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Research Paper

Forecasting the Daily Revenue of a Nitrogen Tire Inflation Service MSME Using the ARIMA Method: An Accounting Approach Based on Financial Accounting Standard for MSME Transaction Records (Case Study: Nitrogen Go-Green Semarang, Central Java, Indonesia)

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ABSTRACT: *Fluctuating daily revenue is a persistent obstacle to financial planning and operational decision-making in micro, small, and medium enterprises (MSMEs). This study analyses the behaviour of daily service revenue and develops an optimal forecasting model using the Autoregressive Integrated Moving Average (ARIMA) method, applied to the accounting transaction records of Nitrogen Go-Green, a nitrogen tire inflation service MSME in Semarang, Central Java, Indonesia. The data set consists of 1,866 daily observations (22 November 2020 – 31 December 2025) obtained by integrating shift-level source documents whose revenue recognition practice is consistent with the Indonesian Financial Accounting Standard for Micro, Small, and Medium Entities (SAK EMKM). The Augmented Dickey–Fuller and KPSS tests produced conflicting signals at the level, so first-order differencing was applied as the conservative treatment, after which both tests confirmed stationarity. Among sixteen candidate specifications, ARIMA(3,1,3) minimised both AIC and BIC, with all parameters statistically significant. On a 30-day holdout sample, the model achieved a one-step-ahead MAPE of 9.94% (highly accurate) and a 30-step dynamic MAPE of 12.31% (accurate). The 30-day-ahead forecast projects daily revenue between approximately Rp826 thousand and Rp925 thousand, totalling about Rp26.16 million, which is translated into a monthly cash receipts budget. The findings demonstrate that orderly SAK EMKM-based bookkeeping, reinforced by shift-level internal control, provides a reliable data foundation for statistical forecasting, revenue budgeting, and variance analysis in MSMEs.*

KEYWORDS: *ARIMA, revenue forecasting, accounting records, cash budgeting, MSME, time series*

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I. INTRODUCTION

Micro, small, and medium enterprises (MSMEs) play a strategic role in the Indonesian economy, particularly in creating employment, raising household income, and strengthening regional economic resilience [10], [11], [12]. The automotive service sector is one of the business fields that continues to expand along with the growing number of motor vehicles. A widely encountered form of automotive service business is the nitrogen tire inflation service, which offers more stable tire pressure, improved fuel efficiency, and longer tire life compared with the use of ordinary compressed air.

Nitrogen Go-Green Semarang, Central Java, Indonesia is an MSME engaged in nitrogen tire inflation services for both two-wheeled and four-wheeled vehicles. In its daily operations, the revenue of this business fluctuates under the influence of various factors, such as the number of customers, working days and public holidays, weather conditions, and the intensity of economic activity around the business location. These fluctuations create challenges for the owner in preparing financial plans, procuring supporting materials, scheduling labour, and formulating business development strategies.

From an accounting perspective, MSMEs in Indonesia are guided by the Financial Accounting Standard for Micro, Small, and Medium Entities (SAK EMKM), which requires simple, orderly, and verifiable recording of transactions as the basis of financial reporting [16]. The entity studied here maintains daily shift-level transaction records in which service revenue is classified by revenue stream, operating expenditures are documented, and physical indicators such as consumable stock and electricity meter readings are recorded alongside the financial figures. Such accounting records are ordinarily used for stewardship and reporting purposes; however, management accounting emphasises that the same information can be exploited for forward-looking purposes, including budgeting, planning, and control [17], [18].

Revenue forecasting is one of the most important managerial accounting instruments for anticipating future business conditions. With a more accurate revenue estimate, business owners can make better decisions concerning cash management, operating cost efficiency, and the determination of sales targets, and can prepare revenue and cash budgets on an objective basis [17]. In practice, however, many MSMEs still estimate future revenue informally on the basis of experience or intuition, so that the results are inaccurate and difficult to use as a foundation for objective decision-making.

The Autoregressive Integrated Moving Average (ARIMA) method is one of the most widely used time-series forecasting techniques because it is able to model the pattern of historical data and produce short-term predictions with a good level of accuracy [1], [2], [3], [4]. The ARIMA model exploits the relationships among observations in previous periods, which makes it suitable for daily revenue data that exhibit fluctuating patterns. Previous studies have shown that ARIMA is effective for forecasting sales, demand, expenditure, and revenue in various sectors [8], [9]. Nevertheless, research that specifically addresses daily revenue forecasting for nitrogen tire inflation service businesses on the basis of the entity's own accounting records is still relatively limited, especially in the context of MSMEs in Semarang, Central Java, Indonesia.

This study aims to analyse the pattern of daily revenue data and to construct the most appropriate ARIMA model for forecasting the daily revenue of Nitrogen Go-Green Semarang, using the integrated accounting transaction records of the entity as the data source. In addition, the study evaluates the accuracy of the resulting model using standard forecast error measures, so that the model can be employed as a supporting tool in financial planning, cash budgeting, and operational decision-making.

The results are expected to make a theoretical contribution to the application of time-series methods to accounting data in the MSME automotive service sector, and a practical contribution to the owner of Nitrogen Go-Green Semarang in improving the quality of revenue planning, cash flow management, and measurable, data-driven business development. Following the structure of this journal, Section II presents the system coordinates, namely the accounting information system that generates the data and the research framework; Section III derives the equations of motion of the revenue process in the form of the ARIMA model; Section IV reports the numerical solution and its appendix; Section V discusses a dynamic simulation inspired by the double pendulum analogy; and Section VI concludes.

II. SYSTEM COORDINATES

In a mechanical system, the coordinates define the state variables whose evolution is being studied. By analogy, the "coordinates" of the revenue system examined in this study are defined by the entity's accounting information system: the source documents that capture each transaction, the classification of revenue streams, and the integrated daily revenue variable that becomes the input of the forecasting model. Conceptually, this study uses daily revenue data as the input for constructing an ARIMA model that produces revenue forecasts for subsequent periods, which are then translated into financial planning recommendations.

2.1 The Accounting Recording System (Source Documents)

The primary data source is the entity's daily transaction record book, maintained per operator shift. Service revenue is classified into three streams: nitrogen inflation revenue (A), tire patching revenue (B) — separated into motorcycles and cars — and other income (C), so that daily turnover is recorded as A + B + C. The same document records operating expenditures with their descriptions, the opening, used, and remaining stock of the consumable fibre material, and the opening and closing readings of the electricity meter. At the end of each week the figures are recapitulated, weekly revenue and expenses are totalled, and the record is signed by the operator and verified by the supervisor. Table 1 summarises the structure of the record.

Field	Description
Day, date, shift, operator	Identification of the recording unit; each day is served by up to two shifts with a named responsible operator
Nitrogen inflation (A)	Cash revenue from nitrogen tire inflation services
Tire patching (B)	Cash revenue from tire patching, recorded separately for motorcycles and cars
Other income (C)	Miscellaneous service income
Turnover (A + B + C)	Total daily service revenue per shift
Expenditures	Nominal amount and description of operating outlays (e.g., overtime payments)

Fibre stock	Opening, used, and remaining units of the consumable patching material
Electricity meter	Opening and closing meter readings and daily consumption in watts
Weekly recapitulation	Weekly revenue, weekly expenses, net weekly revenue, and sign-off by operator and examiner

Table 1: Structure of the daily shift-level transaction record

Two accounting properties of this system deserve emphasis. First, revenue recognition: service revenue is recognised when the service is rendered and cash is received on the same day, a simple treatment that is consistent with the recognition and measurement concepts of SAK EMKM for micro and small entities [16]. Second, internal control: the design of the record embodies several control elements identified in the accounting information systems literature [19] — segregation of recording responsibility by shift and operator, authorisation through the weekly dual sign-off between the operator and the examiner, and an independent physical cross-check, because the recorded revenue can be reconciled against non-financial indicators such as electricity consumption and fibre stock usage. These properties increase confidence that the revenue series used in this study is complete, verifiable, and free from systematic omission.

2.2 Data Integration

All weekly record books from 22 November 2020 to 31 December 2025 were integrated into a single machine-readable data set. Shift-level turnover figures were aggregated by calendar date to obtain the daily service revenue variable Y_t, expressed in thousands of rupiah. The integration produced n = 1,866 consecutive daily observations with no missing calendar days and no zero-revenue days. Table 2 reports the descriptive statistics and Table 3 the annual means.

Statistic	Mean	Median	Std. dev.	Min / Max
Daily revenue (Rp thousand)	743.8	738.0	167.3	144.0 / 1,839.0

Table 2: Descriptive statistics of daily service revenue, n = 1,866 (22 November 2020 – 31 December 2025)

2020*	2021	2022	2023	2024	2025
612.2	713.4	639.0	735.3	818.0	827.5

Table 3: Annual mean of daily revenue in Rp thousand (*2020 covers 22 November–31 December only)

The annual means indicate a rising level of daily revenue over the observation window, from Rp612.2 thousand in late 2020 to Rp827.5 thousand in 2025. This drift in the mean is a first indication that the series may not be stationary in level and motivates the formal stationarity testing carried out in Section IV.

2.3 Research Framework

Diagram 1 summarises the flow of the study: accounting source documents are integrated into a daily revenue ledger; the series is tested for stationarity and differenced where necessary; candidate ARIMA models are identified, estimated, and compared; the selected model is checked diagnostically and evaluated out of sample; and the resulting forecast is translated into a cash receipts budget and operational recommendations for the MSME.

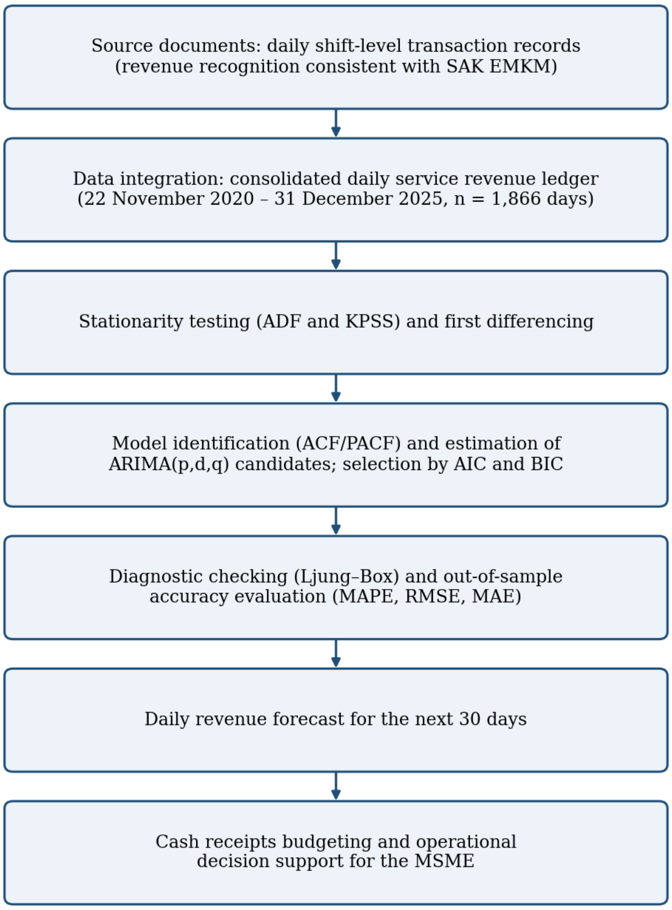

Diagram 1: Research framework, from accounting records to budgeting decisions

III. EQUATIONS OF MOTION

In the double pendulum problem, the equations of motion are the differential equations that govern how the state variables evolve over time. In the present study, the "equations of motion" of the revenue system are the stochastic difference equations of the ARIMA class, which describe how today's revenue depends on its own past values and on past random shocks. This section presents the mathematical model and the analysis procedure, which follows the Box–Jenkins methodology of identification, estimation, diagnostic checking, and forecasting [1], [2].

3.1 General ARIMA Model

The ARIMA model is denoted ARIMA(p,d,q), where p is the autoregressive (AR) order, d is the degree of differencing (I), and q is the moving average (MA) order. In backshift operator notation the general model is written as:

$$\phi(B)(1 - B)^{d} Y_t = \theta(B)\varepsilon_t \tag{1}$$

where Y_t is the daily revenue in period t, B is the backshift operator, $\phi(B)$ is the autoregressive polynomial, $\theta(B)$ is the moving average polynomial, and ε_t is a random error assumed to be normally distributed with zero mean and constant variance [1], [7].

3.2 Autoregressive (AR) Component

The AR model of order p states that the current value is a linear function of its p previous values:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t \tag{2}$$

where c is a constant, ϕ_i are the autoregressive coefficients, and Y_{t-i} is the revenue value at lag i.

3.3 Moving Average (MA) Component

The MA model of order q expresses the current value as a function of current and past forecast errors:

$$Y_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{3}$$

where μ is the process mean, θ_i are the moving average coefficients, and ε_{t-i} are errors from earlier periods.

3.4 ARIMA Model after Differencing

Combining the AR and MA components after differencing yields the ARIMA model:

$$Y'_t = c + \sum_{i=1}^{p} \phi_i Y'_{t-i} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \quad (4)$$

where Y'_t is the revenue series made stationary by differencing, p is the AR order, and q is the MA order.

3.5 Stationarity Testing and Differencing

The daily revenue series must be stationary before it is modelled. Stationarity of the mean is examined with two complementary tests. The Augmented Dickey–Fuller (ADF) test takes non-stationarity (a unit root) as the null hypothesis, so a p-value below 0.05 indicates a stationary series. The KPSS test reverses the hypotheses, taking stationarity as the null, so a p-value below 0.05 indicates a non-stationary series [4], [13]. Using both tests guards against the low power of a single test in long daily series; when the two tests conflict, the conservative treatment is to difference the series. First-order differencing is computed as:

$$Y'_t = Y_t - Y_{t-1} \quad (5)$$

and, if necessary, second-order differencing is applied to the differenced series in the same way.

3.6 Model Identification and Selection

Candidate values of p and q are indicated by the patterns of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the stationary series: a PACF that cuts off at lag p suggests an AR(p) term, while an ACF that cuts off at lag q suggests an MA(q) term [1], [3]. Because these visual patterns are rarely unambiguous in noisy daily business data, a grid of candidate models is estimated and the best specification is selected using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC):

$$AIC = -2 \ln L + 2k \quad (6)$$

$$BIC = -2 \ln L + k \ln n \quad (7)$$

where L is the maximised likelihood, k the number of estimated parameters, and n the number of observations. Lower values indicate a better trade-off between fit and parsimony.

3.7 Diagnostic Checking

The residuals of an adequate model should behave as white noise. This is examined with the Ljung–Box test:

$$Q = n(n+2) \sum_{k=1}^{m} \frac{\hat{\rho}_k^2}{n-k} \quad (8)$$

where Q is the Ljung–Box statistic, n the number of observations, m the number of lags tested, and $\hat{\rho}_k$ the residual autocorrelation at lag k. A p-value above 0.05 indicates white-noise residuals.

3.8 Forecasting and Accuracy Measurement

Once the best model is obtained, the h-step-ahead forecast is the conditional expectation:

$$\hat{Y}_{t+h} = E(Y_{t+h} \mid Y_t, Y_{t-1}, \dots) \quad (9)$$

Forecast accuracy is evaluated with the Mean Absolute Percentage Error (MAPE), the Root Mean Squared Error (RMSE), and the Mean Absolute Error (MAE):

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100\% \quad (10)$$

$$RMSE = \sqrt{\left(\frac{1}{n} \sum_{t=1}^{n} (Y_t - \hat{Y}_t)^2\right)} \quad (11)$$

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |Y_t - \hat{Y}_t| \quad (12)$$

The MAPE value is interpreted using the criteria of Lewis [7], reproduced in Table 4. From an accounting standpoint, MAPE is particularly informative because a percentage error translates directly into the tolerance band of a revenue or cash budget prepared from the forecast [17].

MAPE value	Interpretation
< 10%	Highly accurate
10% – 20%	Accurate
20% – 50%	Reasonably accurate
> 50%	Inaccurate

Table 4: Interpretation criteria for MAPE values [7]

IV. FINDING A NUMERICAL SOLUTION AND APPENDIXES

This section reports the numerical solution of the model on the integrated accounting data. All computations were carried out in Python 3 using the statsmodels library; the estimation script is provided in Appendix A so that the analysis can be reproduced directly from the daily revenue ledger.

4.1 Data Behaviour and Stationarity Testing

Figure 1 plots the 1,866 daily observations. The series fluctuates strongly around a level that rises visibly over the years, consistent with the increasing annual means in Table 3.

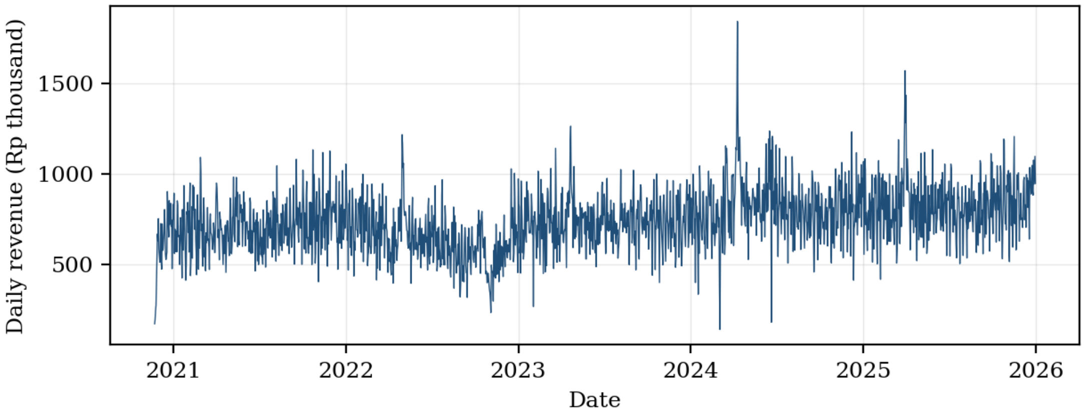

Figure 1: Daily service revenue of Nitrogen Go-Green Semarang, 22 November 2020 – 31 December 2025

Table 5 reports the stationarity tests. At the level, the ADF test rejects the unit-root null ($p = 0.0006$), but the KPSS test simultaneously rejects the stationarity null ($p < 0.01$). The two tests therefore give conflicting signals, a configuration that frequently arises in long series whose mean drifts slowly. Following the conservative treatment described in Section 3.5, first-order differencing was applied. On the differenced series both tests agree: the ADF statistic of −12.110 strongly rejects the unit root, and the KPSS statistic of 0.078 fails to reject stationarity. The series is therefore integrated of order one, and $d = 1$ is used in all subsequent models.

Series	ADF statistic	KPSS statistic	Conclusion
Level Y_t	−4.229 ($p = 0.0006$)	3.803 ($p < 0.01$)	Conflicting; difference conservatively
First difference Y'_t	−12.110 ($p < 0.001$)	0.078 ($p \geq 0.10$)	Stationary ($d = 1$)

Table 5: Stationarity test results for daily revenue (Rp thousand)

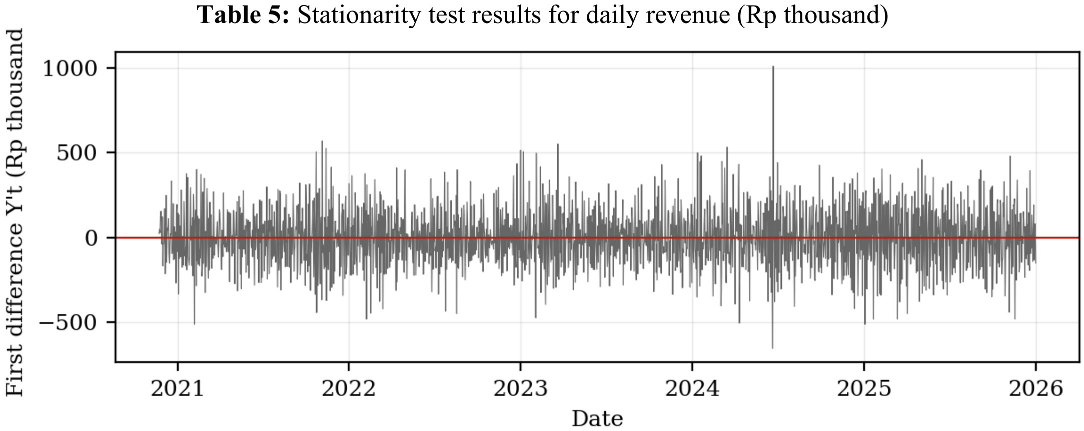

Figure 2: First-differenced daily revenue series Y'_t

4.2 Model Identification

Figure 3 shows the ACF and PACF of the differenced series. Both functions display significant spikes at the first few lags without a clean cut-off, and additional spikes recur around the weekly lags (7, 14, 21), reflecting the weekly rhythm of the business. Because the visual patterns do not point to a single specification, a full grid of non-seasonal candidates with $p \in \{0, 1, 2, 3\}$, $d = 1$, and $q \in \{0, 1, 2, 3\}$ (excluding the trivial $p = q = 0$ case) was estimated on the training sample.

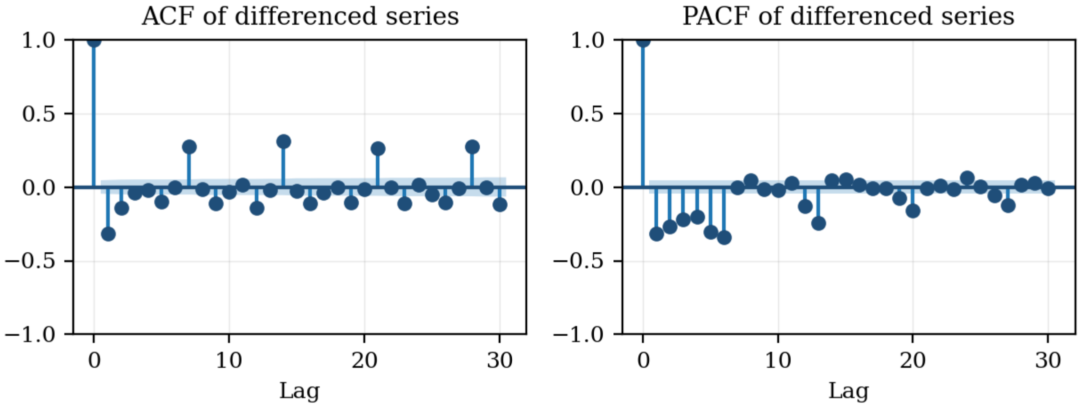

Figure 3: ACF and PACF of the first-differenced series (30 lags)

4.3 Estimation and Model Selection

For honest accuracy assessment, the last 30 days (December 2025) were held out as a testing sample and all models were estimated on the remaining 1,836 training observations. Table 6 reports the information criteria of the candidates, sorted by AIC. ARIMA(3,1,3) attains the minimum of both AIC (23,294.21) and BIC (23,332.82) by a clear margin, and is therefore selected as the best model.

Model	AIC	BIC
ARIMA(3,1,3)	**23,294.21**	**23,332.82**
ARIMA(3,1,2)	23,395.34	23,428.43
ARIMA(2,1,2)	23,398.42	23,426.00
ARIMA(3,1,1)	23,399.00	23,426.58
ARIMA(2,1,1)	23,402.67	23,424.73
ARIMA(0,1,2)	23,404.54	23,421.09
ARIMA(0,1,3)	23,404.79	23,426.85
ARIMA(1,1,2)	23,405.26	23,427.32
ARIMA(1,1,3)	23,405.64	23,433.22
ARIMA(2,1,3)	23,406.03	23,439.12
ARIMA(1,1,1)	23,410.17	23,426.72
ARIMA(0,1,1)	23,523.24	23,534.27
ARIMA(3,1,0)	23,733.49	23,755.54
ARIMA(2,1,0)	23,821.88	23,838.42
ARIMA(1,1,0)	23,954.97	23,966.00

Table 6: Information criteria of candidate models on the training sample (n = 1,836), sorted by AIC

Table 7 presents the parameter estimates of the selected model. All six coefficients are statistically significant at the 1% level. Because the model is estimated on differenced data without a deterministic trend term, no constant is included. The estimated equation of motion of the revenue system is:

$$Y'_t = -0.0932Y'_{t-1} - 0.8280Y'_{t-2} + 0.3502Y'_{t-3} + \varepsilon_t - 0.5152\varepsilon_{t-1} + 0.5179\varepsilon_{t-2} - 0.9573\varepsilon_{t-3} \tag{13}$$

Parameter	Coefficient	Std. error	z	p-value
ϕ_1 (ar.L1)	−0.0932	0.021	−4.368	< 0.001
ϕ_2 (ar.L2)	−0.8280	0.009	−87.258	< 0.001
ϕ_3 (ar.L3)	0.3502	0.021	16.932	< 0.001
θ_1 (ma.L1)	−0.5152	0.010	−52.020	< 0.001
θ_2 (ma.L2)	0.5179	0.011	46.131	< 0.001

θ_3 (ma.L3)	−0.9573	0.010	−97.144	< 0.001
σ^2	20,530	601.5	34.132	< 0.001

Table 7: Parameter estimates of ARIMA(3,1,3) on the training sample

4.4 Diagnostic Checking

The Ljung–Box test on the residuals yields Q(7) = 169.41, Q(14) = 339.66, and Q(21) = 477.69, all with $p < 0.001$, so the white-noise hypothesis is rejected. Inspection of the residual autocorrelations shows that the remaining dependence is concentrated at the weekly lags (approximately 0.24 at lags 7 and 14), confirming that a non-seasonal ARIMA specification cannot fully absorb the weekly seasonal rhythm visible in Figure 3. This finding is reported transparently as a limitation of the specification; its practical consequence is assessed in the next subsection through out-of-sample testing, which measures how well the model actually forecasts despite the unmodelled weekly component. Extending the model to a seasonal SARIMA specification is recommended as future work in Section VI.

4.5 Out-of-Sample Forecast Accuracy

Table 8 evaluates the model on the 30-day holdout sample in two ways. In the one-step-ahead scheme, the model forecasts each day of December 2025 using all information available up to the previous day, which mirrors how a business owner would actually update a daily revenue estimate. In the 30-step dynamic scheme, the model forecasts the entire month at once from the end of November 2025, which mirrors the preparation of a monthly budget. Figure 4 compares both forecasts with the actual data.

Evaluation scheme	MAPE	RMSE	MAE
One-step-ahead (daily updating)	9.94%	110.1	90.8
30-step dynamic (monthly budgeting)	12.31%	130.5	113.6

Table 8: Forecast accuracy of ARIMA(3,1,3) on the December 2025 holdout sample (RMSE and MAE in Rp thousand)

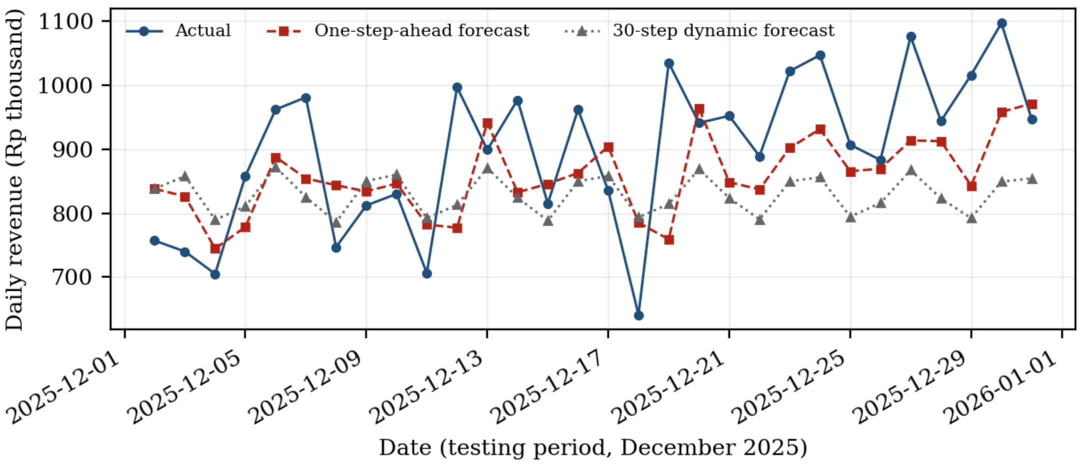

Figure 4: Actual versus forecast daily revenue in the testing period (December 2025)

Under the Lewis criteria in Table 4, the one-step-ahead MAPE of 9.94% falls in the highly accurate category, and the 30-step dynamic MAPE of 12.31% falls in the accurate category. In accounting terms, a monthly cash receipts budget prepared from this model can be expected to deviate from realisation by roughly 12% at the level of individual days, and considerably less at the aggregate monthly level, since daily errors partially offset one another.

4.6 Thirty-Day-Ahead Revenue Forecast

The selected specification was re-estimated on the full sample of 1,866 observations and used to forecast the next 30 days (January 2026). Figure 5 plots the forecast with its 95% prediction interval, and Table 9 lists the first seven days and the monthly total. Daily revenue is projected between approximately Rp826.4 thousand and Rp924.5 thousand, with a mean of Rp872.1 thousand and a 30-day total of about Rp26,162 thousand, or Rp26.16 million. The forecast level lies above the full-sample mean of Rp743.8 thousand, reflecting the continued growth of the business, and the forecast profile retains a mild oscillation inherited from the weekly pattern of the data.

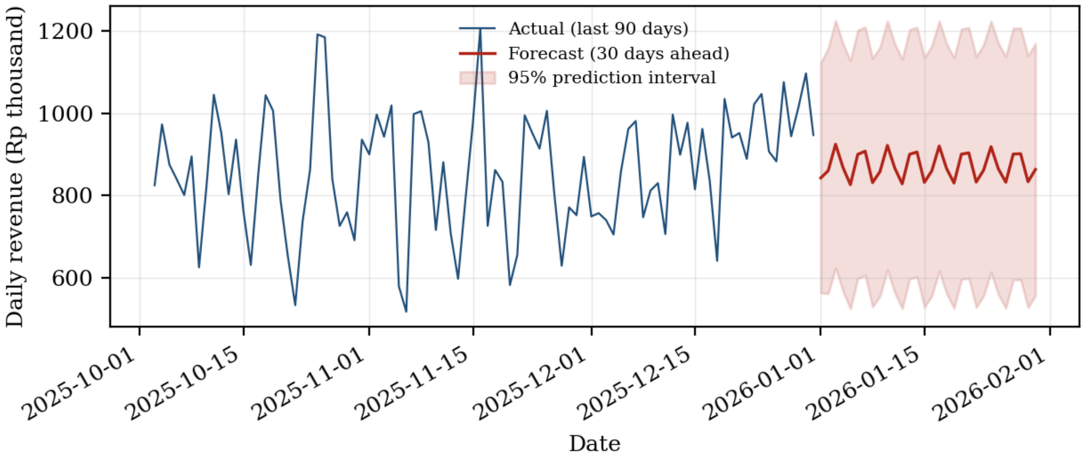

Figure 5: Thirty-day-ahead daily revenue forecast with 95% prediction interval

Date (2026)	Forecast	95% prediction interval
1 January	842.7	562.7 – 1,122.8
2 January	860.1	561.3 – 1,158.9
3 January	924.5	623.4 – 1,225.6
4 January	868.2	566.7 – 1,169.6
5 January	826.4	524.5 – 1,128.4
6 January	900.0	597.7 – 1,202.3
7 January	907.8	605.5 – 1,210.1
Total, 30 days	**26,162.1**	**≈ Rp26.16 million**

Table 9: Point forecasts of daily revenue for the first week of January 2026 (Rp thousand) and the 30-day total

4.7 Accounting Implications of the Numerical Solution

The numerical results translate directly into the entity's accounting cycle. First, the 30-day forecast provides an objective basis for the January 2026 cash receipts budget of approximately Rp26.2 million, replacing intuition-based estimation with a statistically grounded figure whose tolerance band is known from the MAPE [17], [18]. Second, the daily forecasts constitute a benchmark for revenue variance analysis: realised daily revenue can be compared against the forecast, and deviations beyond the prediction interval flag days that warrant managerial investigation. Third, because the underlying data are produced by an SAK EMKM-consistent recording system with built-in physical reconciliation, the forecast inherits the verifiability of the accounting records, strengthening its credibility when used in discussions with lenders or investors [16], [19]. Finally, the projected revenue level supports operational planning that is linked to the same source documents, such as scheduling operators per shift and budgeting electricity and fibre consumption in proportion to expected service volume.

Appendix A: Estimation Script (Python)

```
import pandas as pd
from statsmodels.tsa.stattools import adfuller, kpss
from statsmodels.tsa.arima.model import ARIMA
y = pd.read_csv('daily_revenue.csv', index_col=0,
                parse_dates=True)['omset'] / 1000.0
print(adfuller(y)[:2], kpss(y, regression='c')[:2])
d1 = y.diff().dropna()
print(adfuller(d1)[:2], kpss(d1, regression='c')[:2])
train, test = y[:-30], y[-30:]
grid = [(p, 1, q) for p in range(4) for q in range(4)
        if (p, q) != (0, 0)]
fits = {od: ARIMA(train, order=od).fit() for od in grid}
best = min(fits, key=lambda od: fits[od].aic)   # -> (3, 1, 3)
print(best, fits[best].summary())
fc = ARIMA(y, order=best).fit().get_forecast(30)
```

print(fc.predicted_mean.sum())   # 30-day cash budget basis

V. SIMULATION DOUBLE PENDULUM

The double pendulum is the classical example of a system in which two coupled state variables, each simple in isolation, jointly generate complex and difficult-to-predict motion. This section develops the economic counterpart of that idea for the revenue system studied here. Daily revenue is not a primitive quantity: in accounting terms it is the product of a volume component and a price component,

$$Y_t = P_t \times T_t \tag{14}$$

where P_t is the number of vehicles served on day t and T_t is the average tariff per vehicle. This quantity-times-price identity is exactly the decomposition that management accounting uses to separate a revenue variance into a sales volume variance and a price (tariff) variance [17], [18]. The two components play the role of the two pendulum bobs: each influences the other — tariff changes affect how many customers come, and crowding or idle capacity affects the tariffs and promotions the owner sets — and their interaction produces the complex fluctuation observed in the recorded revenue.

5.1 A Two-Component Dynamic Model

The coupled dynamics are specified as a discrete-time system with cross-effects and damping:

$$P_{t+1} = P_t + \alpha(T_t - \bar{T}) - \beta(P_t - \bar{P}) + \varepsilon_t \tag{15}$$

$$T_{t+1} = T_t + \gamma(P_t - \bar{P}) - \delta(T_t - \bar{T}) + \eta_t \tag{16}$$

where α and γ capture the cross-influence between the components, β and δ are damping factors that pull each component back toward its equilibrium $\bar{P}$ and $\bar{T}$, and ε_t and η_t are random disturbances. The damping terms are the economic analogue of friction in the pendulum system: without them, small shocks would accumulate without bound, whereas with them the system oscillates around its equilibrium in a manner similar to a damped double pendulum.

5.2 Calibration and Simulation Results

The equilibrium values were calibrated to the accounting data of Section II: with an equilibrium volume of $\bar{P}$ = 150 vehicles per day and an equilibrium average tariff of $\bar{T}$ = Rp5.0 thousand, equilibrium revenue equals $\bar{P} \times \bar{T}$ = Rp750 thousand, which is close to the observed sample mean of Rp743.8 thousand per day. The system was simulated for 60 days using the Python program in Appendix B with parameters α = 0.15, β = 0.10, γ = 0.010, δ = 0.08, and a fixed random seed for reproducibility. The simulated revenue has a mean of Rp800.8 thousand, a standard deviation of Rp94.9 thousand, and a range of Rp657.3 – 1,076.1 thousand — the same order of magnitude and a comparable dispersion pattern to the actual series. Figure 6 shows the trajectories of the two components and the resulting revenue.

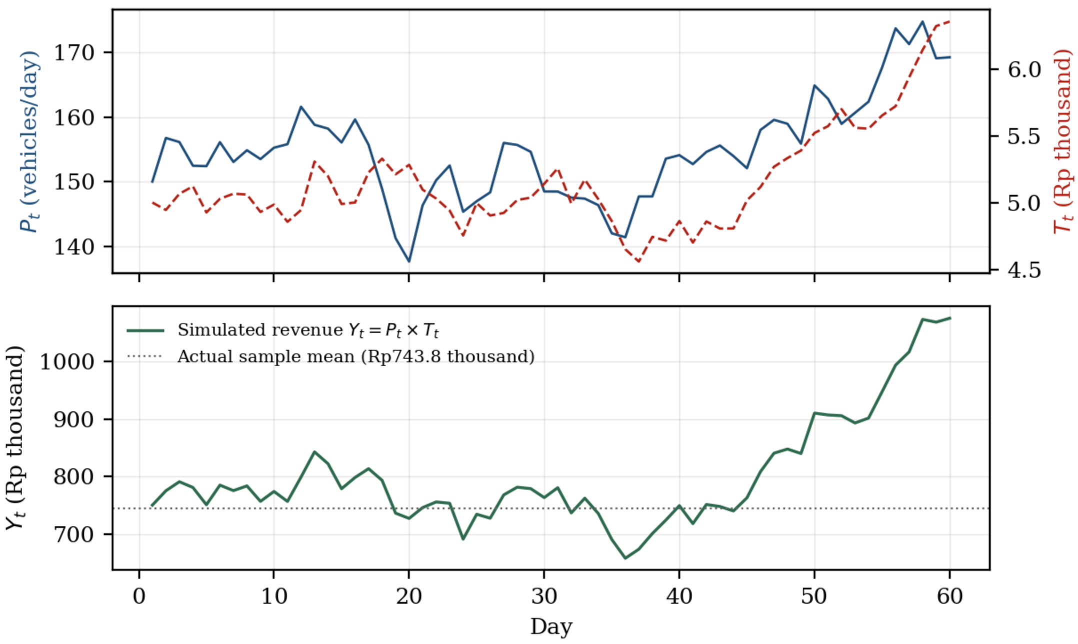

Figure 6: Simulated service volume, average tariff, and daily revenue over 60 days, with the actual sample mean for reference

The simulation reproduces the qualitative behaviour of the recorded data: revenue oscillates irregularly around its equilibrium as the two coupled components exchange influence, in the same way that energy is exchanged between the bobs of a double pendulum. Data generated by this mechanism can also serve as a controlled testbed for the ARIMA pipeline of Section IV, since the analyst knows the true data-generating process and can verify that the identification and estimation procedure recovers sensible dynamics.

5.3 Position of the Pendulum Analogy

For completeness, the equations of motion of the physical double pendulum can be written compactly as $\ddot{\theta}_1 = f(\theta_1, \theta_2, \dot{\theta}_1, \dot{\theta}_2)$ and $\ddot{\theta}_2 = g(\theta_1, \theta_2, \dot{\theta}_1, \dot{\theta}_2)$. It must be emphasised that the double pendulum model is not used to forecast revenue in this study. It serves solely as a methodological analogy illustrating that a business system with a small number of interacting operational variables can display complex dynamic behaviour, which is precisely why a statistical time-series model such as ARIMA — rather than naive extrapolation — is required for reliable forecasting.

5.4 Accounting Interpretation of the Simulation

The two-component formulation carries direct managerial accounting value. Because equation (14) separates revenue into volume and tariff, the entity can decompose any difference between budgeted and realised revenue into a volume variance, $(P_t - \bar{P})\times\bar{T}$, and a tariff variance, $(T_t - \bar{T})\times P_t$, directing attention to whether a shortfall stems from fewer vehicles or lower average tariffs [17]. The simulation additionally provides a scenario tool for budgeting: by adjusting α, γ, or the equilibria, the owner can examine how a tariff revision or a change in customer flow would propagate through revenue before committing to a pricing decision, and the resulting scenarios can be attached to the flexible budget prepared under the management accounting framework [18].

Appendix B: Simulation Program (Python)

```
import numpy as np
np.random.seed(7)
alpha, beta, gamma, delta = 0.15, 0.10, 0.010, 0.08
P_bar, T_bar = 150.0, 5.0      # vehicles/day, Rp thousand
P, T = [150.0], [5.0]
for t_ in range(59):
    eps = np.random.normal(0, 4)
    eta = np.random.normal(0, 0.12)
    P.append(P[t_] + alpha*(T[t_]-T_bar)*10
           - beta*(P[t_]-P_bar) + eps)
    T.append(T[t_] + gamma*(P[t_]-P_bar)
           - delta*(T[t_]-T_bar) + eta)
Y = np.array(P) * np.array(T)   # simulated daily revenue
print(Y.mean(), Y.std(), Y.min(), Y.max())
```

VI. CONCLUSION

This study set out to analyse the pattern of daily revenue and to construct a forecasting model for Nitrogen Go-Green Semarang, Central Java, Indonesia, using the Autoregressive Integrated Moving Average (ARIMA) method applied to the entity's own accounting transaction records. The integration of 1,866 shift-level source documents, whose revenue recognition practice is consistent with SAK EMKM and whose design embodies shift-based segregation, dual sign-off, and physical reconciliation controls, produced a complete and verifiable daily revenue series covering 22 November 2020 to 31 December 2025.

The stationarity analysis produced conflicting signals at the level — the ADF test rejected a unit root while the KPSS test rejected stationarity — so first-order differencing was applied as the conservative treatment, after which both tests confirmed stationarity. Among sixteen candidate specifications estimated on the training sample, ARIMA(3,1,3) minimised both AIC and BIC, and all six of its parameters were statistically significant at the 1% level.

On the 30-day holdout sample of December 2025, the selected model achieved a one-step-ahead MAPE of 9.94%, in the highly accurate category, and a 30-step dynamic MAPE of 12.31%, in the accurate category under the Lewis criteria. Re-estimated on the full sample, the model projects daily revenue for the following 30 days between approximately Rp826 thousand and Rp925 thousand, with a total of about Rp26.16 million, which was translated into the entity's monthly cash receipts budget.

From an accounting perspective, the results demonstrate three things: (1) orderly, SAK EMKM-based bookkeeping in an MSME is not merely a reporting obligation but a data asset that can be leveraged directly for statistical forecasting; (2) the forecast provides an objective basis for revenue budgeting, cash management, operator scheduling, and supplies planning, replacing intuition-based estimation; and (3) the daily forecasts and their prediction intervals form a natural benchmark for revenue variance analysis, with the volume–tariff decomposition of Section V directing managerial attention to the source of any deviation.

The study has limitations. The Ljung–Box diagnostics show that residual autocorrelation remains at the weekly lags, indicating a weekly seasonal component that a non-seasonal ARIMA specification cannot fully capture; the model also excludes external factors such as weather, public holidays, and traffic volume around the business location. Future research is therefore recommended to extend the specification to seasonal SARIMA, to compare ARIMA with exponential smoothing and machine-learning approaches, and to incorporate exogenous variables, in order to obtain forecasts that are more comprehensive and adaptive to changing business conditions.

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