Scientific Nexus

Vol 2(2) 2026:2745
https://doi.org/10.35472/scinexus.2745

RESEARCH ARTICLE

OPEN ACCESS

Comparative analysis of exponential and logistic growth models for predicting motorized vehicle population in Indonesia

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ABSTRACT

The increasing mobility of the Indonesian population has led to a high demand for motorized vehicles, posing significant challenges for infrastructure management and environmental sustainability. This study aims to compare the accuracy of exponential and logistic growth models and to predict the motorized vehicle population in Indonesia. Motorized vehicle data for the period 2015–2022 from the Central Bureau of Statistics (BPS) were processed using MS Excel to determine the parameters for both models and subsequently simulated using MATLAB. The optimal model was selected based on graphical plot results and the lowest Mean Absolute Percentage Error (MAPE) value. The analysis results indicate that the logistic model provides higher accuracy (MAPE = 0.54%) compared to the exponential model (MAPE = 1.50%). The motorized vehicle population is projected to reach 152,520,752 units in 2023 and is expected to continue increasing to 174,657,192 units by 2030. Furthermore, the logistic model demonstrates that the population growth rate will decelerate as it approaches its carrying capacity (K = 189,659,261 units). These findings serve as critical considerations for the government in formulating infrastructure planning and environmental protection strategies against emissions from operating motorized vehicles.

Keywords: Motorized Vehicles, Indonesia, Exponential Growth Model, Logistic Growth Model, MAPE, Population Prediction

PLAIN LANGUAGE SUMMARY

Indonesia has one of the fastest-growing motorized vehicle fleets in the world. Without accurate projections, governments cannot plan roads, reduce congestion, or limit vehicle emissions. This study compared two mathematical models (exponential and logistic) to predict how many motorized vehicles Indonesia will have between 2023 and 2030, using official data from 2015 to 2022. The logistic model proved more accurate (error of 0.54%) than the exponential model (error of 1.50%). It predicts approximately 174.7 million vehicles by 2030, approaching a natural ceiling of around 189.7 million. These findings can guide government decisions on infrastructure investment, public transport development, and environmental policy.

Introduction

Indonesia is one of the countries with the largest population in the world. Although the trend is declining, the average population growth rate in Indonesia for the period 2020–2023 was recorded at 1.11% [1]. This figure is considered high because it exceeds the global average for certain country groups [2]. Population density growth is a primary driver of the expansion in the number of vehicles or transportation modes [3]. Transportation plays a fundamental function in moving goods or people from one location to another [4]. Transportation is divided into three categories: land, sea, and air. Land transportation consists of various types of vehicles, including motorized vehicles and railways. Motorized vehicles themselves encompass several types, including motorcycles, passenger cars (both private and public transportation), buses, and freight vehicles such as trucks.

The increase in the number of motorized vehicles indicates the high mobility needs of Indonesian citizens. The adequacy of public transportation fleets in urban areas is still considered insufficient to meet this high mobility demand [5]. This has resulted in high use of private vehicles. The surge in private vehicle use and ownership is a key factor influencing environmental conditions because it is directly related to increased emissions [6][7]. In addition, rapid motorization poses challenges in traffic management [8]. Policy interventions are needed to address potential negative impacts, such as integrated transportation modeling [9][10]. This modeling will be used to forecast vehicle population growth in the future. Accurate population projections are the foundation for intelligent transportation planning [11].

Vehicle population dynamics can be modeled with kinetic equations [12]. However, this study uses mathematical models, namely exponential and logistic growth models. These models have been widely discussed in various studies, including research on motorized vehicle growth, specifically private four-wheeled vehicles with black license plates in Manado City, which used logistic population model differential equations [13]. Similar research compared ordinary differential equation exponential and logistic models in the population growth of Surabaya City, concluding that the logistic model was the most accurate [14]. Comparative analyses consistently show that logistic models often outperform exponential models [15].

Based on the foregoing, this study examines a comparison of exponential and logistic growth models to predict motorized vehicle growth in Indonesia (covering a broader geographic scope than previous studies) for the years 2023–2030 by comparing MAPE values and graphical model outputs.

Methods

This study was conducted through a series of systematic analytical steps. First, motorized vehicle population data in Indonesia for the period 2015–2022 were collected from the official website of the Central Bureau of Statistics (Badan Pusat Statistik/BPS) of Indonesia. These data served as the empirical basis for all subsequent modeling.

Following data collection, the relative growth rate parameter (r) was determined for both the exponential and logistic models. For the exponential model, r was calculated at each time interval using Equation (3), yielding seven distinct values corresponding to Models I through VII. For the logistic model, r was similarly derived from each time interval using Equation (7), and the carrying capacity (K) was estimated from the first three data points (N_0, N_1, N_2; corresponding to 2015–2017) using Equation (6), producing a single value of K = 189,659,261 units that was held constant across all seven logistic model variants (Models I–VII).

Both sets of models were then applied to calculate the projected motorized vehicle population for the period 2015–2022. The resulting projections were compared against actual BPS data by computing the Mean Absolute Percentage Error (MAPE) for each model variant using Equation (8). Graphical comparisons between model outputs and actual data were generated using MATLAB. The model yielding the lowest MAPE value—and whose graphical curve most closely tracked the actual data—was selected as the best model for each growth type. Finally, the superior model overall was used to project the motorized vehicle population in Indonesia for the years 2023–2030.

Exponential growth model

Thomas Malthus (1798) developed a basic model of population growth known as the exponential growth model. This model assumes a constant growth rate and is also called the Malthusian population growth model [16]. In this model, it is assumed that the population grows without environmental limitations, an assumption that becomes increasingly unrealistic as population size approaches the limits of available resources [17]:

$$dN(t)/dt = rN(t) \ldots (1)$$

The solution of equation (1) is:

$$N(t) = N_0 e^{\wedge}(rt) \ldots (2)$$

where N(t) is the population at time t, N_0 is the initial population, and r is the relative growth rate. If $r > 0$, the population increases exponentially; if $r < 0$, the population declines. The growth rate r is obtained from:

$$r = \ln(N\_t / N_0) / t \ldots (3)$$

Logistic growth model

The logistic growth model, also known as the density-based model, describes population growth influenced by intraspecific competition and density-dependent regulation [18]. This model considers environmental factors and resource availability, with the understanding that population size depends on density level, and birth and death rates are not always constant [19]. The logistic model was developed as a refinement of the exponential growth model to account for finite carrying capacity [20]. Based on the logistic law in which resources have limits, the logistic model shows that at a certain point, the population growth rate declines and the population approaches an equilibrium level [21].

Table 1. MAPE interpretation scale

MAPE Value	Interpretation
< 10%	Highly Accurate
10% – 20%	Good
20% – 50%	Reasonable
> 50%	Poor

Table 2. Motorized Vehicle Population Data 2015–2022

Year	Number of motorized vehicles
2015	105,303,318
2016	112,205,711
2017	118,922,708
2018	126,702,280
2019	133,617,012
2020	136,137,735
2021	142,001,698
2022	148,261,817

Source: Central Bureau of Statistics of Indonesia (BPS, 2022). https://www.bps.go.id

The general form of the logistic growth differential equation is [22]:

$$dN(t)/dt = rN(t)[1 - N(t)/K] \ldots (4)$$

where K is the carrying capacity. The particular solution is [23]:

$$N(t) = K / [1 + e^{(-r(t-t_0))}] \ldots (5)$$

The carrying capacity K is estimated from the first three data points (N_0, N_1, N_2) using [22]:

$$K = (N_1(N_1N_0 - 2N_0N_2 + N_1N_2)) / (N_1^{\,2} - N_0N_2) \ldots (6)$$

The logistic growth rate r is estimated using:

$$r = -\ln[(N_0(N_2 - N_1)) / (N_2(N_1 - N_0))] / t \ldots (7)$$

Mean absolute percentage error (MAPE)

Mean Absolute Percentage Error (MAPE) is the average absolute difference between estimated and actual values expressed as a percentage [24]. This approach is used when the magnitude of the predicted variable is important in assessing prediction accuracy, and is considered one of the most easily interpreted accuracy measures by decision makers [25]. MAPE is also very effective for comparing model performance across different scales [26]:

$$MAPE = (1/n)\ \Sigma|Y\_t - Y'\_t| / Y\_t \times 100\% \ldots (8)$$

where Y_t is the actual population value, Y'_t is the projected value, and n is the number of data points. The MAPE interpretation scale used is from Lewis (1982) [27] (Table 1):

Results

The data used in this study are motorized vehicle population data in Indonesia for the period 2015–2022 obtained from the website of the Central Bureau of Statistics (Badan Pusat Statistik/BPS) of Indonesia (Table 2).

Exponential growth model results

Setting t = 0 for the year 2015, seven exponential models (I–VII) were derived by calculating the growth rate r from each successive time point using Equation (3). The calculated growth rates range from 0.04888 (Model VII) to 0.06349 (Model I). Each model was applied to estimate vehicle populations from 2015 to 2022. The error values (MAPE) for all seven exponential models were calculated using Equation (8). Model V (r = 0.05136, corresponding to the 2015–2020 growth rate) yielded the lowest MAPE of 1.50% (< 10%), indicating high accuracy according to the Lewis (1982) scale. Therefore, the best exponential model is:

$$N(t) = 105{,}303{,}318 \times e^{(0.05136t)}$$

Table 3. Predicted Motorized Vehicle Population 2023–2030

Year	Predicteon ppulation
2023	152,520,752
2024	156,766,425
2025	160,619,147
2026	164,094,193
2027	167,211,519
2028	169,994,280
2029	172,467,541
2030	174,657,192

Logistic growth model results

The carrying capacity was estimated using Equation (6) from the first three data points (2015–2017), yielding K = 189,659,261. Seven logistic models (I–VII) were then derived using growth rates calculated from Equation (7) for each time interval. Growth rates range from 0.02127 (Model VII) to 0.14886 (Model I). Logistic Model I, using the growth rate derived from the 2015–2016 data (r = 0.14886), yielded the lowest MAPE of 0.54% (< 10%), indicating the highest accuracy. The best logistic model is:

$$N(t) = 189{,}659{,}261 \;/\; [(189{,}659{,}261/105{,}303{,}318 - 1)e\text{^}(-0.14886t) + 1]$$

Comparing the MAPE values of the best exponential (1.50%) and logistic (0.54%) models, the logistic model demonstrates superior accuracy. Figure 3 [see original manuscript] illustrates that the actual data values more closely approximate the logistic model curve.

Vehicle population prediction 2023–2030

Using the best logistic model, the projected motorized vehicle population for 2023–2030 is shown Table 3.

The projected figures indicate a continuing increase of approximately 2–4 million units per year, approaching but not exceeding the carrying capacity K by 2030.

Discussion

This study found that the logistic growth model provides superior accuracy compared to the exponential model, both in terms of MAPE calculation (0.54% vs. 1.50%) and graphical fit. This finding aligns with previous studies demonstrating that population systems with bounded carrying capacity are more accurately represented by logistic models [22]. The logistic model is theoretically grounded in the principle that resources are finite, meaning populations cannot grow indefinitely without environmental constraints [18].

The higher intrinsic growth rate estimated by the logistic model (r = 0.14886 per year for Model I) compared to the best exponential model (r = 0.05136 per year for Model V) requires contextual explanation. In the logistic framework, the initial r parameter reflects the maximum per capita growth rate when density effects are minimal (i.e., when N << K), whereas the exponential r represents an average observed rate over the entire study period. The logistic r is thus a theoretical maximum that is progressively dampened by the term (1 − N/K), resulting in the observed deceleration of growth as the population approaches the carrying capacity. This distinction is important for interpreting the models correctly.

The projected increase in motorized vehicles to 174,657,192 units by 2030, with the carrying capacity set at K = 189,659,261 units, implies that Indonesia's vehicle fleet is expected to approach approximately 92% of its estimated saturation level within the decade. This is consistent with vehicle saturation models applied in emerging Asian economies, where logistic growth functions with income-adjusted saturation levels have been used to project vehicle stock [3]. However, it is worth noting that the carrying capacity K was estimated from only three initial data points (2015–2017) using the analytical formula from Tsoularis and Wallace

[22], which may underestimate the true saturation level given the continued strong growth observed through 2022. This limitation should be considered when interpreting long-range projections.

The projection results have important policy implications. The continued growth of the vehicle fleet directly contributes to urban traffic congestion [8] and increased emissions, which are negatively associated with environmental quality [6][7]. These findings can serve as a quantitative basis for the government in formulating transportation policy, infrastructure planning, and environmental protection strategies, including promotion of public transport and emission reduction measures. Future research should incorporate additional variables such as income levels, fuel prices, urbanization rates, and electric vehicle adoption to improve predictive accuracy.

Conclusion

After comparing MAPE values and graphical results, the best model is the logistic growth model: $N(t) = 189{,}659{,}261 / [(189{,}659{,}261/105{,}303{,}318 - 1)e^{(-0.14886t)} + 1]$, with a relative growth rate of approximately 14.89% per year and a carrying capacity of K = 189,659,261 units. The logistic model outperformed the exponential model with a MAPE of 0.54% compared to 1.50%. Using this model, motorized vehicle population predictions for 2023–2030 show a continuing annual increase, reaching 174,657,192 units by 2030, with the growth rate decelerating as the population approaches the carrying capacity.

Acknowledgment

We extend our sincere gratitude to Department of Mathematics Institut Teknologi Sumatera for facilitating the conduct of this research.

Declaration of interest

The authors have no conflicts of interest to declare.

Author contributions

SWA: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft; NR: Conceptualization, Methodology, Supervision, Validation, Writing – review & editing; DMMN: Formal analysis, Software, Visualization, Writing – original draft; NIS: Data curation, Investigation, Writing – original draft

Received: April 1, 2026
Revised: May 6, 2026
Accepted: May 6, 2026
Published: June 29, 2026

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