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DATA-DRIVEN OPTIMIZATION OF RUNWAY OCCUPANCY TIME LANDING: A CASE STUDY ON RUNWAY 06 AT SOEKARNO-HATTA INTERNATIONAL AIRPORT

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Abstract

This study investigates how aircraft speed and altitude at threshold crossing influence Runway Occupancy Time Landing (ROTL) on Runway 06 at Soekarno–Hatta International Airport. A dataset of 2,000 ADS-B landing trajectories from Flightradar24 was analyzed to quantify empirical relationships between threshold parameters and ROTL. The 5% lowest ROTL flights showed substantially higher threshold speeds than the 5% highest ROTL flights, while threshold altitude remained nearly constant, indicating that speed is the dominant operational driver of runway occupancy. A regression-based scoring method was used to identify a representative efficient reference flight, which then served as the baseline for stochastic simulation in the BlueSky ATM Simulator. Threshold speed and altitude were sampled from normal distributions calibrated to the efficient group, and 300 simulated landings were generated. The simulation reproduced efficient operations with a mean ROTL of 51.77 s and a narrow 95% confidence interval of 51.69–51.85 s. The results support a practical recommendation to standardize threshold speed and deceleration profiles as a low-cost strategy to reduce ROTL without infrastructure modification.

Keywords: Runway occupancy, Threshold speed, ADS-B, Stochastic simulation, Bluesky.

1. Introduction

The rapid growth of global air transportation over the past two decades has imposed increasing pressure on airport runway capacity, particularly at major hub airports. Forecasts indicate average annual traffic growth of approximately 3.6% through 2044, with the Asia–Pacific region emerging as the primary driver of this expansion (Airbus, 2025). In Indonesia, this trend is most evident at Soekarno–Hatta International Airport, which recorded more than 54.8 million passengers and over 362,000 aircraft movements in 2023 (TangerangNews, 2025) (AirNav Indonesia, 2024). Under such demand, operational efficiency during aircraft landing becomes a critical determinant of runway throughput and overall air traffic performance (FAA, 2023).

One of the most influential indicators of landing efficiency is Runway Occupancy Time Landing (ROTL), defined as the elapsed time from an aircraft crossing the runway threshold until it fully vacates the runway. ROTL directly affects runway capacity, separation minima, and arrival sequencing, especially in high-density traffic conditions. Pavlin et al. (2006) identify runway occupancy time as a primary limiter of runway capacity, while EUROCONTROL (2023) emphasizes that even marginal reductions in ROTL can yield substantial gains in arrival throughput. Studies on landing dynamics further support this, showing that ROTL is sensitive to both aircraft behavior and runway–taxiway configuration (Galagedera & Samarasekara, 2021)(Maltinti et al., 2024)(Chen et al., 2024).

Globally, ROTL reduction strategies have traditionally focused on infrastructure-oriented solutions, particularly the geometric design of rapid-exit taxiways (RET). ICAO Doc 9157 and FAA AC 150/5300-13B recommend exit angles between 25° and 45°, with preferred exit speeds of approximately 50 kt, to facilitate efficient runway vacating (ICAO, 2005)(FAA, 2024). While such design principles are well established, their effectiveness remains constrained by aircraft operational behavior during the final approach and landing phases, particularly at the threshold crossing. This issue is increasingly relevant in airports where infrastructure expansion is limited by spatial or regulatory constraints (ICAO, 2020a).

Aircraft characteristics at threshold crossing, most notably speed and altitude, play a decisive role in determining flare duration, touchdown point, and subsequent rollout behavior. Lim (2020) demonstrated that variations in approach speed and threshold altitude significantly influence runway occupancy. From an aerodynamic perspective, excessive threshold speed increases kinetic energy and extends deceleration distance, while excessive threshold height prolongs flare and shifts touchdown farther down the runway. These effects collectively increase ROTL, regardless of taxiway geometry (Meijers, 2019)(Nguyen et al., 2022).

The operational relevance of these factors is especially pronounced at Soekarno–Hatta International Airport. Runway 06/24 has a parallel separation of only 500 m, below the ICAO-recommended minimum of 760 m for independent parallel operations, rendering the runway usable exclusively for landings (ICAO Doc 9643, 2020b). As a result, landing efficiency on Runway 06 becomes a dominant constraint on airport capacity. Previous studies reported average ROTL values of 68–69 seconds for Category C and D aircraft on Runway 06, exceeding AirNav Indonesia's operational benchmark of 55 seconds (Juniawan & Putriekapuja, 2023)(Rosmayanti et al., 2024). National policies also emphasize the importance of ensuring safe and efficient air navigation services to accommodate increasing air traffic demand (UU no.1, 2009).

Despite extensive literature on runway performance, most existing studies prioritize infrastructure layout, taxiway geometry, or exit selection over aircraft behavior at the threshold. Research by Meijers (2019) and Gao et al. (2023) highlights the influence of approach speed and aircraft type on ROTL, yet threshold-specific parameters, particularly the combined effect of speed and altitude at threshold, remain insufficiently explored. This imbalance leaves a methodological gap between empirical flight behavior and operational performance modeling. Moreover, prior investigations typically rely on limited flight samples, whereas modern surveillance systems such as ADS-B now allow large-scale, high-resolution analysis of landing behavior (Kumar et al., 2010).

Addressing this gap, the present study adopts a data-driven approach by integrating empirical ADS-B data with stochastic simulation. Approximately 2,000 landing trajectories from Flightradar24 (FR24) were analyzed to extract actual ROTL values from threshold crossing to runway vacating. The methodological validity of using surveillance data for precise ROTL extraction has been demonstrated by Kumar et al. (2010), while statistical reliability is supported by established inferential techniques (Montgomery & Runger, 2018).

To enhance generalizability and predictive capability, empirical findings are validated using the BlueSky Air Traffic Management Simulator, which incorporates EUROCONTROL's BADA performance model (Schornagel, 2022). By modeling threshold speed and altitude distributions derived from the most efficient 5% of observed landings, the simulation framework enables controlled experimentation while preserving operational realism. This hybrid empirical simulation methodology allows for systematic assessment of how small variations in threshold parameters propagate into ROTL outcomes.

The primary objective of this study is to quantify the relationship between aircraft speed and altitude at threshold crossing and ROTL on Runway 06 at Soekarno–Hatta International Airport. Furthermore, the study aims to develop an operationally feasible threshold profile that minimizes ROTL without requiring infrastructure modification, thereby aligning with the practical constraints faced by AirNav Indonesia (AirNav Indonesia, 2015)(Airnav Indonesia, 2025).

The scientific contribution of this article lies in shifting the focus of ROTL optimization from infrastructure-centric solutions to aircraft-centered operational control. By demonstrating that threshold speed is the dominant determinant of ROTL while threshold altitude exerts an indirect influence through flare dynamics, this study provides empirical evidence to support procedural optimization. Practically, the findings offer a data-backed foundation for approach management policies, contributing to more efficient runway utilization at congested multi-runway airports.

2. Methodology

This study employs a quantitative empirical approach, combined with stochastic simulation, within a single-case study framework. The quantitative design enables objective measurement of how aircraft speed and altitude at threshold crossing influence Runway Occupancy Time Landing (ROTL). A case-study framework is appropriate because Runway 06 at Soekarno–Hatta International Airport operates exclusively for landings due to its 500 m parallel separation, a configuration that does not meet ICAO requirements for independent parallel operations (ICAO, 2020b). Stochastic simulation is incorporated to validate empirical findings under controlled variability, ensuring that operational patterns identified in real data are statistically robust rather than incidental. The overall methodological sequence is illustrated in Figure 2-1, which outlines the progression from empirical data collection to simulation-based validation.

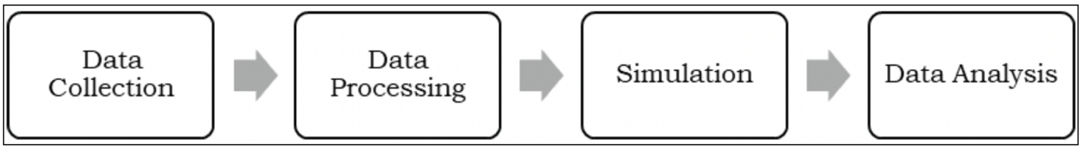

Figure 2-1: Process Flow of Methodology

2.1. Related Works

Research on runway efficiency has traditionally emphasized runway–taxiway geometry, aircraft characteristics, and airport layout as key determinants of runway occupancy. Earlier studies highlight ROTL as a critical factor influencing runway capacity, showing that even small improvements in occupancy time can significantly enhance arrival throughput (Pavlin et al., 2006)(EUROCONTROL, 2023). Infrastructure design guidelines such as ICAO Doc 9157 and FAA AC 150/5300-13B provide detailed criteria for rapid exit taxiways, reflecting the global emphasis on geometric optimization.

More recent investigations have begun to examine operational influences on ROTL. Meijers (2019) and Lim (2020) showed that variations in threshold behaviour, particularly approach speed, substantially affect landing efficiency. Complementary machine learning studies, such as Gao et al. (2023) and Nguyen et al. (2022), identify final approach speed as a dominant predictor of runway occupancy. Although these contributions have advanced the understanding of landing dynamics, most prior work focuses on aircraft states before threshold crossing or on airport infrastructure. The combined effect of speed and altitude at the moment of threshold crossing, a critical transition between airborne and ground roll phases, remains insufficiently examined. This gap motivates the present study, which integrates ADS-B-based empirical analysis with simulation to evaluate threshold-level operational parameters directly.

2.2. Problem Definition

Runway 06 at Soekarno–Hatta International Airport faces unique operational constraints because its 500 m parallel runway spacing prohibits independent parallel operations (ICAO, 2020b). As a result, landing performance on this runway directly affects overall airport arrival capacity. Empirical studies report that the average ROTL for Category C and D aircraft often exceeds the operational benchmark set by AirNav Indonesia (Juniawan & Putriekapuja, 2023) (Rosmayanti et al., 2024). Given that physical expansion of runway and taxiway infrastructure is limited, operational measures rather than geometric redesign become the most feasible avenue for improving efficiency.

The central problem addressed in this study is the absence of a data-driven operational model that quantifies how specific aircraft parameters at threshold crossing influence ROTL. Without such a model, it is difficult for air traffic service providers to implement targeted procedures that meaningfully reduce runway occupancy while remaining compatible with real-world operations.

2.3. Method

2.3.1 Case Study Design and Observation Period

From a design perspective, this study adopts a case study approach focusing on a single runway exit configuration, namely Runway 06–Taxiway M2, and applies quantitative analysis to historical ADS-B data as the primary evidence base. This focused configuration was selected because Runway 06 operates exclusively for landings due to the reduced parallel runway separation, which does not satisfy ICAO criteria for independent parallel operations (ICAO, 2020b). By concentrating on a single runway exit pair, the design enables detailed characterization of operational behavior in a capacity-critical setting while avoiding confounding effects that would arise if multiple runways, multiple exits, or mixed configurations were simultaneously analyzed (Meijers, 2019).

In addition, the case study framework allows empirical patterns extracted from real operations to be systematically transferred into a simulation environment, where stochastic variability can be evaluated under controlled assumptions. This is particularly important for applications in runway capacity and ROTL modelling, where both infrastructure and operational factors interact in non-linear ways (Pavlin et al., 2006)(EUROCONTROL, 2023). By first grounding the analysis in real ADS-B data and then replicating the observed behavior in BlueSky, the study ensures that simulated scenarios remain anchored to realistic operational conditions.

The empirical component of the study was conducted using historical arrival data from July to October 2025, a period representing high traffic intensity and relatively stable operational procedures at Soekarno–Hatta International Airport (AirNav Indonesia, 2024). The spatial focus is limited to Runway 06, with Taxiway M2 as the designated exit, reflecting the dominant landing flow pattern. Geometric information for the runway threshold and M2 exit point was obtained from the AIP Indonesia Vol. II and cross-checked using Google Earth Pro to ensure consistency between the empirical dataset and the simulation environment. This step is critical to align the spatial references in ADS-B data with the runway–taxiway layout used in the BlueSky ATM Simulator (Schornagel, 2022). The runway and taxiway configuration are illustrated in Figure 2-2, which depicts the spatial relationship between Runway 06 and Taxiway M2 at Soekarno–Hatta International Airport.

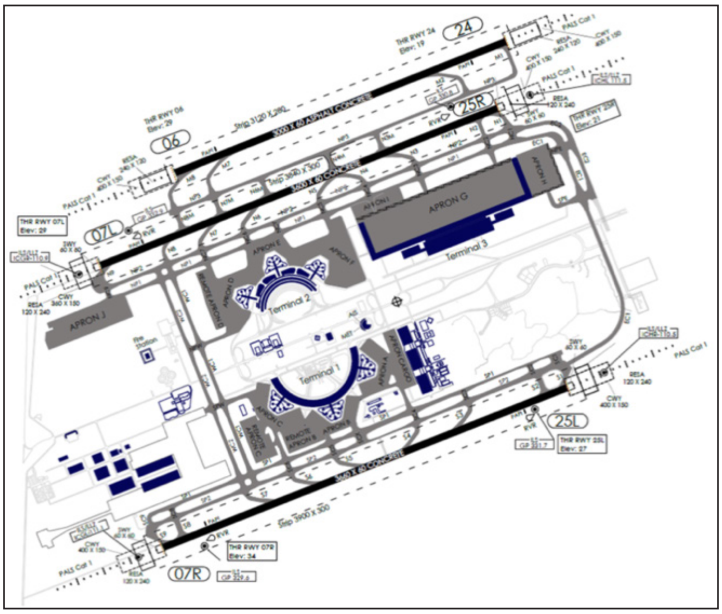

Figure 2-2: Configuration at Soekarno–Hatta International Airport.

2.3.2 Data Collection

This study is based on empirical ADS-B trajectory data obtained from Flightradar24 (FR24), which provides historical records of aircraft position, ground speed, altitude, and timestamps during the approach and landing phases. FR24 was selected as the primary data source because it offers sufficient temporal resolution and wide coverage to reconstruct continuous landing trajectories, and its suitability for extracting runway occupancy metrics has been demonstrated in previous studies that use surveillance data for ROTL estimation (Kumar et al., 2010)(Lim, 2020). The use of ADS-B is particularly advantageous because it enables large-scale analysis of actual operations without requiring access to proprietary radar systems or internal airport databases.

The data collection process focused exclusively on arrival operations at Runway 06 of Soekarno–Hatta International Airport, with Taxiway M2 defined as the runway exit point. This restriction ensures that all analyzed flights share a common runway exit geometry, which is essential for isolating the effect of threshold speed and altitude on ROTL, independent of exit selection variability (Galagedera & Samarasekara, 2021). Each landing trajectory was retrieved from the moment the aircraft approached the runway environment until it vacated the runway. An example of the raw ADS-B trajectory used in this study is illustrated in Figure 2-3, which shows the spatial and temporal evolution of aircraft speed and altitude during the landing roll for a representative flight.

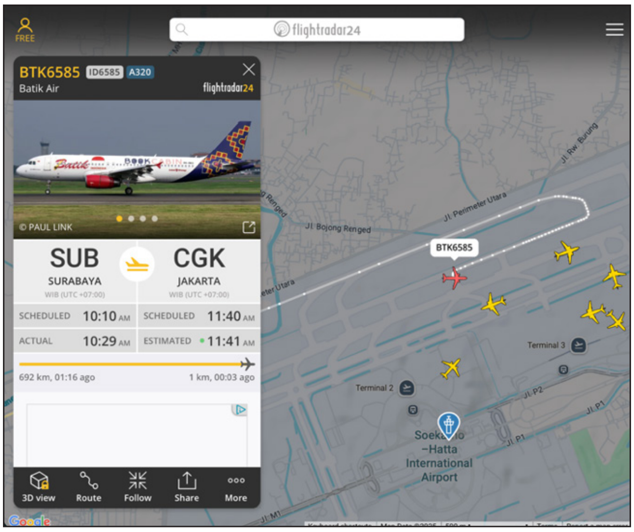

Figure 2-3: Example of landing trajectory from FR24 for Runway 06–M2

To ensure consistency in defining Runway Occupancy Time Landing (ROTL), the start and end points of measurement were standardized. ROTL was defined as the time interval from threshold crossing (t_0) to the moment the aircraft fully vacated the runway via Taxiway M2 (t_1), following AirNav Indonesia's operational definition and aligning with national capacity assessment practices (AirNav Indonesia, 2015)(Airnav Indonesia, 2025). The measurement boundaries for ROTL are illustrated in Figure 2-4. This standardized definition ensures that empirical ROTL values can be consistently compared across flights and later aligned with simulated ROTL in the BlueSky environment.

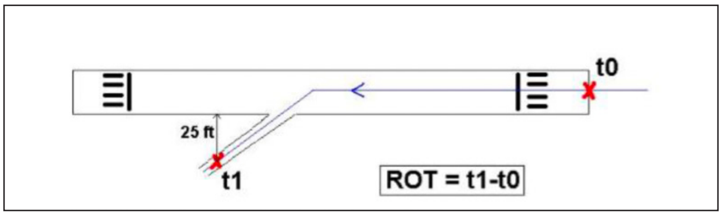

Figure 2-4: Definition of ROTL

The initial dataset consisted of all arrivals recorded during the July–October 2025 period. After preliminary filtering based on runway usage (Runway 06), exit taxiway (M2), and aircraft category (Category C), a total of 2,000 valid landing trajectories were retained. These trajectories represent Category C aircraft, primarily Boeing 737-800 and Airbus A320, which dominate traffic on Runway 06 and are widely used in international ROTL studies (Meijers, 2019)(Juniawan & Putriekapuja, 2023). A summary of the empirical dataset, including the number of flights and key operational characteristics, is provided in Table 2-1.

Table 2-1: Summary of empirical dataset and traffic characteristics.

File	Callsign	Speed (kt)	Altitude (ft)	ROTL (s)
1. IU801.csv	SJV801	128.0	47.63	66
2. IU801.csv	SJV801	129.0	45.66	61
3. IU801.csv	SJV801	133.33	48.14	69
4. JT127.csv	LNI127	145.0	48.65	61
...	...	...	...	...
2000. GA209.csv	GIA209	145.78	58.27	62

2.3.3 Data Processing and Extreme Group Stratification

Raw ADS-B data obtained from FR24 exhibit irregular sampling intervals and varying record lengths across different flights. Therefore, a dedicated data processing pipeline was implemented using Python, specifically the pandas and numpy libraries, to ensure consistency and comparability. First, all trajectories were interpolated to a uniform one-second time resolution. This step allows synchronized analysis of speed and altitude profiles during the landing phase and avoids biases that might arise from variable reporting intervals (Montgomery & Runger, 2018).

Second, each trajectory was trimmed to include only the segment between threshold crossing and runway exit via Taxiway M2. This trimming ensured that subsequent analysis focused exclusively on the runway occupancy phase relevant to ROTL, rather than including approach segments or post-vacating taxi movements. For each processed trajectory, ROTL was calculated as the time difference between t_0 and t_1, as defined previously. This approach is consistent with methodologies used in earlier ROTL extraction research based on surveillance data (Kumar et al., 2010)(Lim, 2020).

To further emphasize operational extremes, the dataset was stratified into the 5% lowest and 5% highest ROTL groups. This extreme group design highlights the contrast between highly efficient and inefficient landing operations and is commonly used in capacity analysis research to identify best practice and worst-case operational envelopes (Pavlin et al., 2006).

After ROTL values were computed for all flights, the dataset was analyzed to explore the relationship between aircraft characteristics at threshold and runway occupancy. Two-dimensional analyses were conducted to examine how threshold altitude and threshold speed influence ROTL. The relationship between altitude and ROTL is shown in Figure 2-5, while the relationship between speed and ROTL is presented in Figure 2-6. These figures provide an initial indication of the relative sensitivity of ROTL to each parameter and visually suggest that threshold speed exerts a stronger influence on ROTL than threshold altitude, an observation that is later confirmed through regression analysis and scoring (Meijers, 2019)(Gao et al., 2023).

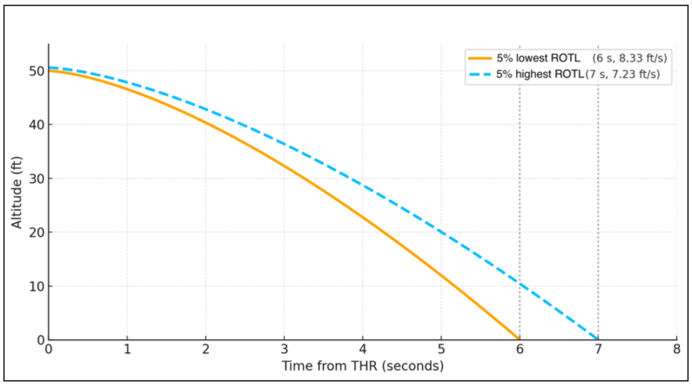

Figure 2-5: Relationship between Altitude and ROTL

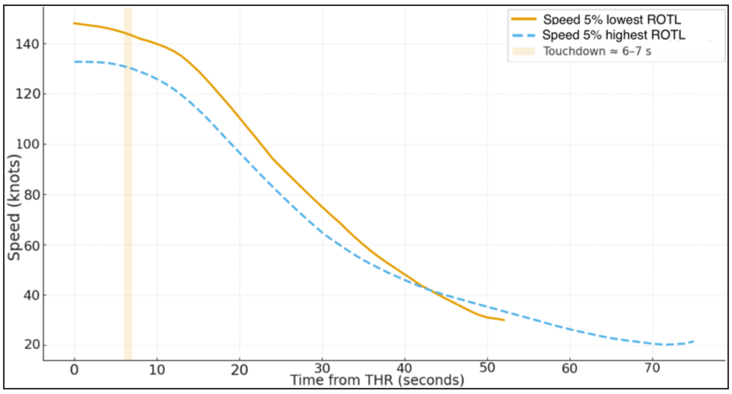

Figure 2-6: Relationship between Speed and ROTL

2.3.4 Reference Flight Scoring

Within the 5% lowest ROTL group, a scoring procedure was applied to identify a reference flight that best represents efficient landing behavior. The objective of this scoring method is to select a flight whose operational characteristics are not only associated with low ROTL but also statistically representative of stable and repeatable efficient operations, thereby avoiding the selection of extreme outliers that may be due to atypical conditions. This approach is consistent with multi-criteria decision-making techniques, where weighted indices are used to rank alternatives based on multiple performance attributes (Chou, 2013).

A composite scoring index was developed by combining normalized values of ROTL, threshold speed, and threshold altitude. The scoring formulation is defined as:

$$Score_i = (0.5 \times R_{norm}) + (0.4 \text{ x } S_{norm}) + (0.1 \text{ x } A_{norm}) \qquad (2\text{-}1)$$

where:

- R_{norm} : the normalized Runway Occupancy Time Landing (ROTL),
- S_{norm} : the normalized threshold speed, and
- A_{norm} : the normalized threshold altitude.

The weighting coefficients (0.5, 0.4, and 0.1) were not assigned arbitrarily. They were derived from a multiple regression analysis conducted on the empirical dataset, in which ROTL was treated as the dependent variable and threshold speed and threshold altitude were treated as independent variables. The relative magnitudes of the standardized regression coefficients were then used to define the proportional contribution of each variable to ROTL, resulting in a higher weight for ROTL itself, followed by threshold speed, and a smaller contribution from threshold altitude (Montgomery & Runger, 2018).

Normalization was applied to ensure all variables were dimensionless and directly comparable within the scoring formulation. The resulting composite score therefore reflects both statistical influence (from regression results) and operational relevance, with lower scores indicating closer alignment to the optimal landing profile. This approach ensures that the selected reference flight captures not only the minimum ROTL but also a balanced combination of realistic speed and altitude values, avoiding extreme or impractical configurations.

For each flight within the 5% lowest ROTL group, the composite score was calculated using the formulation above. Flights with the lowest scores exhibit minimal deviation from the regression-informed optimal operational profile. The ranking outcomes of this scoring process are summarized in Table 2-2.

Table 2-2: Scoring results for identifying the reference efficient flight

File	Speed (kt)	Altitude (ft)	ROTL (s)	R_{norm}	S_{norm}	A_{norm}	Score
908.csv	146	51	51	1.0	0.97	0.99	0.98
1892.csv	151	51	51	1.0	0.95	0.99	0.97
1927.csv	152	51	51	1.0	0.89	0.95	0.95
1620.csv	150	56	51	1.0	0.95	0.66	0.94
...	...	...	...	...	...	...	...
1685.csv	139	59	53	0.0	0.79	0.40	0.36

Based on the minimum composite score, flight 908.csv was selected as the reference flight. This flight demonstrates a balanced combination of low ROTL, stable threshold speed, and consistent threshold altitude, consistent with the regression-based weighting scheme and suitable for use as the baseline case in subsequent stochastic simulation and model validation.

2.3.5 Model Validation and Stochastic Simulation

The final stage of the method involves validating the empirical findings through stochastic simulation using the BlueSky Air Traffic Management Simulator. BlueSky ATM Simulator was selected for this study due to its open-source architecture and its proven capability to model aircraft trajectory dynamics with high temporal resolution. Unlike commercial or infrastructure-oriented simulators that focus primarily on airport layout or traffic flow management, BlueSky allows explicit control and modification of aircraft performance parameters at the threshold, including speed and altitude distributions. This flexibility makes BlueSky particularly suitable for isolating the operational effects of threshold behavior on runway occupancy time while maintaining consistency with real-world ATM logic.

The reference flight 908.csv, identified through the scoring procedure, was adopted as the baseline operational profile. This flight exhibits a mean threshold speed of 146 kt and a mean threshold altitude of 51 ft, which represent the central tendency of efficient landing operations derived from the 5% lowest ROTL group. Using a baseline grounded in real data ensures that simulation scenarios remain operationally realistic (Schornagel, 2022).

To represent realistic operational variability, stochastic perturbations were applied using standard deviations derived from the same efficient group, namely ±9 kt for threshold speed and ±3 ft for threshold altitude. Threshold speed and threshold altitude were modeled using normal distributions centered at these mean values, consistent with common assumptions in aviation performance modelling (Montgomery & Runger, 2018)(Meijers, 2019). The resulting stochastic input space for simulation is illustrated in Figure 2-7, which shows how empirical variability is transferred into the simulation environment.

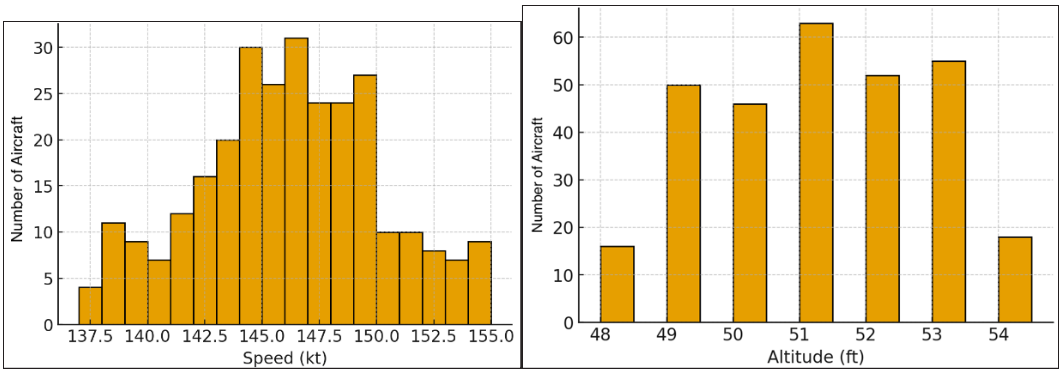

Figure 2-7: Distribution of threshold speed and altitude for stochastic simulation

Simulation scenarios were generated and executed using automated scripts developed in Python, ensuring consistent parameter variation, reproducibility of experiments, and systematic extraction of output variables. The structure and logic of the automation process are illustrated in Figure 2-8, which demonstrates how empirical inputs are translated into multiple simulation runs within the BlueSky framework. This automation is essential for handling larger numbers of simulation runs and for standardizing post processing of outputs.

```
# === Waypoints (THR → Vacated Runway 06) ===
00:00:04>ADDWPT GIA407 -6.114106 106.644097 50 142
00:00:04>ADDWPT GIA407 -6.106734 106.662552 0 49
00:00:04>ADDWPT GIA407 -6.106339 106.664261 0 30
00:00:04>ADDWPT GIA407 -6.106347 106.664730 0 30
00:00:04>LNAV GIA407 ON
00:00:04>VNAV GIA407 ON
```

Figure 2-8: Python based simulation script for BlueSky

A total of 300 simulated landings were executed, each producing a unique combination of threshold speed, threshold altitude, and resulting ROTL. An excerpt of the simulation output prior to statistical aggregation is presented in Table 2-3. Example of stochastic simulation output prior to confidence interval analysis, as shown below:

Table 2-3: Example of stochastic simulation output

File	Speed (kt)	Altitude (ft)	ROTL (s)
1.csv	142	50	52
2.csv	144	51	52
3.csv	150	53	51
4.csv	147	51	52
…	…	…	…
300.csv	147	52	52

Before applying confidence interval analysis, the simulated ROTL results were evaluated using descriptive statistics. Across the 300 simulation runs, the mean simulated ROTL was 51.77 s, with a standard deviation of 0.662 s. These values indicate that, under stochastic variation of threshold speed and altitude, landing performance remains tightly clustered around a narrow operational range.

Initial model validity was assessed by comparing simulated ROTL values with empirical ROTL observed for the reference flight 908.csv. Deviations within ±1 second were considered acceptable, indicating that the BlueSky simulation accurately reproduces real world landing behavior observed in the FR24 dataset (Kumar et al., 2010)(Schornagel, 2022).

To quantitatively assess the stability and reliability of the simulated ROTL outcomes, a 95% confidence interval (CI) was subsequently computed using the Student's t-distribution (Montgomery & Runger, 2018):

$$CI = \bar{x}\bar{x} \pm\pm t_{\alpha/2,n-1} \times\times \frac{s\ s}{\sqrt{n}\sqrt{n}} \qquad (2\text{-}2)$$

where:

- $\bar{x}\bar{x}$: is the sample mean ROTL,
- s : the standard deviation of simulated ROTL,
- n : the number of simulation samples, and
- $t_{\alpha/2,n-1.}$:the t-statistic at a 95% confidence level with n−1 degrees of freedom.

The resulting 95% CI = 51.69–51.85 s demonstrates that the simulated landing performance remains tightly concentrated and statistically stable. This narrow interval confirms that the proposed threshold profile of 146 kt at 51 ft, with stochastic variability derived from the 5% lowest ROTL group, produces highly consistent ROTL outcomes without requiring any modification to existing runway or taxiway infrastructure.

3. Result and Analysis

3.1. Empirical Results

3.1.1 Empirical Characteristics of Threshold Parameters and ROTL

Analysis of 2,000 ADS-B derived landing trajectories on Runway 06 at Soekarno–Hatta International Airport reveals a highly structured and consistent relationship between threshold parameters and runway occupancy behavior. The overall ROTL distribution in the dataset spans from approximately 51 to 76 seconds, with a mean in the range of 61-62 seconds, reflecting a mixture of efficient, nominal, and suboptimal landing operations. What is especially striking is the clear separation between the 5% lowest and 5% highest ROTL groups, which exhibit systematically different operational characteristics even though all flights land on the same runway under similar procedural constraints.

The 5% lowest ROTL flights representing the most efficient landings in the dataset show a mean threshold speed of 148.42 kt, indicating that faster threshold crossings correspond to smoother transitions into the rollout and braking phases. By contrast, the 5% highest ROTL flights have a markedly slower average threshold speed of 132.07 kt, a reduction of more than 16 kt, which substantially affects the aircraft's deceleration profile and prolongs its time occupying the runway. This difference in pre-touchdown kinetic energy significantly affects the early rollout phase, where high variability in braking initiation and speed decay is typically observed.

Threshold altitude demonstrates much smaller variability between efficiency groups, with 50.75 ft for the lowest ROTL flights and 51.43 ft for the highest ROTL flights. A difference of less than 1 ft suggests that altitude at threshold is highly stable across operations, reflecting standardized approach procedures enforced by ATC, airline SOPs, and ILS glideslope geometry. The limited variation also indicates that altitude plays only an indirect role in determining ROTL, mainly by affecting flare timing, sink rate, and touchdown continuity. Given the extremely narrow altitude difference across groups, the empirical evidence clearly positions threshold speed not altitude as the primary operational discriminator between efficient and inefficient runway occupancy outcomes.

3.1.2 Relationship Between Threshold Speed, Altitude, and ROTL

The strong empirical patterns described above are reinforced by the results of statistical modeling. A multiple regression analysis reveals that threshold speed alone accounts for roughly 40% of observed ROTL variation, demonstrating its dominant influence on landing performance. This aligns closely with the visual trends observed in the speed–ROTL scatterplot, where a clear negative correlation indicates that flights crossing the threshold at higher speeds consistently achieve shorter ROTL.

Threshold altitude contributes only about 10% of the variation, consistent with theoretical expectations that altitude serves primarily as a stabilizing parameter rather than a determinant of runway occupancy. Its weaker but noticeable positive correlation with ROTL reflects the fact that aircraft crossing the threshold slightly higher than the nominal 50 ft tend to require longer flare durations, delaying both touchdown and the initiation of deceleration.

When viewed together, the stark contrast between 148.42 kt and 132.07 kt in threshold speed across ROTL groups underscores the dominant role of kinetic energy at threshold. A 16 kt difference represents a significant change in the aircraft’s energy state, affecting braking demand, friction characteristics, and rollout dynamics. These findings strongly support the hypothesis that ROTL on Runway 06 is primarily controlled by final approach speed management, while altitude contributes only in supporting or constraining flare precision.

3.1.3 Identification of the Reference Efficient Profile

To derive a representative model of optimal landing behavior, a weighted scoring system was applied to the 100 flights in the 5% lowest ROTL group. This scoring method incorporates normalized versions of ROTL, threshold speed, and threshold altitude and applies weights of 0.5, 0.4, and 0.1, respectively proportions derived from standardized regression coefficients reflecting each parameter’s predictive power.

Through this systematic evaluation, flight 908.csv emerged as the reference profile. This flight exemplifies the efficient landing pattern observed in the empirical dataset, with a threshold speed of 146 kt, a threshold altitude of 51 ft, and an ROTL of approximately 51–52 seconds. Its values closely match the group means and lie near the centroid of the efficient cluster, making it an ideal baseline for simulation. The selection of this flight ensures that subsequent modeling reflects realistic operational behavior rather than an outlier or an artificially idealized case.

3.1.4 Stochastic Simulation Results

A stochastic simulation using the BlueSky ATM Simulator was conducted to verify whether the efficient profiles observed empirically could be reproduced under controlled but realistic variability. The simulation used normal distributions centered at the empirical means of the efficient group: threshold speed 146 kt (SD 9 kt) and threshold altitude 51 ft (SD 3 ft). A total of 300 simulation runs were executed to ensure statistical robustness and to capture variability reflective of real-world operational conditions.

The simulations produced a mean ROTL of 51.77 seconds with a standard deviation of 0.662 seconds, confirming that efficient landings are characterized by low dispersion and high repeatability. The 95% confidence interval, computed using the t-distribution, spans 51.69 to 51.85 seconds, a very narrow range that indicates stable model behavior and demonstrates that even with stochastic variation, ROTL remains consistently low when threshold parameters are near the efficient profile.

This alignment between empirical and simulated performance validates BlueSky's ability to reproduce realistic landing dynamics and reinforces the empirical insight that threshold speed optimization reliably reduces ROTL, even in a constrained runway environment like Runway 06.

3.1.5 Trajectory-Based Comparison of Raw and Optimized Landings

To further clarify the physical mechanisms underlying the reduction in runway occupancy time, a trajectory-based analysis is performed by comparing the altitude and speed profiles of the raw and optimized landings as functions of both time and horizontal distance from the runway threshold, as shown in Figure 3-1. This analysis provides a process-oriented interpretation that complements the aggregate runway occupancy metrics.

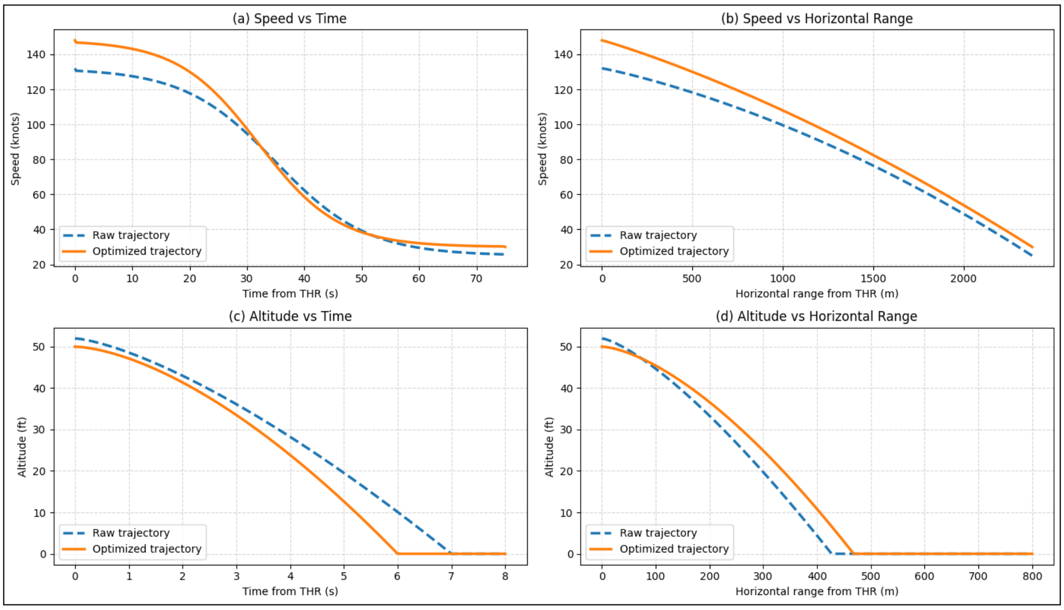

Figure 3-1: Comparison between raw and optimized landing trajectories

The altitude profiles in both time and horizontal distance domains show similar descent trends near the runway threshold, indicating comparable approach geometries for the raw and optimized trajectories. The main difference appears during the flare phase, where the optimized trajectory exhibits a longer flare, resulting in a touchdown location farther from the threshold (approximately 468 m) compared to the raw trajectory (approximately 427 m). This indicates that the optimization primarily modifies the flare strategy rather than the approach path.

Differences in energy management are further observed in the speed profiles during the landing roll. In the time domain, the optimized trajectory crosses the threshold with a higher initial speed and maintains higher speed throughout the rollout, converging smoothly toward taxi speed. When expressed as a function of horizontal distance, the optimized trajectory consistently shows higher speed than the raw trajectory at the same runway position, indicating a more efficient spatial distribution of deceleration.

Overall, the combined altitude–time, altitude–distance, speed–time, and speed–distance analyses demonstrate that the reduction in runway occupancy time is mainly achieved through an extended flare phase and improved kinetic energy management along the runway, without altering the approach geometry or runway exit location.

3.2 Analysis and Interpretation

3.2.1 Dominant Influence of Threshold Speed on ROTL

The numerical contrast between the lowest and highest ROTL groups (148.42 kt vs. 132.07 kt) provides compelling evidence that threshold speed is the principal factor differentiating efficient from inefficient runway occupancy. Higher threshold speeds reduce the duration between threshold crossing and touchdown, minimize flare induced drift, and allow braking actions to begin earlier in the rollout. These mechanisms collectively shorten the runway occupancy period. The findings align strongly with previous research, including Meijers (2020), who identified a direct connection between approach speed and runway clearance time, and Gao et al. (2023), who demonstrated through machine learning models that speed related variables dominate ROTL prediction accuracy.

The aerodynamic logic is straightforward: energy state at threshold determines how rapidly the aircraft stabilizes after touchdown and begins deceleration. From a kinetic energy perspective, aircraft crossing the threshold with excessively low speed possess insufficient energy to achieve a firm and positive wheel–runway contact at touchdown. This lack of positive contact delays the initiation of effective braking, since braking performance depends on stable wheel contact and adequate normal force, ultimately increasing the overall runway occupancy time. A higher threshold speed does not necessarily translate to longer ROTL, as commonly assumed; instead, as shown in this dataset, excessive reduction in speed before threshold leads to unstable flare, late touchdown, and prolonged rollout—precisely the pattern observed in the high ROTL group.

3.2.2 Operational Role of Threshold Altitude

Although the difference in altitude between the lowest and highest ROTL groups is minimal (50.75 ft vs 51.43 ft), altitude still influences flare behavior and touchdown precision. However, the extremely small numerical difference confirms that altitude is not the dominant factor affecting ROTL on Runway 06. This is consistent with stabilized approach criteria established by ICAO and FAA, which emphasize maintaining threshold altitude near 50 ft for predictable landing behavior.

3.2.3 Implications for AirNav Indonesia

The findings provide clear operational implications for AirNav Indonesia. Given that Runway 06 is constrained by a single high demand exit (Taxiway M2) and operates within a suboptimal 500 m runway–taxiway separation, infrastructure modification is both costly and operationally disruptive. The empirical and simulated results demonstrate that optimizing threshold speed around 146 kt, with a practical tolerance of ±9 kt, can reliably reduce ROTL to approximately 51–53 seconds, significantly improving runway occupancy performance without requiring physical changes to airfield geometry. The narrow simulation confidence interval (51.69–51.85 seconds) further confirms that operational performance remains stable even under natural variability in speed and altitude.

These insights point to actionable procedural adjustments that can be applied directly by AirNav Indonesia. Speed management during the final 4 NM is a key lever that ATC can influence through standardized approach speed advisories, ensuring that aircraft enter the threshold crossing in a stable energy state consistent with optimal ROTL outcomes. In addition to overarching speed management strategies, the results of this study support a specific operational recommendation formulated from the empirical and simulation evidence: "Maintain a stabilized approach crossing the threshold at approximately 51 ft AGL and 146 kt (groundspeed). After touchdown, maintain smooth and continuous deceleration to achieve ~50 kt (groundspeed) by ~2,000 m from the threshold, followed by a further reduction to taxi speed 30 kt (groundspeed) before vacating via Taxiway M2."

This recommended landing energy profile is consistent with the behavior of the most efficient flights in the dataset and replicable within realistic operational variability. By ensuring that aircraft transition predictably from airborne to ground roll phases, the runway occupancy window becomes more stable and less susceptible to extended rollout times that degrade throughput. The prescribed deceleration targets not only align with BlueSky simulation outputs but also provide a clear kinetic pathway enabling aircraft to reach a taxi ready speed before reaching the M2 exit point, thereby maximizing the likelihood of vacating the runway without delay.

Collectively, these findings demonstrate that procedural optimization rather than infrastructural expansion offers the most immediate and cost-effective means to enhance arrival efficiency on Runway 06.

4. Conclusions

This study demonstrates that threshold parameters particularly threshold speed play a decisive role in shaping Runway Occupancy Time Landing (ROTL) on Runway 06 at Soekarno–Hatta International Airport. Analysis of 2,000 landing trajectories shows a clear and consistent distinction between efficient and inefficient operations. The 5% lowest ROTL flights exhibit significantly higher threshold speeds (mean 148.42 kt) than the 5% highest ROTL flights (mean 132.07 kt), whereas threshold altitude remains highly stable between groups and contributes only marginally to ROTL variation. These empirical findings are reinforced through stochastic simulation using BlueSky, which replicates efficient landing behavior with a mean ROTL of 51.77 seconds and a narrow 95% confidence interval of 51.69–51.85 seconds. Together, these results confirm that optimized approach energy states rather than geometric or infrastructural factors are the primary determinant of runway occupancy performance at this site.

The findings carry important theoretical implications. They provide quantitative evidence supporting prior aviation research that emphasizes the dominant influence of speed control during final approach on landing efficiency and runway throughput. By demonstrating that threshold speed explains a substantial portion of ROTL variance, the study strengthens existing theoretical frameworks on landing dynamics and offers a refined understanding of how stabilized approach criteria translate into measurable ground performance outcomes.

Practically, the study shows that meaningful improvements to runway capacity can be achieved through procedural optimization without modifying airport infrastructure. The recommended operational profile crossing the threshold at approximately 51 ft AGL and 146 kt groundspeed, followed by smooth deceleration to 50 kt by the 2,000 m mark and reduction to taxi speed before vacating via M2 provides an evidence-based guideline for AirNav Indonesia to standardize efficient landing behavior. Implementation of such speed management strategies during final approach may reduce ROTL variability, increase runway throughput, and enhance overall arrival performance in a manner that is both cost effective and operationally feasible.

The scientific contribution of this research lies in its hybrid empirical simulation approach, integrating large scale ADS-B data with physics based modeling to validate real-world landing behavior. This framework can be applied to other airports seeking to evaluate or optimize runway occupancy performance under constraints such as limited exit configurations, high traffic demand, or limited space for infrastructural expansion.

Several areas warrant further investigation. Future research should examine the influence of meteorological factors such as wind components, precipitation, or runway surface conditions on threshold behavior and ROTL. Extending the model to multi exit or parallel runway environments would enhance generalizability, while the development of machine learning based predictors could support real time optimization of approach speeds for maximizing runway throughput. Incorporating pilot braking behavior and aircraft specific deceleration profiles into simulation models would also refine the accuracy of ROTL predictions.

Overall, this study provides a robust empirical and simulation supported foundation for improving landing efficiency through operational enhancements, offering both theoretical insights and practical recommendations for modern air traffic management.

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