and measuring key performance indicators (KPIs). This triangulated, multi-method approach enhanced the validity of our findings by allowing us to cross-verify information obtained from different sources and to minimize biases associated with any single method.

To ensure the rigor and credibility of our analysis, we applied several validation techniques. First, we used data triangulation to cross-check information derived from staff interviews, surveys, and historical operational documents (Denzin 2017). This enabled us to compare qualitative insights with corresponding quantitative metrics, reducing bias and enhancing the overall reliability of the study. Second, all data underwent thorough cleaning to identify and address discrepancies or missing values before analysis, thereby ensuring internal consistency. Third, we conducted respondent validation by sharing initial interpretations with key stakeholders, including the officers who were interviewed. This process ensured that our findings accurately reflected operational realities. Collectively, these strategies reinforced the validity of both qualitative and quantitative evidence, ensuring that our simulation models were grounded in reliable and credible data (Yin 2018).

4 AS-IS MODEL DEVELOPMENT

Considering the tailored approach as a guiding framework (Figure 2), after recognizing the need to enhance operational efficiency at MIA, the first iteration of the model development process began with constructing a conceptual model that represented the existing operational procedures (i.e., static AS-IS). Drawing on qualitative data collected through stakeholder engagement, a detailed BPMN diagram was developed to depict the current processes at the MIA departure terminal (Figure 3).

The mapped process begins when passengers enter the terminal and initiate the verification procedure by presenting their passports and boarding passes. Depending on their ticket class, passengers are directed to distinct queues; those traveling in first or business class follow a separate path from those in premium and economy class. Upon verification by a police officer at the terminal gate, passengers proceed to their designated check-in counters, where they receive their boarding passes. Subsequently, they advance to the luggage weighing area and then to the security inspection. Security screening is conducted via two lanes: a standard lane for premium economy and economy-class passengers, and a fast-track lane for first- and business-class passengers. Once through security, passengers proceed to their respective boarding gates, with boarding prioritized according to travel class; first and business class passengers board first, followed by those in premium and economy class.

Following the creation of the AS-IS model and its thorough verification of syntax and structure, the interviewees conducted a validation exercise to ensure that the model accurately captured the real-world processes as understood by the officers involved. Once validated, the model was evaluated for inefficiencies and bottlenecks. In doing so, the identified issues were reviewed again by the same personnel to confirm their accuracy and identify any additional inefficiencies that may have been overlooked. The confirmed bottlenecks are visually represented in Figure 3, with red annotations encircling each process activity where inefficiencies were observed.

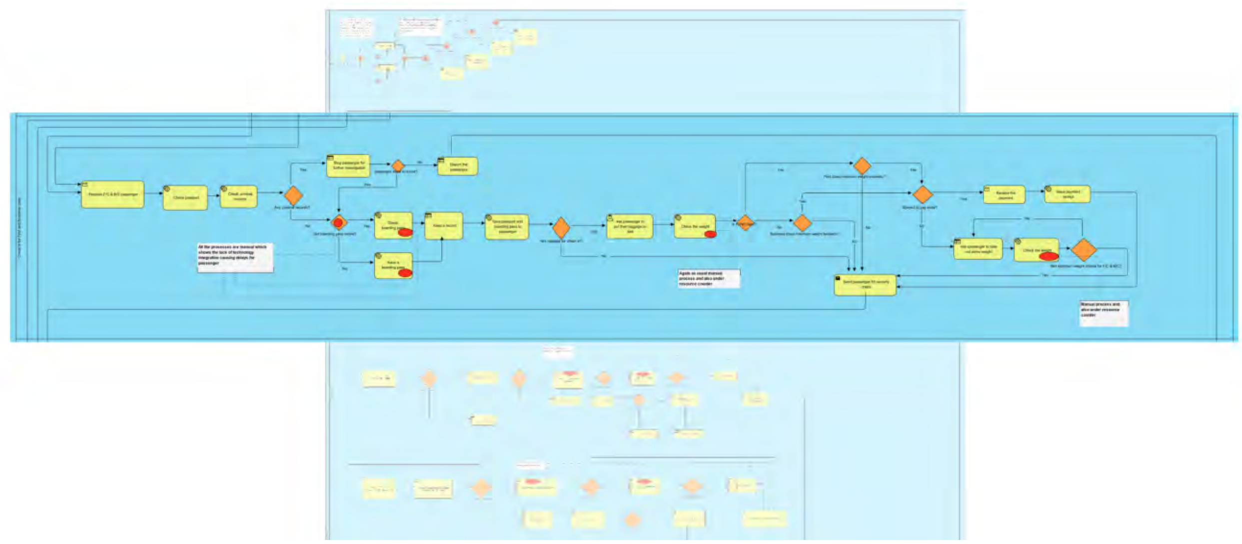

Figure 3: Static AS-IS BPMN model

The inefficiencies ranged from long queues of passengers awaiting multiple checks by a single police officer in the first lane, to the manual handling of check-in procedures in the second and third lanes- designated for different flight classes (i.e., First and Business Class, and Premium Economy and Economy Class)- as well as the manual onboarding of passengers in the final lane, among other issues.

Still within the first iteration, after constructing the static AS-IS model of the departure terminal using BPMN, the next step involved developing a corresponding dynamic AS-IS model (Figure 4). This required translating the BPMN elements, such as activities, events, and decision gateways, into simulation constructs capable of capturing the operational logic, resource dependencies, and time-based behavior inherent in the real-world system. A comprehensive verification process was conducted to ensure the structural and logical accuracy of this transformation, confirming that all elements of the BPMN model were correctly and completely represented in the simulation environment.

Following verification, the dynamic model was validated to assess how well it mirrored the actual performance of the terminal. This was achieved by incorporating both qualitative and quantitative data obtained from stakeholders, including service time measurements and queue statistics. The alignment between the model's behavior and the observed system performance confirmed its representational accuracy. This validated model provided a robust and reliable foundation for exploring future scenarios and testing proposed improvements in subsequent iterations.

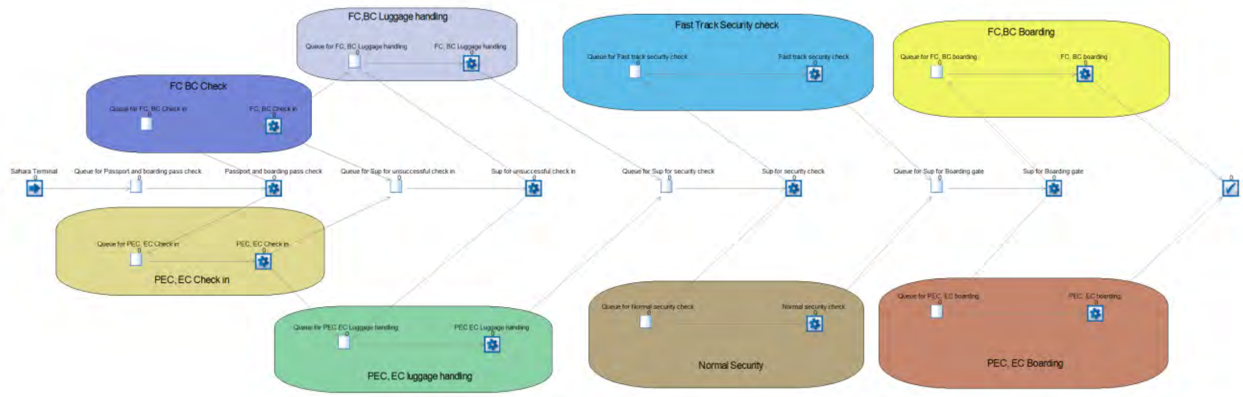

Figure 4: Dynamic AS-IS simulation model in Simul8

Table 1 presents the Key Performance Indicator (KPI) results derived from the AS-IS model. In this study, FC denotes First Class, BC refers to Business Class, PEC to Premium Economy Class, and EC to Economy Class. These KPIs were calculated using the trial calculator feature in Simul8, which provided a 95% confidence interval, indicating the range within which the true average values of the KPIs are likely to fall. A narrower interval between the upper and lower bounds reflects greater precision and confidence in the simulation's predictions. In this study, the confidence intervals ranged from as wide as 1 minute to as narrow as 0.02 minutes, highlighting the high overall accuracy of the simulation results. Additionally, a total of 42 resources were incorporated into the model, aligning with the actual number of staff and officers across the four main operational areas: check-in, luggage handling, security screening, and boarding.

Table 1: AS-IS KPIs

# KPI No.	KPI's Names	Measure	Average Result
1	Queue for FC, BC Check-in	Average time (Mins)	18.34
2	Queue for PEC, EC Check-in	Average time (Mins)	33.71
3	Queue for FC, BC luggage handling	Average time (Mins)	10.21
4	Queue for PEC, EC luggage handling	Average time (Mins)	26.21
5	Queue for Fast Track Security check	Average time (Mins)	9.35
6	Queue for Normal Security check	Average time (Mins)	31.51
7	Queue for FC, BC boarding	Average time (Mins)	13.91
8	Queue for PEC, EC boarding	Average time (Mins)	21.44
9	Number of items completed	Number Completed	75743.48
10	Overall time in the system	Average time (Mins)	158.23

Following a comprehensive analysis of the AS-IS static and dynamic models, TO-BE models were developed to incorporate proposed process improvements aimed at enhancing operational efficiency, increasing throughput, and elevating the overall passenger experience at the MIA departure terminal. This constituted the fourth step in the framework, acting as a bridge between the current operational state and the envisioned future scenario. Proposed enhancements included the introduction of e-Gate check-in, self-service kiosks, technological upgrades to expedite the security screening process, and self-boarding systems.

Data from interviews revealed that airport management had recognized self-service check-in as a viable enhancement and was in the early stages of testing. Other initiatives were included in plans for future development, prioritized as improving security screening first, then self-boarding, followed by e-Gate rollout. However, interviewees showed a keen interest in learning how these initiatives could affect passenger experience, wait times, and total throughput.

5 TO-BE MODEL DEVELOPMENT

Step five of our tailored approach involved creating a static TO-BE model using insights from previous improvement opportunities and AS-IS model bottlenecks. The future operational state across various sectors is depicted in Figure 5 and the e-Gate lane is shown in Figure 6.

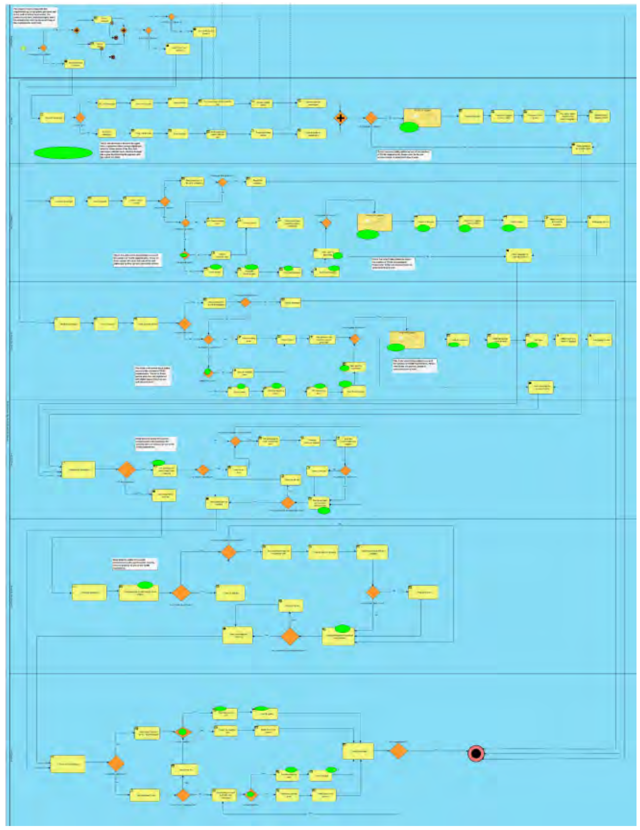

Figure 5: Static TO-BE model

The TO-BE model incorporated several key adjustments, including the addition of a new e-Gate lane, the integration of self-service kiosks into the check-in process, the elimination of redundant security checks enabled by technological enhancements and improvements in task sequencing. As in Step 3 of the first iteration, the sixth step in the second iteration involved converting the revised BPMN model into a simulation model. This updated model incorporates both the already considered self-service kiosks and the proposed future developments while maintaining the same number of resources. The aim was to assess whether significant improvements could be achieved through technological innovations by utilizing existing resources more efficiently across various operational areas.

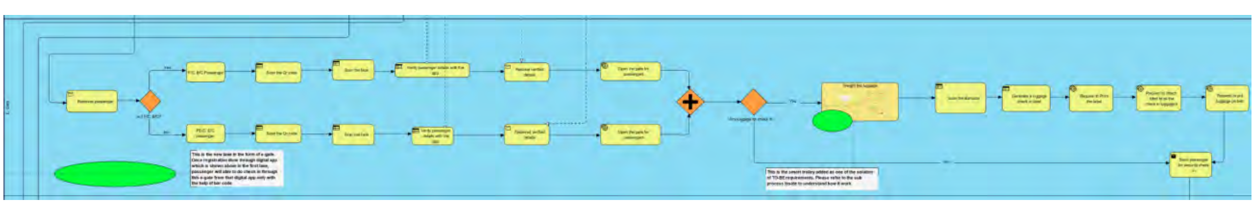

Figure 6: e-Gate lane in static TO-BE model

As model complexity increased with the rising number of passengers, efficient routing and resource utilization enabled us to maintain the total number of resources at 42, despite an 18% increase in passenger throughput. With the introduction of a self-boarding area, which was absent in the AS-IS model, certain KPIs could not be directly compared to previous benchmarks. The average queue waiting times recorded were approximately 55 seconds for First Class and Business Class self-boarding, 1 minute and 15 seconds for Premium Economy Class self-boarding, and 1 minute and 55 seconds for Economy Class self-boarding. Figure 7 illustrates the dynamic TO-BE model.

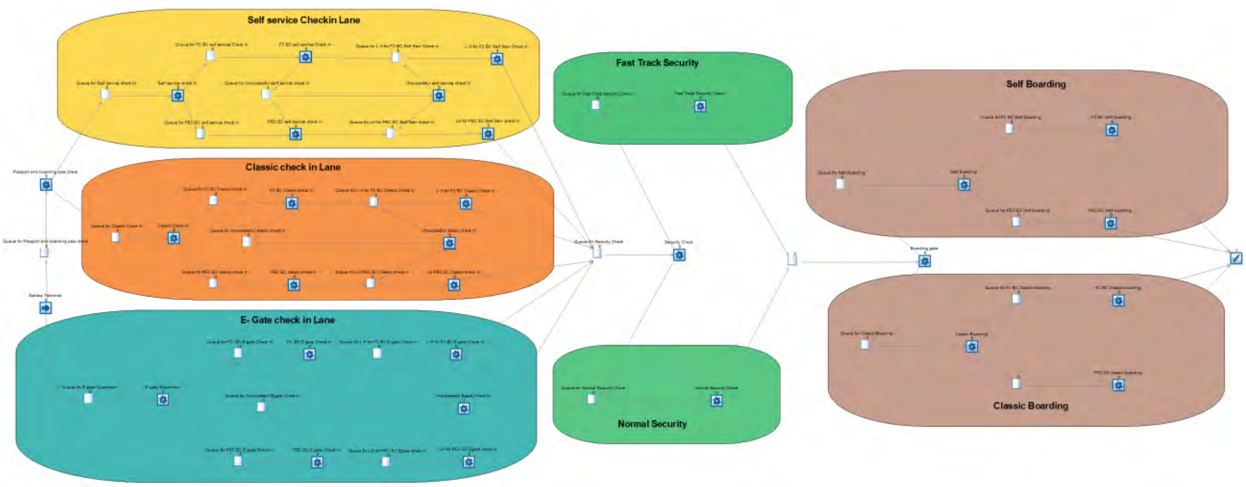

Figure 7: Dynamic TO-BE model

6 DISCUSSION

This study, as mentioned previously, addresses the critical challenge of effectively managing increasing passenger demand at Mumbai International Airport (MIA) by applying a hybrid simulation modelling approach. By integrating static process mapping techniques (i.e., BPMN) with dynamic simulation methodologies, the research provides comprehensive insights into the operational bottlenecks that affect crowd management and passenger flow within airport terminals. This hybrid approach strengthens traditional simulation processes by meticulously outlining each stage of the simulation modelling lifecycle, enabling systematic identification and detailed analysis of existing inefficiencies alongside potential improvements.

After developing the revised dynamic TO-BE model in the second iteration, subsequent steps included experimenting with various configurations to evaluate their impact on KPIs and conducting multiple what-if analyses. Table 2 presents a comparative analysis of KPIs between the current (AS-IS) and proposed future (TO-BE) states of airport operations. The TO-BE model integrates technological advancements such as e-gates, self-service kiosks, enhanced security screening and self-boarding services. Significant reductions in processing times are observed across all assessed areas, particularly in passenger queues related to luggage handling, check-in processes, security checks and boarding procedures. The most notable improvements include an 80% reduction in queue times for first-class and business-class boarding, a 78.92% decrease in passenger and economy-class luggage-handling queues, and a 77.23% improvement in fast-track security checks. Collectively, these enhancements contribute to a 58% reduction in the average time passengers spend within the system, reflecting greater operational efficiency and substantially enhancing the overall passenger experience in the proposed TO-BE scenario.

Table 2: Comparison of AS-IS and TO-BE KPIs

	KPI's name	Measure	AS-IS value	TO-BE value	Change	%Change
1	Queue for FC, BC Check-in	Average time (Mins)	18.34	6.18	-12.16	66.23%
2	Queue for PEC, EC Check-in	Average time (Mins)	33.71	13.38	-20.33	60.29%
3	Queue for FC, BC luggage handling	Average time (Mins)	10.21	2.15	-8.06	78.92%
4	Queue for PEC, EC luggage handling	Average time (Mins)	26.21	8.84	-17.37	66.38%
5	Queue for Fast Track Security check	Average time (Mins)	9.35	2.13	-7.22	77.23%
6	Queue for Normal Security check	Average time (Mins)	31.51	8.29	-23.22	73.7%
7	Queue for FC, BC boarding	Average time (Mins)	13.91	2.74	-11.17	80%
8	Queue for PEC, EC boarding	Average time (Mins)	21.44	5.45	-15.99	74.6%
9	Number of items completed	Average time (Mins)	75743.48	89337.45	-13593.97	18%
10	Overall time in the system	Average time (Mins)	158.23	65	-93	58%

The comparative analysis illustrated in Figure 8 further highlights these improvements, visually demonstrating the significant reduction in queue times and increased throughput achievable through technology integration. Comprehensive training for airport personnel is crucial to ensure the smooth integration and maximum utilization of these newly introduced technologies. Employees must be adequately prepared to identify and resolve technical issues promptly and to assist passengers effectively. Furthermore, it is essential to proactively educate passengers on the use of self-service kiosks, e-gate check-ins, and other technological enhancements to fully realize their benefits. Interactive guides, clear signage, and user-friendly interfaces can facilitate faster and more intuitive passenger movement throughout the airport, reducing confusion and enhancing passenger satisfaction and overall experience.

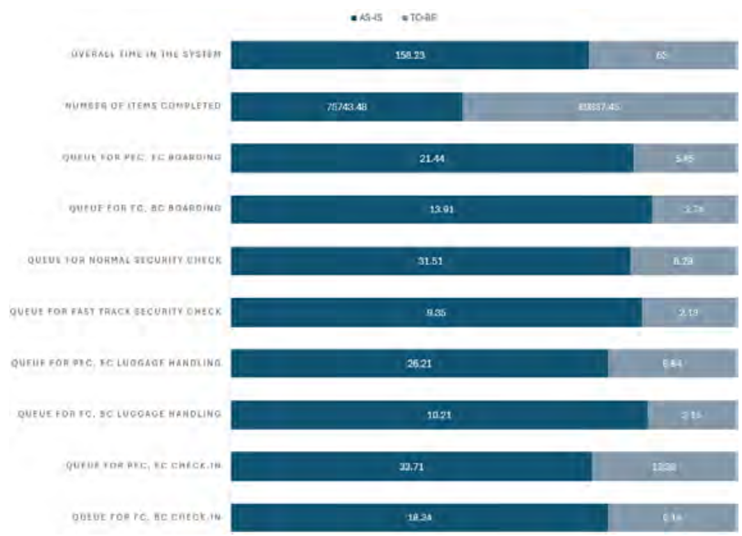

Figure 8: Impact of technological enhancements on passenger waiting times and throughput

The improvements shown in Table 2 highlight the broader movement in the aviation industry towards digitalization and automation of processes. Using a hybrid simulation approach, this study demonstrates how thoughtfully redesigning passenger touchpoints can enhance efficiency, improve resource utilization, and streamline operations without incurring significant infrastructure costs. These results highlight the importance of employing integrated modeling strategies to inform strategic decisions and facilitate gradual improvements, ultimately yielding significant performance gains.

7 CONCLUSION

This paper set out to examine whether a hybrid static–dynamic simulation framework can effectively alleviate capacity pressure at a major Indian hub airport. The study (i) mapped and modeled current processes with detailed accuracy, (ii) measured the performance improvements from technology-enabled redesign, (iii) identified data and computational constraints that limit generalization of the results, and (iv) highlighted specific directions for future research. Together, these elements establish the research as a unique contribution to airport operations scholarship while also indicating how future work can expand its scope and practical influence.

This study significantly advances a relatively underexplored area by showing how hybrid simulation modeling can effectively address complex airport operations. The integrated static-dynamic framework provides a detailed view of process structures and dynamic interactions, supporting specific, data-driven interventions to reduce waiting times, enhance passenger experiences, and increase throughput. Overall, the findings highlight the strategic and operational benefits of hybrid simulation modeling, demonstrating its value as a decision-support tool for airport planners and operators seeking sustainable growth and efficiency.

One of the key limitations encountered during this study was the challenge of acquiring data from MIA. While relevant data are available via their website, they are not publicly accessible. Also, to address stakeholders' concerns, we provided comprehensive assurances by distributing a Participant Information Sheet, securing informed consent through consent forms, and presenting ethical approval documentation granted by the university. Furthermore, analysis of the findings highlighted that the dataset used was both extensive and complex, simulating the behaviors of approximately 95,000 passengers. However, due to constraints in computational capacity, the system available for simulation modeling was not sufficiently powerful, which led to prolonged durations for experimentation and the execution of what-if scenarios. Additionally, to accurately capture the intricacies of airport operations, both static and dynamic modeling methodologies necessitated certain assumptions and simplifications. These, in turn, may have introduced discrepancies between the model's projections and actual outcomes, as they could not fully reflect the complexities of real-world conditions.

As depicted by the statistics presented in Section 2, air travel in India is experiencing a steady increase, thereby creating significant opportunities for integrating machine learning (ML) and artificial intelligence (AI) into check-in procedures and passenger services, such as the deployment of smart trolleys. By analyzing passenger flow data, AI-driven systems are capable of accurately forecasting peak periods, dynamically allocating resources, and enhancing operational efficiency, which in turn improves the passenger experience. Given that this model proposes solutions, including e-gates and self-service kiosks, predictive maintenance systems can be implemented to anticipate potential equipment failures through continuous data analysis. This proactive strategy ensures uninterrupted terminal operations by addressing issues before they emerge. Future research may also investigate strategies aimed at minimizing the environmental impact of terminal operations, given the aviation industry's growing emphasis on sustainability. Such an approach could encompass initiatives aimed at reducing carbon emissions, establishing comprehensive waste management programs, and adopting energy-efficient technologies throughout terminal facilities.

REFERENCES

Airports Authority of India. 2024. "Airports Authority of India Annual Report 2023–24". Airports Authority of India. http://www.aai.aero/sites/default/files/AAI%20AR_2024_ENG_05.12.2024.pdf, accessed 16th March.

Chen, Y., C. L. Wu, and N. K. Ma. 2022. "A Heuristic-Based Airport Shopping Behavior Model with Agent-Based Simulation". In *2022 Winter Simulation Conference (WSC)*, 1–12. https://ieeexplore.ieee.org/abstract/document/10015502

Denzin, N. K. 2017. The Research Act: A Theoretical Introduction to Sociological Methods. London: Routledge.

Dorton, S. and D. Liu. 2016. "Effects of Baggage Volume and Alarm Rate on Airport Security Screening Checkpoint Efficiency Using Queueing Networks and Discrete Event Simulation". Human Factors and Ergonomics in Manufacturing & Service Industries 26.

Groot, M. 2018. "Optimize Landside Airport Operations Using a Discrete Event Simulation". Delft University of Technology. https://repository.tudelft.nl/record/uuid:b4f724e5-791d-42ec-83c8-68df0a418e35

Guizzi, G., T. Murino, and E. Romano. 2009. "A Discrete Event Simulation to Model Passenger Flow in the Airport Terminal". *11th WSEAS International Conference on Mathematical Methods and Computational Techniques in Electrical Engineering (MMACTEE'09)*, September 1–3, 2009, Vouliagmeni, Athens, Greece, 427–434.

Indian Express. 2025. "Mumbai International Airport Saw 54.8 Million Passengers in 2024, 6.3 % More than 2023". https://indianexpress.com/article/cities/mumbai/mumbai-international-airport-passengers-9782970/, accessed 17th April.

International Air Transport Association. 2024a. "India Benefits from Further Liberalisation". https://www.iata.org/en/iata-repository/publications/economic-reports/india-benefits-from-further-liberalization, accessed 16th March.

International Air Transport Association. 2024b. "20-Year Air Passenger Forecast". https://www.iata.org/en/publications/store/20-year-passenger-forecast, accessed 16th March.

Janssen, S., A. Sharpanskykh, and R. Curran. 2019. "AbSRiM: An Agent‐Based Security Risk Management Approach for Airport Operations". Risk Analysis 39:1582‐1596.

Ma, X., Z. He, P. Yang, X. Liao, and W. Liu. 2023. "Agent-Based Modelling and Simulation for Life-Cycle Airport Flight Planning and Scheduling". *Journal of Simulation* 18(1):15–28.

Malandri, C., M. Briccoli, L. Mantecchini, and F. Paganelli. 2018. "A Discrete Event Simulation Model for Inbound Baggage Handling". Transportation Research Procedia 35:295–304.

Manataki, I. E., and K. G. Zografos. 2010. "Assessing Airport Terminal Performance Using a System Dynamics Model". *Journal of Air Transport Management* 16(2):86–93.

Moodie Davitt Report. 2025. "Chhatrapati Shivaji Maharaj International Reports Steady Growth with 54.8 Million Passengers in 2024". https://moodiedavittreport.com/chhatrapati-shivaji-maharaj-international-reports-steady-growth-with-54-8-million-passengers-in-2024/, accessed 17th April.

Munasingha, K. and V. Adikariwattage. 2020. "Discrete Event Simulation Method to Model Passenger Processing at an International Airport". In 2020 Moratuwa Engineering Research Conference (MERCon), 401–406.

Orhan, I., and G. Orhan. 2020. "Modelling and Managing Airport Passenger Flow: A Case of Hasan Polatkan Airport in Turkey". *International Journal of Aviation Science and Technology* 1(2):71–79.

Peng, Y., G. Wei, J. Sun, and S. Bin. 2014. "Evaluation of Airport Capacity Through Agent Based Simulation". *International Journal of Grid and Distributed Computing* 7:165–174.

Robinson, S. 2004. Simulation: The Practice of Model Development and Use. Chichester, UK: Wiley.

Taylor, S. J., P. Abbott, T. Young, and R. Grocott-Mason. 2014. "Student Modeling & Simulation Projects in Healthcare: Experiences with Hillingdon Hospital". In *2014 Winter Simulation Conference (WSC)*, 3650–3661. https://ieeexplore.ieee.org/abstract/document/7020194

Travel Daily Media. 2025. "Mumbai International Airport Witnesses 54.8 Million Passengers in CY2024". https://www.traveldailymedia.com/mumbai-international-airport-witnesses-54-8-million-passengers-in-cy2024/, accessed 17th April.

Verma, A., D. Tahlyan, and S. Bhusari. 2020. "Agent Based Simulation Model for Improving Passenger Service Time at Bangalore Airport". Case Studies on Transport Policy 8:85–93.

Wu, C. and K. Mengersen. 2013. "A Review of Models and Model Usage Scenarios for an Airport Complex System". Transportation Research Part A: Policy and Practice 47:124–140.

Yin, R. K. 2018. Case Study Research and Applications: Design and Methods. 6th ed. Thousand Oaks, California: SAGE.

AUTHOR BIOGRAPHIES

ARMIN KASHEFI is a Lecturer in the Department of Computer Science at Brunel University of London. He holds an MSc and a PhD in Information Systems Management. His research interests span modeling and simulation and extend to the fields of digital innovation and transformation. He leads the business process modeling and simulation module, and his current research investigates emerging themes in simulation-based research within Information Systems and the adoption of digital technologies across various sectors. His email address is armin.kashefi@brunel.ac.uk and his website is https://www.brunel.ac.uk/people/armin-kashefi.

FARIS ALWZINANI is a Lecturer (Assistant Professor) in the Computer Science Department at Brunel University of London, where he also earned his MSc and PhD in Information Systems. He leads the Digital Innovation and Strategy module and has extensive experience teaching a variety of undergraduate and postgraduate courses. His research focuses on business process modelling, digital transformation and the application of digital technologies in areas such as healthcare and smart cities. His email address is Faris.Alwzinani@brunel.ac.uk and his website is https://www.brunel.ac.uk/people/faris-alwzinani.

NOAMAN MALEK is an IT Operations Analyst at Bestway Group, with a background in Business Computing. He graduated from Brunel University London in 2024 with a BSc (Hons) in Business Computing. His academic interests include business process modelling, simulation, and digital transformation in operations. He is currently involved in various business process improvement initiatives aimed at enhancing the performance of the service sector. His email address is Noaman.Malek@Bestway.co.uk