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Delay predictive analytics for airport capacity management

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ABSTRACT

Local delay predictions are crucial for optimizing airport capacity management, enhancing overall resilience, efficiency, and effectiveness of airport operations. This paper delves into the development and comparison of state-of-the-art predictive analytics techniques—spanning rule-based simulations, queuing models, and data-driven approaches—and demonstrates how they can empower informed decision-making toward mitigating the impact of potential delays across the whole spectrum of capacity management initiatives—from long-term strategic capacity planning to near real-time air traffic flow management. Using real-world data for four major airports in Southeast Asia, we comprehensively assess the performance of different methods and highlight the improved predictive capabilities achievable through data-driven methods and the incorporation of sophisticated features. Results show that (i) embedding queuing model features into machine learning models effectively captures congestion dynamics and nonlinear patterns, resulting in an improvement in predictive accuracy; (ii) incorporating advanced day-of features – lightning strikes, wind conditions, and propagated delays from prior hours – further enhances prediction accuracy, yielding MAE gains ranging from 15% to 30%, contingent on the specific airport; (iii) in cases where limited information is available (years to months in advance of operations), conventional simulation and queuing models emerge as robust alternatives. Ultimately, we conceptualize and validate a delay prediction framework for airport capacity management, characterizing the different planning phases based on their specific delay prediction requirements and identifying appropriate methods accordingly. This framework offers practical guidance to airport authorities, enabling them to effectively leverage delay predictions into their airport capacity management practices.

1. Introduction

Over the past decades, commercial aircraft movements worldwide have experienced significant growth, with a compound annual growth rate of 3.2% between 2010 and 2019 (ACI, 2010, 2019). This trend was abruptly interrupted by the COVID pandemic; however, clear signs of recovery are now evident, with demand rebounding at a faster pace than anticipated (IATA, 2019). As a result, the resurgence of air travel has reignited the challenges of air traffic congestion and flight delays, once again emphasizing the necessity for effective airport capacity management.

Airport capacity management (ACM) aims to address air traffic congestion and its associated issues by effectively aligning supply and demand through a combination of supply-side and demand-side interventions. Different ACM interventions are typically employed: (i) years in advance, capacity planning decisions address investments in airport infrastructure through the development

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of airport master plans; (ii) months in advance, strategic scheduling decisions are made to determine the number of flights to accommodate and their schedule at the airport through the implementation of slot allocation mechanisms; (iii) months to days in advance, strategic flow management decisions are made to prepare initial flight plans before the actual operating conditions are known; (iv) day-ahead to hours in advance, pre-tactical flow management decisions are made to adjust the initial flight plans based on additional information concerning the availability of airport resources, weather forecasts, and other relevant factors; and (v) near-real time, tactical flow management decisions are made, involving the dynamic management and adjustments of landing and takeoff operations, as well as real-time reassessment of flight plans.

Regardless of the particular intervention's scope, airport capacity management boils down to addressing a fundamental trade-off: accommodating as much flight demand as possible while ensuring seamless and safe air traffic operations. In practice, this translates into developing and managing airport capacity to optimize efficiency metrics and economics targets – e.g., capital investments at the strategic level, flight rescheduling and cancellations at the tactical level, air traffic flow management at the operational level – while mitigating flight delays. Predicting flight delays is therefore pervasive across the whole spectrum of capacity management interventions and crucial to adequately inform these decisions.

Nonetheless, anticipating flight delays remains an exceptionally challenging task due to their intrinsic and largely unavoidable uncertainty. This uncertainty stems from a variety of factors, including contingent/exogenous elements (e.g., weather conditions, temporal features, aircraft defects, etc.), congestion-related factors, and network cascading dynamics (i.e., the portion of delay that ripples through complex networks of interconnected flights) (Birolini and Jacquillat, 2023). Various methodologies have been developed to model and anticipate the occurrence and propagation of flight delays. In the airport capacity management domain, these range from high-fidelity simulation models that accurately replicate aircraft operations (Odoni, 1997) to more aggregate and approximate analytical models such as queueing models (Shone et al., 2021). More recently, the increased availability of data and computing technologies have fostered the development and use of machine learning, either independently or in conjunction with other methods (Carvalho et al., 2021).

In addition to the intrinsic complexities of predicting flight delays, different levels of airport capacity management entail distinct decisions, time scopes, and levels of aggregation. This renders a *one-fits-all* solution impractical. Instead, the diversity and heterogeneity of control variables, data availability, and delay drivers throughout the planning horizon necessitate tailored methodologies that effectively capture the specific characteristics of each planning stage.

This paper sets out to conceptualize a unified framework to provide guidance on how to predict delays and leverage them toward resilient airport capacity management. In addition to exploring state-of-the-art simulation and analytical methods, we thoroughly demonstrate the benefits of stand-alone and hybrid data-driven methods. We also assess the impact of various features, ranging from aggregate aircraft movements, to weather-related on-time information, which become available at the different ACM stages. Using readily available trajectory-level Automatic Dependent Surveillance-Broadcast (ADS-B) data from four major airports in South-East Asia, we validate the proposed framework and methods through comprehensive experimentation and analysis.

Specifically, this paper makes the following contributions:

1. *Provide a comprehensive unified framework to predict flight delays across the whole spectrum of airport capacity management interventions.* We first review the existing literature on flight delay prediction – 200+ papers reviewed – and identify the main airport capacity management phases along with their associated requirements for flight delay predictions. We propose a framework that takes into account the varying requirements for flight delay prediction at different phases. The framework encompasses methods and features, tailored to the level of granularity and scope of each phase, providing practical insights to enhance airport operations and optimize resource allocation toward resilient capacity management.
2. *Propose a data-driven approach for extrapolating airport local delays through the use of readily available surveillance datasets.* A primary challenge to managing delays for airport capacity management – even before getting into the prediction task – is to characterize local delays, i.e., delays occurring in a close neighborhood of the terminal airspace. This is not straightforward as such delays are not directly observed from real-world data. We design and deploy a data-driven pipeline – including unsupervised machine learning (clustering), anomaly detection, and dimensionality reduction techniques – to engineer data features and compute airport local delays from fine-grained trajectory-level Automatic Dependent Surveillance-Broadcast (ADS-B) data. The resulting methodology adheres to the ICAO standard definition for characterizing local delays (ICAO, 2023), ensuring consistency with industry best practices and accuracy in our analysis. Moreover, it benefits from scalability and generalizability, making it applicable to other airports with minimal customization. By enabling airport operators and planners to extract meaningful insights from ADS-B data, our methodology provides a valuable capability for characterizing and managing local delays on a large scale.
3. *Develop innovative methods and engineer features to predict airport local delays.* We first assemble a set of strong and novel predictors of local delays—spanning congestion-, temporal-, route-, and weather-related factors (e.g. wind, convective weather conditions). We then apply a variety of predictive analytics techniques – such as rule-based simulations, queueing models, and machine learning (linear regression, GBM, random forest, neural networks, and vector machines) – and evaluate and compare their effectiveness in various application settings. Similar to Birolini and Jacquillat (2023) we propose a hybrid queuing-based machine learning model for local delays that combines the advantage of queuing models (in capturing congestion dynamics) and machine-learning (in accounting for contingent factors and complex nonlinear patterns). The results obtained demonstrate the benefits of advanced predictive analytics and feature engineering to support the different types of interventions and decisions across the ACM spectrum.

4. *Comprehensively validate the proposed framework using real-world data for four major airports in South East Asia, namely Singapore (SIN), Hong Kong (HKG), Kuala Lumpur (KUL), and Bangkok (BKK).* Through extensive experimentation using real-world data for whole year of 2019, we first evaluate the predictive capabilities of the proposed models. As we moved from simpler models that use only a limited set of features to more advanced modeling approaches that leverage ML and queuing methods while incorporating all the available features, we observed significant improvements in predictive accuracy achieving R^2 ranging from 0.45 to 0.67 and MAE values spanning 1.2 to 2.7 min across airports. We then provide practical recommendations for their adoption in the real-world environment. Specifically, we investigate the use of delay predictive models in conjunction with prescriptive analytics to support slot allocation, ground delay programs, and air traffic flow management. Our findings demonstrate that ACM prescriptive methods contribute to alleviate congestion, and can be strengthen by explicitly endogenizing delay predictive analytics. Ultimately, this empirical assessment represent an important stand-alone contribution as one of the largest empirical studies in airport capacity management using real-world data from the fast-growing region of South-East Asia.

In the remainder of this paper, we first conduct a comprehensive literature review on different methods for flight delay prediction (Section 2). In Section 3, we present the proposed data-driven approach for computing local delays using real-world ASD-B datasets. In Section 4, we introduce the empirical setting, develop different predictive methods, and systematically compare their prediction performance. In Section 5, we put forth and validate a comprehensive framework for flight delay assessment in ACM. Ultimately, in Section 6, we conclude the paper and provide directions for future research.

2. Flight delay prediction

Flight delays have significant adverse impacts and detrimental consequences, affecting not only passengers and airlines but also the broader economy and the environment. They lead to inefficient operations, increased carbon emissions, and passenger disaffection, resulting in significant monetary losses for airlines and airports, as well as demand detriment and a reduction in overall societal welfare (Ball et al., 2010).

Depending on the unit and scope of analysis, flight delays can be classified into local delays (at the segment level), schedule-delays (at the flight level), and network delays (at the network level).

– *Local delays.* Local delays measure the difference between the "unimpeded" time required to complete a specific flight segment (e.g., from an entry fix of the terminal airspace to a runway) and the actual time taken to complete that segment, accounting for localized factors like congestion, weather, and other operational factors. Local delays represent the portion of delays that stem exclusively from inefficiencies within the airport or a specific controlled airspace segment. Accordingly, these delays are highly relevant to devise effective capacity management interventions at individual airports.
– *Schedule delays.* Schedule delays (or total flight delays) measure the difference between the scheduled time of a flight and its actual time of operation. Schedule delays consider the whole flight and encompass all delay drivers along its duration, including during departure, en-route, and at the arrival airport. Airports can use this information to identify recurrent deviations from schedules and create more resilient flight plans that account for the uncertainty in flight schedules. Nonetheless, flight schedule delays are not under control of a single airport.[1]
– *Network delays.* Studies focused on network delays investigate the propagation dynamics and interdependencies among airports within an airspace system. Their focus lies in analyzing the cascading effects of disruptive events, such as adverse weather conditions or airport closures, in order to pinpoint the most critical nodes in the network. By analyzing network delays, air traffic managers can gain valuable insights into the operational impacts of disruptions and use this information to support their decision-making at the network level (e.g., by employing ground delay programs).

Fig. 1 shows the differences between scheduled delays (in orange) and local delays (in blue) — estimated using the procedure to be introduced in Section 3. Scheduled delays tend to increase systematically throughout the day due to network delays. In contrast, local delays more closely correlate with the number of movements (in green). Local delays are more closely tied to the actual causes of congestion, whereas scheduled delays are influenced by delays originating in other parts of the air transport network.

Predictive methods for flight delay prediction can be broadly categorized into three categories: (i) rule-based simulation models (Section 2.1), (ii) queuing models (Section 2.2), and (iii) data-driven models (Section 2.3). The main difference between these models lies in the methodologies they use to predict delays. Rule-based simulation models can estimate delays using a bottom-up approach, replicating the system's functioning based on predefined operational rules and assumptions, typically implemented through traditional simulation techniques such as discrete event simulation or agent-based modeling. Queuing models, on the other hand, are analytical approaches that use mathematical equations to represent and analyze queueing systems, like those found in airport operations. Data-driven models depend on the data itself to identify and learn patterns, ranging from basic statistical regression techniques to sophisticated machine learning and neural network algorithms.

Next, we systematically review the state-of-the-art of flight delay modeling with a greater emphasis on local delays. Local delays take center stage in our study, as they are the most pertinent delays to appraise and consider when evaluating airport capacity management decisions.

[1] On the other hand, schedule delays are crucial for robust airline planning. By effectively anticipating flight delays and incorporating such information into their planning, airlines can proactively build robust aircraft and crew rotations by allocating buffer times after critical flights, i.e., those more prone to incurring large delays, and thus mitigate severe downstream impacts—a well-documented practice in the literature (see,e.g., Lan et al., 2006; Brueckner et al., 2021; Birolini and Jacquillat, 2023).

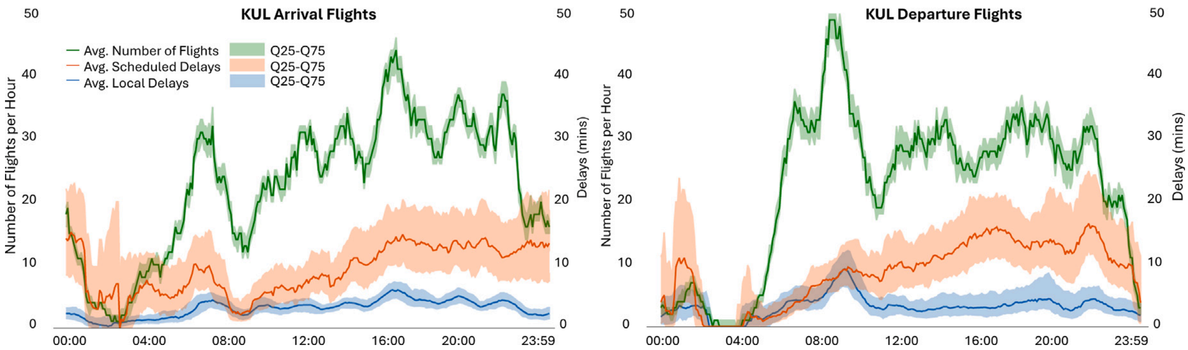


Fig. 1. Schedule delays vs. Local delays. The plot displays the average hourly delays along with the 25th and 75th percentiles for one year at Kuala Lumpur International Airport (KUL), for arrivals (left) and departures (right).

2.1. Simulation models

Simulation techniques are widely used in industries such as logistics and manufacturing (Terzi and Cavalieri, 2004), and have also found extensive applications in air traffic performance evaluation and capacity management (Odoni, 1997). Microscopic simulations, which model individual aircraft movements in detail across the airport and airspace network replicating with high fidelity the physical layout of the airport and surrounding airspace, are particularly useful for design and operational decision-making. They enable the evaluation of the benefits of physical or procedural modifications and investigate the impact of increased traffic. Over the years, various commercial simulation software has been developed and is currently in widespread use at airports worldwide. The most prominent ones are: SIMMOD (Advanced Simulation Tool for Analyses), TAAM (Total Airspace and Airport Modeller), AirTOP (Airport and Airspace Fast-Time Simulation), and CAST (Scalable and Modular Aviation Software).

SIMMOD was developed by ATAC in the late 1980's while funded by FAA (FAA, 1989). It uses discrete-event simulation to mimic aircraft movements across an airspace network, adopting a node-link based structure in which the airspace network is represented as a series of links connecting nodes. SIMMOD has found applications in numerous research studies and projects worldwide, primarily focused on analyzing the trade-off between airfield capacity and local delays when assessing the impact of capacity expansions and/or changes in air traffic control procedures (Trani et al., 1992; Martel, 2001; Santana and Mueller, 2003; Erzberger et al., 2004; Chao et al., 2008; Wei and Siyuan, 2010; Bubalo and Daduna, 2011; Lee and Balakrishnan, 2012; Cetek et al., 2014; Li et al., 2015, 2017; LI et al., 2017; Aydoğan and Çetek, 2018; Krstić Simić and Babić, 2020).

TAAM followed SIMMOD in the early 1990s, developed by The Preston Aviation Solutions group, which is currently owned by Jeppesen. Unlike SIMMOD, TAAM adopts a 3D structure that allows for a better investigation of 4D aircraft trajectory performance (Munoz Hernandez and Soler, 2017). Over the past three decades, TAAM has been extensively used by civil aviation authorities, airlines, and airports worldwide (Boesel et al., 2001). Similar to SIMMOD, TAAM has been applied in various research studies related to airfield capacity and local delays (Offerman, 2001; Bazargan et al., 2002). Additionally, TAAM has been used for computing sector capacities and workload (Alipio et al., 2003; Yousefi and Donohue, 2004; Harris et al., 2006; Parambath, 2020) and to conduct safety assessments of UAS integration within a non-segregated airspace (Neto et al., 2017).

Another prevalent simulation tool is AirTOP, which was developed in the late 2000s by Transoft Solutions Inc based in Canada. Since then, it has been used to assess and improve the operations of over 100 major airports around the world (Transoft, 2023). Similar to TAAM, it simulates aircraft trajectories using a 3D structure. The literature features various applications of AirTOP in airfield capacity estimation and local delay prediction, as well as investigating the propagation of delays across airspace networks (Günther et al., 2015; Kreuz et al., 2016; Li et al., 2016; Sidiropoulos et al., 2018; Di Mascio et al., 2021; Sekine et al., 2021; Hirabayashi et al., 2022). Furthermore, AirTOP has been instrumental in validating and calibrating lower-fidelity models of aircraft trajectory optimization, such as TOMATO (Rosenow et al., 2017, 2019).

Ultimately, CAST stands as a widely-adopted simulation software currently in use by over 50 airports and civil aviation authorities worldwide (ARC, 2023). Developed in the early 2000s, its primary strength lies in accurately modeling passenger flow within airport terminals (which is beyond the scope of this paper). CAST also includes airside modules (CAST aircraft and CAST airspace), which enable simulations of air traffic operations in a similar fashion as TAAM and Airtop (Šabić et al., 2021).

Other simulation software have been utilized in various studies over the years – such as RAMS (Reorganized ATC Mathematical Simulator) developed by Eurocontrol (Czech and Crook, 1994); HERMES (Heuristic Runway Movement Event) developed by CAA/NATS (Richards and Hobbs, 2003); the Airport Machine, developed by Airport Simulation International (Yazdani and Scarborough, 2001); and Total AirportSim, developed by LeTech for IATA (Tung, 2002) – but their outreach and application have been more localized. Please refer to Appendix E, Table E.9 for a summary of simulation studies and applications in airport management.

Overall, simulation models are highly valuable tools for airports to evaluate the potential impact of infrastructure or operational changes. They provide unique capabilities to simulate future scenarios, allowing airport operators to make informed decisions based on accurate predictions. Despite the numerous benefits, the utilization of simulation models comes with certain challenges. First, the development of large-scale simulations of airport operations is notoriously computationally expensive, which may limit the ability to test numerous scenarios and systematically scan the solution space. Additionally, the calibration and validation of these models can be complex and time-consuming, requiring access to extensive data sets and meticulous attention to detail.

2.2. Analytical models

Analytical models use mathematical expressions to model queuing dynamics, allowing for the estimation of capacity and delays. These expressions can be solved either in closed form or numerically. Unlike simulation, analytical models are generally computationally fast and do not require detailed datasets for calibration. They are also less labor-intensive and simpler to use. Analytical models have found wide applications in airport and air traffic management. An extensive review of existing analytical models for predicting flight delays is provided by Shone et al. (2021).

Most of the analytical models of airport congestion are based on queuing theory. The resemblance to a queuing system is clear: runways can be viewed as "servers" that process aircraft (customers) in the form of landing or takeoff permissions.

Deterministic queueing models are within the first type of queueing models used to model airfield operations (Hubbard, 1978; Newell, 1979; Shumsky, 1995). These models rely on a set of flow-balance equations with fixed demand and service rates. Despite their simplicity, these models possess limitations attributable to their inability to account for variability in both airport demand and service rates — on the demand side, variability arises from factors such as aircraft mechanical problems, slow processing of passengers in terminals, or propagated delays from other airports. On the service side, this variability stems from factors like weather conditions, air traffic management performance, and aircraft type.

Stochastic queueing models therefore emerge as an alternative — i.e., queuing models in which demand and service rates are characterized by probability distributions.

Stationary stochastic queueing models are the simplest form of stochastic queueing models and offer the advantage of mathematical tractability, as exact expressions can often be derived. Stationary queueing models have been applied to flight delay prediction in various studies (e.g., Rue and Rosenshine, 1985; Marianov and Serra, 2003; Bäuerle et al., 2007; Grunewald, 2016). However, stationary queueing models assume steady-state conditions, where changes in demand rates are considered negligible and only occurring over long periods of time. This assumption is typically not valid in air transportation, as demand is highly influenced by flight schedules that vary throughout the day (Odoni and Roth, 1983).

Non-stationary queueing models relax the steady-state assumption and thus reasonably represent the core of existing analytical models for flight delay prediction. The first attempt of modeling local delays using non-stationary queueing models can be attributed to Galliher and Wheeler (1958), who modeled aircraft landings as a M(t)/D(t)/c(t) queueing system (Kendall, 1953)—i.e. the demand for landings is modeled as a Poisson process, and the airport service is modeled as a deterministic process. Following this work, Koopman (1972) investigated the queueing dynamics of an airport operating both landings and take-offs while sharing a common runway. It concluded that delays could be bounded by the results of two independent queueing systems – M(t)/D(t)/s and M(t)/M(t)/s – the former modeling the service times as a deterministic process, while the latter modeling it as a Poisson process. Koopmans' work was extended by Hengsbach and Odoni (1975) to consider the case of multiple-runway airports. Later, Kivestu (1976) generalized Koopmans' work by proposing the use of M(t)/Ek(t)/s queuing systems, where service times are modeled using an Erlang distribution. Additionally, Kivestu (1976) developed a fast, practical numerical approximation to solve the M(t)/Ek(t)/s, which became known as the DELAYS algorithm. Computational experiments performed by Malone (1995) demonstrated the accuracy of the DELAYS algorithm to approximate the exact solution of M(t)/Ek(t)/1. To date, the DELAYS algorithm remains one of the most prominent analytical approaches used in flight delay prediction (Stamatopoulos et al., 2004; Mukherjee et al., 2005; Lovell et al., 2007; Churchill et al., 2008; Hansen et al., 2009; Pyrgiotis et al., 2013; Vaze and Barnhart, 2012; Jacquillat and Odoni, 2015b; Pyrgiotis and Odoni, 2016; Jacquillat et al., 2017). In parallel, numerous other queueing models have been developed using different approximations and/or queueing settings (Bäuerle et al., 2007; Stolletz, 2008; Nikoleris and Hansen, 2012; Caccavale et al., 2014; Gwiggner and Nagaoka, 2014; Simaiakis and Balakrishnan, 2009; Shone et al., 2019; Itoh and Mitici, 2019).

The literature on applications of queueing models to airport capacity management is vast. Bookbinder (1986) analyzed the impact of capacity expansions on local delays at several US airports. Stamatopoulos et al. (2004) developed MACAD (MANTEA Airfield Capacity And Delays model), a decision-support tool that integrates various analytical models, including DELAYS, to estimate the capacity and delays associated with every element of the airfield system. Several authors have investigated the use of congestion management schemes, such as slot allocation and congestion pricing, in managing the evolution of airport local delays (Daniel, 1995; Mukherjee et al., 2005; Vaze and Barnhart, 2012; Jacquillat and Odoni, 2015b; Pyrgiotis and Odoni, 2016; Jacquillat and Vaze, 2018). Queueing models have proved to be also valuable tools for simulating airport departure processes and optimize control procedures, such as optimal push-back times, selecting the most efficient taxiway routes, and executing of gate holdings (Pujet et al., 1999; Simaiakis and Balakrishnan, 2009; Simaiakis et al., 2013; McFarlane and Balakrishnan, 2016; Badrinath and Balakrishnan, 2017; Badrinath et al., 2020; Itoh et al., 2022; Hebert and Dietz, 1997). Similarly, studies have focused on various aspects of the arrival process, such as arrival sequencing and metering, runway assignment, and ground delay program strategies (Bolender and Slater, 2000; Itoh and Mitici, 2019; Anderson et al., 2000; Shone et al., 2019; Jacquillat and Odoni, 2015a; Jacquillat et al., 2017). Different trajectory management concepts, such as trajectory-based operations, have also been investigated (Nikoleris and Hansen, 2012; Hansen et al., 2009).

In addition to their primary application for local delay prediction, queuing models have also been used to investigate delay propagation across airport networks. Examples of such models include AND and LMINET (Pyrgiotis et al., 2013; Long et al., 1999, respectively). These models have been widely applied to study delay propagation in various regions, such as the airspace network of the United States (Shortle et al., 2003; Tien et al., 2011; Wan et al., 2013; Zhou et al., 2011; Wanke et al., 2012; Taylor et al., 2012; Taylor and Wanke, 2013; Tandale et al., 2008; Wang et al., 2018a), Europe (Baspinar et al., 2016), and China (Lin et al., 2021). Please refer to Appendix E, Table E.10 for a summary of applications of queueing models in airport management.

In summary, queuing models provide a valuable approach for assessing and dissecting airport capacity management procedures at a macroscopic level. Compared to simulation counterparts, these models require less detailed inputs and can be run rapidly. However queuing models may oversimplify airport operations by representing airports as basic queuing systems at a high level of abstraction. This can limit the reliability of the predictions, particularly when it comes to supporting more detailed operational decisions. Airport managers and researchers should therefore approach the use of queuing models with caution and complement them with other methods and real-world data for greater accuracy and reliability.

2.3. Data-driven models

Data-driven models harness the power of empirical historic data to analyze patterns and forecast flight delays. Their primary advantage lies in their ability to leverage vast amounts of information to identify key influencing factors and capture intricate patterns responsible for flight delays. This is especially beneficial for modeling dynamics that are difficult to express mathematically or understanding complex interactions that are challenging to anticipate, such as the impact of weather conditions, seasonal effects, and unique features specific to airlines or airports. Unlike simulation and analytical models, which adopt a *bottom-up* approach by relying on assumptions and principles to model airport operations, data-driven models take a *top-down* approach by empirically capturing the effects of various factors on flight delays without explicit assumptions or pre-defined equations regarding airport and air traffic operations.

In the existing current literature, the majority of data-driven models focus on schedule delays — i.e. about two-thirds of the research papers reviewed, see Appendix E, Table E.11. Many of these studies apply conventional statistical methods to investigate the occurrence of schedule delays, either at the airport-level (Mueller and Chatterji, 2002; Aljubairy et al., 2016; Sternberg et al., 2016), or at the network-level (Jetzki, 2009; Du et al., 2018; Rodríguez-Sanz et al., 2018). Other studies have employed conventional regression methods to predict the extent of flight delays and explore their underlying factors (Mazzeo, 2003; Abdel-Aty et al., 2007; Pejovic et al., 2009; Klein et al., 2010; Deshpande and Arıkan, 2012). The advent of advanced predictive analytics has led to a significant upsurge in the use of machine learning techniques for schedule delay prediction, particularly since 2014. Specifically, Rebollo and Balakrishnan (2014) applied random forest methods to predict schedule delays and investigate the impact of their propagation across the US airspace network. Choi et al. (2016) employed various machine learning techniques, including decision trees, random forests, and K-Nearest Neighbors to predict arrival on-time performance at US airports, while Kim et al. (2016) applied neural networks. Karakostas (2016) used Bayesian networks to analyzed the propagation of delays. Since 2017, a total of 41 papers deploying data-driven methods for predicting schedule delays (or their propagation) have been identified (see Appendix E for a complete list of these contributions and brief description of each).

The literature on using data-driven models for predicting local delays is however relatively scarce. Related work can be found in two adjacent streams focusing on: (i) the prediction of aircraft arrival trajectories, and (ii) the prediction of taxiway operations.

In the field of aircraft trajectory prediction, researchers have made significant progress in leveraging trajectory information – such as the entry fix of a flight, its heading direction, speed, altitude and prior position – to predict an aircraft's future position, speed, and altitude (De Leege et al., 2013; Wang et al., 2018b, 2020; Lee et al., 2016b). Simultaneously, another approach involved clustering techniques to analyze historical aircraft trajectory patterns, facilitating predictions about the cluster to which each upcoming flight will be assigned (Hong and Lee, 2015; Murça and de Oliveira, 2020; Xuhao et al., 2021). Finally, others have taken a broader perspective, focusing on predicting estimated arrival times based on the TMA entry time while considering higher-level factors like congestion and sequencing pressures (Basturk and Cetek, 2021; Zhang et al., 2022).

In the context of taxi predictions, the primary focus has been on the prediction of taxi routes and speeds by leveraging data such as gate departure times, aircraft types, weather conditions, and runway configurations. Reinforcement learning techniques have been applied for this specific purpose, as evident in the works of Balakrishna et al. (2008), and Balakrishna et al. (2010). Additionally, a wide array of methods has been explored in this domain, including conventional regression approaches (Jordan et al., 2010; Srivastava, 2011; Ravizza et al., 2013) and various machine learning algorithms (Ravizza et al., 2014; Lee et al., 2016a; Diana, 2018; Yin et al., 2018; Herrema et al., 2018; Tran et al., 2020; Li et al., 2020; Wang et al., 2021; Lim et al., 2021).

Current data-driven models are primarily designed to predict flight path features such as aircraft trajectories, speeds, and altitude profiles. While these models can indirectly estimate local delays through trajectory predictions, they are not specific for that purpose. Furthermore, they fall short in supporting strategic or tactical airport capacity decision-making, which requires long-term planning and higher levels of data aggregation — i.e. simulating individual aircraft trajectories over extended periods, such as a year, season, or month, can be excessively complex, time-consuming, and error-prone. Thus, there is a critical need for alternative approaches that balance accuracy and computational efficiency to support decision-making processes at higher levels of airport capacity management.

This paper contributes to the existing literature in two major ways. Firstly, it extrapolates local delays from historical data and employs supervised data-driven methods to directly predict these delays. Secondly, the paper develops a set of incremental models, ranging from simpler models utilizing aggregate features to more complex specifications leveraging near real-time finer-grained predictors. This comprehensive exploration aims to elucidate the accuracy-complexity trade-off and highlight the potential of employing machine learning techniques across the entire spectrum of capacity management interventions.

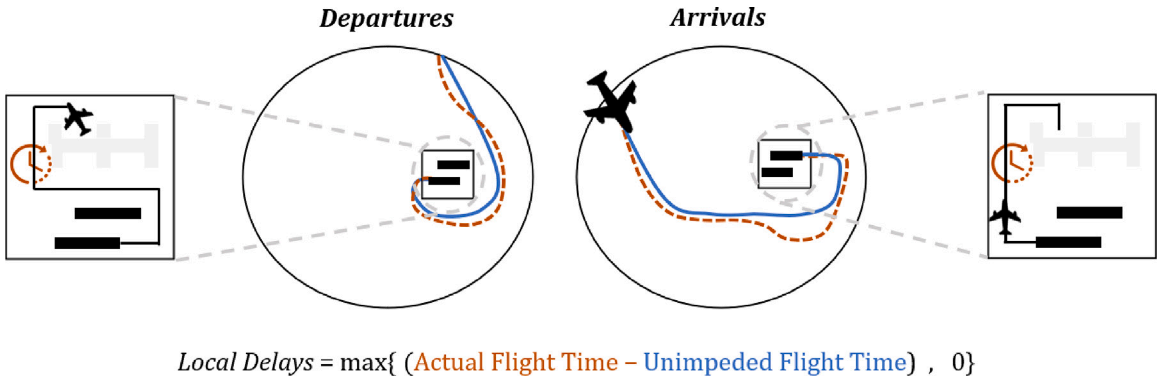


Fig. 2. Estimation of local delays. This figure depicts the terminal airspace region of an airport. The takeoff phase is represented by the flight path from the runway to the circle, while the landing phase is represented by the reverse path. The unimpeded flight path is shown in blue, while the actual flight path is shown in orange. In addition to delays that occur during the landing and takeoff phases of a flight, local delays also include any additional time spent by aircraft in the taxiways.

3. Data-driven approach to quantify airport local delays

Local delays are calculated as the difference between the actual time taken to complete a flight segment and the corresponding unimpeded time (see Fig. 2 for an illustration). While the former is directly observed from data, the latter is not and, therefore, needs to be accurately inferred.

In this section, we outline a procedure comprising six steps for extrapolating local delays, as illustrated in Fig. 2. This procedure adheres to the ICAO definition of local delays (ICAO, 2023) and ensures scalability to other airports with minimal customization. It is designed to use trajectory-based Automatic Dependent Surveillance–Broadcast (ADS-B) datasets, which are readily available for purchase from various online sources globally. Numerous providers offer ADS-B data; in this paper, we use Radarbox (2023). Generally, with minor differences depending on the source, ADS-B datasets contain detailed information on flight trajectories, including coordinates, altitude, and speed at different waypoints along flight paths. They may also include general flight information, such as flight ID, airline operator, aircraft type, and both scheduled and actual arrival and departure gate times (see Fig. 3). We now summarize the main steps of the proposed procedure:

1. *Identifying Entry and Exit Fixes*. To accurately calculate local delays, first we need to identify the route taken by each flight. The first step in identifying these routes is to determine the waypoint fixes that each flight have used to enter/exit the terminal airspace. We utilize clustering methods for this purpose. First, we identify the closest observation recorded to the boundary of the terminal airspace region (set at 100 NM) within a buffer of 20 NM.[2] We then perform a k-means clustering analysis on these data points to identify common patterns and group flights accordingly (see Fig. 4 - left).
2. *Determining Assigned Runway and Operational Direction*. After identifying the entry and exit fixes utilized by each flight, the next step is to determine the operational direction and runway used. To achieve this, we analyze the location of the nearest recorded data point to the airport centerpoint and measure the distance from it to each of the runways edges. To ensure the accuracy of this process, we obtain the nearest point to the runway considering a buffer of 2.5 NM to 10 NM from the runway.[3] The minimum distance obtained establishes the runway used by each flight and its operational direction.
3. *Grouping Flights by Standard Landing/Takeoff Routes*. Once we have identified the entry/exit fixes, runway utilized, and operational direction, we can identify the routes utilized and group flights accordingly. Fig. 4 illustrates the results of this process for arrivals at Singapore airport during the first week of May in 2019. In total, we have identified 14 routes (7 entry fixes $\times$ 2 operational directions), represented in different colors.
4. *Estimating Landing/Takeoff and Entry/Exit times*. Before comparing times within each group and obtain an estimate of unimpeded time by route, an important additional step is needed to geographically standardize the observations. This is due to the uneven distribution of data points in space.[4] To address this issue, we employ a tailored extrapolation method. For each movement, we identify the data point closest to a reference buffer—set at 100 NM for computing entry/exit times, and

[2] Some flights may lack recorded information near to the TMA boundaries. To mitigate this issue, we only include flights with data points within 20 NM of the TMA boundary. This threshold enables us to keep a high percentage of flights in our dataset while ensuring accurate delay estimations. After applying this threshold, we observe that 91% to 94% of the flights remain in our dataset.

[3] To ensure the accuracy of this process, we obtain the nearest point to the runway considering a buffer of 2.5 NM to 10 NM from the runway. This buffer range serves two purposes. Firstly, data points closer than 2.5 NM from the airport typically represent the taxiways or aircraft stands. Including them in the analysis would cause discrepancies in identifying the runway used and operational direction. Secondly, data points located beyond the 10 NM buffer range are significantly further away from the airport and may not accurately represent the aircraft's position during landing or takeoff. Overall, we observed that only 2% to 4% of the flights lacked datapoints conforming to these conditions.

[4] As evident from the cloud of entry/exit points not being fully aligned along the 100 NM buffer in Fig. 4 (left).

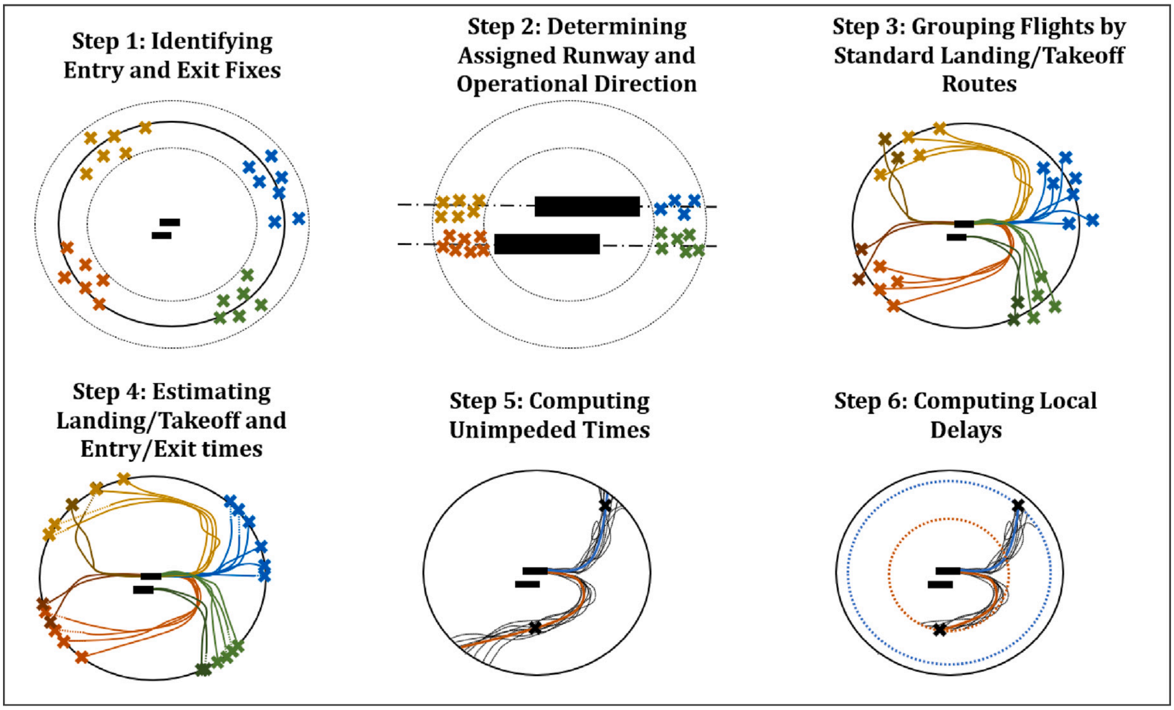


Fig. 3. Steps for local delays estimation.

at 2.5 NM for computing landing/take-off times. We then extract information on the aircraft's heading direction and average acceleration, and then extrapolate accordingly to obtain estimates of Entry/Exit times and Landing/Takeoff times (see Fig. 2 (Step 4), where the dots are precisely located along the buffer circle).

5. *Computing Unimpeded Times*. To compute unimpeded times three steps are required (as illustrated in Fig. 5): (i) We first identify the reference flight among the flights operating the same route. In accordance with ICAO recommendations (ICAO, 2023), we utilize the 20th percentile of sorted transit times from historic data to determine the reference flight; (ii) We then backtrack the reference flight to identify the coordinate point representing the segment distance located at 100 NM from the airport (following the route's path rather than a straight line). This accounts for the fact that routes have different lengths; (iii) Finally, we calculate the unimpeded time for each route flown by each aircraft type as the time taken by the reference flight to cover the 100 NM segment distance.
6. *Computing local delays*. Once we have identified the reference flight and its corresponding entry/exit coordinate, we draw a circle with a radius equal to the distance between the airport and the reference coordinate. By applying the extrapolation method described in Step 4, we determine the new corrected entry/exit times of each flight (i.e. the time that a flight is at exactly 100 NM segment distance from the airport — see Fig. 2). To determine the local delays, we then subtract the time taken by each flight to travel from/to the reference radius to/from the runway, with the unimpeded time calculated in Step 5.

4. Models development and comparison

In this section, we first introduce the empirical setup (Section 4.1). We then present the formulation and development of the predictive models for flight delay prediction and systematically evaluate their accuracy.

In accordance with the methodological review conducted in Section 2, we consider a simulation model (Section 4.2), a queuing model (Section 4.3), and a set of incremental data-driven methods (Section 4.4).

4.1. Experimental setup and performance metrics

We analyze four major airports in Southeast Asia: Singapore (SIN), Hong Kong (HKG), Kuala Lumpur (KUL), and Bangkok (BKK). Using actual ADS-B flight data from Radarbox (2023), we first extrapolate local delays for all flights in 2019 employing the methodology outlined in Section 3.[5] Next, we calculate the rolling average hourly delays at 15-min intervals. Summary statistics

[5] We omitted some days due to insufficient data; nevertheless, more than 95% of the days in 2019 were retained for analysis.

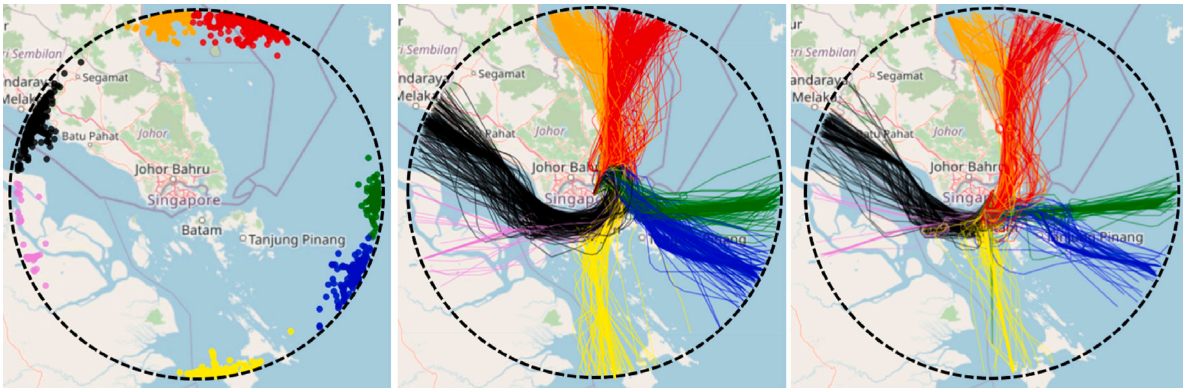


Fig. 4. Grouping flights by standard landing/takeoff routes using Singapore airport data (1st week of May in 2019).

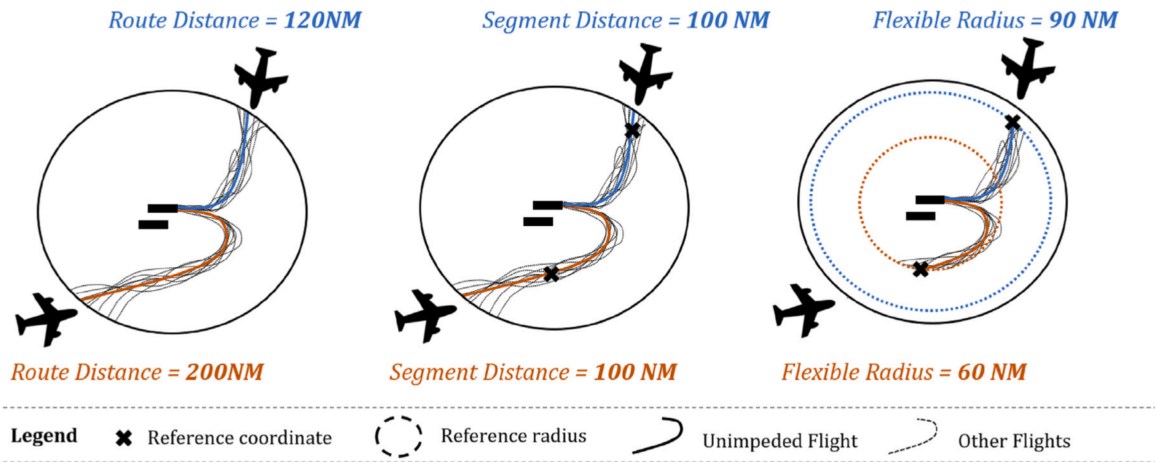


Fig. 5. Steps for computing the unimpeded time of a route: After assigning each aircraft to a specific route, it becomes clear that the time taken to travel between routes can vary significantly due to differences in route length. For example, the orange route is considerably longer than the blue route. To calculate the unimpeded time accurately, we cannot rely solely on the point at which a flight crosses the TMA boundary as the entry/exit time. Doing so would be influenced by the variability in travel times and create a bias toward flights that take longer routes. To overcome this issue, we suggest fixing a segment distance (100 NM in this paper). With this distance established, we can calculate a flexible radius for each route. The intersection of each flight route and this flexible radius determines the reference entry/exit times for computation of local delays.

Table 1
Summary statistics of local delays in 2019 by airport.

Type	Airport	Observ.	Avg. (s)	Std.Dev. (s)	Min. (s)	Q05 (s)	Q25 (s)	Q50 (s)	Q75 (s)	Q95 (s)	Max. (s)
Arrivals	SIN	28,640	256	209	0	58	120	193	322	666	1792
	HKG	27,600	293	243	0	46	115	215	401	794	1777
	BKK	28,720	387	295	0	50	172	317	520	984	1799
	KUL	28,480	244	134	0	82	158	224	301	473	1619
Departures	SIN	28,640	488	321	0	116	275	428	626	1065	4136
	HKG	27,600	462	299	0	83	235	397	626	1044	3638
	BKK	28,720	465	278	0	102	256	393	577	1026	3444
	KUL	28,480	383	250	0	80	200	313	480	940	2974

for departure and arrival local delays segmented by airport are presented in Table 1. We can observe a notable difference between departure delays and arrival delays, with departure delays being more significant. This is reasonable, considering that it is generally easier to delay flights on the ground than in the air.[6]

[6] We also observe that KUL experienced comparatively smaller delays. This may be potentially attributed to the recent opening of a third runway, thereby increasing its operational capacity compared to the other three airports that operate with two runways for similar levels of traffic.

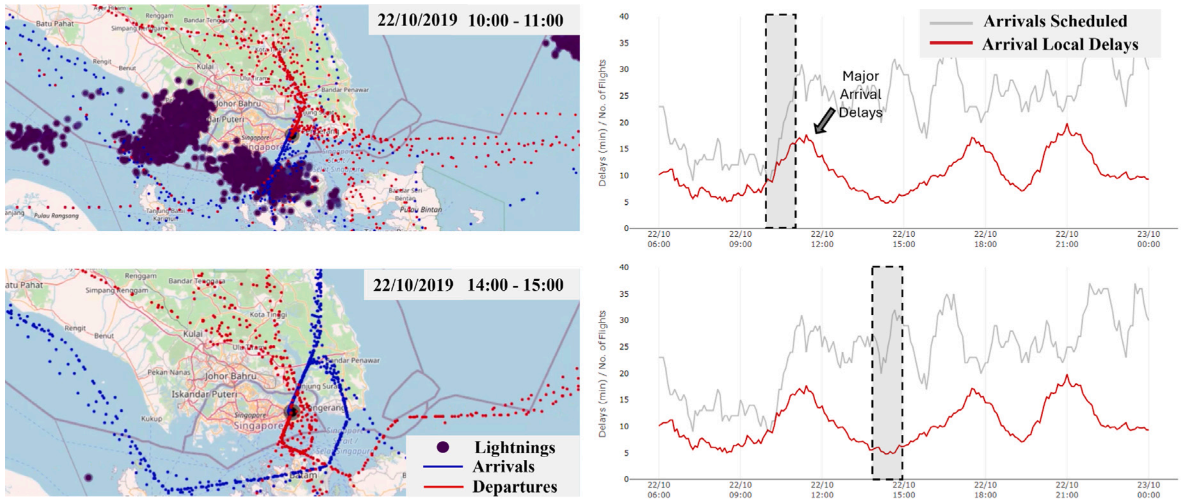


Fig. 6. Spatial location of the flights and lightning observations (left); Estimated average hourly delays (right): Three periods of intense lightning events were observed — specifically from 10 am to 11 am, 5 pm to 6 pm, and 7 pm to 9 pm. We plotted two hours of this day, from 10 am to 11 am (top left), corresponding to a period with lightning observations, and from 2 pm to 3 pm (bottom left), corresponding to a period without lightning observations.

We augment the resulting dataset by integrating weather-related information from two distinct sources: (i) convective weather data from Vaisala Inc (Vaisala, 2023) – a leading global weather measurement company – including the coordinates of all lightning observations in 2019 within a 200 km radius from the studied airports; (ii) detailed weather conditions for each airport from openly available Meteorological Aerodrome Reports (METARs) (IEM, 2023), encompassing comprehensive data on wind conditions (characterized by speed and altitude), visibility, temperature, precipitation and relative humidity.

Fig. 6 illustrates the level of granularity inherent in the compiled dataset, considering a sample day at Singapore Airport. The left side of the figure presents the coordinates of all arrival and departure flights within specific hours, as well as the lightning observations (in purple). On the right side of Fig. 6, we plot the estimated average hourly delays for arrivals and departures. We observe from the plot that the peaks of local delays occur precisely during periods with lightning observations, while no significant delays occur during periods with no lightning observations.

Following customary procedure, we randomly partition our data into two distinct samples: a training (70%) and a testing (30%) set. Each model is first calibrated, fine-tuning its parameters using the training data. Then, we gauge its predictive performance out-of-sample, that is, on the unseen instances contained in the testing set.

In the following, we employ a range of performance metrics, including the Mean Average Error (MAE), the Root Mean Square ($RMSE$), and the coefficient of determination (R^2). Moreover, we consider two different degrees of granularity, which are representative of the levels of detail of different airport capacity management applications:

1. Hourly Delays: We assess the models' predictive performance in directly forecasting delays for each specific hour (e.g., the average local flight delays between 8–9 a.m. of any given day in 2019). Given the high variability and multitude of contingent factors influencing flight delays, this prediction task is particularly challenging. By investigating hourly-specific delay predictions, we seek to explore the influence and variability of contingent factors on the formation of flight delays, and the model capabilities to predict them.
2. Aggregate Hourly Delays: We assess the models' predictive performance in predicting average hourly delays throughout the entire year. These are obtained by taking the mean of day-specific estimates to come up with a consolidated estimate proxying the delay intensity within each time interval of one hour (e.g., the average delay between 8–9 a.m. in 2019). The consideration of aggregated metrics allows us to filter out the influence of day-specific fluctuations, directing our attention toward delays that manifest under typical/nominal conditions. This enables the examination of overarching patterns and trends in flight delays at each airport, which is key in informing strategic airport planning (as noted in Jacquillat and Odoni, 2015a).

Throughout the rest of this paper, we use the notation R^2, MAE, and $RMSE$ to refer to the performance metrics calculated on an hourly basis. Conversely, we denote the aggregate performance metrics as R^2_{agg}, MAE_{agg}, and $RMSE_{agg}$.

4.2. Simulation model

To construct our simulation model, we used CAST (ARC, 2023) — a state-of-the-art software for airport micro simulation (refer to Section 2.1, for details). Fig. 7 illustrates the output of our design process. These models demand a thorough gathering of the airport's layout data, encompassing runways, taxiways, and stands, in addition to the precise formulation of operational rules applicable to each specific area of the airport. Owing to the extensive development time and the requirement for detailed information to build

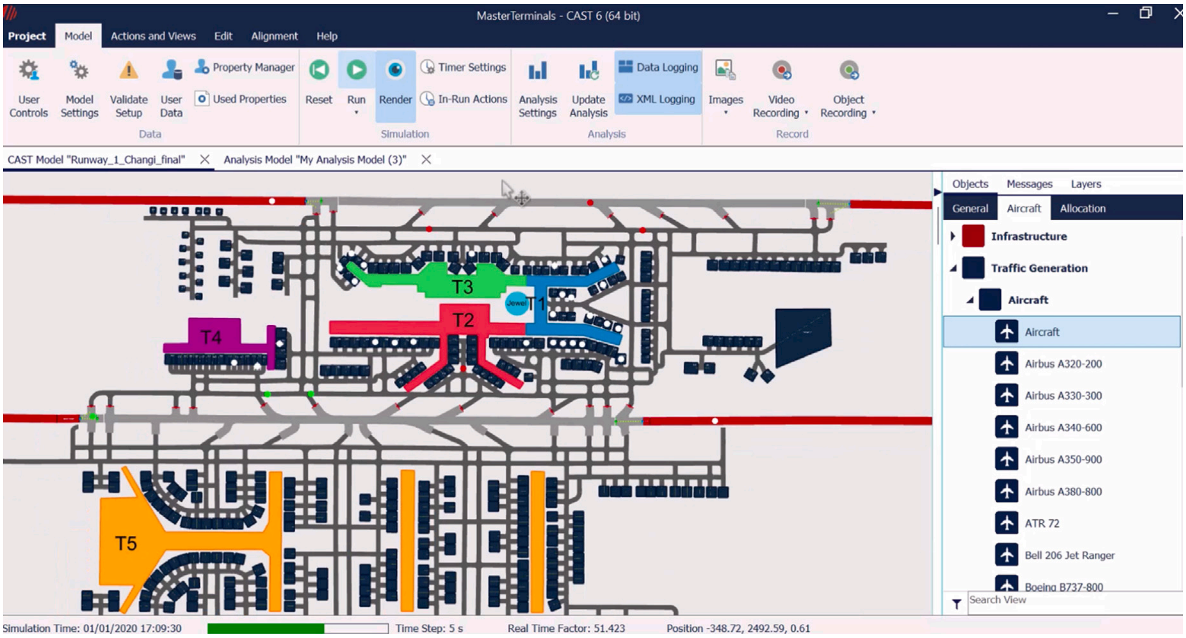


Fig. 7. CAST simulation representation for Singapore Airport.

such complex models, we limited our development to a simulation model for Singapore Airport (SIN). This contrasts with the other methods described in subsequent sections, where we developed models for all the airports considered in this paper, underscoring a fundamental limitation of simulation models: their reliance on close collaborations with airports and access to proprietary data, thereby hindering their generalizability.

To calibrate our simulation model, we experimented with various design parameters, focusing particularly on changing three key operational rules: (i) separation requirement rules, in which we applied ICAO separations, but played with safety buffers to search for more accurate results; (ii) runway utilization rules, where we tested rules for runway assignment. We initially assumed dedicated runways (one runway used only for arrivals, and the other runway used only for departures). We then introduced the possibility of some runway sharing based on congestion levels, which more closely resemble the actual practices observed at Singapore Airport; (iii) off-block approval rules to control the number of aircraft queuing in the taxiways and departure positions, effectively simulating the impact of taxi operations on ground controllers' workload — further details on the design and calibration process are presented in Appendix A.

Our results demonstrate that the simulation model effectively predicts local delays under nominal conditions, as indicated by an R^2_{agg} value of 0.83 for arrivals and 0.72 for departures (refer to Tables 6 and 7, 1st column). On the other hand, the R^2 value is relatively low—0.28 for arrivals and 0.16 for departures. This result is expected, considering that average hourly delays on a daily basis are strongly influenced by various specific daily operational conditions, which are challenging to accurately capture through simulation without resorting to ad-hoc calibrations tailored to each specific day.

4.3. Queueing model

To construct our queuing model, we used the DELAYS algorithm developed by Kivestu (1976)—a state-of-the-art queuing model for airport operations (refer to Section 2.2, for details).

We modeled each airport using two dynamic and stochastic $M(t)/E_k(t)/1$ queuing models, one for predicting arrival local delays and the other for predicting departure local delays. The state-transition diagram is presented in Appendix B.

Similar to prior studies (e.g., Pyrgiotis et al., 2013; Jacquillat and Odoni, 2015b), we calibrate the model by fine-tuning its parameters – the service rates and the Erlang coefficient – using a randomized grid-search approach. After many iterations, the model with the highest performance on the training dataset was selected, and its accuracy was gauged on the testing dataset.

The results show that the queueing model performs well when predicting average hourly delays under nominal conditions (R^2_{avg} ranging from 0.54 to 0.86), but it struggles to predict delays on a daily basis (R^2 ranging from 0.12 to 0.37)—performing slightly worse than the simulation (refer to Tables 6 and 7, 1st and 2nd columns). This discrepancy is expected due to the inherent simplicity of queueing models compared to simulations, which can better capture airport layout-specific intricacies. Additionally, both queueing models and simulations share a common challenge in accurately incorporating and generalizing time-specific considerations for delay predictions, unless addressed through ad-hoc calibration.

4.4. Machine learning models

We now turn to the development of data-driven models of flight delays. The first step involved the engineering of pertinent features. We classified these features into five categories:

(i) *Congestion-related features*: These features are tailored to proxy the systemic drivers of air traffic congestion. They are functions of the number of movements simultaneously handled in any given time period, or during adjacent periods, as sources of demand-supply imbalances.
(ii) *Temporal-related features*: These features capture latent time-dependent data patterns: Monthly dummies account for seasonal variations (in weather or demand patterns), while Hour dummies may capture trends in ATC performance variability throughout the day.
(iii) *Route-related features*: These features describe how flights are distributed across the various routes within the terminal maneuvering area (TMA) toward characterizing patterns and potential congestion in the air.
(iv) *Weather-related features*: These features describe the weather conditions in the proximity of the airport at any given time toward better comprehending how atmospheric conditions affect local flight delays.
(v) *Near real-time features*: The purpose of these features is to predict delays by extrapolating information from previous periods (essentially utilizing lagged data) toward capturing the temporal lingering effects of previous delays or disruptions.

The next step involved defining the model specifications. To address the varying data availability in airport capacity management applications, we employed an incremental model-building approach. Specifically, we explored six distinct model specifications, each based on a specific set of features under consideration, as outlined in Table 3. The range of feature settings span from a basic model specification (M2), considering only two predictors (i.e., the number of arrivals and departures), to an advanced model (M8), encompassing all the features mentioned in Table 2, including near real-time delay information up to one hour preceding each flight operation.

Finally, turning to the methods, we explored conventional statistical regression methods and various supervised machine learning techniques, encompassing Linear Regression (LR), Gradient Boosting (GBM), Random Forest (RF), Neural Networks (NN), and Support Vector Machines (SVM). We conducted several validation steps to improve the models' performance, including hyperparameter tuning, cross-validation, and feature selection[7]—some less influential features were tested but ultimately omitted from the final model specifications to maintain sparsity, as indicated in Table 2. Additionally, we have also compared against classification models to demonstrate the superiority of regression (i.e., continuous response) models, and highlighted the enhanced capabilities of data-driven approaches compared to linear models, not only in inferring accurate (mean) delay point estimates but also in modeling their probabilistic distributions.

We now summarize the main insights from the results obtained.

First, we compare the performance of various model specifications in predicting the average outcome, specifically the mean expected delay — for simplicity, we measure the accuracy by aggregating all observations of airports and types of movements. Our analysis, detailed in Table 4, highlights the benefits of incremental model specifications, ranging from Model M2, which includes only two predictors, to Model M7 that incorporates the full spectrum of available features. The results show a substantial improvement in the R^2 values, increasing from a range of 0.23 to 0.29 in Model M2 to between 0.60 and 0.64 in Model M7. Additionally, there is a noticeable reduction in the percentage of absolute errors across observations. For example, in analyzing the 50th percentile observation, we observe a reduction in the percentage absolute error ranging from −9 p.p. to −13 p.p. depending on the method used. Concerning the methods, we find that ensemble methods (specifically, GBM and RF) along with NN slightly outperform simpler methods such as LR or SVM, as presented in Table 4. Nevertheless, even the simpler LR performs commendably in average terms. This effectiveness is partly due to the inclusion of queuing delays as predictors, which helps to capture the nonlinear aspects of delays. For instance, the percentage of absolute errors recorded by LR is only marginally higher than that of GBM with differences ranging from +1 p.p. to +2 p.p. when analyzing the 50th percentile observation.

Next, we compare the performance of regression methods against classification methods — for simplicity, we restrict our discussion to GBM (i.e. the machine learning model with generally superior performance, see Table 5); and consider a delay classification threshold of 5 min (resulting in approximately one-third of the observations being classified as delayed).[8] Table 5 reports the usual confusion matrix KPIs in a tabular form for the different model specifications. Alongside the True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN) ratios, it reports the Recall, or True Positive rate, underscoring the ability of the model to correctly identify positive instances out of all actual positive instances, and the Precision metric, measuring the proportion of true positive predictions out of all positive predictions made by the model, which are key to properly evaluate and select the best approach for our predictive task. Not surprisingly and consistently with above, we find that moving from M2 to M7 significantly increases the model's performance. More interestingly, we observe that both regression and classification models yield similar overall results. However, when the default cut-off threshold of 0.5 is applied in classification models, the regression approach yields higher true positives and significantly lower false negatives, leading to higher recall values, ranging from +19 percentage points (p.p.) in M2 to +7 p.p. in M7. On the other hand, the classification approach results in fewer false positives, indicating higher precision. In absolute terms, the regression GBM accurately identifies a significant portion (78%–80%) of true

[7] The development of machine learning models was done in Python, using the scikit-learn and keras libraries.
[8] We performed additional testing using other methods and different thresholds and the insights proved robust.

Table 2
Definition and aim of predictive features.

	Feature	Description	Aim
Congestion related			
Features included	nr_arr_1hr	Number of arrivals in previous hour	To measure the number of aircraft operating in the terminal airspace
	nr_dep_1hr	Number of departures in previous hour	
	Qdelays_arr	Arrival delays predicted from the queueing model	To measure the dynamic and non-linear behavior of queues
	Qdelays_dep	Departure delays predicted from the queueing model	
Other features tested	nr_arr_Xmin	Number of arrivals in previous X minutes	To measure the number of aircraft operating in the terminal airspace under different temporal scales
	nr_dep_Xmin	Number of departures in previous X minutes	
Temporal related			
Features included	month_X	Month dummy variable	To capture monthly hidden effects, such as typical weather and demand patterns
	hour_X	Hour dummy variable	To capture hour hidden effects, such as typical demand patterns or ATC performance
Other features tested	week_x	Week dummy variable	To capture week-day hidden effects, such as typical demand patterns or ATC performance
Route related			
Features selected	nr_arr_1hr_rX	Number of arrivals in previous hour using route X	To measure the number of aircraft operating in specific routes of the terminal airspace
	nr_dep_1hr_rX	Number of departures in previous hour using route X	
	avg_min_sep_1hr	Average minimum separation between aircraft in the final approach	To measure the average separation between aircraft of different type due to separation requirements
	op_change	Dummy variable indicating a change in runway operational direction	To capture the impact of changes in runway operational direction
Other features tested	nr_arr_Xmin_rX	Number of arrivals in previous X mins using route X	To measure the number of aircraft operating in specific routes under different temporal scales
	nr_dep_Xmin_rX	Number of departures in previous X mins using route X	
	share_arr_1h_rx	Percentage share of aircraft using route X in previous hour	To measure the share of aircraft operating in specific routes of the terminal airspace
	share_dep_1h_rx	Percentage share of aircraft using route X in previous hour	
	share_arr_1h_acftX	percentage share of arrival flights operated by aircraft type X	To measure the share of aircraft types in the terminal airspace
	share_arr_1h_acftx	percentage share of departure flights operated by aircraft type X	
Weather related			
Features selected	nr_lighting_X_Ynm_1hr	Number of lightnings observed in a hour within a range of X to Y NM from the airport	To measure the number of lightning occurrences and their impact
	wind_speed_1hr	Average wind speed (knots) in the previous hour	To capture the impact of wind speed in aircraft operations
	wind_drct_1hr	Wind direction recorded in degrees from true north in the previous hour	To capture the impact of the wind direction in aircraft operations
	vsby_1hr	Average visibility in miles observed in the previous hour	To capture the impact of poor visibility in aircraft operations

(*continued on next page*)

positives, with occasional overlabeling. Conversely, the classification GBM correctly identifies 61%–71% of true positives, with a relatively minor overestimation of delays.

In summary, we opted for a regression approach for two main reasons. First, predicting continuous values offers additional insights without the need for setting threshold criteria, facilitating a more seamless integration with prescriptive analytics that rely on total delay metrics derived from individual observations. Second, the evidence shows that the regression approach tends to identify a higher proportion of critical delays with a degree of conservatism, which aligns with our prediction task. While classification models can be calibrated to prioritize false negatives, such calibration would need to be tailored to each airport, introducing additional complexity.

Table 2 (*continued*).

Other features tested	nr_lighting_X_Ynm_Zmin	Number of lightning observed in previous Z mins within a range of X to Y NM from the airport	To measure the number of lightning occurrences and their impact under different temporal scales
	tmpf_1hr	Average temperature (celsius) in the previous hour	To capture the impact of the temperature in aircraft operations
	prcpt_1hr	Average precipitation (mm) in the previous hour	To capture the impact of precipitation in aircraft operations
	relh_1hr	Average relative humidity (%) in the previous hour	To capture the impact of humidity in aircraft operations
	alti_1hr	Average pressure altimeter (inches) in the previous hour	To capture the impact of pressure in aircraft operations
Near-real time related			
Features selected	delay_avg_1hr_Xmin	Lagged variable that measure the average hourly delays in the previous X periods	To capture the impact of propagated delays from previous periods

Table 3
Model specifications.

Model ID	Features					
	nr_arr_1hr nr_dep_1hr	nr_arr_1hr nr_dep_1hr Qdelays_arr Qdelays_dep	All congested related features	All route related features	All weather related features	Near real-time related features
M2	Yes	No	No	No	No	No
M3	Yes	Yes	No	No	No	No
M4	Yes	Yes	Yes	No	No	No
M5	Yes	Yes	Yes	Yes	No	No
M6	Yes	Yes	Yes	Yes	Yes	No
M7	Yes	Yes	Yes	Yes	Yes	Yes (1-h ahead)

Table 4
Model performance comparison.

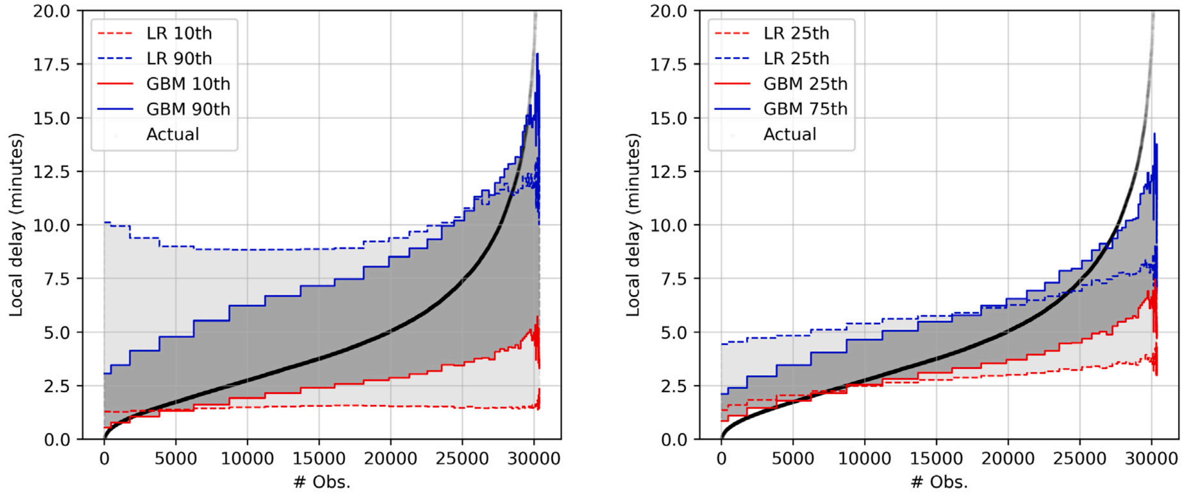
	GBM		LR		RF		NN		SVM	
	R^2	% Abs.Error[a]	R^2	% Abs.Error[a]	R^2	% Abs.Error[a]	R^2	% Abs.Error[a]	R^2	% Abs.Error[a]
M2	**0.29**	**[16,35,63]**	**0.29**	[17,37,68]	0.27	**[16,35,63]**	**0.29**	[16,36,65]	0.23	[23,42,62]
M3	**0.34**	**[15,33,60]**	0.33	[16,34,63]	0.30	[15,34,61]	**0.34**	[16,34,61]	0.28	[22,41,60]
M4	**0.42**	**[14,30,56]**	0.41	[15,32,59]	0.41	**[14,30,56]**	**0.42**	**[14,30,56]**	0.38	[16,33,53]
M5	**0.44**	**[14,30,55]**	0.42	[14,32,58]	**0.44**	**[14,30,55]**	0.43	**[14,30,55]**	0.38	[15,33,54]
M6	**0.48**	**[13,29,54]**	0.45	[14,31,58]	**0.48**	**[13,29,54]**	**0.48**	[14,29,54]	0.42	[15,32,55]
M7	**0.64**	**[12,26,47]**	0.62	[13,27,50]	0.61	[12,26,48]	**0.64**	**[12,26,47]**	0.60	[14,29,51]

[a] % absolute errors of the [25th, 50th, 75th] percentile observations.

Table 5
Model features.

Methods	Model	True Positive TP	False Positive FP	False Negative FN	True Negative TN	Recall TP/(TP+FN)	Precision TP/(TP+FP)
Classif. GBM	M2	21.27%	10.15%	13.34%	55.24%	61%	68%
Classif. GBM	M3	21.26%	8.83%	13.35%	56.57%	61%	71%
Classif GBM	M4	22.89%	8.50%	11.72%	56.90%	66%	73%
Classif. GBM	M5	22.98%	8.27%	11.62%	57.12%	66%	74%
Classif. GBM	M6	23.44%	8.22%	11.17%	57.17%	68%	74%
Classif. GBM	M7	24.64%	6.85%	9.97%	58.54%	71%	78%
Reg. GBM	M2	27.57%	20.79%	7.04%	44.60%	80%	57%
Reg. GBM	M3	26.53%	16.98%	8.08%	48.41%	77%	61%
Reg. GBM	M4	26.87%	14.53%	7.74%	50.86%	78%	65%
Reg. GBM	M5	26.89%	14.36%	7.72%	51.03%	78%	65%
Reg. GBM	M6	27.10%	14.37%	7.51%	51.03%	78%	65%
Reg. GBM	M7	27.00%	11.65%	7.61%	53.74%	78%	70%

Ultimately, we analyze the benefits of data-driven approaches against linear regression in deriving meaningful delay prediction intervals. Note that this is a critical aspect of advanced airport capacity management, as it allows for a more comprehensive assessment of robustness that goes beyond solely relying on deterministic average delay outcomes but also incorporates the inherent and residual (yet still significant) uncertainty of delay estimates. Fig. 8 illustrates the estimated prediction intervals around the



(a) 10-90 percentile intervals (b) 25-75 percentile intervals.

Fig. 8. Prediction intervals. Figure representing the actual observations (black dots) and the estimated prediction intervals (estimated as the average over 30-second intervals) using model specification M6, with solid lines for the GBM method and dashed lines for the LR method.

actual observations, represented by the black dots sorted by delay in ascending order, obtained by training our gradient boosting and linear regressions with a quantile loss function.[9] Fig. 8 reports the estimated 10th–90th (Fig. 8(a)) and 25th–75th (Fig. 8(b)) quantile intervals. First, both GBM and linear approach returned satisfactory out-of-sample performance, returning a fraction of testing observations that fall between the predictions very close to the expected coverage—49%–50% for the 25th–75th case and 78% and 80% for the 10–90th case for GBM and the linear model, respectively. Examining the patterns, the superiority of GBM becomes evident. The linear model yields wider and flatter bounds, resembling a horizontal strip that shows little sensitivity to the data. In contrast, the prediction intervals generated by GBM are narrower (on average, −18% – -34% compared to the LR ones) and their width increases with the delay length. This is expected, as extended delays are the most challenging to predict and less prevalent in the data—as evidenced by the decreasing density of actual data points (greater transparency of the black curve) as delay values increase. Furthermore, the prediction intervals generated by GBM more closely align with the observed data pattern, underscoring stronger predictive capabilities. Nonetheless, it is important to note that the range of variability remains significant. This is a widely acknowledged issue regarding delay forecasting models – as observed, for example, in recent papers leveraging big data and advanced data-driven models (e.g., Birolini and Jacquillat, 2023) – highlighting the importance of accounting for the distribution of delay estimates when integrating them into prescriptive analytics solutions.

4.5. Summary of model comparisons

We now summarize the evidence gathered from the comparison of the various models tested. Tables 6 and 7 report the performance metrics for the different approaches considered — simulation model (M0), queueing model (M1) and machine learning models (M2–M7). Next, we summarize the key takeaways:

1. In general, the performance of machine learning models is superior to that of simulation and queueing models, with a remarkable decrease in the MAE ranging between 15% to 30%, contingent on the airport and type of movement (i.e. arrival or departure). Machine learning has an advantage over other methods in that it can leverage historical data to learn and adapt to different scenarios, allowing it to factor in the impact of various operational considerations on local delays.
2. Despite these strengths, the most rudimentary machine learning model, M2, which incorporates only two features (number of arrivals and number of departures), underperforms when compared to its simulation/queueing counterparts. This suggests that, particularly in strategic applications requiring the appraisal of future scenarios of increased demand and capacity, the benefits of simple ML compared to conventional methods are limited.
3. By incorporating the predictions from the queuing model (M1) into the machine learning model (M2), accuracy can be improved by up to 8% for the MAE (M3), contingent on the airport and type of movement (i.e. arrival or departure). This is corroborated by the SHAP plot (Fig. 9), emphasizing the significance of combining both machine learning and queuing models to capture the non-linear dynamics inherent in queueing behavior.

[9] We use a Pinball loss function as implemented in Python's scikit-learn package. More details can be found in Koenker (2005).

Table 6
Model results for arrivals: M0 — simulation model; M1 — queueing model; M2 to M7 — GBM model.

Airport	Metric	Model								Metric	Model							
		M0	M1	M2	M3	M4	M5	M6	M7		M0	M1	M2	M3	M4	M5	M6	M7
SIN	$R2$	0.28	0.26	0.24	0.28	0.35	0.38	0.44	0.63	$R2_{agg}$	0.83	0.85	0.69	0.84	0.97	0.97	0.96	0.97
	MAE (s)	111	110	117	113	106	104	102	89	MAE_{agg} (s)	33	31	41	31	16	17	17	17
	$RMSE$ (s)	189	189	192	188	178	174	166	135	$RMSE_{agg}$ (s)	43	41	57	42	20	21	22	21
HKG	$R2$	–	0.31	0.27	0.31	0.38	0.40	0.45	0.66	$R2_{agg}$	–	0.81	0.78	0.85	0.96	0.97	0.96	0.97
	MAE (s)	–	139	142	137	129	127	124	97	MAE_{agg} (s)	–	36	39	34	22	19	20	19
	$RMSE$ (s)	–	215	200	194	184	181	174	138	$RMSE_{agg}$ (s)	–	52	54	47	29	23	26	24
BKK	$R2$	–	0.37	0.35	0.42	0.53	0.51	0.54	0.67	$R2_{agg}$	–	0.73	0.53	0.80	0.98	0.98	0.98	0.98
	MAE (s)	–	152	159	146	131	133	131	114	MAE_{agg} (s)	–	58	76	53	20	20	19	19
	$RMSE$ (s)	–	220	226	214	193	195	190	161	$RMSE_{agg}$ (s)	–	75	102	72	28	28	28	27
KUL	$R2$	–	0.19	0.25	0.26	0.32	0.34	0.43	0.50	$R2_{agg}$	–	0.86	0.86	0.89	0.96	0.96	0.98	0.98
	MAE (s)	–	81	78	77	74	72	70	67	MAE_{agg} (s)	–	22	17	15	10	10	8	7
	$RMSE$ (s)	–	117	122	121	116	114	106	101	$RMSE_{agg}$ (s)	–	28	23	21	13	13	10	10

Table 7
Model results for departures: M0 — simulation model; M1 — queueing model; M2 to M7 — GBM model.

Airport	Metric	Model								Metric	Model							
		M0	M1	M2	M3	M4	M5	M6	M7		M0	M1	M2	M3	M4	M5	M6	M7
SIN	$R2$	0.16	0.13	0.19	0.22	0.29	0.31	0.35	0.46	R^2_{agg}	0.72	0.64	0.58	0.68	0.82	0.85	0.86	0.86
	MAE (s)	152	154	152	149	142	140	138	131	MAE_{agg} (s)	39	37	42	36	22	20	20	20
	$RMSE$ (s)	202	202	201	198	189	187	182	172	$RMSE_{agg}$ (s)	51	47	54	47	30	27	26	26
HKG	$R2$	–	0.12	0.24	0.26	0.31	0.30	0.36	0.57	R^2_{agg}	–	0.66	0.68	0.72	0.85	0.87	0.83	0.88
	MAE (s)	–	177	176	173	167	167	160	135	MAE_{agg} (s)	–	39	40	36	26	24	25	23
	$RMSE$ (s)	–	233	229	227	220	221	213	178	$RMSE_{agg}$ (s)	–	56	56	53	41	38	42	33
BKK	$R2$	–	0.12	0.16	0.18	0.38	0.38	0.39	0.45	R^2_{agg}	–	0.71	0.69	0.76	0.85	0.86	0.86	0.85
	MAE (s)	–	170	168	166	144	143	143	139	MAE_{agg} (s)	–	57	60	55	30	28	29	29
	$RMSE$ (s)	–	227	225	223	197	197	196	191	$RMSE_{agg}$ (s)	–	75	77	71	40	36	36	37
KUL	$R2$	–	0.13	0.18	0.19	0.41	0.41	0.51	0.60	R^2_{agg}	–	0.54	0.55	0.57	0.79	0.83	0.84	0.84
	MAE (s)	–	159	157	156	132	131	124	114	MAE_{agg} (s)	–	41	44	41	30	30	28	28
	$RMSE$ (s)	–	222	220	220	192	191	177	161	$RMSE_{agg}$ (s)	–	51	56	51	37	35	35	34

4. The availability of more information that become available closer to actual operations has the potential to improve predictive accuracy significantly. For instance, incorporating delay data from the preceding 15 min yields refined predictions, consistently achieving an R^2 exceeding 0.8 across all instances. This outcome is not surprising, given that delays are predominantly influenced by propagation dynamics. Fig. 10 illustrates the progression of R^2 accuracy at various levels of near real-time delay information (i.e., delay information for 15-, 60-, 180-, etc. minutes prior to operations).
5. The impact of convective weather on airport operations is significant. Fig. 9 demonstrates that incorporating the number of lightning occurrences in the vicinity of the airport (within a range of 0 to 50 NM) has a substantial influence on improving the accuracy of our models, particularly in Singapore, Bangkok, and Hong Kong. Furthermore, this effect is more pronounced when we focus exclusively on periods with lightning events. Fig. 11 compares the R^2 values obtained by M5 and M6 for Singapore and Kuala Lumpur, considering different thresholds of the number of lightning observations — e.g. when the threshold is set at 0, there is a decrease in R^2 from M5 to M6 by 15% and 25% for Singapore and Kuala Lumpu, respectively; as the threshold is adjusted, for example to a minimum of 600 lightning occurrences, M6 shows a significant improvement in R^2, with increases of 60% and 80% for Singapore and Kuala Lumpur, respectively.

5. Flight delay prediction evaluation framework

In this section, we introduce a comprehensive framework for flight delay prediction that integrates various levels of decision-making in airport capacity management (ACM). This framework is intended to serve as a new benchmark for researchers and practitioners, assisting them in identifying the most appropriate models and data inputs for their specific research or operational needs within the broader context of airport capacity management.

We have expanded the traditional three-level classification of ATFM instruments (strategic, pre-tactical, and tactical) as outlined by ICAO (2007) to encompass five levels of ACM instruments. This broader framework includes both short-term (ICAO, 2007) and long-term (Gillen et al., 2016) ACM instruments. Table 8 provides an overview of this framework, summarizing the key aims of each ACM instrument, the critical role of flight delay predictions, and the relevant features and methods associated with each level.

Following this, we provide a detailed discussion of each ACM instrument, examining the applicability and deployment of the delay prediction methods outlined in this paper. We also demonstrate how these methods can enhance the efficiency of airport operations through various application examples.

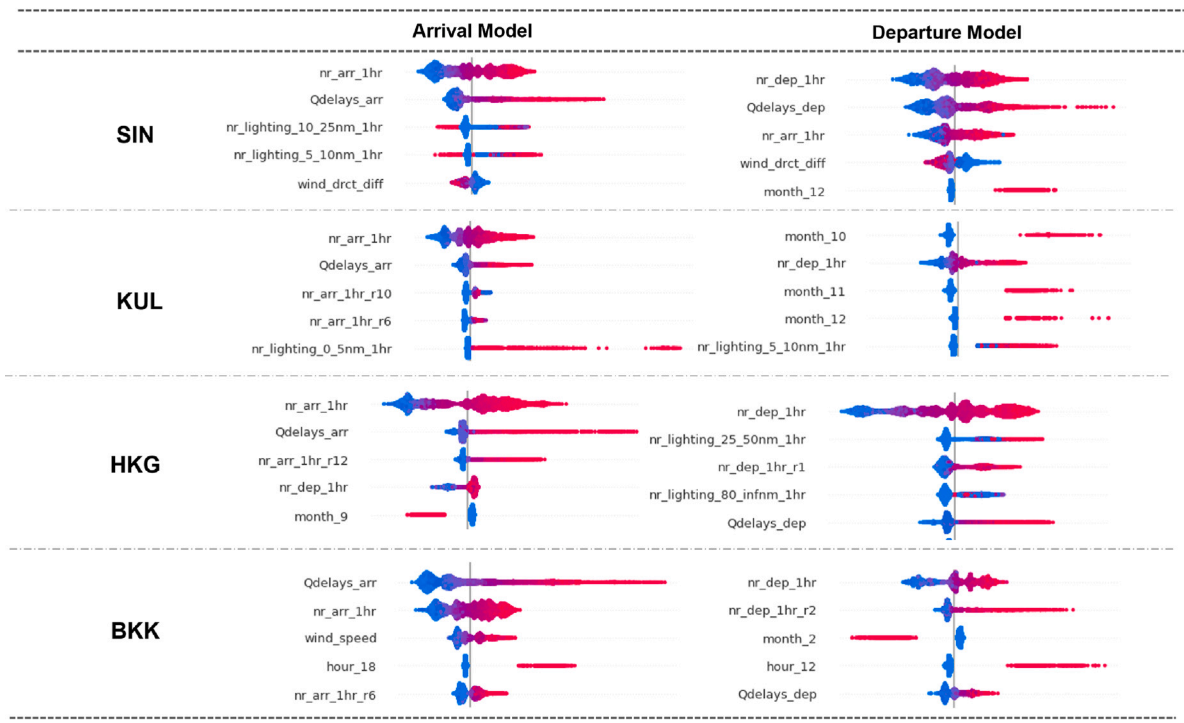


Fig. 9. SHAP plot illustrating the top 5 features with more importance in predicting local delays at each airport and type of movement.

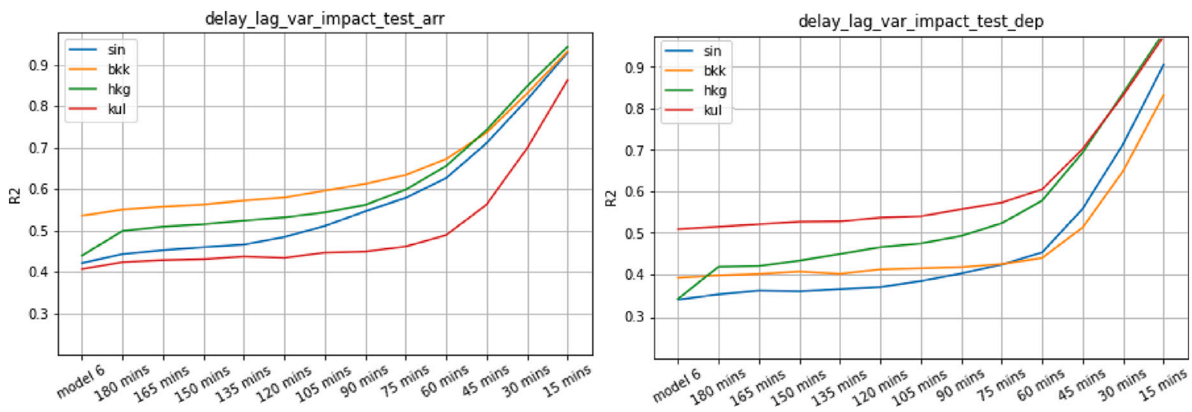


Fig. 10. Impact of near real-time delay information on model accuracy, ranging from M6 (where no delay information is considered) to a model where average hourly delays observed in the preceding 15-min window are incorporated as predictors.

5.1. *Capacity planning (years before)*

Capacity planning is the process of carefully analyzing and predicting an airport's future needs and creating plans to meet those requirements. To do this, airports develop master plans that outline a roadmap for future investments, such as new runways, taxiways, gates, and other infrastructure.

Simulation models are valuable tools for conducting capacity planning studies. They possess the unique ability to meticulously replicate changes in airport layouts and evaluate their repercussions across diverse scenarios, such as changes in both demand patterns and air traffic control procedures. Simulations require considerable computational power and time to run (e.g. approximately 15 min to simulate a single day of operations at Singapore Airport using our CAST model). However, this is not a significant concern during the capacity planning phase, as decisions are made years before actual implementation. As noted in Section 2.1, it is important to recognize that the development of accurate simulations requires setting very precise rules. This means that a deep understanding of airport operations and close collaboration with airport experts are critical to ensure the accuracy of the what-if scenarios to be evaluated in this phase. Significant errors can occur if the models are not properly calibrated and validated.

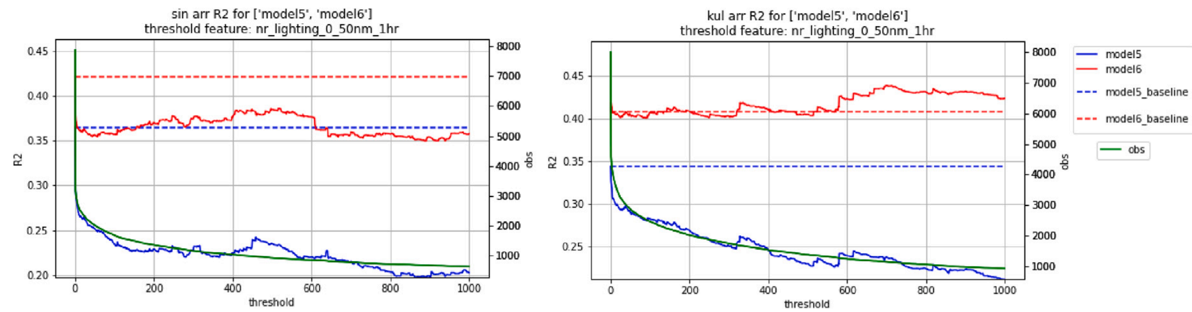


Fig. 11. Model accuracy (R^2) across different threshold levels for the total number of lightning occurrences within a 1-h timeframe and a 50 NM radius for SIN airport (left) and KUL airport (right): Dotted red and blue lines represent R^2 values for M5 (without weather features) and M6 (with weather features) using all observations. Solid red and blue lines show varied R^2 values at different threshold levels of lightning occurrences. The green line depicts the number of observations retained for each threshold. Notably, M6 maintains consistent R^2 regardless of the threshold, highlighting the advantage of incorporating weather-related features in predicting delays during periods with significant lightning occurrences in contrast to M5.

Analytical models can be an alternative for quick assessment of capacity planning alternatives. However, the DELAYS model (M1) discussed in this paper may not provide the level of detail required for this purpose. This is because the model employs a simplified approach to represent airport capacity by means of using a single service rate distribution. Nonetheless more complex methods leveraging advanced network of queue models to represent the different phases of airport operations (Simaiakis and Balakrishnan, 2009; Simaiakis et al., 2013; Itoh and Mitici, 2019), or Simulation-based queuing models (such as MACAD (Stamatopoulos et al., 2004)), can partly overcome this limitation and contribute to evaluate changes in airport layout and operating procedures at a quicker and more aggregate level.

Machine learning models (M2 to M7) may not be the most suitable choice for capacity planning. First, sophisticated models (M4–M7) with advanced features are often ill-suited for this purpose. The advantages of using more detailed models that account for contingent factors are outweighed by the challenges associated with predicting these variables given the substantial time gap and uncertainty. Second, simpler and more generalized ML models (M2–M3) encounter similar limitations to queuing models. Overall, ML models struggle to effectively capture emerging factors or events that were not present in historical data. This is especially pertinent in cases involving new layouts and procedures, which are, in fact, central considerations in the realm of capacity planning.

5.2. Strategic slot allocation (years to 6 months before)

The allocation of airport slots is a critical process that aims to prevent over-scheduling and ensure the efficient use of airport resources. Slot coordinators are responsible for assigning slots to airline slot requests in an unbiased, transparent, and non-discriminatory manner (WWACG et al., 2022). The number of slots made available per hour is determined by airport authorities – referred to as declared capacity – based on a comprehensive assessment of airport maximum throughput capacity and its reliability under different operating conditions. The slot allocation process occurs twice every year, six months in advance of operations. Although this process occurs biannually, the decisions made during this phase can carry significant and enduring consequences. Airlines stand to receive historical benefits when they are assigned slots, and these valuable allocations can be retained for many years into the future.

In this context, leveraging delay predictions assume a vital role. It empowers slot coordinators to delicately balance accommodating the maximum number of flights during preferred times while proactively anticipating peaks in demand and schedule patterns that might otherwise lead to substantial delays. While simulation models may serve this purpose, their lengthy execution and development time can become a limitation when testing various slot allocation solutions. To overcome this concern, the adoption of lower-fidelity models, noted for their faster execution, offers a more suitable avenue. A promising option lies in utilizing queueing models such as DELAYS (M1), which are inherently well-suited for studying demand-supply interactions. Queueing models offer the advantage of straightforward calibration, thereby further enhancing their practicality and efficiency in this context.

As discussed in Section 4, the incorporation of queuing models into data-driven models can deliver even superior performance while retaining scalability and computation efficiency. Given the predictive needs and data availability at the time of slot allocation, semi-aggregate models, such as M3/M4, appear promising alternative, which complement queuing delays with temporal features and support a more refined capturing of congestion dynamics and inherent delay patterns.

Fig. 12 illustrates the potential benefits of employing semi-aggregate data-driven models, such as model M4, in assessing and optimizing declared capacity and slot allocation decisions. The example provides a visualization of predicted delays before and after slot allocation is performed—a slot allocation algorithm has been developed, which redistributes slot requests subject to user-defined airport's declared capacities.(see Appendix C - Algorithm 1).[10] The results show that, prior to slot allocation, there is a noticeable peak

[10] The algorithm effectively ensures that the total number of slots allocated matches the number of slots requested (i.e., no rejection) by efficiently redistributing them to neighboring hours with lower demand.

Table 8
Airport capacity management — Levels of intervention.

	ACM instruments	Capacity planning	Strategic slot allocation	Strategic flow management	Pre-Tactical flow management	Tactical flow management
ACM description	Time frame	Years before	Years to 6 months before	Months to days before	A day to hours before	Real time
	Aim	Determine airport capacity requirements for future capacity expansion	Prevent airport over-scheduling by controlling the number of slots allocated to airline flight requests	Develop flight plans to ensure orderly distribution of air traffic flows across the airspace network, and efficient utilization of airport capacity	Revise flight plans to cope with day to day factors originated from disruptive events (e.g. severe weather conditions) or from delay propagation from other airports	Execution of the previously agreed flight plans, monitoring of the situation and update of flight plans if required
	Input information	Existing infrastructure conditions and alternatives Demand Projections ATC general rules –	Existing infrastructure conditions Slot Requests ATC general rules –	Existing infrastructure conditions Flight schedules ATC general rules and ad-hoc constraints –	Existing infrastructure conditions Revised flight plans ATC general rules and ad-hoc constraints Weather forecasts	Existing infrastructure conditions Real-time flight position ATC general rules and ad-hoc constraints Real-time weather
	Output Analysis	Botleneck identification Airport master planning	Airport capacity declaration Slot allocation	Develop flight plans ATM resource planning	Revise flight plans Ground delay programs	Real-time air traffic instructions
Delay prediction	Need for delay prediction	Analyze the trade-off between capacity and projected demand of different infrastructure expansion alternatives	Analyze the trade-off between declared capacity and demand for slots	Analyze the trade-off between demand across different airspace routes and the capacity of the airport/airspace	Analyze the trade-off between demand across different airspace routes and the capacity of the airport/airspace while accounting for weather forecasts	Analyze the trade-off between real-time demand across different airspace routes and the capacity of the airport/airspace while accounting for weather conditions
	Congestion-related features	Yes	Yes	Yes	Yes	Yes
	Temporal-related features	No	Yes	Yes	Yes	Yes
	Route-related features	Partly	Partly	Yes	Yes	Yes
	Weather-related features	No	No	No	Yes	Yes
	Near real-time features	No	No	No	No	Yes

in delays occurring between 6 pm and 7 pm, amounting to approximately 24 min of delays. After slot allocation, and considering a declared capacity limit set at 33 movements per hour, this peak is reduced to around 14 min (a reduction of 42%). Additionally, no periods are expected to experience average hourly delays exceeding 15 min, and the duration of periods with delays surpassing 10 min has been significantly cut from approximately 4 h to just 2 h.

This example clearly illustrates the advantages of slot allocation and emphasizes the crucial role that delay predictive analytics can play in aiding airport slot coordinators. To fully leverage the benefits of delay predictive analytics, it is important to complement its application with prescriptive tools that aid in making slot allocation decisions aligned with the interests of both airlines and airports. Large slot displacements can lead airlines to abandon their requested slots and cancel the corresponding flights. For example, Pouget et al., 2023 observed at CDG airport that the likelihood of a flight displaced by 30 minutes being scheduled was only about 60% compared to a flight with no displacement.

Several tools are currently available and have been utilized by slot coordinators for many years to support slot allocation decisions, such as PDC SCORE, T-Systems SAMS, SLOTIX, or GESLOT (refer to WWACG, 2023). State-of-art optimization models for slot allocation primarily focus on minimization of displacements (Zografos et al., 2012; Ribeiro et al., 2018, 2019), with recent contributions accounting for additional objectives such as passenger connections (Birolini et al., 2023), airline fairness

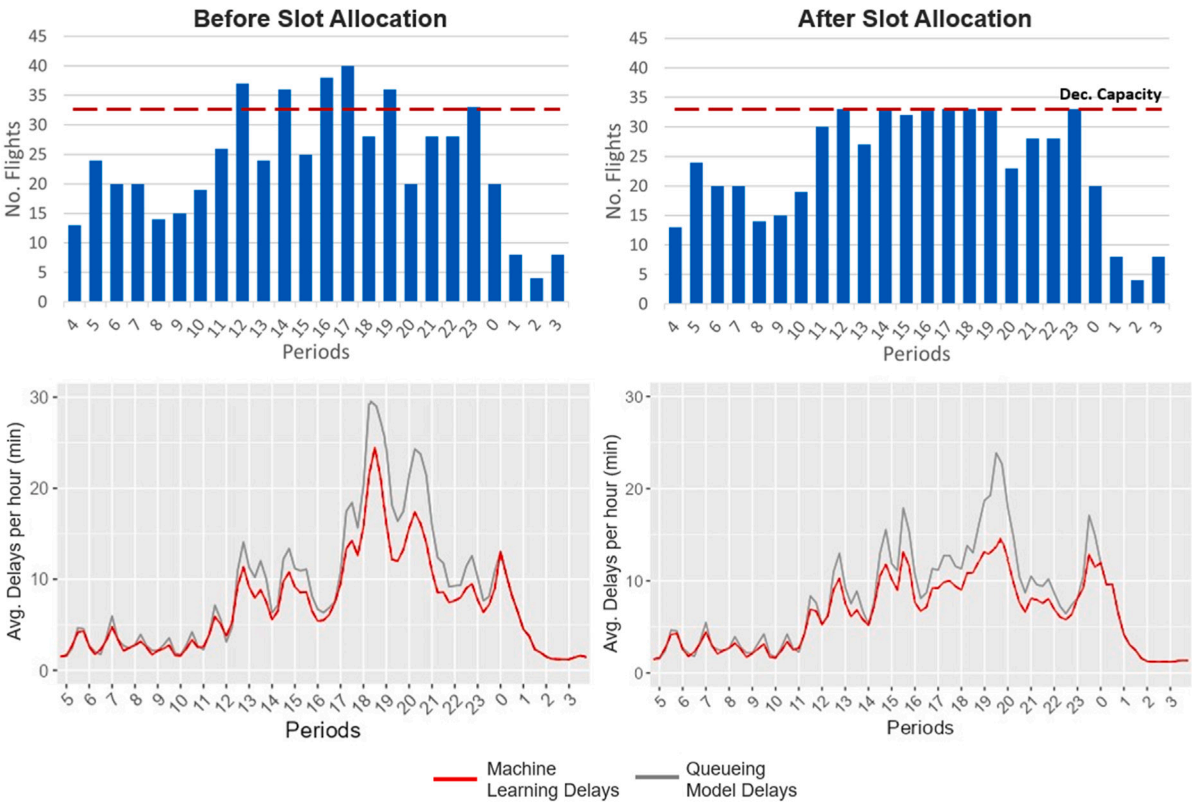


Fig. 12. Impact of slot allocation on flight delays.

and equity (Fairbrother et al., 2020) and type of service/market preferences (Jorge et al., 2021). In line with the focus of the paper, Jacquillat and Odoni (2015b) incorporated the DELAYS model into a slot allocation algorithm that focuses on interventions based on delay limits instead of fixed declared capacities. Similarly, Katsigiannis and Zografos (2023) used the DELAYS queueing model to compare alternative schedules from a multi-objective slot allocation model. To the best of our knowledge, no study has yet incorporated and validated the use data-driven delay predictions into slot allocation optimization algorithms.

5.3. Strategic flow management (months to days before)

The slot allocation process provides crucial information, such as flight schedules and aircraft fleets, which are used to construct preliminary flight plans for each aircraft operation. This involves planning the route structure of flights to ensure a smooth and orderly distribution of air traffic flows across the airspace network. At the same time, resource planning is carried out to ensure the safe provision of services with adequate allocation of air traffic controllers to airspace sectors. While the strategic flow management is a network problem typically solved by centralized entity (FAA, Eurocontrol), it also requires detailed considerations within individual airports and terminal airspaces (TMA). The proposed local delay prediction approaches are targeted to support these assessments.

As we approach the day of operations, the utilization of simulation models poses challenges due to the significant run times. At this stage, there is a need to develop models that can effectively evaluate various airfield and air traffic flow management strategies, delivering both rapid and accurate outcomes. While queuing models like DELAYS (M2) offer speed, they are too simplistic for this purpose, as they fail to capture crucial features related to the varying air traffic flow across different routes. Model M5, as presented in this paper, offers a potential solution by incorporating route-related features into queueing models through machine learning.

We have simulated the impact of different distribution settings of air traffic flows around Singapore airport using M5. Interestingly, we observed that estimated delays only vary by up to 1% depending on the setting of flows considered. This slight variation can be attributed to the fact that most of the routes utilizing the same runway tend to share the same final approach segment, making the runway the main bottleneck and therefore main source of delays. Yet other bottlenecks may occur in the terminal airspace. Because M5 only incompasses a queueing model, it may not be able to capture the non-linear behavior of queues across these bottlenecks, exactly for the same reason M3 is better than M3. Therefore more advance queueing network models (such as Itoh and Mitici, 2019; Simaiakis et al., 2013) may produce better results, and may have the potential to be improved through integration of machine learning methods (as done for M2 to create M3).

We conducted simulations to assess the impact of different distribution settings on air traffic flows around Singapore airport using the M5 model. Our findings highlight that the estimated delays exhibit minimal variance, typically up to 1%, across the various flow settings we examined. This limited variability in results may be attributed to M5's reliance on a single queueing model, potentially lacking effectiveness in capturing the non-linear behavior inherent in networks of queues associated with diverse available routes. To address this limitation, the integration of advanced queueing network models, as proposed in Itoh and Mitici (2019) and Simaiakis et al. (2013), holds promise for enhancing precision. These models can benefit from further refinement through the integration of machine learning methods.

As for other ACM intervention levels, the integration of prescriptive models with predictive analytics is key in optimizing the decision-making processes effectively. In this regard, the topics of aircraft runway sequencing and scheduling have been extensively studied, with the first optimization model proposed in 1976 by Dear (1976). Numerous researchers have since contributed models considering various methods, objectives, and constraints (See Ikli et al., 2021 for a review). Recently, runway scheduling has expanded to encompass the broader terminal airspace, optimizing not only sequencing but also speeds and route distribution. Prominent studies in this domain include works by (Sama et al., 2017; Ma et al., 2019; Henry et al., 2022; Ng et al., 2024). Furthermore, addressing fuel consumption and emissions through aircraft sequences to enable continuous descent operations has gained significant attention (Tian et al., 2018). Lastly, some research has focused on investigating the impact of the number of flights on ATC workload (Sergeeva et al., 2017; Liu et al., 2018).

Despite the expanding body of research dedicated to optimizing terminal airspace operations with considerations for efficiency, the environment, and safety, there has been limited analysis of the integration of data-driven methods to address the uncertainty and non-linear behavior of delays. This gap in research represents an important avenue for further exploration.

5.4. Pre-tactical flow management (a day to hours before)

This phase focuses on implementing measures in the hours leading up to operations, aimed at fine-tuning the strategic flight plans implemented earlier. In this phase, day-to-day factors such as weather forecasts become critical and more accurate. The pre-tactical instruments involve the imposition of flow control restrictions to limit the number of aircraft arriving at a specific sector or airport. Examples of these measures include (i) rescheduling flights to later periods of the day, (ii) rerouting traffic flows to less congested routes and/or airspace sectors, and (iii) implementing ground delay programs (GDP), which involve assigning departure delays at the origin airport, ensuring that aircraft arrive later than their originally scheduled arrival time at the destination.

A key challenge lies in determining the optimal airport acceptance rate — a limit on incoming air traffic approaching the airport. This parameter plays a crucial role in ensuring the effective implementation of Ground Delay Programs (GDP) and proactive air traffic management, ultimately minimizing the risk of airborne holding. Given the dynamic nature of factors such as adverse weather or increased congestion due to delay propagation, there is a frequent need to recalibrate airport acceptance rates. Utilizing data-driven methods that can accurately capture the effects of these contingent factors becomes essential in supporting the calibration of airport acceptance rates. For example, Model M6 offers a rapid assessment of the impact on airborne delays under current weather conditions, providing valuable insights for optimizing airport acceptance rates.

Fig. 13 depicts a simulation of a day with heavy lightning events between 6PM to 10 PM, along with the corresponding predicted average hourly delays before and after GDP implementation — a GDP algorithm has been developed (see Appendix 2).[11] The flight schedule used for analysis (Fig. 13 - left) is based on the scheduled obtained after slot allocation (Section 5.2, Fig. 12 - right). Due to the anticipated onset of convective weather, substantial delays are now expected. Specifically, there is a noticeable spike in hourly delays exceeding 15 min, lasting for a duration of one hour. By adjusting the airport acceptance rate to 30 movements per hour during the forecasted convective weather period (as opposed to the standard 33 used for slot allocation), significant reductions in delays can be achieved. Specifically, we observe that by making this adjustment, delays consistently remain below 15 min.

GDPs are widely implemented in both Europe and the United States, where Collaborative Decision-Making (CDM) practices have been in use for several years. To aid airport and air traffic managers in this endeavor, a combination of prescriptive and predictive tools is being utilized. The development of optimization models to support GDP implementation is not recent (Odoni, 1987). Since then, numerous other researchers, such as Richetta and Odoni (1993), Ball et al. (2003), and Mukherjee et al. (2012) have proposed various models that take into account uncertainties and the dynamic nature of the process. In recent years, there has been a shift toward exploring more data-driven approaches in GDP research. The focus is on capturing the influence of contingent factors, such as weather, on airport acceptance rates while supporting GDP implementation (Murça and Hansman, 2018; Liu et al., 2020).

5.5. Tactical flow management (real time)

Tactical flow management refers to the set of actions taken during the actual operation of air traffic to optimize the efficiency and safety of flights. It involves taking specific actions during the operation of flights, such as rerouting or adjusting the sequencing of arrivals and departures, to avoid congestion and ensure smooth operations. Near-real-time information is critical in making these decisions, as it enables air traffic controllers to quickly evaluate the situation and determine the best course of action. For example, if congestion is detected in the terminal airspace area, controllers may need to delay some aircraft to prevent them from flying at a lower altitude, which would result in increased fuel consumption and emissions.

Currently, advanced ATM systems seamlessly incorporate rule-based algorithms to support ATC in making aircraft sequencing decisions within the terminal airspace areas. These systems, known as Arrival Manager (AMAN) and Departure Manager (DMAN),

[11] The primary distinction from the slot allocation algorithm lies in the fact that, since we are already in the day of operations, flights can only be delayed to later periods. This is in contrast to the slot allocation algorithm, which permits flights to be rescheduled to earlier times, as it is planned months in advance.

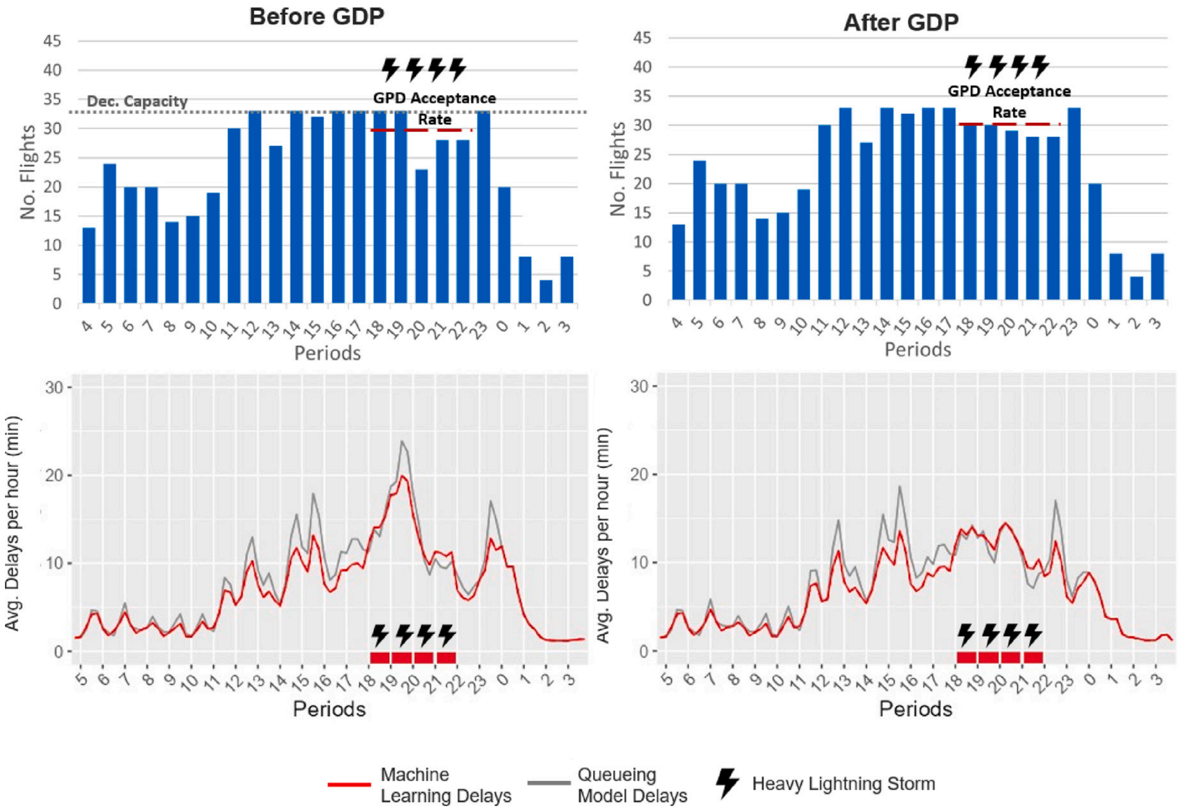


Fig. 13. Impact of GDPs on flight delays.

have been successfully implemented in various countries — such as TBFM in the USA, and MAESTRO, OSYRIS, or 4D-Planner in Europe. Leveraging a comprehensive array of data, including flight plans, radar information, weather conditions, local airspace details, and route information, these systems are designed with the primary goal of aiding ATCs in maintaining minimum separations and ensuring the efficiency of runway throughput.

Recent research, has focused on enhancing these systems through a combination of optimization and reinforcement learning methods (Toratani, 2019; Henry et al., 2022) while incorporating machine learning techniques to leverage historical data for capturing contingent factors (Jun et al., 2022). Notwithstanding, this remains a pivotal challenge to address, given the constraint of computation time, juxtaposed with the existence of real-time available data, which underscores its promising potential for further exploration.

6. Conclusions

This paper presents a comprehensive assessment of delay predictive analytics to support effective airport capacity management (ACM). The study explores the different phases of ACM, emphasizing the need for delay predictive analytics and the input information required at each phase. A key contribution of this work is the development of a structured framework for flight delay prediction that integrates various levels of decision-making within ACM. This framework serves as a benchmark for researchers and practitioners, guiding them in selecting appropriate models and data inputs tailored to their specific operational needs within the broader context of ACM.

The framework was developed through an extensive review of diverse modeling approaches for flight delay predictions, including rule-based simulations, queuing models, and data-driven methodologies. These approaches were evaluated across different definitions of delay (local, scheduled, and network delays) based on insights drawn from over 200 scholarly papers. Recognizing the specific nature of ACM, we identified local delays as the most critical for prediction within this context. To validate our framework, we applied the various methods to real-world data from four major Southeast Asian airports – Singapore, Kuala Lumpur, Bangkok, and Hong Kong – introducing innovative features related to congestion, temporal patterns, routes, and weather conditions. The accuracy of these methods was assessed using a range of metrics. Finally, we deconstructed airport capacity management into five key phases, detailing the necessary methods and features tailored to each phase's granularity and scope. Practical insights were provided to enhance airport operations, optimize resource allocation for resilient capacity management, and future directions were discussed.

The key takeaways from the paper are as follows:

- Our review of over 200 papers reveals that delay predictive analytics in aviation has been extensively explored, but with significant variability in focus. Studies differ in the types of delays predicted, the applications and purposes of the models, and the methods employed. This variability underscores the fragmented nature of existing research, which often targets singular applications without a clear, unified framework. Our work addresses this gap by providing a holistic, structured approach to delay prediction within the specific context of ACM.
- The study identifies local delays as pivotal for effective airport capacity management. Unlike network-wide delays, which airlines typically manage, local delays occur within the airport's immediate environment and can be more directly influenced by ATCs and Airport Managers. By focusing on local delays, this research aligns predictive analytics with the operational realities of ACM.
- Local delays are significantly more challenging to quantify than scheduled delays — which are simply calculated as the difference between scheduled and actual times. Estimating local delays requires the integration of geospatial information and historical data to identify nominal patterns, adding a layer of complexity to the process. Our research shows that ADS-B data when processed appropriately as proposed in this paper, can be leveraged to estimate local delays accurately.
- The results show that machine learning models outperform traditional methods in predicting local delays, particularly as more detailed information becomes available closer to the day of operation. These models achieved strong performance metrics, with R^2 values going up to 0.85–0.95 when near-real time (within 15 min before operations) information is incorporated.
- However, while machine learning excels with abundant, high-quality, near-real time data, its reliance on such data poses challenges in the earlier stages of ACM, where information is typically sparse (i.e., months to years prior to operations). In these contexts, simulation and queuing models provide robust alternatives, maintaining high accuracy levels with R^2_{agg} ranging from 0.54 to 0.86 even with limited data.
- Results also show that hybrid queuing-based machine learning models can lead to better models by combining the advantage of queuing models (in capturing congestion dynamics) and machine-learning (in accounting for contingent factors and complex nonlinear patterns); being suitable alternatives at stages in which some information is already available but not yet very precise.
- Beyond predictive accuracy, this research explores the integration of delay predictive models with prescriptive analytics to support critical ACM functions such as slot allocation, ground delay programs, and air traffic flow management. The findings suggest that this integrated approach not only enhances operational efficiency but also strengthens ACM's ability to proactively manage and mitigate congestion, thereby improving overall airport performance. Although this area has been explored, it remains underdeveloped. A key direction for the future of airport capacity management involves augmenting delay predictive models with prescriptive optimization to support decisions across the various stages of the capacity management process. Further exploration into robust analytics frameworks that leverage estimated delays and their uncertainties is seen as a promising direction.

CRediT authorship contribution statement

Nuno Antunes Ribeiro: Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Jordan Tay:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Wayne Ng:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Sebastian Birolini:** Writing – original draft, Supervision, Methodology, Data curation, Conceptualization.

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Appendix A. CAST simulation design and calibration process

This section outlines the procedural steps involved in crafting and fine-tuning the CAST simulation model utilized in our study. We describe the various objects and rules created, along with the specific CAST commands used to adjust modeling parameters. While this section is tailored specifically for CAST, we contend that the general procedural framework is adaptable to other simulation software platforms that may incorporate analogous commands akin to those found in CAST. Fig. A.14 provides an overview of the main steps and objects involved in developing the simulation model in CAST, which are further elaborated below:

(i) The first step involves designing the airport layout in CAST. For this task, we use AutoCAD, leveraging its "From Map" feature to enable drawing on top of satellite imagery. The outcome of this step is presented in the left side of Fig. A.14.

(ii) In the second step, we import the AutoCAD file into CAST. The import process may require manual adjustments to ensure that the network is well connected. Additionally, we must specify the objects in the network corresponding to the runway, taxiway, and stand sets.

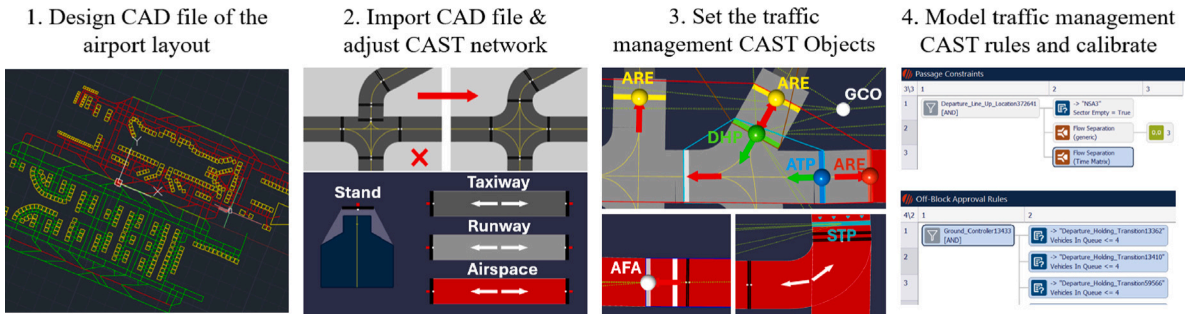

Fig. A.14. CAST modeling steps.

(iii) The third step involves setting the fundamental objects required to model airport operations in CAST. CAST provides an extensive set of objects for various purposes; among these, we highlight six particularly relevant for our model: (i) Departure Holding Position (DHP) - sets the location where aircraft line up before takeoff. Here, we can specify the aircraft separation requirements for departures; (ii) Arrival Final Approach (AFA) - analogous to DHP, this object sets the holding location for arriving aircraft where they can wait before landing. In this object, we can define aircraft separation requirements for arrivals; (iii) Departure End of the Runway (DER) & Arrival Runway Exit (ARE) - establish the runway boundaries. In these objects we can specify that no other aircraft can utilize the runway while an aircraft is on the runway; (iv) Arrival Threshold Position (ATP) - marks where an aircraft lands. This object is employed to establish the runway occupancy times (ROC); (v) Sector Transition Position (STP) - utilized to delineate sectors within the airfield and airspace. In our model, this object is used to create the runway assignment rules; (vi) Ground Controller Object (GCO) - enables the setting of off-block approval rules for departing flights, allowing to control the number of aircraft in the taxiways.

(iv) The fourth step involves coding the simulation rules and setting the parameters to accurately model the airport operations in CAST. This step requires the expert judgment of individuals working at the airport. The rules and parameters are defined within the objects established in step (iii), employing a system of conditional trees for this purpose. While some rules serve as hard constraints and thus do not require calibration (e.g., ensuring that only one aircraft can be on the runway at any time), others may necessitate calibration. We have categorized these rules into four main groups: (i) Separation requirement rules, which dictate the minimum distances between arriving and departing aircraft; (ii) Runway assignment rules, which set a limit on the number of aircraft queuing at the DHP before an aircraft can leave its stand; and (iv) Runway usage rules, which define the expected runway occupancy times based on the chosen runway exit (ARE). Fig. A.15 displays the conditional trees modeled in CAST for these rules.

Separation requirements are defined at the DHP and AFA for departures and arrivals, respectively. Fig. A.15(a) displays the condition tree for DHP, indicating that a departure can only take place under three conditions: (i) the runway must be empty (Sector Empty = True); (ii) the forthcoming arrival must be at a minimum distance from the runway (illustrated as 3 NM in the figure); and (iii) the preceding departure must have occurred more than a specified number of minutes earlier, as dictated by a time matrix — the user can adjust these time matrix by specifying safety buffers. Fig. A.15(b) presents a similar decision framework for arrivals. In this case, the model assesses the number of flights in the DHP queue. Depending on the queue size, various separation requirements (time matrix) are applied. The logic behind this is to increase the separation between arrivals when there are aircraft queuing for departure, thereby potentially creating a window to accommodate a departure in between arrivals.

The runway assignment rules are specified in the STP. Note that Singapore Airport operates with a system of two independent runways: one primarily for arrivals and the other for departures. However, during moments of low traffic on the departure runways, some arrivals may use the departure runway. This decision is reflected in the conditional tree presented in Fig. A.15(c). If the number of aircraft approaching the departure runway is less than a certain threshold (illustrated as 3 in the figure), then CAST checks the number of arrivals already queuing for each of the runways and selects the one with the smallest queue.

The off-block approval rules are set to control the number of aircraft queuing in the departure position. Fig. A.15(d) presents the condition tree which sets that departing flights can only leave the stand when less than a certain threshold of aircraft are queueing to depart (illustrated as 4 NM in the figure).

Finally, the runway usage rules determine the probability of using a runway exit, contingent upon the size of the aircraft — Fig. A.15(e) solely illustrates the case for light aircraft, yet other weight categories were also considered. Additionally, CAST also allows to input the average runway occupancy time for an aircraft of a specific weight categor from the moment of touchdown until each runway exit.

The calibration of simulation models such as CAST is inherently airport-specific due to the vast number of parameters and rules that require fine-tuning. This specificity limits the model's generalizability across different airport environments. The calibration process is notably labor-intensive. Each parameter and rule must be manually configured, rigorously tested, and subjected to multiple

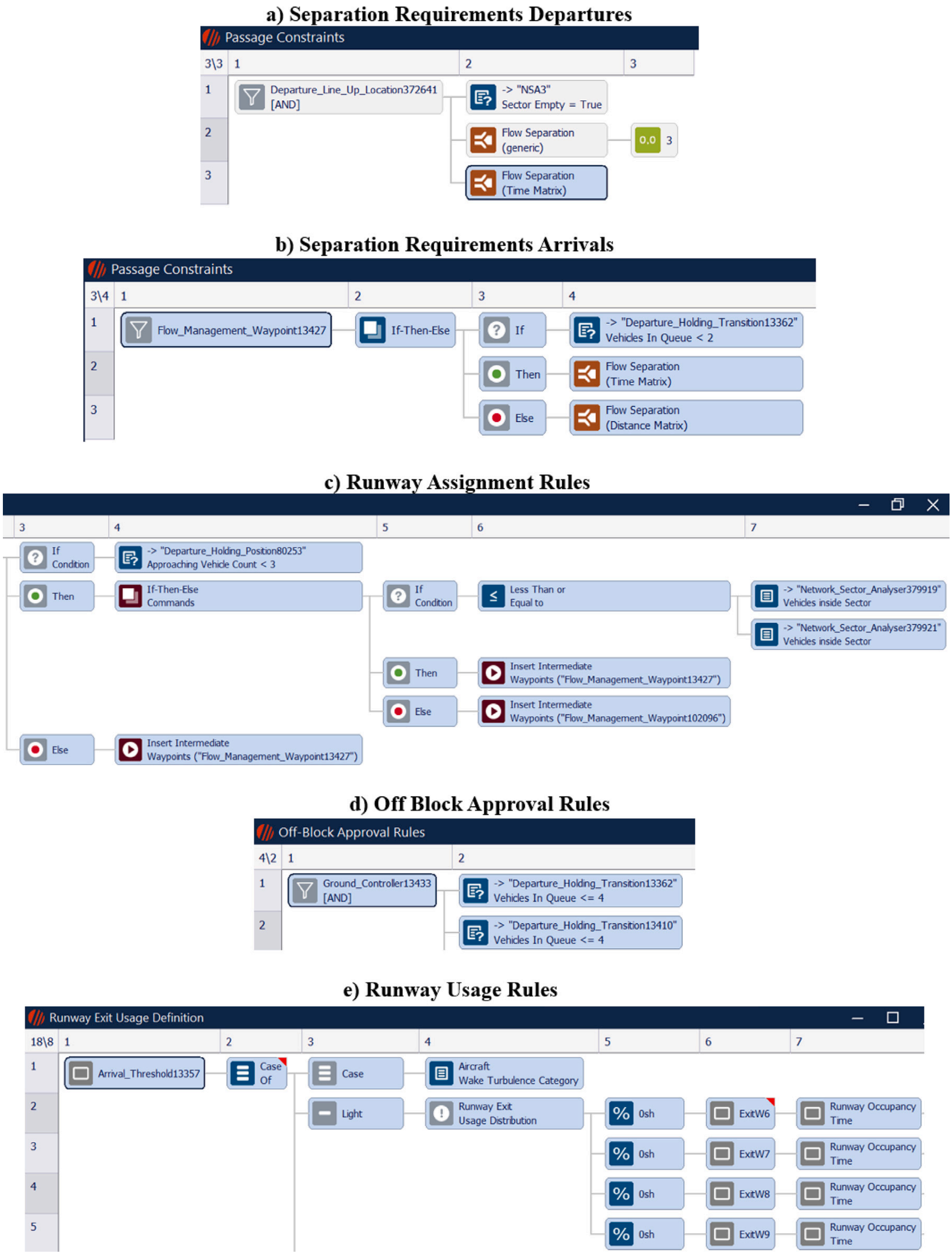

Fig. A.15. CAST tree conditions.

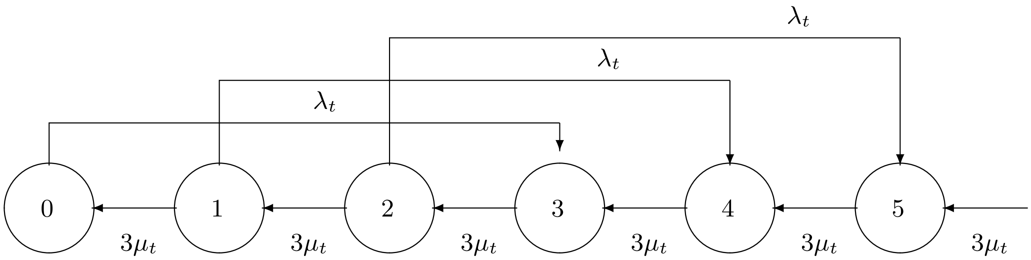

Fig. B.16. State-transition diagram of the $M(t)/E_3(t)/1$ queuing system.

iterations to ensure accuracy. Moreover, this requires a comprehensive understanding of airport operations management, making it critical for modelers to work closely with airport managers to capture the operational nuances accurately. Furthermore, running simulations can be time-consuming. For instance, simulating a single day of airport operations takes around 30 min. This highlights a significant drawback of using simulation models: their development and execution are both time and labor-intensive. Despite these challenges, the detailed nature of these models offers a high degree of accuracy. This precision makes them particularly valuable for testing future scenarios. The core part of the paper elaborates further on this aspect, underscoring the models' utility in strategic planning.

Appendix B. DELAYS model state diagram

The system's state-transition diagram representing DELAYS is depicted in Fig. B.16. It is constructed based on an Erlang process of order 3 and rate μ, modeled as three Markovian "stages of work" completed at a rate of 3μ each. The state i signifies the number of remaining stages of work. Let u denote a continuously varying time index, and $P_i(u)$ represent the probability of being in state i at time u. Eqs. (B.1)–(B.5) present the Chapman–Kolmogorov first-order differential equations governing the evolution of $P_i(u)$ during the period s, where u ranges from $(s-1)S$ to sS. The practical queue capacity is denoted by N, and the system starts empty at the beginning of the day.

$$\frac{dP_0(u)}{du} = -\lambda_t P_0(u) + k\mu_t P_1(u) \tag{B.1}$$

$$\frac{dP_i(u)}{du} = -(\lambda_t + k\mu_t)P_i(u) + k\mu_t P_{i+1}(u) \qquad \forall i \in \{1,\dots,k\} \tag{B.2}$$

$$\frac{dP_i(u)}{du} = \lambda_t P_{i-k}(u) - (\lambda_t + k\mu_t)P_i(u) + k\mu_t P_{i+1}(u) \qquad \forall i \in \{k+1,\dots,(N-1)k\} \tag{B.3}$$

$$\frac{dP_i(u)}{du} = \lambda_t P_{i-k}(u) - k\mu_t P_i(u) + k\mu_t P_{i+1}(u) \qquad \forall i \in \{(N-1)k+1,\dots,kN-1\} \tag{B.4}$$

$$\frac{dP_{kN}(u)}{du} = \lambda_t P_{k(N-1)}(u) - k\mu_t P_{kN}(u) \tag{B.5}$$

Appendix C. Slot allocation algorithm

See Algorithm 1.

Appendix D. GDP algorithm

See Algorithm 2.

Algorithm 1 Slot Allocation Algorithm

```
Inputs: N_t: Number of slot requests per hour; C_t: Declared capacity per hour.
Outputs: Updated N_t: Adjusted number of slot requests per hour for each period t in T.
T ← 24                                      ▷ Number of periods (hours)
for t ← 1 to T do
    if N_t[t] > C_t[t] then
        S ← N_t − C_t                       ▷ Calculate the number of slot requests to be displaced S
        e ← t − 1                           ▷ Earlier time slot
        l ← t + 1                           ▷ Later time slot
        while S > 0 and (e≥ 1 or l ≤ T) do
            if e ≥ 1 and N_t[e] < C_t[e] then
                A ← min(C_t[e] − N_t[e], S) ▷ Number of slots to make available in period e
                N_t[e] ← N_t[e] + A         ▷ Allocate flights to earlier period.
                S ← S − A
            end if
            if l ≤ T and N_t[l] < C_t[l] then
                A ← min(C_t[l] − N_t[l], S) ▷ Number of slots to make available in period l
                N_t[l] ← N_t[l] + A         ▷ Allocate flights to later period.
                S ← S − A
            end if
            e ← e −1
            l ← l +1
        end while
    end if
end for
return N_t                                  ▷ Return the updated N_t with adjusted number of slot requests per hour.
```

Algorithm 2 GDP Algorithm

```
Inputs: N_t: Number of flights per hour; C_t: Acceptance rate per hour.
Outputs: Updated N_t: Adjusted number of flights per hour.
T ← 24                                      ▷ Number of periods (hours)
for t ← 1 to T do
    if N_t[t] > C_t[t] then
        S ← N_t − C_t                       ▷ Calculate the number of flights to be displaced S
        l ← t + 1                           ▷ Later time slot
        while S > 0 and (e≥ 1 or l ≤ T) do
            if l ≤ T and N_t[l] < C_t[l] then
                A ← min(C_t[l] − N_t[l], S) ▷ Number of slots to make available in period l
                N_t[l] ← N_t[l] + A         ▷ Allocate flights to later period.
                S ← S − A
            end if
            l ← l +1
        end while
    end if
end for
return N_t                                  ▷ Return the updated N_t with adjusted number of flights per hour.
```

Appendix E. Literature review

Simulation models. See Table E.9.

Queuing models. See Table E.10.

Data-driven models. See Table E.11.

Table E.9
Simulation models.

Article	Type of delays	Type of movement	Method	Purpose
Trani et al. (1992)	Local delays	Arrivals, Departures	SIMMOD	Investigated the impact of different runway exit designs
Czech and Crook (1994)	Local delays	Arrivals, Departures, Enroute	RAMS	Presented the Reorganized ATC Mathematical Simulator (RAMS) developed by Eurocontrol
Kleinman et al. (1997)	Network delays	Arrivals, Departures, Enroute	SIMMOD	Investigated the benefits of ground holding decisions to reduce network delay propagation.
Martel (2001)	Local delays	Arrivals, Departures	SIMMOD	Computed capacity estimations under different runway and apron configurations in YUL
Offerman (2001)	Local delays	Arrivals, Departures, Enroute	TAAM	Computed capacity estimates for AMS; Computed airspace sector capacities
Yazdani and Scarborough (2001)	Local delays	Arrivals, Departures	Airport machine	Computed capacity estimates for BWI using the Airport Machine simulation model
Bazargan et al. (2002)	Local delays	Arrivals, Departures	TAAM	Computed the capacity of PHL under different proposed expansion alternatives
Tung (2002)	Local delays	Arrivals, Departures, Enroute	Airport-Sim	Presented the AirportSim simulation model
Santana and Mueller (2003)	Local delays	Arrivals, Departures	SIMMOD	Conducted an analysis of delays and travel times under different physical and operational scenarios in GRU
Bodoh and Wieland (2003)	Local delays	Arrivals, Departures	TAAM	Developed parallel computation algorithms to improve TAAM computation performance
Alipio et al. (2003)	Network delays	Arrivals, Departures, Enroute	TAAM Arena	Evaluated the impact of the use of dynamic airspace super sectors
Shortle et al. (2003)	Network delays	Arrivals, Departures, Enroute	TAAM	Tested the impact of using lower-fidelity airspace networks so as to reduce computational performance of TAAM
Richards and Hobbs (2003)	Local delays	Arrivals, Departures, Enroute	NATS	Presented the HERMES (Heuristic Runway Movement Event) model
Erzberger et al. (2004)	Local delays	Arrivals, Departures	SIMMOD	Investigated the performance of the automated arrival scheduling system (Traffic Management Advisor) developed by NASA for FAA.
Yousefi and Donohue (2004)	Network delays	Arrivals, Departures, Enroute	TAAM	Estimated the sector workload for the entire US National Airspace System for a day of operations
Harris et al. (2006)	Network delays	Arrivals, Departures, Enroute	TAAM Arena	Evaluated the impact of the use of dynamic airspace super sectors
Chao et al. (2008)	Local delays	Arrivals, Departures	SIMMOD	Analyzed the trade-off between capacity and delays in XMN
Gao et al. (2008)	Network delays	Arrivals, Departures, Enroute	SIMMOD	Analyzed the delay propagation in the Pearl River Delta multi-airport system in China
Wei and Siyuan (2010)	Local delays	Arrivals, Departures	SIMMOD	Investigated the performance of various runway utilization strategies in CKG
Bubalo and Daduna (2011)	Local delays	Arrivals, Departures	SIMMOD	Developed capacity and delays analysis at BER under different scenarios of future demand.
Lee and Balakrishnan (2012)	Local delays	Arrivals, Departures	SIMMOD	Investigated the impacts on ground delays caused by the uncertainty on pushback times, taxi speeds, and runway separation times in DTW.
Cetek et al. (2014)	Local delays	Arrivals, Departures	SIMMOD	Applied SIMMOD to identify and solve bottlenecks in the airspace and the airfield network of ISL

(*continued on next page*)

Table E.9 (*continued*).

Li et al. (2015)	Local delays	Arrivals, Departures	SIMMOD	Investigated the performance of closely spaced parallel runways under different operational modes of utilization.
Günther et al. (2015)	Local delays	Arrivals, Departures	Airtop	Analyzed the impact of severe weather disruptive events in airport delays
Kreuz et al. (2016)	Network delays	Arrivals, Departures, Enroute	Airtop	Studied the effect of restricted airspace on the ATM system
Li et al. (2016)	Network delays	Arrivals, Departures	Airtop	Developed optimization algorithm for flight trajectory planning across the airspace of China
Li et al. (2017)	Local delays	Arrivals, Departures	SIMMOD	Investigated the performance of closely independent parallel runways under different operational modes of utilization.
LI et al. (2017)	Local delays	Arrivals, Departures	SIMMOD	Investigated the performance of airfield systems with lateral runways under different operational modes of utilization.
Neto et al. (2017)	Local delays	Arrivals, Departures, Enroute	TAAM	Conducted a safety assessment analysis of UAS integration within a non-segregated airspace
Kaltenhäuser et al. (2017)	Local delays	Arrivals, Departures, Enroute	Airtop	Analyzed the impact of space transportation on air traffic management
Rosenow et al. (2017)	Network delays	Arrivals, Departures, Enroute	TOMATO	Developed an trajectory optimization algorithm for the free routing airspace scheme
Munoz Hernandez and Soler (2017)	Local delays	Enroute	TAAM	Simulated aircraft trajectories using optimization algorithm for conflict detection and resolution
Aydoğan and Çetek (2018)	Local delays	Enroute	SIMMOD	Analyzed the use of point merge approach for en route traffic
Sidiropoulos et al. (2018)	Local delays	Arrivals, Departures	Airtop	Developed framework to optimize terminal airspace operations in multi-airport systems
Rosenow et al. (2019)	Network delays	Arrivals, Departures Enroute	Airtop	Investigated the impact of the 4D free route concept in the European airspace network
Krstić Simić and Babić (2020)	Local delays	Arrivals, Departures	SIMMOD	Investigated various aircraft sequencing strategies under different runway systems.
Parambath (2020)	Local delays	Arrivals, Departures	TAAM	Computed airport sector capacity in the Chennai airspace region
Di Mascio et al. (2021)	Local delays	Arrivals, Departures	Airtop	Investigated the impact of the Departure and Arrival MANager systems on airport throughput capacity
Sekine et al. (2021)	Local delays	Arrivals, Departures	Airtop	Investigated the impact of RECAT separations on the airport throughput capacity of HND
Šabić et al. (2021)	Local delays	Arrivals, Departures	CAST	Simulated the impact of different parameters using CAST, and applied neural networks to evaluate the correlation between those parameters
Hirabayashi et al. (2022)	Local delays	Enroute	Airtop	Analyzed the impact of the free route concept over the North Pacific

Table E.10
Queueing models.

Article	Type of delays	Type of movement	Method	Purpose
Galliher and Wheeler (1958)	Local delays	Arrivals	M(t)/D(t)/c	Modeled landing delays using a M(t)/D(t)/c queueing model
Koopman (1972)	Local delays	Arrivals and departures	M(t)/M(t)/1 and M(t)/D(t)/1	Modeled airport local delays in a single runway (landing and take-off) using a M(t)/M(t)/1 and a M(t)/D(t)/c queueing model
Hengsbach and Odoni (1975)	Local delays	Arrivals and departures	M(t)/M(t)/c and M(t)/D(t)/c	Modeled airport congestion in multiple runways (landing and take-off) using a M(t)/M(t)/1 and a M(t)/D(t)/c queueing model
Kivestu (1976)	Local delays	Arrivals	M/Ek(t)/s	Modeled airport local delays using a M/Ek(t)/s queueing system
Bookbinder (1986)	Local delays	Arrivals and departures	M(t)/M(t)/1/K	Modeled airport local delays at various airports in USA
Daniel (1995)	Local delays	Arrivals and departures	M(t)/D/s/K	Modeled landing delays at Minneapolis airport using a M(t)/D(t)/s/K queueing model, and investigated the benefits of congestion pricing
Malone (1995)	Network delays	Arrivals and departures	Network of M(t)/Ek(t)/1	Analyzed the accuracy of DELAYS model, and conceptualized AND (see Pyrgiotis et al., 2013)
Peterson et al. (1995)	Local delays	Arrivals	Semi-Markov model	Modeled airport local delays using a deterministic recursive algorithm
Hebert and Dietz (1997)	Local delays	Departures	M(t)/M(t)/1 and M(t)/Ek(t)/1	Modeled take-off delays at LGA airport using M(t)/Ek(t)/1 queueing model with server absences
Lee et al. (1997)	Local delays	Arrivals and departures	M(t)/M(t)/1, M(t)/D(t)/1 and M(t)/Ek(t)/1	Modeled local delays at various airports in USA using different queueing models, and analyzed the benefits of using new ATM technologies
Long et al. (1999)	Network delays	Arrivals and departures	Network of M(t)/Ek(t)/1	Developed queuing network model (LMINET) to study the impact of air traffic management interventions across the US airspace network
Pujet et al. (1999)	Local delays	Departures	M(t)/Ek(t)/1	Develop queueing models to simulate airport departure processes at Boston Airport, and analyzed the impact of departure control procedures
Anderson et al. (2000)	Local delays	Arrivals and departures	M(t)/Ek(t)/1	Modeled local delays at various airports in USA, and investigated several arrival and departure control strategies (e.g. gate holding)
Bolender and Slater (2000)	Local delays	Arrivals	M/M/c and M/D/c	Modeled landing delays at multiple runways airports, and investigated runway scheduling strategies
Shortle et al. (2003)	Network delays	Arrivals and departures	Jackson Networks	Modeled the airspace network of US using a Jackson network structure, and investigated methods to reduce network complexity by removing low utilization nodes
Stamatopoulos et al. (2004)	Local delays	Arrivals and departures	M(t)/Ek(t)/1	Developed decision support system for airport strategic planning (MACAD), which integrates the DELAYS model
Mukherjee et al. (2005)	Local delays	Arrivals and departures	M(t)/Ek(t)/1	Applied DELAYS to analyzed the effects of several congestion management schemes
Lovell et al. (2007)	Local delays	Arrivals and departures	M(t)/Ek(t)/1	Applied DELAYS algorithm and investigated methods for calibrating it using real data
Churchill et al. (2008)	Local delays	Arrivals and departures	M(t)/Ek(t)/1	Applied DELAYS algorithm and investigated methods for calibrating it using real data
Tandale et al. (2008)	Network delays	Arrivals and departures	Jackson networks with M/M/c nodes	Modeled the airspace network of US using a Jackson network structure, and investigated the impact of uncertainties on traffic flow efficiency
Stolletz (2008)	Local delays	Arrivals and departures	M(t)/G2(t)/1	Modeled landing and take-off delays using a M9t) G2(t) queueing systems approximated as a Stationary backlog-carryover (SBC)
Hansen et al. (2009)	Local delays	Arrivals	M(t)/Ek(t)/1	Applied DELAYS algorithm to investigate the potential benefits of trajectory-based operations
Long and Hasan (2009)	Network delays	Arrivals and departures	Network of M(t)/Ek(t)/1	Expanded LMINET (see Long et al., 1999)
Simaiakis and Balakrishnan (2009)	Local delays	Departures	Monte Carlo	Develop queueing models to simulate airport departure processes at Boston Airport, and analyzed the impact of taxi operations on fuel burn and emissions
Tien et al. (2011)	Network delays	Arrivals and departures	Stochastic network flow model	Developed queueing network model of the US National Airspace Systems

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Table E.10 (*continued*).

Zhou et al. (2011)	Network delays	Arrivals and departures	Stochastic network flow model	Developed queueing network model of the US National Airspace Systems
Nikoleris and Hansen (2012)	Local delays	Arrivals	PSRD/D/1	Modeled landing delays using a PSRD/D/1 queueing model, and analyzed different trajectory management concepts
Taylor et al. (2012)	Network delays	Arrivals and departures	Stochastic network flow model	Developed queueing network model of the US National Airspace Systems
Vaze and Barnhart (2012)	Network delays	Arrivals and departures	Network of M(t)/Ek(t)/1	Applies AND model to analyzed the impact of demand management strategies in the US airport network
Wanke et al. (2012)	Network delays	Arrivals and departures	Stochastic network flow model	Development of strategic airspace network tool to strategic air traffic flow management
Wan et al. (2013)	Network delays	Arrivals and departures	Stochastic network flow model	Developed queueing network model of the US National Airspace Systems
Lovell et al. (2013)	Local delays	Arrivals and departures	M(t)/M(t)/1 and M(t)/Ek(t)/1	Developed approximated method to solve M(t)/Ek(t)/1 queueing systems that can be extended to airport networks
Pyrgiotis et al. (2013)	Network delays	Arrivals and departures	Network of M(t)/Ek(t)/1	Developed AND algorithm that applies DELAYS in a network of airports
Taylor and Wanke (2013)	Network delays	Arrivals and departures	Stochastic network flow model	Development of strategic airspace network tool to strategic air traffic flow management
Caccavale et al. (2014)	Local delays	Arrivals	PSRD/D/1	Modeled landing delays at Heathrow airport using a PSRD/D/1 queueing model
Gwiggner and Nagaoka (2014)	Local delays	Arrivals	M/G/1 and PSRD/G/1	Modeled air traffic flows in Japanese airspace using PSRD/G/1
Simaiakis et al. (2013)	Local delays	Departures	M(t)/Ek/1	Develop queueing models to simulate airport departure processes at Boston Airport, and analyzed departure control policies
Jacquillat and Odoni (2015b)	Local delays	Arrivals and departures	M(t)/Ek/1	Applies the DELAYS model to optimize airport scheduling decisions and runway utilization at JFK airport
Jacquillat and Odoni (2015a)	Local delays	Arrivals and departures	M(t)/Ek/1	Applies the DELAYS model to optimize the control of airport service rates at New York's airports
Nikoleris and Hansen (2016)	Local delays	Arrivals	PSRD/G/1	Analyzed the effect of trajectory prediction on runway occupancy times
Baspinar et al. (2016)	Network delays	Arrivals and departures	Network of M(t)/Ek(t)/1	Analyzed the effect of local disturbances on European airports using a network queueing model
McFarlane and Balakrishnan (2016)	Local delays	Departures	D(t)/Ek(t)/1	Develop queueing models to simulate airport departure processes at LGA Airport, and analyzed departure control policies
Pyrgiotis and Odoni (2016)	Network delays	Arrivals and departures	Network of M(t)/Ek(t)/1	Applies the DELAYS model to analyze the impact of scheduling limits in Newark airport
Badrinath and Balakrishnan (2017)	Local delays	Departures	M(t)/G(t)/1	Develop queueing models to simulate airport departure processes at LGA Airport, and analyze departure control policies
Jacquillat et al. (2017)	Local delays	Arrivals and departures	M(t)/Ek/1	Applies the DELAYS model to analyze the dynamic control of runway configurations
Jacquillat and Vaze (2018)	Local delays	Arrivals and departures	M(t)/Ek/1	Applies the DELAYS model to optimize scheduling interventions with airline equity
Wang et al. (2018a)	Network delays	Arrivals and departures	M(t)/M(t)/s/s and Cm(t)/Ck/s/s	Developed a coxian queueing model to simulate traffic flow in the US airspace
Shone et al. (2019)	Local delays	Arrivals and departures	M(t)/Ek(t)/1 and PSRD/Ek(t)/1	Modeled landing delays using a PSRD/D/1 queueing model, and developed a dynamic optimization algorithm to tactical control of scarce resources at busy airports
Itoh and Mitici (2019)	Local delays	Arrivals	G/G/c	Developed a multi-server queuing model (G/G/c) to predict arrival delays in an extended area of the destination airport
Itoh and Mitici (2020)	Local delays	Arrivals	G/G/c	Develop queueing models to simulate airport arrival processes at Tokyo airport

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Table E.10 (*continued*).

Badrinath et al. (2020)	Local delays	Arrivals and departures	Various Queueing Models	Developed network of queueing models to simulate airport surface operations and investigate the impact of uncertainty on Off-Block time
Lin et al. (2021)	Network delays	Arrivals and departures	M(t)/Ek/1	Develop network queueing model to simulate delay propagation across the China airspace network
Zhao et al. (2022)	Local delays	Arrivals and departures	M/G/1	Developed queueing network model using point-wise stationary approximation to predict delays of a multi-airport system (Macao, Hong Kong and Guangdong)

Table E.11
Data-driven models.

Article	Type of delays	Type of movement	Method	Purpose
Mueller and Chatterji (2002)	Schedule delays	Both	Statistical analysis	Applied statistical analysis to assess the origin of schedule delays at major US airports
Mazzeo (2003)	Schedule delays	Arrival	Regression methods gradient boosting machines	Applied regression methods to investigate the causes of schedule delays in US, and investigate their impact on airline competition
Xu et al. (2005)	Scheduled delays	Both	Regression methods Bayesian networks	Applied Bayesian Network methods to investigate the impact of the propagation of scheduled arrival delays on scheduled departure delays..
Bratu and Barnhart (2005)	Schedule delays	Both	Statistical analysis	Investigated the impact of scheduled delays on passengers' propagated delays
Abdel-Aty et al. (2007)	Schedule delays	Arrival	Regression methods	Applied regression methods to investigate the causes of arrival delays at Orlando Airport
Levy and Rappaport (2007)	Local delays	Arrival	Regression methods	Applied regression methods to predict taxi-in times at Detroit airport
Balakrishna et al. (2008)	Local delays	Departure	Reinforcement learning	Applied reinforcement learning methods to predict taxi-out times at JFK
Xu et al. (2008)	Network delays	Both	Regression methods	Applied linear regression methods to investigate delay propagation in the US airspace
Tu et al. (2008)	Schedule delays	Departure	EM algorithm	Developed statistical methods to predict departure scheduled delays and delay propagation of flights operated by United Airlines in Denver Airport
Pejovic et al. (2009)	Schedule delays	Both	Regression methods	Applied regression methods to analyze the impact of weather on departure on-time performance.
Jetzki (2009)	Network delays	Both	Statistical analysis	Applied statistical analysis to investigate the propagation of network delays in Europe
Sridhar and Chen (2009)	Schedule delays	Both	Regression methods	Applied regression methods to predict schedule delays at US airports considering the impact of weather
Klein et al. (2010)	Schedule delays	Both	Regression methods	Applied regression methods and queueing models to predict schedule delays at US airports considering the impact of weather
Balakrishna et al. (2010)	Local delays	Departure	Reinforcement learning	Applied reinforcement learning methods to predict taxi-out times at TPA airport
Jordan et al. (2010)	Local delays	Departure	Regression methods	Applied regression methods to predict taxi times at Dallas (DFW) airport
Nayak and Zhang (2011)	Network delays	Arrival	Regression methods	Applied regression methods to evaluate the impact of delays at a single airport on the US airspace network.
Srivastava (2011)	Local delays	Departure	Regression methods	Applied regression methods to predict taxi-times at JFK airport
Deshpande and Arıkan (2012)	Schedule delays	Arrival	Regression methods	Applied regression methods to investigate how airline scheduled block times affect on-time performance
Fleurquin et al. (2013)	Network delays	Both	Agent-based models	Applied data-driven agent based model to analyze the delay propagation in the US airspace network
Liu and Willsky (2013)	Network delays	Both	Gaussian Graphical model	Developed Gaussian Graphical models to study the propagation of schedule delays in the US airspace network
Ravizza et al. (2013)	Local delays	Both	Regression methods	Applied regression methods to predict taxi-times at Stockholm and Zurich Airports

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Table E.11 (*continued*).

Rebollo and Balakrishnan (2014)	Schedule delays Network delays	Departure	Random forest	Applied random forest algorithms to predict schedule delays and their propagation across the US airspace network
Ravizza et al. (2014)	Local delays	Both	Regression methods Support vector machines Decision trees Fuzzy Rule-Based Systems	Applied various machine learning methods to predict taxi times at Stockholm and Zurich Airports
Hong and Lee (2015)	Local delays	Arrival	Regression methods Clustering	Applied regression and clustering methods to predict aircraft arrival times by incorporating probabilistic information about trajectory patterns
De Leege et al. (2013)	Local delays	Arrival	Regression methods Neural networks	Applied machine learning methods to trajectory prediction for sequencing and merging of traffic following fixed arrival routes in the TMA
Aljubairy et al. (2016)	Schedule delays	Both	Statistical analysis	Analyzed schedule delays at major airports in China and their correlation with weather conditions.
Belcastro et al. (2016)	Schedule delays	Arrival	Random forest	Applied random forest to predict arrival on-time performance of US flights considering weather conditions.
Campanelli et al. (2016)	Network delays	Both	Agent-based Models	Compared the results of two different models for predicting delay propagation across US and European airports.
Choi et al. (2016)	Schedule delays	Arrival	Decision trees Random forest AdaBoost k-Nearest-Neighbors	Applied various machine learning methods to predict arrival on-time performance of US flights considering weather conditions.
Karakostas (2016)	Schedule delays	Departure	Bayesian networks	Applied Bayesian network models to analyze the propagation of schedule arrival delays on departure schedule delays
Kim et al. (2016)	Schedule delays	Both	Neural networks	Applied neural network methods to predict the on-time performance of flights at various airports in the US.
Sternberg et al. (2016)	Schedule delays	Both	Statistical analysis	Applied statistical analysis to investigate the causes of delays in Brazilian airports
Lordan et al. (2016)	Local delays	Both	Regression methods	Applied regression methods to predict taxi-times at Barcelona Airport
Lee et al. (2016a)	Local delays	Departure	Regression methods Random forest	Applied machine learning methods to predict taxi-out times at CLT airport
Lee et al. (2016b)	Local delays	Arrival	Stochastic models	Developed a stochastic model to predict descent aircraft trajectories and predict the estimated time of arrival (ETA) of flights at SDF
Chung et al. (2017)	Schedule delays	Both	Neural networks	Applied neural network methods to predict arrival delays and optimize airline block times and crew scheduling
Ding (2017)	Schedule delays	Arrival	Regression methods Decision trees Naïve Bayes	Applied regression methods to predict arrival on-time performance
Thiagarajan et al. (2017)	Schedule delays	Both	Decision trees Random forest AdaBoost Gradient Boosting Machines Neural networks	Applied machine learning methods to predict on-time performance of US domestic flights
Horiguchi et al. (2017)	Schedule delays	Departure	Random forests, XGBoost, Neural networks	Applied machine learning methods to predict delays and fuel consumption of specific airline routes
Manna et al. (2017)	Schedule delays	Both	Gradient Boosting Machines Decision tree	Applied gradient boosted decision trees to predict schedule delays of US domestic flights
Du et al. (2018)	Network delays	Both	Causality Networks	Developed a delay causality network model to understand the propagation of flight delays at Chinese airports
Rodríguez-Sanz et al. (2018)	Network delays	Both	Causality Networks	Statistical analysis of different types of delays: local delays; schedule delays; and propagation of arrival delays into departure delays

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Table E.11 (*continued*).

Moreira et al. (2018)	Schedule delays	Both	Neural networks Vector Machines Random forest Naives Bayes	Applied various machine learning methods to predict different classes of on-time performance of Brazilian flights
Wang et al. (2018b)	Local delays	Arrival	Neural Network Clustering	Applied Neural networks and Clustering methods to predict airborne trajectories
Zhu et al. (2018)	Local delays	Arrival	Gradient Boosting Machines XGBoost Random forest	Applied various machine learning methods to predict en-route local delays for flights traveling between DEN, ORD and IAH
Diana (2018)	Local delays	Departure	Regression Methods Support Vector Machines Random forest Gradient Boosting Machines Decision trees	Applied various machine learning methods to predict taxi-out times at SEA airport
Yin et al. (2018)	Local delays	Departure	Regression Methods Support Vector Machines Random forest	Applied various machine learning methods to predict taxi-out times at Shanghai Airport
Herrema et al. (2018)	Local delays	Departure	Neural networks Decision trees Reinforcement Learning	Applied various machine learning methods to predict taxi-out \times at CDG airport
Chakrabarty et al. (2019)	Schedule delays	Arrival	Support Vector Machines Random forest, k-Nearest-Neighbors Gradient Boosting Machines	Applied various machine learning methods to predict arrival on-time performance of flights operated by American Airlines
Qin et al. (2019)	Network delays	Both	Agent-based Models	Applied agent based simulation to investigated network delay propagation across Chinese airports
Etani (2019)	Schedule delays	Arrival	Support Vector Machines Gradient Boosting Machines Random forest Decision trees	Applied various machine learning methods to predict arrival on-time performance of flights operated by Peach Aviation (Japanese Low cost airline)
Rodríguez-Sanz et al. (2019)	Schedule delays	Arrival	Bayesian Networks	Applied Bayesian Networks to predict schedule arrival delays and investigate the contribution of local delays, to these delays
Yu et al. (2019)	Schedule delays	Departure	Neural networks Support Vector Machines k-Nearest-Neighbors Regression Methods	Applies Neural networks integrated with Support Vector Regression methods to predict schedule delays of various flights in China
Gui et al. (2019)	Schedule delays	Arrival	Neural Network	Applied different Neural Networks architectures to predict arrival schedule delays across several routes and airports
Wu et al. (2019)	Schedule delays	Departure	Support Vector Machines k-Nearest-Neighbors Random forest	Applied an improved SVM to predict departure schedule delays at Beijing Airport
Shao et al. (2019)	Schedule delays	Departure	Gradient Boosting Machines Linear Regression Neural Networks Support Vector Machines	Applied various Machine Learning Methods to predict Schedule delays of US flights
Ai et al. (2019)	Network delays	Both	Neural networks	Applied Neural networks to predict network delays across China Airspace

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Table E.11 (*continued*).

Chen and Li (2019)	Schedule delays	Both	Random forest	Applied Random forest to predict schedule delays of US flights while considering propagation of delays from previous operations
Fernandes et al. (2020)	Schedule delays	Departure	Random forest Support vector machines Neural networks	Applied various machine learning methods to identify the factors influencing schedule delays of charter flights in Europe
Lambelho et al. (2020)	Schedule delays	Both	Gradient Boosting Machines Random forest Neural networks	Applied various machine learning methods to predict on-time performance and cancellations of flights at London Heathrow
Yazdi et al. (2020)	Schedule delays	Arrival	Random forest Neural networks Gradient Boosting Machines	Applied Neural networks to predict arrival on-time performance on US flights
Esmaeilzadeh and Mokhtari-mousavi (2020)	Local delays	Departure	Support Vector Machines	Applied SVM to predict departure delays at three major New York Airports, and investigate the source of those delays (weather, gate delays, taxi delays, etc.)
Qu et al. (2020)	Schedule delays	Arrival	Neural networks Random forest Decision trees Support vector machines	Applied Neural networks to predict arrival on-time performance of US flights, considering the impact of weather
Jiang et al. (2020)	Schedule delays	Arrival	Support vector machines Decision trees Random forest Neural networks	Applied various machine learning methods to predict arrival on-time performance of US flights, considering the impact of weather
Murça and de Oliveira (2020)	Local delays	Arrival	Gaussian mixture model Clustering	Applied clustering and GMM methods to predict aircraft arrival trajectories in the TMA of Guarulhos Airport
Wang et al. (2020)	Local delays	Arrival	Regression Methods Gaussian mixture model k-Nearest Neighbors Neural networks Decision trees	Applied Neural networks and Clustering methods to predict airborne trajectories
Tran et al. (2020)	Local delays	Both	Random forest	Applied Random forest to predict aircraft tax-times and speeds at Singapore airport
Li et al. (2020)	Local delays	Both	Neural networks Support vector machines Random forest Regression Methods	Applied Neural networks to predict taxi-times at Hong Kong airport
Dou (2020)	Schedule delays	Arrival	Regression Methods Support vector machines Gaussian mixture model	Applied GBM and Essemble Methods to predict arrival on-time performance of US flights
Zhang and Ma (2020)	Schedule delays	Departure	Gaussian mixture model	Applied GBM to predict departure on-time performance at EWR
Guo et al. (2020)	Schedule delays	Departure	Neural networks	Applied Neural networks to predict departure on-time performance
Huo et al. (2020)	Schedule delays	Arrival	Random forest Regression Methods k-Nearest-Neighbors Naives Bayes	Applied various Machine Learning Methods to predict arrival on-time performance at Hong Kong airport
Zhang et al. (2020)	Network delays	Both	Epidemiologic models	Applied epidemological models to predict network delay propagation

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Table E.11 (*continued*).

Truong (2021)	Schedule delays	Arrival	Bayesian networks	Applied Bayesian methods to predict the probability of arrival delays in US flights.
Cai et al. (2021)	Network delays	Departure	Regression methods Support vector machines Neural networks	Applied Neural networks to predict delay propagation across the Chinese airspace network
Basturk and Cetek (2021)	Local delays	Arrival	Random forest Neural networks	Applied Random forest and Neural Networks to predict the estimated time of arrival (ETA) at ISL, given the time of departure from the origin airport, or the time entering the arrival TMA.
Rodríguez-Sanz et al. (2021)	Schedule delays	Arrival	Bayesian networks	Applied Bayesian Networks to investigate the impact of weather on on-time performance of Brazilian flights
Wang et al. (2021)	Local delays	Both	Gradient Boosting Machines Random forest Neural networks	Applied various machine learning methods to predict taxi-times at Hong Kong, Manchester and Zurich Airports
Lim et al. (2021)	Local delays	Departure	Neural networks	Applied Neural networks to predict taxi-out times at Atlanta Airport
Xuhao et al. (2021)	Local delays	Arrival	Random forest Clustering	Applied clustering methods to identify historical arrival trajectory patterns at Shanghai Airport, and then applies random forest to predict the trajectory pattern of each flight
Bao et al. (2021)	Network delays	Both	Neural networks	Applied Neural networks and Clustering to predict network-wide delays across US
Yi et al. (2021)	Schedule delays	Both	Random forest k-Nearest-Neighbors Regression Methods Naïve Bayes	Applied various Machine Learning methods to predict on-time performance of flights at Boston Airport
Li and Jing (2021)	Network delays	Both	Random forest	Applied Random forest to investigate network delays across US airports
Guo et al. (2021)	Schedule delays	Departure	Random forest Neural networks Regression Methods	Applied Random forest to predict departure on-time performance at Beijing Airport
(Alla et al., 2021) (Check literature)	Schedule delays	Arrival	Neural Network Decision trees Gradient Boosting Machines	Applied Neural networks to predict arrival on-time performance of flights in US
Lu et al. (2021)	Schedule delays	Arrival	Gradient Boosting Machines	Applied GBM to predict arrival on-time performance of Chinese Flights
Li and Jing (2022)	Network delays	Arrival	Random forest k-Nearest-Neighbors Regression Methods Neural networks	Applied Random forest to investigate network delays across Chinese Airports
Bisandu et al. (2022)	Schedule delays	Arrival	Neural networks Gradient Boosting Machines Support vector machines	Applied Neural networks to predict the number of flights delayed in US
Zhang et al. (2022)	Local delays	Arrival	Regression methods Random forest Support Vector Machines k-Nearest-Neighbors	Applied Machine Learning methods to predict the Estimated Time of Arrival of flights in Guangzhou airport, given the time they enter in the TMA.

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Table E.11 (*continued*).

Wang et al. (2022)	Schedule delays	Arrival	Neural networks Random forest k-Nearest-Neighbors	Applied various Machine Learning methods to predict the distribution of delays (i.e. average and standard deviation), across different flight routes at Guangzhou airports
Birolini and Jacquillat (2023)	Schedule delays	Arrival	Regression methods Random forest XGBoost	Applied machine learning + queueing models to predict schedule delays in support to optimization of day-ahead aircraft routings

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