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A BI-OBJECTIVE SLOT ALLOCATION MODEL UNDER AIRPORT CAPACITY AND RESOURCE UTILIZATION

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Degree of Master of Science in Engineering

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Thesis/Dissertation submitted in partial fulfilment of the requirements for the degree
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DECLARATION

Candidate

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ABSTRACT

The aviation sector faces increasing pressure to balance rising demand for flights with limited airport infrastructure. Airport performance remains hindered by inefficient slot allocation and underused resources. A lack of detailed analysis between demand and declared capacity has sparked widespread discussions among policymakers regarding capacity expansion. However, recent research shows that most airports do not fully utilize their declared capacity for operations. Instead, they often choose to enhance capacity through infrastructure development. Requests from airlines for additional slots are sometimes rejected, potentially causing billions of dollars in annual losses due to poor management of existing slot allocations. While many previous studies offered optimization solutions, a practical approach involves better utilization of available resources to allocate new slots and utilize unused capacity rather than expanding capacity. This research introduces a bi-objective mathematical model aimed at achieving two goals: improving resource utilization (including runway, apron, and terminal gate capacity) through new slot scheduling and considering real-time constraints to optimize delay propagation while maintaining separation minima. Bandaranaike International Airport (BIA) serves as a case study to validate the model. The MATLAB-developed linear programming model increased average airside resource utilization to 62.7% on peak days, up from 44.9%. During critical hours, the new schedule effectively reduced traffic intensity, delays, and congestion. A comparison of cumulative delays, based on propagated delays in specific operations between the optimized and non-optimized schedules, highlights the significant benefits of implementing optimized scheduling systems. The proposed slot allocation model can serve as a decision-support tool for the aviation industry, facilitating slot allocation for new entrants and reducing delays across existing flight schedules through more efficient resource utilization.

Keywords: air transport, slot allocation, minimizing delays, declared capacity, capacity expansions

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1. INTRODUCTION

1.1 Background

Air transportation, as a crucial mode of connectivity, necessitates meticulous management and coordination within its network (Dixit et al., 2023). It also plays a significant role in regional integration, economic development, and disaster responses in areas with limited alternatives (Bonser, 2019; International Air Transport Association (IATA), 2023). And therefore, in areas where land transportation options are limited, air transport emerges as a vital "lifeline service." Several studies have also highlighted that aviation has become central to globalization, the mobility of people, and the transportation of goods across regions (De Oliveira et al., 2022; Sheng et al., 2019).

Over 6 billion passengers embarked on domestic and international flights worldwide in 2012, a number projected to surge by at least 50% by 2025 (Farhadi et al., 2014). IATA's forecast anticipates a 3.5% compound annual growth rate in passenger numbers, with the Asia-Pacific region poised to experience the highest surge (Hu et al., 2022). Thereby, a traffic forecast conducted by the Airports Council International (ACI) has presented that the passenger traffic is expected to reach over 19 billion by 2040, which will have a heavy impact on major airports ("Annual World Airport Traffic Report," 2023).

However, the escalating demand for air travel has strained the declared capacities of many airports globally, particularly those with a single runway (Feng et al., 2023; Kistan et al., 2017). This capacity shortfall has notably impacted airports like BIA, Sri Lanka, prompting discussions among policymakers about the need for infrastructure expansion. Challenges such as funding constraints, approval processes, and environmental considerations hamper the expansion of airport capacities (Mehndiratta & Kiefer, 2003). Consequently, stakeholders are increasingly exploring demand management solutions as alternatives to merely expanding infrastructure to alleviate escalating congestion issues.

The declared capacity of an airport hinges on various resources, divided into landside and airside categories (S. Galagedera et al., 2021). Landside resources encompass aircraft parking locations, passenger terminals, and access roads, while airside resources include taxiways, runways, and airspace. Among these resources, passenger terminal capacities and runway capacities significantly influence an airport's declared capacity. While much research has focused on optimizing runway capacities to enhance aircraft operations, sustainable approaches like the implementation of Rapid Exit Taxiways offer promising solutions (S. Galagedera et al., 2021). These taxiways minimize unnecessary taxiing and runway occupancies, thereby saving time, costs, labour, and fuel. However, effective implementation requires appropriate coordination and assessment of the airport's requirements. EUROCONTROL has implemented collaborative decision-making and dynamic runway scheduling as resource-efficiency strategies to manage congestion as short-term measures (*Airport Collaborative Decision-Making (A-CDM) Impact Assessment | EUROCONTROL*, 2016). Inefficient use of allocated slots can lead to heightened workloads and low-capacity thresholds, especially in airports with a single runway. This challenge will exacerbate with the surge in passengers, freight transport, and airlines, exacerbating the disparity between air travel demand and available resources (Feng et al., 2023). In the interim, coordinating slots and airport facilities offers a pragmatic solution to manage congested infrastructure until expansion procedures are required (International Air Transport Association (IATA), 2023).

Slot allocation is a pivotal aspect of airport operations, representing the utilization of declared capacity. In essence, a slot denotes a specific time window during which an authorized aircraft utilizes airport infrastructures to provide services. This concept, known as slot control, plays a vital role in managing demand at airports by constraining the number of aircraft within set timeframes (Mehndiratta & Kiefer, 2003). Slot allocation becomes critical during peak hours and when traffic volume exceeds the airport handling capacity, requiring accurate balancing of supply and demand (Castelli et al., 2012). Thus, slot allocation mechanisms serve as key tools in both administrative schedule coordination processes and airspace routing management, as guided by IATA protocols.

Within congested airports, slots represent a scarce resource that must be distributed among competing users (Zografos & Jiang, 2019). Factors such as runway capacity, terminal infrastructure, and other operational constraints limit the availability of slots, underscoring the critical importance of slot allocation optimization in the aviation sector. Slot allocation strategically balances air transport demand and airport capacity while mitigating Air Traffic Flow Management (ATFM) delays (Delahaye & Wang, 2022; Makhtoumi, 2023). Despite efforts to minimize delays through ATFM policies, real-time delays often exceed expectations by a considerable margin (Ivanov et al., 2017). Slot allocations, overseen by slot coordinators, consider policy rules and availability to serve the needs of airlines and the public. The current system aims to manage traffic demand peaks by adjusting arrival and departure requests to periods of lower demand (Pellegrini et al., 2017).

IATA's World Slot Guidelines (WSG) provide a standardized framework for slot allocation, which is conducted biennially during the winter and summer seasons. WSG is recognized as the industry standard for managing scheduled operations at Level 2 airports and allocating slots at Level 3 airports (International Air Transport Association (IATA), 2023). Level 2 airports, also known as facilitated airports, may face congestion at specific times, necessitating mutually agreed-upon schedule modifications between facilitators and airlines. In contrast, Level 3 airports lack sufficient infrastructure for demand-capacity management, often due to government-imposed restrictions (International Air Transport Association (IATA), 2023). The classification of 154 airports as scheduled facilitated (Level 2) and 198 as schedule coordinated (Level 3) underscores the critical need for optimizing slot allocation coordination (Feng et al., 2023; Ribeiro et al., 2018).

However, the current slot allocation system faces criticisms regarding transparency, economically efficient utilization of capacity, and inconsistencies between allocated slots and flight plans (Zografos & Jiang, 2019). Inadequate transparency of slot information impacts stakeholders' ability to assess the fairness of slot allocations and their implications on various stakeholders, including airlines and passengers (Zografos & Jiang, 2019). Several researchers have also highlighted the inefficiency of the “grandfather rights” system in adapting to dynamic market changes and conditions (Hou et al., 2025; Madas & Zografos, 2008). Addressing these challenges requires effective stakeholder engagement and a deeper understanding of the consequences of slot restrictions on the aviation industry. As a solution, several slot management techniques such as auction-based systems, priority scoring models, and market-based slot trading frameworks have been tested and introduced (Iatrou & Alamdari, 2005; Ivanov et al., 2017). These methods haven't, however, completely addressed important problems like adaptability, equitable distribution, and slot transparency. While (Ivanov et al., 2017) emphasized the current models' limited responsiveness to real-time demand and capacity variations, (Iatrou & Alamdari, 2005) pointed out the danger of market dominance in auction systems.

Allocating slots without considering operational restrictions, which can vary based on different runway operation modes, may result in underutilization of runway capacity and challenges in arranging flight plans within acceptable time-of-delay limits (S. Wang et al., 2023). Past studies have highlighted instances where erroneous decisions were made to expand airport facilities despite comprehensive capacity analyses. Inefficient slot allocation leads to over 10% of allocated slots remaining unused, even at congested airports where demand exceeds capacity (Picard et al., 2019). For instance, Colombo (BIA) airport currently operates at only 50% of its runway capacity, with forecasted demand not expected to reach maximum capacity for another 7-8 years. Hence, optimizing available resources rather than constructing new infrastructure holds crucial significance for the global economy and air travel. Effective slot utilization requires a transparent and impartial assessment of declared capacity before optimization, which is a critical initial step in the slot allocation process. This assessment is essential for moving forward and attaining a reliable solution.

Inadequate management can lead to airline slot requests being rescheduled to earlier or later times than originally intended due to physical constraints imposed by airport capacity. In some cases, airlines may have their slot requests waived off, and dominant airlines may be unable to schedule flights at their preferred times (Katsigiannis & Zografos, 2023). Such scenarios result in economic losses for airports. A 2019 study by the Federal Aviation Administration (FAA) revealed that airplane delays cost airlines $24 billion annually in lost revenue and direct operating costs (Jorge et al., 2021; Nakahara et al., 2011; Ribeiro et al., 2025). When slots need to be displaced or replaced, coordinators and airlines collaborate to make decisions, considering factors such as previous scheduling experiences, airline preferences, and the rules outlined in the World Slot Guidelines (WSG). The availability of slots can constrain airlines' operations at specific airports, potentially limiting their ability to expand into international and intercontinental markets. This constraint highlights the importance of efficient slot allocation practices in supporting airlines' growth and improving the overall efficiency of the aviation industry.

For an airport to achieve optimization, it must undergo full coordination, ensuring that the number of flights scheduled per hour aligns with the airport's declared capacity (Corolli et al., 2014). In response to increased demand, airlines worldwide have expanded their networks and deployed larger aircraft. However, relying solely on changes implemented by airlines does not offer long-term solutions. While many studies have proposed optimization solutions for existing flight schedules, efficient utilization of available resources to allocate new time slots and utilize unused capacity is equally critical for the air transportation sector, surpassing the necessity for capacity expansions. The approach in this research emphasizes the importance of proactive strategies aimed at maximizing the efficiency of existing resources to address growing demand in the aviation industry.

1.2 Problem statement

Many airports, especially in developing countries, remain underused despite increasing air traffic, mainly because of ineffective slot allocation methods. Requests for slots are often denied or rescheduled by airlines, leading to delays, reduced operational efficiency, and significant financial losses. Instead of adopting new processes or adjusting in real-time to limitations such as separation minima and delay propagation, current slot allocation systems focus mostly on optimizing fixed schedules. These restrictions make it harder to use the declared airport capacity effectively, causing worse traffic during busy times. Although expensive and time-consuming, infrastructure expansions are frequently proposed. A more dynamic, optimization-based approach to slot allocation is urgently needed to better utilize existing capacity, improve scheduling flexibility, and reduce delays without constructing new infrastructure.

1.3 Objectives

The objective of this research is to propose a model that uses the available infrastructure and resources related to airside components at the airport to optimize slot allocation procedures while reducing hourly traffic intensity during peak hours within a specific range. The model will also be capable of optimizing real-time delay propagation by considering operational delays. The proposed model will focus solely on airports with single runways. Bandaranaike International Airport (BIA) will serve as the case study to validate the proposed model.

The following is the summary of the objectives of this research:

- To develop a mathematical model to enhance the slot allocation efficiency and minimize traffic intensity at peak hours
- To optimize delay propagation due to operational delays
- To propose a decision-support tool for the aviation industry to allocate slots for new entrants while using the available resources efficiently.
- Analysis of the current schedule data from BIA to determine the traffic mix, aircraft mix, and traffic intensity, and validation of the model using real data from BIA.

1.4 Thesis outline

The sections are divided as follows: Chapter 1 – Introduction, where the background on airports and airport slot allocations is discussed along with information on the case study. Chapter 2 – Literature Review, where past studies related to airport slot allocation are reviewed to identify methodologies and research gaps. Chapter 3 – Methodology, where the objectives based on the literature and the research method are discussed step by step. Chapter 4 – Results and Discussion, where the methodology discussed earlier is applied, and the results obtained are showcased and discussed. Chapter 5 – Conclusions and Recommendations, where conclusions are drawn based on the results and comments are made on recommendations and future work.

2. LITERATURE REVIEW

2.1 Slot allocation

The slot allocation process, overseen by IATA, unfolds biannually, six months prior to operations, constituting the Initial slot allocation stage. During this phase, coordinators evaluate slot requests for acceptance or rejection, employing tools such as the PDC score and T-system SAMs; however, these tools lack optimization capabilities. In the absence of a growth in available airport slots over time, Air Traffic Flow Management (ATFM) adopts three primary stages for slot allocation: strategic slot scheduling, pre-tactical phase, and operational phase (D. Wang & Zhao, 2020). These structured phases aim to balance efficiency and fairness while overcoming systemic congestion issues (European ATM Master Plan - Benefits and Investment Needs, 2024).

Existing literature predominantly focuses on methodologies for slot allocation during the strategic and pre-tactical stages, aiming to mitigate delays and associated costs (Katsigiannis & Zografos, 2021). Studies, such as that by (Katsigiannis & Zografos, 2021), have assessed the current slot allocation system, highlighting its significance within ATFM and its three main phases: Primary allocation, Slot returns, and Slot exchanges and transfers. This model acts as the foundation for global coordination systems such as the Worldwide Airport Slot Guidelines (WSG), which accommodates equitable and transparent slot distribution (International Air Transport Association (IATA), 2023; Zografos & Jiang, 2019). Evaluations recognize the role of historical precedence, also known as grandfather rights, in primary allocation, with studies by (Castelli et al., 2012) proposing a monetary compensation approach to address cost interdependencies among airlines. However, cost increments pose challenges to optimization efforts. Other than that, several critiques on “grandfather right” shows the hindering possibility on entry to dynamic market which will reduce the efficiency in slot allocations (Hou et al., 2025; Madas & Zografos, 2008).

The FIFO (First in First Out) strategy, as discussed by (Grunewald et al., 2017), has been utilized in slot allocation but raises concerns regarding unequal treatment of aircraft and potential queue build-ups. Administrative rules, coordinated by administrators, are employed to enhance traffic management efficiency, although (Cavusoglu & Macário, 2021) argue that current slot allocation systems often fail to reflect the scarcity of airport slots fairly, leading to economic inefficiencies. Some studies have also pointed out that strict FIFO and administrative rules could result in delays during peak hours (Campanelli et al., 2016; Pellegrini et al., 2017). Which could neglect the business models and passenger connectivity needs.

In addition to the existing system, researchers have proposed various optimization methodologies for slot allocation, including market-driven and administrative approaches. Market-driven mechanisms focus on economic factors, while administrative approaches involve non-monetary adjustments such as airport expansions and congestion management frameworks. Slot trading, slot auctions, and congestion pricing are some of the economically efficient market-based systems proposed for decision making and adaptive slot allocations (Iatrou & Alamdari, 2005; Ivanov et al., 2017). These approaches combined balance economic efficiency with fairness and transparency (Ribeiro et al., 2018; Zografos & Jiang, 2019). These methodologies, extensively discussed in the review below, aim to enhance demand management within the aviation sector by addressing slot allocation challenges comprehensively.

A key research gap in this area is the inability to handle slot distribution at crowded airports, despite extensive studies on allocation systems. Additionally, insufficient examination of slot request data to determine Level 3 airport demand relative to declared capacities has led to gaps in evaluating real demand patterns. These limitations constrain the effectiveness of policy and resource planning, especially in fast-growing aviation hubs.

2.2 Slot-scheduling problem

Slot scheduling, a critical component in the management of airport usage for airlines, involves the meticulous preparation and organization of time frames (Madas & Zografos, 2008). This process begins with the establishment of a scheduling period, which is subsequently divided into fixed-length intervals, known as slots. The allocation of these slots is paramount for optimizing airport resources efficiently. Slot scheduling therefore represents a complex multi-objective operational challenge which addresses fairness, efficiency and connectivity under the presence of priority rules and guidelines (Katsigiannis et al., 2021; Zografos & Jiang, 2019).

According to (Androutsopoulos et al., 2020), one of the primary challenges faced by coordinators is devising a master schedule that not only meets the practical needs but also ensures profitability for all competing airlines. While previous studies have delved into multi-objective programming models to analyse trade-offs within the slot allocation process, there remains a notable gap in understanding the overarching trade-offs across different levels of the slot hierarchy (Castelli et al., 2012; Delahaye & Puechmorel, 2000; Madas & Zografos, 2006; S. Wang et al., 2023).

In response to this gap, (Katsigiannis et al., 2021) introduced the Tri-Objective Slot Allocation Model (TOSAM), which considers demand-based fairness, maximum schedule displacement, and total schedule displacement. Their research findings indicate that systematically considering these trade-offs leads to enhanced slot scheduling performance. Similarly, (Zografos & Jiang, 2019) proposed a fairness metric for slot scheduling, aiming to balance fairness and efficiency objectives simultaneously.

However, a persistent challenge in slot scheduling lies in the consideration of historical slot usage rights and their implications for scheduling efficiency, as highlighted by (Zografos & Jiang, 2019). Moreover, decisions made by air traffic coordinators concerning slot displacement can have significant ramifications for airlines. Even minor displacements of less than 30 minutes can profoundly impact flight scheduling, as evidenced by logistic regression analysis (Pouget et al., 2023).

In such scenarios, relying solely on administrative rules may prove inadequate in addressing the issues stemming from improper slot coordination and management. Therefore, a comprehensive understanding of these dynamics is essential for optimizing slot scheduling processes and ensuring smooth airline operations. Some recently developed models have incorporated network-level considerations such as connectivity and inter-airport fairness, which enables more cohesive schedule optimization through hub-and-spoke systems (Keskin & Zografos, 2023). A major research limitation lies in the oversimplified constraints and objectives used in existing models, which often fail to capture real-world scheduling complexity. Furthermore, the impact of slot scheduling on individual airlines is inadequately addressed, with many models' prioritizing aggregate efficiency while overlooking airline-specific implications.

2.3 Market-driven slot allocation

Capacity at congested airports is typically quantified in terms of slots, as noted by (Madas & Zografos, 2008). Currently, severe congestion poses a significant challenge that requires immediate attention, and to address this issue, there are calls for the reform of existing policies, with suggestions focusing on the introduction of mechanisms for slot allocation based on market principles and the reduction or elimination of historical precedence (Castelli et al., 2012; Madas & Zografos, 2008). The proposal for market-driven slot allocation mechanisms encompasses various contexts, including pool slot auctions enhanced by secondary trading, a percentage of slot auctions bolstered by secondary trading, and secondary trading itself. (Madas & Zografos, 2008) emphasize the overarching objective of establishing a methodological framework for evaluating and selecting the most suitable slot allocation strategy based on a range of policy criteria and priorities tailored to each type of airport.

Despite the potential benefits, (Cardadeiro & Gata, 2023) highlight that slot allocation procedures worldwide continue to rely predominantly on administrative rules, with market mechanisms still underutilized. They introduce a novel market-based slot allocation procedure, suggesting that it could lead to more efficient slot allocation procedures, thereby enhancing the economic impact of aviation and contributing to the reduction of CO2 emissions. The PAUSE mechanism, discussed in their research, is touted as one of the most promising market mechanisms globally. This mechanism comprises two stages: simultaneous, multiple-round auctions where bidders submit bids for specific properties, followed by composite bidding to facilitate the realization of player synergies. However, the implementation of this mechanism raises concerns about the potential downgrade in transparency of slot details among airlines.

The reluctance to adopt market mechanisms is attributed to various factors, including coordination authorities' hesitance to address identified hazards, expenses associated with surplus slots, the influence of origin-destination pairing and air transport fares, and distortions of competition. In response to these risks, the Federal Aviation Administration (FAA) in the United States introduced the Collaborative Decision Making (CDM) initiative, aiming to decentralize decision-making processes with potential economic impacts on airlines through collaboration with the airlines whenever feasible (Vossen & Ball, 2006). Although CDM is administrative rather than market-based, studies show it can mimic some market efficiencies through real-time slot reallocation and dynamic pricing signals (*Airport Collaborative Decision-Making (A-CDM) Impact Assessment | EUROCONTROL*, 2016; Corrigan et al., 2014).

(Rassenti et al., 1982) advocate for an airport slot allocation process that allocates specific slots to airline flights willing to pay more, citing financial efficiency as a primary consideration. They propose a sealed-bid combinatorial auction that enables airlines to offer a range of backup bids for combinations of specific airport landing or takeoff slots that are compatible with their flight schedules. However, concerns arise regarding the observed slot allocation efficiencies, as they may not adequately manage excessive demand and mitigate the criticality of airport infrastructure limitations. (Avenali et al., 2015) contribute by evaluating the marginal value of each slot to end-users, considering both quantity and quality aspects of air transport service provision. Their findings suggest that incentive prices, rather than prices determined solely by market interactions, could better align social and private decisions regarding the use of slots. However, the noted gap is that they caution against potential drawbacks, such as valuations not reflecting the social value of carriers and the risk of dominant carriers monopolizing prominent slots, thereby limiting opportunities for new entrants (Y. Wang et al., 2023). There is also a lack of research examining the fairness and equity impacts of market-based mechanisms, particularly for new entrants. Additionally, environmental factors, such as emissions trade-offs, are rarely integrated into market-driven allocation models, despite their increasing importance in aviation policy.

2.4 Congestion management and delay optimization

Once again, (Madas & Zografos, 2010) have posed the question of whether demand management or capacity enhancement is the solution to the current aviation dilemma. This question arises from the growing disparity between airport capacity and traffic. Addressing this issue entails considering the demand-to-capacity ratio yet determining which aspect of this ratio takes precedence remains pivotal. Excessive demand over capacity results in runway queues, aircraft delays, suboptimal slot utilization, misallocations, and constraints on peak-time slot availability, all stemming from airport capacity limitations. These issues not only reduce operational efficiency but also increase environmental and economic costs, as observed across studies on delay impacts at major hubs (European ATM Master Plan - Benefits and Investment Needs, 2024; Sanz & Rubio, 2023).

Various demand management strategies—such as congestion control, emission and noise regulation, and administrative rules—have been studied to address airport inefficiencies. Researchers aim to develop a policy compatibility framework that guides the selection of the most suitable approach for each airport type, based on priorities established by stakeholders such as policymakers, airlines, operators, and researchers. The proposed methodological framework offers guidance for selecting the most compatible strategy based on these criteria (Ball et al., 2010; Gillen & Morrison, 2005; Logan & Tunkel, 2024; A. Zhang & Zhang, 2010). To manage demand in accordance with slot requests and ensure alignment with initial slot requests, highly efficient, multi-objective models have been introduced. For instance, (Ribeiro et al., 2018) proposed the Priority-Based Slot Allocation Model (PSAM), designed to comply with declared capacity constraints and assess such requirements. While the current system predominantly relies on administrative rules and practices over time, some research has leveraged existing regulations to manage demand. (Pellegrini et al., 2017) introduced an administrative-based demand management procedure utilizing a linear integer programming model. This approach has yielded exceptional computational performance, although it has raised concerns regarding confidentiality between airlines. In cases where flight slots remain unused and historical slot pools cannot be altered, there arises a need for a method to allocate slots for the vacant capacity. (S. Wang et al., 2023) introduced a model considering flight waveforms and important resource nodes as limitations to address vacant capacity, primarily focusing on optimizing slot allocation for strategic and tactical phases. These optimization techniques have led to significant delay reductions and additional slot allocations, enhancing system efficiency (Grunewald et al., 2017; Ivanov et al., 2017).

According to (Yang et al., 2023), airspace management faces significant challenges, particularly in safety and efficiency. The aim of optimization techniques is to identify the optimal solution, minimizing parameters to achieve the global minimum on a worldwide scale. Optimization approaches can be based on scheduled allocation and plan-based strategies, aimed at minimizing delay costs by creating an optimal allocation strategy for the current-time horizon. (Yang et al., 2023) demonstrated that delay optimization models can reduce flight delay costs by at least 5.85% compared to the current First-In-First-Out (FIFO) strategy. However, these optimization techniques may not fully address operations in time-varying airspace. To address delay distribution among subsequent flights, (Ivanov et al., 2017) proposed a two-level mixed-integer optimization model to tackle en-route demand-capacity imbalance and enhance airport slot adherence. However, the cost efficiency of implementation fell short of expectations. (Grunewald et al., 2017) highlighted the current regulatory framework's inability to mitigate needless wait times before customers receive service, attributing it to fluctuations caused by factors such as weather influences, delayed departures, or short-notice changes. Their approach involved setting user-driven priorities regarding airlines' transport performance (slot quality and adherence) to enhance resource utilization efficiency. This methodology was applied to process real data pseudo demand for a runway under prioritization strategies through the evaluation of simulation scenarios.

Air traffic congestion results in extremely high costs for airlines and airline operators (Corolli et al., 2014). Overscheduling, airport hubbing, delayed check-ins, technical malfunctions, and other factors are the primary reasons for delays. (Shambour & Abu-Hashem, 2023) have proposed that, by controlling traveler movements at an airport's terminal through checkpoints for passports, customs, baggage handling, and in arrival and departure lobbies, slot allocation optimization is possible.

Some of the strategies found for flight delay reductions by (Ribeiro et al., 2025) are modified internal airline business procedures, deployed reserve crews for flights, and enhanced air traffic flow management, etc... But the viability and effectiveness of these strategies have not been studied. Delay is mentioned as the most significant performance indicator of transport systems. Two approaches have been suggested for the congestion problem at airports by (Xiao et al., 2013). One is to expand the airports, and the other is to enhance the allocation and/or pricing systems. The problem with airport expansion is that capacity adjustments can only be achieved over time, as it is a lengthy process to build the necessary infrastructure. Price improvements will, if they stay within capacity limitations, aid in maximizing social welfare and achieving efficiency. Price and capacity options have been investigated simultaneously in the majority of the other studies (Brueckner, 2009; Fan & Odoni, 2002; Hou et al., 2025; A. Zhang & Zhang, 2010). The study addresses an uncertain demand modelled by a continuous probability distribution, focusing solely on capacity selection while keeping total airport capacity fixed. The methodology adjusts slot numbers, treating service quality as the decision variable. However, challenges arise from aircraft ground movement congestion, complicating routing and scheduling. To mitigate this, an alternative graph model is proposed, optimizing two objectives: minimizing taxiing delays and reducing pollution emissions (based on total waiting time) (Adacher et al., 2018).

(Feng et al., 2023) have said that there are two ways to address the current problem: managing airport demand and expanding the capacity supply. Past slot allocation models have used either airport network or single-airport approaches. This study adopts a bi-objective single-airport model, aiming to maximize noise reduction while optimizing scheduling efficiency (minimizing slot displacements). However, a key limitation is that the model does not account for tactical interventions, which could affect real-time adjustments and operational flexibility. Since the literature has not addressed the network-wide slot allocation problem very often, (Keskin & Zografos, 2023) have introduced a novel approach where individual airport schedules are considered as input to assess a whole network slot allocation process and have been optimally adjusted by taking interdependencies between flight connecting pairs of airports into account. Other than for single airport models, (D. Wang & Zhao, 2020) We have proposed a simultaneous optimization model that considers uncertain capacity for allocating airport network slots. The model proposed is said to be robust (conducive to sustainable and stable decision-making). These models can help mitigate scheduling conflicts in the worst-case scenario. However, the airline preferences must be sacrificed for reliable decisions that the model must make. Recent work have collaborated in environmental considerations rather than completely relying on multi-objective models (Feng et al., 2023; Ferreira et al., 2024).

Although these studies have introduced several optimization techniques, there should be a limit to the minimum number of delays that can be achieved by using the demand management strategies stated. To study that, (Vaze & Barnhart, 2012) have shown that competitive airline scheduling decisions have led to significant inefficiencies in the use of airport infrastructure, introducing a network delay simulator that calculates delays under different capacity scenarios. One advantage of this approach is that it has shown the differentiation in delays caused by insufficient capacity and inefficient utilization of capacity. The development of an aggregated timetable and fleet assignment problem, which involves forming an integer linear programming model, has also been addressed by the latest research approaches. The industry's adoption of scheduling simulators, such as X-Plane, now integrates these findings into commercial scheduling platforms, indicating a translation from research to practice (Lockwood, 2021).

Incentive-based research has been done to focus on providing a motive for the aircraft operators to effectively increase their operational efficiencies. Estimating the resource availability and allocating priorities as an incentive have been tried out by (Grunewald, 2016). Performance-based priorities are utilized to minimize secondary delays and enhance system fairness, with incentives applied at both strategic and operational levels. While queuing theory serves as the incentive model, relying solely on it is insufficient for effectively optimizing waiting times. (Farhadi et al., 2014) have suggested considering runway configuration, scheduling strategy, and aircraft separation standards as interrelated tri-factors to optimize waiting times. The study identifies two key research gaps in airport slot allocation. First, existing literature focuses on optimizing aircraft performance but overlooks runway performance in the planning stages, thereby failing to incorporate infrastructure efficiency. Second, most research examines departures and arrivals separately, neglecting mixed-mode operations (i.e., simultaneous departures and arrivals), which limits their practical applicability. Addressing these gaps could improve runway utilization and scheduling effectiveness. (Ricardianto et al., 2022) They have stated that the problem with the current system is that aircraft movements exceed the available capacity, leading to long queues. Similar to the previous literature, Queuing theory has been applied using historical runway utilization data to develop simulation models for optimizing airport operations. Inputs include arrival intervals, service times, and take-off delays. Although increasing parking stands and taxiways could enhance runway capacity, such infrastructure expansion is often not economically viable.

According to (Chen et al., 2025), the limited number of runway slots is a critical factor that can significantly impact the global aviation market. Slot management is crucial for optimizing runway capacity and reducing congestion, with slot shortages directly affecting airport profitability. Due to limited infrastructure, meeting rising demand is challenging. A queuing-based model using historical aircraft data and multiple theoretical distributions (e.g., M/M/1, M/G/1, M/R/1) has been proposed to analyse runway performance and support automated demand management systems. Comparative analysis indicates that runway economics studies now incorporate these models to evaluate investment benefits versus operational gains (*Airport Economics Manual*, 2013).

(Pilon et al., 2021) have used the User-Driven Prioritisation Process (UDPP), which gives airlines more flexibility when making plans in tight circumstances. The User-Driven Prioritisation Process (UDPP) considers factors such as route, aircraft type, crew, and passenger flow to enhance flexibility and cost efficiency. It is recommended as a backup when existing systems fail, but it faces criticism for lacking fairness among airlines. As said by (Nakahara et al., 2011), Congestion at the airport surface is one area where system inefficiencies are particularly noticeable, and the idea of "ration by schedule" has been proposed as a method for allocating slots. A surface congestion management procedure aims to keep airport operations within capacity during peak demand, reducing fuel use, emissions, and taxi-out time. Reported benefits include saving 14,800 hours of taxi-out time, 5 million gallons of fuel, and 48,000 metric tons of CO_2 annually. However, it may negatively impact airport traffic flow and taxi-in times. Continued analysis suggests that "ration by schedule" remains one of the best-known surface congestion mitigators, though updated policies need to incorporate equity across airlines (Bengi & Lance, 2010).

2.5 Rapid Exit Taxiways (RETs)

According to an undergraduate study conducted at the University of Moratuwa, Sri Lanka, leveraging rapid exit taxiways is suggested to address the escalating demand for aviation services while upholding safety standards. These taxiways, interlinking runways, and parking stands are recognised as crucial components in expediting aircraft exit procedures, thus facilitating subsequent operations. The conventional exits are located at 90 degrees to the runway, while rapid exit taxiways are constructed at an angle of 17–30 degrees. However, research indicates that external factors, such as pilot behaviour, may hinder the efficiency of rapid exit taxiways (S. Galagedera et al., 2021). Despite potential inefficiencies, these taxiways have been found to decrease runway occupancy times, thereby augmenting operational capacities (S. Galagedera et al., 2021). To optimise their positioning, logistic regression models have been employed, considering excursion-risk and veer-off risk (S. Galagedera et al., 2021). Notably, the proximity of exits to runway thresholds correlates with increased veer-off risk, prompting recommendations for wider taxiways and larger radii to mitigate such risks. Furthermore, (J. Zhang et al., 2022) have developed a mathematical model, utilising genetic ant colony algorithms, to determine the optimal number of rapid exit taxiways, prioritising the minimisation of comprehensive runway occupancy time. These findings underscore the significance of strategic planning and optimisation in the design and management of airport infrastructures, particularly in accommodating burgeoning aviation demands while ensuring safety standards are upheld.

Despite the emergence of many delay optimisation models, there is a noted lack of consideration for uncertainties, such as weather-induced variability, that affect real-time operations. Furthermore, existing research rarely addresses real-time slot misallocations and their cascading impact on airline network connectivity. There is also insufficient focus on unused capacity at airports, and limited investigation into how errors in declared airport capacity assessments can distort optimization results. The rationale for this research is based on the practical needs of the airport on a daily basis. To obtain optimal solutions, the model needs to consider real scenarios with valid assumptions. A fundamental factor to be considered while modelling and managing traffic flow is the actual throughput of the airport network (Kistan et al., 2017). Therefore, considering the research gaps in the literature, the main objective is to utilise available airside resources efficiently to optimise slot allocation by allocating new time slots to utilise the unused capacity while minimising peak hour traffic intensities, rather than implementing capacity expansion decisions. In addition, the model built will also have the capability to optimise real-time delay propagation throughout the schedule, considering separation minima.

2.6 Constraints

Any factor that can limit the performance of a system by also limiting the output can be called a constraint. At airports, over time, even non-constraining resources can become constraining due to disturbances and past events. Management of constraints determines the final throughput of an airport. There are three types of constraints: physical, market and political. This research will be based on the physical constraints where the airport resources act as the critical sector.

A five-step process has been provided by the Theory of Constraints (TOC) to ease the identification and use of constraints in modelling:

1. Identify the system constraint(s)
2. Make the best use of the identified constraint(s)
3. Prioritize the identified constraint(s) over less affecting constraint(s)
4. Improve the constraint(s)
5. Return to Step 1

Airport operational constraints can include various factors which affect its functional efficiencies. These factors have a high probability of change when considering different types of airports. An overview of the primary limitations of airport slot allocation issues taken into consideration in the body of the current literature is given in Table 1.

Table 1: Constraints Used in Literature

Constraint	Description
Capacity (Runway, Terminal, Apron, etc.)	The number of aircraft movements the airport can handle within a period. Also, certain infrastructure has certain capacity limitations.
Peak Hours	The time of day/week/month when the airport is the busiest in operations.
Slot Prioritization	Priorities based on special agreements. Or emergency services.

Historic Rights	Airlines working with the airport for a long period of time can have special preferences compared to others.
Turnaround Times	This period is known as the time the aircraft uses the airport, from arrival until departure.
Accessibility	The number of slots corresponds to the airport's capacity.
Route Requirements	Slots must be available at both the origin airport and the destination airport.
Route Duration	The journey between the origin and the destination should be under a certain time limit.

Out of the above-mentioned constraints, historic rights, route requirements and route durations are given less priority in this research because the major focus is on slot allocation at the airport, considering its resources and aircraft performances. Additionally, several novel real-time constraints have been introduced.

3. METHODOLOGY

3.1 A Bi-objective Resource Allocation Model

This mathematical model is created by simplifying a real-world problem into a structured framework by determining the appropriate variables, parameters, and constraints. Then, using mathematical expressions, the relationships between these variables and parameters are expressed. In order to capture the key features of the system while maintaining the model's analytical feasibility and ability to yield insightful information, rational assumptions and simplifications have also been considered.

3.1.1 Hypothesis

A hypothesis has been formulated to identify the immutable factors affecting airport operations. These statements are realistic and must be considered in modelling.

- Individual airports have been considered in modelling (Single-Airport System).
- Flight slot is not a free point in time. Each slot has a specific start and end time, with a corresponding interval. The interval defines the period during which the aircraft is authorised to operate at the airport.
- Input data for the model, including aircraft operation times, are based on historical scheduling data gathered.
- The capacity of the airport relative to gate capacity, apron capacity and runway capacity is calculated based on theoretical findings.
- The times of the historical data set are not adjusted and will be assumed to be fixed for a flight season.
- The arrival time and departure times provided in the data collected are the wheel blocking times and wheel unblocking times at the parking positions, respectively.

3.1.2 Resource modelling

Resource selection for the modelling is based on the major airport sectors and aircraft operations at an airport. According to (ITCSA, 2023), the major sectors of an airport are shown in Table 2:

Table 2: Major Elements of an Airport

Terminal Building	The airport's "public" area, known as the terminal or terminal building, is where all baggage handling, security checks, and boarding procedures take place. Among the many amenities offered by terminals to assist passengers before or after their flight are cafeterias, restaurants, restrooms, and currency exchange services.
Control tower	The control tower is the area assigned to monitor and assist aircraft during take-off and landing. These responsibilities related to air traffic supervision are carried out by air traffic controllers. The controllers are responsible for informing the pilot about the prevailing conditions at the airport, including air traffic, atmospheric conditions (such as wind and visibility), and the optimal routes to land on a clear runway or take off under ideal circumstances. They use radar to track the flight paths and radio the pilot for updates.
Apron	The apron, which is the paved area adjacent to airport terminals, is equivalent to the aircraft parking area. This is the area where passengers load and unload their bags from the aircraft. The amount of air traffic the airport handles, the distance between aircraft, the size of the aircraft, and the operational capacity required for loading and unloading, all depend on the apron's overall length and width.
Taxiways	The taxiway is comprised of all the roads that connect an airport's various areas, such as the terminal, hangar, and apron, to the runway and to one another. Occasionally, they are made of concrete and paved. The width and configuration of the taxiways must be adequate to allow aircraft turns as they move through the different areas of the airport.

Runways	The runway is one of an airport's most prominent and important features. Its measurements (length and width), placement, and subsequent upkeep must all be exact for both take-off and landing. The runway is a lengthy, typically asphalt or concrete strip that is sufficiently wide to guarantee the highest level of safety during take-off and landing. The size of the largest aircraft expected to land at the airport, the orography of the surrounding area, and the airport's elevation are some of the factors that determine its dimensions.

Terminal buildings act as a medium for passenger movements where the major connection between the ground access system and the aircraft is established. Passenger and cargo preparation for air travel occurs in terminal buildings, where screening, customs, immigration handling, and documentation processes are conducted. Out of the above-mentioned sectors, the existing literature has considered the following key critical resources related to the airside component of the airport for modelling purposes:

- Time resources
- Runway resources
- Apron resources

The terminal building and control tower operations are not under the scope of this research and therefore have not been considered for modelling purposes. The above resource selection is based on the major concerns of aircraft slot allocations, aircraft performances, runway capacities, and apron capacities. Another reason for not selecting terminal building resources is based on the simplicity in optimising either of its capacity or passenger and cargo handling operations. Simple optimisation can be achieved by implementing adjustments in the number of service operators at the airport. Since control tower operations deal with tactical, real-time air traffic control rather than strategic scheduling choices, they were not included. Furthermore, control tower operations are not the main focus of this study because they can be easily optimized using well-known real-time air traffic management systems and decision-support tools.

3.1.3 Representation of airside resources

Figures 1 and 2 below show the aerial view of the BIA, which consists of the Runway, Taxiway, and Aprons, the main physical resources of the airside section in an airport.

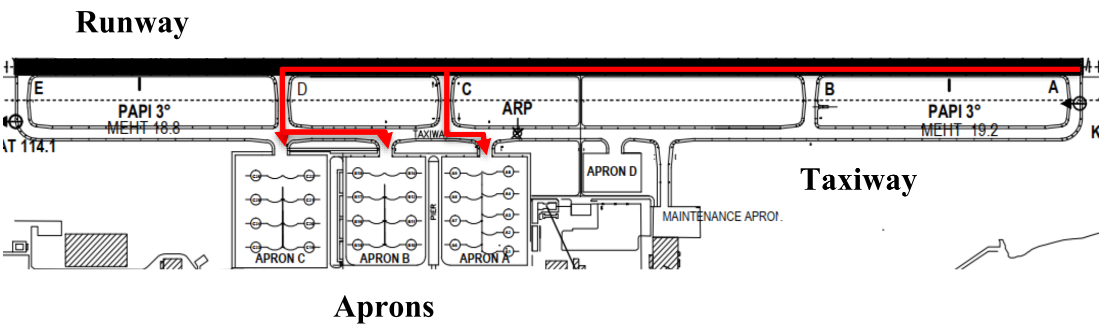

Figure 1: Arrival Routes

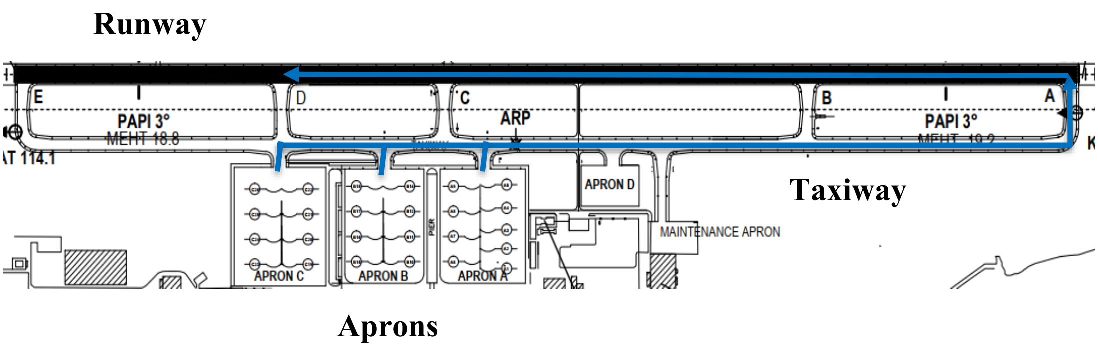

Figure 2: Departure Routes

Considering all the resources mentioned above, tasks can be assigned to each flight operation. The following are the key resource point sequences for arrivals and departures:

For arrivals:

Runway → Taxiway → Apron

For departures:

Apron → Taxiway → Runway

3.1.4 Parameters and variables

Tables 3 and 4 represent the set of parameters and variables, respectively, used for the model considering the key resources mentioned above.

Table 3: Parameters for Modelling

t	Hour $t \in T$, where T denotes the set for number of hours in a day, $T = \{1,2,3,4 \dots \dots \dots 24\}$
a	Arrival aircraft $a \in A \cup \bar{A}$, where A denotes the set for current arrivals and $\bar{A}$ denotes the set for new arrivals
d	Departure aircraft $d \in D \cup \overline{D}$, where D denotes the set for current departures and $\overline{D}$ denotes the set for new departures
r	Runway $r \in R$, where R denotes the set for number of runways
y	Taxiway $y \in Y$, where Y denotes the set for number of taxiways
RC	Hourly runway capacity (aircrafts/hour)
p	Parking slot $p \in P$, where P denotes the set for number of parking slots
AC	Hourly apron capacity (aircrafts/hour)
X	Minimum separation time between consecutive departure operations (mins)
Q	Minimum separation time between consecutive arrival operations (mins)
Z	Minimum separation time between consecutive arrival and departure operations (mins)
k	Terminal gate $k \in K$, where K denotes the set for number of terminal gates
τ	Minimum turnaround time between arrival and departure of the same operation (hours)

Table 4: Variables for Modelling

$TT_{a,r,y,p}$	Aircraft taxiing times of an arrival aircraft a, from runway r, through taxiway y, to parking position p
$TT_{d,p,y,r}$	Aircraft taxiing times of a departure aircraft d, from parking position p, through taxiway y, to runway r
ETC_p^a	Estimated time for current arrival a at parking position p, $a \in A$, $p \in P$
ETC_p^d	Estimated time for current departures d from parking position p, $d \in D, p \in P$
ETC_r^a	Estimated time for current arrivals a at runway r, $a \in A, r \in R$
ETC_r^d	Estimated time for current departures d from runway r, $d \in D$, $r \in R$
ETN_p^a	Estimated time for new arrivals a at parking position p, $a \in \bar{A}$, $p \in P$
ETN_p^d	Estimated time for new departures d from parking position p, $d \in \bar{D}$, $p \in P$
ETN_r^a	Estimated time for new arrivals a at runway r, $a \in \bar{A}, r \in R$
ETN_r^d	Estimated time for new departures d from runway r, $d \in \bar{D}, r \in R$
ATC_p^a	Actual time for current arrivals a at parking position p, $a \in A, p \in P$
ATC_p^d	Actual time for current departures d from parking position p, $d \in D$, $p \in P$
ATN_p^a	Actual time for new arrivals a at parking position p, $a \in \bar{A}, p \in P$
ATN_p^d	Actual time for new departures d from parking position p, $d \in \bar{D}$, $p \in P$
ρC_t	Traffic intensity per hour t for current operations, $t \in T$
ρN_t	Traffic intensity per hour t for new operations, $t \in T$
ρ_t	Overall traffic intensity per hour t, $t \in T$

Airport slots are related to time zones. According to the hypothesis, the flight slot is not a free point in time. Therefore, the first step is to define the time zone parameters relevant to the day of operation (parameter t). And accordingly, a parameter for the arriving and departing aircraft is introduced (parameter a and d).

Airport runways are used to operate take-off and landing operations of aircraft. Airport congestion is directly related to the runway operations, and to minimise that, the number of runways can be increased. In preparation for flight schedules, it is essential to consider the constraints and operational capacities of the runway and taxiway resources (parameters r and y). The runway capacities can vary according to changes in weather and other airspace limitations; however, the capacity will mostly be a fixed number (parameter RC).

Parking positions are used to park an aircraft while it completes its service at the airport terminals, which are connected through the aprons (parameter p). An airport has a set of terminal gates available (parameter k), which act as entrance and exit points to and from the terminal areas where passengers access their flights. These gates are directly connected to each parking position through air bridges. Once the aircraft is parked, jet bridges are used to connect the terminal gate to the aircraft door, providing access for passengers to board and disembark. At locations where, terminal gates are not available, boarding stairs are used to give access for passengers to move in and out of an aircraft. Since number of parking slots does not define the capacity of the apron, the apron capacity should also be considered as a constraint (parameter AC).

For consecutive operations at an airport, there can be several modes of operation. They are departure – departure (parameter X), arrival – arrival (parameter Q) and arrival – departure (parameter Z) modes respectively. For each of these operations, a specified separation minimum has to be imposed to maintain safe distance between consecutive flights. The inability to adhere to the separation minima can lead to fatal crashes due to the involvement of turbulences. The separation minima can be calculated separately which considers the factors such as aircraft speed, aircraft mix and other ICAO guidelines.

Each aircraft gets access from the runway r to the parking position p or vice versa via taxiway routes (the individual exits and the path parallel to the runway are all together considered as the taxiway). A set of parameters are defined for the taxiing times for the purpose of task modelling (parameter $TT_{a,r,y,p}$ and $TT_{d,p,y,r}$). Once an aircraft arrives at the entrance point to an apron, the aircraft moves at a low, steady pace up to the parking stand. Once the terminal area operations are over, the aircraft undergoes a push-back manoeuvre until it reaches the taxiway. At certain airports like BIA, only one aircraft at a time can enter the apron. Figure 3 below shows 2 apron areas at BIA to represent the push-in and push-back distances covered.

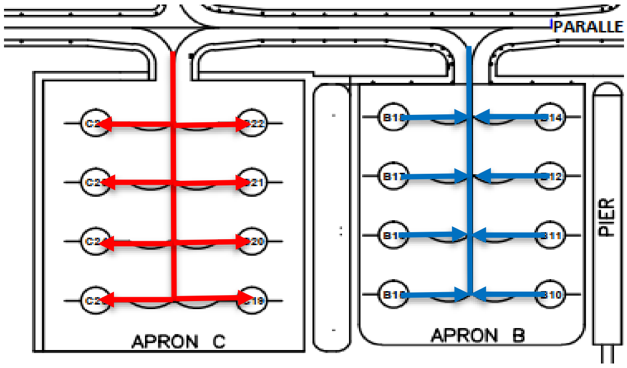

Figure 3: Apron Taxiing Manoeuvres

When considering the taxiing time variables, the push-in and push-back manoeuvre times have been included. Meanwhile, in certain situations where two aircraft depart and arrive through the same route from the runway to the apron, a waiting time may be imposed. For these variables, waiting times have also been included.

According to the time zone, a set of available slots for either arrivals or departures can be defined. As the objective of this modelling, a new set of slots will be created. Therefore, the set defining the new additional slots can also be defined.

Note: All estimated or actual arrival and departure times at the parking position are defined as the actual times when the flight docks and undocks at a parking stand, respectively. And the estimated or actual arrival and departure times at the runway represent the real-time landing and take-off operations (parameters ETC, ETN, ATC and ATN).

3.1.5 Task modelling

To access the available slots and the new slots for the scheduled flights, a set of decision variables as shown in Table 5 has to be set up for each arrival slot and departure slot:

Table 5: Decision Variables

$C_{p,t}^{a}$	$C_p^a = 1$, if a slot is allocated at p for a current arriving aircraft a with estimated arrival time ETC_p^a, during hour t; otherwise, $C_{p,t}^{a} = 0$, $a \in A$, $p \in P$, $t \in T$
$C_{p,t}^{d}$	$C_p^d = 1$, if a slot is allocated at p for a current departing aircraft d with estimated departure time ETC_p^d, during hour t; otherwise, $C_{p,t}^{d} = 0$, $d \in D$, $p \in P$, $t \in T$
$N_{p,t}^{a}$	$N_p^a = 1$. if a slot is allocated at p for a new arriving aircraft a with estimated arrival time ETN_p^a, during hour t; otherwise, $N_{p,t}^{a} = 0$, $a \in \bar{A}$, $p \in P$, $t \in T$
$N_{p,t}^{d}$	$N_p^d = 1$, if a slot is allocated at p for a new departing aircraft d with estimated departure time ETN_p^d, during hour t; otherwise, $N_{p,t}^{d} = 0$, $d \in \bar{D}$, $p \in P$, $t \in T$

3.1.6 Traffic intensity

The traffic intensity of the operations is defined as the ratio of the number of arrivals and the number of departures each hour. Therefore, the following can be derived for the current and new slots:

$$\rho C_t = \frac{\sum_{a \in A} \sum_{p \in P} C_{p,t}^{a}}{\sum_{d \in D} \sum_{p \in P} C_{p,t}^{d}}$$

for given t (hour), $t \in T$

$$\rho N_t = \frac{\sum_{a \in \bar{A}} \sum_{p \in P} N_{p,t}^a}{\sum_{d \in \bar{D}} \sum_{p \in P} N_{p,t}^d}$$

for given t (hour), $t \in T$

3.1.7 Objective functions

By considering the set of tasks and decision variables, the first objective is to increase the utilization of the declared capacity (min (RC, AC) while adding new slots considering a variety of constraints while minimizing the traffic intensities in peak hours of the overall system with both the new allocations and current allocations, which in result will reduce queuing delays in the apron area.

$$\max \sum_{p \in P} \left(\sum_{a \in \bar{A}} N_{p,t}^a + \sum_{d \in \bar{D}} N_{p,t}^d \right)$$

$$\min \rho_t = \frac{\sum_{a \in A} \sum_{p \in P} \left(C_{p,t}^a + N_{p,t}^a \right)}{\sum_{d \in D} \sum_{p \in P} \left(C_{p,t}^d + N_{p,t}^d \right)}$$

for given t (hour), $t \in T$

The second objective is to optimize delay. For optimization, the requirement is to minimize the cumulative delay of all operations per day. This can be derived as follows:

$$\min \sum_{p \in P} \sum_{a \in A \cup \bar{A}} \left(\left| ETC_p^a - ATC_p^a \right| + \left| ETN_p^a - ATN_p^a \right| \right)$$

$$\min \sum_{p \in P} \sum_{d \in D \cup \bar{D}} \left(\left| ETC_p^d - ATC_p^d \right| + \left| ETN_p^d - ATN_p^d \right| \right)$$

For current operations, the above function is based on the operational fact that ETC of operations cannot be changed. This is because the current schedules of airports should be preserved without any changes to ensure fairness and equity for airlines. However, ATC of operations are subject to change according to real-time delays (flight delay, delay due to weather, etc.)

Since the new operations are introduced through modelling ETN and ATN of operations are subjected to change.
According to this objective function, once an operation is delayed, the ATC or ATN of operations will be optimized considering the constraints to minimize the delay difference compared to their respective ETC and ETN.

3.1.8 Constraints

Constraint 1: Runway operational mode constraints

A set of relationships can be built up considering the operation times for each flight's arrivals and departures.

For new slots:
For arrivals: The landing time of a new aircraft (ETN_r^a) added to the taxing in time $\left(TT_{a,r,y,p}\right)$ will be equal to the total of the estimated arrival time $\left(ETN_p^a\right)$.

$$ETN_r^a + TT_{a,r,y,p} = ETN_p^a$$

For departures: The take-off time of a new aircraft (ETN_r^d) will be equal to the total of the taxing in time $\left(TT_{d,p,y,r}\right)$, the estimated departure time $\left(ETN_p^d\right)$.

$$ETN_r^d = ETN_p^d + TT_{d,p,y,r}$$

Since ETN_r^a and $ETN_r^d$are relative to ETN_p^a and ETN_p^drespectively, the following constraints can be proposed according to the separation minima required for each mode of operation.

Mode 1: Departure – Departure (DD) Mode

$$\sum_{r\in R}\sum_{d\in \bar{D}}|ETN_r^d - ETN_r^{d\pm1}| \geq X$$

Other possible combinations for DD separation mode:

$$\sum_{r\in R}\sum_{d\in D}|ETC_r^d - ETC_r^{d\pm1}| \geq X$$

$$\sum_{r\in R}\sum_{d\in D\cup\bar{D}}|ETC_r^d - ETN_r^d| \geq X$$

Mode 2: Arrival – Arrival (AA) Mode

$$\sum_{r\in R}\sum_{a\in \bar{A}}|ETN_r^a - ETN_r^{a\pm1}| \geq Q$$

Other possible combinations for AA separation mode:

$$\sum_{r\in R}\sum_{a\in A}|ETC_r^a - ETC_r^{a\pm1}| \geq Q$$

$$\sum_{r\in R}\sum_{a\in A\cup\bar{A}}|ETC_r^a - ETN_r^a| \geq Q$$

Mode 3: Arrival – Departure (AD) Mode

$$\sum_{r\in R}\sum_{a\in \bar{A}}\sum_{d\in \bar{D}}|ETN_r^a - ETN_r^d| \geq Z$$

Other possible combinations for AD separation mode:

$$\sum_{r\in R}\sum_{a\in A}\sum_{d\in D}|ETC_r^a - ETC_r^d| \geq Z$$

$$\sum_{r\in R}\sum_{a\in A}\sum_{d\in \bar{D}}|ETC_r^a - ETN_r^d| \geq Z$$

$$\sum_{r\in R}\sum_{a\in \bar{A}}\sum_{d\in D}|ETN_r^a - ETC_r^d| \geq Z$$

Constraint 2: Runway and apron operational capacity constraints

The runway and apron operational capacities have usually been assessed for either a 1-hour period or 15-minute period. This model will be constrained based on 1-hour period capacity constraints. For each hour, the model will consider the minimum value out of runway capacity and apron capacity. As mentioned before, the model considers the operational capacities as a constant.

$$\sum_{a\in A\cup \bar{A}}\sum_{d\in D\cup \bar{D}}\sum_{p\in P} C_{p,t}^a + C_{p,t}^d + N_{p,t}^a + N_{p,t}^d \leq \min\,(RC, AC)$$

for given t (hour), $t \in T$

Constraint 3: Outbound and Inbound slot difference

After introducing incremental slots, the overall system might not run smoothly. Therefore, to ensure smooth operational performance and efficient air traffic operations, a slot difference has been introduced for both outbound and inbound flights. Through this constraint, the traffic intensity will be minimized even after an increment in number of slots.

$$\min \sum_{p\in P}\left|\sum_{a\in A\cup \bar{A}}\left(C_{p,t}^a + N_{p,t}^a\right) - \sum_{d\in D\cup \bar{D}}\left(C_{p,t}^d + N_{p,t}^d\right)\right|$$

for given t (hour), $t \in T$

Constraint 4: Turnaround time for each operation

Between the arrival and departure of an individual aircraft, several processes take place. The most common out of all is the passenger boarding process. Other than that, cleaning the aircraft and fuelling are also some of the main services that an aircraft goes through. To allocate sufficient time for these services between the aircraft's arrival and departure, a minimum turnaround time must be established.

$$\sum_{p\in P}\sum_{a\in \bar{A}}\sum_{d\in \bar{D}}\left|ETN_p^{a(i)} - ETN_p^{d(i)}\right| \geq \tau$$

i refers to the operation that arrives and departs after the considered turnaround time.

Constraint 5: Current schedule traffic intensity bounds

The current schedule traffic intensity will be assessed as a constraint in generating the new schedule. The reason is to maintain the airport regulations and its system stability.

$$\rho_t \leq \rho C_t$$

For

$$\rho C_t > 1$$

for given t (hour), $t \in T$

The reason for $\rho C_t > 1$ acting as the range of consideration for the constraint is because the system will be considered as unstable for traffic intensities greater than 1, and therefore, the objective should be to minimize the instability.

And the $\rho C_t < 1$ values can be affected after modelling since the reduced traffic intensities above 1 will be distributed to the surrounding time intervals.

3.1.9 Evaluation 1: Average airside resource utilization rate

The changes in resource utilizations after modelling will be represented as a rate of the minimum capacity usable at the airport. The average is calculated for the total of 24 hours. The following equation shows the basic rate calculation:

$$Avg.\, airside\ resource\ utilization\ rate = \left(\frac{\sum_{a \in A \cup \bar{A}} \sum_{d \in D \cup \bar{D}} \sum_{p \in P} C_{p,t}^{a} + C_{p,t}^{d} + N_{p,t}^{a} + N_{p,t}^{d}}{\min(RC, AC)}\right) \times 100\%$$

for given t (hour), $t \in T$

3.1.10 Evaluation 2: Hourly gate utilization rate

Similar to the evaluation of airside resource utilization rates, it is of critical importance to evaluate how the terminal gate utilizations are affected after modelling. The following equation shows the basic rate calculation:

$$Hourly\ gate\ utilization\ rate = \left(\frac{\sum_{a \in A \cup \bar{A}} \sum_{d \in D \cup \bar{D}} \sum_{p \in P} C_{p,t}^{a} + C_{p,t}^{d} + N_{p,t}^{a} + N_{p,t}^{d}}{k}\right) \times 100\%$$

for given t (hour), $t \in T$

3.1.11 Evaluation 3: One sample t-test

A statistical analysis will be conducted on the model results obtained for delay reduction.

A statistical technique for determining whether a sample's mean deviates significantly from a known or predicted value is the one-sample t-test. When dealing with small sample sizes and an unknown population standard deviation, it is especially helpful. The test was used in this investigation to determine whether the optimisation model's average delay reduction was statistically significant above zero, hence demonstrating the effectiveness of the model.

3.2 Case study: Bandaranaike International Airport (BIA)

Bandaranaike International Airport (BIA) [IATA code: CMB], also known as Katunayake Airport, serves both public and military purposes, acting as the hub for Cinnamon Air and Sri Lankan Airlines, the country's national airline. The Airport and Aviation Services (Sri Lanka) Ltd. acts as the airport authority. The airport features a single runway with a 04/22 orientation. The runway is 3,441 m long and 45 m wide in dimension. The airport comprises 29 total parking bases across five aprons. There are five taxiway exits perpendicular to the runway. As per records in 2019, the total number of aircraft movements, the total number of passengers and the total capacity of the airport were 62,880/year, 9,957,502/year and 274,044 MT (Logistics Cluster, 2022) respectively. According to the Civil Aviation Authority of Sri Lanka, traffic (both aircraft and passenger growth) at BIA is observed to be growing at a rate of 7% per annum.

At BIA, airport expansion to add new resources through construction of new infrastructure has begun under two packages, A and B, which commenced in December 2020. Package A includes the construction of the new passenger terminal, which will increase the passenger handling capacity at BIA up to 15 million passengers per annum. The construction of the new terminal has been granted approval based on the annual reports provided by AASL, which state that passenger growth is predicted to be 5-6% each year. Under Package B, the construction of a new apron area and taxiways connecting the apron began as of November 2021. The new apron area (approximate area of 210,000 m^2) provides an addition of 23 parking stands, and the taxiways are constructed on an approximate area of 17,000 m^2. In May 2015, the Ministerial Committee discussion suggested constructing a parallel second runway for BIA as an improvement. However, over time, the available runway has been resurfaced to expand its width by 15m (7.5m from each side), upgrading the runway code from “4E” to “F”. These upgrades to the runway are said to be sufficient for the next 20 years' growth, also allowing access to larger aircraft, such as the Airbus A380, which was considered one of the main objectives for suggesting the construction of a second runway. (Silva et al., 2017). Despite these constructions and improvements, the possibility of utilising the maximum possible outcome of the runway and the available resource capacities has not been duly assessed by capacity assessments.

3.2.1 Data collection

For slot allocation optimization, it is essential to have accurate information on existing airline schedules and the sequence of airport operations. Accordingly, instead of relying on publicly available data from online flight tracking platforms, official data was obtained directly from the Civil Aviation Authority. These data are more accurate since the website tracking data can possess a time lag and incorrect information. The past flight records from the Aviation Department in Sri Lanka were provided on request. The data provided is for one operation week (From Monday to Sunday). The 'Carrier' column indicated the different types of airlines. The carrier information has been altered to ensure the privacy of the airlines. And therefore, instead of airline names, the carriers have been numbered.

The primary task is to analyse and identify the peak hours and days for one operation week at BIA using the collected data. After that, the following will be calculated:

- Airside resource capacities.
- Traffic Mix depending on the arrivals and departures.
- Aircraft Mix depending on aircraft types.

3.2.2 Defining parameters and input data used for the modelling

As the base reference, the current schedule provided by the Civil Aviation Authority will be used as the current/initial slots. The slots will be imported to the MATLAB model from Excel. The day 7 – Sunday schedule at BIA will be used since the highest number of aircraft operations was recorded on that day. The arrivals and departure schedules will be separated into two sets as C^a and C^d respectively.

Since BIA will be used as the case study to run the MATLAB model, the number of runways at BIA will be taken into consideration. Therefore, the base value for the number of runways will be 1. When considering other airports, the number of runways can vary. Similarly, for BIA, only 1 parallel taxiway exists.

Currently, the BIA consists of 29 parking spaces and will be used as input to the MATLAB model. At BIA, there are a total of 14 terminal gates. Gates 1 to 4 and Gates 5 to 14 are separated as follows:

- Gate 1 to 4 are all located downstairs on the ground floor and are designated as "R" gates. There's a shared security check, stuffy waiting areas, no food or drink establishments, no restrooms, and bus transportation to the aircraft at these gates. The passengers get into the aircraft by means of boarding stairs.
- Gate 5 to 14 are accessible after going through security and the duty-free shopping area, and they are situated along the same concourse on the upper floor. Those gates are assessed with remote jet bridges to assess passenger movements from the gate to the aircraft.

3.3 Hypothetical scenario

Assumed a single runway airport with one parallel taxiway. The airport consists of only one apron with ten parking stands and ten terminal gates allocated for each parking space. Through analysis, it has been found that the runway capacity is less than 15 flights per hour, and the apron capacity is less than 9 flights per hour. These parameters can be listed as follows:

Therefore,

$R = \{1\}$

$Y = \{1\}$

RC $\leq$ 15 aircrafts per hour

$P = \{1,2,3,4,5,6,7,8,9,10\}$

AC $\leq$ 9 aircrafts per hour

Assume the current schedule consists of 6 arrival flights and 6 departure flights. The following Table 6 represents the schedule of estimated arrivals and departures at the parking stand.

Table 6: Operations Before Modelling - Hypothetical

Time (t)	Operation Description	Identity
00:10	Current arrival 1, $a = 1, p = 1, a \in A, p \in P$	$ETC_1^1 = 00{:}10$
00:50	Current arrival 2, $a = 2, p = 4, a \in A, p \in P$	$ETC_4^2 = 00{:}50$
01:10	Current arrival 3, $a = 3, p = 6, a \in A, p \in P$	$ETC_6^3 = 01{:}10$
01:15	Current arrival 4, $a = 4, p = 7, a \in A, p \in P$	$ETC_7^4 = 01{:}15$
01:30	Current arrival 5, $a = 5, p = 8, a \in A, p \in P$	$ETC_8^5 = 01{:}30$
01:30	Current departure 1, $d = 1, p = 9, d \in D, p \in P$	$ETC_9^1 = 01{:}30$
01:40	Current arrival 6, $a = 6, p = 9, a \in A, p \in P$	$ETC_9^6 = 01{:}40$
01:50	Current departure 2, $d = 2, p = 10, d \in D, p \in P$	$ETC_{10}^2 = 01{:}50$
02:10	Current departure 3, $d = 3, p = 1d \in D, p \in P$	$ETC_1^3 = 02{:}10$
02:30	Current departure 4, $d = 4, p = 2, d \in D, p \in P$	$ETC_2^4 = 02{:}30$
02:40	Current departure 5, $d = 5, p = 3, d \in D, p \in P$	$ETC_3^5 = 02{:}40$
02:45	Current departure 6, $d = 6, p = 4, d \in D, p \in P$	$ETC_4^6 = 02{:}45$

The final expected outcome of the model is to increase the number of arrivals and departures per hour (increase the slot allocations) to a maximum. As a result of this increment, the higher traffic intensities observed throughout the current schedule is expected to reduce. This change is dependent on the increments in slots allocated.

Apart from slot allocations, an optimization is expected when certain operations are delayed. In simple terms, the cumulative delay observed is expected to reduce after modelling.

4. RESULTS AND DISCUSSION

4.1 Aircraft and passenger movements at BIA

Bandaranaike International Airport (BIA) currently consists of one terminal, with another terminal under construction. The available terminal has a passenger capacity of 6 million passengers per annum, according to the records provided by the Civil Aviation Authority. With the addition of the second terminal, the capacity will increase to 15 million per annum (an increase of 9 million). The Civil Aviation Authorities have predicted that the number of passenger movements will increase to 15 million by 2025. Since passenger flow is heavily dependent on aircraft movement, forecasting both passenger and aircraft movements can be done simultaneously.

Figure 4 shows the annual passenger movements at BIA from 2011 to 2022, together with the number of aircraft movements.

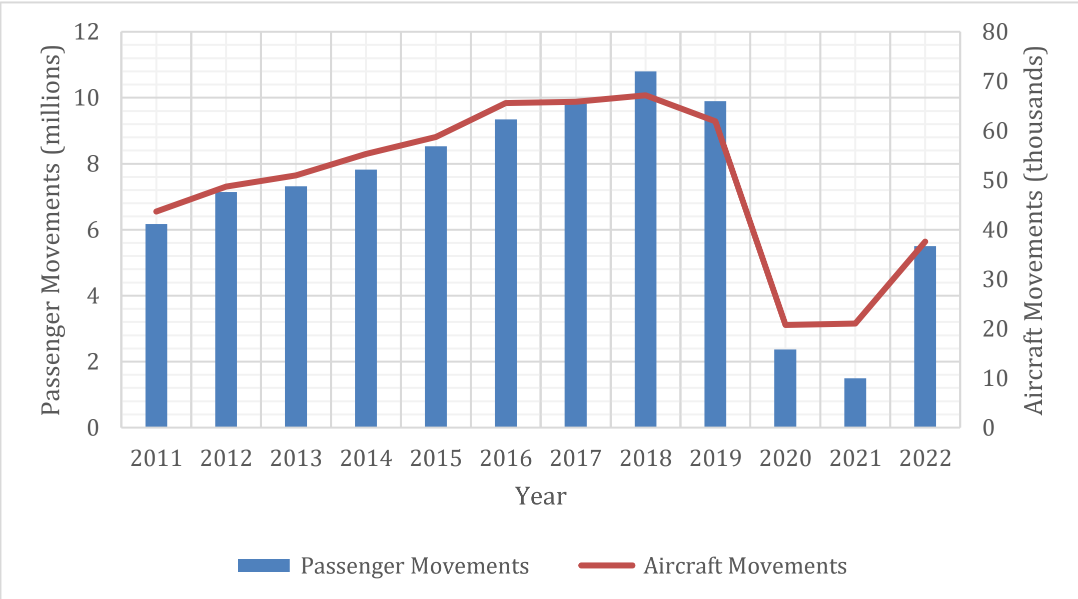

Figure 4: Aircraft and Passenger Movements at BIA

BIA has been using a total of 1,258 slots for an operational week for both arrivals (629 slots) and departures (629 slots). Figure 5 shows the usage of the of slots for each day for either one of the operations (arrival or departure).

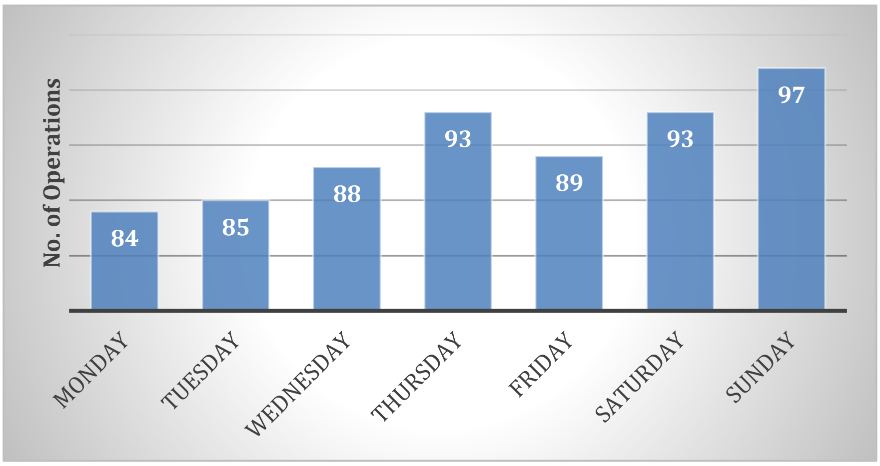

Figure 5: Current Slot Usage at BIA for a Typical Week of Operation

Since Sunday was found to be the peak day out of an operational week, the rest of the data analysis will be done on that day. The traffic mix was obtained as a scattered pie chart (Figure 6) where the number of arrivals and departures are separated into each aircraft type and converted into a percentage out of the total number of operations. The most frequently operated carriers are the A32B, A333, A320 and A321 with an airport utilization above 10%.

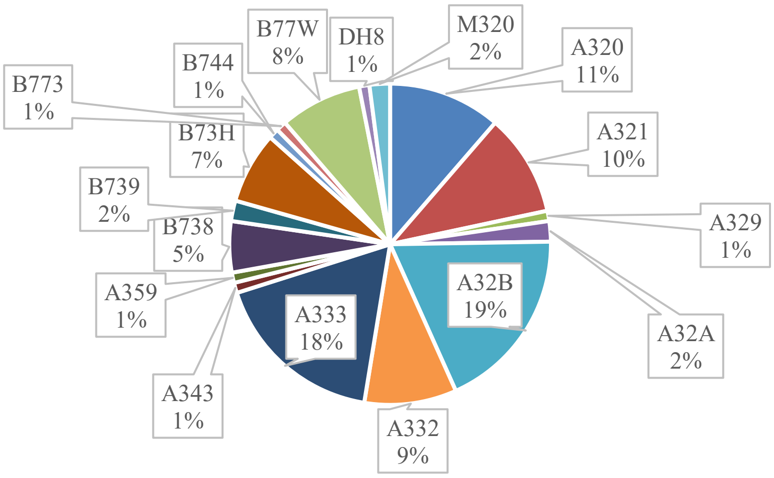

Figure 6: Scattered Pie Chart of the Traffic Mix at BIA, (Peak Day – Sunday)

Other than the Traffic Mix, the Aircraft Mix can also be found out. This is achieved by categorizing the aircraft types. The aircraft types can be mainly separated into two categories as follows:

- H (Heavy) – Aircraft weighing more than 136,000kg *(Wide-Body Aircraft, Very Large Aircraft (VLA) and Cargo Aircraft)*
- M (Medium) – Aircraft weighing less than 136,000kg *(Narrow-Body Aircraft and Regional Aircraft)*

The aircraft type categorization is based upon the wake turbulence parameters introduced by ICAO (International Civil Aviation Organization). This categorization is crucial for determining the separations of the aircrafts. The aircraft mix was also calculated for the peak day by taking the percentage of each category among the total number of flights.

The aircraft mix with the ICAO categorization is shown below in Table 7.

Table 7: Aircraft Mix Observed at BIA During a Peak Day – Sunday

ICAO Categorization	Aircraft Type	Count	Percentage (%)
Heavy	A332	9	9.3
Heavy	A333	17	17.5
Heavy	A343	1	1.0
Heavy	A359	1	1.0
Heavy	B744	1	1.0
Heavy	B773	1	1.0
Heavy	B77W	8	8.2
Medium	A320	11	11.3
Medium	A321	10	10.3
Medium	A329	1	1.0
Medium	A32A	2	2.1
Medium	A32B	18	18.6
Medium	B738	5	5.2
Medium	B739	2	2.1
Medium	B73H	7	7.2
Medium	DH8	1	1.0
Medium	M320	2	2.1
	Total	97	100

Table 7 shows that the highest number of operations are carried out by the Aircraft type of 32B, and the least number of operations are carried out by aircraft types of 329, 343, 359, 744, 773 and DH8. In total, during a peak day (Sunday), 38 heavy aircrafts (39.2%) and 59 medium aircrafts (60.8%) are operated.

According to the aircraft mix in Table 7, most of the aircraft in operation are 'Medium' category aircraft. This categorisation of aircraft is essential to identify the separation minima, which depend on the aircraft mix. The calculated separation minima have been used in the model to optimize the slot allocation and delay.

4.1.1 Runway capacity usage

According to the analysis, the highest number of operations conducted in a single day was 194 (a total of 97 operations for each arrival and departure), which occurred on Sundays. And the maximum number of operations conducted per hour was found to be 13 (10 Arrivals and 3 departures). The airside capacity of an airport is a key consideration when allocating slots. Only for the allocated number of slots, aircraft will be operated. Therefore, the maximum number of slot allocations per hour on a peak day can be confirmed as 13. According to the undergraduate study conducted at the University of Moratuwa, Sri Lanka, the declared capacity of the BIA runway has been found to be 26 flights/hour. Utilization is the measure of how much of the space or workforce is being used at that moment.

In the case of operations at BIA, utilization is found to be 50%. Therefore, this concludes that BIA is operating at 50% of its declared runway capacity and the runway is not used to its maximum capability. And even if the aircraft movements are increased with an estimated growth of 7% per annum (SLAA, 2021), the runway capacity will not be entirely utilised for another 7-8 years' time.

4.1.2 Apron capacity usage

BIA consists of four aprons now, with another apron under construction. The available aprons are designated by code names Alpha, Bravo, Charlie, and Delta, with 9, 8, 8, and 4 parking stands, respectively. The apron Delta is usually allocated for local aircraft operations and unscheduled operations. The newly constructed apron, given the code name "Echo," is designed to provide 23 parking stands. Currently, the total number of parking stands available is 29, which is sufficient as of the runway capacity (26 flights/hour). With the new apron, a total of 52 parking spaces will be available.

The gate capacity can be estimated considering the following assumptions:

1. Maximum turnaround time for a heavy aircraft is 1 hour, and for a medium aircraft is 45 minutes.
2. The positioning time for push-in and pushback manoeuvres at the apron is 10 minutes for all operations.
3. A buffer time of 15 minutes must be implemented to ensure sufficient time for any operational delays

Accordingly, for BIA, the gate capacity has been calculated as 18 flights/hour.

$$C_g = \frac{25}{(60 + 10 + 15) \div 60} = 18\, flights/hour$$

4.1.3 Minimum taxiing in and taxiing out times

Research was done on the evaluation of CO_2 emissions during taxiing phase at BIA by (Dissanayaka et al., 2020) have represented the average taxiing in times and out times depending on the aircraft mix. The analysis has shown that the unimpeded taxiing out times are 9 minutes and 8 minutes for Heavy and Medium aircraft, respectively. And the unimpeded taxiing in times of 4 minutes for both Heavy and Medium aircraft.

At BIA, the push-in and push-back cycle time was estimated using the data gathered from Flightradar24. Several aircraft operations were observed, and an average cycle time was calculated. Therefore, the input time for the model will be 6 minutes, as calculated. However, considering that there are 3 aprons, the separation times for aircraft will have an impact of only 1/3rd of the push-in/push-out cycle time.

4.1.4 Separation minima

According to the (International Air Transport Association (IATA), 2023), between heavy and medium categorised aircraft, the non-radar wake turbulence separation times are as follows:

- between departure – departure mode (δ) is 3 minutes.
- between arrival – arrival mode (σ) is 2 minutes.
- between either departure – arrival mode or arrival – departure mode (φ) is 2 minutes (The IATA guidelines have considered the same scenario for both modes).

Between heavy and medium categorized aircraft, the minimum radar wake turbulence separation distance (ω) The distance between arrival and arrival mode, or departure and departure mode, is 5Nm.

For this research, the maximum of the non-radar/radar wake turbulence separation time/distance has been used to calculate the separation minima. This will allow us to ensure safe margins.

According to the ICAO categorization, airline jets are categorized into type C, where the general approach speed (V_r) is 121 – 140 knots. This can also go up to 240 knots at emergency/final missed approaches. As an input value, 140 knots will be used.

For airports with several aprons (x), the separation time required within the apron must be considered according to push-in/push-back times (PI). Additional delay buffer (W) should also be considered to adhere unavoidable delays. Pushback and push-in times were adjusted considering the availability of multiple aprons, under the assumption of independent and parallel apron access. For simplification, the average time was divided by the number of aprons to reflect reduced waiting due to multiple service points. However, this assumes that apron capacity is fully utilized and dynamically allocated.

For Departure – Departure (DD) mode:

$$X = max\left(\delta \middle| \frac{\omega}{V_r}\right) + \frac{PI}{x} + W$$

$$X = max\left(3 \middle| \frac{5Nm}{140\ knots}\right) + \frac{6}{3} + 2$$

$$X = max(3|2.14) + 2 + 2$$

$$X = 7\ mins$$

For Arrival – Arrival (AA) mode:

$$Q = max\left(\sigma \middle| \frac{\omega}{V_r}\right) + \frac{PI}{x} + W$$

$$Q = max\left(2 \middle| \frac{5Nm}{140\ knots}\right) + \frac{6}{3} + 2$$

$$Q = max(2|2.14) + 2 + 2$$

$$Q = 6.14\ mins$$

$$Q \approx 7\ mins$$

For Arrival – Departure (AD) or Departure – Arrival (DA) mode:

$$Z = \varphi + \frac{PI}{x} + W$$

$$Z = 2 + \frac{6}{3} + 2$$

$$Z = 2 + 2 + 2$$

$$Z = 6\ mins$$

4.2 Hypothetical scenario results

The hypothetical scenario shown under methodology section will be modelled through multiple iterations until the optimum results are obtained.
Considering the constraints, the following schedule shown in Table 8 was generated after modelling. The results show how new slots have been introduced to utilize the declared capacity while keeping the current operations unchanged.

Table 8: Operations After Modelling - Hypothetical

Time	Operation Description	Identity	Flight Number
00:10	Current arrival 1, $a = 1, p = 1, a \in A, p \in P$	$ETC_1^1 = 00{:}10$	UA2301
00:16	New departure 1, $d = 1, p = 2, d \in \bar{D}, p \in P$	$ETN_2^1 = 00{:}16$	
00:22	New arrival 1, $a = 1, p = 2, a \in \bar{A}, p \in P$	$ETN_2^1 = 00{:}22$	UA3002
00:28	New departure 2, $d = 2, p = 3, d \in \bar{D}, p \in P$	$ETN_3^2 = 00{:}28$	
00:34	New arrival 2, $a = 2, p = 3, a \in \bar{A}, p \in P$	$ETN_3^2 = 00{:}34$	UB2570
00:40	New departure 3, $d = 3, p = 4, d \in \bar{D}, p \in P$	$ETN_4^3 = 00{:}40$	
00:50	Current arrival 2, $a = 2, p = 4, a \in A, p \in P$	$ETC_4^2 = 00{:}50$	UA9010
00:56	New departure 4, $d = 4, p = 5, d \in \bar{D}, p \in P$	$ETN_5^4 = 00{:}56$	
01:02	New arrival 3, $a = 3, p = 5, a \in \bar{A}, p \in P$	$ETN_5^3 = 01{:}02$	
01:10	Current arrival 3,	$ETC_6^3 = 01{:}10$	
01:15	Current arrival 4, $a = 4, p = 7, a \in A, p \in P$	$ETC_7^4 = 01{:}15$	
01:21	New departure 5, $d = 5, p = 8, d \in \bar{D}, p \in P$	$ETN_8^5 = 01{:}21$	
01:30	Current arrival 5, $a = 5, p = 8, a \in A, p \in P$	$ETC_8^5 = 01{:}30$	
01:30	Current departure 1, $d = 1, p = 9, d \in D, p \in P$	$ETC_9^1 = 01{:}30$	
01:40	Current arrival 6, $a = 6, p = 9, a \in A, p \in P$	$ETC_9^6 = 01{:}40$	

01:50	Current departure 2, $d = 2, p = 10, d \in D, p \in P$	$ETC_{10}^{2} = 01:50$	
01:57	New arrival 4, $a = 4, p = 10, a \in \bar{A}, p \in P$	$ETN_{10}^{4} = 01:57$	
02:10	Current departure 3, $d = 3, p = 1, d \in D, p \in P$	$ETC_{1}^{3} = 02:10$	UA2301
02:17	New arrival 5, $a = 5, p = 1, a \in \bar{A}, p \in P$	$ETN_{1}^{5} = 02:17$	
02:30	Current departure 4, $d = 4, p = 4, d \in D, p \in P$	$ETC_{4}^{4} = 02:30$	UA9010
02:40	Current departure 5, $d = 5, p = 3, d \in D, p \in P$	$ETC_{3}^{5} = 02:40$	UB2570
02:45	Current departure 6, $d = 6, p = 2, d \in D, p \in P$	$ETC_{2}^{6} = 02:45$	UA3002

Note: For clarity, some hypothetical airline references have been included to illustrate the turnaround times. The turnaround times are as follows:

UA2301 Aircraft = 2 Hours

UA3002 Aircraft = 2 Hours and 23 Minutes

UB2570 Aircraft = 2 Hours and 6 Minutes

UA9010 Aircraft = 1 Hour and 40 Minutes

The new schedule created satisfies all the constraints in the following way:

Constraint 1: Runway operational mode constraints

Satisfied

From analysis, the minimum separation parameters for each mode were calculated for constraint 1 and have been addressed accordingly:

Mode 1: Departure – Departure (DD) Mode

$$\sum_{r \in R} \sum_{d \in \bar{D}} |ETN_r^d - ETN_r^{d \pm 1}| \geq 7$$

$$\sum_{r \in R} \sum_{d \in D} |ETC_r^d - ETC_r^{d \pm 1}| \geq 7$$

$$\sum_{r\in R}\sum_{d\in D\cup\bar{D}} |ETC_r^d - ETN_r^d| \geq 7$$

Mode 2: Arrival – Arrival (AA) Mode

$$\sum_{r\in R}\sum_{a\in\bar{A}} |ETN_r^a - ETN_r^{a\pm1}| \geq 7$$

$$\sum_{r\in R}\sum_{a\in A} |ETC_r^a - ETC_r^{a\pm1}| \geq 7$$

$$\sum_{r\in R}\sum_{a\in A\cup\bar{A}} |ETC_r^a - ETN_r^a| \geq 7$$

Mode 3: Arrival – Departure (AD) Mode

$$\sum_{r\in R}\sum_{a\in\bar{A}}\sum_{d\in\bar{D}} |ETN_r^a - ETN_r^d| \geq 6$$

$$\sum_{r\in R}\sum_{a\in A}\sum_{d\in D} |ETC_r^a - ETC_r^d| \geq 6$$

$$\sum_{r\in R}\sum_{a\in A}\sum_{d\in\bar{D}} |ETC_r^a - ETN_r^d| \geq 6$$

$$\sum_{r\in R}\sum_{a\in\bar{A}}\sum_{d\in D} |ETN_r^a - ETC_r^d| \geq 6$$

Constraint 2: Runway and apron operational capacity constraints

Satisfied

Slots in each hour is less than the declared capacity (minimum of RC or AC).

Constraint 3: Outbound and Inbound slot difference

Satisfied

$$\min \sum_{p\in P} \left| \sum_{a\in A\cup\bar{A}} \left(C_{p,t}^a + N_{p,t}^a\right) - \sum_{d\in D\cup\bar{D}} \left(C_{p,t}^d + N_{p,t}^d\right) \right|$$

$$|(6+5) - (6+5)| = 0$$

The following Table 9 shows the number of operations, and the traffic intensity for the respective hours:

Table 9: Number of Operations and Hourly Traffic Intensities Before and After Modelling – Hypothetical

Hour	**Initial Arrivals**	**Final Arrivals**	**Initial Departures**	**Final Departures**	**Initial Traffic Intensity**	**Final Traffic Intensity**
1	2	4	0	4	Inf	1
2	4	6	2	3	2	2
3	0	1	4	4	0	0.25

Therefore,
Constraint 5: Current schedule traffic intensity bounds
Satisfied
The current schedule is observed to have peak traffic intensities during the first hour. Through modelling, a balance in operations has been observed, which has resulted in reduced traffic intensity.

With these results, it can be concluded that the first objective is satisfied.

Now, considering the real scenario, the scheduled aircraft might get delayed. Therefore, the model should be capable of adjusting the schedule to adhere to the delay while reducing the cumulative delay propagated to future operations.

<u>Example 1</u>

For demonstration, assume that the "Current arrival 1 (UA2301)" gets delayed by 29 minutes. Due to this delay in the arrival, the corresponding departure of this operation will be delayed as well, considering the service time. It is assumed that the corresponding departure will also be delayed by 29 minutes, considering that the service time will be utilized as planned. The model will adjust the schedule as shown in Table 10: (the 3rd column represents the delay compared to the scheduled time)

Note: The optimized schedule represented ETC's and ETN's. The schedules below represent the delay implemented in the actual scenario and therefore will represent ATC's and ATN's

Table 10: Delay Propagation After Modelling (Example 1) – Hypothetical

Time	**Operation Description (ATC & ATN)**	**Delay (mins)**	**Flight Number**
00:16	New departure 1	0	
00:22	New arrival 1	0	
00:28	New departure 2	0	
00:34	New arrival 2	0	
00:39	Current arrival 1	29	UA2301
00:45	New departure 3	5	
00:51	Current arrival 2	1	
00:57	New departure 4	1	
01:03	New arrival 3	1	
01:10	Current arrival 3	0	
01:15	Current arrival 4	0	
01:21	New departure 5	0	
01:30	Current arrival 5	0	
01:30	Current departure 1	0	
01:40	Current arrival 6	0	
01:50	Current departure 2	0	
01:57	New arrival 4	0	
02:17	New arrival 5	0	
02:30	Current departure 4	0	

02:40	Current departure 3	29	UA2301
02:46	Current departure 5	6	
02:53	Current departure 6	8	

When an operation is delayed, either a current operation or a new operation, the delay gets propagated to other operations as well. In that scenario, the model has adjusted the operations adjacent to the delayed operation as shown in Table 8, considering the separation times to minimize the cumulative delay as an optimization task.

It is observed that the current schedule operations are also affected. This is a possible occurrence in the real scenario. The objective is to minimize the delay propagated to the adjacent operations. If there was no increase in slot allocations, the current schedule operations might not have been affected since the operations have a considerable time difference apart from each other. But through optimization, the objective is to utilize the airport capacity to the maximum possible while minimizing the delay propagated.

At the end, from "New departure 5" operation itself, there will be no delay propagated, and the scheduled operations will run smoothly. But, considering the turnaround time specified for the UA2301 aircraft (2 Hours), the delayed arrivals will subsequently delay their respective departure as well, as mentioned before.

- The cumulative delay of the adjusted schedule **after optimization is 80 minutes.**

If the optimization is not done, the schedule will be yielded as in Table 11:

Table 11: Delay Propagation Without Modelling (Example 1) – Hypothetical

Time	Operation Description	Delay (minutes)	Flight Number
00:16	New departure 1	0	
00:22	New arrival 1	0	

00:28	New departure 2	0	
00:34	New arrival 2	0	
00:39	Current arrival 1	29	UA2301
00:45	New departure 3	5	
00:55	Current arrival 2	5	
01:01	New departure 4	5	
01:07	New arrival 3	5	
01:15	Current arrival 3	5	
01:20	Current arrival 4	5	
01:26	New departure 5	5	
01:32	Current arrival 5	5	
01:38	Current departure 1	5	
01:45	Current arrival 6	5	
01:55	Current departure 2	5	
02:01	New arrival 4	5	
02:17	New arrival 5	0	
02:30	Current departure 4	0	
02:39	Current departure 3	29	UA2301
02:46	Current departure 5	6	
02:53	Current departure 6	8	

It is observed that multiple operations have been delayed by the same time, continuously. This is because, without optimization, the aircraft will operate according to the initially scheduled time difference between each operation. The reason is that, considering the real scenario, there are multiple resources in the airport (runway capacity, taxiway capacity, apron gate capacity, etc.) which are always constrained. Through optimization, consideration of separation minima and effective slot allocation, the delay propagation can be reduced.

The delay propagation will not end if the schedule is not optimized.

- Under these conditions, the cumulative delay **without optimization is 132 minutes.**

And it is clear that the optimization procedures are capable of minimizing the delay by **52 minutes**.

And therefore, objective 2 is also satisfied.

<u>Example 2</u>

Considering another example, assume that the “Current arrival 2 (UA9010)” gets delayed by 10 minutes. The model will adjust the schedule as shown in Table 12:

Table 12: Delay Propagation After Modelling (Example 2) – Hypothetical

Time	**Operation Description**	**Delay (minutes)**	**Flight Number**
00:10	Current arrival 1	0	
00:16	New departure 1	0	
00:22	New arrival 1	0	
00:28	New departure 2	0	
00:34	New arrival 2	0	
00:40	New departure 3	0	
00:56	New departure 4	0	
01:00	Current arrival 2	10	UA9010
01:06	New arrival 3	4	
01:12	Current arrival 3	2	
01:18	Current arrival 4	3	
01:24	New departure 5	3	
01:30	Current arrival 5	0	

01:30	Current departure 1	0	
01:40	Current arrival 6	0	
01:50	Current departure 2	0	
01:57	New arrival 4	0	
02:10	Current departure 3	0	
02:17	New arrival 5	0	
02:40	Current departure 5	0	
02:40	Current departure 4	10	UA9010
02:47	Current departure 6	2	

- The cumulative delay of the adjusted schedule **after optimization is 34 minutes.**

If the optimization is not done, the schedule will be yielded as shown in Table 13:

Table 13: Delay Propagation Without Modelling (Example 2) – Hypothetical

Time	Operation Description	Delay (minutes)	Flight Number
00:10	Current arrival 1	0	
00:16	New departure 1	0	
00:22	New arrival 1	0	
00:28	New departure 2	0	
00:34	New arrival 2	0	
00:40	New departure 3	0	
00:56	New departure 4	0	
01:00	Current arrival 2	10	UA9010
01:06	New arrival 3	4	
01:14	Current arrival 3	4	
01:19	Current arrival 4	4	

01:25	New departure 5	4	
01:34	Current arrival 5	4	
01:34	Current departure 1	4	
01:44	Current arrival 6	4	
01:54	Current departure 2	4	
02:01	New arrival 4	4	
02:14	Current departure 3	4	
02:14	New arrival 5	4	
02:40	Current departure 5	0	
02:40	Current departure 4	10	UA9010
02:47	Current departure 6	2	

The delay propagation will not end if the schedule is not optimized.

- Under these conditions, the cumulative delay **without optimization is 66 minutes.**

And it is clear that the optimization procedures are capable of minimizing the delay by **32 minutes**.

4.3 Case study simulation results

4.3.1 Resource utilization

Using MATLAB, the linear programming slot allocation model was successfully solved considering the capacity and operational constraints of the airport. The resource utilization has increased after modelling as compared through the calculation of utilization rates and the bar charts shown in Figure 7 and 8. In other words, the airport can operate at almost 1/3rd of the maximum possible capacity, efficiently utilizing its resources.

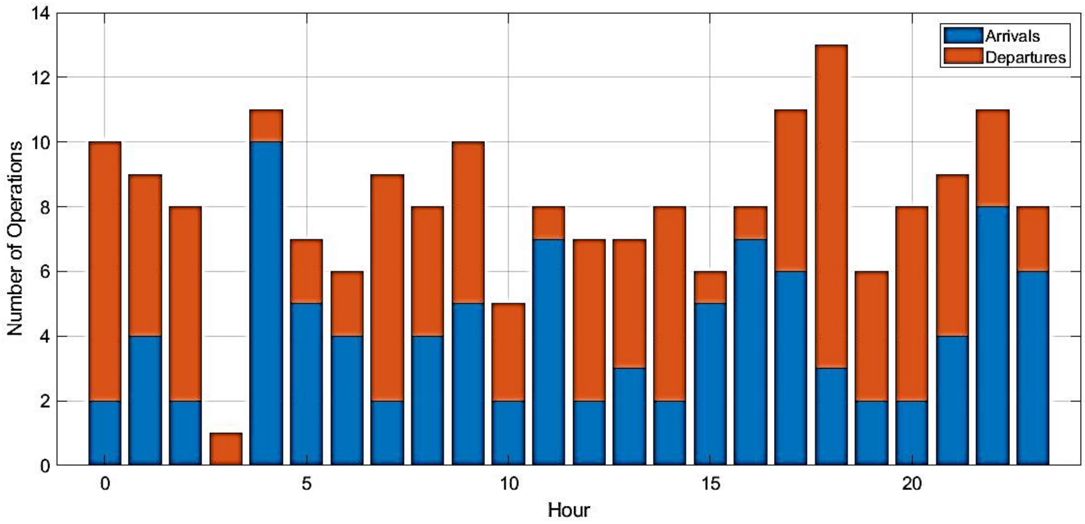

Figure 7: Number of Operations on a Peak Day – Before Modelling

The current schedule comprises a total of 194 slots during a peak day, evenly distributed between 97 departures and 97 arrivals. The airside resource utilization rate was calculated according to section 3.1.9 as an average of 44.9% throughout the day. Essentially, the airport operates below half of its potential capacity.

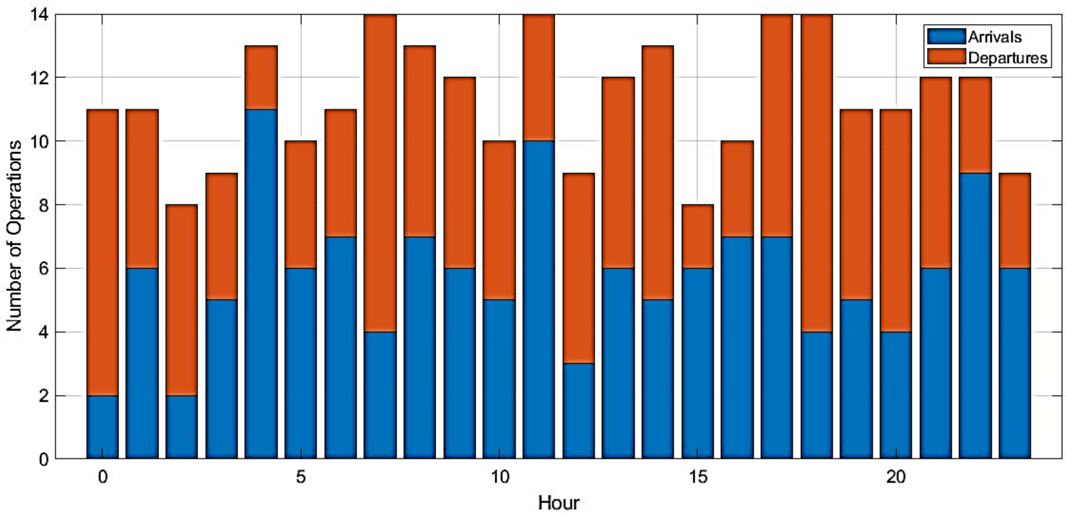

Figure 8: Number of Operations on a Peak Day – After Modelling

Post-optimization, the final schedule emerges as a more robust configuration. It accommodates a total of 271 slots, effectively handling increased traffic. Specifically, there are 139 arrivals and 132 departures. The airside resource utilization rate of the new schedule (considering all available slots) significantly improves to an average of 62.7% calculated as in section 3.1.9.

4.3.2 Slot increments each hour

For each, the number of arrivals and departures in the current and final schedules can be compared as a percentage change, as shown in Table 14. The colour variation on the slot increments each hour, as displayed in Table 14, offers a surface view of which hours are the most vacant for a greater number of slot allocations at the airport. Filling colors give an idea of how much of a slot increment is observed each hour. The color ranges from red to green, where red indicates no changes and green signifies modifications, representing maximum increment. This provides a clear insight for slot coordinators or relevant authorities when allocating vacant slots and planning their respective schedules for the day.

Table 14: Slot Increments Each Hour

Hour	**Arrivals**			**Departures**		
	Current Schedule	**Final Schedule**	**% change**	**Current Schedule**	**Final Schedule**	**% change**
1	2	2	0	8	9	13
2	4	6	50	5	5	0
3	2	2	0	6	6	0
4	0	5	-	1	4	300
5	10	11	10	1	2	100
6	5	6	20	2	4	100
7	4	7	75	2	4	100
8	2	4	100	7	10	43
9	4	7	75	4	6	50
10	5	6	20	5	6	20
11	2	5	150	3	5	67

12	7	10	43	1	4	300
13	2	3	50	5	6	20
14	3	6	100	4	6	50
15	2	5	150	6	8	33
16	5	6	20	1	2	100
17	7	7	0	1	3	200
18	6	7	17	5	7	40
19	3	4	33	10	10	0
20	2	5	150	4	6	50
21	2	4	100	6	7	17
22	4	6	50	5	6	20
23	8	9	13	3	3	0
24	6	6	0	2	3	50
Total	97	139		97	132	

4.3.3 Changes in traffic intensity

Table 15 shows the distribution of the traffic intensities before and after optimisation. The colour variation represented gives an idea how the modelling has impacted the traffic intensities each hour. The color ranges from blue to red, where blue indicates lower traffic intensities and red indicates higher traffic intensities.

Table 15: Traffic Intensity Distribution

Hour	Current Schedule Traffic Intensity	Final Schedule Traffic Intensity
1	0.25	0.22
2	0.80	1.20
3	0.33	0.33
4	0.00	1.25
5	10.00	5.50
6	2.50	1.50

7	2.00	1.75
8	0.29	0.40
9	1.00	1.17
10	1.00	1.00
11	0.67	1.00
12	7.00	2.50
13	0.40	0.50
14	0.75	1.00
15	0.33	0.63
16	5.00	3.00
17	7.00	2.33
18	1.20	1.00
19	0.30	0.40
20	0.50	0.83
21	0.33	0.57
22	0.80	1.00
23	2.67	3.00
24	3.00	2.00

The model has considered the current schedule traffic intensity as bounds when maximizing the slot allocation. As a result, from the simulated model, the optimal solution for the distribution of the number of slots for each hour has been obtained. For this optimal solution, with maximum utilization rate obtained, the traffic intensities of the new schedule have been distributed as well. The reason for the changes depends on the maximum number of arrivals and departures obtained through optimization, since traffic intensity is the ratio of the rate of arrivals and departures each hour. Table 15 above shows how the higher traffic intensities (traffic intensities > 1) have been distributed to adjacent times of the day (with traffic intensities < 1), allowing much smoother operations during the day. At certain hours, the traffic intensity is > 1 (considered to be critical/peak hours), and as said by queuing theory, at these times the delay occurrence is said to have reached infinity, and the arrival rate plays the crucial role.

Figure 9 below shows the comparison of changes between the new schedule and the current schedule relative to traffic intensities. The figure illustrates how the modelling procedures have reduced the traffic intensity levels, which exceed 1 during critical/peak hours. The main benefits of distributed traffic intensities are reduced congestion and enhanced resource utilization, allowing for smoother operations during peak hours.

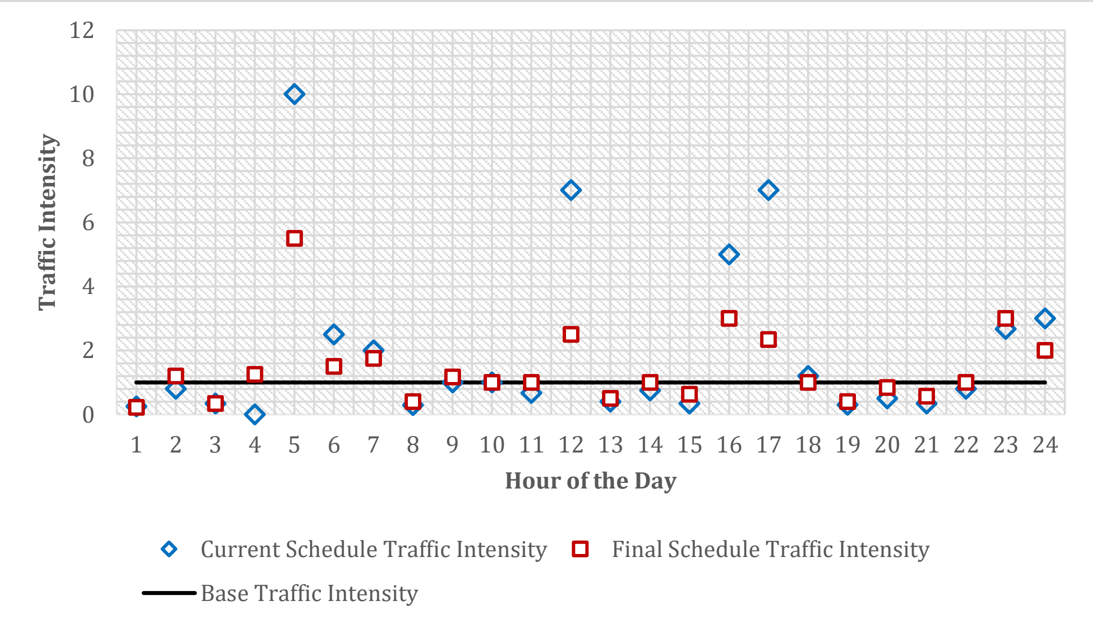

Figure 9: Comparison of Traffic Intensities Between Final and Current Schedule

4.3.4 Terminal gate utilization

Table 16 and Figure 10 below shows the comparison of current gate utilization rate and the expected, final gate utilization, as a percentage of the available terminal gates relative to the total number of operations at each hour, for a peak day, calculated according to section 3.1.10.

Table 16: Terminal Gate Utilization

Hour	Current Gate Utilization (%)	Final Gate Utilization (%)
1	71.4	78.6
2	64.3	78.6
3	57.1	57.1
4	7.1	64.3
5	78.6	92.9
6	50.0	71.4
7	42.9	78.6
8	64.3	100.0
9	57.1	92.9
10	71.4	85.7
11	35.7	71.4
12	57.1	100.0
13	50.0	64.3
14	50.0	85.7
15	57.1	92.9
16	42.9	57.1
17	57.1	71.4
18	78.6	100.0
19	92.9	100.0
20	42.9	78.6
21	57.1	78.6
22	64.3	85.7
23	78.6	85.7
24	57.1	64.3

The colour variation represented gives an idea how the modelling has impacted the terminal gate utilization. The color ranges from red to green, where red indicates lower terminal gate utilization and green indicates higher terminal gate utilization.

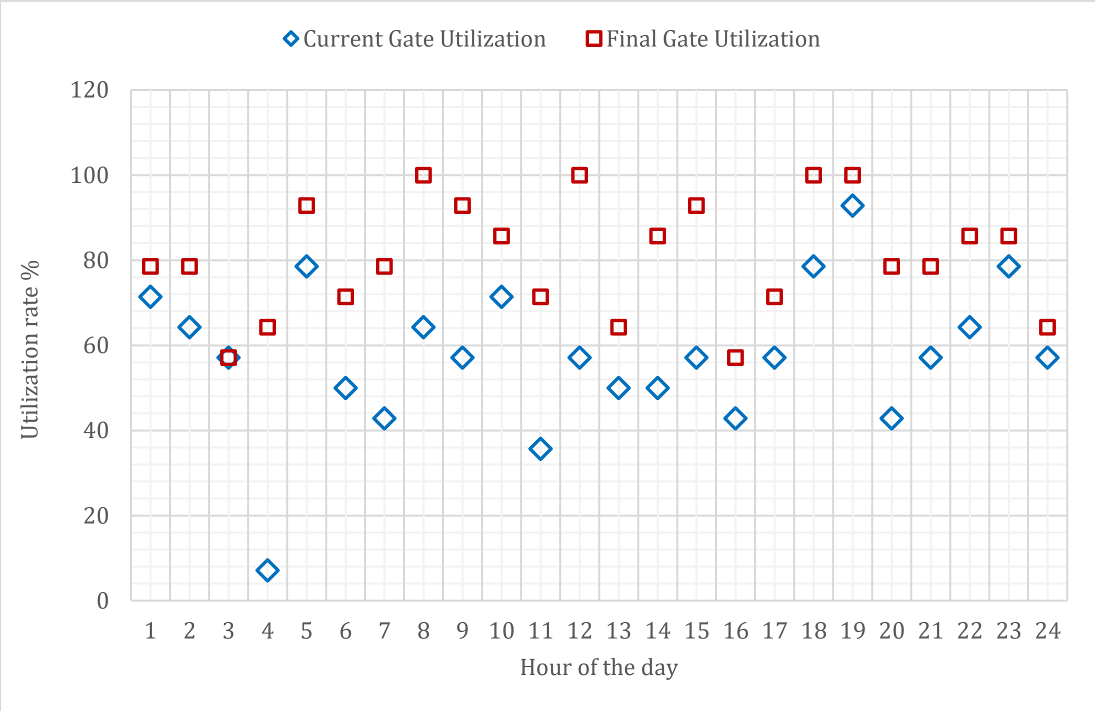

Figure 10: Terminal Gate Utilization – Graphical Representation

The representation above indicates that the gate utilization rates have increased after optimization, indicating that the terminals will be more occupied. Higher utilization rates will increase the number of passenger movements at the terminal area. With that, the terminal building should have the capacity to handle increased passenger movements. The terminal building handling capacity can be optimized by implementing the newest technology, such as self-check-in counters, and by increasing the number of passenger handling operators at the airport. This optimization is not under the scope of this research and therefore has not been considered for modelling purposes. The reason is based on the simplicity in optimizing either of its capacities or passenger and cargo handling operations. Simple optimization can be achieved by implementing adjustments in the number of service operators at the airport.

Once the terminal gate utilizations are increased, the need for infrastructure expansions can be mitigated since an increased number of slots are introduced to generate extra revenue.

4.3.5 Delay optimization

The developed model has used delay management strategies for cumulative delay minimization under several operational constraints. Table 17 below illustrates how the cumulative delay of the optimized schedule is compared to the cumulative delay of the schedule without being optimized when a certain set of operations is delayed with pre-defined scenarios. (Note: The cumulative delay represents the total delay in a 24-hour period.) For example, if schedule arrival four is delayed by 40 minutes, the impact in terms of overall delay per day is assessed under current and modelled conditions in scenario 1. Likewise, many scenarios are presented in Table 17 to illustrate the positive outcomes from the model. It is assumed that only one operation is delayed for the day (24 hours) under scenarios 1 to 10 for simplicity. The model also has the capacity to handle multiple changes and still produce a positive outcome, as illustrated in scenarios 11 and 12. A considerable set of samples (both arrivals and departures) was selected as if they had different operational times and flight types. This enables the possibility to compare a wide range of delay scenarios.

The model follows a rescheduling algorithm which considers the minimum separation time, turnaround times, slot availability and other resource allocation constraints. The primary objective of this approach is to minimize the total propagated delay

.

Table 17: Cumulative Delay for Selected Operations

Scenario	**Operations Delayed**	**Delay Imposed (mins)**	**Cumulative delay - Optimized (mins)**	**Cumulative delay – Not Optimized (mins)**
1	Current arrival 4	40	1,351	1,634
2	New departure 11	60	1,021	1,160
3	Current departure 36	120	943	998
4	New arrival 40	30	202	227
5	Current arrival 49	20	711	830
6	New departure 26	50	599	950
7	Current departure 69	80	354	470
8	New arrival 35	100	330	354
9	Current arrival 91	30	79	87
10	New departure 35	20	38	20

11	Current arrival 5, New departure 13, Current departure 37	21 + 33 + 43	1,867	2,249
12	Current arrival 48, New departure 28, Current departure 65, New arrival 37, Current arrival 92	19 + 35 + 39 + 51 + 57	762	967

The highest improvement in optimization can be seen for scenario 11 with a 382-minute reduction in cumulative delay.

As mentioned under section 3.1.11, the one-sample t-test has been conducted, and the results have been represented in Table 18. The objective is to determine whether the mean delay reduction is significantly greater than zero.

Table 18: Statistical Analysis Results

Variable	**Result**
Sample size	12
Sample mean	140.80 minutes
Sample standard deviation	136.50 minutes
t-statistic	3.57
Degrees of freedom	11
One-tailed p-value	0.0022

The results on the one-sample t-test have provided strong basis and proof that the proposed model can reduce the cumulative delay significantly. The evaluated scenarios were strategically selected involving both arrivals and departures, over a range of delay events throughout a day. The sample mean of 140.80 minutes and standard deviation of 136.50 minutes shows that there is a substantial improvement in delay optimization. Apart from that, the t-statistic of 3.57 and p-value of 0.0022 shows that the result is statistically significant at the 5% level and hence proves that the chance of randomness of obtaining such delay reduction is less than 1%.

The advantages of optimized scheduling in aviation are substantial. First, it reduces the ripple effect of delays, ensuring that subsequent flights are less affected. This helps maintain better adherence to schedules and minimizes disruptions across the network. Additionally, optimized scheduling improves resource utilization by reducing idle time for aircraft, ground crews, and airport infrastructure. These improvements lead to cost savings, including reduced fuel consumption, lower maintenance requirements, and minimized labour expenses. Furthermore, by ensuring more timely arrivals and departures, optimized scheduling enhances passenger satisfaction, which is critical for airlines and airport operators striving to provide reliable and punctual services. Figure 11 visually demonstrates the effectiveness of the model.

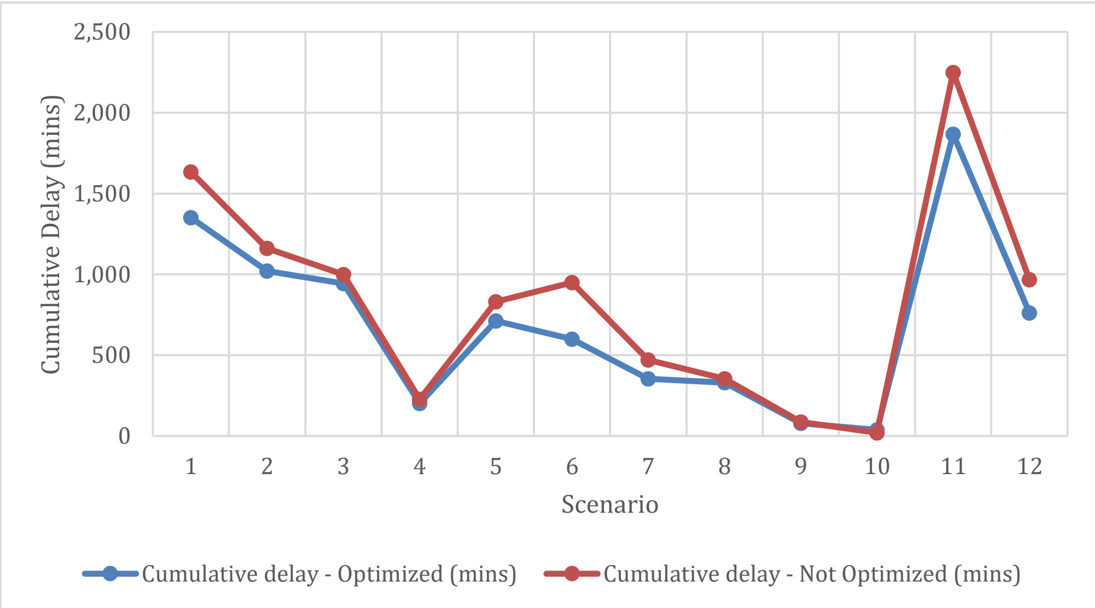

Figure 11: Cumulative Delay Comparison

Across various scenarios, the optimized scheduling consistently results in lower cumulative delays, emphasizing the importance of systematic delay management in aviation operations.

One key observation is the ripple effect of delays in flight schedules. An imposed 40-minute delay, for example, causes a cumulative delay of 1,351 minutes in the optimised scenario for "Current arrival 4" as opposed to 1,634 minutes in the non-optimized scenario. Timely scheduling changes can prevent ripple delays in subsequent procedures, as this 283-minute decrease illustrates. In the same way, a 60-

minute delay for "New departure 11" highlights the effectiveness of the optimization strategy by lowering total delays from 1,160 minutes in the non-optimized situation to 1,021 minutes in the optimized case.

For operations that involve greater delays, the advantages of optimized scheduling are even more noticeable. For instance, with optimized scheduling, a 120-minute imposed delay in "Current departure 36" results in a total delay of 943 minutes, as opposed to 998 minutes in the non-optimized scenario. This notable decrease demonstrates how a well-planned schedule may more efficiently absorb and disperse the effects of severe delays. Optimization lowers cumulative delays, even for minor ones like "Current arrival 91" with 30 minutes or "New departure 35" with 20 minutes. Even if the effects are less noticeable in these situations because of the lower starting delays, it also shows how consistently effective scheduling is at maintaining operational stability.

The optimization methodology still performs well in more complicated situations with several operations being delayed. The cumulative delay decreased from 2,249 minutes (non-optimized) to 1,867 minutes (optimized) in Scenario 11, where three operations were delayed (Current arrival 5 by 21 minutes, new departure 13 by 33 minutes, and Current departure 37 by 43 minutes). This represents a significant 382-minute reduction. Similar to this, five operations, current arrival 48, new departure 28, current arrival 65, new arrival 37, and current arrival 92, were all delayed at the same time in Scenario 12, with delays varying from 19 to 57 minutes. The optimized model saved 205 minutes by reducing the cumulative delay from 967 minutes to 762 minutes, even in the face of such complex scenarios.

Through optimisation, the ripple effect of delay can be minimised. Therefore, the idling time of aircraft due to other operations being delayed will be reduced. With this approach, the increased utilisation of declared capacity can be realised while ensuring that current operations are not affected.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Rather than pursuing costly infrastructure expansions, this study focuses on enhancing the utilization of existing airport capacities, particularly in single-runway airports through the implementation of optimized scheduling strategies. The objectives were prioritized into two crucial areas: (1) optimizing the use of airside resources, such as runway and apron operations, and (2) reducing waiting times and cumulative delays while considering practical operational limitations. To facilitate this need, a bi-objective slot allocation model was developed, considering the airside resources of an airport.

The mathematical model developed incorporates flight operation timings, aircraft separation requirements, and traffic intensity limitations. To verify the model's practicality and significance in a real-world setting, Bandaranaike International Airport (BIA) was used as a case study. The model enables more effective use of current infrastructure by reorganizing underutilized resource capacities, especially during peak demand periods, rather than suggesting costly capacity expansions.

Three primary performance areas provided the framework for the evaluation: (1) the average airside resource utilization rate overall, (2) the average gate utilization in the terminal area, and (3) the delay propagation performance in the event of unexpected delays. The findings demonstrated encouraging operational improvements: BIA's average airside utilization rate increased from 44.9% to 62.7% on a typical peak day while adhering to the constraints introduced. Likewise, gate utilization increased over several hourly intervals, indicating improved terminal space administration. Beyond efficiency, increased utilization has several advantages. By offering more flight options, it enhances passenger satisfaction, optimizes existing infrastructure, and boosts airport revenue through landing fees and service charges. Additionally, it improves the airport's capacity to handle delays and draws in more airlines by offering competitive slot bidding, which supports both economic expansion and operational resilience.

Assessing the suggested model's ability to manage delay propagation in the face of actual delays was another significant objective of this research. The optimized solution continuously decreased cumulative delays, according to a comparison of the optimized and non-optimized schedules. With a p-value of 0.0022 and an average improvement of 140.80 minutes per case, a one-sample t-test applied to twelve representative delay scenarios validated the statistical significance of this reduction, offering strong evidence of the model's robustness and reliability.

In conclusion, this study provides a valuable and expandable optimization model for controlling airside capacity at airports with limited space. It demonstrates how, without undergoing physical expansion, airports can significantly increase throughput, reduce delays, and boost overall service reliability through strategic slot allocation and delay-optimized scheduling. These results highlight how crucial intelligent scheduling models are to the advancement of efficient, sustainable, and passenger-focused airport operations. This work's applicability across various airport environments may be expanded in the future by adding more complexities like airline-specific priorities, real-time operational disruptions, and environmental impacts.

5.2 Recommendations

Many parameters constrain the final throughput of the model, and key parameters have been considered in this model development. Therefore, future work should focus on other constraints such as air traffic control capacity, noise restrictions, security measures, airspace congestion, weather, and maintenance-related issues. Furthermore, it is recommended that the model be tested across airports with multiple runways and taxiways to assess its adaptability. While the model remains valid for such settings, minor modifications may be necessary to accommodate unique operational characteristics and constraints observed at different airports.

In conclusion, this research has proposed a decision-supporting slot allocation model for airports like BIA to maximize their airside resource utilizations while optimizing delay under operational conditions. The findings and recommendations presented in this thesis provide a valuable foundation for the airport authorities, policy makers, and industry stakeholders to improve slot management. And as a result, an efficient, sustainable, and competitive industry can be built for the future.

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