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Forecasting Land Acquisition Financing Requirements for Optimizing Budget Execution in National Strategic Projects: A Time Series Approach

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Keywords: *ARIMA; Artificial Neural Network; budget absorption; land acquisition financing; National Strategic Project; time series forecasting*

Abstract

This study addresses the persistent shortfall between planned and realized budgets for land acquisition financing of Indonesia's National Strategic Projects (Proyek Strategis Nasional/PSN), a shortfall that directly undermines the annual budget absorption rate used as a key performance indicator for the management of state investment funds allocated for land procurement. Method: this study compares two forecasting approaches, the Autoregressive Integrated Moving Average (ARIMA, extended to Seasonal ARIMA where required) and the Artificial Neural Network (ANN), to project the monthly land acquisition financing requirements of PSN across two categories, the Toll Road sector and the Non-Toll Road sector, using monthly realization data managed by the Indonesia Asset Management Agency (Lembaga Manajemen Aset Negara/LMAN) from 2017 through the first quarter of 2026. Forecast accuracy was evaluated using the Mean Absolute Percentage Error (MAPE) and, where the data contained values close to zero, the Symmetric Mean Absolute Percentage Error (sMAPE). Results: the ANN model consistently outperformed its statistical counterpart in both sectors. For the Toll Road sector, ANN achieved a MAPE of 49.01% against 80.93% for ARIMA, while for the Non-Toll Road sector, ANN achieved an sMAPE of 64.08% against 81.53% for SARIMA. Based on the ANN projections for the remaining nine months of 2026, the total financing requirement for land acquisition across all PSN sectors is estimated at Rp10.69 trillion, corresponding to a fund absorption rate of only 40.16% of the currently available budget. Implications: these findings suggest that machine learning approaches offer a more reliable basis for expenditure planning in this context, and that the persistently low absorption rate points to a continuing need for more accurate, data-driven budget execution planning at the ministry and agency level.

Keywords: *ARIMA; Artificial Neural Network; budget absorption; land acquisition financing; National Strategic Project; time series forecasting*

INTRODUCTION

Infrastructure development for basic services and connectivity plays a decisive role in strengthening the foundation of a national economy and improving the quality of life of a population, and is widely regarded as a primary engine of economic growth (Hosny et al., 2022). Beyond its physical dimension, infrastructure management is equally a matter of planning and stakeholder coordination, both of which ultimately shape national productivity and public welfare (Sumaryana et al., 2025). Among the prerequisites for infrastructure delivery, land availability is often the most difficult to secure; land acquisition accounted for 24% of all strategic infrastructure issues reported for the first semester of 2023, ahead of financing and funding, licensing, construction, and spatial planning combined (KPPIP, 2023). In response, the Indonesian government has pursued accelerated infrastructure delivery by guaranteeing land availability and financing through the National Strategic Project (PSN) program, financed through the state budget and coordinated by the Indonesia Asset Management Agency (Lembaga Manajemen Aset Negara/LMAN), which has managed a cumulative land acquisition budget of Rp174.94 trillion since fiscal year 2016, of which only Rp150.22 trillion (85.87%) had been realized as of the first quarter of 2026 across 140 projects.

Given the government's constrained fiscal resources, careful planning of the budget proposed for PSN land acquisition financing has become a determinant of project success, since the core tasks of managing a public infrastructure budget are to allocate funds effectively, ensure optimal utilization, and maximize the function of a limited budget within its constraints (Huang et al., 2010). In practice, however, the agencies that require land for PSN have not been able to accurately predict their financing needs, a shortfall directly visible in the budget absorption figures. In 2023, the Directorate General of Budget at the Ministry of Finance began developing an early-stage projection model for budget revenue planning based on data analytics (Anggaran, 2024), but comparable attention has not yet been directed toward forecasting expenditure, including the planning of land acquisition disbursements, even though such a projection underpins a key performance indicator for fund absorption and would allow financing needs to be planned across, rather than only within, a single fiscal year.

The institutional mechanism through which this financing flows helps explain why the problem is difficult to resolve through revenue-side planning alone. Under Ministry of Finance Regulation No. 139/PMK.06/2020, the ministry or agency that requires land for a given PSN first proposes a budget allocation; the Committee for Acceleration of Priority Infrastructure Delivery then sets financing priorities across competing proposals; and LMAN finalizes an annual list of prioritized land acquisition financing that becomes the basis for disbursement (Huang et al., 2010). Because disbursement is ultimately triggered by payment requests submitted by the requiring agency, and those requests characteristically cluster toward the end of the fiscal year as agencies work to maximize their reported absorption, the resulting monthly series is shaped as much by administrative timing as by the underlying pace of physical land acquisition, a structural feature that any forecasting model applied to this series must be able to accommodate.

Time series analysis offers one path toward such a projection by identifying historical patterns in a sequence of chronologically ordered observations (Box et al., 2015). Forecasting methods applied to time series data are generally grouped into statistical methods, artificial intelligence methods, and hybrid methods combining the two; statistical methods remain the most widely used, yet frequently struggle to deliver accurate forecasts when a series exhibits complex, non-linear structure, a limitation the Artificial Neural Network (ANN) is intended to address (Mediavilla et al., 2022). The Autoregressive Integrated Moving Average (ARIMA) model projects future values as a function of a series' own past values and incorporates an integration term to accommodate non-stationarity (Dos Santos et al., 2025), whereas ANN is commonly applied for its capacity for self-directed learning and high accuracy on data in which non-linearity has been identified (Tarmanini et al., 2023).

The stakes attached to this KPI are not merely administrative. Because the annual percentage of PSN land acquisition fund absorption feeds directly into the performance evaluation on which the Minister of Finance's decisions to grant incentives or impose sanctions are based, a systematic shortfall in absorption, sustained over several fiscal years as documented later in this study, carries consequences for the requiring ministries and agencies well beyond the immediate delay to any single infrastructure project. An accurate forward projection of financing needs is therefore not simply a technical exercise but a direct input to how budget performance is judged at the ministerial level.

A number of studies have compared the two methods across different forecasting contexts. Tarmanini et al. (2023) forecast short-term electricity load and found ANN achieved a MAPE of 1.80% compared with 2.61% for ARIMA, concluding that ANN handles non-linear structures more effectively while ARIMA remains limited to linear ones. Mahdi and Al-Share (2025), studying pharmaceutical sales in the United States under the disruption of the Covid-19 pandemic, proposed a hybrid ARIMA-NN model and found it more reliable than conventional ARIMA. Not all evidence points the same way, however: in a more physically constrained domain, Fara et al. (2021) found ARIMA more efficient and accurate than ANN in forecasting photovoltaic energy production, suggesting that the relative advantage of either method depends on the structure of the series being forecast rather than holding as a universal rule. Hybrid architectures combining both approaches have also been shown to outperform either method used alone in financial forecasting (Hajirahimi & Khashei, 2016).

Table 1. Summary of Selected Prior Studies Comparing ARIMA and Machine Learning Forecasting Methods

Study	Application domain	Methods compared	Key finding
Tarmanini et al. (2023)	Short-term electricity load	ARIMA, ANN	ANN achieved lower MAPE (1.80%) than ARIMA (2.61%)
Mahdi & Al-Share (2025)	Pharmaceutical sales, United States	ARIMA, hybrid ARIMA-NN	Hybrid ARIMA-NN reached 93.9% accuracy versus conventional ARIMA
Fara et al. (2021)	Photovoltaic energy production	ARIMA, ANN	ARIMA more efficient and accurate than ANN (lower rRMSE)
Hajirahimi & Khashei (2016)	Financial market forecasting	ARIMA, ANN, hybrid architectures	Hybrid ARIMA-ANN models outperformed either method used alone
Napitupulu et al. (2022)	Stock market prediction during COVID-19	ANN-based machine learning	ANN captured pandemic-driven volatility more effectively than linear benchmarks

Read together, these studies suggest that the relative advantage of ARIMA versus ANN is not fixed but depends on whether the underlying process is closer to a smooth, physically constrained system, in which case a linear statistical model may already perform well, or closer to an administratively or behaviorally driven process with irregular shocks, in which case the added flexibility of a neural network, or of a hybrid architecture combining both approaches, tends to yield a meaningful accuracy gain. PSN land acquisition financing, which depends on discrete administrative decisions, annual budget-cycle incentives, and occasional external disruptions such as audit findings, falls conceptually closer to the latter category, motivating the comparative approach adopted in this study.

Building on this body of work, and on the gap between the Ministry of Finance's revenue-side projection initiative and the continued absence of a comparable expenditure-side model for PSN land acquisition, this study asks: (1) how can PSN land acquisition financing requirements be projected for the Toll Road and Non-Toll Road sectors; (2) how do the forecasting accuracies of

ARIMA and ANN compare for each sector; and (3) what does the resulting projection imply for PSN land acquisition financing overall. Correspondingly, this study aims to forecast financing requirements for both sectors using the better-performing of the two methods, to compare their accuracy, and to analyze the resulting projection through the end of the forecast horizon. Its novelty lies in applying and comparing ARIMA and ANN specifically to the expenditure side of PSN land acquisition financing, an area that, unlike budget revenue planning, has not previously been addressed through a data-driven projection model, and in translating the resulting forecast into an explicit estimate of the fund absorption rate implied for the current fiscal year. The analysis is limited to monthly realization data from 2017 through the first quarter of 2026 and to a forecast horizon extending through March 2027, and does not account for external factors, such as macroeconomic or socio-political conditions, that may also influence realization patterns.

METHODS

This study uses a quantitative, comparative time series forecasting design. The data are secondary monthly records of the realized rupiah value of PSN land acquisition financing, obtained from LMAN's internal records, covering the Toll Road sector from May 2017 through March 2026 (107 observations) and the Non-Toll Road sector, which aggregates dams, railways, irrigation, seaports, the national tourism strategic area, raw water projects, and the new national capital, from March 2018 through March 2026 (97 observations); the later start date for the Non-Toll Road sector reflects that financing in that category only began in 2018. The two sectors are analyzed separately because the Toll Road sector accounts for 81.23% of total PSN land acquisition allocation, compared with 18.77% for the combined Non-Toll Road categories.

For each sector, the data were divided into training, validation, and testing subsets, with the final 12 months of available data (April 2025 to March 2026) reserved for testing in both the ARIMA/SARIMA and ANN models to allow a direct comparison of forecast accuracy. ARIMA modeling was carried out in R (RStudio) following the standard Box-Jenkins procedure: stationarity in variance was assessed through the Box-Cox transformation and stationarity in mean through the Augmented Dickey-Fuller test, applying differencing where required; candidate orders were identified from the autocorrelation and partial autocorrelation functions of the stationary series and compared using Akaike's Information Criterion; each candidate's parameters were tested for statistical significance; and the residuals of the retained model were checked for white noise using the Ljung-Box test and for normality using the Shapiro-Wilk test (Box et al., 2015; Bowerman & O'Connell, 1993; Biu et al., 2019). Where non-seasonal ARIMA left residual autocorrelation at longer, annual-cycle lags, the specification was extended to a Seasonal ARIMA (SARIMA) model incorporating a seasonal term at lag 12.

ANN modeling was carried out in Python on a cloud-based platform (Google Colab), adopting a feedforward Multilayer Perceptron (MLP) architecture for its capacity to represent non-linear structure (Nadaf et al., 2025). For each sector, the series was normalized to the [0,1] range using min-max scaling, then modeled with a 24-period lookback window and a 20% dropout rate as a safeguard against overfitting given the resulting reduction in effective training samples. The optimal hyperparameter combination, namely the number of neurons, learning rate, batch size, and number of epochs, was identified through grid search, retaining the configuration with the lowest validation loss for forecasting over the testing period.

Forecast accuracy for each method was evaluated using the Mean Absolute Percentage Error (MAPE), calculated as MAPE = (1/n) times the sum, over all n periods in the testing set, of the absolute difference between the actual value and the forecasted value divided by the actual value, expressed as a percentage (Suryatna et al., 2021). Because certain months in the Non-Toll Road series recorded realization values close to zero, which inflates MAPE disproportionately by dividing the forecast error by a near-zero denominator, forecast accuracy for that sector was additionally evaluated using the Symmetric Mean Absolute Percentage Error (sMAPE), which instead divides the absolute error by the sum of the actual and forecasted values and thereby bounds the maximum error contribution at 200% rather than allowing it to grow unbounded. For each sector, the method achieving the lower error value on the testing period was adopted as the basis for a forward 12-month projection of land acquisition financing requirements, from April 2026 through March 2027.

Model selection among ARIMA candidates additionally relied on Akaike's Information Criterion (AIC), computed as AIC equals negative two times the log-likelihood of the fitted model plus two times the number of estimated parameters, with the candidate achieving the lowest AIC carried forward for significance testing. This penalizes additional parameters that do not meaningfully improve fit, which is particularly relevant here given the relatively short monthly series (fewer than 110 observations in either sector) and the corresponding risk that a more heavily parameterized ARIMA specification would simply overfit the training data without improving genuine forecasting performance on the held-out testing period.

All computation was performed on standard desktop and cloud computing resources; ARIMA/SARIMA estimation in R required no specialized hardware, while ANN training in Google Colab used default CPU/GPU runtime allocation. No personally identifiable information is contained in the dataset, which consists solely of aggregated monthly rupiah disbursement totals by sector; accordingly, no additional ethical clearance was required beyond the institutional data-access permission obtained to use LMAN's internal realization records for research purposes. To support reproducibility, all model specifications, hyperparameter grids, and train/validation/test splits are reported in full above rather than summarized qualitatively, consistent with established recommendations for transparent forecasting research (Petropoulos et al., 2022).

RESULTS AND DISCUSSION

Toll Road Sector: Descriptive Statistics and Model Identification

The Toll Road sector realization series (May 2017 to March 2026, 107 observations) had a mean of Rp1.168 trillion and a standard deviation of Rp0.809 trillion, with a minimum of Rp0.00073 trillion in September 2018, when only a single project was disbursed that month, and a maximum of Rp3.868 trillion in December 2020, coinciding with the year-end concentration of payment requests typically observed as agencies work to maximize annual budget absorption.

Table 2. Descriptive Statistics of Toll Road and Non-Toll Road Land Acquisition Financing Realization

Statistic	Toll Road (Rp trillion)	Non-Toll Road (Rp trillion)
Number of observations	107	97
Mean	1.168	0.261
Standard deviation	0.809	0.169
Minimum	0.00073	0.000
Maximum	3.868	0.830

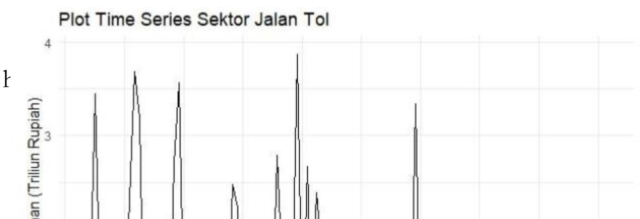

Figure 1. Time Series Plots of Toll Road and Non-Toll Road Land Acquisition Financing Realization

The Toll Road training data (May 2017 to May 2024, 85 observations) yielded a Box-Cox lambda of 0.68, indicating the series was not stationary in variance; after transformation, lambda rose to 1.49. The Augmented Dickey-Fuller test on the transformed series returned a p-value of 0.01, confirming stationarity in mean without further differencing. The resulting autocorrelation and partial autocorrelation plots pointed to a subset ARIMA structure, and six candidate specifications were compared by AIC (Table 3).

Table 3. Candidate ARIMA Models by AIC, Toll Road Sector

Model	AIC
ARIMA(1,0,0)	68.265
ARIMA(1,0,1)	70.258
ARIMA(3,0,0)	65.630
ARIMA([1,3],0,1)	65.528
ARIMA([1,3],0,0)	64.635
ARIMA(3,0,1)	67.451

ARIMA([1,3],0,0) achieved the lowest AIC, with both the AR(1) coefficient (0.376, $p < 0.001$) and the AR(3) coefficient (−0.242, $p = 0.015$) statistically significant, and was accordingly retained as the best ARIMA specification for the Toll Road sector. Table 4 reports the full parameter estimates and Table 5 summarizes the residual diagnostics used to confirm that the model was adequate before it was carried forward to forecasting.

Table 4. Parameter Significance Test, ARIMA([1,3],0,0), Toll Road Sector

Parameter	Estimate	p-value	Decision
AR(1)	0.376	0.000146	Significant
AR(3)	−0.242	0.015436	Significant
Intercept	1.065	< 2.2e-16	Significant

Diagnostic checking of the retained model confirmed that its residuals satisfied the white-noise assumption, with Ljung-Box p-values well above 0.05 at every lag examined, and the normality assumption, with a Shapiro-Wilk p-value of 0.544. A representative subset of the Ljung-Box results across the tested lag range is reported in Table 5.

Table 5. Ljung-Box White-Noise Test Results (Selected Lags), ARIMA([1,3],0,0), Toll Road Sector

Lag	1	6	12	18	24
p-value	0.720	0.891	0.827	0.173	0.110

Non-Toll Road Sector: Descriptive Statistics and Model Identification

The Non-Toll Road sector realization series (March 2018 to March 2026, 97 observations) had a mean of Rp0.261 trillion and a standard deviation of Rp0.169 trillion, with a minimum of Rp0.000 trillion in June 2019, when an audit finding by the Financial and Development Supervisory Agency required a period of policy harmonization during which no realization occurred, and a maximum of Rp0.830 trillion in December 2021. The series is visibly more volatile than the Toll Road series in relative terms, but concentrated on a much smaller average monthly disbursement, which is precisely the condition under which the standard MAPE metric becomes unreliable and a symmetric alternative is warranted.

The Non-Toll Road training data (March 2018 to July 2024, 77 observations) yielded a Box-Cox lambda of 0.42; after transformation, lambda rose to 1.06. The initial Augmented Dickey-Fuller test returned a p-value of 0.2194, indicating the series was not yet stationary in mean, so first-order differencing was applied, after which the ADF p-value fell to 0.01. Eight candidate ARIMA specifications on the differenced series were compared by AIC (Table 6), with ARIMA(2,1,4) achieving the lowest value; however, its MA(4) term was not significant ($p = 0.935$), and the next-best candidate by AIC, ARIMA(3,1,1), likewise contained a non-significant MA(1) term ($p = 0.945$). The third-best candidate, ARIMA(0,1,1), had its sole parameter significant ($p < 0.001$), but its residuals showed remaining autocorrelation at lags 10 through 24, pointing to an unmodeled annual cycle, and the specification was accordingly extended to a seasonal model.

Table 6. Candidate ARIMA and SARIMA Models by AIC, Non-Toll Road Sector

Model	AIC
ARIMA(1,1,1)	−46.550
ARIMA(0,1,1)	−47.931
ARIMA(3,1,1)	−48.303
ARIMA(2,1,4)	−52.025
SARIMA(0,1,1)(1,0,0)^{12}	−49.431
SARIMA(0,1,1)(0,1,1)^{12}	−22.015

Extending ARIMA(0,1,1) to a seasonal specification, SARIMA(0,1,1)(1,0,0)^{12} achieved the lowest AIC among the seasonal candidates, with both the MA(1) term and the seasonal AR(1) term significant (Table 7), and its residuals satisfied both the white-noise assumption at every lag from 1 through 24 and the normality assumption (Shapiro-Wilk $p = 0.666$), and was accordingly retained as the best specification for the Non-Toll Road sector.

Table 7. Parameter Significance Test, SARIMA(0,1,1)(1,0,0)^{12}, Non-Toll Road Sector

Parameter	Estimate	p-value	Decision
MA(1)	−0.823	< 2e-16	Significant
Seasonal AR(1)	0.235	0.057	Significant

ANN Modeling and Hyperparameter Optimization

For the Toll Road sector, grid search over 36 hyperparameter configurations identified 32 neurons, a learning rate of 0.01, a batch size of 8, and 50 epochs as the configuration achieving the lowest validation loss (0.002627). For the Non-Toll Road sector, grid search over 24 configurations identified 32 neurons, a learning rate of 0.0005, a batch size of 8, and 50 epochs as achieving the lowest validation loss (0.015785), summarized alongside the Toll Road result in Table 8. In both sectors, the configurations achieving the lowest validation loss consistently favored the largest neuron count tested (32) paired with a batch size of 8, suggesting that additional model capacity, rather than a smaller batch size, was the more useful lever for generalization given the limited effective training sample created by the 24-period lookback window.

Table 8. Best ANN Configuration by Validation Loss, Both Sectors

Sector	Neurons	Learning rate	Batch size	Epochs	Validation loss
Toll Road	32	0.01	8	50	0.002627
Non-Toll Road	32	0.0005	8	50	0.015785

```
Top 5 Models:
    neurons  learning_rate  batch_size  epochs  val_loss
34       32           0.01           8      50  0.002627
25       16           0.01           8      50  0.004399
24       16           0.01           4      50  0.005462
33       32           0.01           4      50  0.005538
7         4           0.01           8      50  0.005634
```

```
Top 5 Models:
    neurons  learning_rate  batch_size  epochs  val_loss
19       32         0.0005           8      50  0.015785
9         8         0.0010           8      50  0.016345
22       32         0.0100           4      50  0.016990
11        8         0.0100           8      50  0.017908
16       16         0.0100           4      50  0.018391
```

Figure 2. Hyperparameter Optimization Results (Top 5 MLP Configurations), Toll Road and Non-Toll Road Sectors

Forecast Accuracy Comparison

For the Toll Road sector, ARIMA([1,3],0,0) produced a nearly flat forecast across the testing period (June 2024 to March 2026) that failed to track the fluctuation in actual realization, yielding a MAPE of 80.93%, while the ANN model, though it also struggled with sudden or extreme fluctuations, followed the general direction of actual realization more closely and achieved a MAPE of 49.01% (Table 9). For the Non-Toll Road sector, SARIMA(0,1,1)(1,0,0)^{12} produced a similarly flat forecast, yielding an sMAPE of 81.53%, while ANN achieved an sMAPE of 64.08% (Table 10). In both sectors, ANN's advantage is consistent with its greater capacity to represent the non-linear, administratively driven disbursement pattern of the series, including the year-end concentration of payment requests, a pattern statistical models built on linear dependence structure are less able to capture (Tarmanini et al., 2023).

Table 9. Actual versus ARIMA and ANN Forecasts, Toll Road Sector, April 2025 to March 2026 (Rp trillion)

Period	Actual	ARIMA	ANN
April 2025	0.520	1.142	0.731
May 2025	0.644	1.138	0.761
June 2025	0.494	1.134	0.689
July 2025	0.805	1.132	0.856
August 2025	0.635	1.132	0.907
September 2025	0.677	1.133	0.770
October 2025	0.438	1.134	0.980
November 2025	0.478	1.135	0.845
December 2025	0.929	1.134	1.191
January 2026	0.385	1.134	0.736
February 2026	0.397	1.134	0.752
March 2026	1.014	1.134	0.839
MAPE	–	80.93%	49.01%

Table 10. Actual versus SARIMA and ANN Forecasts, Non-Toll Road Sector, April 2025 to March 2026 (Rp trillion)

Period	Actual	SARIMA	ANN
April 2025	0.151	0.303	0.1637
May 2025	0.157	0.330	0.2112
June 2025	0.151	0.297	0.1878
July 2025	0.090	0.257	0.1875
August 2025	0.048	0.315	0.1464
September 2025	0.158	0.313	0.1191
October 2025	0.166	0.312	0.1620
November 2025	0.088	0.307	0.1608
December 2025	0.416	0.304	0.1882
January 2026	0.016	0.308	0.1276
February 2026	0.075	0.305	0.1540
March 2026	0.020	0.306	0.1434
sMAPE	–	81.53%	64.08%

As Tables 9 and 10 show, the ARIMA and SARIMA forecasts remain relatively constant throughout the testing period in both sectors, whereas the ANN forecasts vary from month to month and generally follow the movements in the actual values more closely. In the non-toll road sector, this difference is reflected in the lower sMAPE value produced by ANN, at 64.08%, compared with 81.53% for SARIMA. Nevertheless, ANN still exhibits substantial forecasting errors in periods with exceptionally high or low actual values. The most noticeable deviation occurs in December 2025, when the actual value increases to Rp0.4163 trillion, while the ANN forecast reaches only Rp0.1882 trillion. This condition may reflect the year-end concentration of payment requests, which neither model fully anticipates. The shared limitation indicates that both methods rely primarily on historical patterns without receiving an explicit indicator of the fiscal year-end or budget cycle. Future forecasting models could therefore incorporate calendar-based or budget-cycle variables to improve their ability to anticipate such seasonal fluctuations.

Table 11. Forecast Accuracy Comparison Summary, Testing Period April 2025 to March 2026

Sector	Statistical model	Statistical error	ANN error
Toll Road	ARIMA([1,3],0,0)	MAPE 80.93%	MAPE 49.01%
Non-Toll Road	SARIMA(0,1,1)(1,0,0)^{12}	sMAPE 81.53%	sMAPE 64.08%

Projected Financing Requirements

Based on the better-performing ANN models, financing requirements were projected 12 months ahead, from April 2026 through March 2027. For the Toll Road sector, projected monthly values range from approximately Rp0.73 trillion to Rp1.34 trillion, with the highest value projected for December 2026, consistent with the historical year-end pattern. For the Non-Toll Road sector, projected monthly values range from approximately Rp0.06 trillion to Rp0.18 trillion over the same horizon, a substantially narrower range that reflects both the smaller scale of this sector and the smoothing tendency of the underlying neural network.

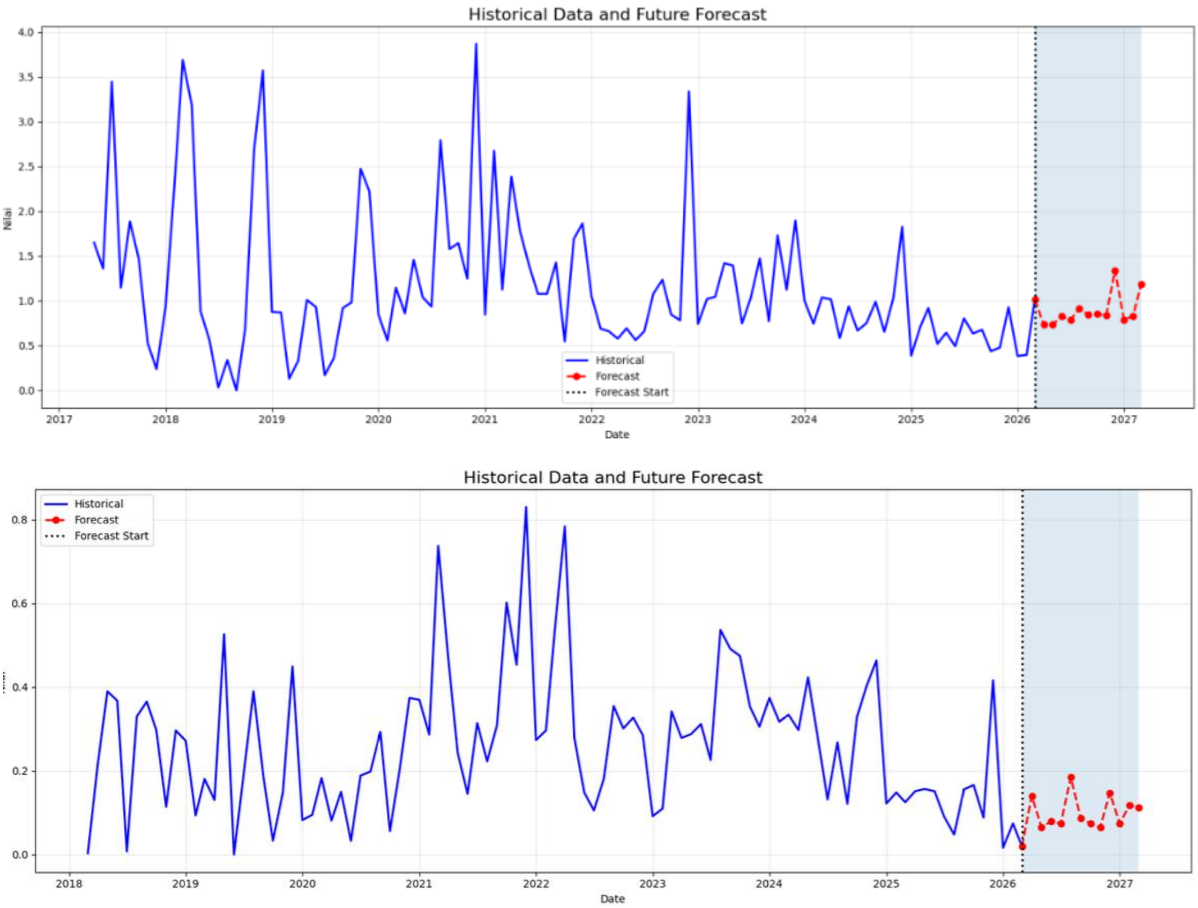

Figure 3. Historical Data and 12-Month-Ahead ANN Forecast, Toll Road and Non-Toll Road Sectors

Table 12. Projected Land Acquisition Financing Requirements, April 2026 to March 2027 (Rp trillion)

Period	Toll Road	Non-Toll Road
April 2026	0.735	0.140
May 2026	0.733	0.066
June 2026	0.825	0.079
July 2026	0.786	0.074
August 2026	0.916	0.185
September 2026	0.844	0.087
October 2026	0.852	0.074

November 2026	0.837	0.064
December 2026	1.341	0.148
January 2027	0.789	0.074
February 2027	0.830	0.118
March 2027	1.187	0.113

DISCUSSION

Beyond the sector-level forecasts, historical trends in fund availability further illustrate the persistence of the absorption problem this study addresses. Between 2017 and 2025, the annual PSN land acquisition absorption rate ranged from a high of 73.26% in 2017 to a low of 26.21% in 2025, with no clear improving trend over the nine-year period (Table 13), a pattern that suggests the shortfall in accurate expenditure planning identified in the introduction has persisted despite year-to-year fluctuation in the amount of funds made available.

Table 13. Annual PSN Land Acquisition Fund Availability, Realization, and Absorption Rate, 2017 to 2025 (Rp trillion)

Year	2017	2018	2019	2020	2021	2022	2023	2024	2025
Available funds	16.00	36.33	46.23	44.35	38.86	44.84	54.22	43.52	36.08
Realized funds	11.72	21.25	13.88	19.91	22.86	16.05	18.21	14.99	9.45
Absorption (%)	73.26	58.50	30.02	44.90	58.82	35.78	33.58	34.44	26.21

Combining the ANN-based projections for both sectors over the remaining nine months of 2026 with actual realization recorded from January to March 2026 yields an estimated total land acquisition financing requirement of Rp10.69 trillion across all PSN sectors for the year, against which the resulting projected fund absorption rate is 40.16% of currently available funds. While this represents an improvement over the 26.21% absorption recorded in 2025, it remains well below the levels achieved earlier in the observation period, underscoring the continued need for more accurate, forward-looking financing plans if PSN land acquisition is to be executed at a pace consistent with project completion targets.

The consistency of ANN's advantage across both sectors, despite their markedly different scale and volatility, reflects its greater capacity to capture non-linear structure in a series shaped less by smooth underlying dynamics than by discrete, administratively driven disbursement events. This pattern is broadly consistent with the literature comparing ARIMA and ANN, in which ANN or hybrid ARIMA-NN approaches have generally outperformed standalone ARIMA when a series exhibits pronounced non-linearity or irregularity (Tarmanini et al., 2023; Mahdi & Al-Share, 2025), though it also stands in contrast to studies in more physically constrained domains, such as photovoltaic energy production, where ARIMA has been found to outperform ANN (Fara et al., 2021). This contrast suggests that the relative advantage of either method depends substantially on the structure of the series being forecast rather than holding as a universal rule, and that PSN land acquisition financing, being driven by administrative and budget-cycle factors rather than a physically constrained process, falls closer to the class of series in which ANN's flexibility is an advantage.

At the same time, even the best-performing ANN models in this study left a non-trivial share of forecast error unexplained, particularly around sudden, large disbursements, indicating room for further refinement. Hybrid ARIMA-ANN architectures, which have been shown to outperform either model used alone by combining the linear structure captured by ARIMA with the non-linear structure captured by ANN (Hajirahimi & Khashei, 2016), represent one promising direction. Incorporating external explanatory variables, such as fiscal-year budget-cycle indicators or macroeconomic conditions, not considered in the present univariate framework, represents another.

Table 14. Accuracy Improvement of ANN over Statistical Benchmarks, This Study Compared with Prior Literature

Study	Domain	Statistical error	ANN/ML error
This study – Toll Road	PSN land acquisition financing	MAPE 80.93%	MAPE 49.01%
This study – Non-Toll Road	PSN land acquisition financing	sMAPE 81.53%	sMAPE 64.08%
Tarmanini et al. (2023)	Short-term electricity load	MAPE 2.61%	MAPE 1.80%
Mahdi & Al-Share (2025)	Pharmaceutical sales (US)	Conventional ARIMA	ARIMA-NN, 93.9% accuracy
Fara et al. (2021)	Photovoltaic energy production	rRMSE 22.3%	rRMSE 25.3% (ARIMA lower)

Placed alongside this prior literature, the accuracy gain from ANN observed in the present study is proportionally larger than in Tarmanini et al. (2023), where both methods already achieved low single-digit MAPE, and is directionally consistent with Mahdi and Al-Share (2025), where a neural-network-augmented model likewise outperformed a conventional statistical baseline. The comparison also usefully illustrates the boundary of that advantage: in Fara et al. (2021), where the forecasted quantity, photovoltaic energy production, is governed by comparatively regular physical and astronomical cycles, the statistical model was the more accurate of the two. Land acquisition financing, by contrast, is governed by administrative decisions and budget-cycle incentives that do not repeat with the same regularity, which is consistent with ANN's comparatively large advantage in both sectors examined here.

The magnitude of the errors reported here also carries a practical implication for how the resulting forecasts should be used. A MAPE or sMAPE in the range of 49% to 64% is far from negligible, and management should treat the monthly point forecasts in Tables 9, 10, and 12 as indicative planning inputs rather than precise commitments, particularly for months in which historical realization has been most volatile, such as the turn of the fiscal year. This is consistent with the broader forecasting literature's finding that even well-performing models chosen through rigorous, competition-style evaluation still leave a meaningful share of error unexplained on real-world series (Makridakis et al., 2018), and argues for pairing any model-based projection with a margin of managerial judgment rather than treating it as a substitute for judgment altogether.

From a policy perspective, the low absorption rate implied by the projection, 40.16% against a KPI that ties budget performance to incentives and sanctions under the governing Ministry of Finance regulation, suggests that the constraint on PSN land acquisition may lie less in the availability of funds than in the pace at which requiring ministries and agencies submit disbursement requests to LMAN. If so, a forecasting model of the kind developed here could be used not only to plan the aggregate budget but also to flag, on a rolling basis, months in which actual disbursement is falling behind the model's projection, giving management an early signal to intervene before the shortfall accumulates into a large year-end gap.

CONCLUSION

This study compared ARIMA (extended to SARIMA for the Non-Toll Road sector) and Artificial Neural Network models in projecting the land acquisition financing requirements of Indonesia's National Strategic Projects. ANN consistently outperformed the statistical benchmark in both sectors: for the Toll Road sector, ANN achieved a MAPE of 49.01% against 80.93% for ARIMA; for the Non-Toll Road sector, ANN achieved an sMAPE of 64.08% against 81.53% for SARIMA. Based on the better-performing ANN models, financing requirements were projected through March 2027, and combining these projections with realized values from the first quarter of 2026 indicates a total PSN land acquisition financing requirement of approximately Rp10.69 trillion for the year, implying a fund absorption rate of 40.16% of currently available funds, an improvement over 2025 but still well below the levels achieved in earlier years.

In terms of practical recommendation, LMAN and the ministries and agencies that submit land acquisition financing proposals could adopt the ANN-based projection approach demonstrated here as a supplementary planning tool, using it to set more realistic monthly disbursement targets and to flag, on a rolling basis, months in which actual realization is diverging materially from the projected path so that corrective action can be taken before a shortfall accumulates over the fiscal year. Given the size of the errors still present in the best models estimated here, such a tool should complement rather than replace the judgment of budget planners, particularly around the turn of the fiscal year when historical realization has been most volatile.

These findings support the conclusion that data-driven expenditure planning, of the kind demonstrated here, could meaningfully improve the pace at which PSN land acquisition budgets are executed. As both methods in their present form rely solely on the historical values of the series being forecast, this study's main limitation is its univariate scope; the generalizability of the specific accuracy figures reported here is further limited to the two sectors and the observation period examined. Future research is accordingly encouraged to combine time series analysis with external explanatory factors, such as macroeconomic conditions or budget-cycle indicators, and to examine hybrid ARIMA-ANN architectures as a means of capturing both the linear and non-linear components of PSN land acquisition financing behavior.

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