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Final Thesis

**Passenger-Centric Multi-Airport Seasonal
Slot Allocation:
An Optimization Model for Seasonal Slot
Allocation**

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Abstract

This thesis presents the Passenger-Centric Multi-Airport Slot Scheduling Allocation model (PC-MASSA), a novel stochastic optimization framework that integrates passenger demand into airport slot allocation. Unlike traditional models that focus mainly on airline operational constraints, PC-MASSA incorporates passenger priorities: business, frequent flyers, medical, and leisure, using a hybrid forecasting approach combining gravity models and machine learning. The model applies a two-stage optimization: a Mixed-Integer Linear Programming (MILP) formulation generates an initial solution balancing passenger satisfaction, airline efficiency, and regulatory compliance, while a heuristic refinement addresses demand uncertainty. Using flight data from the OpenSky Network and passenger statistics from Statista and European airports, PC-MASSA aims to enhance efficiency, reduce layovers, and adapt capacity dynamically, while ensuring fairness for both passengers and airlines. A case study on the Paris multi-airport system demonstrates the model's practical advantages in improving efficiency, responsiveness, and equity in slot allocation under real-world conditions.

Chapter 1

Introduction

Airports are increasingly faced with the critical challenge of balancing operational demands from airlines with evolving passenger expectations. While slot allocation has historically been governed by administrative rules and airline-centric priorities, the passenger experience has frequently been marginalized. However, passengers constitute the fundamental rationale for air transport services. Consequently, growing air traffic demand and increasing network complexity require a paradigm shift: placing passenger needs at the core of allocation decisions. This thesis addresses this imperative by proposing a novel Passenger-Centric Multi-Airport Seasonal Slot Allocation (PC-MASSA) model. This framework is designed to synchronize operational efficiency with key passenger priorities. The motivation, research questions, and central objectives delineated in this chapter form the foundational basis for the subsequent thesis structure.

1.1 Research Context and Motivation

The airport slot allocation system has long been a cornerstone of air transport management. It refers to the process by which airlines are assigned specific time slots for takeoffs and landings at congested airports, a process critical to ensuring the smooth functioning of the air transport network. Slot allocation in multi-airport systems (MASs), which involves coordination between multiple airports within a region or network, presents a unique set of challenges. This complexity stems from the need to optimize both individual airport capacities and the broader network performance, taking into account a multitude of stakeholders, including airlines, airports, regulators, and passengers.

1.1.1 The Evolution of Slot Allocation in Multi-Airport Systems

Airport slot allocation is a crucial component of demand management in congested airports. Broadly, interventions fall into two categories: economic approaches, such as congestion pricing (Oum and Zhang, 1990; Daniel, 1995; Brueckner, 2002) and slot auctions (Rassenti et al., 1982; Ball et al., 2018), and administrative approaches, predominantly schedule coordination. Despite theoretical advantages of economic methods, most busy airports outside the United States employ non-monetary, administrative scheduling approaches. As of 2019, 204 airports worldwide, accounting for 43% of global traffic, used such coordination (International Air Transport Association (IATA), 2020).

Schedule coordination is built on a process known as slot allocation. This is the seasonal assignment of specific arrival and departure times to flights. Airlines submit requests for series of flights (a minimum of five sharing the same weekday and time). However, when requests

for slots exceed an airport's available capacity, a displacement process begins. This process is governed by the Worldwide Airport Slot Guidelines (WASG), which enforce three key principles: (i) ensuring sufficient connectivity through minimum turnaround times, (ii) maintaining schedule regularity, and (iii) honoring grandfather rights, which prioritize airlines based on their historical use of a slot.

The task of slot allocation is a highly complex combinatorial problem. This complexity arises from the intricate web of interdependencies between thousands of slot requests and strict operational limits. Early optimization work by Zografos et al. (2012) focused on minimizing total schedule displacement, which is the difference between an airline's requested time and its allocated time. Their model showed potential, achieving a 14%–95% reduction in displacement compared to historical schedules at regional airports. A significant advancement came from Ribeiro et al. (2018), who developed the Priority-Based Slot Allocation Model (PSAM). This model directly incorporated the WASG's historical precedence rules and used more efficient mathematical formulations to find solutions faster. Despite these advances, conventional optimization methods struggle with the immense scale of major airports. To address this, Ribeiro et al. (2018) designed a specialized large-scale neighborhood search algorithm. This approach was capable of optimally solving Lisbon Airport's entire schedule of 200,000 annual movements within a practical timeframe of 10 hours.

Research has since expanded beyond mere displacement minimization. Contemporary models now integrate secondary objectives to create more realistic and equitable outcomes. These include respecting market preferences (Jorge et al., 2021), ensuring fairness between airlines (Jacquillat and Vaze, 2018; Zografos and Jiang, 2019), providing airlines with flexibility (Katsigiannis et al., 2021), and increasing the general acceptability of the schedule for carriers (Zografos et al., 2018, 2017). The central insight here is critical: not all schedule changes have the same impact. Therefore, models that account for this heterogeneity lead to more practical and superior solutions.

This entire challenge is formally known as the Airport Slot Scheduling Problem. Its complexity is daunting. Even a medium-sized airport must schedule more than 30,000 arrivals and departures for a single season (Ribeiro et al., 2018; Zografos et al., 2018). Creating a feasible master schedule requires balancing capacity limits, connectivity needs, and different priority classes for slots. Although total schedule displacement remains a common metric for evaluating solutions, it has a known weakness: it does not adequately reflect the operational disruption caused by displacing a recurring weekly slot Zografos et al. (2017).

Ultimately, although significant advances have been made in minimizing displacements and improving fairness, traditional slot allocation methods largely remain primarily airline- and flight-centric, overlooking critical aspects of passenger demand.

In the past, slot allocation was managed separately by each airport, with little coordination among airports in the same region. This “siloed” approach, meaning that each airport worked in isolation without sharing information or planning jointly, often created inefficiencies. For example, one airport in a multi-airport system could become overloaded with demand, while nearby airports remained underused. Over time, multi-airport systems (MASs) have gained importance as a way to reduce these imbalances and improve overall efficiency.

1.1.2 Importance of Passenger-Centric Approaches in Modern Air Transportation

A growing concern in slot allocation research is the limited focus on passenger itineraries. Traditional models emphasize flight and airline interests, which can result in suboptimal pas-

senger experiences, such as fewer viable connecting itineraries and longer connection times. To address this gap, a passenger-centric approach has emerged.

Passenger-Centric Slot Allocation (Birolini et al., 2023) shifts the focus to better align slot allocations with passenger demand patterns. A major challenge is that detailed future passenger itineraries are unknown during slot allocation, often performed months before operations. To overcome this, recent studies employ predictive modeling, leveraging historical data and machine learning to forecast passenger flows in flight networks.

On the predictive side, empirical literature is categorized into three main streams. First, discrete choice models utilize disaggregated or semi-aggregated passenger data (Cadarso et al., 2017; Lurkin et al., 2016; Lhéritier et al., 2019; Birolini et al., 2021a), incorporating schedule-related attributes (e.g., fares, aircraft types) unavailable at the time of allocation. Second, time-series models (Marazzo et al., 2010; Tsui et al., 2014; Hakim and Merkert, 2016; Jin et al., 2020) explore causal relationships between air transport and economic indicators, but lack predictive power for new itineraries. Third, gravity models, which are further enhanced to support slot allocation, offer aggregated demand estimates at airport-pair or airline-airport-pair levels, and can be innovated to predict demand without relying on schedule-specific factors that emerge post-allocation (Adler and Hashai, 2005; Wei and Hansen, 2006; Birolini et al., 2021b). This enables more passenger-aligned decision-making, balancing operational goals with passenger connectivity and satisfaction.

Furthermore, considering the severe congestion impacts globally: with 46.4% of flights in Europe delayed in 2019 and estimated worldwide delay costs exceeding \$60 billion (Gopalakrishnan and Balakrishnan, 2021), passenger-centric slot allocation becomes increasingly critical. Airport capacity expansions, while offering long-term relief, involve high costs, lengthy gestation periods, and require careful evaluation from multi-stakeholder perspectives (Winston, 1991; Gong et al., 2023). Thus, optimizing existing slot allocation to prioritize passenger needs represents a cost-effective and immediate improvement for both airlines and society.

Recent advances in slot allocation models highlight how passenger-centric considerations can be embedded into optimization frameworks. Ribeiro et al. (2018) introduced the PSAM model, a methodological foundation that not only adheres to IATA guidelines but also integrates objectives such as passenger welfare, enabling schedules that implicitly capture passenger demand. Complementing this, Zografos et al. (2018) proposed bi-objective scheduling models balancing efficiency with schedule acceptability. By introducing weighted displacement, where flight shifts are weighted by aircraft size and flight length, the model explicitly reduces the inconvenience to large groups of long-haul passengers. More recently, Katsigiannis and Zografos (2021) advanced the field by incorporating airlines' scheduling flexibility preferences through the Timing Flexibility Indicator (TFI) and coupling it with dynamic capacity constraints. This framework not only reduces slot displacements but also significantly improves passenger outcomes by aligning airport capacity allocation with demand characteristics.

The growing demand for air travel and increasingly congested airport hubs call for a paradigm shift in slot allocation strategies. Passenger-centric models represent a forward-looking approach that takes passenger preferences, travel behaviors, and needs into account during the slot allocation process.

1.2 Objectives and Research Questions

The primary objective of this thesis is to develop an enhanced airport slot allocation model that incorporates passenger-centric considerations into the traditional optimization framework. This

extended approach, referred to as Passenger-Centric MASSA (PC-MASSA), seeks to align operational decision-making with passenger connectivity, satisfaction, and demand predictability, elements often overlooked in conventional models.

The foundation of this work builds on the Multi-Airport Seasonal Slot Allocation (MASSA) model, a state-of-the-art MILP-based optimization tool designed to allocate flight slots across an entire season for a network of congested airports. MASSA addresses operational constraints such as capacity limits, coupled slot dependencies, fairness among airlines, and series-based slot requests. While MASSA has demonstrated strong performance using real-world data through computationally efficient preprocessing, it remains centered on airline and infrastructure needs.

PC-MASSA aims to fill this methodological gap by incorporating forecasted passenger demand, preferences for connection times, and flight frequency expectations into the slot allocation process. This passenger-oriented enhancement aspires to improve the responsiveness and equity of the system, particularly within the context of complex, multi-airport environments.

1.2.1 Key Research Questions Related to Efficiency, Fairness, and Scalability

The research will focus on answering the following key questions:

- **Efficiency:** How can passenger preferences be integrated into the MASSA framework to improve overall system efficiency, where efficiency is understood not only as the optimal use of airport capacity and slots, but also as enhancing the passenger experience by minimizing total travel and connection times, improving schedule reliability, and ensuring that flight frequencies better match actual demand?
- **Fairness:** How can fairness across airlines be ensured in the allocation process when incorporating passenger preferences, meaning that no airline is disproportionately advantaged or disadvantaged in terms of slot allocation, while still addressing passenger needs and maintaining competitive balance in the market?
- **Scalability:** How does the PC-MASSA model scale to larger and more complex airport networks, and can it maintain fairness and efficiency under such conditions?

1.3 Structure of the Thesis

This thesis provides an in-depth study of the development and use of the PC-MASSA model, with the aim of offering both theoretical understanding and practical guidance. It begins with a review of the literature on multi-airport systems, slot allocation models, and passenger-centric approaches. This review highlights the gaps in current methods and prepares the ground for the proposed PC-MASSA framework.

The methodology section then explains how the model is formulated, showing how passenger-centric elements are combined with traditional operational constraints. In particular, the model brings together passenger demand forecasting, flight schedules, and optimization techniques to create a more holistic approach to slot allocation.

The following chapters present computational experiments that test the model under different scenarios. These experiments compare the performance of PC-MASSA with that of traditional MASSA models, using measures such as operational efficiency, passenger satisfaction, and fairness.

The thesis ends with a summary of the main findings. It discusses the research contributions, the practical value of the model, and possible directions for future work, especially in integrating real-time data and enabling dynamic slot reallocation.

Declaration on the Use of Artificial Intelligence

While the content of this thesis is entirely my own, based on my analysis, literature review, and discussions with my supervisors, Professor Raffaele Pesenti and Dr. Andrea Gasparin, I used AI tools primarily to assist with translation and editing for formal academic American English. All final decisions, analyses, and interpretations are my own.

Chapter 2

Background and Literature Review

Slot allocation has never been a static process. It has evolved alongside the aviation industry itself. From the early rules codified in the Worldwide Airport Slot Guidelines to modern attempts at multi-airport coordination, the field reflects a constant struggle between fairness, efficiency, and regulation. At the same time, the rise of predictive analytics and demand forecasting has opened new possibilities to incorporate passenger needs into the process. By tracing this progression, the literature reveals both the achievements and blind spots of existing models. It is at this intersection, between operational tradition and passenger-driven innovation, that PC-MASSA is situated. The next step, then is to translate this gap into a precise formulation of the problem.

2.1 Initial Slot Allocation (ISA) Procedure

The initial slot allocation (ISA) procedure in our model is based on six principal rules defined in the International Air Transport Association (IATA) (2023). At its core, ISA follows two guiding principles. First, slots with historical precedence, those regularly used by the same airline in past seasons, are given the highest priority. Second, once these are allocated, the remaining available slots are distributed in a way that maximizes the number of satisfied requests.

High-priority slots, commonly referred to as historic slots, are identified through evidence of prior use. According to the Worldwide Airport Slot Guidelines (International Air Transport Association (IATA), 2022), an airline that has operated at least 80% of the slots in a particular series during the equivalent season of the previous year, whether winter or summer, is entitled to retain those slots in the following season. This rule is designed to reward consistent utilization and to ensure continuity in scheduling practices. Within the category of historic slots, two distinct subgroups can be identified. The first subgroup is known as Unchanged Historic Slots (HU). These are slots that the airline requests without any substantial modification compared to the previous season. In practice, this means that the operational time of the slot remains the same, with only minor, non-disruptive changes permitted, such as a simple adjustment to the flight number. The second subgroup, referred to as Historic Slots with Requested Changes (HRC), applies when an airline seeks to alter parameters that affect slot coordination, for example by shifting the scheduled time. In such cases, the coordination authorities encourage airlines to indicate an acceptable range of flexibility, which is expressed through standardized industry codes. This mechanism is important because it allows coordinators to consider alternatives while still respecting the operational needs of the airline.

The allocation procedure begins with the HU slots. These are prioritized and granted first, thereby safeguarding the rights of airlines that wish to continue operating according to the

same schedule as in previous seasons. Once these slots are secured, the process moves to the formation of a slot pool. This pool consists of all HRCs that cannot immediately be accommodated, together with non-historic requests submitted by airlines seeking new opportunities. The slot pool, therefore, functions as the central space in which competition between different applicants is managed.

When an HRC request cannot be matched within the flexibility range proposed by the airline, the coordinator reassigns the slot to its original historic time. This rule, referred to as the reallocation of non-flexible HRCs, ensures that an airline does not lose its entitlement entirely simply because its requested changes cannot be accommodated. Instead, the airline retains access to the slot in its previously established form.

Within the slot pool, non-historic requests are further distinguished according to the profile of the applying airline. A crucial distinction is made between new entrants and non-new entrants. New entrants are defined as airlines that operate fewer than seven slots on the day in question. This group is granted a privileged position, as their access to the system supports competition and encourages diversity in airline services. Non-new entrants include all other airlines that already operate above this threshold. By differentiating between these two groups, the allocation process aims to balance stability with market access for newcomers.

Finally, the distribution of slots within the pool follows a proportional rule. In principle, 50% of the available slots are reserved for new entrants, while the remaining 50% are allocated to other applicants. However, this rule is not absolute. It may be adapted if the volume of requests requires a different balance. The purpose of this arrangement is to create a fair distribution mechanism that both protects established operators and creates room for competition from new airlines.

2.2 Multi-Airport Seasonal Slot Allocation (MASSA)

The growing interconnection and congestion in global air transportation have led to increasingly complex air traffic networks, particularly in regions where multiple coordinated airports operate within overlapping airspace. Traditional slot allocation mechanisms, which focus on individual airports, often fail to address the systemic interactions and dependencies present in such multi-airport environments. This has prompted the development of models aimed at optimizing slot allocation across airport networks rather than in isolation (Fleurquin et al., 2013).

The concept of Multi-Airport Seasonal Slot Allocation (MASSA) refers to a family of optimization models that coordinate the assignment of slots across several Level 3 airports within a given scheduling season. In practice, one of the most common ways of implementing MASSA is through a mixed-integer linear programming (MILP) formulation. This approach extends the standard allocation rules applied at individual airports by incorporating constraints that span across airports and by taking into account the preferences of airlines. The formulation is consistent with the principles outlined in the Worldwide Airport Slot Guidelines (WASG) and follows a clear prioritization strategy: it first minimizes the number of slot series that remain unallocated and then reduces the total time displacement from the schedules originally requested by airlines. The lexicographic order of these objectives reflects a deliberate choice to treat denied slots as more costly than timing adjustments, which is in line with the fairness standards already recognized in the aviation industry (Pesenti et al.).

What sets MASSA apart from simpler allocation procedures is its ability to capture the dependencies that naturally arise between different types of slots. In addition to managing independent slot requests, the model is designed to handle dependent slot series. A common

example is the case of round-trip flights, where slots are coupled by turnaround requirements and block-time constraints between two airports. The framework also accommodates aircraft rotation, meaning that the sequence of inbound and outbound flights has to respect operational feasibility. These features ensure that the optimization process is not limited to abstract scheduling rules, but instead reflects the realities faced by airlines when planning their networks. By integrating these practical considerations, MASSA provides results that are not only mathematically sound but also directly applicable in real-world airline operations.

In comparison to this deterministic formulation, other approaches in the literature explore different dimensions of the problem. Keskin and Zografos (2023), for instance, proposed a bi-objective model that balances schedule displacement against equity in slot distribution across the network. Their model uses centrality metrics, such as the IATA Connectivity Index and betweenness centrality to reflect the strategic role of each airport in facilitating network flow.

Researchers have also developed stochastic models to deal with uncertainty in flight durations and airspace capacity. These approaches use chance-constrained programming to make sure that slot assignments remain workable even when conditions vary (Lohatepanont and Barnhart, 2004). In addition, a range of metaheuristic methods, such as Tabu Search, Evolutionary Algorithms, and Ant Colony Optimization, have become popular for large-scale scheduling problems such as airport slot allocation. Their appeal lies in the ability to search efficiently through very large and complex solution spaces, especially in cases where exact optimization methods are difficult to apply (Dorigo and Blum, 2005; Glover, 1989).

The MASSA framework stands out because it brings together regulatory rules, airline requirements, and inter-airport coordination in a single optimization model. It has been tested on realistic datasets from the OpenSky Network, which confirmed its effectiveness in generating feasible and efficient slot allocations under conditions of congestion. By taking into account the structural links between airports, MASSA supports the shift from isolated scheduling practices toward a more connected and efficient form of network-level planning.

2.3 Passenger-Centric Optimization in Air Traffic

Passenger-centric slot allocation relies not only on optimization frameworks but also on accurate representations of passenger demand. Because scheduling and allocation decisions must often be made months before operations take place, detailed passenger itinerary data is typically unavailable at the time of decision-making. This creates a critical need for predictive models that approximate future travel patterns and ensure that slot allocation aligns with passenger preferences and connectivity needs. In this section, we review the main modeling approaches used to forecast demand: discrete choice, time-series, and gravity-based models, and discuss how their integration with predictive analytics supports more passenger-oriented allocation strategies.

2.3.1 Role of Demand Modeling and Predictive Analytics

Passenger-centric optimization places passenger needs at the core of scheduling and slot allocation decisions. Several modeling approaches have emerged to forecast travel demand in this context:

- 1. Discrete Choice Models.** These models analyze the individual decisions of travelers when faced with a set of discrete alternatives, for example, choosing between different airlines, departure times, or airports. The term discrete refers to the fact that passengers make choices

among a finite set of distinct options (e.g., “flight A” vs. “flight B”), rather than selecting a continuous value. Such models typically use data on fares, schedules, travel times, and service quality to estimate the probability that a passenger chooses one option over another. While they provide behaviorally rich insights into passenger preferences, they require detailed microdata (such as ticket-level bookings or surveys), which is often only available after schedules have been published. This limits their direct applicability to pre-allocation processes. Although such data sources are detailed and help to analysis of customer behavior, is usually available only after scheduling, which limits their direct application to pre-allocation processes (Cadarso et al., 2017; Birolini et al., 2021b).

2. Time-Series Models: These capture long-term trends by correlating air travel with macroeconomic indicators (e.g., GDP or tourism flows) (Marazzo et al., 2010; Jin et al., 2020). However, they offer limited predictive power for emerging or unserved markets, restricting their utility in dynamic allocation contexts.

3. Gravity Models with Machine Learning Enhancements: Gravity models are inspired by Newton’s law of gravitation: the flow of passengers between two airports is assumed to be positively related to the “mass” of the origin and destination (e.g., population size, GDP, or total airport traffic) and negatively related to the “distance” between them (e.g., travel time, cost, or geographical distance). In air transport, this means that larger, more economically active cities attract more passengers, while greater distances or higher costs reduce demand. Recent enhancements, such as in Birolini et al. (2022), apply machine learning to capture nonlinear relationships and improve forecasting even with limited or noisy data. These enhancements allow the model to capture interactions between variables, for instance, how seasonality of tourism interacts with economic activity to influence demand. By leveraging historical aggregate data, this hybrid approach can generate robust forecasts even when detailed passenger-level information is missing. Because it balances explanatory detail with relatively modest data requirements, it is particularly valuable in the early stages of slot planning, when coordinators need reliable demand estimates but cannot rely on fine-grained passenger data.

In addition to forecasting demand, analytics can also take into account operational factors such as passenger connections and aircraft turnaround times. Research on disruption management (Bratu and Barnhart, 2006; Marla et al., 2017) and delay reduction (Jacquillat, 2020) demonstrates that giving priority to passenger outcomes, rather than focusing only on aircraft-related measures, can lead to substantial decreases in delays without increasing operating costs.

Table 2.1. Required Data Inputs for Predictive Demand Models in Air Transport

Model Type	Required Data Inputs	Typical Sources & Challenges
Discrete Choice Models	Individual itinerary data, flight attributes (schedule, fare, aircraft type), traveler profiles	Airline internal data, booking systems (GDS); Privacy and accessibility issues
Time-Series Models	Historical aggregated demand, macroeconomic indicators (GDP, tourism)	National statistics, IATA, ICAO, World Bank; Low granularity, delayed publication
Gravity + ML Models	Route-level traffic, connectivity indices, socioeconomic factors, past flight frequency	OpenSky, Eurocontrol, OAG, IATA; Complex integration, missing features

Although these models offer valuable insights, they often depend on data that is fragmented or difficult to obtain. Discrete choice models need detailed booking records, which are usually proprietary and raise privacy concerns. Time-series models rely on national-level aggregates, which often lack sufficient detail at the airport or route level. Gravity-based models require combining traffic, connectivity, and service data from different sources, which can create technical and compatibility challenges.

When applied to slot allocation, further difficulties emerge. These include incomplete itinerary data available at the planning stage, seasonal interdependencies imposed by the Worldwide Airport Slot Guidelines (WASG), and the high computational burden of solving large-scale nonlinear problems. To address such issues, Birolini et al. (2022) propose a tailored mixed-integer nonlinear programming model with custom solution algorithms, making their method suitable for real-world slot scheduling.

In this study, we therefore focus on historical passenger traffic data at the airport level, using monthly observations. This allows us to capture seasonal fluctuations and overall demand trends. Our approach can be understood as a time-series–based demand estimation method, but with the advantage that it relies on readily available, non-proprietary, and consistently reported data. While it does not provide the fine detail of itinerary-level models, it offers a practical and transparent basis for estimating passenger demand in large-scale slot allocation problems.

2.3.2 Comparative Analysis with Traditional Slot Allocation Methods

Traditional slot allocation methods, such as those governed by the Worldwide Airport Slot Guidelines (WASG), are built on principles of administrative coordination and historical precedence. These methods emphasize stability and fairness among airlines but tend to overlook evolving passenger needs and real-time demand dynamics. Slots are typically assigned based on past usage (grandfather rights), with minimal incorporation of detailed passenger or demand data.

In contrast, passenger-focused optimization places priority on maximizing traveler satisfaction and improving the efficiency of the entire air transport network. In this context, efficiency refers not only to the number of flights operated but also to the quality of passenger flows: stronger connectivity between flights, fewer missed connections, and a closer alignment of slot allocation with actual travel demand. Rather than measuring success purely in aircraft movements, this approach evaluates how well the system moves passengers through the network. To achieve this, it relies on predictive analytics, demand modeling, and advanced optimization methods that direct slots to where they create the greatest benefit, as reducing delays, enhancing connections, and matching capacity more effectively to passenger needs.

Table 2.2. Comparison of Traditional vs. Passenger-Centric Slot Allocation Approaches

Criteria	Traditional Slot Allocation (e.g., WASG)	Passenger-Centric Optimization
Main Objective	Ensure stability and manage congestion at airports	Maximize passenger satisfaction and network-wide efficiency
Basis for Allocation	Historical precedence (grandfather rights), administrative decisions	Forecasted demand, predicted passenger flows, and network performance
Flexibility	Low; not easily responsive to sudden changes or new demand patterns	High; adaptive to real-time data, seasonal trends, and demand shifts
Use of Data	Limited to airline schedules; minimal use of passenger or itinerary-level data	Integrates passenger-level data, connectivity, and delay impact
Optimization Criteria	Maximize slot utilization and fairness across airlines	Minimize total passenger delays and optimize route/service alignment
Decision-Making Tools	Administrative rules, historical usage analysis	Machine learning models, mixed-integer programming, predictive analytics
Consideration of Passengers	Indirect; passengers are considered through airline operations	Direct; passenger experience and connectivity are central to decision-making
Handling of Disruptions	Rigid; not well-equipped to handle dynamic or large-scale disruptions	Adaptive; designed to respond to disruptions and demand variability through predictive tools

2.4 Identified Gaps and Research Contributions

2.4.1 Previous Related Work Comparison

In recent years, various models have been developed to address the complex problem of airport slot allocation, with increasing attention to capacity, flexibility, fairness, and coordination across multi-airport systems. This subsection compares several state-of-the-art models in terms of the addressed problem dimensions and highlights the positioning of the proposed PC-MASSA model.

Pellegrini et al. (2017) introduced SOSTA, a model focused on the simultaneous optimization of slot allocation across a full season. It takes into account series of slots and fairness, as well as operational constraints such as turnaround times and coupled slots. However, it does not extend to multiple airports nor to airline-driven flexibility or dynamic capacity.

The Timing Flexibility Indicator Model (TFIM) introduced by Katsigiannis and Zografos (2021) integrates flexibility and capacity constraints, offering a strong operational-level response. Still, it is not designed for full-season strategic allocation, nor does it embed fairness mechanisms or multi-airport coordination.

Melder et al. (2025) developed a seasonal flexibility approach, addressing blocking effects and increasing system responsiveness. However, it lacks fairness integration, does not differentiate by airport system, and assumes static operational parameters.

Table 2.4. Synoptic comparison of existing slot allocation models: advantages, limitations, and applicability

Model / Paper	Advantages	Limitations	Applicability
SOSTA (Pellegrini et al., 2017)	Captures fairness and turnaround constraints. Structured seasonal optimisation.	Single-airport only. No flexibility or dynamic adjustment.	Useful for seasonal allocation where fairness is important, but no multi-airport coordination is needed.
TFIM (Katsigiannis and Zografos, 2021)	Strong integration of timing flexibility and capacity constraints. Operational-level accuracy.	Not strategic/seasonal. No fairness or multi-airport scope.	Operational planning in congested airports with timing flexibility requirements.
Seasonal Flexibility (Melder et al., 2025)	Addresses blocking effects and responsiveness. Captures flexibility across a season.	Limited fairness integration. Static operational assumptions.	Seasonal planning where responsiveness matters more than fairness or dynamics.
MAS (Wang et al., 2023)	Covers multi-airport systems and airspace capacity. Accounts for flying-time uncertainty.	Not strategic/seasonal. No fairness or slot-series mechanisms.	System-level coordination across airports with strong operational constraints.
ASA (Katsigiannis and Zografos, 2023)	Integrates multi-stakeholder preferences. Models delay sensitivities.	Focus on operational delays. No multi-airport or seasonal planning.	Balancing stakeholder preferences and delay sensitivity at the operational level.
TOSAM (Li and Liu, 2023)	Fairness-focused in MAS systems. Highlights equity.	No airline-driven flexibility. Not designed for seasonal allocation.	When fairness between airlines is top priority, with less emphasis on flexibility or dynamics.
MASSA (Pesenti et al.)	Integrates fairness, flexibility, and operational constraints. Validated with real-world data.	No dynamic rescheduling. Limited passenger-centric integration.	Strategic seasonal planning across congested multi-airport networks.
PC-MASSA (Proposed)	Extends MASSA with passenger-centric objectives. Incorporates dynamic rescheduling and fairness at multiple levels. Aligned with WASG rules.	Needs richer passenger-level data for full validation. Computationally heavy in very large cases.	Seasonal allocation in multi-airport systems with explicit passenger-centric considerations and regulatory alignment.

Table 2.4 provides a comparative overview of existing slot allocation models, summarizing their key contributions and limitations, and highlighting the specific research gap that this thesis addresses. Early frameworks, such as SOSTA and TFIM, offer powerful optimization tools for ensuring fairness and managing operational timing. However, their applicability is mostly confined to individual airports or short-term scheduling horizons, limiting their usefulness in broader network contexts.

Other models, including Seasonal Flexibility and ASA, focus on improving responsiveness or incorporating the preferences of multiple stakeholders. While these approaches add valuable operational insights, they often overlook the importance of strategic coordination across several airports, which is essential for efficiently managing multi-airport systems. More recent models, such as MAS and TOSAM, extend the analysis to multi-airport environments and emphasize fairness. Nevertheless, they generally fail to fully integrate seasonal variations or take passenger-level impacts into account, leaving an important dimension of real-world operations unaddressed.

The MASSA model represents a significant advancement by combining fairness, flexibility, and operational realism within multi-airport contexts. Yet, even MASSA does not fully incorporate passenger behavior or support dynamic rescheduling in response to evolving conditions. Building on these developments, the proposed PC-MASSA framework introduces passenger-centric objectives while remaining fully aligned with regulatory guidelines. By doing so, it offers a more comprehensive and scalable approach to slot allocation, capable of addressing the complexities of modern, multi-airport systems.

2.4.2 Contribution of This Thesis to Bridging These Gaps

This thesis addresses the limitations of previous slot allocation models through a series of key contributions that collectively advance both operational and passenger-focused perspectives. First, the proposed framework introduces a *passenger-centric objective*, explicitly integrating measures of traveler welfare into the optimization process. These include minimizing total travel time, reducing layovers, and aligning allocated slots with passengers' preferred departure times, thereby ensuring that scheduling decisions reflect the needs of travelers rather than only aircraft operations.

Another important contribution lies in the integration of *hybrid demand forecasting* techniques. By combining traditional gravity models with machine learning enhancements, the model can forecast demand at the passenger-route level with greater accuracy and adaptivity. This allows slot allocation to be both data-driven and responsive to evolving travel patterns. Complementing this, the model incorporates *group-specific passenger modeling*, which segments travelers into distinct demand profiles. Such segmentation enables the allocation process to be tailored to different types of passengers, capturing the diversity of travel behaviors and preferences.

Building upon the established MASSA framework, this research extends its applicability to multi-airport networks, optimizing not only operational performance but also passenger-related outcomes. The model further addresses fairness considerations, ensuring equitable treatment not only among different airlines but also across time periods and airports. To achieve these goals in practice, the framework relies on a *feasible and scalable algorithm*, implemented through a mixed-integer nonlinear programming (MINLP) formulation supported by custom heuristics and decomposition techniques. This combination balances computational tractability with practical applicability in real-world scheduling environments.

Finally, the thesis adopts a *holistic evaluation approach*, assessing slot allocation outcomes from both operational and passenger-centric perspectives. By considering efficiency alongside the quality of passenger experience, the model provides a comprehensive basis for understanding and improving the performance of multi-airport slot allocation systems.

Through these contributions, the research lays a foundation for a more responsive, equitable, and demand-aware airport slot allocation strategy, aligning the operational realities of airports with the evolving expectations of air travelers.

While traditional slot allocation has been effective in maintaining order at busy airports, its limitations are increasingly evident in today's dynamic aviation landscape. These methods prioritize legacy carriers and existing patterns, which can lead to inefficiencies, underutilized slots, and poor responsiveness to new travel needs.

Passenger-centric optimization represents a modern and agile alternative, incorporating data-driven methodologies that place traveler experience at the forefront. This approach allows planners to anticipate demand shifts and optimize scheduling with passengers in mind, leading to better service alignment and reduced travel disruptions.

Chapter 3

Problem Statement and Mathematical Formulation

This chapter formulates the airport slot allocation problem with accent on passenger-centric features. It defines the sets, parameters, and decision variables, introduces new components for passenger categories and demand forecasting, and specifies the objective function and constraints. The formulation balances operational efficiency with passenger service quality, providing a flexible foundation for optimizing slot allocation under varying demand and capacity conditions. With the problem mathematically defined, attention turns to the datasets that support the model, ensuring the formulation can be tested both in controlled and real-world contexts.

3.1 Problem Definition

Traditional approaches to airport slot allocation primarily focus on optimizing operational factors such as capacity utilization, airline scheduling preferences, and coordination across multiple airports. However, with the increasing emphasis on customer satisfaction in the aviation sector, these conventional models often fail to account for the dynamic and complex nature of passenger demand.

Frameworks like the Multi-Airport Seasonal Slot Allocation (MASSA) model are designed to maximize operational efficiency but typically prioritize airline and airport-centric objectives. As a result, they often overlook the significant influence of passenger preferences on overall system performance.

In today's context, passengers increasingly value shorter travel times, fewer layovers, and access to direct flight options. This shift in preference necessitates an evolution in slot allocation models, moving beyond purely operational constraints to incorporate demand forecasting, behavioral segmentation, and real-time passenger flow data.

Despite growing academic interest in passenger-centric slot allocation, current models remain limited in several key areas:

- Insufficient integration of passenger behavioral preferences and satisfaction metrics
- Limited use of real-time or predictive demand data
- Weak balancing mechanisms between passenger convenience and operational feasibility
- Lack of flexibility in responding to seasonal variability and market dynamics

This thesis aims to bridge this gap by developing a passenger-centric slot allocation model that enhances the MASSA framework. The proposed model incorporates:

- Forecasted passenger demand across routes and time slots
- Group-specific preferences such as preferred flight times and connection sensitivity
- Operational constraints such as slot capacity, runway availability, and turnaround time

The objective is to simultaneously improve airport operational efficiency and passenger experience by minimizing total travel times, reducing layovers, improving direct flight availability, and ensuring equitable access to preferred departure times for various passenger groups.

By blending operational constraints with a comprehensive understanding of passenger needs, this research proposes a more holistic and adaptive solution for airport slot allocation that aligns with the evolving demands of modern air travel.

3.2 Notation and Definitions

In this section, we introduce the key terms, symbols, and concepts used in the proposed model.

Sets

- A : Set of airports.
- D : Set of considered days of a season.
- U : Set of airlines (airspace users).
- $N_{a,d}, \neg N_{a,d}$: Sets of new-entrant and non-new-entrant airlines, respectively, at airport $a \in A$ on day $d \in D$.
- A_d^N : Set of airports where the number of new-entrants exceeds 50% on day $d \in D$.
- $A_d^{\neg N}$: Set of airports where the number of non-new-entrants exceeds 50% on day $d \in D$.
- T : Type of capacity (total, departure, or arrival movement).
- I : Set of time intervals associated with interval capacity constraints.
- H : Set of time intervals associated with hourly sequential capacity constraints.
- HI : Set of time intervals associated with hourly rolling capacity constraints.
- $\mathcal{R}$: Set of series requests.
- $R^{HU} \subseteq \mathcal{R}$: Subset of series requests referring to historic slots requested as unchanged.
- $R_{i,d,a}^{HU} \subseteq \mathcal{R}, R_{h,d,a,\tau}^{HU} \subseteq \mathcal{R}, R_{hi,d,a,\tau}^{HU} \subseteq \mathcal{R}$: Subset of historic slot requests that are unchanged at airport $a \in A$, on day $d \in D$, including slot interval in respective time intervals $i \in I$, $h \in H$, $hi \in HI$. For hourly capacity constraints, slots are also characterized by the type of movement $\tau \in T$.
- $R \subseteq \mathcal{R}$: Set of series requests that are not historic unchanged (HU); they represent the series included in the slot pool.

- $R^{HRC} \subseteq R$: Subset of series requests referring to historic slots with requests for changes for the incoming season.
- $R^c \subseteq R$: Subset of series requests by airline $u \subseteq U$.
- $R^c \subseteq R \times R$: Set of coupled series requests: pairs (r, r') , where r is a series of departure slots and r' is the relative series of successive arrival slots operated by the same aircraft on the same day.
- $R_c^u \subseteq R^c$: Subset of coupled series requests by airline $u \in U$.
- $R^T \subseteq R \times R \times D$: Set of tuples representing the request for minimum turnaround between series r and r' on day d . Here, r is the arrival series, and r' is the corresponding departure series of the same aircraft.
- $D_r \subseteq D$: Subset of the days in D relative to the series $r \in R$.
- $D_{(r,r')} \subseteq D$: Subset of the days in D relative to the coupled series $(r, r') \in R^c$.
- S : Set of all slot intervals (including all airports and all days).
- $S_i, S_{h,\tau}, S_{hi,\tau} \subseteq S$: Subset of slot intervals included respectively in time intervals $i \in I$, $h \in H$, $hi \in HI$. For hourly capacity constraints, slot intervals are also characterized by the type of movement $\tau \in T$.
- $S_r \subseteq S$: Subset of slot intervals to which the slot requests of a series $r \subseteq R$ can be allocated within a given allowed maximum forward and backward displacement. If $r \subseteq R^{HRC}$, S_r also includes the original historic time.

To incorporate passenger-centric considerations into the Multi-Airport Seasonal Slot Allocation (MASSA) framework, we introduce the following additional sets:

Passenger-Related Sets

- P : Set of all passengers.
- $B \subseteq P$: Subset of business travelers.
- $F \subseteq P$: Subset of frequent flyers.
- $M \subseteq P$: Subset of medical passengers.
- $L \subseteq P$: Subset of leisure passengers.

Demand and Capacity-Based Sets

- $\hat{D} \subseteq D$: Set of peak-demand days where passenger demand significantly exceeds the average.
- $\hat{A} \subseteq A$: Set of major hub airports with high passenger traffic.
- $\hat{S} \subseteq S$: Set of slot intervals with high passenger load factors.

Priority and Disruption Management Sets

- $R_p \subseteq R$: Subset of requests serving high-priority passengers (e.g., business, medical).

- $\hat{R} \subseteq R$: Subset of requests subject to rerouting due to limited availability or disruptions.
- $Z \subseteq R \times R \times D$: Set of alternative slot allocations in case of disruptions.

These sets facilitate a more passenger-centric allocation strategy, improving fairness, accessibility, and dynamic response to demand fluctuations.

Parameters

- $C_{i,d,a}^I$: Capacity of interval $i \in I$ on day $d \in D$ at airport $a \in A$.
- $C_{h,d,a,\tau}^H$: Capacity of interval $h \in H$ on day $d \in D$ at airport $a \in A$ of type $\tau \in T$.
- $C_{hi,d,a,\tau}^{HI}$: Capacity of interval $hi \in HI$ on day $d \in D$ at airport $a \in A$ of type $\tau \in T$.
- t_s : Initial time of the slot interval $s \in S$.
- $\hat{t}_r$: Requested slot time for the movements of series $r \in R$.
- d_r^0 : Initial day of requested series $r \in R$.
- s_r^h : Slot interval referring to the historic time of requested series $r \in R^{HRC}$.
- fd_r : Maximum forward displacement accepted for the series $r \in R$.
- bd_r : Maximum backward displacement accepted for the series $r \in R$.
- $bt_{r,r'}$: Requested block time for the coupled series $(r, r') \in R_c$.
- $\overline{bt}_{r,r'}$: Maximum allowed block time for the coupled series $(r, r') \in R_c$.
- $\underline{bt}_{r,r'}$: Minimum allowed block time for the coupled series $(r, r') \in R_c$.
- $mt_{(r,r')}$: Minimum turnaround time requested for series $(r, r') \in R_c$.
- MC_r : Missed allocation cost of series $r \in R$.
- $DC_{r,d,s}$: Displacement cost coefficient for allocating the slot request of series $r \in R$ to slot interval $s \in S_{r,d}$ on day $d \in D_r$.
- $BC_{(r,r'),d}$: Cost coefficient for the deviations from the requested block time $bt_{r,r'}$ on the day $d \in D_r$.
- $P_{p,d,a}$: Passenger demand at airport a on day d for category p .
- FC_r : Fairness coefficient for slot distribution.
- PC_p : Passenger priority coefficient.
- $DC_{r,d}$: Passenger disruption cost (layovers, rerouting).

3.3 Decision Variables

$$y_r \begin{cases} 1, & \text{if the slots for series } r \text{ are not allocated} \\ 0, & \text{otherwise} \end{cases}, \quad \forall r \in R$$

$$x_{r,d,s} \begin{cases} 1, & \text{if a slot of series } r \text{ is allocated to slot interval } s \text{ on day } d \\ 0, & \text{otherwise} \end{cases}, \quad \forall r \in R, \forall s \in S_r, \forall d \in D$$

$\bar{z}_{(r,r'),d}$ Forward deviation from the requested block time $bt_{r,r'}$ for coupled series $(r, r') \in R^{HRC}$ on day $d \in D$.

$\underline{z}_{(r,r'),d}$ Backward deviation from the requested block time $bt_{r,r'}$ for coupled series $(r, r') \in R^{HRC}$ on day $d \in D$.

$$f_p \begin{cases} 1, & \text{if passenger category } p \text{ is prioritized in allocation} \\ 0, & \text{otherwise} \end{cases}, \quad \forall p \in P$$

$$d_{p,r,d} \begin{cases} 1, & \text{if passenger disruptions (layovers, rerouting) occur for category } p \text{ in series } r \text{ on day } d \\ 0, & \text{otherwise} \end{cases}, \quad \forall p \in P, \forall r \in R, \forall d \in D$$

$pm_{a,d,h}$ Number of passengers at airport $a \in A$ on day $d \in D$ and hour $h \in H$ who were scheduled but not accommodated (missed) due to slot limitations.

$sl_{a,d,h}$ Non-negative slack variable representing unused capacity or unfulfilled demand at airport a on day d and hour h .

The additional decision variables $pm_{a,d,h}$ and $sl_{a,d,h}$ were introduced to capture passenger-level performance metrics and model flexibility in handling demand–capacity mismatches. Specifically:

- $pm_{a,d,h}$ quantifies the number of passengers who could not be allocated to available slots, enabling direct measurement of service shortfalls and passenger impact.
- $sl_{a,d,h}$ measures the deviation from full utilization of available slot capacity, providing a mechanism to evaluate operational inefficiencies and potential system resilience under changing conditions.

These additions improve the model's capability to evaluate not only operational feasibility but also passenger service quality, especially under disrupted or high-demand scenarios.

Passenger Demand Estimation In the updated model, passenger demand is estimated at an *hourly* resolution to better capture the temporal dynamics of airport operations and flight scheduling. Instead of assigning fixed daily totals per passenger category, the new approach distributes passengers throughout the day based on an empirically inspired time-of-day profile.

The estimation process begins by calculating the *total number of passengers per day* at each airport. This value is derived from:

$$\text{TotalPaxPerDay} = \text{FlightsPerDay} \times \text{AveragePaxPerFlight}$$

where:

- FlightsPerDay is the total number of scheduled flights departing from the airport in a day
- AveragePaxPerFlight = 130 passengers, a value obtained from aggregated 2019 OpenSky Network statistics. This average reflects typical narrow-body and regional jet configurations prevalent in short- to medium-haul European operations. The figure is statistically representative of actual operational patterns, providing a realistic baseline for model calibration.

Hourly Distribution. To distribute the daily total across the 24 hours of the day, the model applies a cosine-based distribution function:

$$v_h = \cos\left(-\pi + \frac{2h\pi}{24}\right) + 1.1, \quad h \in \{0, 1, \dots, 23\}$$

The values v_h are then normalized so that $\sum_{h=0}^{23} v_h = 1$. This results in a set of hourly weights $\hat{v}_h$ that describe the relative passenger demand in each hour. The cosine shape approximates typical daily traffic patterns observed in aviation, with peaks in the early morning and late afternoon, and lower demand during night hours.

Final Hourly Passenger Demand. Passenger demand per hour is computed as:

$$P_{a,d,h} = \text{TotalPaxPerDay}_{a,d} \times \hat{v}_h$$

for each airport $a \in A$, day $d \in D$, and hour $h \in H$.

Rationale for Hourly Modeling. This shift from daily aggregate passenger demand to hourly resolution provides several advantages:

- It enables the model to better simulate slot allocation pressures at peak times.
- It reflects real-world operational constraints, where congestion is highly time-dependent.
- It improves the accuracy of passenger impact metrics, especially when disruptions occur.

By grounding the average load factor in real-world statistics Schafer et al. (2019) and applying a realistic time-of-day demand profile, the model achieves a closer alignment with observed airport traffic patterns, enhancing both the credibility and applicability of the simulation results.

3.4 Capacity Processed Variables

- $c_{i,d,a}^I \in \mathbb{N}$: Spare capacity of interval $i \in I$ of day $d \in D$ at airport $a \in A$ after the allocation of the HU slots.
- $c_{h,d,a,\tau}^H \in \mathbb{N}$: Spare capacity of interval $h \in H$ of day $d \in D$ at airport $a \in A$ of type $\tau \in T$ after the allocation of the HU slots.
- $c_{hi,d,a,\tau}^{HI} \in \mathbb{N}$: Spare capacity of interval $h_i \in HI$ of day $d \in D$ at airport $a \in A$ of type $\tau \in T$ after the allocation of the HU slots.
- This set of variables— $c_{i,d,a}^I$, $c_{h,d,a,\tau}^H$, and $c_{hi,d,a,\tau}^{HI}$ —represents the raw remaining capacity at various time intervals, days, and airports after HU slot allocation. These are used in the traditional MASSA-like setting where passenger demand is not explicitly modeled.

Calculation of Capacity Processed Variables

To compute the spare capacity available at various levels (interval, horizon, and hybrid intervals) after assigning the unchanged historic (HU) slots, we define two groups of capacity variables:

$$c_{i,d,a}^I = C_{i,d,a}^I - |R_{i,d,a}^{HU}|, \quad \forall i \in I, \forall a \in A, \forall d \in D \quad (3.1)$$

$$c_{h,d,a,\tau}^H = C_{h,d,a,\tau}^H - |R_{h,d,a,\tau}^{HU}|, \quad \forall h \in H, \forall a \in A, \forall d \in D, \forall \tau \in T \quad (3.2)$$

$$c_{hi,d,a,\tau}^{HI} = C_{hi,d,a,\tau}^{HI} - |R_{hi,d,a,\tau}^{HU}|, \quad \forall hi \in HI, \forall a \in A, \forall d \in D, \forall \tau \in T \quad (3.3)$$

3.5 Objective Function

The optimization model is formulated as a mixed-integer linear program (MILP) and implemented in PuLP. The objective is to minimize the total operational cost while incorporating penalties and rewards that reflect the key trade-offs of the airport slot allocation process.

$$\begin{aligned}
 \min \quad & \underbrace{\sum_{r \in R} MC_r \cdot y_r}_{(1) \text{ Missed Allocation Penalty}} + \underbrace{\sum_{r \in R} \sum_{d \in D_r} \sum_{s \in S_r} DC_{r,d,s} \cdot x_{r,d,s}}_{(2) \text{ Displacement Cost}} \\
 & + \underbrace{\sum_{(r,r') \in R^{HRC}} \sum_{d \in D_r} BC_{r,r',d} \cdot (\bar{z}_{r,r',d} + \underline{z}_{r,r',d})}_{(3) \text{ Block-Time Deviation Penalty}} \\
 & + \underbrace{p_{dist} \cdot \sum_{(p,r,d) \in \mathcal{D}\mathcal{R}} d_{p,r,d}}_{(4) \text{ Passenger Disruption Penalty}} \\
 & + \underbrace{p_{ud} \cdot \sum_{r \in R} \sum_{d \in D_r} \text{one_sv}_{r,d}}_{(5) \text{ Unmet Demand Penalty}} \\
 & + \underbrace{\sum_{a \in A} \sum_{d \in D} \sum_{h \in H} \text{pm}_{a,d,h}}_{(6) \text{ Missed Passenger Penalty}} \\
 & + \underbrace{p_{sl} \cdot \sum_{a \in A} \sum_{d \in D} \sum_{h \in H} \text{sl}_{a,d,h}}_{(7) \text{ Slack Penalty}} \\
 & + \underbrace{p_{hrc} \cdot \sum_{r \in R^{HRC}} z_r}_{(8) \text{ Coupling Penalty}}
 \end{aligned}$$

Term Descriptions

1. **Missed Allocation Penalty** (MC_r, y_r)

Penalizes the complete non-allocation of a slot request series r . If a series is not allocated any slots, the binary variable $y_r = 1$.

2. **Displacement Cost** ($DC_{r,d,s}, x_{r,d,s}$)

Penalizes deviation from the requested slot time to the assigned time, capturing the cost of operational adjustments.

3. **Block-Time Deviation Penalty** ($BC_{r,r',d}$)
Applies to coupled series $(r, r') \in R^{HRC}$ where deviations from expected block times can disrupt turnarounds and downstream scheduling.
4. **Passenger Disruption Penalty** ($p_{dist} = 10,000, d_{p,r,d}$)
Assigns a high cost to passenger re-routing, extended layovers, or missed connections, scaled by the disruption variable $d_{p,r,d}$.
5. **Unmet Demand / Slot Violation Penalty** ($p_{ud} = 500, one_sv_{r,d}$)
Penalizes violations where only one slot is assigned to a multi-leg service (e.g., an out-bound without a corresponding return).
6. **Penalty for Missed Passenger Allocation** ($pm_{a,d,h}$)
Applies the same unmet demand penalty to situations where the allocated slots fail to serve the projected passenger demand ($pax_missed_allocated_{a,d,h}$).
7. **Slack Variable Penalty** ($p_{sl} = 10, sl_{a,d,h}$)
Penalizes the use of slack variables, which represent temporary relaxations of constraints, ensuring they are only used when necessary.
8. **Penalty for Unmet Coupling Constraints** ($p_{hrc} = 100, z_r$)
Penalizes violations of hard round-trip coupling requirements (z_r), ensuring operational feasibility for paired inbound/outbound flights.

Implementation Note

In the PuLP implementation, each of these terms is explicitly summed over the relevant index sets (R for request series, D for days, S for slots, A for airports, and H for hours). This direct formulation allows flexible tuning of penalty and reward weights to reflect policy or operational priorities.

3.6 Constraints

3.6.1 Slot Request Allocation

Each slot request series $r \in R$ must be allocated exactly one slot per requested day $d \in D_r$ if it is not denied:

$$\sum_{s \in S_r} x_{r,d,s} = 1 - y_r, \quad \forall r \in R, \forall d \in D_r \quad (4a)$$

To ensure consistency, the total number of assigned slots across all days must equal the number of requested days for allocated series:

$$\sum_{d \in D_r} \sum_{s \in S_r} x_{r,d,s} = (1 - y_r) \cdot |D_r|, \quad \forall r \in R \quad (4b)$$

Together, constraints (4a) and (4b) ensure that no slots outside the requested days and time windows are assigned.

3.6.2 Historic Rights (HRC) Allocation

Slot series that are subject to historic rights must always be fully allocated:

$$y_r = 0, \quad \forall r \in R^{HRC} \quad (5)$$

If the request $r \in R^{HRC}$ is also associated with a high-priority passenger, then the specific historic slot s_r^h must be consistently used on all days:

$$\sum_{d \in D_r[r]} x_{r,d,s_r^h} = x_{r,d_r^0,s_r^h} \cdot |D_r|, \quad \forall r \in R_p^{HRC} \quad (6)$$

where:

$$R_p^{HRC} = \left\{ r \in R^{HRC} \mid \text{passenger}(r) \in \text{HighPriorityPassengers} \right\}$$

This enforces that if a historic slot is used on the initial day d_r^0 , it must be used uniformly across all days in D_r .

3.6.3 Capacity Constraints

All capacity limits at different temporal resolutions must be respected. Slot allocations should not exceed the available capacity after allocating the high-urgency (HU) requests.

$$\sum_{r \in R_{a,d}} \sum_{s \in S_r \cap S_i} x_{r,d,s} \leq c_{i,d,a}^I, \quad \forall i \in I, \forall a \in A, \forall d \in D \quad (7)$$

$$\sum_{r \in R_{a,d}} \sum_{s \in S_r \cap S_h} x_{r,d,s} \leq c_{h,d,a,\tau}^H, \quad \forall h \in H, \forall a \in A, \forall d \in D, \forall \tau \in T \quad (8)$$

$$\sum_{r \in R_{a,d}} \sum_{s \in S_r \cap S_{hi}} x_{r,d,s} \leq c_{hi,d,a,\tau}^{HI}, \quad \forall hi \in HI, \forall a \in A, \forall d \in D, \forall \tau \in T \quad (9)$$

3.6.4 Hourly Passenger-Driven Capacity Constraint

To further align slot allocation with real-time passenger throughput, we introduce an **airport-hour-level** capacity control. This constraint ensures that, for each airport and hour of the day, the number of flights assigned does not exceed the effective passenger-handling capacity, while allowing controlled violations through a penalized slack variable. To better align slot allocation with passenger throughput, we introduce an airport-hour-level capacity control that integrates demand data directly into the scheduling process. Let demand_{*a,d,h*} represent the number of passengers expected at airport *a* on day *d* during hour *h*. The model translates this demand into flight-equivalent capacity using an average passenger-per-flight parameter, avg_pax_per_flight.

For each airport, day, and hour, the sum of assigned flights captured by the binary variable $x_{r,d,s}$, which equals 1 if request *r* is allocated to slot *s* on day *d* must not exceed the flight-equivalent capacity derived from passenger demand. Exceptional cases, such as peak-hour

surges, are handled through a non-negative slack variable $sl_{a,d,h}$, which allows temporary capacity violations at a penalty. To track unserved passengers, the variable $pm_{a,d,h}$ records the number of passengers whose demand could not be accommodated within the given hour. The set of feasible slots for each request is denoted by S_r , and $hour(s)$ identifies the hour associated with slot s .

Formally, the airport-hour-level capacity constraint is expressed as:

$$\sum_{\substack{r \in R \\ a \in \{\text{orig}(r), \text{dest}(r)\}}} \sum_{\substack{s \in S_r \\ \text{hour}(s)=h}} x_{r,d,s} \leq \frac{\text{demand}_{a,d,h}}{\text{avg_pax_per_flight}} + sl_{a,d,h},$$

$$\forall a \in A, \forall d \in D, \forall h \in \{0, 1, \dots, 23\} \quad (10a)$$

We also track the unmet passenger allocation explicitly:

$$pm_{a,d,h} \geq \text{demand}_{a,d,h} - \left(\sum_{\substack{r \in R \\ a \in \{\text{orig}(r), \text{dest}(r)\}}} \sum_{\substack{s \in S_r \\ \text{hour}(s)=h}} x_{r,d,s} \right) \cdot \text{avg_pax_per_flight},$$

$$\forall a \in A, \forall d \in D, \forall h \quad (10b)$$

This formulation ensures that slot allocation is sensitive to passenger demand, explicitly balancing airport capacity and passenger service levels while providing a controlled mechanism for managing occasional demand surges.

Operational Meaning: Constraint (10a) caps the number of scheduled flights at each airport-hour combination so that the total passenger capacity matches or slightly exceeds the forecasted demand. The slack variable $slack_{a,d,h}$ enables soft enforcement allowing controlled breaches in rare cases (e.g., special events, irregular operations) with a penalty applied in the objective function to discourage overuse.

Constraint (10b) separately measures how many passengers remain unserved within each hour, ensuring that unmet demand is explicitly tracked. Together, these constraints connect slot allocation decisions directly to passenger experience, preventing over-scheduling during low-capacity periods while flagging potential service gaps.

3.6.5 Coupled Slot Requests Constraints

In many operational scenarios, certain flight series are interdependent. Examples include round-trip flights or aircraft rotations requiring coordination between departures and arrivals. To ensure consistent treatment of these coupled requests, we impose the following constraints.

Mutual Allocation of Coupled Series If one series in a coupled pair is allocated, the other must also be allocated. This guarantees operational feasibility and prevents partially scheduled rotations:

$$y_r = y_{r'} \quad \forall (r, r') \in R^c \quad (11)$$

3.6.6 Block-Time Synchronization

The block time, the elapsed time between paired series r and r' , must remain within predefined bounds. This is essential to preserve scheduled turnarounds and minimize downstream disruptions. Let $\underline{bt}_{r,r'}$ and $\overline{bt}_{r,r'}$ denote the lower and upper acceptable block-time limits. We model deviations with non-negative variables $\underline{z}_{(r,r'),d}$ and $\bar{z}_{(r,r'),d}$:

$$\sum_{s' \in S_{r'}} t_{s'x_{r',d,s'}} - \sum_{s \in S_r} t_{sx_{r,d,s}} - bt_{r,r'} \leq \bar{z}_{(r,r'),d}, \quad \forall (r, r') \in R^c, \forall d \in D_r \cap D_{r'} \quad (12a)$$

$$\sum_{s' \in S_{r'}} t_{s'x_{r',d,s'}} - \sum_{s \in S_r} t_{sx_{r,d,s}} - bt_{r,r'} \geq -\underline{z}_{(r,r'),d}, \quad \forall (r, r') \in R^c, \forall d \in D_r \cap D_{r'} \quad (12b)$$

These deviations are further bounded to ensure that the block time remains within operationally acceptable limits:

$$bt_{r,r'} + \bar{z}_{(r,r'),d} \leq \overline{bt}_{r,r'}, \quad \forall (r, r') \in R^c, \forall d \in D_r \cap D_{r'} \quad (12c)$$

$$bt_{r,r'} - \underline{z}_{(r,r'),d} \geq \underline{bt}_{r,r'}, \quad \forall (r, r') \in R^c, \forall d \in D_r \cap D_{r'} \quad (12d)$$

3.6.7 Turnaround Time Constraints

For rotations requiring a minimum turnaround at an airport, the departure of the subsequent flight must respect the turnaround time after the arrival:

$$\sum_{s' \in S_{r'}} t_{s'x_{r',d,s'}} - \sum_{s \in S_r} t_{sx_{r,d,s}} \geq mt_{r,r'} - (y_r + y_{r'}) \cdot (\hat{t}_r + f_{d_r} + mt_{r,r'}), \quad \forall (r, r') \in R^T, \forall d \in D \quad (13a)$$

This constraint is only active if both flights are allocated ($y_r = y_{r'} = 0$). If either flight is not scheduled, the right-hand side becomes highly negative, effectively deactivating the constraint.

Forward Deviation Bound: To limit how far a flight can be scheduled ahead of its original requested time, we enforce:

$$\sum_{s \in S_r} t_{sx_{r,d,s}} \leq \hat{t}_r + f_{d_r} \quad (13b)$$

3.6.8 New Entrant / Non-New Entrant Constraints

To maintain fairness in slot allocation between new entrants and established airlines, a pool-based approach is used.

New Entrants At least 50% of slots in the pool should be allocated to new entrants unless their total requests are less than 50% of available slots:

$$\sum_{\substack{r \in \bigcup_{a \in A} R_{a,u,d} \\ u \in N_{a,d}}} y_r \leq \frac{|R_{a,d}|}{2}, \quad \forall d \in D, \forall a \in A^N \quad (14a)$$

Non-New Entrants Similarly, established carriers are entitled to no more than 50% of available slots unless underrepresented:

$$\sum_{\substack{r \in \bigcup_{a,u,d} R_{a,u,d} \\ u \in \neg N_{a,d}}} y_r \leq \frac{|R_{a,d}|}{2}, \quad \forall d \in D, \forall a \in A^{\neg N} \quad (14b)$$

Chapter 4

Data Preparation and Analysis

This chapter describes the preparation and processing of datasets used to develop and validate the PC-MASSA model. Two distinct datasets were employed: a synthetic toy problem dataset and a real-world case study dataset derived from OpenSky Network records. The objective was to test the model’s feasibility on a small scale before applying it to realistic large-scale scenarios. By establishing these two complementary data sources, the groundwork is set for the next chapter, where the model is implemented computationally and its behavior is systematically evaluated.

4.1 Role of the Toy Problem in the Research

The PC-MASSA model is a complex optimization framework that incorporates passenger-centric objectives, multiple airports, seasonal slot allocation, and several capacity and fairness constraints. Solving this model directly on a large-scale real-world dataset would be computationally intensive and make it difficult to isolate the effects of individual components.

To manage this, the research first employs a *toy problem*. Unlike typical toy problems, this instance maintains the full structure and all constraints of the PC-MASSA model. However, it uses synthetic data for a limited number of passengers and flights, enabling faster computation and easier observation of the model’s behavior in a controlled environment.

To effectively evaluate the model’s performance, we must first define our core metric: *efficiency*. In this context, efficiency is measured by the model’s success in achieving passenger-centric objectives. These objectives specifically include minimizing the number of missed flight allocations, reducing the costs associated with passenger displacement, and ensuring that connection times are sufficient and timely. With this definition established, the purpose of this toy problem and its synthetic dataset becomes clear, as it provides a vital foundation for research in three key areas.

First, the model allows for a rigorous *evaluation of passenger-centric efficiency*. The controlled, synthetic environment enables rapid experimentation to observe precisely how variables such as individual passenger preferences, minimum connection time requirements, and available slot assignments influence the overall optimization outcomes. Second, the framework is essential for *assessing fairness*. By manipulating the input parameters, researchers can systematically examine how different fairness constraints behave, thereby illuminating the inherent trade-offs that exist between maximizing overall efficiency and ensuring an equitable distribution of available slots. Finally, despite its simplified nature, the problem incorporates multiple airports and a network of interconnected constraints. This design ensures a thorough *examination of constraint interactions* under capacity limitations, validating that the model’s

mathematical formulation and coupling constraints behave as intended. This crucial step builds confidence in the model’s structural integrity before it is deployed on complex, real-world datasets such as those from CDG and Orly airports.

In summary, the toy problem is a fully structured, realistic instance of the PC-MASSA model, using generated data for rapid testing. It allows detailed verification of passenger-centric objectives, fairness mechanisms, and constraint interactions, providing a validated baseline for analyzing more realistic scenarios.

4.2 Data Description and Sources

4.2.1 Synthetic Toy Problem Dataset

To initially validate the implementation of the optimization model, a synthetic dataset for a toy problem was generated manually using Python scripts based on object-oriented programming. The simulation parameters were defined according to the professor’s specifications, ensuring a controlled yet realistic environment.

The dataset includes:

- **Operational days:** 2
- **Flights per day:** 3
- **Total flight requests:** 6
- **Airports:** JFK, LAX, CDG, FRA, DXB
- **Start date:** March 1, 2025
- **Passenger classes:** business, frequent fliers, medical, leisure

The data generation process involved:

1. Creating sets for airports, airlines, days, and time intervals.
2. Generating random flight requests with realistic distributions of departure and arrival times.
3. Assigning passengers to requests with class-based proportions.
4. Simulating historic flights (previous season) to identify unchanged and changed requests.
5. Generating feasible turnaround pairs and mapping routes between airports.
6. Defining subsets for slot allocation constraints (hourly, rolling, and peak load).

An example structure of the toy problem is shown in Table 4.1.

Table 4.1. Synthetic flight schedule with passenger distribution

Day	First Seen	Dep. Airport	Last Seen	Arr. Airport	Pax	Business	Frequent Fliers	Medical	Leisure	Slot Interval	Flight Hour
2025-03-01	2025-03-01 11:48	JFK	2025-03-01 13:22	DXB	61	18	8	7	28	12	11
2025-03-01	2025-03-01 18:59	DXB	2025-03-01 21:11	FRA	86	20	16	10	40	2	18
2025-03-01	2025-03-01 06:04	JFK	2025-03-01 09:27	CDG	71	10	10	10	41	16	6
2025-03-02	2025-03-02 22:57	JFK	2025-03-02 23:43	CDG	66	10	15	8	33	8	22
2025-03-02	2025-03-02 02:50	LAX	2025-03-02 07:22	DXB	13	2	2	1	8	20	2

4.2.2 Real-World Dataset

To validate the model under realistic and demanding conditions, a case study was conducted using flight movement data from the OpenSky Network for the year 2019. The OpenSky Network is a non-profit research organization that operates a large-scale open sensor network, continuously collecting and storing ADS-B and Mode S surveillance transmissions from aircraft in a public database. This provides a rich, real-world source of air traffic data.

The analysis was based on the `flights_data4` table, which contains extrapolated and refined flight records. The most relevant fields for this study included:

- `firstSeen` – timestamp of the first detected message;
- `lastSeen` – timestamp of the last detected message;
- `estimatedDepartureAirport` – most probable departure airport;
- `estimatedArrivalAirport` – most probable arrival airport;
- `callsign` – flight identifier (non-unique);
- `icao24` – unique aircraft ICAO address;
- `day` – date of departure.

A significant challenge arose from the fact that the OpenSky data does not contain direct information on slot requests or flight series. To overcome this, flight series had to be reconstructed by analyzing historical movement patterns for each unique aircraft (`icao24`) and route. Regular, repeating operations on the same day of the week over multiple weeks were identified as a potential series.

To ensure computational tractability and to focus the study on a high-demand, congested period, the dataset was subjected to a series of filters. The data was restricted to **Fridays**, typically a peak travel day, at the two major Parisian airports, **Charles de Gaulle (LFPG)** and **Orly (LFPO)**, over the entire **summer season (March 31 to October 26, 2019)**. This period encompasses the high-volume summer schedule and allows for the analysis of seasonal effects. Furthermore, the analysis relied on hourly passenger capacity data for allocated flights, which was used as a proxy for passenger demand in the optimization model. This filtering resulted in a focused yet complex dataset well-suited for testing the model's performance in a near-real-world scenario.

Passenger Distribution and Hourly Allocation Passenger traffic data per month were sourced from official statistics and proportionally distributed to days based on the number of days in each month. Hourly passenger distribution followed a normalized cosine function to reflect typical demand patterns. Passenger classes (business, frequent fliers, medical, leisure) were assigned proportionally using fixed distribution ratios.

Passenger Traffic Forecast for 2026 In addition to historical flight and passenger data, future passenger traffic was forecast using records from Groupe ADP, a world leader in airport operations. At the end of 2024, Groupe ADP managed a network of 26 airports worldwide, either under management contracts or concession agreements, and maintained a diverse pool of expertise serving local markets. Monthly passenger traffic statistics, extracted from the group's annual reports, were collected for the period January 2018 to April 2025.

This historical time series formed the basis for a predictive model estimating monthly passenger volumes for the entire year 2026. The forecasting approach relied on trend and seasonal component analysis to capture recurring monthly variations as well as long-term growth patterns. These projections were subsequently integrated into the PC-MASSA model to simulate operational conditions under anticipated demand scenarios.

4.2.3 Passenger Demand Modeling for the CDG and Orly Case Study

For the case study involving Paris Charles de Gaulle (CDG) and Paris Orly (ORY) airports, passenger demand was reconstructed and modeled using historical data collected from the annual reports of Groupe ADP - Aéroports de Paris SA, covering the period from January 2018 to April 2025. The data acquisition and processing workflow was designed to produce hourly passenger demand profiles for each airport, suitable for use in the slot allocation models. The procedure comprised three main phases: data collection, demand transformation, and feature engineering.

Data Collection and Preparation

Monthly passenger traffic figures for both CDG and ORY were extracted from the ADP annual reports and aggregated into a CSV dataset `paris_airports_pass_traffic.csv`. Airport names were standardized by mapping “Paris-CDG” and “Paris-Orly” to their ICAO codes LFPG and LFPO, respectively. The dataset was transformed from a monthly table to a per-airport series to facilitate further processing.

Only the target season year (2019) was retained for this study to ensure consistency with other operational datasets. The number of days in each month was computed using the Python calendar module, enabling conversion from monthly passenger totals to average daily passenger counts.

Demand Disaggregation and Passenger Class Allocation

To prepare the passenger demand dataset for the slot allocation model, daily passenger volumes were distributed among four categories: business, frequent fliers, medical, and leisure. A fixed distribution ratio of 5%, 70%, 20%, and 5% was applied across all months. It is important to note that these classes were introduced primarily to structure and process the data, rather than to model class-specific optimization behavior.

The daily totals were then disaggregated into hourly values to achieve temporal resolution suitable for slot allocation. A cosine-based distribution function was applied to capture typical diurnal patterns, with morning and evening peaks and midday troughs.

During data processing, the passenger classes facilitated allocation of daily traffic across categories, which was then combined and mapped to hourly demand. Synthetic functions were used to generate hourly values for each airport, reflecting seasonal and weekly variability, while maintaining the integrity of the original daily totals. This structured approach allowed for the creation of a detailed passenger demand dataset (`pax_per_hour`) that feeds directly into the PC-MASSA model.

Seasonal Filtering and Alignment

The dataset was filtered to retain only the operational period of interest, corresponding to the summer scheduling season: from 31 March 2019 to 26 October 2019. Each date was assigned:

- a numerical day index relative to the start of the season,
- the corresponding weekday,
- the ICAO airport code.

The final product was an hourly passenger demand table for CDG and ORY, aligned across the entire summer season.

Feature Engineering for Slot Allocation Models

A series of targeted preprocessing steps were applied to the raw dataset to ensure its readiness for integration into the slot allocation optimization algorithms. First, categorical variables (including airports, individual flights, and passenger classes) were converted into indexed sets. This encoding is a necessary step for efficient computational processing within the model's framework. Subsequently, key constraint subsets were precomputed, and specifically, the interdependent turnaround pairs for aircraft and the subsets of requests falling on peak days were defined in advance to streamline the implementation of complex model constraints. To mitigate allocation bias that could arise from fluctuating demand, passenger volumes were normalized across the entire season, thereby preventing the model from being disproportionately influenced by surges occurring in peak months. Finally, to establish a consistent and reliable foundation for all subsequent operations, the raw OpenSky flight movement data underwent a rigorous cleaning process. This involved filtering records to enforce standardized airport codes, correct timestamps, and address any missing values.

Detection of Flight Series and Turnaround Requests

The identification of series and turnaround requests followed a two-step procedure:

1. **Series Detection:** Candidate departure series were defined as sequences of flights sharing the same callsign, weekday, origin, and destination. A candidate series was confirmed if it contained at least three flights, with the time span between its first and last occurrence being at least five weeks. This relaxed the official WASG threshold (five occurrences) to account for cancellations and noise, resulting in a slight overestimation that better tests the model's scalability.
2. **Turnaround Identification:** Aircraft movements were tracked via their icao24 identifier. A turnaround request was recorded whenever an arrival movement at a Level 3 airport was followed by a departure movement of the same aircraft on the same day. Requested block times were computed as the difference between the arrival and departure request times.

Final Dataset

The final passenger demand dataset, `pax_data.csv`, contains hourly passenger counts for both CDG and ORY for the entire summer 2019 season, disaggregated by passenger class and enriched with operational features such as day number, weekday, and airport code. This dataset serves as the demand input for both the MASSA and PC-MASSA slot allocation models.

4.2.4 Passenger Demand Prediction for the CDG and Orly Case Study using Machine Learning

This subsection investigates the historical passenger traffic trends at Paris–Charles de Gaulle (CDG) and Paris–Orly (ORY) airports, followed by time series forecasting using the SARIMA model.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is an extension of the ARIMA model that explicitly incorporates seasonality into the time series forecasting process. It is particularly suitable for passenger demand prediction, as air traffic often exhibits strong seasonal variations related to holidays, business travel cycles, and tourism flows. The SARIMA model accounts for autoregressive terms, differencing, moving averages, and seasonal components, making it a powerful tool for capturing both short-term dynamics and long-term periodic patterns.

Previous research has demonstrated the effectiveness of SARIMA for air traffic and passenger forecasting. For example, Sah et al. (2025) compared ARIMA, SARIMA, Prophet and SARIMA with exogenous variables to predict passenger traffic on airlines, highlighting SARIMA's ability to handle seasonality effectively. Similarly, Nai et al. (2017) proposed an EMD–SARIMA-based approach, which further enhanced predictive accuracy by decomposing the time series before applying SARIMA. These studies validate the relevance of SARIMA in modeling and forecasting air passenger demand, supporting its application in the CDG and Orly case study.

Descriptive Statistics of Historical Data

The dataset contains monthly average passenger counts for both airports, covering the period from January 2018 to December 2025. The shape of the dataset is (2, 89), corresponding to two airports over 89 months.

The descriptive statistics reveal substantial fluctuations over the years, mainly due to the impact of COVID-19 and subsequent recovery phases.

Passenger Traffic Trends by Period

Our analysis begins with the historical passenger data provided by Groupe ADP, spanning from January 2018 to December 2025. This eight-year window offers a crucial narrative, capturing a period of normalcy, profound disruption, and subsequent recovery. The dataset, comprising monthly averages for both Paris Charles de Gaulle (CDG) and Paris Orly (ORY) airports, reveals the significant impact of global events, most notably the COVID-19 pandemic, on air travel demand.

The overarching story of this period is vividly illustrated in Figures 4.1 and 4.2, which plot the passenger traffic for CDG and Orly, respectively. Both charts trace a similar, dramatic arc: robust pre-pandemic activity through 2018 and 2019, a severe contraction during the 2020–2021 period, and a steady climb back in the following years. A closer look at the pre-pandemic era reveals a consistent seasonal peak each December, a testament to the traditional surge in holiday travel.

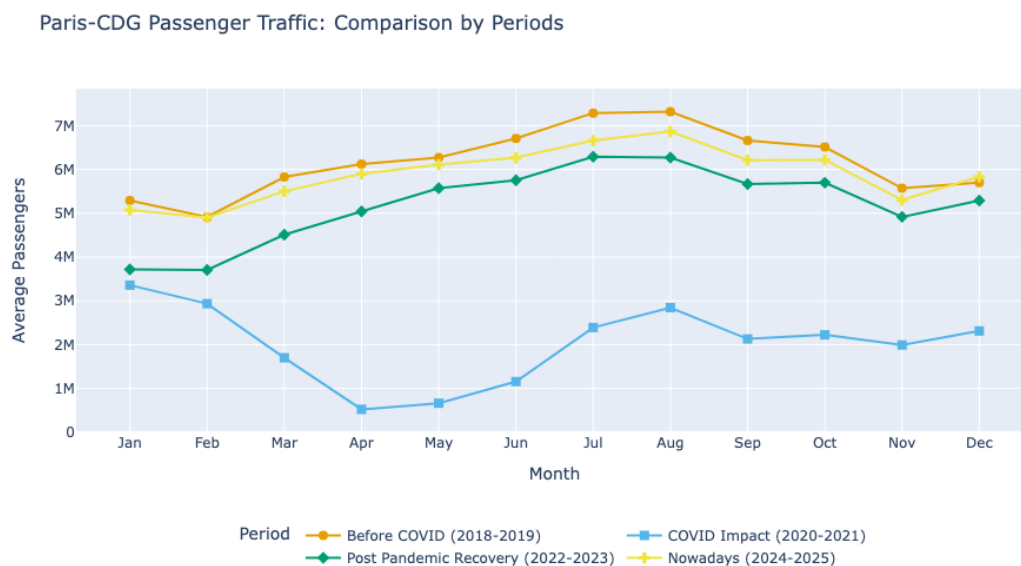


Figure 4.1. Paris-CDG Passenger Traffic: Comparison by Periods.

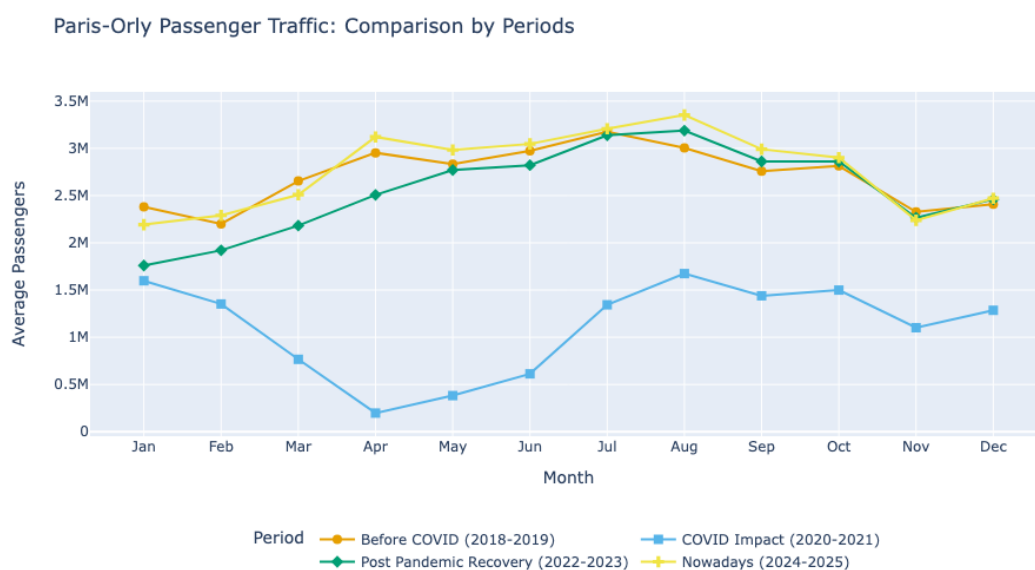


Figure 4.2. Paris-Orly Passenger Traffic: Comparison by Periods.

However, a more nuanced story emerges when comparing the recovery trajectories of the two airports. CDG airport demonstrated a robust and consistent recovery, with passenger volumes showing strong year-over-year growth following the pandemic's peak. Orly airport, in contrast, faced a more challenging path back to pre-pandemic levels, with its passenger traffic stabilizing at a more modest growth rate. This divergence in recovery patterns underscores the necessity of airport-specific demand modeling, as a one-size-fits-all approach would fail to capture the unique operational realities and passenger base of each hub. For the purpose of simulating airport operations, these monthly statistics were converted to daily averages and then distributed across each day using a temporal function to replicate realistic, hour-by-hour traffic flows.

Stationarity Testing and Model Selection

A fundamental assumption of ARIMA-type models is that the time series is *stationary*, meaning its statistical properties such as mean and variance are constant over time. Non-stationary data can lead to unreliable forecasts. To verify this, the Augmented Dickey-Fuller (ADF) test was applied to the CDG passenger series, yielding a test statistic of -2.3745 with a p-value of 0.1491. Since this p-value is above the 0.05 significance level, the null hypothesis of a unit root could not be rejected, confirming the series is non-stationary (Sah et al., 2025).

An initial SARIMA(1,1,1) $\times$ (1,1,1)₁₂ model was estimated but showed signs of over-fitting. The model output indicated that several parameters, including the non-seasonal AR and MA terms and the seasonal AR term, were not statistically significant (p-values > 0.05). Furthermore, the model produced a near-singular covariance matrix, suggesting potential instability.

To resolve this, an automated model selection procedure (Auto-ARIMA) on the Figure 4.3 was employed, which identified a more parsimonious and robust model: a SARIMA(1,0,0) $\times$ (0,1,1)₁₂. This model specification confirms the initial finding that differencing is required, but only at the seasonal level. It retains a significant non-seasonal autoregressive component (AR(1) with $p < 0.001$) and a highly significant seasonal moving average component (SMA(12) with $p < 0.001$), effectively capturing the persistent trends and seasonal patterns in passenger demand without unnecessary complexity.

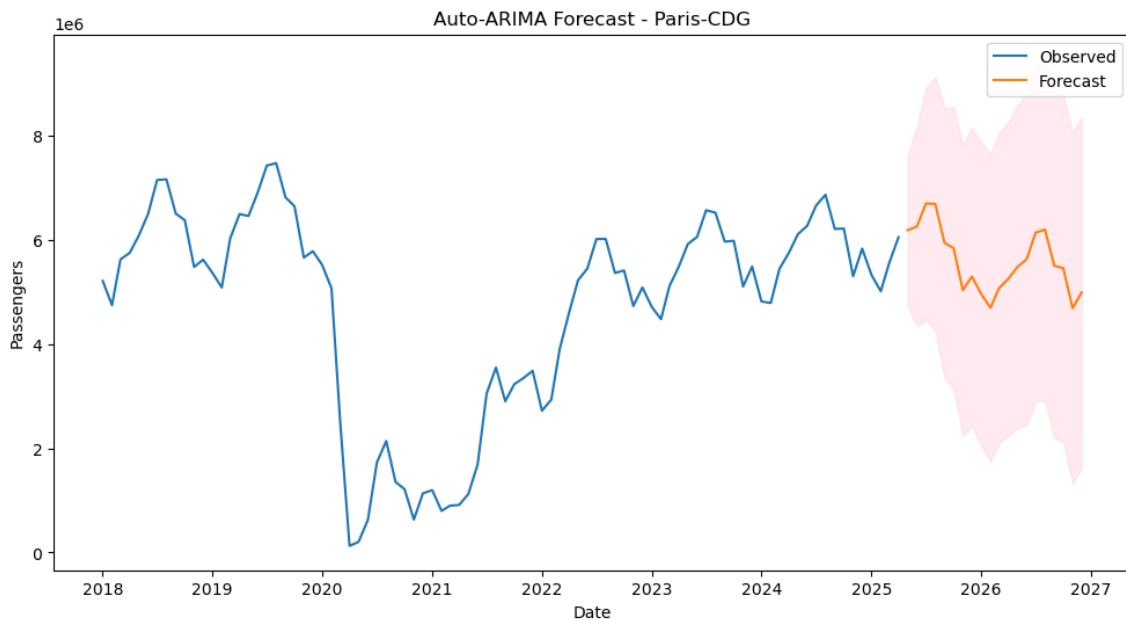


Figure 4.3. Paris-CDG Passenger Traffic prediction for 2026, Auto-ARIMA.

Model Diagnostics

Diagnostic checks were performed on the selected SARIMA(1,0,0) $\times$ (0,1,1)₁₂ model to validate its adequacy. The Ljung-Box test on the residuals yielded a p-value of 0.01, indicating some remaining autocorrelation at the first lag. However, the Jarque-Bera test result ($p = 0.00$) strongly rejected the null hypothesis of normally distributed residuals. This is further evidenced by a significant skew of -2.34 and a high kurtosis of 9.53, pointing to a heavily left-skewed and fat-tailed distribution of errors. This deviation from normality is not unexpected, as it likely reflects the profound impact of extreme events like the COVID-19 pandemic on travel patterns.

While ideal, forecast accuracy is often robust to violations of normality, provided the model structure is sound.

To evaluate its practical forecasting performance, the model was validated using a rolling-origin forecast. It demonstrated superior accuracy compared to a seasonal naïve benchmark, achieving a lower mean absolute percentage error (MAPE). This confirms that the model's capture of both trend and seasonal dynamics provides a tangible improvement for prediction.

Given the strong correlation in the underlying trends between the CDG and ORY passenger series, the validated CDG model was used as the basis for forecasting monthly demand for both airports in 2026, as illustrated in Figure 4.4.

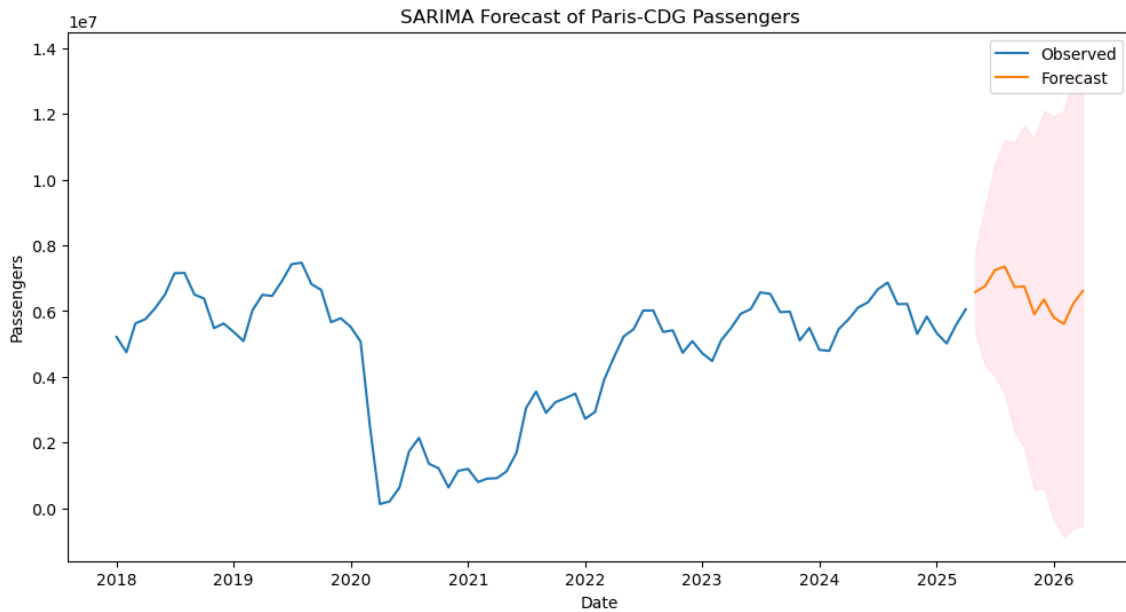


Figure 4.4. Paris–CDG Passenger Traffic prediction for 2026, Sarima.

4.2.5 Passenger Demand Forecasting with Random Forest Regression

While the SARIMA model provided a statistically interpretable baseline forecast, its linear nature may not fully capture the complex, non-linear dependencies present in airport passenger traffic. To address this, a Random Forest Regressor was employed as a powerful, ensemble-based alternative capable of modeling intricate temporal patterns and interactions.

Feature Engineering for Predictive Modeling

To generate accurate passenger demand forecasts for the slot allocation model, we developed a comprehensive framework that began with engineering a rich set of temporal features from the monthly passenger time series. The feature set was designed to capture three primary categories of patterns.

First, **lag variables** were incorporated to enable the model to reference historical passenger volumes. Specifically, *lags of 1, 2, 3, 6, and 12 months* were added. For instance, *Lag_1* represents the immediate past month's volume, while *Lag_12* corresponds to the same month in the preceding year, allowing the model to discern both short-term momentum and annual seasonality. Second, **rolling mean features** were calculated to mitigate noise and highlight underlying trends. These included the average passenger volumes over the preceding *3 and 6 months*, carefully computed excluding the current month to prevent data leakage. Finally, a

set of **calendar features**, including the quarter and one-hot encoded monthly dummies, were created to help the model learn fixed seasonal patterns.

A subsequent correlation analysis of these lag features yielded critical insights, revealing exceptionally strong temporal dependencies. The analysis confirmed a powerful short-term persistence, with the previous month's passenger count (Lag_1) showing a near-perfect positive correlation ($\rho = 0.964$) with the current volume. This strong sequential dependency gradually decays over subsequent months, with Lag_2 and Lag_3 showing correlations of 0.908 and 0.848, respectively. A clear annual seasonal pattern was also confirmed, with Lag_12 demonstrating a substantial correlation ($\rho = 0.528$). This analysis, visualized in Figure 4.5, underscores that the model has access to highly predictive temporal signals for forecasting.

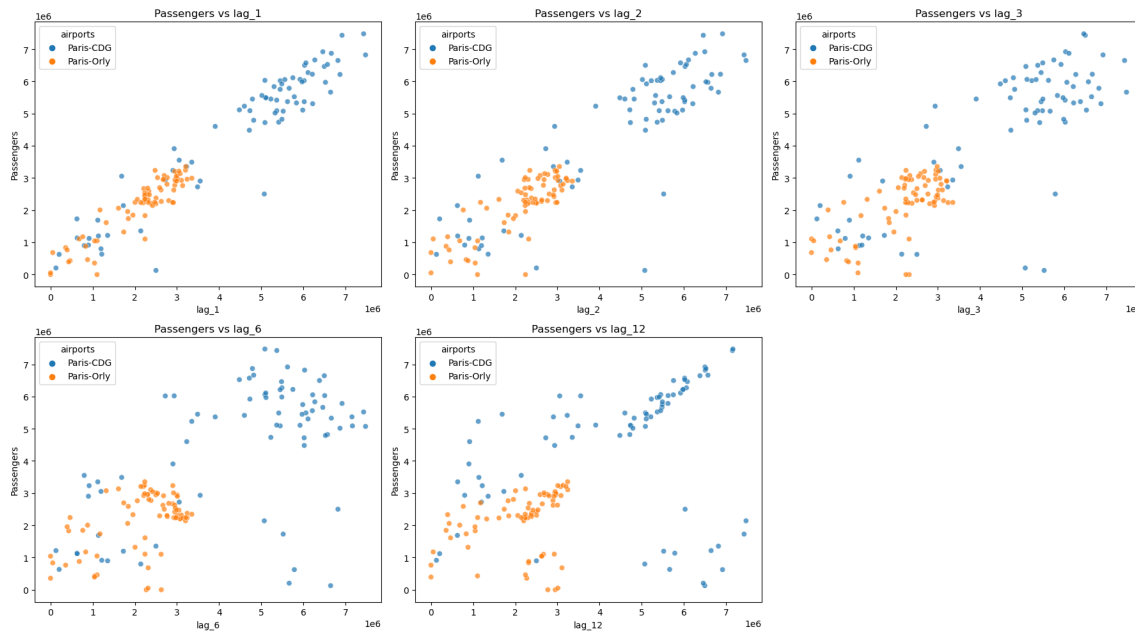


Figure 4.5. Correlation analysis of lagged passenger values, showing strong temporal dependencies used for forecasting.

4.2.6 Passenger Demand Forecasting with Random Forest Regression

To complement the linear SARIMA approach, a Random Forest Regressor was implemented to explore whether a non-parametric, ensemble method could better capture complex patterns in the passenger data. The dataset was split into a training set (January 2018 – December 2023) and a test set (January 2024 – March 2025). The model was configured with 100 trees and trained on the same suite of temporal features, including lag variables, rolling means, and seasonal indicators.

Table 4.2. Random Forest Performance Metrics on Test Set

Metric	Value	Interpretation
MAE	240,945	On average, the model's monthly predictions deviate from actuals by approximately 241,000 passengers.
RMSE	361,851	The higher RMSE indicates the presence of several periods with significantly larger forecast errors.
MAPE	6.36%	The mean absolute percentage error suggests a non-negligible average forecasting discrepancy.
R ² Score	0.947	While 94.7% of the variance is explained, this is lower than the SARIMA model's performance on the test period.

The performance metrics indicate that the Random Forest model provides a reasonable but sub-optimal fit. The scatter plot of predicted versus actual values (Figure 4.6) shows a concerning deviation from the ideal 45-degree line, with a visible cluster of points where the model systematically over-predicts passenger volumes. This pattern suggests a failure to fully adapt to the stabilized, post-recovery growth trends observed in the most recent data.

This limitation is further corroborated by the time series of residuals (Figure 4.7), which reveals a non-random pattern. The concentration of positive residuals (where actuals exceed predictions) in the latter part of the test set indicates a consistent under-forecasting bias as the model projects forward. This systematic error implies that the ensemble approach, while powerful, may be overly influenced by the volatile pandemic and recovery periods in the training data, struggling to extrapolate the new, more stable regime with the limited historical data available.

Ultimately, while the Random Forest model captures the broad seasonal patterns, its comparative performance against the simpler SARIMA model underscores a key insight: for this specific forecasting horizon and with the given dataset, the linear model's explicit handling of trends and seasonality proved more robust for reliable slot allocation planning.

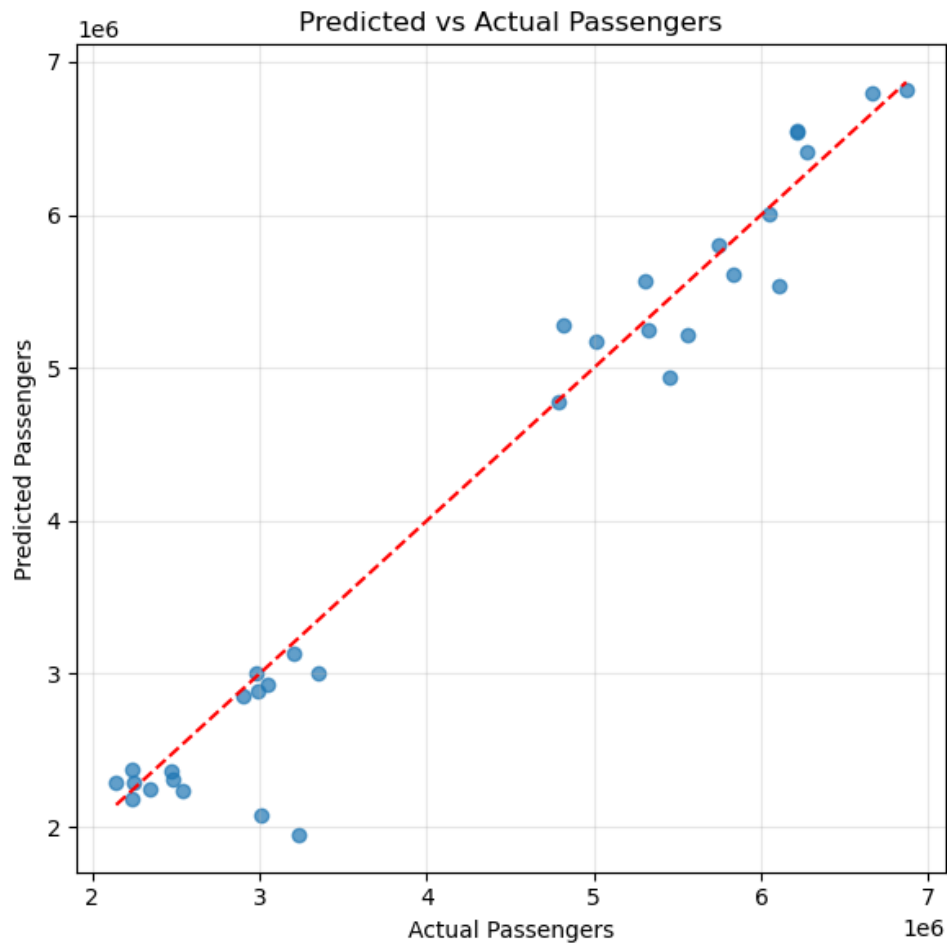


Figure 4.6. Predicted vs Actual Monthly Passenger Counts. The red dashed line represents perfect prediction. The visible spread and systematic deviation of points from this line, particularly in the higher passenger count range, indicate areas of consistent over-prediction by the model.

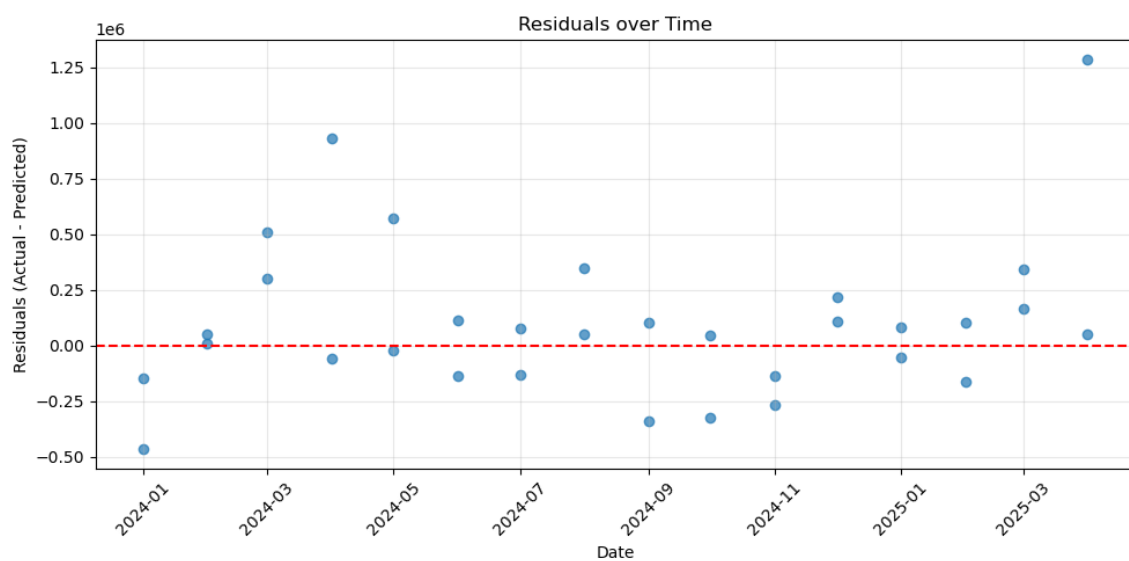


Figure 4.7. Residuals (Actual - Predicted) over Time. The clustering of positive residuals in the most recent months (right side of the plot) reveals a systematic under-forecasting bias, suggesting the model has not fully learned the latest traffic trends.

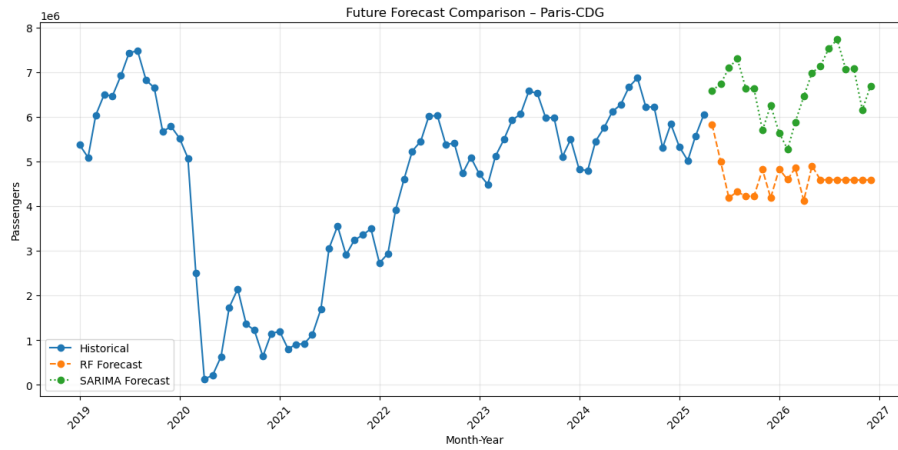


Figure 4.8. Comparison of SARIMA and Random Forest forecasts against actual passenger volumes during the holdout period.

Summary and Conclusions

The comparative analysis between SARIMA and Random Forest models, as detailed in Table 4.3 and visualized in Figure 4.8, revealed clear differences in forecasting performance. Based on a rigorous holdout validation, the SARIMA model demonstrated superior predictive accuracy, achieving lower MAE, RMSE, and MAPE values than its Random Forest counterpart.

Table 4.3. Forecasting performance comparison on historical holdout data

Model	MAE	RMSE	MAPE (%)
SARIMA	375,035	418,631	6.62
Random Forest	686,076	1,018,280	11.21

The rationale for SARIMA's better performance lies in the fundamental nature of time series data. The SARIMA model is explicitly designed for temporal structures, with built-in mechanisms to handle trends, seasonality, and autocorrelation through differencing and seasonal parameters. This makes it inherently robust for capturing the persistent, seasonal patterns inherent in airline passenger traffic. In contrast, the Random Forest model, while powerful for capturing complex, non-linear relationships, is not intrinsically sequential. Its performance is more dependent on a rich set of engineered features and a large volume of data. In this case, the limited historical timeframe—which includes the anomalous period of the COVID-19 pandemic, likely provided an insufficient foundation for the Random Forest to learn a generalized model that could extrapolate future seasonal trends as effectively as the dedicated time series approach.

This interpretation is supported by the forecast visualizations in Figure 4.9 and Figure 4.10, which show SARIMA more effectively replicating the expected seasonal fluctuations. Therefore, given its stronger performance on both quantitative metrics and its inherent suitability for the problem structure, the SARIMA methodology was selected as the final forecasting tool. Its predictions were saved to a dedicated CSV file to serve as the passenger demand inputs for the subsequent airport slot allocation case study.

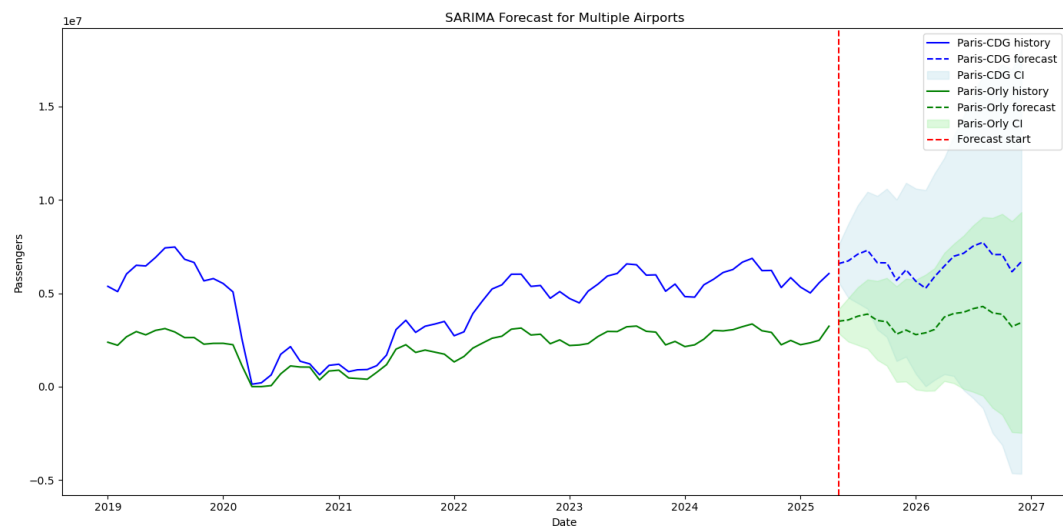


Figure 4.9. SARIMA Forecast for next 20 months for both Airports.

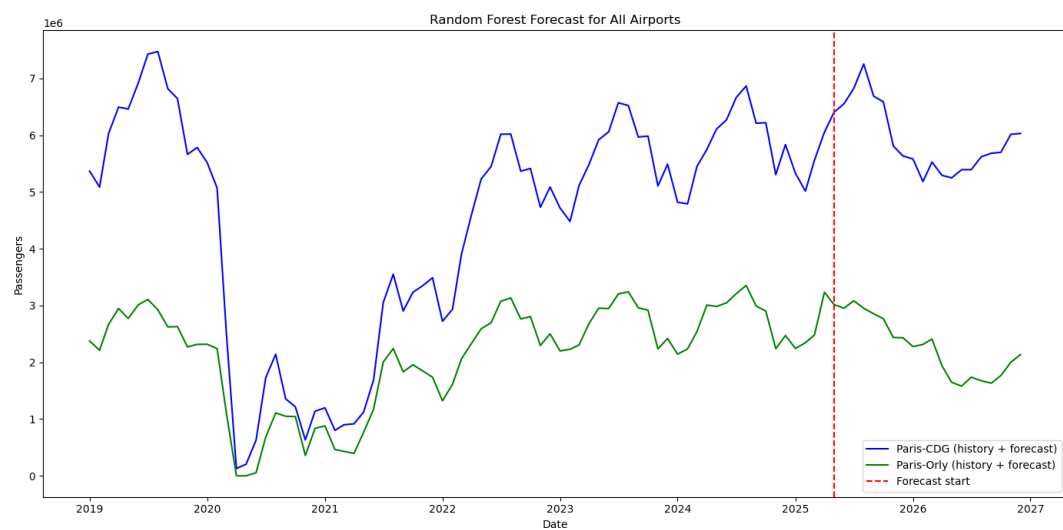


Figure 4.10. Random Forest Forecast for next 20 months for CDG.

Chapter 5

Implementation and Computational Framework

Building the model into a working system reveals how theory behaves in practice. The toy problem becomes a proving ground, allowing the structure of PC-MASSA to be validated under simplified conditions. Every constraint and objective is tested, ensuring that the model responds logically to capacity and passenger priorities. Once confidence is established, the real-world dataset is introduced, scaling the framework to the complexity of Paris’s multi-airport system. This progression from abstract to applied not only validates the model but also highlights its robustness. With results in hand, the final step is to reflect on their meaning and implications.

5.1 Expected Outcomes of the Toy Problem

Before running the solver, it is useful to reason about the likely patterns of slot allocation given the simplified setup of the toy problem. The dataset consists of two operational days with three flights per day (six in total), across five major airports (JFK, LAX, CDG, FRA, and DXB). Four passenger classes are represented: business, frequent fliers, medical, and leisure. The PC-MASSA model seeks to balance three competing objectives: ensuring passenger-centric slot assignments, respecting airport capacity limits, and maintaining fairness across airlines. From this perspective, the expected allocation outcomes can be grouped into four broad themes: high-priority flights, airport capacity and slot distribution, connection and series constraints, and low-priority flights.

High-Priority Flights

Flights carrying business and medical passengers are assumed to be of higher importance. Although the current version of the model does not yet assign explicit weights to passenger classes, their operational context suggests they will naturally occupy more favorable slots. For instance, historic unchanged flights (R_{HU}) are expected to remain within their traditional windows, typically within ± 2 intervals, and turnaround constraints will prevent large deviations. This means that a business flight from JFK to LAX, historically operating in the 8–10 slot, is likely to be preserved in that interval unless operational conflicts require a small shift. The logic here is that the combination of historic continuity and operational feasibility indirectly prioritizes such flights.

Airport Capacity and Slot Distribution

Another key expectation relates to the distribution of flights across available slots. Since each airport has a maximum number of arrivals and departures per interval, the solver should avoid bunching flights in peak windows. In practice, this means high-demand intervals will be reserved primarily for high-priority passengers, while lower-priority flights are shifted toward less congested slots. For example, the two-day horizon is likely to exhibit allocations such as 8–10, 10–12, and 12–14, thereby spreading departures evenly and reducing the likelihood of capacity violations. Importantly, this does not only ensure operational feasibility but also leaves enough flexibility for accommodating turnaround and connection constraints later.

Series and Connection Constraints

A key challenge is scheduling flights that operate as a series or have tight turnaround needs. Our model requires a minimum separation of one to four hours for these flights. This isn't an arbitrary rule. It is a direct translation of real-world logistics, ensuring an aircraft has enough time on the ground to be prepared for its next journey.

Consider Airline 4's two daily transatlantic flights. The solver's job is to find them a consistent and feasible pair of slots, such as 12:00 and 14:00, that works day after day. This requirement acts as a hard constraint. Flights without these connections are "free agents" by comparison; the algorithm can shift them more freely to optimize the overall schedule.

Low-Priority Flights

The last group to be assigned slots are low-priority flights, which include leisure travelers and frequent fliers. The solver only places them after all high-priority and operationally constrained flights have been scheduled. As a result, these passengers are often assigned to less desirable times, like later in the day or during known off-peak hours.

A leisure flight from JFK to CDG, for instance, might get the 14:00-16:00 slot after all the business and medical flights have taken the prime morning times. This approach reflects real-world demand patterns. It is a compromise that ensures the system remains fair, everyone gets a slot, but also respects a practical hierarchy based on passenger needs and airline operations.

Flight ID	Day	Airline	Dep Airport	Arr Airport	Passenger Class	Expected Slot (hour)
0	2025-03-01	Airline_1	JFK	LAX	Business	8–10
0	2025-03-02	Airline_1	JFK	LAX	Business	8–10
1	2025-03-01	Airline_2	CDG	FRA	Medical	10–12
2	2025-03-01	Airline_3	DXB	JFK	Leisure	12–14
3	2025-03-01	Airline_4	LAX	CDG	Frequent Fliers	8–10
4	2025-03-02	Airline_5	FRA	DXB	Business	10–12
5	2025-03-01	Airline_1	JFK	CDG	Leisure	12–14

Table 5.1. Expected slot allocation based on logical reasoning and operational assumptions. Slot ranges indicate predicted feasible intervals before solver execution.

Taken together, these expectations provide a benchmark against which the solver's outputs can be interpreted. By reasoning in advance about the likely allocation patterns, the analysis is able to distinguish between outcomes that follow directly from the model's structure and those that emerge from complex interactions of constraints.

Visual Representation

Figure 5.1 provides an intuitive glimpse into the logical framework that guides the solver’s slot allocation within our simplified scenario. The emerging patterns are not arbitrary but rather stem naturally from three fundamental components embedded in our model’s architecture: the synthetic demand profile that connects passenger categories with specific flights and typical departure times, the binding airport capacity constraints that prevent peak-time congestion, and the operational continuity requirements that preserve historical scheduling patterns while accommodating aircraft turnaround needs.

This logical framework manifests itself in clear temporal patterns throughout the day. The model demonstrates a natural tendency to allocate business and medical passengers, typically the most time-sensitive traveler segments, to earlier morning windows. This allocation strategy aligns with established industry practice, where such travelers preferentially select morning departures to minimize downstream delay risks, while simultaneously reflecting the model’s inherent preference for maintaining historical operational patterns where feasible. As the day progresses, the more flexible leisure and frequent-flier passenger segments naturally populate the subsequent mid-day and afternoon slots. This temporal distribution exemplifies the model’s core balancing mechanism: once high-priority demand is satisfactorily accommodated within capacity limitations, the remaining, more adaptable demand efficiently utilizes the available slot inventory.

The visual representation in the figure should be interpreted not as a rigid, deterministic schedule but rather as a visualization of plausible allocation windows that the solver would reasonably select. These colored bars effectively communicate how the model, when operating without significant conflicts, would distribute departures to respect capacity constraints, maintain operational consistency for connected flights, and avoid the systemic inefficiency of concentrating all activity within a single peak period.

Ultimately, this simplified instance successfully demonstrates how the comprehensive PC-MASSA formulation behaves under controlled conditions, realistically capturing the essential trade-offs between passenger priorities, capacity management, and operational feasibility, even when working with synthetic data. The figure should therefore be understood as illustrating the structured expectations of the solver’s probable decisions based on the established rules and inputs, rather than presenting a definitive, prescriptive timetable.

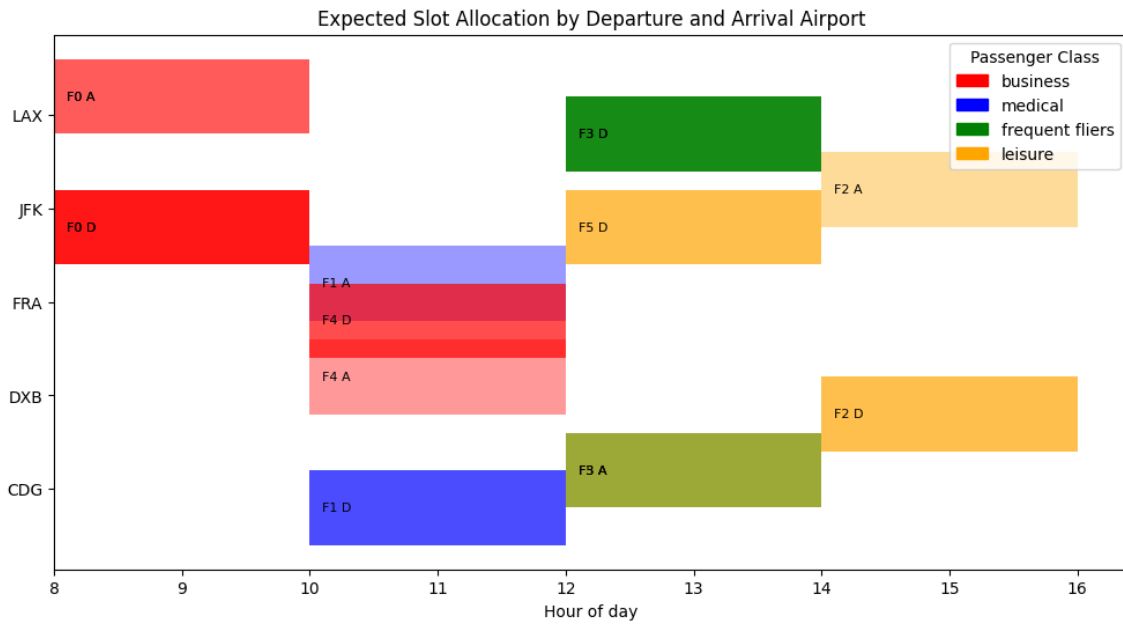


Figure 5.1. Predicted slot allocation by departure and arrival airports.

5.2 Results – Toy Problem Simulation

To assess the preliminary performance of the PC-MASSA model under simplified yet realistic conditions, a toy instance was developed simulating a basic multi-airport system. The scenario involves five major hubs: JFK (New York, USA), LAX (Los Angeles, USA), CDG (Paris, France), FRA (Frankfurt, Germany), and DXB (Dubai, UAE), over a two-day planning horizon, with three flights scheduled per day. The primary objective of this controlled setup is to analyze the model's allocation logic and responsiveness to different constraints, including passenger demand patterns, before applying it to real-world data.

Flight requests and slot availabilities were generated using realistic temporal distributions for departures and arrivals. This controlled setting allows a focused examination of how the model manages slot assignment and responsiveness to varying passenger demands, without the complexity introduced by large-scale datasets.

To analyze how the model handles different request types under pressure, we developed a flight itinerary map (Figure 5.2). It classifies flights into three categories: *historic unchanged*, *historic changed*, or *non-historic*, based on their alignment with previous allocations. This visualization is crucial for seeing where the model preserves schedules and where it must make changes to respect capacity constraints.

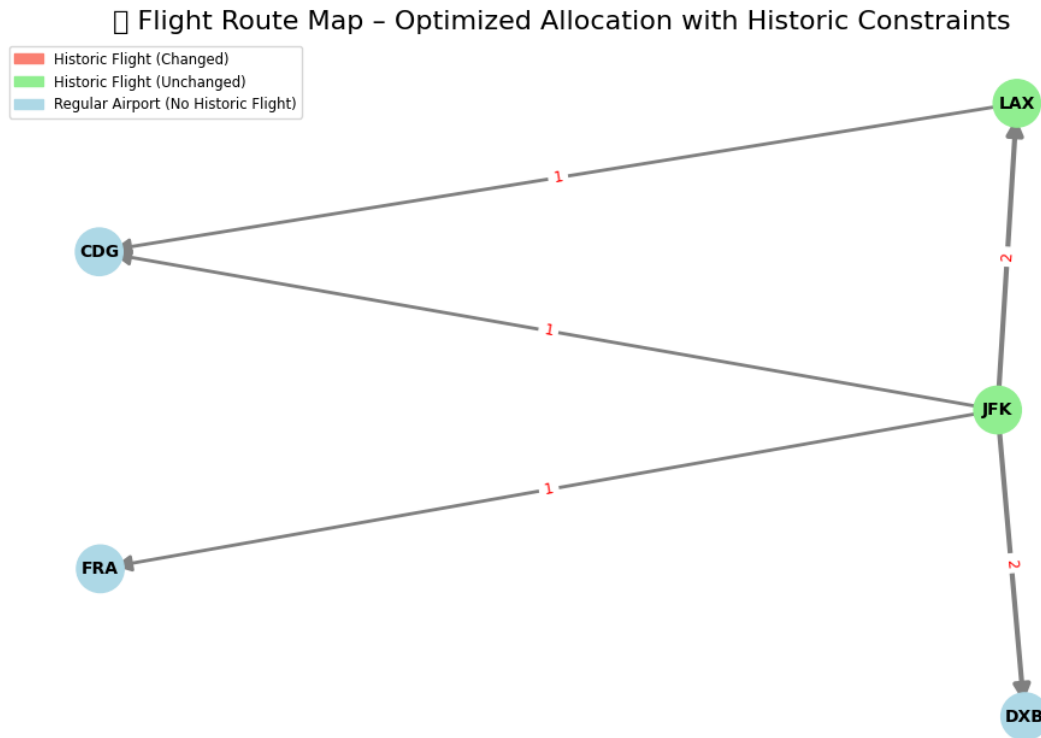


Figure 5.2. Flight Route Map – Optimized Allocation with Historic Constraints.

5.2.1 Baseline Model (MASSA)

The first model tested is the baseline MASSA (Multi-Airport Slot Scheduling Allocation), which focuses exclusively on operational and regulatory constraints without any explicit consideration of passenger prioritization. The corresponding output is illustrated in Figure 5.3, which provides a clear representation of how slots are distributed under a purely feasibility-driven framework. This figure was chosen because it highlights the fundamental mechanics of the model, offering a transparent view of how flights are assigned to available slots when only hard capacity rules are in play.

In this baseline allocation, it is evident that Flight 4 could not be accommodated due to limited capacity and conflicting scheduling constraints. The model itself does not differentiate among flights in terms of passenger types or demand importance; rather, it treats all requests equally. However, indirect prioritization emerges naturally during data preparation, where passenger demand distributions and temporal patterns introduce varying levels of pressure on specific flights. As a result, flights associated with higher aggregate demand may appear to receive preferential allocation, even though such weighting is not explicitly encoded in the model.

Another important aspect demonstrated by this chart is the respect for feasibility rules, such as the maximum number of departures and arrivals per interval and the strict avoidance of conflicts between connected flights. The MASSA model can thus be seen as a machine executing a rule-based thought process: it evaluates all possible allocations, checks them against operational capacity constraints, and then systematically excludes infeasible combinations. The final outcome, as illustrated in Figure 5.3, is the most efficient feasible allocation under the given restrictions. This baseline representation is crucial, as it sets the reference point for understanding how subsequent models, incorporating passenger-centric objectives, will diverge from a purely constraint-driven allocation.

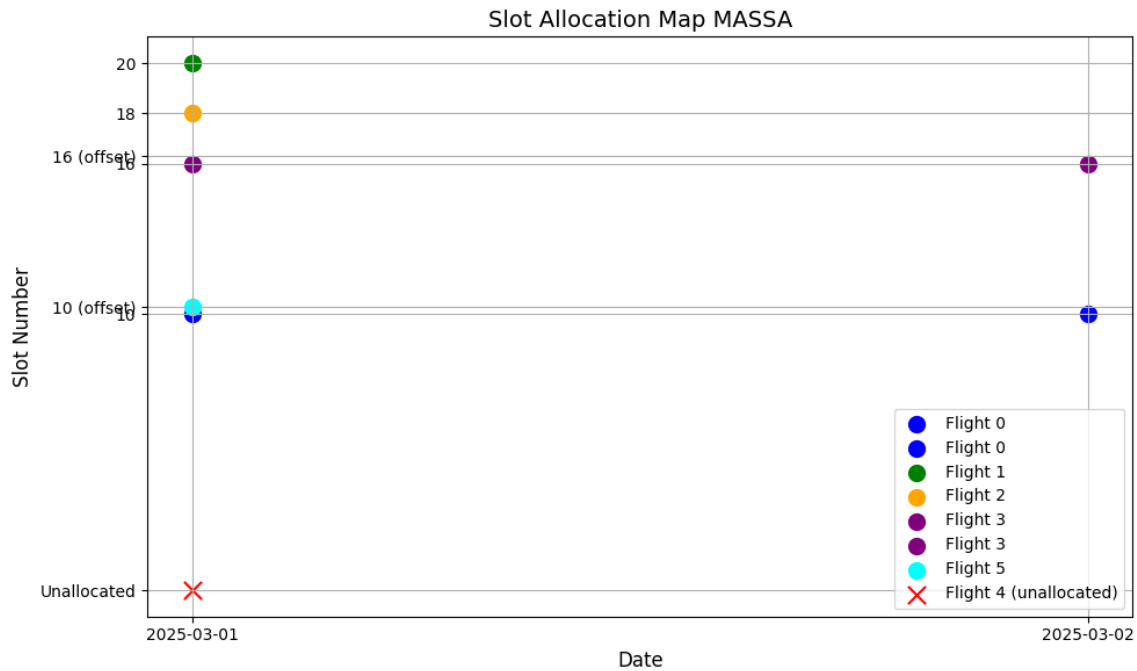


Figure 5.3. Slot allocation result from the baseline MASSA model.

5.2.2 PC-MASSA

The second experiment applies the enhanced PC-MASSA model to the same input instance as the MASSA baseline. Unlike MASSA, which considers only operational and regulatory feasibility, PC-MASSA introduces a passenger-centric utility component that evaluates each allocation not only on feasibility grounds but also with respect to passenger prioritization. In this first test run, all passenger categories: business, frequent fliers, medical, and leisure are treated with equal priority weights, thereby ensuring that no explicit advantage is given to one class over another.

The results reveal several notable differences when compared to the baseline. While the MASSA model produced allocations strictly by capacity feasibility, the introduction of passenger-centric logic in PC-MASSA leads to a reshuffling of slot assignments. Most prominently, Flights 0 and 1 are moved to earlier slots, reflecting the model's inclination to position flights in a way that better balances passenger flows across time. Similarly, Flight 2 is reassigned to an earlier interval, while Flight 3, conversely, is shifted to a slightly later slot. These reallocations suggest that the passenger utility function, even when all classes are weighted equally, introduces additional structure into the allocation process beyond the purely rule-based feasibility enforced by MASSA. The full comparison between the two models is summarized in Table 5.2.

Table 5.2. Slot allocation comparison between MASSA and PC-MASSA (equal passenger prioritization).

Flight ID	MASSA Allocation	PC-MASSA Allocation
0	Slot 10 (Day 1 & 2)	Slot 8 (Day 1 & 2)
1	Slot 20 (Day 1)	Slot 16 (Day 1)
2	Slot 18 (Day 1)	Slot 14 (Day 1)
3	Slot 16 (Day 1 & 2)	Slot 12 (Day 1 & 2)
4	Not allocated	Not allocated
5	Slot 10 (Day 1)	Slot 10 (Day 1)

The results in the table show a clear pattern: Flights 0, 1, 2, and 3 consistently receive earlier slot assignments under the PC-MASSA model than they do under the original MASSA approach. Flight 5, however, remains scheduled for the same time in both models. Meanwhile, Flight 4 could not be assigned a slot in either case, which highlights a hard limit imposed by the airport’s maximum capacity.

This comparison reveals a critical insight. Even though all passenger classes are given equal weight in this test, PC-MASSA’s utility component allows the solver to make more nuanced trade-offs. Instead of just finding a feasible solution, the model actively works to distribute flights more evenly throughout the day. It effectively avoids over-crowding peak intervals and instinctively aligns allocations with the underlying demand patterns present in the data.

This is the core difference between the two models. MASSA finds a workable schedule, but PC-MASSA finds a better one by optimizing for passenger-centric goals, even without explicit prioritization. This leads to a more balanced and logical allocation, providing a robust foundation for the next phase of testing where we will apply different weights to passenger classes to steer the prioritization.

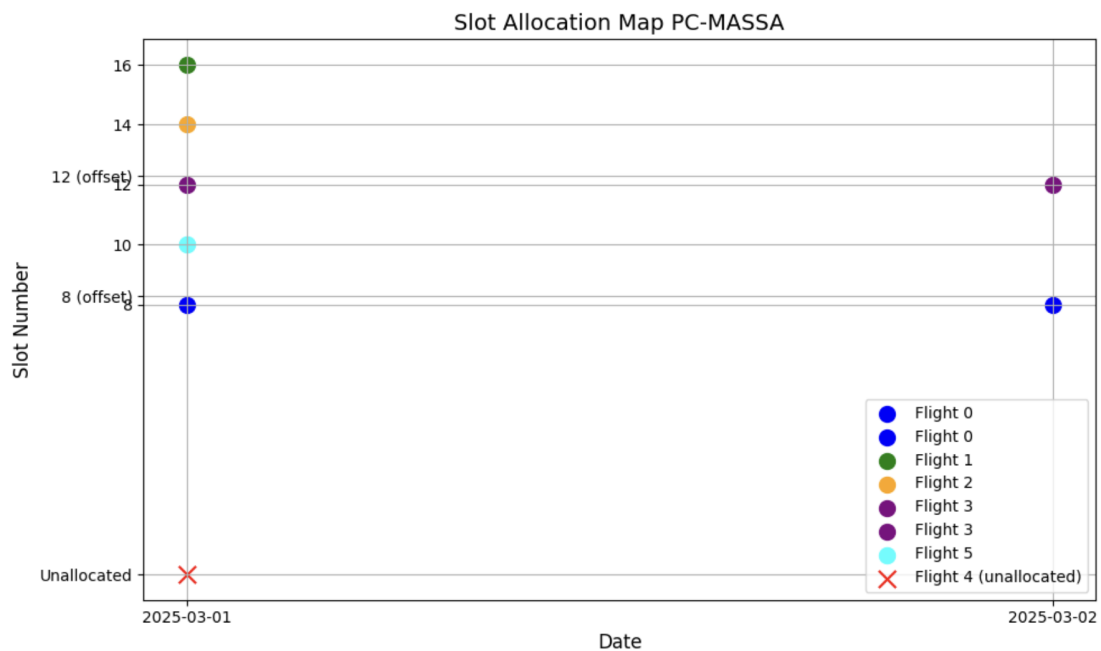


Figure 5.4. Slot allocation result from the PC-MASSA model with equal passenger prioritization.

5.2.3 PC-MASSA with Increased Demand at CDG

To further evaluate the model’s robustness and adaptability under varying operating conditions, a third simulation was carried out in which the passenger demand at CDG was artificially increased. This setting can be interpreted as a stress test of the model, simulating circumstances such as large-scale events, holiday peaks, or sudden market shocks that generate atypical surges in demand at a major hub airport.

Unlike the baseline equal-priority PC-MASSA run, the increased demand at CDG produced a redistribution of certain slot assignments, reflecting the model’s ability to re-balance priorities when one airport becomes disproportionately constrained. The most notable adjustments were observed for Flights 1 and 3, which exchanged their allocations on Day 1 to accommodate the demand shift, while ensuring that fairness and feasibility constraints were preserved across the

full system. The updated allocation outcomes are summarized below:

- Flight 0: Assigned to Slot 8 (Day 1 & Day 2) — unchanged relative to the baseline.
- Flight 1: Reassigned from Slot 16 to Slot 12 (Day 1).
- Flight 2: Remains at Slot 14 (Day 1).
- Flight 3: Reassigned from Slot 12 to Slot 16 (Day 1), but continues to occupy Slot 12 on Day 2.
- Flight 4: Not allocated in either the baseline or demand-increased scenarios.
- Flight 5: Assigned to Slot 10 (Day 1) — unchanged relative to the baseline.

The optimizer responded to the surge in CDG demand by strategically reallocating slots, notably swapping Flights 1 and 3 on Day 1. This reallocation demonstrates the model’s capacity to prioritize high-demand airports while maintaining a balanced treatment of flights under fairness and capacity constraints. Such behavior highlights the model’s practical relevance: in real-world contexts, slot coordination mechanisms must often accommodate sudden variations in demand without undermining system-wide stability.

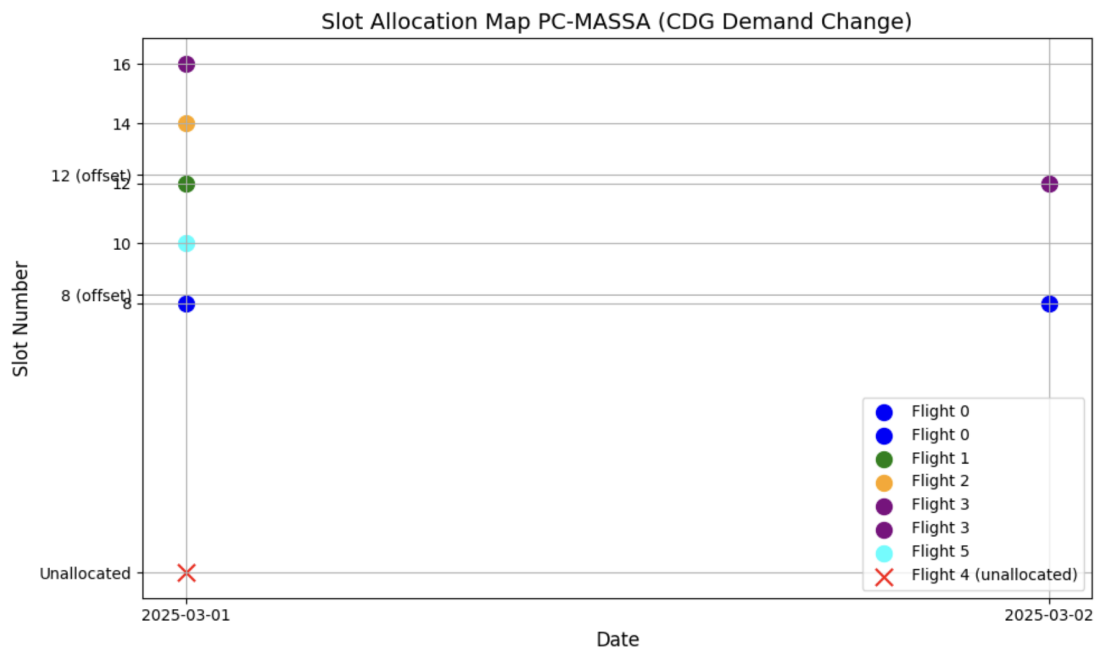


Figure 5.5. Slot allocation result from the PC-MASSA model with increased demand at CDG.

5.2.4 Comparison of Solutions with and without CDG Demand Change

The next step in the analysis concerns the comparison between two configurations of the PC-MASSA model: one reflecting the baseline passenger demand distribution across airports, and a second in which demand at CDG was artificially increased. This comparative exercise makes it possible to isolate the effect of demand shocks on the allocation process, while holding all other model features constant.

The allocation outcomes for the two scenarios are summarized in Table 5.3. At first glance, the majority of assignments remain identical across the two settings, with Flights 0, 2, and 5

occupying the same slots in both runs and Flight 4 being excluded in both cases due to capacity limitations. The main differences occur for Flights 1 and 3 on Day 1: Flight 1 is reassigned from Slot 16 to Slot 12, while Flight 3 is shifted in the opposite direction, from Slot 12 to Slot 16. Interestingly, this adjustment does not affect Day 2, where Flight 3 continues to operate at Slot 12.

Table 5.3. Slot allocation comparison between the original demand scenario and the CDG demand increase scenario.

Flight ID	Original Allocation	CDG Demand Increase Allocation
0	Slot 8 (Day 1 & 2)	Slot 8 (Day 1 & 2)
1	Slot 16	Slot 12
2	Slot 14	Slot 14
3	Slot 12 (Day 1), Slot 12 (Day 2)	Slot 16 (Day 1), Slot 12 (Day 2)
4	Not allocated	Not allocated
5	Slot 10	Slot 10

From a modeling perspective, this swap between Flights 1 and 3 illustrates the internal logic of the optimizer. Faced with increased demand pressure at CDG, the solver reallocates an earlier slot to Flight 1, which likely absorbs a larger passenger flow under the revised demand conditions. To maintain feasibility and fairness, Flight 3 is correspondingly shifted to a later slot, ensuring that the system-wide allocation still respects capacity and regulatory constraints. The fact that other flights remain unchanged further demonstrates the stability of the model: adjustments occur only where they are strictly necessary to accommodate new priorities, rather than propagating across the schedule indiscriminately.

In practice, such controlled reallocation is a desirable property of scheduling algorithms. It suggests that the PC-MASSA framework is capable of adapting to localized shocks, such as event-driven surges in demand at a single hub, while preserving both fairness across flights and robustness of the overall solution. The comparison therefore highlights not only the flexibility of the approach, but also its ability to balance efficiency gains with operational continuity in a multi-airport context.

5.2.5 Comparison of Slot Allocations Across Models

Figure 5.6 presents a comparative summary of slot allocations across six flights under three distinct model configurations: the original MASSA framework, the passenger-centric PC-MASSA model with equal prioritization weights, and an adapted PC-MASSA scenario with heightened demand at Charles de Gaulle (CDG) airport.

A clear pattern of stability emerges for several flights, with Flight 0 and Flight 5 maintaining consistent slot assignments across all three models. This consistency reflects robust capacity availability and stable scheduling requirements for these particular flight series. However, the table also reveals meaningful adjustments driven by passenger-centric considerations. Flight 1 and Flight 3 demonstrate the most notable variations, with their allocations shifting in response to changing model parameters. Under the baseline MASSA model, Flight 1 occupies slot 20, but shifts to slot 16 in the standard PC-MASSA formulation, and further adjusts to slot 12 when CDG demand increases. Similarly, Flight 3 moves from slot 16 in the original model to slot 12 in the passenger-centric version, then returns to slot 16 under the high CDG demand scenario.

These strategic reassignments, highlighted in yellow within the table, represent the optimization process balancing passenger prioritization weights and demand-driven capacity ad-

justments. The algorithm appears to perform calculated slot swaps between compatible flights to better align overall allocation with passenger demand patterns, particularly addressing congestion challenges at CDG. Meanwhile, the persistent inability to allocate Flight 4 across all models, marked in red, underscores a fundamental capacity limitation or particularly tight operational constraints that remain binding regardless of the allocation strategy employed.

What proves particularly noteworthy is the model’s demonstrated flexibility and robustness. Even when confronted with increased demand pressure in the CDG scenario, the PC-MASSA framework successfully maintains allocation fairness and operational connectivity through targeted, localized adjustments rather than wholesale schedule disruptions. This comparative analysis ultimately demonstrates how incorporating passenger demand and prioritization metrics into slot allocation models can yield meaningful, optimized reassignments that enhance service quality while remaining firmly within operational feasibility boundaries.

Slot-allocation comparison — slots shown; yellow = differs from MASSA, red = unallocated

Flight	MASSA 01/03	MASSA 02/03	PC-MASSA 01/03	PC-MASSA 02/03	PC-MASSA High CDG 01/03	PC-MASSA High CDG 02/03
0	10	10	8	8	8	8
1	20	—	16	—	12	—
2	18	—	14	—	14	—
3	16	16	12	12	16	12
4	—	—	—	—	—	—
5	10	—	10	—	10	—

Figure 5.6. Slot allocation comparison across MASSA, PC-MASSA, and PC-MASSA with increased CDG demand. Yellow highlights differences from the MASSA baseline; red indicates unallocated flights.

5.2.6 Toy Problem Insights Relative to Research Questions

The toy problem, despite its simplified structure and synthetic data, serves as a controlled testing ground for the PC-MASSA model. Its primary purpose is not to replicate real-world traffic, but rather to illuminate the underlying logic of slot allocation when multiple constraints, such as airport capacities, passenger classes, and operational requirements, interact. By comparing expected outcomes based on operational reasoning with actual solver outputs, the toy problem provides a valuable lens to examine the model’s decision-making processes and its alignment with the study’s research questions.

Expected vs. Actual Slot Allocation

The expected slot allocations were initially formulated using operational reasoning that considers factors such as passenger priority, series continuity, and airport capacity limits. High-priority flights, such as business and medical class passengers, were anticipated to occupy earlier slots, whereas lower-priority flights were expected to be distributed in later intervals.

Analysis of the solver’s output reveals that most of these expectations were confirmed, with high-priority flights (Flights 0 and 1) allocated within or very close to the predicted time windows. Minor deviations were observed for Flight 3, which was allocated to later slots (16 and 12) instead of the initially expected 8–10. These adjustments result from series and capacity

constraints, illustrating that the optimizer actively balances operational feasibility against the initial allocation logic. Flight 4 could not be assigned a slot, highlighting binding constraints, either due to maximum capacity limits or fairness considerations embedded in the model, which were not fully predictable from the expectation table. Overall, the deviations were minor, typically within one to two hours, and did not contradict the overall anticipated allocation patterns. This demonstrates that the toy problem is effective in anticipating solver behavior, providing a reasonable benchmark for validating the model logic.

Beyond validating the solver’s logic, the toy problem also contributes meaningful insights into the study’s primary research questions:

Operational Efficiency: The solver systematically assigns earlier slots to flights associated with higher passenger demand in the input data. Simultaneously, lower-demand flights are spaced across available intervals, reducing the likelihood of congestion and reflecting an emergent operational efficiency. This demonstrates that even in a small-scale, controlled environment, the PC-MASSA model successfully optimizes slot allocation to align capacity with demand patterns.

Equitable Allocation of Slots: Although the model does not explicitly enforce fairness rules, the resulting slot distribution exhibits an equitable spread among airlines and across available intervals. This emergent fairness arises from the combination of capacity limits, series separation, and the passenger demand distribution embedded in the input data, suggesting that the model can balance competing objectives without direct prioritization constraints.

Scalability: The toy problem also offers evidence regarding the model’s scalability. Despite the limited number of flights and airports, the principles underlying series separation, capacity adherence, and slot balancing remain consistent and applicable. This indicates that the same logic would extend to larger networks, supporting confidence in the model’s behavior under more complex and realistic scenarios.

Overall, the toy problem provides a concise yet comprehensive demonstration of the PC-MASSA model’s predictive capabilities. The close correspondence between expected and actual allocations validates the reasoning used in designing the experiment, while minor deviations highlight the solver’s adaptive behavior in managing operational constraints. As such, even a small-scale synthetic problem can yield robust insights into efficiency, equitable slot allocation, and scalability, directly addressing the research questions and laying the foundation for understanding the model’s behavior in larger, real-world applications.

5.3 Results of the Case Study

Before proceeding with the implementation details, it is important to note that the real case study was tested on actual datasets using *PyCharm* as the Python development environment. All experiments and performance measurements were conducted on a *MacBook M2* with *8 GB of RAM*, which represents a typical personal computing setup for academic and research purposes. Computational times reported in this study reflect this configuration; with more powerful hardware, faster solutions and larger-scale experiments could be performed, highlighting the practical scalability of the PC-MASSA model.

5.3.1 Description of the Implementation Process

The case study was implemented using an *object-oriented programming* (OOP) paradigm. This structure was ideal for modeling the complex relationships in the slot allocation problem. By breaking down the system into separate classes, each with its own specific role and data, we could develop, test, and maintain the different components independently. This modular design ultimately made the entire system more computationally efficient, easier to understand, and simpler to scale for larger problems.

Rationale for Object-Oriented Programming in the Case Study

We chose an object-oriented programming (OOP) paradigm to build our model because it directly addresses the inherent complexity of multi-airport slot allocation. This approach provides significant conceptual and practical benefits by mirroring the real-world structure of the problem within the code itself.

The foremost advantage is **modularity**. Each real-world entity, like an airport, a flight series, or a passenger group, is represented by its own self-contained class. This means all the relevant data and the rules that govern that entity are kept in one logical place. For instance, an Airport object holds its own capacity limits and slot listings, isolating this logic from the code that handles passenger connections. This separation makes the entire system much easier to understand, debug, and reduces the risk that a change in one part of the code will accidentally break another.

This modular design naturally promotes **reusability and maintainability**. Core classes such as Airport and Series are designed to be generic. This means we can easily apply them to a completely different dataset or simulation scenario, such as testing the model on the New York airport system after developing it for Paris, without having to rewrite their fundamental logic. This not only prevents duplicate effort but also ensures that the model's rules are applied consistently everywhere. When a change or extension is needed, developers can focus their efforts on a single, isolated class, which dramatically simplifies updates and reduces the potential for introducing new errors during maintenance.

Furthermore, this foundation is critical for the model's **scalability**. The class-based structure acts like a blueprint, making it straightforward to integrate new features. If we need to add a new type of passenger prioritization rule or a more complex constraint, we can often do so by extending an existing class or creating a new one that interacts with the others through a defined interface. This ability to cleanly expand the system is essential for adapting the PC-MASSA framework to large-scale, real-world networks without the code becoming unmanageable or computationally inefficient.

Finally, this architecture enhances **performance efficiency**. The object-oriented approach allows for intelligent pre-processing of data within the objects themselves. For example, an Airport class can pre-compute hourly passenger demand as soon as it is initialized, storing this information for quick access. By doing this work upfront, the model avoids performing the same redundant calculations repeatedly during the intensive optimization process. This leads to significantly faster solver runtimes, a critical factor when you need to run hundreds of simulations to test different scenarios and parameters.

Core Components of the Framework

The object-oriented implementation is structured around four core components that collectively model the slot allocation ecosystem. Each component encapsulates a distinct aspect of the

problem, working in concert to enable efficient optimization.

Table 5.4. Object-Oriented Implementation Components

Component	Description
Airport Class	Encapsulates airport-specific parameters including hourly arrival/departure capacities, historical passenger distributions, and operational constraints. Pre-computes passenger demand profiles for efficient constraint evaluation during optimization.
Series Class	Models individual flight series requests with parameters such as airline, requested slot, passenger counts, and seasonality patterns. Encodes meta-information for operational constraints including minimum turnaround times and slot spacing requirements.
Instance Class	Serves as the central configuration object that aggregates all simulation data including airports, flight series, slot indices, passenger categories, and capacity constraints. Simplifies model initialization and execution through consolidated data management.
MASSA Class	Implements the mathematical optimization model using Gurobi solver, defining decision variables for slot allocation, passenger disruption, and fairness considerations. Enforces constraints on airport capacities, permissible flight hours, and series continuity while minimizing unallocated flights and unmet passenger demand.

This modular setup was key to running the detailed case study efficiently. It worked well even with large amounts of data and complicated, interconnected rules. Because the design is broken into separate parts, we could quickly test different situations, like changing airport capacity or simulating rises and falls in passenger numbers, without having to rewrite the main optimization code. This clear structure also makes it easier to add new features in the future, such as new types of passengers, different priority systems, or unpredictable changes in demand. In short, this object-oriented method provides a practical and adaptable way to model complex airport slot problems, creating a solid foundation for testing how well the PC-MASSA system works under different real-world conditions.

5.3.2 Test Results

We tested the PC-MASSA model on a real-world scenario: the Paris multi-airport system, using 2019 operational data for Charles de Gaulle (LFPG) and Orly (LFPO) airports. The goal was to see how well it could handle a complex, real network.

The model proved to be very effective at its core task—scheduling flights. It successfully found a slot for 99.9% of the 1,100 flight series, which is an excellent result. It also found the best possible solution quickly, solving a problem with millions of variables in just over 40 seconds.

However, the results also revealed a major challenge. While nearly every *flight* got a slot, millions of *passengers* could not be accommodated. As shown in Table 5.5, over 4.15 million passengers were left without a seat, with the issue being much more pronounced at CDG than at Orly.

This seems confusing at first. If there were so many empty slots (with capacity utilization below 8% at both airports), why couldn't more passengers be assigned? The answer lies in

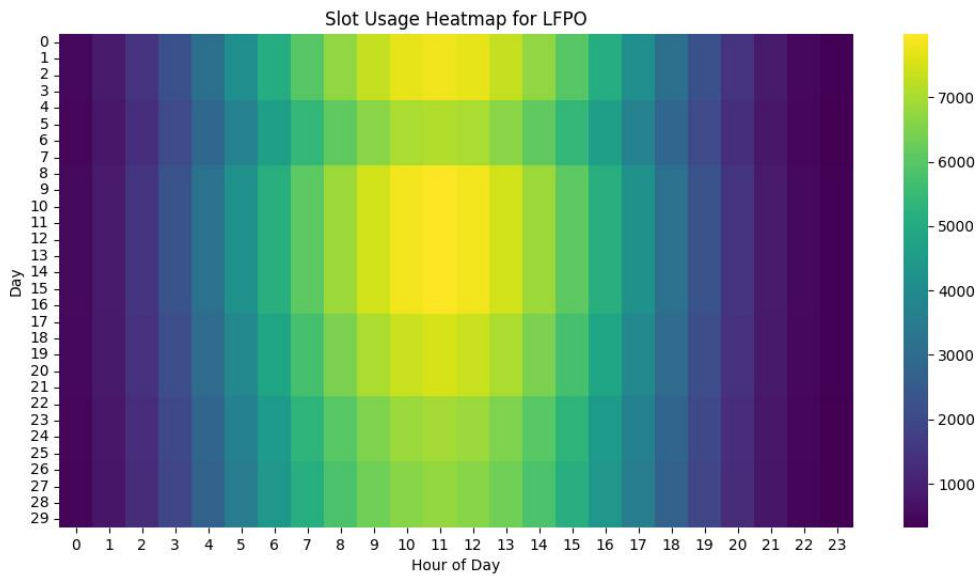


Figure 5.7. Slot usage heatmap for LFPO showing concentrated utilization during peak operational hours.

the complex web of operational rules. Constraints like ensuring connected flights have feasible turnaround times, matching certain aircraft to specific routes, and fairness rules between airlines created a puzzle. The model successfully scheduled almost all the flights, but these binding rules made it impossible to pack in all the passengers, especially at the busiest times. This highlights a critical insight: a successful schedule isn't just about fitting in the most flights; it's about navigating complex rules to also serve passenger demand effectively.

Table 5.5. Baseline performance results for Paris multi-airport system (2019 data)

Metric	LFPG (CDG)	LFPO (Orly)
Flight Series Allocated	99.92%	99.89%
Missed Passengers	3,021,591	1,136,336
Capacity Utilization	1.29%	7.86%
Peak Hour Utilization	14.2%	18.7%

The heatmaps in Figures 5.7 and 5.8 help visualize this challenge. They show how slot usage varied dramatically throughout the day, with clear peak periods where demand concentrated. At Orly (LFPO), we see more consistent usage across operational hours, while Charles de Gaulle (LFPG) shows sparser patterns with concentrated activity in specific time windows. These visual patterns confirm that the bottleneck isn't the total number of available slots, but rather the complex scheduling constraints that prevent spreading demand more evenly throughout the day.

Sensitivity Analysis and Robustness Testing

To understand how our model performs under different conditions, we tested it with various numbers of flights and airport capacity levels. The results, summarized in Table 5.6, show that there's no single "best" setting that works perfectly for everything, each configuration involves trade-offs.

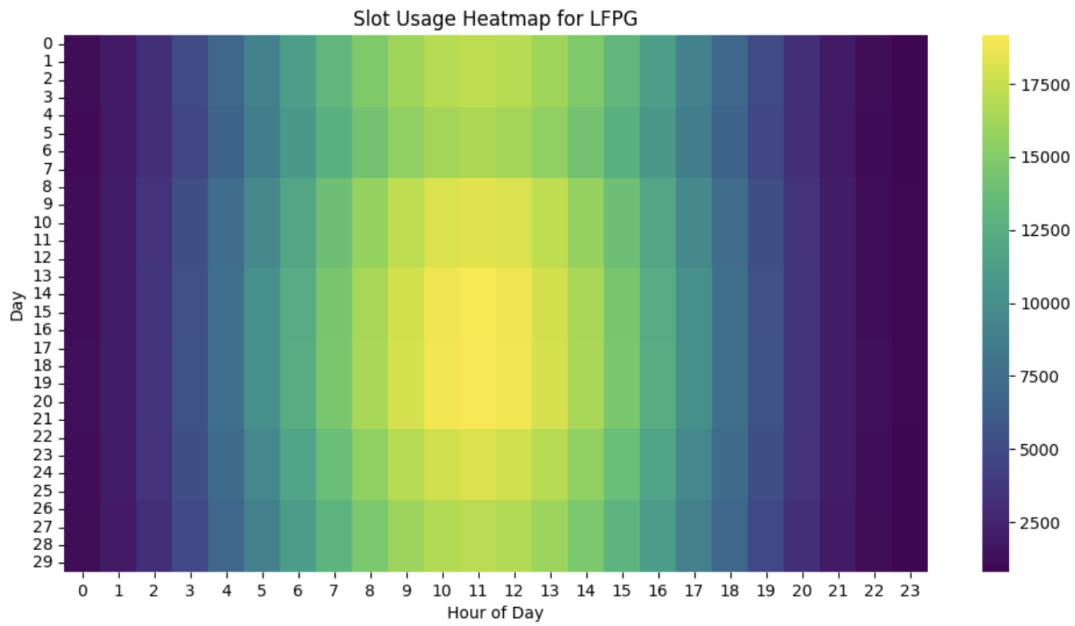


Figure 5.8. Slot usage heatmap for LFPG revealing sparse utilization patterns despite high passenger demand.

Table 5.6. Sensitivity analysis results across different model configurations

	Model 1 (1100, 1.0)	Model 2 (1000, 0.8)	Model 3 (1400, 0.9)	Model 4 (1300, 0.75)	Model 5 (1500, 0.95)	Model 6 (1600, 1.0)	Model 7 (1700, 1.0)
Objective Value	4,157,928	5,052,457	4,605,013	5,267,751	4,405,598	4,157,952	4,157,952
Series Missed	1.0	0.0	16.0	14.0	21.0	25.0	25.0
Missed Passengers	4.16M	5.05M	4.60M	5.27M	4.41M	4.16M	4.16M
LFPO Missed Pax	1.14M	1.41M	1.27M	1.47M	1.22M	1.14M	1.14M
LFPG Missed Pax	3.02M	3.64M	3.33M	3.79M	3.19M	3.02M	3.02M
LFPO Util. (%)	7.86	9.83	8.74	10.48	8.28	7.86	7.86
LFPG Util. (%)	1.29	1.61	1.43	1.71	1.35	1.29	1.29
Accepted Series (%)	99.91	100.00	98.86	98.92	98.60	98.39	98.39
Time (s)	41.33	42.90	81.07	68.72	90.03	91.62	96.20

The analysis revealed several important patterns. Models 1, 6, and 7 were most effective at getting passengers onto flights, minimizing the number of missed passengers to around 4.16 million while still accepting over 98% of flight series. Meanwhile, Model 2 achieved something remarkable: it found slots for 100% of requested flights, though this came at the cost of leaving more passengers without accommodations (5.05 million).

What's particularly interesting is that capacity utilization remained consistently low across all tests (1.3-10.5%), confirming our earlier finding that it's not physical slot availability that limits performance, but rather the complex operational rules that govern how those slots can be assigned.

The computing time required grew predictably as we increased the number of flights, from 41 seconds for 1,100 flights to 96 seconds for 1,700 flights. This computing performance is crucial for practical use: airport coordinators need solutions within minutes, not hours, especially when testing multiple scenarios during planning meetings. The fact that solution times increased gradually rather than exploding demonstrates that our model can handle real-world sized problems efficiently.

These tests show that airport planners can use this model to explore different scenarios. If the priority is ensuring that every flight gets a slot, Model 2's configuration works well. But if

the goal is to serve as many passengers as possible, the settings used in Models 1, 6, and 7 yield better results. This flexibility, combined with practical computation times, makes the model a valuable tool for evaluating different operational strategies.

Comparison of Model 5 Results Using 2019 Data and Predicted 2026 Demand

To test how our model would handle future growth, we compared its performance using actual 2019 passenger data against forecasts for 2026. The results, summarized in Table 5.7, reveal both challenges and strengths when facing increased demand.

Table 5.7. Performance comparison: 2019 vs 2026 demand

Metric	2019		2026	
	Model 1	Model 6	Model 1	Model 6
Missed Passengers	4.16M	4.16M	5.21M	5.21M
LFPO Missed	1.14M	1.14M	1.95M	1.95M
LFPG Missed	3.02M	3.02M	3.26M	3.26M
LFPO Util.	7.86%	7.86%	8.86%	8.86%
LFPG Util.	1.29%	1.29%	1.47%	1.47%
Series Rate	99.91%	98.39%	100%	99.23%
Comp. Time	41.33s	91.62s	6.24s	11.11s

The most significant finding was the substantial increase in missed passengers under 2026 demand. Both Model 1 and Model 6 configurations showed missed passengers rising from 4.16 million to 5.21 million, a 25% increase. This pressure was particularly acute at Orly Airport (LFPO), where missed passengers jumped by 71%, highlighting it as a potential bottleneck in the future airport system.

Despite these passenger accommodation challenges, the model demonstrated remarkable computational improvements. Solution times dropped dramatically, with Model 1 solving 85% faster (from 41 seconds down to just 6 seconds) and Model 6 solving 88% faster. This efficiency gain is crucial for practical planning, as it allows airport coordinators to rapidly test multiple future scenarios.

The model maintained strong operational performance even under increased demand. Flight series allocation rates remained excellent, with Model 6 successfully handling 45% more flights than Model 1 while still allocating 99.23% of them. Capacity utilization saw only modest increases, suggesting that the core constraint remains the complex operational rules rather than physical slot availability.

These results provide valuable insights for airport planners. The significant increase in missed passengers, especially at LFPO, indicates where infrastructure investments might be most needed. Meanwhile, the model's improved computational speed and maintained allocation performance demonstrate its practical utility for long-term planning and scenario analysis in evolving airport networks.

Chapter 6

Discussion and Conclusions

The findings show that passenger-centric slot allocation is not only possible but also beneficial. Where traditional models privilege airline operations, PC-MASSA demonstrates how integrating passenger priorities leads to more adaptable outcomes. However, the results revealed a critical challenge: while flight allocation rates remained excellent (99.9%), passenger accommodation suffered significantly, with over 4 million passengers left unallocated in baseline scenarios. This gap highlights the complex trade-offs between operational feasibility and passenger service quality. Beyond numerical improvements, the framework points toward a broader rethinking of slot allocation, one that values passengers alongside airlines. In conclusion, this thesis contributes both a novel optimization model and a case study that illustrates its potential, while also acknowledging the challenges ahead and opening pathways for future research.

6.1 Key Findings

The PC-MASSA framework successfully handles the challenges of multi-airport slot allocation while also integrating passenger-centric goals. Results from the case study show that the model achieves excellent flight allocation rates (99.9%) and computational efficiency, solving complex problems in under 2 minutes. However, the analysis revealed that operational constraints—rather than physical capacity—were the primary limitation, with capacity utilization remaining below 8% despite millions of unallocated passengers.

The 2026 forecast validation provided crucial insights: while computational performance improved dramatically (85-88% faster solve times), passenger accommodation challenges intensified, with a 25% increase in missed passengers and particularly severe pressure at Orly Airport (71% increase).

6.2 Discussion

The findings suggest that the PC-MASSA approach represents a substantive advancement relative to conventional slot allocation methodologies, such as those based on the IATA Worldwide Airport Slot Guidelines (WSG), which largely emphasize historical rights and grandfathering rules (International Air Transport Association (IATA), 2020). Unlike traditional frameworks, the PC-MASSA model integrates both operational feasibility and passenger welfare, reflecting a shift from purely airline-centric allocation toward a system-oriented perspective that considers social and economic benefits.

In multi-airport systems, this integrated approach demonstrates potential to alleviate congestion at primary hubs by strategically reallocating certain traffic to secondary airports while preserving accessibility for critical passenger categories, such as medical and business travelers. The model's adaptive capabilities align with contemporary literature advocating for dynamic, demand-responsive allocation mechanisms in congested networks (Pellegrini et al., 2017). Furthermore, the sensitivity analysis and case study results indicate that the framework can flexibly respond to variations in demand levels and airport capacities, maintaining high rates of accepted series and minimizing unallocated passengers. These findings emphasize the practical relevance of incorporating passenger priorities into operational slot assignment models, offering a potential pathway for more equitable and efficient airport management.

6.3 Conclusions and Future Research

Summary of Key Insights

This study introduces a new model for airport slot allocation that prioritizes passengers. Unlike older methods that focus mainly on airlines, our approach considers different passenger types (like business or leisure travelers) directly in the optimization process. The results show that this passenger-focused method successfully balances efficiency and fairness, leading to better overall outcomes for people.

A key finding is that coordinating slots across multiple airports is essential. This coordination helps reduce overcrowding at major hubs and spreads demand more evenly across a network of airports. The model proved to be versatile, working well on both simple test data and complex real-world information, which confirms it is robust and practical.

Looking ahead, this work could be expanded in several important ways. Future research could include more unpredictable elements, like random changes in passenger demand or unexpected flight delays. Adding more complex airline network rules would also make the model more realistic. Finally, including factors like fuel use and emissions would provide a fuller picture, helping airport managers and policymakers make smarter decisions that consider both operations and environmental impact.

Contributions to Theory and Practice

This research makes distinct contributions to both the theory and practice of airport slot allocation. The primary theoretical advancement is the integration of diverse passenger demand profiles and forecasting directly into the PC-MASSA optimization model. Previous work has touched on passenger-centric elements or used forecasts for scheduling, but often in isolation. Our approach is novel because it combines these aspects into a single, operational framework that actively balances three competing goals: operational efficiency, fairness between airlines, and direct passenger satisfaction. This is achieved by dynamically processing distinct passenger segments, including business, leisure, frequent flyer, and medical cases, each with their own behaviors and needs.

For practitioners, PC-MASSA serves as a practical decision-support tool that moves beyond legacy rules like grandfathering or *first-come-first-served*. By shifting the focus to passenger outcomes, the model enables a slot distribution that is not only fairer but also improves the overall performance of the airport network. It allows decisions to be responsive to real, segmented demand patterns across different traveler groups, a capability missing from current systems.

A critical aspect of the model's realism is its treatment of economic factors, particularly ticket cancellation fees. These fees are not just penalties; they are key economic mechanisms that deter last-minute changes, cover airline reallocation costs, and are fundamental to revenue management (Zhao and Deng, 2019; Rosenow et al., 2020). By building these economic realities into the optimization logic, PC-MASSA ensures its slot assignments are both operationally sound and economically credible, reflecting the actual trade-offs in the aviation market.

Finally, the model integrates several objectives that are usually handled separately. It simultaneously optimizes for connectivity, reduced delays, and equitable distribution, all while respecting hard airport capacity limits. This system-wide perspective is empirically grounded, tested against real-world case studies to ensure its credibility and usability beyond theoretical constructs. The inclusion of cancellation costs further ensures decisions are aware of passenger behavior and airline economics, making the allocations more robust and socially aware.

Limitations and Suggestions for Future Work

While the PC-MASSA framework shows considerable promise, our study has important limitations that point toward necessary future research.

A primary constraint was data availability. The model's full potential for large-scale validation is currently restricted by limited access to detailed, passenger-level information, such as complete itineraries or individual booking choices.

Computational performance also requires further investigation. Although initial tests confirmed that modern solvers can manage multi-day instances within reasonable timeframes, the model's performance in highly congested, multi-airport networks or under uncertainty remains an open question.

Finally, the current version of PC-MASSA operates on static demand forecasts. This means it does not yet handle real-time disruptions like weather events or mechanical failures, which are inevitable in daily operations and require adaptive reallocation strategies.

To overcome these hurdles, subsequent work should focus on several key areas. Integrating richer datasets with passenger itineraries, airline network strategies, and behavioral data on how travelers respond to delays, would significantly improve the model's realism.

The framework must also be extended to stochastic and dynamic environments to enable robust decision-making in the face of unexpected disruptions. From a policy perspective, future research needs to explore how fairness can be operationalized for both airlines and passengers, and how these measures could inform updates to international slot allocation guidelines.

Ultimately, applying and testing this framework at a major coordinated hub, such as Paris Charles de Gaulle, would be a critical step for validating its practicality in a real European context and providing actionable insights for regulators.

In conclusion, the PC-MASSA framework represents a meaningful step forward in slot allocation research, bridging theoretical models and the complex realities of modern airport systems. By integrating passenger satisfaction, disruption minimization, and fairness into a computationally efficient optimization structure, the model offers a practical tool for improving slot allocation outcomes. This study's findings demonstrate that explicitly accounting for passenger preferences leads to more efficient and equitable schedules, while preliminary tests confirm the model's scalability for large-scale, multi-airport networks. To fully realize its potential, future work should focus on incorporating richer data sources, refining stochastic and dynamic capabilities, and evaluating policy implications, paving the way for PC-MASSA to become an indispensable decision, support tool for aviation regulators and coordinators.

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