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Artificial Neural Network–Based Forecasting for Airside Capacity Planning at a Data-Scarce Regional Airport: Case of Sugimanuru, Indonesia

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ABSTRACT: Accurate demand forecasting was essential for sustainable airport capacity planning, particularly at small regional airports characterized by volatile and data-scarce traffic patterns. This study developed an Artificial Neural Network (ANN)–based forecasting framework to predict passenger demand and aircraft movements at Sugimanuru Airport, Indonesia, and to translate projections into airside capacity planning requirements. Researchers normalized historical operational data from 2017–2025 using the min–max technique before developing a feed-forward backpropagation ANN model. Model performance was evaluated using key indicators—the coefficient of determination (R^2), root mean square error (RMSE), mean absolute percentage error (MAPE)—along with a review of residual patterns, benchmarked against linear regression and ARIMA for comparison. The ANN performed notably better, achieving $R^2 > 0.90$ while reducing prediction errors well below those of the alternative models. Long-term uncertainties prompted scenario analyses for low, medium, and high growth paths. In the medium-growth scenario, by 2035, passenger numbers could rise to 97,000, requiring 2–3 Code C stands and an apron expanded to approximately 12,000–13,000 m^2, in accordance with ICAO Annex 14 and FAA AC 150/5300-13A specifications. Overall, the study presented a straightforward, repeatable ANN setup suitable for under-resourced regional airports, highlighting AI's role in guiding infrastructure development and supporting risk-informed planning strategies.

KEYWORDS: Artificial neural network; airport capacity planning; ai-based forecasting; airside development; regional airport planning.

1. Introduction

Air transport drives regional economies by improving access, facilitating travel, and linking remote areas to urban centers through reliable passenger and cargo operations. Growing air traffic requires careful planning of airside infrastructure, runways, taxiways, and aprons, to ensure safety, efficiency, and long-term durability. Airport planning must align with Indonesia's SISTRANAS framework and global safety standards to maintain resilient and future-ready infrastructure [1, 2]. Sugimanuru Airport, located in West Muna Regency, serves as the primary domestic gateway for Muna Island and plays a strategic role in regional accessibility and socio-economic development. The airport currently operates a 1,600 × 30 m runway, a 110 × 80 m apron, and an approximately 1,800 m² passenger terminal designed mainly for ATR-72 aircraft operations. Despite its strategic role, recent operational data showed fluctuations and mostly declines, in passenger numbers, cargo volume, and flight movements. This unpredictability placed significant pressure on the Class III UPBU management team when planning long-term airside expansions. Relying solely on short-term trends risked overbuilding or underbuilding facilities, compromising efficiency and incurring unnecessary costs [3]. Accurate traffic forecasting is therefore essential for effective airport planning. Traditional methods, such as linear regression or trend-line projections, assume steady, linear growth, which often fails to reflect real-world conditions. Regional airports frequently experience nonlinear demand patterns, abrupt fluctuations, and structural disruptions caused by route suspensions, policy interventions, limited airline operations, or temporary service interruptions. These factors reduce the predictive accuracy of conventional statistical models and increase uncertainty in long-term infrastructure planning [4, 5].

Artificial Neural Networks (ANN) have demonstrated considerable promise in addressing these challenges. ANN models can capture complex nonlinear patterns and adapt to incomplete or noisy data. Previous studies have shown that ANN effectively predicts passenger numbers, cargo volumes, and flight movements at major airports with stable historical records [6–12]. However, small regional airports, particularly in developing countrieshave seen limited application of ANN due to sparse data, volatile demand, and operational disruptions. Most existing research focuses on model accuracy while neglecting the translation of forecasts into practical engineering requirements aligned with global standards. This leaves a critical gap: forecasting tools rarely inform airside infrastructure planning for data-limited airports experiencing unpredictable growth. Consequently, predictions are seldom converted into specifications for runways, taxiways, or aprons in accordance with ICAO Annex 14 or FAA AC 150/5300-13A requirements, leaving planners without a clear link between demand projections and infrastructure needs [13–17].

This study addresses that gap by integrating ANN-based traffic forecasts with standard airport design criteria, focusing on a 30-year airside expansion plan for Sugimanuru Airport. The approach not only predicts passenger and flight growth but also translates projections into actionable plans for runway slots, taxiway layouts, apron expansions, and aircraft stands. ANN performance was compared with conventional methods, including linear regression and ARIMA, under conditions of volatile and sparse data. We hypothesized that ANN would outperform traditional statistical models in capturing the complex growth patterns of passenger and flight demand at regional airports. The resulting forecasts also provided more reliable estimates for long-term infrastructure requirements, supporting adaptive and sustainable planning. By combining advanced data analytics with engineering standards, this framework offers a practical, replicable approach for small, data-limited airports and provides tangible tools to guide infrastructure development under uncertain conditions.

2. Materials and Methods

2.1. Selection of ANN input variables.

This study adopted a quantitative forecasting framework based on Artificial Neural Networks (ANN) to estimate future air traffic demand and provide evidence-based recommendations for long-term airside infrastructure development at Sugimanuru Airport. The research was conducted between June and August 2025 through a combination of field observations and secondary operational data obtained from the Class III Airport Operating Unit (UPBU). Field observations were carried out to verify existing runway, taxiway, apron, and aircraft parking facilities, ensuring consistency between operational data and the actual physical infrastructure. Secondary datasets covering the period 2017–2025 were used as input variables for the ANN model. These variables included both demand metrics and physical airside characteristics that influence airport capacity, such as airport land size, annual domestic passenger numbers, aircraft types in operation, cargo volumes, apron dimensions, runway strip width, taxiway specifications, and total aircraft movements. Integrating traffic statistics with infrastructure parameters enabled the ANN to capture nonlinear relationships between increasing demand and spatial limitations—an issue common in regional airports with volatile traffic patterns [6]. Table 1 summarizes the operational and infrastructure variables used in the ANN model, providing a baseline profile of Sugimanuru Airport during the study period. This dataset was used directly for training and validating the forecasting model. Figure 1 presents the location of Sugimanuru Airport, from a national overview down to the site level, providing a geographic context for the infrastructure assessment.

Table 1. Summary of secondary data collected for ANN Modeling (2017–2025).

No.	Data Category	Description / Value
1	Airport land area	134.2 ha
2	Domestic passenger numbers	72 passengers
3	Aircraft types in operation	ATR 72
4	Cargo volume	75 m³
5	Apron area	110 × 80 m²
6	Runway strip width	75 m
7	Taxiway dimensions	1,600 × 30 m
8	Annual aircraft movements	56 movements

2.2. Research design and data collection.

Before building the model, the data were cleaned and preprocessed to improve reliability and enhance the ANN's learning capability. Incomplete or inconsistent records were first verified and corrected, followed by min–max normalization to standardize all variables within a range of 0 to 1. Normalization is widely recommended in neural network applications to improve convergence stability and prevent large-scale variables from dominating the training process [18, 19]. The annual operational dataset was then organized into supervised time-series sequences suitable for forecasting analysis. The dataset was split into training and testing subsets using a 60%–40% ratio to evaluate the model's generalization capability and predictive robustness, in line with established machine learning validation practices [20–24]. A feed-forward backpropagation ANN model was employed due to its proven effectiveness in modeling nonlinear transportation demand patterns and forecasting aviation traffic [20–22]. Model performance was evaluated using four key metrics: mean squared error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2). Together, these metrics assessed prediction accuracy, error magnitude, and the model's explanatory power [21].

2.3 ANN modeling and hyperparameters.

The forecasting framework employed a multilayer perceptron (MLP) consisting of an input layer, a single hidden layer, and an output layer. The input layer comprised eight neurons representing the operational and infrastructure variables. The hidden layer contained twelve neurons, enabling the network to capture nonlinear patterns without overfitting the sparse time-series data. The output layer consisted of a single neuron representing either passenger demand or aircraft movements. The hidden layer used the ReLU activation function, a standard choice in forecasting networks due to its computational efficiency and ability to avoid vanishing gradients [20]. This function was defined as:

$$f(x) = \max(0,x) \quad (1)$$

The model was optimized using the Adam optimizer, which adaptively adjusted learning rates and incorporated momentum for stable gradient updates during training. Model settings included a learning rate of 0.001, a batch size of 4, up to 500 epochs, and mean squared error (MSE) as the loss function. To reduce overfitting caused by the limited annual observations, an early stopping mechanism was applied with a patience parameter of 25 epochs. Training automatically terminated when validation loss did not improve within this interval. This approach ensured that the model captured the main traffic trends rather than short-term fluctuations or noise [22–27]. Ultimately, the ANN achieved R^2 values above 0.90 on both training and test datasets, demonstrating strong predictive performance and reliability.

2.4. Airside evaluation.

The ANN forecasts were directly translated into airside requirements using global airport standards. ICAO Annex 14 and FAA AC 150/5300-13A guidelines were followed to define dimensions and operational criteria for runways, taxiways, aprons, and aircraft stands. Peak-hour demand derived from projected passenger numbers and flight operations informed the sizing of future parking stands. Apron expansion requirements were calculated based on standard aircraft stand dimensions, taxi-lane clearance, maneuvering space, and safety margins according to international aerodrome planning practices [28–30]. This approach converted demand forecasts into concrete engineering specifications, ensuring safe, efficient, and durable airport infrastructure.

3. Results and Discussion

3.1. Handling traffic anomalies (2023–2024).

Data history revealed a sharp decline in traffic during 2023–2024, with passenger numbers dropping to just 27 in 2024 and total flights reduced to only two operations. These drastic reductions were caused by route shutdowns and operational disruptions at Sugimanuru Airport. Such extreme fluctuations posed challenges for time-series training and risked skewing long-term forecasts. To address this, we applied strict min–max normalization during preprocessing to standardize variable scales. An early stopping mechanism curtailed ANN training before overfitting occurred on these extreme outliers. Additionally, scenario-based forecasting was incorporated to stabilize long-term projections and prevent extrapolation errors. These measures allowed the model to capture underlying recovery trends rather than being overly influenced by the short-term traffic crash. Figure 2 illustrates the 2023–2024 anomaly, showing a steep drop in passengers and flights compared with previous years. Similar disruptions have affected other regional airports due to route suspensions or operational challenges [26]. Our ANN model successfully mitigated the impact of trend skew by focusing on bounce-back patterns rather than solely on the decline. This approach aligns with Gu and Guo [10], who demonstrated that neural networks effectively handle aviation shocks better than traditional time-series methods.

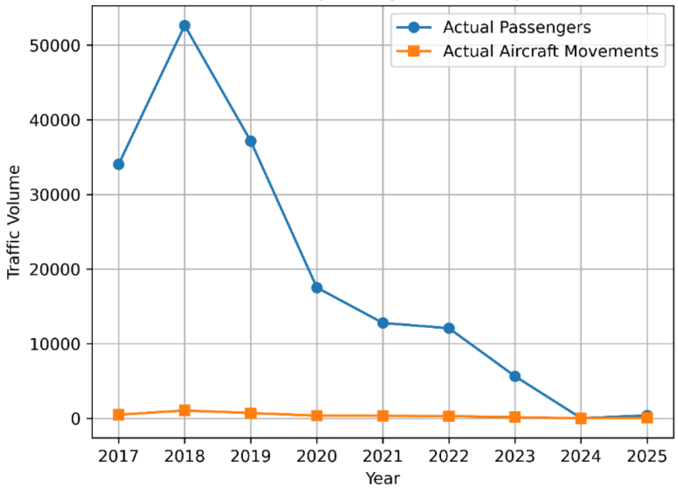
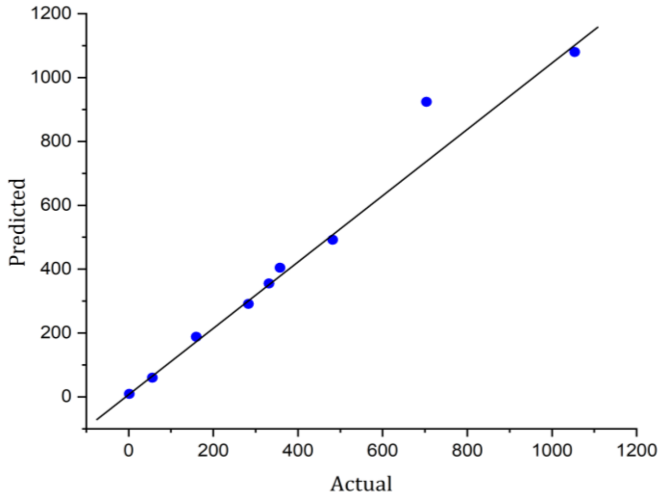


Figure 2. Historical Traffic Anomaly at Sugimanuru Airport (2017–2025).

3.2. Forecasting results.

Using operational data from 2017–2025, the ANN model first learned the historical traffic patterns at Sugimanuru Airport, including periods of rapid growth, sudden declines, and recovery phases. Notably, the sharp drop in 2023–2024—when passenger numbers fell to a mere 27 and aircraft movements dropped to only two—posed a significant challenge for forecasting. Such extreme anomalies could easily distort conventional time-series models, producing either underestimates or unrealistic extrapolations for future demand. By applying strict min–max normalization during preprocessing, the data were standardized between 0 and 1, mitigating scale differences and preventing large outliers from dominating the training process. Early stopping during training also prevented the ANN from overfitting to short-term shocks, allowing the model to focus on longer-term trends and recovery patterns rather than temporary crashes. To further ensure reliability in long-term projections, scenario forecasting was implemented. This approach allowed the ANN to explore low, medium, and high-growth possibilities while remaining grounded in observed historical trends. Consequently, the model captured the rebound effect after the 2023–2024 anomaly, reflecting the likely recovery of regional air traffic as routes reopened and operations stabilized. Figure 3 illustrates how the ANN predicted aircraft movements track actual historical values, highlighting its ability to model nonlinear and volatile trends common in small regional airports. Table 2 presents the detailed historical aircraft movements alongside ANN predictions, providing a clear view of model performance and future projections. The table shows both the ability of the ANN to replicate past fluctuations and the forecasted growth up to 2035. These results indicate that aircraft movements could reach approximately 1,866 operations by 2035, signaling that current runway and taxiway capacities may become insufficient, thus necessitating careful airside capacity planning.



Figures 3. Aircraft movements predicted vs actual.

Table 2. Aircraft movement forecasting (2017–2035).

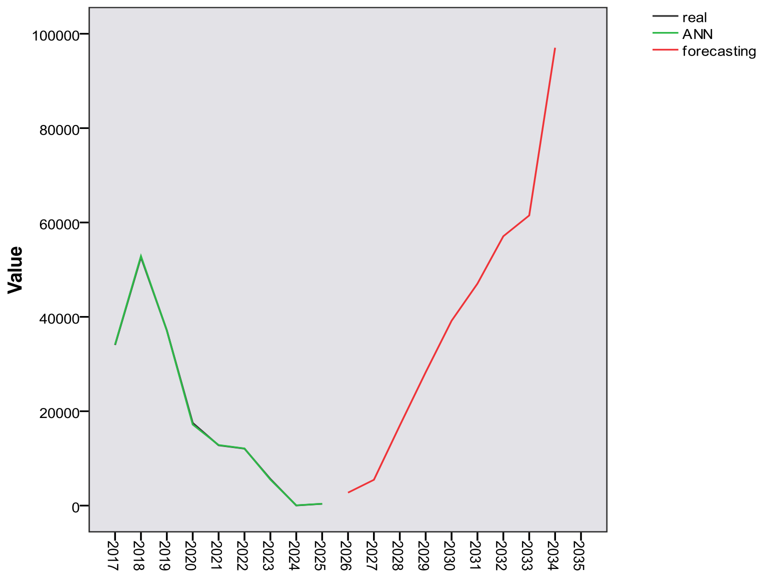
No	Year	Actual Movements	Predicted by ANN
1	2017	482	492
2	2018	1054	1080
3	2019	704	924
4	2020	358	404
5	2021	332	355
6	2022	283	291
7	2023	160	188
8	2024	2	9
9	2025	56	60
10	2026	N/A	343
11	2027	N/A	497
12	2028	N/A	738
13	2029	N/A	942
14	2030	N/A	1088
15	2031	N/A	1120
16	2032	N/A	1165
17	2033	N/A	1255
18	2034	N/A	1478
19	2035	N/A	1866

Passenger traffic at Sugimanuru Airport mirrored the trends observed in aircraft movements, showing periods of growth, sharp declines, and gradual recovery. The most extreme drop occurred in 2023–2024, when passengers fell to just 27, reflecting route closures, operational disruptions, and broader local challenges. Such extreme fluctuations posed a challenge for traditional forecasting methods, which tend to either smooth out sudden shocks or exaggerate recovery trends. By contrast, the ANN model captured these nonlinear dynamics effectively, learning both the collapse and the subsequent rebound in passenger numbers. Table 3 presents both historical passenger data and ANN predictions, providing a comprehensive view of past patterns and anticipated growth up to 2035. The data show how the ANN model handled erratic fluctuations and projected steady, nonlinear growth, offering a robust basis for translating forecasts into airside infrastructure requirements.

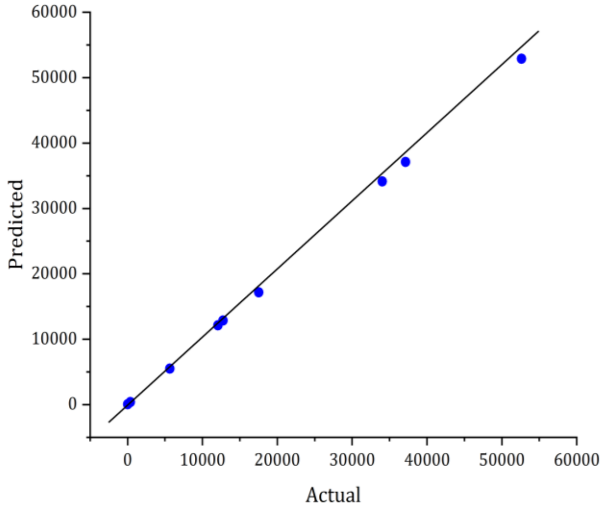
Table 3. Passenger traffic forecasting (2017–2035).

No	Year	Actual Passengers	Predicted by ANN
1	2017	34,039	34,121
2	2018	52,643	52,873
3	2019	37,134	37,089
4	2020	17,523	17,176
5	2021	12,776	12,839
6	2022	12,073	12,109
7	2023	5,642	5,511
8	2024	27	61
9	2025	374	391
10	2026	N/A	2,744
11	2027	N/A	5,467
12	2028	N/A	16,974
13	2029	N/A	28,260
14	2030	N/A	39,168
15	2031	N/A	47,040
16	2032	N/A	57,085
17	2033	N/A	61,495
18	2034	N/A	73,900
19	2035	N/A	97,032

Preprocessing measures, including min–max normalization and early stopping, ensured that the model did not overfit to extreme low points, while scenario forecasting provided a structured way to explore low, medium, and high-growth trajectories. This approach allowed the ANN to focus on medium- to long-term recovery patterns, generating forecasts that were realistic, grounded in historical trends, and sensitive to sudden shocks in the dataset. Figures 4 and 5 illustrate the predicted passenger traffic against historical values, highlighting how the ANN accurately captured the nonlinear ups and downs, particularly the bounce-back following 2023–2024. The passenger growth curve here matches ANN forecasts from Srisaeng et al. and Jafari and Lewison [26, 14]—both saw regional airports snap back fast after demand hits. Our nonlinear pattern backs that up: once routes reconnect, regional air traffic bounces quicker than expected. Compared with SARIMA-based forecasting results presented by Gu et al. [10], the ANN model provides smoother long-term growth representation under volatile traffic conditions. The projected passenger volume of approximately 97,000 by 2035 therefore represents a realistic medium-term recovery trajectory rather than exponential overestimation.



Figures 4. Graph of passenger movement.



Figures 5. Passenger traffic: predicted vs actual.

3.3. Benchmarking with traditional models.

To evaluate the robustness and reliability of the ANN model, we benchmarked its performance against conventional forecasting methods, specifically Linear Regression and ARIMA. These traditional models are widely used in aviation demand studies due to their simplicity and interpretability, but they rely on assumptions of linearity and stationary trends, which may not hold for volatile regional airports such as Sugimanuru. Historical traffic data at Sugimanuru exhibited sharp drops in 2023–2024 and irregular rebounds, presenting a challenging environment for conventional models. Table 4 presents the comparative performance metrics—coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE)—for each model. The ANN model achieved an R^2 of 0.90, substantially higher than ARIMA (0.80) and Linear Regression (0.70), indicating that the neural network captured 90% of the variability in historical traffic data. Likewise, ANN's RMSE of 0.031 and MAPE of 5.40% were significantly lower than the corresponding metrics of ARIMA (RMSE = 0.065; MAPE = 11.60%) and Linear Regression (RMSE = 0.082; MAPE = 14.20%). These results confirm that ANN outperformed traditional methods in both predictive accuracy and error minimization.

Table 4. Comparative forecasting model performance.

Model	R^2	RMSE	MAPE
Linear Regression	0.7	0.082	14.20%
ARIMA	0.8	0.065	11.60%
ANN	0.9	0.031	5.40%

The ANN model excelled particularly in capturing nonlinear recovery trends after the severe traffic drop in 2023–2024. Linear Regression and ARIMA tended to underpredict rebounds or smooth out sharp changes, failing to represent the actual bounce-back patterns observed at the airport. This aligns with findings by Ari and Ozfirat and Tsui et al. [1,27], who reported that neural networks consistently outperform traditional statistical methods in volatile aviation demand forecasting. Similarly, Chen and Ai [6] demonstrated that ANN maintains strong post-shock prediction capability, which is critical for planning resilient infrastructure in dynamic regional airports. By directly benchmarking against these models, the study confirms that ANN is the most suitable tool for long-term airside planning at data-scarce and irregularly trafficked airports like Sugimanuru.

3.4. Scenario-Based Forecasting.

Recognizing the inherent uncertainty in long-term airport traffic, the study implemented scenario-based forecasting to provide a range of possible demand outcomes. Single-scenario projections risk over- or underestimating infrastructure needs, particularly in volatile regional airports such as Sugimanuru. To mitigate these risks, three demand growth scenarios were developed: low growth (15%), medium growth (ANN baseline), and high-growth (optimistic recovery). Each scenario represents a plausible trajectory for passenger traffic up to 2035, reflecting variations in route connectivity, economic activity, and regional air travel demand. Table 5 summarizes the projected passenger volumes for 2035 under each scenario. The medium-growth scenario, based directly on ANN predictions, reached approximately 97,000 passengers and serves as the baseline for infrastructure planning. It balances the need for sufficient capacity without committing to unnecessary overbuild, thereby minimizing wasted investment. The low-growth scenario (58,000 passengers) provides a conservative estimate, ensuring resilience under subdued demand conditions, while the high-growth scenario (121,000 passengers) prepares the airport for rapid recovery or unexpected surges in traffic. Scenario-based forecasting aligns with best practices in international airport planning, as emphasized by Graham and other aviation experts, who recommend multiple demand pathways to enhance investment robustness and prevent capacity mismatches. This study's approach integrates ANN's predictive strength with scenario planning, offering planners both precise forecasts and flexible growth envelopes.

Table 5. Passenger forecast scenarios for 2035.

Scenario	2035 Passengers
Low Growth (15%)	58,000
Medium Growth (ANN Baseline)	97,000
High Growth (Optimistic Recovery)	121,000

3.5 Explicit Translation to ICAO/FAA Airside Standards

To convert the ANN forecast results into actionable infrastructure requirements, apron sizing and stand allocation were carried out following ICAO Annex 14 guidance and FAA AC 150/5300-13A specifications. The process begins with calculating the basic apron area required for the expected number of aircraft stands. The formula applied was:

$$\text{Required Apron Area} = \text{Number of Stands} \times \text{Stand Area}$$

For Code C aircraft typically operating at Sugimanuru Airport, such as ATR 72, Boeing 737, or Airbus A320, the standard stand dimension is approximately 60 m × 60 m, giving a stand area of 3,600 m^2. For the projected requirement of three stands in 2035, the preliminary apron area is $3\times3{,}600=10{,}800$ m^2.

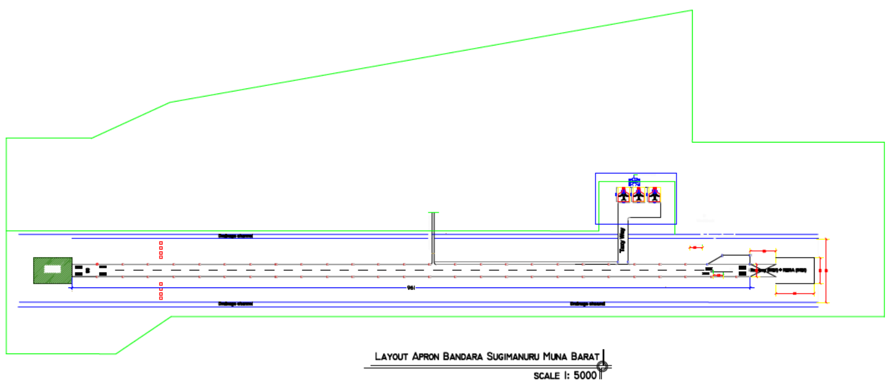
However, geometric stand dimensions alone do not account for operational safety requirements. ICAO and FAA standards require additional space for maneuvering and safety, including taxi-lane clearance (23 m width for Code C), wingtip clearance ($\geq$ 7.5 m per side), and pushback safety margins ($\geq$ 18–20 m). After incorporating these buffers, the total apron requirement rises to approximately 12,000–13,000 m^2. This adjustment ensures safe aircraft movements, efficient pushback operations, and reduces potential congestion during peak traffic periods, aligning with best practices outlined in ICAO Annex 14 and the Aerodrome Design

Manual [12, 13]. The recommended dimensional standards are summarized in Table 6, providing a concise reference for planners and engineers. These values also resonate with previous regional airport expansion studies, such as Pasandín and Pérez [21], where including operational buffers significantly increased effective apron area beyond theoretical stand footprints. This highlights that practical airside design must integrate both aircraft stand geometry and the necessary safety margins to achieve operational reliability.

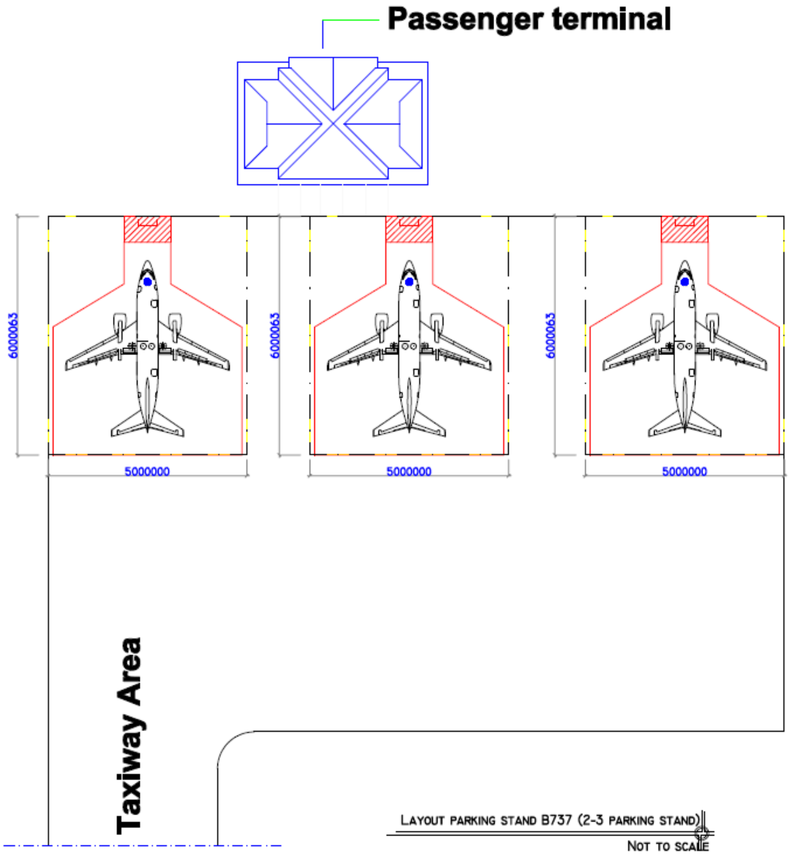
Table 6. Recommended ICAO and FAA parameters for airside development.

Description	ICAO/FAA Recommendation
Aircraft Type	ATR 42/72, B737, A320
Terminal Configuration	Linear / Single-Level (Nose-In)
Stand Size	55–60 m × 60 m (3,000–3,600 m²)
Taxi-Lane Width	23 m (Code C)
Pushback Clearance	≥ 18–20 m
Wingtip Clearance	≥ 7.5 m per side
Initial Apron Area	12,000–13,000 m²

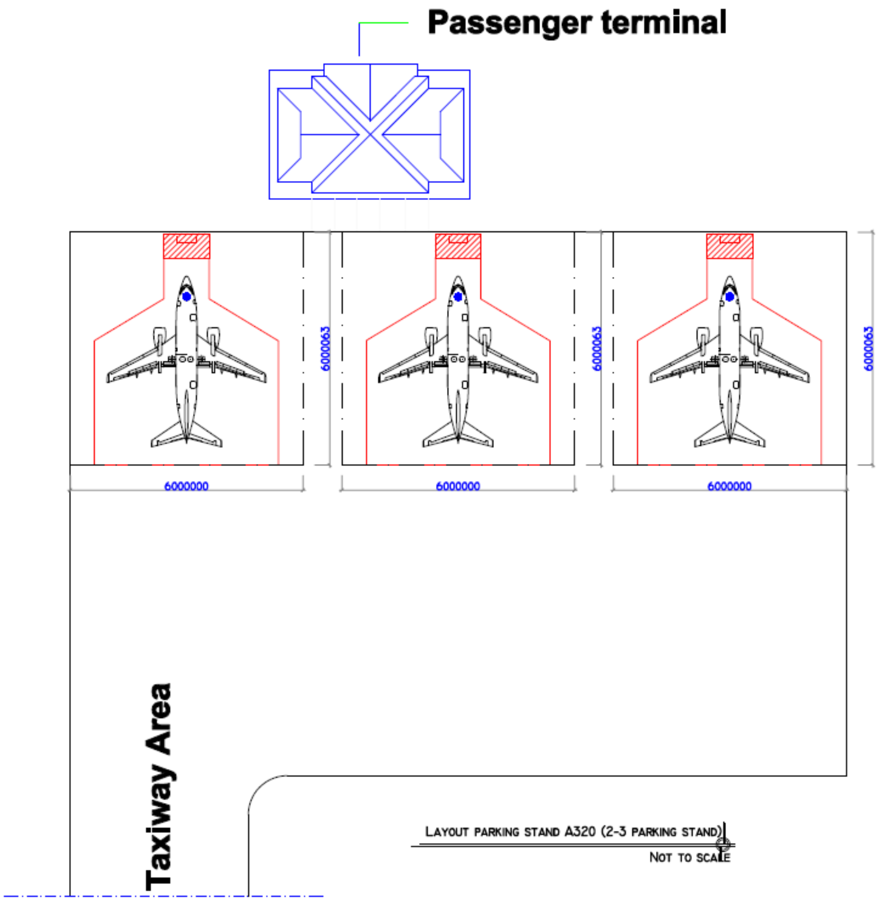
The spatial arrangement of the proposed apron expansion and overall airside development at Sugimanuru Airport, as depicted in Figure 7, provides a practical roadmap for accommodating future traffic growth while adhering to ICAO and FAA standards. The layout integrates predicted increases in passenger numbers and aircraft movements, ensuring that the airport can handle projected peak-hour operations efficiently. Detailed stand configurations for Boeing 737 and Airbus A320 aircraft are shown in Figures 8 and 9, respectively, highlighting how each aircraft type is allocated adequate parking space, wingtip clearance, and pushback zones. By explicitly mapping individual aircraft positions, the design accounts for safe maneuvering, taxi-lane circulation, and potential simultaneous operations without congestion, which is critical for regional airports with limited apron space. The integration of ANN-based forecasts into the airside design process allows planners to align infrastructure expansion directly with anticipated demand, rather than relying solely on historical trends or rule-of-thumb sizing. For instance, projected passenger volumes reaching approximately 97,000 by 2035, coupled with an estimated 1,866 aircraft movements, necessitate not only additional stands but also optimized circulation paths and operational buffers. This evidence-driven approach reduces the risk of under- or overbuilding and ensures that investments are proportionate to actual growth scenarios. Furthermore, the design framework provides flexibility, allowing adjustments for different aircraft types, seasonal fluctuations, or unexpected route changes. Overall, linking predictive analytics with concrete ICAO/FAA standards equips airport planners with a resilient, long-term strategy, transforming forecast outputs into actionable, safe, and operationally efficient airside infrastructure.



Figures 7. Proposed airside development layout of Sugimanuru airport.



Figures 8. Parking stand layout for Boeing 737 aircraft.



Figures 9. Parking stand layout for Airbus A320 aircraft.

3.6. Overall interpretation

The integrated findings indicate that existing airside facilities at Sugimanuru Airport will be insufficient to accommodate projected demand growth. Under the medium-growth scenario, the airport is expected to handle approximately 97,000 passengers and 1,866 aircraft movements by 2035. Without phased apron expansions and additional Code C stands, operational bottlenecks are likely to emerge, reducing efficiency and compromising safety margins. Therefore, scaling up apron space, optimizing taxiway layouts, and implementing modular terminal expansions are recommended to maintain operational resilience. This study's methodology combining anomaly adjustments, model benchmarking, scenario-based forecasting, and direct translation of forecasts to ICAO/FAA standards, strengthens its practical relevance. It addresses common critiques regarding clarity and applicability in regional airport planning. The approach mirrors recent best practices in AI-assisted airport forecasting highlighted by Kanavos et al. and Zhang and Zhang [15, 30], who emphasize integrating predictive models with engineering and regulatory frameworks to produce actionable, real-world infrastructure guidance. By bridging forecasts with operational strategies, the study provides a robust template for planning in data-sparse regional airports.

3.7. Policy and managerial implications.

The ANN-based forecasting framework offers a clear, stepwise approach for airside infrastructure upgrades at regional airports. By converting predicted traffic into geometric specifications aligned with ICAO Annex 14, planners can stage apron expansions strategically, reducing overbuild risks while keeping operations flexible during uncertain recovery periods. This evidence-driven approach also supports Indonesia's SISTRANAS goals, facilitating smart, scalable regional airport development grounded in actual traffic trends [9].

3.8. Limitations and future research.

Despite its strengths, this study has several limitations. First, the time-series data spans only nine years (2017–2025), which constrains the detection of long-term trends; extending the dataset would likely improve model stability and forecasting accuracy. Second, the analysis focuses on a single airport, limiting the generalizability of the findings; multi-airport studies would enable comparative insights and broader validation. Third, macro-level factors such as GDP, tourism, population shifts, and fuel prices were not incorporated, though they can significantly influence air traffic patterns. Additionally, the limited dataset increases the risk of overfitting, even with normalization and early-stopping mechanisms applied. Future research could address these challenges through several avenues: implementing hybrid ANN-LSTM models to better capture complex temporal patterns, collecting multi-airport datasets for broader benchmarking, applying uncertainty analysis such as Monte Carlo simulations to generate probabilistic forecasts, integrating network-level connectivity models to assess traffic redistribution effects, and including socioeconomic and multi-modal transport variables to enhance demand prediction accuracy. Incorporating these improvements would strengthen the robustness of ANN-based forecasting and expand its practical applicability for regional airport planning. Similar short-data issues have been reported in other ANN aviation studies, where limited historical coverage undermines long-term predictive reliability [15, 26]. Moreover, integrating socioeconomic and macroeconomic variables has been recommended to improve forecast precision and the relevance of infrastructure planning decisions [30].

6. Conclusions

This study developed an ANN forecasting framework to project long-term air traffic and airside infrastructure requirements at Sugimanuru Airport. The model achieved strong R^2 values above 0.90, demonstrating robust performance under volatile regional traffic conditions. Forecasts indicate approximately 97,000 passengers and 1,866 aircraft movements by 2035, surpassing current airside capacities. In response, ICAO and FAA standards necessitate apron expansions for three Code C aircraft stands, totaling roughly 12,000–13,000 m^2, to maintain operational safety and efficiency. By directly linking ANN forecasts with international aerodrome regulations, this framework provides a practical bridge from traffic projections to actionable infrastructure development. The study contributes to regional airport planning literature by demonstrating the applicability of AI-based forecasting in data-sparse environments. It offers a replicable framework that supports evidence-driven infrastructure decisions, guiding sustainable growth for emerging regional airports.

Author Contribution

Panci Yocing contributed to the conceptualization of the study, development of the research framework, data analysis, ANN modeling, and preparation of the initial manuscript draft. La Ode Ichlas Syahrullah Yunus contributed to data acquisition, preprocessing, model validation, interpretation of results, and critical revision of the manuscript. Rajab Jandipo Kaebansiha contributed to airside infrastructure assessment, formulation of development recommendations based on ICAO/FAA standards, visualization (tables, charts, and figures), and final manuscript editing.

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Competing Interest

The authors declare that they have no competing interests, financial or non-financial, that could be perceived as influencing the work reported in this manuscript. The research was conducted independently, and no external organization influenced the study design, data analysis, interpretation of results, or the preparation of the manuscript.

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