

Article

A Bi-Objective Optimization Model for Integrated Gate Assignment and Departure Scheduling in Congested Airport Operations

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Abstract

This study addresses an integrated airport gate assignment and departure scheduling problem under capacity constraints while explicitly accounting for the operational role of apron resources. A bi-objective mixed integer linear programming model is developed to jointly determine gate or apron assignments and departure times by considering passenger transfer times, taxi operations, runway separation, and schedule deviations. The first objective minimizes a normalized composite measure of passenger transfer burden, taxi penalties, and departure schedule deviation, whereas the second objective minimizes apron usage. The epsilon constraint method is used to generate exact Pareto-efficient solutions. Computational experiments on synthetically generated congested hub airport instances with 20 flights show that increasing physical gate capacity from 3 to 5 improves the average value of Objective 1 from 1.37 to 0.92 and reduces average apron usage from 10.00 to 4.00 flights. In the highlighted 20-flight and 5-gate scenario, increasing apron usage from 3 to 5 assignments reduces the standard deviation of departure time deviations from 8.0 to 7.6 min. The results show that selective apron usage improves system-level schedule stability and that gate capacity and apron flexibility should be evaluated jointly in tactical airport planning.

Keywords: gate assignment; flight departure scheduling; multi-objective optimization; mathematical model; epsilon constraint method

1. Introduction

Hub airports operate under tightly interconnected gate, apron, taxiway, and runway constraints, meaning that localized inefficiencies can rapidly propagate into missed passenger connections, departure delays, and inefficient use of airside infrastructure. In such settings, gate assignment cannot be treated solely as a passenger transfer and service quality issue, but must also be addressed as a critical tactical coordination problem that directly affects taxi processes, runway sequencing, and the stability of departure banks [1,2]. This challenge becomes particularly acute when physical gate expansion is economically impractical or operationally infeasible, forcing airport planners to rely selectively on remote apron stands as a means of absorbing short-term congestion.

The existing literature has advanced airport gate assignment research in several important directions. Robust and disruption-oriented approaches have improved assignment feasibility under uncertainty, while exact optimization techniques such as branch and price



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and column generation have strengthened the ability to solve larger-scale instances [3–7]. A related stream of research has broadened the analytical scope by incorporating apron allocation, runway operations, or ground movement decisions in order to better reflect the interdependent nature of airside operations [8,9]. However, these studies generally optimize only part of the decision environment jointly, or they account for passenger transfer effects only indirectly.

The major scientific problem addressed in this study is how to jointly assign flights to terminal gates or remote apron stands while simultaneously adjusting departure times under gate occupancy, aircraft readiness, taxi time, and runway separation constraints, without neglecting passenger transfer quality. This problem remains insufficiently explored because gate assignment studies typically assume fixed departure schedules, whereas departure scheduling models often abstract from gate-level congestion, apron usage, and gate-to-gate passenger transfer burdens [10,11]. Consequently, the literature still lacks an exact integrated framework capable of quantifying how operational flexibility derived from apron usage reshapes the trade-off between passenger service quality and schedule robustness in congested hub airport environments.

To address this gap, this study develops a bi-objective mixed integer linear programming model for integrated gate assignment and departure scheduling at congested hub airports. The proposed model jointly determines gate or apron assignments and departure times while explicitly incorporating passenger transfer times, taxi operations, piecewise-linear schedule deviation costs, and runway separation requirements. The ϵ constraint method is employed to generate Pareto-efficient solutions and to reveal how operational performance changes as gate usage is progressively restricted or relaxed. Therefore, the study contributes both a unified exact optimization framework and practical managerial insight into how selective apron utilization reshapes the trade-offs among passenger service, schedule adherence, and operational efficiency under congested hub airport conditions.

Accordingly, this study examines three research propositions. P1: Integrating gate assignment and departure scheduling within a single exact framework provides a richer representation of airport congestion than treating these decisions sequentially. P2: Limited apron flexibility improves system-level schedule stability under congested conditions, even when some individual flights experience larger local deviations. P3: The operational value of apron usage is contingent on physical gate scarcity, meaning that gate capacity and apron flexibility must be evaluated jointly rather than independently.

The study makes four contributions. (1) It develops an exact bi-objective mixed integer linear programming formulation that jointly captures gate or apron assignment, departure time adjustment, runway separation, passenger transfer burden, taxi time, and schedule deviation penalties in one framework. (2) It uses the epsilon constraint method to generate exact Pareto-efficient solutions rather than a single weighted solution, thereby preserving managerial interpretability of the trade-off between operational performance and apron usage. (3) It quantifies how gate capacity and apron flexibility interact through computational experiments and shows that apron usage functions as a tactical congestion buffer rather than merely a last resort overflow option. (4) It provides actionable implications for airport and airline planners by identifying the operating conditions under which selective apron usage improves schedule stability and passenger service outcomes.

2. Literature Review

Airport gate assignment is generally defined as the problem of assigning flights to available terminal gates or remote stands over time while maintaining both passenger service quality and operational efficiency under limited airport capacity [12]. In the literature, this problem is commonly modeled through recurring dimensions such as aircraft-gate

compatibility, temporal overlap feasibility, passenger walking distance and transfer convenience, apron or remote stand usage, and robustness against schedule disturbances [2]. As airport congestion has intensified, studies have increasingly moved beyond basic gate occupancy decisions toward richer formulations that incorporate apron assignment hierarchies, multiple objectives, and operational reliability considerations [13,14]. Accordingly, airport gate assignment is now treated not merely as a static allocation problem, but as a broader airport operations problem in which passenger service, infrastructure utilization, and schedule reliability must be balanced simultaneously [2,12]. In more recent integrated extensions, gate and apron decisions have also been linked to adjacent airside decisions such as runway allocation and surface movement coordination [9,15].

Two directions have been particularly influential within mathematical optimization for gate assignment. First, robustness and disruption responsiveness have been strengthened through models that explicitly hedge against delay uncertainty or support reassignment decisions when disruptions occur. Ref. [6] develop robust optimization with a solution-dependent uncertainty budget to control overlap risk, and [7] propose an optimization framework for gate reassignment under disruptions. Second, large-scale exact methods have advanced through branch and price and column generation, enabling richer constraints and improved scalability, including chance-constrained branch and price for probabilistic overlap control [4], branch and price that explicitly trades off robustness and efficiency [5], and column generation for combinational gate structures in multi-objective settings [16]. Related exact work also expands constraint realism in specific contexts, such as safety constraints in harbor apron operations [3]. Across these contributions, runway departure sequencing and take-off separation are typically outside the core formulation, even though gate decisions shape taxi-out processes and can constrain feasible departure schedules under tight runway capacity.

The literature has progressed from single objective formulations toward multi-objective models that explicitly represent trade-offs among passenger walking, robustness, and operational efficiency [2]. More recent contributions incorporate sustainability and operational realism, such as accounting for environmental impacts associated with remote stands and shuttle bus operations and by refining passenger transfer-related measures [16]. Concurrently, exact algorithmic developments have improved the tractability of large-scale variants, including branch and price methods that incorporate operational and safety-related constraints and support more complex objective structures [3,5].

More recent studies also show that solution approaches to gate assignment and closely related reassignment problems have become increasingly diverse. Ref. [17] developed a branch-and-price framework that improves jetway utilization through a gate-plan-based exact formulation, while [18] combined imitation learning with a genetic algorithm to improve scalability and practical responsiveness in large assignment settings. In disruption-oriented contexts, ref. [19] studied gate reassignment under gate closures using both exact and approximation procedures to generate efficiency–stability trade-offs, and [20] proposed a hierarchical column-and-row generation approach for disruption-driven aircraft gate reassignment with transfer passenger connections. These studies indicate that the literature no longer relies only on conventional mathematical programming but increasingly incorporates decomposition, hybrid metaheuristics, and disruption-responsive solution designs to address richer and more realistic gate assignment environments.

Integrated airside optimization has increasingly treated the airport as a coupled system rather than a set of independent resources. Pretactical models jointly assign apron stands and runways to improve surface efficiency and manage taxiing interactions [9]. Other formulations integrate gate assignment with taxi path scheduling and pushback time delay, often through hierarchical or bilevel structures to represent interacting decisions [8]. Multi-

objective joint gate and runway scheduling has also been studied, with explicit service and environmental components such as apron usage, ground-air coordination, carbon emissions, and noise, which are commonly solved using evolutionary multi-objective methods [15]. Complementary runway side research integrates runway assignment with other operational decisions, such as approach trajectory optimization, to enhance capacity use and reduce inefficiencies [1]. Surface scheduling studies further emphasize runway separation and node link capacity constraints at scale [11]. Within the limited capacity scheduling perspective, ref. [10] optimized departure time assignments under capacity constraints using mixed integer linear programming; however, their formulation does not explicitly account for passenger transfer structures or gate-to-gate transfer times as primary drivers of service performance.

Despite these advances, an integration gap remains at the interface of gate assignment and departure scheduling under runway separation constraints. Surface arrival and departure scheduling studies show that adjusting operational times under runway and taxiway constraints can reduce delay, but gate allocation is commonly treated as fixed or secondary rather than jointly optimized [11]. Conversely, models that assign departure times to manage demand capacity imbalance typically abstract from gate system dynamics and passenger connectivity, focusing on aligning requested and assigned departure times under capacity and separation constraints [10]. As a result, the coupling between gate or apron allocation, taxi-out time, and feasible runway-constrained departure sequences remains insufficiently represented in models that also treat passenger transfer service quality as a primary performance driver.

In contrast to existing studies, this research explicitly integrates gate assignment, departure time optimization, runway separation, passenger transfer times, and apron usage within a unified multi-objective gate assignment and departure scheduling framework. The model captures the trade-off between service quality and apron utilization under congested conditions, allowing limited apron flexibility to be used as a robustness mechanism rather than a last option. By employing an ϵ -constraint approach, the proposed formulation generates exact Pareto-efficient solutions that quantify how congestion mitigation, passenger waiting, and taxi time performance evolve as apron usage is relaxed.

Table 1 presents a structured comparison of representative studies on airport gate assignment and related scheduling problems. The studies are evaluated across six key modeling dimensions: the study's scope, whether departure times are introduced as decision variables, the inclusion of a runway separation formulation, consideration of passenger transfer effects, modeling of apron or remote stand usage, and the solution approach adopted. Contrary to the existing literature, the present study integrates all major operational aspects and passenger transfers within a unified optimization framework.

Table 1. Summary of related studies.

Study	Scope of the Study	Departure Time Optimized	Runway Separation Formulation	Passenger Transfer Consideration	Apron Usage	Solution Approach
[6]	Robust gate assignment	No	No	No	No	Binary Programming
[7]	Gate reassignment under disruptions	No	No	Indirect	No	Integer programming
[9]	Joint apron and runway assignment	No	Yes	No	Yes	Lexicographic optimization
[8]	Integrated ground movement	Indirect	Indirect	No	Yes	Bilevel programming

Table 1. Cont.

Study	Scope of the Study	Departure Time Optimized	Runway Separation Formulation	Passenger Transfer Consideration	Apron Usage	Solution Approach
[4]	Chance-constrained gate assignment	No	No	Indirect	No	Branch and price
[5]	Robustness and efficiency in gate assignment	No	No	No	Yes	Branch and price
[3]	Gate assignment with safety constraints	No	No	No	Yes	Branch and price
[16]	Gate assignment with combinational gates	No	No	Yes	Yes	Column generation
[15]	Joint gate and runway scheduling	Indirect	Yes	Indirect	Yes	Multi-objective evolutionary optimization Scheduling and constraint-based methods
[11]	Surface arrival and departure scheduling	Yes	Yes	No	No	Mixed integer linear programming
[10]	Departure time assignment under limited capacity	Yes	Yes	No	No	Bi-objective mixed integer linear programming with ε -constraint
This study	Integrated gate assignment and departure scheduling	Yes	Yes	Yes	Yes	

Existing studies can be grouped into three main model families. The first group focuses on robust gate assignment and gate reassignment. These models are strong in handling overlap risk, robustness, and local gate feasibility, but they generally treat departure timing and runway sequencing as exogenous [4–7]. The second group addresses integrated airside coordination, including apron runway assignment, gate taxi coordination, or joint gate runway scheduling. Their main advantage is a broader operational view of the airport system, yet passenger transfer burdens are often simplified and exact trade-off analysis is not always emphasized [8,9,15]. The third group centers on departure scheduling under limited capacity. These studies represent runway side congestion and departure feasibility well, but gate-level passenger and apron decisions are typically omitted [10,11]. Therefore, the literature still lacks an exact integrated model that simultaneously optimizes gate assignment, departure timing, runway separation, passenger transfers, and apron usage within a single decision framework.

Table 1 confirms that the present study occupies a distinct position in the literature. No representative study in Table 1 combines exact gate assignment, explicit departure time optimization, runway separation, passenger transfer considerations, and apron usage in a single bi-objective mixed integer linear programming framework. This gap justifies the research need addressed here. The proposed model is designed to capture the operational trade-off that hub airport planners deal with whether to preserve terminal gate usage

at the cost of higher system congestion, or to use apron flexibility to improve schedule feasibility and passenger service under tightly constrained conditions in real life. Overall, the literature review shows that the main gap is not the absence of gate assignment or departure scheduling models individually, but the lack of an exact integrated framework that jointly captures gate or apron assignment, departure timing, runway separation, and passenger transfer effects. This observation directly motivates the methodological structure of the present study.

3. Methodology

3.1. Problem Description

This study addresses an integrated gate assignment and departure scheduling problem at an airport operating in a mixed environment with both connecting and non-connecting passengers. A set of arriving and departing flights must be assigned to available terminal gates or to an apron if required over a finite planning horizon. Each flight is characterized by a scheduled departure time, service (turnaround) time, and gate-dependent taxi-in and taxi-out times.

The problem accounts for passenger transfers between inbound and outbound flights. Each transfer passenger group is associated with a predetermined inbound flight and a predetermined outbound flight. The walking time passengers experience depends on the pair of gates to which these two flights are assigned. The total passenger transfer burden is measured in passenger minutes and reflects passenger inconvenience due to gate-to-gate walking distances within the airport. Also, operational performance concerns through taxi times and schedule deviation for both the airport and airlines. Taxiing effort is represented by the total taxi time for each flight, including both taxi-in and taxi-out. It depends on the assigned gate. Departure time deviations from the schedule are allowed within predefined limits and are penalized asymmetrically using piecewise-linear cost functions to reflect increasing operational disruption for larger deviations. The problem assumptions are given in the following:

- The airport is assumed to operate with a single runway, which requires sequencing departures to satisfy minimum take-off separation times.
- Physical gates have limited capacity and can serve only one flight at a time. The apron is modeled as a remote stand overflow resource with sufficiently large capacity for the tested instances, so apron saturation is intentionally not binding in the baseline model. This stylized assumption isolates the value of remote stand flexibility and allows the study to quantify how apron usage relieves gate congestion. Future extensions can impose an explicit apron capacity limit by adding constraints on the maximum number of simultaneous apron assignments.
- The operational cost of taxiing is modeled using a piecewise-linear function of total taxi time, reflecting increasing marginal cost for longer taxi durations due to fuel consumption, congestion, and controller workload.
- Flights are allowed to depart earlier or later than their scheduled departure times within predefined upper bounds. Earliness and lateness are penalized using piecewise-linear cost functions to capture their nonlinear operational impact.
- Passenger transfer inconvenience owing to walking in the airport is measured linearly in passenger minutes.
- Each transfer passenger group is associated with exactly one inbound flight and one outbound flight. Passengers transfer only between this fixed inbound–outbound flight pair.
- All flight schedules, service times, taxi times, walking times, and passenger group information are treated as known and deterministic over the planning horizon. This de-

terministic structure is a tactical baseline assumption intended to reveal the structural interaction between gate assignment and departure scheduling before introducing stochastic effects such as weather variability, technical disruptions, aircraft readiness uncertainty, or passenger connection disturbances.

3.2. Notation

The notation used in the proposed model is summarized below. Sets and indices are first introduced, followed by model parameters and decision variables.

Sets and Indices
I : Set of flights, $I = \{1, 2, \dots, I \}$ G : Set of gates, $G = \{1, 2, \dots, G \}$ $a \in G$: The apron with unlimited capacity P : Set of transfer passenger groups, $P = \{1, 2, \dots, P \}$ i, k : Flight index, $i, k \in I$ g, h : Gate index, $g, h \in G$ $G^{\text{phys}} = G \setminus \{a\}$: Set of physical gates p : Passenger group index, $p \in P$
Parameters
t_i^a : Scheduled Arrival time of flight i , $t_i^a \in Z^+$ t_i^{rd} : Scheduled Departure time of flight i , $t_i^{rd} \in Z^+$ s_i : Turnaround/service time at gate for flight i , $s_i \in Z^+$ τ_g^{in} : Taxi – in time for flight i to gate g , $\tau_g^{\text{in}} \in Z^+$ τ_g^{out} : Taxi – out time for flight i from gate g , $\tau_g^{\text{out}} \in Z^+$ τ^{upper} : Upper bound for taxi time, $\tau^{\text{upper}} \in Z^+$ $n_{p,i}^{\text{in}}$: $\begin{cases} 1; \text{if flight } i \text{ is inbound for group } p, n_i^{\text{in}} \in I \\ 0; \text{otherwise} \end{cases}$ $n_{p,i}^{\text{out}}$: $\begin{cases} 1; \text{if flight } i \text{ is outbound for group } p, n_i^{\text{out}} \in I \\ 0; \text{otherwise} \end{cases}$ S^{gate} : Minimum time between consecutive assignments of the same gate, $S^{\text{gate}} \in Z^+$ S^{rwy} : Minimum runway takeoff separation time, $S^{\text{rwy}} \in Z^+$ E^{max} : Maximum allowed earliness time, $E^{\text{max}} \in Z^+$ L^{max} : Maximum allowed lateness time, $L^{\text{max}} \in Z^+$ c_1, c_2, c_3 : Lateness Costs, $c_1, c_2, c_3 \in R^+$ j_1, j_2, j_3 : Earliness Costs, $j_1, j_2, j_3 \in R^+$ k_1, k_2, k_3 : Taxi time Costs, $k_1, k_2, k_3 \in R^+$ LT_1, LT_2 : Lateness Thresholds, $LT_1, LT_2 \in Z^+$ ET_1, ET_2 : Earliness Thresholds, $ET_1, ET_2 \in Z^+$ TT_1, TT_2 : Taxi Time Thresholds, $TT_1, TT_2 \in Z^+$ w_p : Number of passengers in transfer group p , $w_p \in Z^+$ $u_{g,h}$: Transfer time between gates g and h , $u_{g,h} \in Z^+ \cup \{0\}$ M^{gate} : Big M number for gate constraint, $M^{\text{gate}} \in Z^+$ M^{rwy} : Big M number for runway constraint, $M^{\text{rwy}} \in Z^+$ N_{tr} : Normalization parameter for passenger waiting time cost, $N_{tr} \in Z^+$ N_{tx} : Normalization parameter for taxi time cost, $N_{tx} \in Z^+$ N_{dev} : Normalization parameter for schedule time deviation, $N_{dev} \in Z^+$

Parameters
α : Weight of the normalized passenger transfer burden, $\alpha \in Z^+$
β : Weight of taxi operational penalty, $\beta \in Z^+$
γ : Weight of the normalized schedule deviation penalty, $\gamma \in Z^+$
Decision Variables
$x_{i,g}$: $\begin{cases} 1, & \text{if flight } i \text{ is assigned to gate } g \\ 0, & \text{otherwise} \end{cases}$
t_i^d : Actual gate departure time (pushback/leave gate) of flight i
st_i : Gate service start time for flight i
to_i : Takeoff time for flight i
τ_i^{in} : Taxi-in times implied by assignment for flight i
τ_i^{out} : Taxi-out times implied by assignment for flight i
T_i : Total taxi time for flight i
E_i : Earliness time from scheduled departure time for flight i
L_i : Lateness time from scheduled departure time for flight i
$z_{i,k}$: $\begin{cases} 1, & \text{if flight } i \text{ takes off before flight } k \mid i < k \\ 0, & \text{otherwise} \end{cases}$
$o_{i,k,g}$: $\begin{cases} 1, & \text{if flight } i \text{ is assigned before flight } k \text{ at gate } g \mid i < k, g \in G^{phys} \\ 0, & \text{otherwise} \end{cases}$
$y_{p,g,h}$: $\begin{cases} 1, & \text{if passenger group } p \text{ is transferred from gate } g \text{ to gate } h \\ 0, & \text{otherwise} \end{cases}$
l_i^1, l_i^2, l_i^3 : Auxiliary decision variables for schedule lateness of flight i
e_i^1, e_i^2, e_i^3 : Auxiliary decision variables for schedule earliness of flight i
tc_i^1, tc_i^2, tc_i^3 : Auxiliary decision variables for taxi-in and out time cost of flight i
C_{late} : Cost of total lateness time
C_{early} : Cost of total earliness time
C_{taxi} : Cost of total taxi time
C_{tr} : Total transfer passengers walking time

Unless otherwise stated, all time-related parameters and decision variables are measured in minutes. Passenger transfer burden is measured in passenger minutes. Run times reported in the computational study are measured in seconds. Because the first objective combines normalized components, Objective 1 is dimensionless and should be interpreted as a composite performance index rather than a physical quantity in a single unit.

3.3. Mathematical Formulation

Given the deterministic and tactical nature of the problem, a mixed integer linear programming formulation is adopted because it can explicitly represent assignment decisions, time ordering relations, and piecewise-linear penalty structures within a single exact framework. The formulation is particularly suitable for the present problem because gate occupancy conflicts, runway sequencing, and apron assignment choices are all governed by binary logic, while departure times and related penalties are continuous. Alternative sequential approaches would require the gate assignment and departure scheduling decisions to be optimized separately, which can produce feasible but suboptimal solutions because a gate assignment that appears attractive in isolation may lead to poor taxi performance or infeasible runway sequences once departure timing is considered.

A bi-objective mathematical model is proposed, with one objective function combining heterogeneous performance measures, including passenger transfer walking time and

operational penalty costs. To ensure dimensional consistency and comparable magnitudes across criteria, each objective component is normalized by a problem-dependent scaling parameter computed a priori from model inputs using the scaling constants: N_{tr} , N_{tx} , and N_{dev} . Before introducing the model representation, the procedure for generating each scaling constant is described.

N_{tr} is the normalization parameter for passenger transfer cost. It is calculated by considering the highest walking time between gates for all that for each passenger group can be assigned, as shown in Equation (1). For each passenger group p , exactly one gate pair (g, h) becomes active through the assignment variables. Therefore, a valid upper bound-based normalization is obtained by assuming that each group experiences the worst feasible assignment which is the apron or apron walking time.

$$N_{tr} = \sum_{p \in P} w_p \max \left(u_{g,h} \right) \Big|_{g=a, h=a} \quad (1)$$

N_{tx} is the normalization parameter for the cost of total taxi time. Taxiing penalties are measured in cost units using a piecewise-linear function. A normalization parameter is obtained by assuming a conservative upper bound on total taxi time across all flights, where τ^{upper} denotes an upper bound on taxi time per flight, as shown in Equation (2)

$$N_{tx} = |I| \tau^{upper} \quad (2)$$

N_{dev} is the normalization parameter for the actual schedule deviation from the predetermined departure flight time. Schedule deviation penalties are modeled using piecewise-linear cost functions for earliness and lateness, as shown in Equations (3) and (4) respectively. Each piecewise functions, ϑ^{late} and $\vartheta^{earliness}$, return the maximum lateness and earliness penalties per flight, respectively. The normalization parameter is computed as an upper bound on the maximum attainable deviation cost by evaluating these piecewise functions at their respective upper bounds L^{max} and E^{max} , as shown in Equation (5).

$$\vartheta^{late}(L_i) = \begin{cases} c_1 L_i, & 0 \leq L_i \leq LT_1 \\ c_1 LT_1 + c_2 (L_i - LT_1), & LT_1 < L_i \leq LT_2 \\ c_1 LT_1 + c_2 (LT_2 - LT_1) + c_3 (L_i - LT_2), & LT_2 < L_i \end{cases} \quad (3)$$

$$\vartheta^{earliness}(E_i) = \begin{cases} j_1 E_i, & 0 \leq E_i \leq ET_1 \\ j_1 ET_1 + j_2 (E_i - ET_1), & ET_1 < E_i \leq ET_2 \\ j_1 ET_1 + j_2 (ET_2 - ET_1) + j_3 (E_i - ET_2), & ET_2 < E_i \end{cases} \quad (4)$$

$$N_{dev} = |I| \left(\vartheta^{late}(L^{max}) + \vartheta^{earliness}(E^{max}) \right) \quad (5)$$

Using the above normalization parameters, the following section presents the mathematical formulation of the proposed bi-objective optimization model.

$$\text{Minimize } \alpha \frac{C_{tr}}{N_{tr}} + \beta \frac{C_{taxi}}{N_{tx}} + \gamma \frac{C_{late} + C_{early}}{N_{dev}} \quad (6)$$

$$\text{Minimize } \sum_{i \in I} x_{i,a} \quad (7)$$

Subject to,

$$\sum_{g \in G} x_{i,g} = 1 \quad \forall i \in I \quad (8)$$

$$\tau_i^{in} = \sum_{g \in G} \tau_g^{in} x_{i,g} \quad \forall i \in I \quad (9)$$

$$\tau_i^{out} = \sum_{g \in G} \tau_g^{out} x_{i,g} \quad \forall i \in I \quad (10)$$

$$st_i = t_i^a + \tau_i^{out} \quad \forall i \in I \quad (11)$$

$$to_i = t_i^d + \tau_i^{in} \quad \forall i \in I \quad (12)$$

$$t_i^d = st_i + s_i \quad \forall i \in I \quad (13)$$

$$E_i \geq t_i^{rd} - t_i^d \quad \forall i \in I \quad (14)$$

$$L_i \geq t_i^d - t_i^{rd} \quad \forall i \in I \quad (15)$$

$$E_i \leq E^{max} \quad \forall i \in I \quad (16)$$

$$L_i \leq L^{max} \quad \forall i \in I \quad (17)$$

$$st_k \geq t_k^d + S^{gate} - M^{gate} (3 - x_{i,g} - x_{k,g} - o_{i,k,g}) \quad \forall g \in G^{phys}, \forall i, k \in I \mid i < k \quad (18)$$

$$st_i \geq t_k^d + S^{gate} - M^{gate} (2 - x_{i,g} - x_{k,g} + o_{i,k,g}) \quad \forall g \in G^{phys}, \forall i, k \in I \mid i < k \quad (19)$$

$$to_k \geq to_i + S^{rwy} - M^{rwy} (1 - z_{i,k}) \quad \forall i, k \in I \mid i < k \quad (20)$$

$$to_i \geq to_k + S^{rwy} - M^{rwy} (1 - z_{i,k}) \quad \forall i, k \in I \mid i < k \quad (21)$$

$$\sum_{i \in I} n_{p,i}^{in} = 1 \quad \forall p \in P \quad (22)$$

$$\sum_{i \in I} n_{p,i}^{out} = 1 \quad \forall p \in P \quad (23)$$

$$y_{p,g,h} \leq \sum_{i \in I} n_{p,i}^{in} x_{i,g} \quad \forall p \in P, \forall g, h \in G \quad (24)$$

$$y_{p,g,h} \leq \sum_{i \in I} n_{p,i}^{out} x_{i,h} \quad \forall p \in P, \forall g, h \in G \quad (25)$$

$$y_{p,g,h} \geq \sum_{i \in I} n_{p,i}^{in} x_{i,g} + \sum_{i \in I} n_{p,i}^{out} x_{i,h} - 1 \quad \forall p \in P, \forall g, h \in G \quad (26)$$

$$l_i^1 \leq LT_1 \quad \forall i \in I \quad (27)$$

$$l_i^2 \leq LT_2 \quad \forall i \in I \quad (28)$$

$$L_i = l_i^1 + l_i^2 + l_i^3 \quad \forall i \in I \quad (29)$$

$$C_{late} = \sum_{i \in I} (l_i^1 c_1 + l_i^2 c_2 + l_i^3 c_3) \quad (30)$$

$$e_i^1 \leq ET_1 \quad \forall i \in I \quad (31)$$

$$e_i^2 \leq ET_2 \quad \forall i \in I \quad (32)$$

$$E_i = e_i^1 + e_i^2 + e_i^3 \quad \forall i \in I \quad (33)$$

$$C_{early} = \sum_{i \in I} (j_1 e_i^1 + j_2 e_i^2 + j_3 e_i^3) \quad (34)$$

$$T_i = \tau_i^{in} + \tau_i^{out} \quad \forall i \in I \quad (35)$$

$$tc_i^1 \leq TT_1 \quad \forall i \in I \quad (36)$$

$$tc_i^2 \leq TT_2 \quad \forall i \in I \quad (37)$$

$$T_i = tc_i^1 + tc_i^2 + tc_i^3 \quad \forall i \in I \quad (38)$$

$$C_{taxi} = \sum_{i \in I} (tc_i^1 k_1 + tc_i^2 k_2 + tc_i^3 k_3) \quad (39)$$

$$C_{tr} = \sum_{p \in P} \sum_{g \in G} \sum_{h \in G} w_p u_{g,h} y_{p,g,h} \quad (40)$$

$$y_{p,g,h} \in (0, 1) \quad \forall p \in P, \forall g, h \in G \quad (41)$$

$$o_{i,k,g} \in (0, 1) \quad \forall i, k \in I, \forall g \in G \quad (42)$$

$$z_{i,k} \in (0, 1) \quad \forall i, k \in I \quad (43)$$

$$x_{i,g} \in (0, 1) \quad \forall i \in I, \forall g \in G \quad (44)$$

$$T_i, E_i, L_i, l_i^1, l_i^2, l_i^3, e_i^1, e_i^2, e_i^3, tc_i^1, tc_i^2, tc_i^3, \tau_i^{out}, \tau_i^{in}, to_i, st_i, t_i^d \geq 0 \quad \forall i \in I \quad (45)$$

The proposed mathematical model has bi-objectives. The objective function combines heterogeneous performance measures, including total passenger transfer walking time, total cost of taxi times for all flights and total cost of departure time schedule deviation, as shown in Equation (6). The objective minimizes a weighted sum of normalized transfer

passenger minutes, piecewise-linear taxi time costs, and schedule deviation penalties. Passenger transfer walking time is modeled linearly. It is assumed that each additional minute contributes uniformly to passenger inconvenience. In contrast, taxi time and schedule deviation are penalized using piecewise-linear functions to capture their nonlinear operational impact. It is assumed that longer durations incur disproportionately higher costs. To ensure dimensional consistency, each component is normalized by a problem-dependent scaling parameter with the same physical unit, yielding a dimensionless composite objective. Parameters α, β, γ are nonnegative, dimensionless weights that quantify the relative importance of passenger transfer burden, taxiing effort, and schedule adherence, respectively. These weights are preference parameters specified within the normalized objective and kept fixed across all scenarios so that the reported performance changes can be attributed to gate capacity and apron flexibility rather than to reweighting across experiments. Accordingly, the study does not estimate these parameters statistically from observed data; instead, they serve to preserve a stable composite objective structure for tactical comparison across scenarios. Since each objective component is normalized by a same-unit scaling factor, the resulting terms are unitless and can be combined linearly. The second objective aims to minimize apron usage within the planning horizon, promoting the assignment of flights to physical gates when feasible, as shown in Equation (7).

Equation (8) assigns each flight to exactly one gate or to the apron. Equations (9) and (10) define the taxi-in and taxi-out times implied by the selected gate assignment, respectively. These constraints return the corresponding taxi-in and taxi-out times for each flight. Equations (8)–(10) are adapted from the study of [10]. Equations (11) and (12) define the gate start time and take-off time of each flight, respectively. The gate start time shows when a flight begins occupying the assigned gate, while the take-off time shows when the flight departs from the runway. Equation (13) returns the service completion time before departure. It is the earliest time that the flight can depart.

Equations (14)–(17) define the earliness and lateness components of departure time deviations. Equation (14) computes the earliness when the actual departure time occurs earlier than the scheduled departure time, whereas Equation (15) computes the lateness when the actual departure time exceeds the scheduled time. Equations (16) and (17) impose upper bounds on earliness and lateness, respectively. Equations (18) and (19) prevent gate overlap at physical gates. When two flights are assigned to the same physical gate, these constraints ensure that exactly one flight precedes the other in time. The apron a is treated as a virtual stand with unlimited capacity; thus, gate non-overlap constraints are imposed only for $g \in G^{phys}$.

Equations (20) and (21) impose runway separation constraints by enforcing a take-off ordering between flights. Since the airport operates with a single runway, no two flights are allowed to take off simultaneously. Equations (22)–(26) represent the transfer-passenger linking constraints. Equations (22) and (23) ensure that each passenger group is associated with exactly one inbound and one outbound flight. Equations (24) and (25) determine the arrival and departure gate assignments for each passenger group, respectively. Equation (26) guarantees that each passenger group is assigned to exactly one gate-to-gate transfer pair.

Equations (27)–(30) model the cost components associated with lateness. Equations (27)–(29) decompose the lateness of each flight into predefined cost segments based on penalty thresholds, enabling the calculation of a piecewise-linear lateness cost. Equation (30) computes the total lateness cost. Equations (31)–(34) define the earliness-related cost components. Equations (31)–(33) similarly decompose the earliness of each flight into cost segments according to the specified thresholds, while Equation (34) calculates the total earliness cost. Equations (35)–(39) model the taxi-time cost structure. Equation (35) computes the

total taxi time for each flight as the sum of taxi-in and taxi-out times. Equations (36)–(38) allocate taxi time across predefined cost segments to represent the piecewise-linear taxi cost function, and Equation (39) calculates the total taxiing cost. Equation (40) computes the total walking time for passenger transfers between assigned gate pairs for all passenger groups. Finally, Equations (41)–(45) define the domain and sign constraints of the decision variables. The formulation links passenger service and airside operations in a way that single-resource models cannot. The model does not treat apron usage as a purely residual assignment option. Instead, apron usage becomes an explicit tactical flexibility variable whose value can be assessed against passenger transfer burden, taxi time, and schedule deviation. This integrated structure constitutes the key methodological contribution of the study.

3.4. Epsilon (ϵ)—Constraint Method

The ϵ -constraint method is one of the well-known methods to solve Multi Objective Mathematical Programming (MOMP) problems [21,22]. In a general multi-objective problem, one objective is optimized while the remaining objective or objectives are transferred into the constraint set through ϵ bounds. By systematically varying the ϵ values, a set of Pareto-efficient solutions can be generated. MOMP is shown in Equation (46). x is the vector of decision variables in the set of feasible X and $f_1(x), f_2(x), \dots, f_k(x)$ are the k objectives.

$$\begin{array}{ll} \text{Minimize} & f(x) = f_1(x), f_2(x), \dots, f_k(x) \\ \text{subject to} & x \in X \end{array} \quad (46)$$

The ϵ -constraint method involves finding the best solution to one of the objective functions by using the others as constraints. These constraints are added to the model's constraint part, as shown in the following representation:

$$\begin{array}{ll} \text{Minimize} & f_l(x) \\ \text{subject to} & f_i(x) \leq \epsilon_i, \forall i = 1, \dots, k | i \neq l \\ & x \in X \end{array} \quad (47)$$

The Pareto set is generated with the ϵ -constraint approach by optimizing the primary objective while bounding the secondary objective with an ϵ limit. The efficient solutions to the problem are obtained by varying the ϵ parameter for each objective function. This procedure is especially suitable for the present study because it preserves the exact mixed integer structure of the model and provides a direct managerial interpretation of each nondominated solution. For this reason, the method is preferable here to a purely weighted aggregation and also provides an exact benchmark for future studies using heuristic or evolutionary multi-objective procedures.

This study ϵ -constraint method was applied to obtain the Pareto set for the proposed bi-objective mathematical programming model. The aim is to reveal explicit trade-offs between operational performance and apron usage rather than collapse both objectives into a single weighted score. In weighted sum formulations, solutions may be sensitive to weight selection and some efficient points can remain undiscovered when one objective is discrete or weakly varying. This issue is relevant here because apron usage is integer valued and often changes in threshold-like steps. By optimizing the primary objective while imposing an upper bound on apron usage, the ϵ constraint method produces a transparent set of Pareto-efficient solutions that decision makers can interpret directly in terms of how many apron assignments are accepted.

The proposed model is particularly relevant for large hub airports because such environments exhibit dense departure banks, high gate competition, and substantial transfer passenger flows. In these settings, apron stands can serve as tactical flexibility resources when terminal gates become congested, but their use must be balanced against passen-

ger inconvenience, taxi burden, and departure instability. The integrated formulation is designed to support exactly this trade-off by evaluating gate assignment and departure timing simultaneously rather than sequentially.

The methodological role of the proposed approach should also be understood relative to alternative solution paradigms. Unlike genetic algorithms, particle swarm optimization, and other evolutionary multi-objective procedures that approximate Pareto sets through iterative population updates, the present formulation produces exact Pareto-efficient solutions for the tested instances. Likewise, unlike fuzzy preference-based approaches that primarily support ranking or weighting under ambiguity, the present model preserves explicit operational constraints and an exact scheduling feasibility within a mathematical programming framework. For this reason, the proposed method is positioned as an exact benchmark and decision support model for tactical planning, while heuristic and metaheuristic approaches remain important candidates for future large-scale extensions.

In summary, the proposed methodology combines an exact integrated mixed integer linear programming formulation with an ϵ constraint solution procedure so that both model validity and managerial interpretability are preserved. This allows the empirical study to examine not only whether feasible schedules can be produced, but also how operational performance changes as apron flexibility is deliberately restricted.

4. Empirical Study

All computational experiments were conducted on a computer equipped with an Intel Core i5 processor (1.8 GHz), 12 GB of RAM, running Windows 11 Pro.

4.1. Data

The empirical study focuses on a congested hub airport setting because this is the environment in which gate scarcity, passenger connections, and departure sequencing interact most strongly. The instance size of 20 flights over a 240 min planning horizon was selected to reproduce a dense departure bank while keeping the exact multi-objective model computationally tractable across repeated experiments. This setting is appropriate for evaluating the operational role of apron flexibility because the resulting schedules are sufficiently congested to create meaningful trade-offs among gate usage, taxi performance, passenger transfers, and departure deviations. The single-runway setting was adopted as a tractable baseline, consistent with runway scheduling literature in which single-runway formulations are commonly used to isolate core sequencing interactions, preserve exact solvability, and provide a benchmark before extending the problem to more complex multi-runway environments [23,24].

The dataset is not drawn from a specific real airport. Instead, it is synthetic but operationally structured, designed to reproduce the main interactions observed in congested hub airport departure banks. This choice was made because the primary objective of the study is methodological development and transparent trade-off analysis under controlled conditions. Therefore, the present experiments should be interpreted as reproducible computational experiments rather than empirical validation on archival airport operations data. The model structure is general, but the calibration adopted here is most appropriate for congested hub airport settings with strong gate competition, transfer passenger pressure, and runway sequencing interactions.

For reproducibility, each instance was generated from an identical data creation logic and a specified random seed. Scheduled departure times were generated in ascending order by recursively adding random inter-departure gaps drawn from a bounded uniform distribution $[-1, 1]$. Service times were drawn from a normal distribution with a mean of 50 and a standard deviation of 8, then truncated to preserve operational realism. Trans-

fer passenger groups were created by pairing inbound flights with feasible downstream outbound flights within a forward connection window of 1 to 6 subsequent flights, and passenger group sizes were drawn from a discrete uniform distribution between 5 and 30 passengers. Taxi-in and taxi-out times were generated for each flight gate pair, with apron-related values set higher than terminal gate values to reflect the operational disadvantage of remote stands. Walking times were assigned deterministically from the gate distance matrix, with 0 min for same-gate transfers, 18 min for gate–apron transfers, and 25 min for apron–apron transfers. The same generation mechanism was applied across all seeds so that observed differences could be attributed to gate capacity and apron flexibility rather than changes in model structure.

To evaluate the proposed gate assignment and departure scheduling model at a busy airport, data is constructed. Gate “0” represents the apron in the data. For each instance, the following procedure is applied:

1. A fixed number of flights is generated within a finite planning horizon.
2. Scheduled departure times are generated in ascending order with inter-departure gaps drawn from a uniform distribution with a small mean value, ensuring dense scheduling.
3. Each flight is assigned an arrival time consistent with the scheduled departure time and turnaround requirements, and service time is generated by a normal distribution with a predefined mean and standard deviation.
4. Gate-dependent taxi-in and taxi-out times are generated randomly, yet incur higher taxi times than apron-to-apron and apron-to-gate assignments.
5. Passenger transfer times are generated deterministically by assigning fixed values for apron-to-apron and gate-to-apron movements, zero time for same-gate transfers, and a linearly increasing walking time proportional to the absolute distance between distinct physical gates.
6. Passenger connections are generated by randomly linking flights to subsequent departures within a limited horizon, with associated passenger walking times uniformly distributed between predefined minimum and maximum values.

Using different random seeds, new datasets are generated within the same framework. The data generated using seed 101 includes Flight Data, Gate Data, Passenger and Flight Connection Data, and Passenger Walking Time Between Gates Data, which are presented in Appendix A Table A1, Table A2, Table A3 and Table A4, respectively. The parameter values used in data generation are shown in Table 2.

Table 2. Parameters.

Definition	Notation	Value
Number of flights, gates and passenger groups	$ I , G , P $	20, 5, 7
Taxi Time Upperbound	τ^{upper}	30
Lateness Cost Coefficient	c_1, c_2, c_3	0.3, 0.8, 3
Earliness Cost Coefficient	j_1, j_2, j_3	0, 0.5, 0.8
Taxi Cost Coefficient	k_1, k_2, k_3	0.5, 1, 3
Minimum time gap between consecutive gate assignments	s^{gate}	10
Minimum runway separation time	s^{rwy}	2
Maximum earliness time	E^{max}	20
Maximum lateness time	L^{max}	30
Lateness time thresholds	LT_1, LT_2	5, 15
Earliness time thresholds	ET_1, ET_2	5, 15

Table 2. Cont.

Definition	Notation	Value
Taxi time thresholds	TT_1, TT_2	10, 20
Big M numbers	M^{gate}, M^{rwy}	10,000, 10,000
Normalization parameters	N_{tr}, N_{tx}, N_{dev}	3175, 600, 63.5
Epsilon value	ε_i	1, ..., 20

4.2. Pareto Analysis of Gate–Apron Trade-Offs

In this section, 20 flights and 5-physical-gate scenarios are examined to evaluate the trade-off between schedule adherence and apron utilization. Figure 1 shows the resulting Pareto frontier, which identifies the set of non-dominated solutions that satisfy both objectives. Each point on the frontier corresponds to a feasible schedule. Any reduction in the first objective would necessitate increased apron usage, as shown in Objective 2. The Pareto chart highlights three solutions, Solution 1, Solution 2 and Solution 3, with different apron usages 3, 4 and 5, respectively.

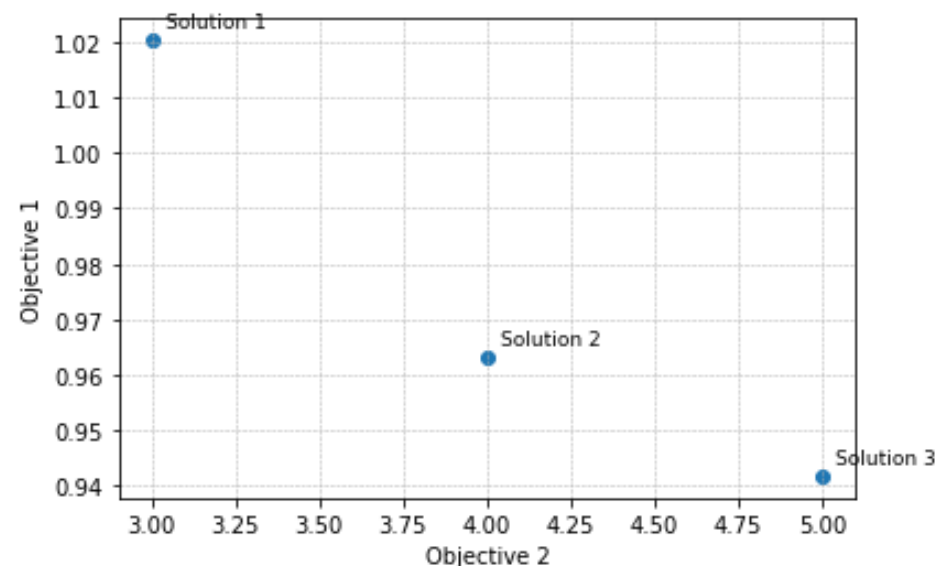


Figure 1. Pareto frontier under the 20-flight 5-gate experiment.

In this study, robustness refers to the schedule's capability to absorb gate and runway congestion with minimal deviation from planned departure times and passenger service levels. Therefore, higher Objective 1 indicates low-robust solutions. The results show a significant trade-off between minimizing apron usage and improving schedule robustness. Increased reliance on apron stands has been shown to reduce operational costs, but the benefit is negligible after four flights. This suggests that the apron's limited flexibility is sufficient to achieve most of the robustness gains.

Figure 2 shows flight-based departure time deviations from actual departure times for a Pareto solution. Deviations in departure times are present throughout the planning horizon. However, solution results remain similar in the early stage with no clear differentiation across apron configurations. Differences emerge in the middle of the planning horizon, where the three-apron solution shows increased variability while the higher apron utilization remains stable. In the late stage, this divergence becomes more significant, with the three-apron case showing stronger fluctuation patterns. In contrast, the five-apron solution maintains a smoother deviation profile. This effect is also reflected in the dispersion metrics. The standard deviation of departure time deviations decreases from 8.0 min in the three-apron case to 7.6 min in the five-apron case. The results show that limited

apron usage leads to larger schedule deviations, as flights have fewer options to absorb disruptions. Allowing more apron usage helps contain these disruptions and produces a more stable departure schedule. This illustrates the trade-off between using apron capacity to manage congestion and relying on schedule adjustments to maintain feasibility.

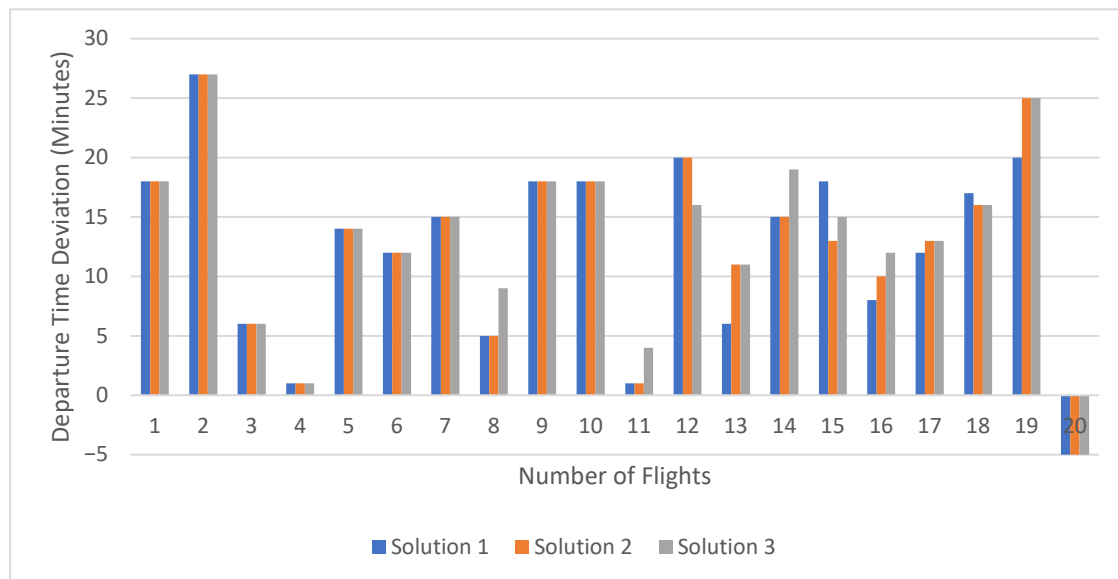


Figure 2. Departure time deviations across Pareto solutions under the 20-flight 5-gate experiment.

A flight level comparison of the highlighted Pareto solutions shows that the trade-off is concentrated in the middle and late portions of the planning horizon rather than being uniformly distributed across all departures. Relative to the three-apron solution, the five-apron solution leaves the first seven flights unchanged but changes the schedule deviations of flights 8 and 11 to 19. The largest increases are observed for flights 13 and 19, whose deviations rise by five minutes, followed by flights 8, 14, and 16 with four-minute increases. In contrast, flight 12 improves by four minutes and flight 15 by three minutes. This pattern indicates that additional apron flexibility is primarily used to smooth system-wide sequencing pressure and reduce delay dispersion in the congested part of the departure bank, even if some individual flights absorb larger local deviations.

The underlying mechanism is that apron assignments relax gate blocking in the most congested part of the departure bank and thereby enlarge the set of feasible pushback and takeoff sequences. Once a limited number of flights is shifted to the apron, the model gains enough flexibility to reduce knock-on congestion in gate occupancy, taxi processes, and runway sequencing. The marginal benefit then diminishes because the main gate conflicts have already been absorbed. This is why additional apron usage improves system-level stability yet does not produce uniform improvement for every individual flight.

4.3. Sensitivity Analysis Under Varying Gate Capacities

All experiments were conducted on synthetically generated instances following the data structure described in Section 3.1. Each instance consists of 20 flights scheduled within a finite planning horizon (240 min) under different levels of gate capacity. Three physical gate availability levels are considered: 3, 4, and 5. For each gate configuration, 10 independent instances were generated using different random seeds with 20 epsilon values to assess robustness while fixing the number of flights, number of gates, and operational parameters.

Table 3 presents the experimental results. Each random seed produces a different number of Pareto-optimal solutions depending on the number of available physical gates

at the airport. The use of apron stands increases substantially as the number of physical gates decreases. When gate capacity becomes more constrained, apron assignments become more attractive for managing flight intensity. The value of Objective 1, which captures both passenger walking time between gate pairs and operational costs, decreases significantly at both its minimum and maximum levels. This indicates that gate assignments, runway constraints, and schedule deviations become more manageable as apron usage increases.

Table 3. Summary table of computational study.

Number of Gates	Seed Number	Number of Pareto Solutions	Min Number of Apron Used	Max Number of Apron Used	Min Objective 1 Value	Max Objective 1 Value
3	101	2	9	10	1.33	1.21
3	102	1	10	10	1.48	1.48
3	103	1	9	9	1.12	1.12
3	104	2	10	11	1.46	1.37
3	107	2	10	11	1.48	1.48
4	101	2	6	7	1.10	1.06
4	102	1	7	7	1.26	1.26
4	103	1	6	6	0.92	0.92
4	104	2	7	8	1.08	0.98
4	107	1	7	7	1.06	1.06
4	110	1	7	7	1.13	1.13
5	101	3	3	5	1.02	0.94
5	102	1	4	4	1.07	1.07
5	103	2	3	4	0.79	0.79
5	104	1	4	4	0.86	0.86
5	107	1	4	4	0.89	0.89
5	110	1	5	5	0.97	0.97

Sensitivity experiments across multiple seeds show that the number and composition of Pareto-efficient solutions vary by instance. In several experiments, only one or two non-dominated solutions are observed, reflecting discrete apron decisions and threshold behavior under strong operational constraints. However, reducing gate availability systematically increases the minimum required apron usage and worsens the best attainable operational cost. The cross-scenario results show that physical gate capacity and apron flexibility interact strongly. When the number of physical gates increases from 3 to 5, the average value of Objective 1 improves from 1.37 to 0.92, the average number of apron assignments falls from 10.00 to 4.00, the average schedule deviation declines from 14.28 to 12.84 min, the average total taxi time declines from 20.94 to 18.08 min, and the average passenger walking time decreases from 9.85 to 5.02 min. These changes show that larger gate capacity improves the full system rather than only one isolated performance measure. At the same time, the persistent presence of apron usage even in the 5-gate case indicates that apron stands remain operationally valuable under dense schedules, although their role shifts from necessity to selective flexibility.

More detailed performance results for each Pareto-optimal solution are reported in Tables 4–6 for the 3-, 4-, and 5-physical-gate configurations, respectively. For each solution, the corresponding objective function values, the random seed, and the applied ε -constraint values are presented. The results indicate that computational time increases substantially as the number of gates grows, rising from 6.36 s for the 3-gate configuration to 33.28 s for the 5-gate configuration, reflecting the higher optimization effort required as model complexity increases. Model complexity is evaluated as the product of the number of flights and the number of gates, $|I|^2|G|$.

Table 4. Performance results under the 3-physical-gate scenario.

Seed Number	Pareto Solutions	ε_i	Objective 1	Objective 2	Run Time (s)	Avg. Schedule Deviation	Avg. Total Taxi Time	Avg. Walking Time/Passenger (min)
101	1	9	1.33	9	4.81	14.25	20.25	10.42
101	2	19	1.21	10	1.16	14.45	20.80	6.17
102	1	18	1.48	10	6.78	14.30	21.90	10.77
103	1	10	1.12	9	1.32	12.45	20.05	5.19
104	1	10	1.46	10	13.53	14.05	20.20	13.64
104	2	12	1.37	11	7.67	14.15	20.90	10.37
107	1	10	1.48	10	10.17	14.30	21.70	11.30
107	2	11	1.48	11	9.61	14.65	22.35	10.24
110	1	11	1.38	10	2.15	15.95	20.30	10.57
Avg. Std. Dev.			1.37	10.00	6.36	14.28	20.94	9.85
			0.13	0.71	4.35	0.89	0.85	2.59

Table 5. Performance results under the 4-physical-gate scenario.

Seed Number	Pareto Solutions	ε_i	Objective 1	Objective 2	Run Time (s)	Avg. Schedule Deviation	Avg. Total Taxi Time	Avg. Walking Time/Passenger (min)
101	1	6	1.10	6	23.54	13.7	19.15	7.48
101	2	8	1.06	7	15.91	13.6	19.6	5.44
102	1	7	1.26	7	82.04	13.85	20.4	8.40
103	1	18	0.92	6	8.66	11.7	18.45	3.88
104	1	7	1.08	7	19.48	13.25	18.55	7.22
104	2	8	0.98	8	7.66	13.35	19.25	3.92
107	1	11	1.06	7	24.92	13.7	20.25	3.82
110	1	10	1.13	7	14.86	15.4	19.6	6.14
101	1	6	1.10	6	23.54	13.7	19.15	7.48
Avg. Std. Dev.			1.07	6.87	24.63	13.57	19.41	5.79
			0.10	0.64	24.02	1.01	0.71	1.81

Table 6. Performance results under the 5-physical-gate scenario.

Seed Number	Pareto Solutions	ε_i	Objective 1	Objective 2	Run Time (s)	Avg. Schedule Deviation	Avg. Total Taxi Time	Avg. Walking Time/Passenger (min)
101	1	3	1.02	3	67.49	12.80	17.80	8.69
101	2	4	0.96	4	26.78	13.15	18.25	6.23
101	3	14	0.94	5	22.56	13.70	18.80	4.59
102	1	18	1.07	4	39.42	13.20	18.60	7.74
103	1	3	0.79	3	20.22	10.85	16.90	3.63
103	2	12	0.79	4	13.65	11.10	17.40	2.33
104	1	19	0.86	4	28.22	12.90	17.55	4.40
107	1	4	0.89	4	26.45	12.45	18.40	4.14
110	1	8	0.97	5	54.75	15.45	19.00	3.45
Avg. Std. Dev.			0.92	4.00	33.28	12.84	18.08	5.02
			0.10	0.71	17.52	1.37	0.71	2.10

Each component of Objective 1 is reported separately. The metric Avg. |Schedule Deviation| represents the absolute schedule deviation, accounting for both earliness and lateness. For the 3-gate configuration, the average schedule deviation, average total taxi time, and average walking time per passenger are 14.28, 20.94, and 9.85 min, respectively. For the 4-gate configuration, these values range from 1.07 to 13.57 min for Avg. |Schedule Deviation|, 6.87–19.41 min for average total taxi time, and 5.79–24.63 min for average walking time per passenger. In the 5-gate configuration, the corresponding values are 12.84, 18.08, and 5.02 min, respectively.

Overall, the computational experiments highlight a trade-off between gate capacity utilization and operational robustness as infrastructure scarcity increases. As the number of available physical gates decreases, the model progressively assigns flights to apron stands, thereby reducing schedule deviations, taxi times, and passenger transfer times at the expense of increased remote stand usage. Conversely, when apron usage is constrained, the model compensates by increasing controlled earliness or lateness, increasing passenger walking distances, and increasing taxi times. The resulting Pareto fronts confirm that the proposed formulation effectively captures realistic trade-offs in airport operations.

Figure 3 presents the stacked cost components of the non-dominated solutions obtained under different gate configurations. In the figure, each label is structured as G–S–P, where G denotes the number of gates, S the random seed, and P the Pareto solution index. Each bar therefore represents a distinct Pareto-optimal solution for a given scenario. As observed, transfer cost is consistently the dominant component, often accounting for more than half of the total cost, while taxi cost forms the second-largest share and schedule cost remains relatively minor and stable across solutions. For configurations with fewer gates ($G = 3$), both transfer and taxi costs tend to be higher, reflecting congestion and limited assignment flexibility. As the number of gates increases ($G = 4$ and $G = 5$), taxi costs generally decrease, whereas transfer costs exhibit more variability, indicating a trade-off between improved aircraft movement and passenger connection efficiency. Overall, the figure demonstrates that reductions in one cost component are often accompanied by increases in another, highlighting the interdependence of cost dimensions in the proposed model.

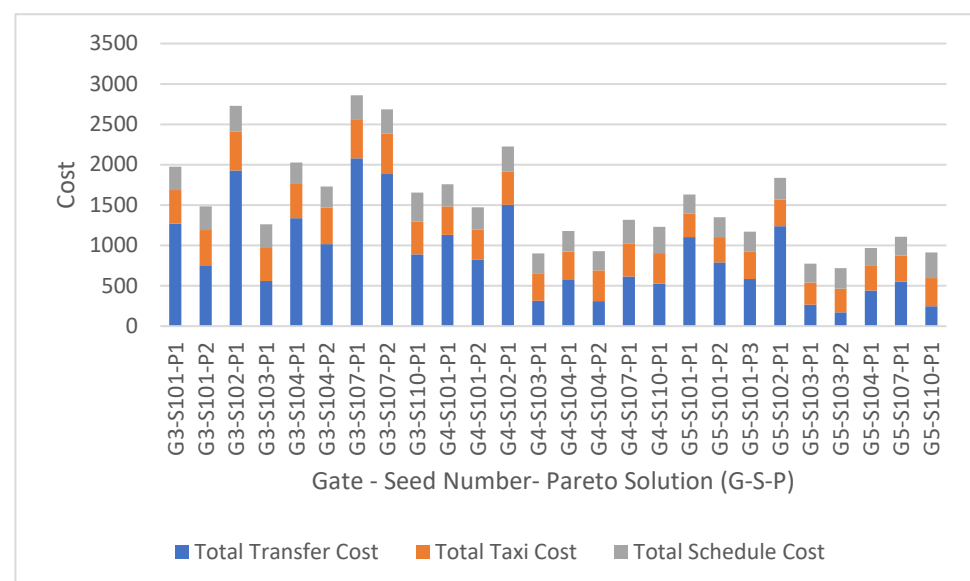


Figure 3. Cost decomposition of Pareto solutions under different gate configurations.

Overall, the empirical findings show that apron flexibility is most valuable when gate capacity is scarce and congestion propagates into the middle and late portions of the departure bank. The key insight is not that more apron usage always improves every flight,

but that selective apron usage stabilizes the schedule at the system-level and generates exact, interpretable trade-offs for tactical planning.

These findings also clarify the incremental value of the integrated approach relative to the studies summarized in Table 1. Robust gate assignment models such as [4–6] improve gate feasibility and robustness, but they do not show how gate decisions alter feasible departure timing under runway separation. Departure scheduling studies such as [10,11] capture runway side congestion, yet they do not explicitly measure passenger transfer burdens or apron-based gate relief. Integrated airside models such as [8,9,15] broaden the operational scope, but passenger transfer quality or exact Pareto analysis is not simultaneously central in the same way. The present study adds value by quantifying, within one exact framework, how apron usage, passenger transfer burden, taxi performance, and departure deviations move together as gate capacity changes.

A multi-runway extension would also affect both the tractability and the trade-off structure of the problem. Additional runway assignment and runway-specific separation decisions would enlarge the binary search space and make an exact solution more difficult as airport size and traffic density increase. At the same time, the Pareto frontier would likely become richer, because some congestion currently absorbed through apron usage and departure time adjustment could instead be managed through runway assignment flexibility. Similar observations appear in recent integrated gate runway and multi-runway scheduling studies, where increased operational flexibility is accompanied by greater computational burden and the need for more advanced solution procedures [25].

5. Conclusions

This study developed a bi-objective mixed integer linear programming model for integrated gate assignment and departure scheduling in congested hub airports. Its principal methodological contribution lies in representing, within a single exact optimization framework, gate or apron assignment, departure time adjustment, runway separation, passenger transfer burden, taxi time, and schedule deviation penalties that are typically treated only partially or sequentially in the existing literature. To the best of the author's knowledge, prior exact studies have not jointly captured these operational and passenger-related dimensions in one integrated hub airport model while also generating an explicit Pareto frontier between apron utilization and overall operational performance. By solving the formulation through an ϵ constraint procedure, the study produced interpretable Pareto-efficient solutions that reveal this trade-off directly and provide an exact benchmark for future heuristic, stochastic, and larger-scale extensions.

The computational findings show that apron usage should not be interpreted merely as an undesirable last resort. Instead, selective apron utilization acts as a tactical flexibility option that improves schedule stability and reduces delay dispersion at the system level, even though some individual flights may experience larger local deviations. In the highlighted 20-flight and 5-gate experiment, increasing apron usage from 3 to 5 assignments reduced the standard deviation of departure time deviations from 8.0 to 7.6 min, indicating a smoother schedule profile. Across the broader sensitivity analysis, the value of apron utilization was greatest when gate capacity was scarce. As the number of physical gates increased from 3 to 5, the average value of Objective 1 improved from 1.37 to 0.92, average apron usage declined from 10.00 to 4.00 flights, average schedule deviation decreased from 14.28 to 12.84 min, average total taxi time declined from 20.94 to 18.08 min, and average passenger walking time fell from 9.85 to 5.02 min. These results indicate two main findings. First, apron usage is most valuable under congested and gate scarce conditions, where it absorbs operational pressure that would otherwise appear as greater delay, longer taxi processes, and higher passenger transfer burden. Second, increasing terminal gate capacity

improves performance not in a single metric only, but simultaneously across schedule reliability, airside efficiency, passenger convenience, and reliance on remote stands. Together, these findings show that selective apron usage and available gate capacity should be evaluated jointly, because their interaction directly shapes both operational efficiency and passenger service outcomes in hub airport operations.

From a managerial perspective, the model provides a decision support tool for selecting operating policies that match congestion conditions and service priorities. Airport and airline planners can use the Pareto frontier to determine how much apron utilization is acceptable in exchange for improved schedule feasibility and reduced system-wide disruption. This is particularly relevant for hub airports with dense connection structures, where gate allocation and departure timing decisions cannot be evaluated independently. This makes the framework especially relevant for tactical planning at congested hub airports where terminal gate scarcity and connection pressure must be managed simultaneously.

From a policy perspective, the findings suggest that remote stand and apron resources should be planned as part of an integrated congestion management strategy rather than treated only as emergency overflow infrastructure. For airport operators, this means that decisions on gate expansion, apron allocation rules, towing policies, and transfer passenger service design should be evaluated jointly. For airlines and coordinators, the results imply that dense departure banks and connection intensive schedules may require controlled apron usage policies to maintain system stability. More broadly, the study supports the view that tactical airport capacity management should account simultaneously for terminal, surface, and runway interactions when congestion mitigation policies are designed.

The study also has limitations that define important directions for future research. The computational experiments are based on synthetically generated data and a stylized single-runway environment, so the present implementation should be interpreted as a tactical baseline and exact benchmark model rather than a fully scaled real-time decision tool. The observed increase in computation time from 6.36 s in the 3-gate configuration to 33.28 s in the 5-gate configuration indicates that larger hub scale instances will likely require decomposition, matheuristic, or metaheuristic acceleration. In addition, the current model does not impose an explicit apron capacity limit and does not incorporate stochastic disruptions in aircraft readiness, weather, taxi processes, or passenger connections. Future research should therefore validate the formulation with real airport datasets, introduce explicit apron capacity constraints, extend the model to multi-runway operations, analyze disruption scenarios, and benchmark the exact formulation against alternative multi-objective approaches such as weighted sum models, lexicographic optimization, evolutionary algorithms, and large neighborhood search procedures.

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Appendix A

Table A1. Flight data.

Flight Number	Arrival Time (min)	Scheduled Departure Time (min)	Service Time (min)
1	12	54	53
2	22	63	61
3	34	81	45
4	45	97	45
5	56	104	54
6	66	111	45
7	78	121	51
8	90	137	44
9	100	152	62
10	112	157	56
11	122	165	36
12	133	183	58
13	144	196	51
14	156	202	53
15	166	212	52
16	177	220	43
17	188	229	46
18	198	244	55
19	209	256	60
20	219	263	29

Table A2. Gate data.

Gate Number	Taxi-In Time (min)	Taxi-Out Time (min)
0 (Apron)	12	14
1	8	7
2	8	7
3	7	10
4	8	10

Table A3. Passenger and flight connection data.

Connection Number	Inbound Flight Number	Outbound Flight Number	Connecting Passenger Number
1	4	9	26
2	7	12	16
3	10	11	26
4	15	17	30
5	16	20	9
6	17	18	14
7	18	19	6

Table A4. Passenger walking time between gates data.

From Gate	To Gate	Walking Time (min)
0	0	25
0	1	18
0	2	18
0	3	18
0	4	18
0	5	18
1	0	18
1	1	0
1	2	5
1	3	10
1	4	15
1	5	20
2	0	18
2	1	5
2	2	0
2	3	5
2	4	10
2	5	15
3	0	18
3	1	10
3	2	5
3	3	0
3	4	5
3	5	10
4	0	18
4	1	15
4	2	10
4	3	5
4	4	0
4	5	5
5	0	18
5	1	20
5	2	15
5	3	10
5	4	5
5	5	0

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