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EID Al-Fitr Homecoming Traffic Prediction to Anticipate Continuity on the Jakarta-Cikampek Toll Road

Ayu Dwi Rahmawati[1], Saut Panggabean Sinaga[2], Novi Indah Earlyanti[3]
Indonesian National Police Traffic Corps, Jakarta, Indonesia[1]
Police Science College (STIK – PTIK), Jakarta, Indonesia[2,3]
adrahmawati99@gmail.com[1], saut@stik-ptik.ac.id[2], noviindahearlyanti@stik-ptik.ac.id[3]

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Abstract

Purpose: This study focuses on homecoming traffic flow prediction for sustainable anticipation to overcome the surge in traffic flow on the Jakarta-Cikampek Toll Road. This study aims to identify traffic patterns based on historical data, develop a time-series prediction model (ARIMA), and evaluate congestion levels using the Volume Capacity Ratio (VCR). The main issue is the high traffic flow during homecoming, which requires predictive and proactive approaches. This study uses concepts and theories such as traffic management, traffic flow characteristics, and time series prediction models (ARIMA and decomposition). This quantitative study analyzed historical data from Jasa Marga (2019–2024).

Research Methodology: This quantitative study analyzed historical data from Jasa Marga (2019–2024). Analytical techniques included in this study, such as stationarity tests, ARIMA parameter identification, and VCR calculations, were used to assess congestion.

Results: The results indicate that peak homecoming traffic occurs from H-5 to H-1, whereas returning traffic peaks from H+2 to H+5. The SARIMA (1,1,2) $(2,1,2)^{22}$ model was more accurate in capturing seasonal patterns than the decomposition model. The VCR indicator is more than 1.0 during peak days, which indicates a congested road. These findings support traffic management strategies, such as contraflow and one-way systems. In conclusion, historical data-based prediction models can be used to effectively anticipate future traffic congestion.

Conclusions: Historical data models can effectively anticipate congestion and support contraflows in urban traffic.

Limitations: Stakeholders must enhance their data, infrastructure, awareness, and sustainable transportation.

Contributions: This study used the Jakarta–Cikampek Toll Road for the results.

Keywords*: ARIMA, Jakarta-Cikampek Toll Road, SARIMA, Traffic Engineering, VCR*

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1. Introduction

The high mobility of Indonesians, including the tradition of going home for Eid al-Fitr, demonstrates strong sociocultural characteristics in seeking a better life and fostering relationships (Fuad, 2011; Japarudin, 2023). This annual tradition causes a surge in traffic volume, especially on strategic routes such as the Jakarta-Cikampek Toll Road, which connects Greater Jakarta with Central and East Java (Oktavio & Indrianto, 2019). Data from Jasa Marga show an increasing trend in the number of vehicles passing through the Cikampek Utama Toll Gate from 2020 to 2024, with an anomalous decrease in 2020 owing to mobility restrictions during the pandemic.

Based on this trend, it is estimated that the 2025 homecoming flow will surge as economic conditions improve and political dynamics change in the coming years. Therefore, effective traffic management is crucial (Kadarisman, Arubusman, & Kania, 2014). In this regard, the National Police's PRESISI Program, which emphasizes a predictive approach, is highly relevant to the present study. The National Police, particularly the Traffic Corps (Korlantas), utilize technology and data to implement real-time traffic engineering, such as one-way systems, contrast flows, and rest area management (Empat Pilar Transformasi, 2022; Evanita, Noersasongko, & Pramunendar, 2016).

For example, in 2022, the Traffic Corps (Korlantas) modified the starting point of the one-way system from KM 47 to KM 70 and implemented a contraflow to address traffic congestion in Bandung. However, the policies adopted are often situational and not fully based on predictive approaches (Hendrawan, 2020; Rio, 2024). However, data-driven methods, such as time-series analysis and machine learning, have proven effective in other countries. The Volume, Capacity, and Ratio (VCR) approach is an analytical framework that can be used to scientifically understand congestion patterns (Febrianaa, Salima, & Darwisa, 2022; Risdiyanto, 2014; A. R. Wibowo, 2017).

The V/C ratio can predict potential congestion, whereas the average speed is an indicator of traffic engineering effectiveness (Febrianaa et al., 2022). This study aims to develop a historical data-based exodus traffic prediction model using the VCR approach to support sustainable traffic engineering decisions on the Jakarta-Cikampek Toll Road. Therefore, the research results are expected to contribute to the Indonesian National Police Traffic Corps (Korlantas Polri) and related parties by designing more efficient, predictive, and adaptive traffic strategies.

2. Literature Review

2.1 Understanding the Homecoming Flow

Mudik (homecoming) is a distinctive Indonesian tradition, particularly in Java, reflecting efforts to maintain a balance between rural and urban life. This tradition is important for migrants to return home, reconnect, reminisce about the past, and reaffirm family ties (Fuad, 2011; Hamidah, Salam, & Susanti, 2017). Similar phenomena have been observed in other countries, such as the Lunar New Year in China, Thanksgiving in America, and Diwali in India, where people travel en masse to their hometowns to celebrate holidays. In Indonesia, the desire to mudik often stems from an emotional longing for one's hometown after moving to a large city for economic improvement (Hamidah et al., 2017; Karimullah, 2021).

Sorokin (1959) in *Social and Cultural Mobility* stated that social mobility is the movement of individuals within a social structure that can be triggered by economic factors, education, employment, and incompatibility with the social environment. He divided mobility into horizontal and vertical (Ita Yulianto, 2019; Marta, Fauzi, Juanda, & Rustiadi, 2020). Mudik is included in horizontal mobility because it does not change social status, but only changes location temporarily (Alkatiri, Mokodompit, & Paramata, 2025; Suryawan, Husainah, Latuconsina, Pahala, & Sumardi, 2025). However, it still plays an important role in maintaining family solidarity and social balance between the cities and villages.

Sorokin also explained that social mobility can accelerate social integration and carry the risk of instability. Mobility opportunities are not always equal because they depend on access to channels such as education and social organizations. For example, the joint homecoming program of companies or state-owned enterprises is a form of horizontal social mobility facilitation (Ogushi, Roy, & Kaski, 2025; A. R. Wibowo, Soesanti, & Widyawan, 2018). From Robert K. Merton's perspective through *Strain Theory*, the tradition of going home can also be seen as a response to social pressure (Baderan, Lantowa, Makur, & Idji, 2025).

The tension between the strong desire to go home and limited means can cause social stress or even deviant behavior (Putra, Indriani, Midiastuty, Suranta, & Rahmat, 2025; Turner, 2013). Furthermore, going home becomes a means of relieving alienation due to the pressures of industrial culture and capitalism, which make people feel alienated from their true selves. In this context, going home functions as a process of reflection and spiritual healing (Fuad, 2011; Machmud, Imbran, & Baderan, 2025; M. Wibowo & Widayanti, 2023).

2.2 Toll Road Traffic Management

Traffic management is the process of regulating an existing road system to achieve specific goals without the need to build new infrastructure (Harahap et al., 2018; Risdiyanto, 2014). This management encompasses four main functions: physical changes to the road system, non-physical changes (such as one-way systems and parking arrangements), information provision (signs, markings, and routes), and tariff-setting. Traffic management is more effective when it is implemented before severe congestion occurs.

This strategy is an important alternative for building new roads, which have social impacts and are not always effective in reducing congestion (Muslih, Abduljabbar, & Joni, 2023; Risdiyanto, 2014). Toll road traffic management is crucial to address the surge in mobility during the homecoming period. Traffic management during the homecoming period requires technical, tactical, and operational strategies to ensure smooth flow, safety, and user comfort (C. J. Khisty & Lall, 2005; Risdiyanto, 2014). Key strategies include:

1. Traffic Engineering: Implementation of *one-way* and *contraflow*, as well as toll access arrangements.
2. Monitoring and Surveillance: Use of CCTV, drones, and traffic control teams.
3. Rest Area Management: Capacity management and provision of emergency facilities.
4. Speed Control: *Speed Guns*, ETLE, and Speed Information Boards.
5. Information and Communication: Coordination with navigation applications, digital boards and traffic radio broadcasts.
6. Security and Safety: Security posts, highway patrols, ambulances, and towing services are provided.
7. Temporary Capacity Increase: Use of alternative routes and functional toll roads.
8. Education and Socialization: Safety campaigns and dissemination of alternative route guides.

2.3 Traffic Flow Characteristics

Traffic flow is a complex phenomenon influenced by various factors, such as increased vehicle volume, which generally reduces speed, and random interactions between vehicle and driver characteristics. Therefore, traffic flow can be modeled stochastically *(* probability-based) or *deterministically* (certainty-based) (C. J. Khisty, . Dan B. Kent Lall., 2005).

Three main parameters were used to analyze the traffic flow (Risdiyanto, 2014; PKJI, 2023).

1. **Traffic Flow Volume**.
   Volume is defined as the number of vehicles passing a point per unit of time, expressed as smp/h or vehicles per hour. The general formula is:
   $$\mathbf{Q} = \frac{N}{T} \tag{1}$$
   Q = Volume (smp/hour)
   N = Number of vehicles (vehicles)
   T = Observation time (hours)
   Volume is an important component of traffic engineering because it describes the intensity of movement at a particular point.

2. **Traffic Flow Speed**.
   Speed is defined as the distance traveled divided by the travel time.
   $$V = \frac{S}{T} \tag{2}$$
   V = Speed (km/h, m/s)
   S = Distance traveled (km, m)
   T = Travel time (hours, seconds)

There are three known types of speed:

- *Spot speed:* vehicle speed at a certain point
- *Running speed:* average speed when the vehicle is moving
- *Journey speed*: The effective speed between two points refers to the travel speed as the main indicator of road segment performance.

3. **Traffic Flow Capacity**

Capacity is the maximum volume of vehicles that can pass through a road under normal conditions (Risdiyanto, 2014). Capacity formula:

$$C = Co \; x \; FCw \; x \; FCsp \; x \; FCsf \; x \; FCcs \tag{3}$$

C = Capacity (smp/hour)
Co = Basic Capacity (smp/hour)
FCw = Road width adjustment factor
FCsp = Direction separation adjustment factor (only for unexpected roads)
FCsf = Side and shoulder obstacle adjustment factor
FCcs = City size adjustment factor

The above equation can be expressed as follows:

- *Basic capacity*: ideal conditions without interference
- *Possible capacity:* under existing conditions
- *Practical capacity:* when there is high density and slowdown

2.4 Decomposition and Arima Forecasting Models

Forecasting is a method for predicting future events based on past data patterns using mathematical and statistical methods (Cryer & Chan, 2008; Wei, 2006). The goal was to obtain the best approximation of future events. Two commonly used methods are decomposition and ARIMA (Annisa Khoiri, 2023; Ramadhan & Nugraha, 2023).

1. Decomposition Method

This method separates time-series data into four components.

- Trend (Tt): long-term change (up/down)
- Cycle (Ct): recurring long-term fluctuations
- Seasonal (It): constant periodic fluctuations
- Error (Et): random or random element

The four steps above can be formed in a multiplicative or additive form

$$X_t = I_t \; x \; T_t \; x \; C_t \; x E_t \qquad \text{or} \qquad X_t = I_t + T_t + C_t + E_t \tag{4}$$

The four steps of decomposition remove seasonality, calculate trends, separate cycles, and identify errors (Wei, 2006).

2. Time Series Model

Data observations are based on a fixed time sequence, such as daily, monthly, or yearly (Wei, 2006).

3. ARIMA (Autoregressive Integrated Moving Average) model

A combination of autoregressive (AR) and moving average (MA) models with the *d component* as a differentiator. This model analyses trends, seasonality, and autocorrelation in the data (Cryer & Chan, 2008; Wei, 2006). Parameter determination is performed by testing for stationarity, determining p, d, qp, d, and q, and evaluating the model using the AIC and BIC criteria. The model is denoted as ARIMA (p, d, q). Tools such as Excel, Minitab, R, EViews, and Python facilitate modelling and visualization.

Considering the problems that have been identified and the theories that have been described, this study formulates the following framework:

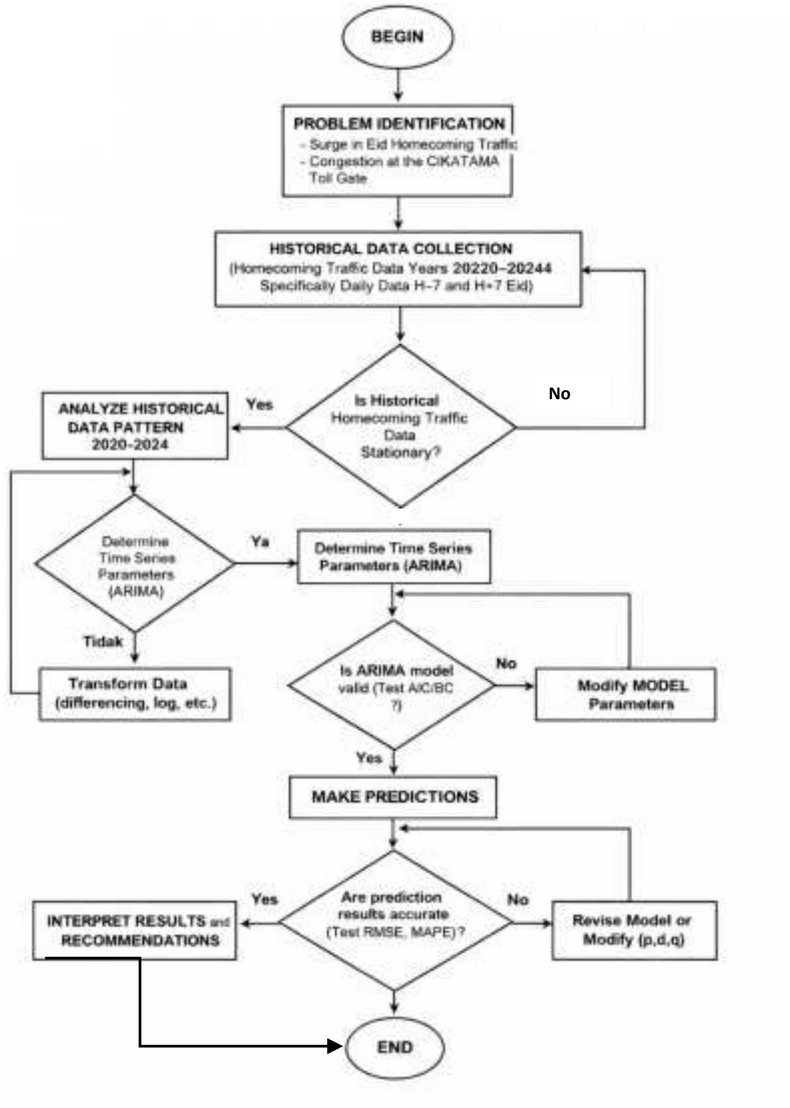

Figure 1. Research flowchart of ARIMA based homecoming traffic prediction

3. Research Methodology

This study uses a quantitative approach with a predictive method based on time-series analysis to analyze historical traffic flow data on the Cikampek Toll Road, especially leading up to the Eid al-Fitr holiday. The main model used is the Autoregressive Integrated Moving Average (ARIMA), which can capture autocorrelation, long-term trends, and seasonal patterns in the data through stationarity testing, parameter determination (p, d, q), and model evaluation using AIC and BIC. For comparison, a time-series decomposition model was also used to separate the data into trend, seasonal, and residual components to identify fluctuations in the exodus flow.

The study population comprised historical data on vehicle traffic flow on the Cikampek Toll Road for several years leading up to Eid al-Fitr, and the sample was selected purposively from 2000 to 2024, with a focus on data from D-7 to D+7 of Eid, containing vehicle volume, vehicle type, and peak density times. The main variable in this study was the daily traffic volume, with predictor variables including seasonal patterns, long-term trends, noise (random errors), and peak days of exodus. These two analysis methods were used to generate accurate predictions of future homecoming traffic patterns, thereby supporting sustainable traffic-management strategies. Minitab version 19 software is used for the analysis to avoid the limitations of manual calculations. (Alghamdi, Elgazzar, Bayoumi, Sharaf, & Shah, 2019; Kumar & Vanajakshi, 2015; Liu & Shin, 2025).

The data collection technique in this study was carried out through a documentation method utilizing secondary data from relevant agencies, such as Jasa Marga and the Transportation Agency. The collected data included daily traffic flow during the Eid al-Fitr homecoming period, vehicle type data, peak density times, and vehicle distribution by day and by hour. The data collection process began with source identification, selection, and verification of the completeness and consistency of the data, and initial data processing into a time-series dataset for further analysis (Chen, Wang, Hua, & Zhao, 2022). Two main data analysis techniques were used: ARIMA and time series decomposition. ARIMA was performed through the stages of data processing, component identification, modeling, validation, prediction, and visualization.

The model was evaluated using AIC, BIC, and RMSE. The decomposition model was used to understand the trend, seasonality, and residual components without stationarity requirements, as in the ARIMA model. The two methods were compared in terms of their approach, stationarity requirements, and intended use. In addition, this study applied Velocity, Capacity, Ratio (VCR) analysis to measure traffic efficiency during homecoming flow. The VCR was analyzed based on the average vehicle speed, toll road capacity, volume-to-capacity ratio, and their impact on congestion. The analysis was conducted at critical points, such as toll gates and rest areas. The VCR results are used as a basis for developing traffic management strategies, such as lane engineering, travel time adjustments, and increasing vehicle flow speeds. Through case studies and scenario comparisons, the VCR analysis demonstrated its potential to support more efficient and responsive traffic policies for the surge in homecoming traffic (Kumar & Vanajakshi, 2015).

4. Results and Discussions

4.1 Data Analysis of the Number of Vehicles Passing Through the Cikatama Toll Gate 2019–2024

Data observation in this study focused on the Cikampek Utama (Cikatama) Toll Gate, a strategic route connecting Jakarta with Central and East Java, especially during the Eid al-Fitr exodus period. This 73-kilometer toll road has an average capacity of 60,000 vehicles per day and experiences a volume spike of up to 200% during the peak exodus period. The data used were sourced from PT. Jasa Marga for the period 2019–2024, covering 22 observation days each year (D-10 to D+10), with a total of 132 daily samples, categorized by vehicle direction—towards Trans Java and into Jakarta.

Model testing was conducted using ARIMA and decomposition approaches, each of which requires the data to be in a time-series form, have trends, seasonality, random fluctuations (residuals), and a sufficient data length. The ARIMA model requires stationary data, whereas decomposition does not. The data must also be void-free or handled through interpolation or average estimation to maintain the consistency of the analysis. The ARIMA process includes model identification, parameter estimation, diagnosis, evaluation, and forecasting, whereas decomposition is used to understand the data components before entering the prediction stage.

4.1.1 Model Identification (Problem)

Problem identification aims to determine the most appropriate model, either decomposition or ARIMA, by analyzing the trend, stationarity, and seasonality of data. If these three components are satisfied, the prediction process can be performed. The parameter determination was performed using Minitab version 21.

a. Data Analysis of the Cikatama Toll Gate (Trans Java Direction)

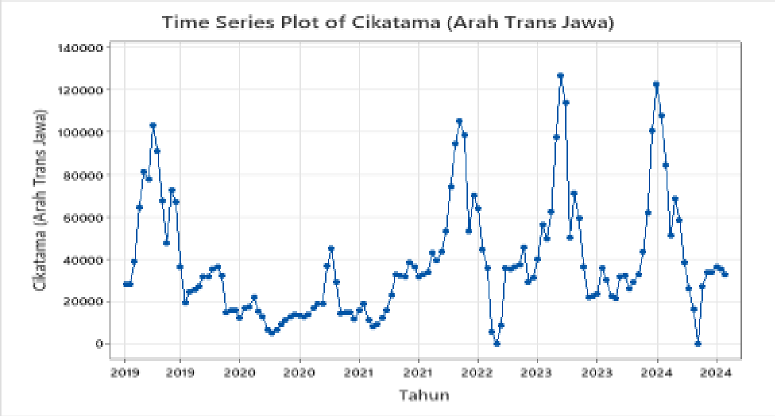

Figure 2. Graph of the number of vehicles passing through the toll gate Cikatama (Trans Java direction) 2019 – 2024

The image above shows that the data have a recurring pattern, and the highest peak of vehicle density data in 2019, on the 4th day (D-4) before Eid al-Fitr, amounted to 103,077 vehicles. Likewise, the peak density on the 3rd day (D-3) in 2022 was 105,016 vehicles, then on the 3rd day (D-3) was 126,876 vehicles, on the 2nd day (D-2) was 114,227 vehicles in 2023, on the 5th day (D-5) was 100,811 vehicles, on the 4th day (D-4) was 122,607 vehicles, and on the 3rd day (D-3) was 107,717 vehicles in 2024.

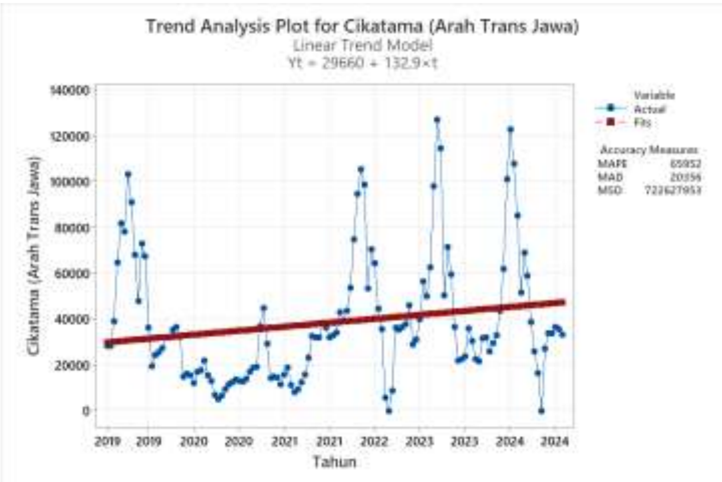

Figure 3. Graph of trend in number of vehicles passing through toll gates Cikatama (Trans Java direction) 2019 – 2024

The red line shows the increasing trend in vehicle flow at the Cikatama Toll Gate. However, the MAPE value of 65.952% indicates a very large prediction error and a highly inaccurate model. The MAD of 20,356 and MSD of 722,627,953 also indicate that the model failed to capture the data pattern, likely because of the outliers or high variability. Re-evaluation of the data and selection of an alternative model are necessary to improve prediction accuracy.

b. Analysis of Cikatama Toll Gate Data on Return Flow of Vehicles (Jakarta Inflow)

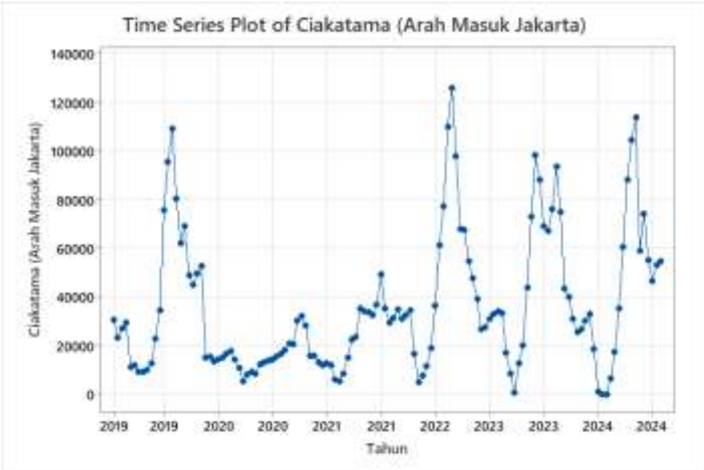

Figure 4. Graph of the number of vehicles passing through the Cikatama toll gate (Jakarta inflow) 2019 – 2024

The data show a recurring peak in vehicle density every two to four days after Eid al-Fitr, with the highest recorded three days after Eid al-Fitr in 2019, with 109,166 vehicles recorded. Similar peaks were observed in 2022, 2023, and 2024. Meanwhile, in 2020 and 2021, vehicle volumes dropped drastically by approximately 50% owing to mobility restrictions during the Covid-19 pandemic, in line with government travel restrictions.

Figure 5. Trend graph of number of vehicles through the gate Cikatama toll road (Jakarta inflow) 2019 – 2024

A MAPE value of 151% indicates that the average prediction error far exceeds the actual value, rendering the model highly inaccurate. The MAD of 20,483 is also considered high compared with the maximum data scale of 140,000. Meanwhile, an MSD of 727,194,471 indicates the presence of outliers or high variability that the model missed. Overall, this model fails to capture the data patterns and requires improvements through transformation or differentiation.

4.1.2 Prediction Estimation Using Decomposition Method

Decomposition or the ARIMA method can be used to predict homecoming traffic events in 2025. The Decomposition model excels because it explicitly separates data into trend, seasonal, and residual components, making the data patterns easier to interpret. If the trends and seasonal patterns in the data are strong, this model tends to capture the natural characteristics of the data accurately.

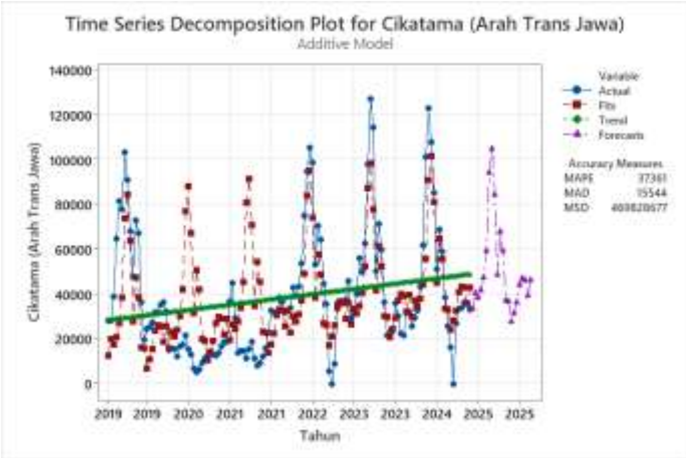

Figure 6. Prediction graph using the decomposition method for the number of vehicles passing through the Cikatama toll gate (Trans Java direction) in 2025

The predicted 2025 exodus traffic towards the Trans-Java route (purple line) is still below the 2023 and 2024 exodus traffic (blue lines or actual data). This is unconvincing considering that exodus traffic is expected to increase by approximately 1% to 2%. The trend line, which still follows the fit line (green line), indicates a less than optimal pattern. A comparison table between the actual 2024 data and 2025 predictions demonstrates this difference.

Table 1. Prediction using the decomposition method of the number of vehicles passing the Cikatama toll gate (Trans Java direction) in 2025

No. Sample	**Year**	**Day**	**Cikatama (Trans Java Direction)**	**Sample No.**	**Year**	**Day**	**Prediction (Trans Java Direction)**
...	...	...	...		2025	H-10	40478
111	2024	H-10	25927	133		H-9	38273
112		H-9	29390	134		H-8	41457
113		H-8	32786	135		H-7	47518
114		H-7	43358	136		H-6	59191
115		H-6	61863	137		H-5	94154
116		H-5	100811	138		D-4	104979
117		D-4	122607	139		H-3	84408
118		H-3	107717	140		H-2	48520
119		H-2	84913	141		H-1	68019
120		H-1	51298	142		H1	59081
121		H1	68750	143		H2	37106
122		H2	58673	144		H+1	36533
123		H+1	38533	145		H+2	27638
124		H+2	25823	146		H+3	31480
125		H+3	16229	147		H+4	36247
126		H+4	0	148		H+5	44262
127		H+5	27075	149		H+6	46884
128		H+6	33616	150		H+7	46257
129		H+7	33800	151		H+8	39338
130		H+8	36501	152		H+9	46335
131		H+9	35451	153		H+10	36687
132		H+10	33000	154	...	...	...

The 2025 exodus flow prediction using a decomposition model showed peak vehicle flow on the 5th, 4th, and 3rd days before Eid, with a slight decrease in vehicle flow at the Cikatama Toll Gate heading towards Trans Java. This decrease was influenced by significant changes in the 2021 and 2022 data, which affected the prediction unless both data sets were excluded. The prediction equation model for the number of vehicles exiting Trans-Java is as follows:
The form of the prediction equation model (***Linear Trend***) for the number of vehicles leaving (Trans Java) is,

$$\mathbf{Y_t = 219660 + 133*T \text{ (T Prediction time)}} \quad \mathbf{(5)}$$

Predictions were made using the decomposition method in Minitab by selecting the multiplication mode and generating a continuous prediction graph.

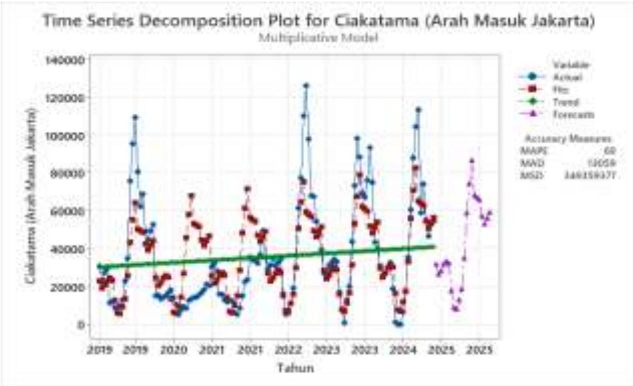

Figure 6. Prediction graph using decomposition method number of vehicles passing through the Cikatama toll gate (Jakarta entry direction) 2019 – 2024

The 2025 exodus traffic forecast for Jakarta shows that the predicted value (blue) is still below the 2023 and 2024 exodus traffic forecasts (black line or actual data) and is consistent with the fit line. Although the results are not optimal, this prediction provides sufficient information regarding the days with potential traffic congestion.

Table 2. Prediction using vehicle number decomposition method those passing through the Cikatama toll gate (entrance to Jakarta) 2025

No. Sample	Year	Day	Cikatama (Direction to Jakarta)	Sample No.	Year	Day	Prediction (Direction to Enter Jakarta)
...	...	...	...	133	2025	H-10	31804.6
111	2024	H-10	30,951	134		H-9	33506.9
112		H-9	25,660	135		H-8	37013.2
113		H-8	26,700	136		H-7	38726.6
114		H-7	30,191	137		H-6	42298.9
115		H-6	32,828	138		H-5	23037.4
116		H-5	18,802	139		D-4	13604.2
117		D-4	1,170	140		H-3	11160.5
118		H-3	0	141		H-2	17105,1
119		H-2	0	142		H-1	25605.9
120		H-1	6,444	143		H1	43598.9
121		H1	17,398	144		H2	64957.7
122		H2	35,419	145		H+1	81269.2
123		H+1	60,617	146		H+2	93295.1
124		H+2	88,044	147		H+3	74268.1
125		H+3	104,268	148		H+4	72910.4

126		H+4	113,455	149		H+5	72270.8
127		H+5	58,810	150		H+6	60198.5
128		H+6	74,016	151		H+7	59393.9
129		H+7	55,126	152		H+8	57030.0
130		H+8	46,690	153		H+9	56701.2
131		H+9	52,958	154		H+10	39820.3
132		H+10	54,526	...		...	...

Predictions of the return flow of homecoming vehicles in 2025 using a decomposition model showed that the peak flow of vehicles passing through the Cikatama toll gate towards Jakarta decreased. However, overall, there was an increase in the number of vehicles every day, with an increasing data distribution. The form of the prediction equation model (*Linear Trend*) is as follows:

$$\mathbf{Y_t = 2\ 1822 + 2\ 1\ 1 * T} \quad \textbf{(6)}$$

4.1.3 Prediction Estimation Using the Arima Method (Sarima)

a. Stationarization of Data on the Number of Vehicles Passing the Cikatama Toll Gate (Trans Java Direction)

Figure 7. Minitab acf and PACF commands number of vehicles via the cikatama toll gate (Trans Java direction) 2019 – 2024

The ACF and PACF graphs for the number of vehicles passing through the Cikatama Toll Gate (Jakarta Inflow) in 2019–2024 show that the data are not yet stationary because the lag exceeds 0.5, and there is one PACF line that passes the value of 0.5. This indicates that the mean, variance, and covariance of the data change over time. Therefore, differencing is necessary to make the data stationary**.**

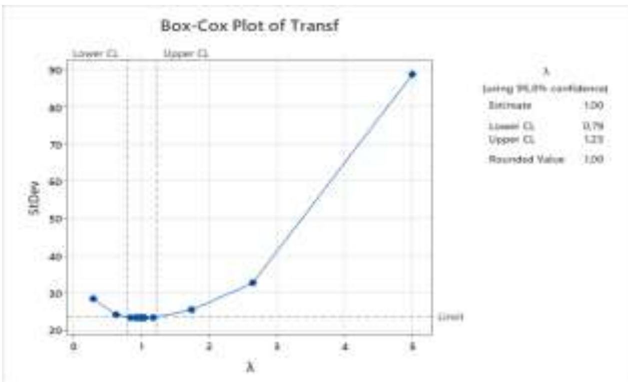

Figure 8. Results of the *Ljung-Box test* number of vehicles passing cikatama toll gate (Trans Java direction) 2019 – 2024

The result is a Rounded Value of 1, meaning that the data are stationary in terms of variance. The "Transf" data were then processed to obtain the stationary data on average.

Augmented Dickey-Fuller Test

Null hypothesis: Data are non-stationary
Alternative hypothesis: Data are stationary

Test Statistic	P-Value	Recommendation
-3,92651	0,002	Test statistic <= critical value of -2,88404. Significance level = 0,05 Reject null hypothesis. Data appears to be stationary, not supporting differencing.

Figure 9. Adf test results acf and PACF transformation graphs data on the number of vehicles passing through the Cikatama toll gate (Trans Java direction) 2019 – 2024

Based on the results of the augmented Dickey (ADF) test, the following can be explained.

1. Hypothesis in ADF Test: H_0 (Null Hypothesis): Data are not stationary (have a unit root), and H_1 (Alternative Hypothesis): Data are stationary (do not have a unit root).
2. Results: Test Statistic = – 3.92651 with Critical Value ($\alpha = 5\%$) = - 2.88404 with P-Value = 0.0 0 2 (less than 0.05).
3. Test Decision: Because the test statistic (– 3, 92651) is smaller than the critical value (- 2, 8 8404), then reject H_0. The P-Value of 0.0 0 2 < 0.05 indicates that we have enough evidence to reject H_0, which means that the data are considered stationary on average at the 5% significance level.
4. Conclusion: There is no need to differencing the "Transf" data because the data are already stationary on average. Therefore, differencing is neither necessary nor recommended because it can lead to over-differencing, which eliminates important information from the data

No residual autocorrelation (Ljung-Box Test)

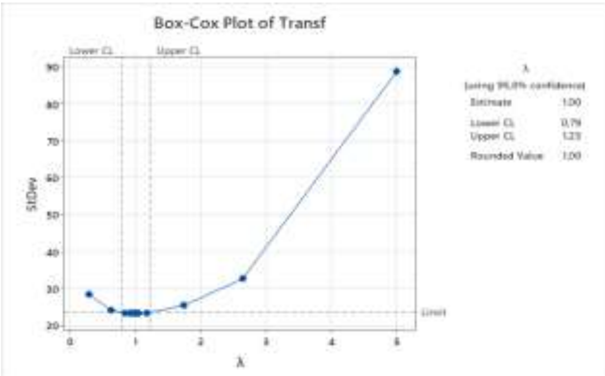

Figure 10. Results of the *Ljung-Box* residual test for vehicle number data through the Cikatama toll gate (Jakarta entry flow) 2019 – 2024

A Rounded Value of 1 means that the data no longer have residual autocorrelation. Therefore, we can continue to find the Arima parameter values (p,d,q).

Selecting Parameter Values (p, d, q) According to ACF and PACF

The ACF and PACF residual plots for the Cikatama data (Trans Java direction) show all values within the significance limits with no clear autocorrelation pattern. This indicates that the residuals are autocorrelation-free; thus, the model adequately captured the data structure.

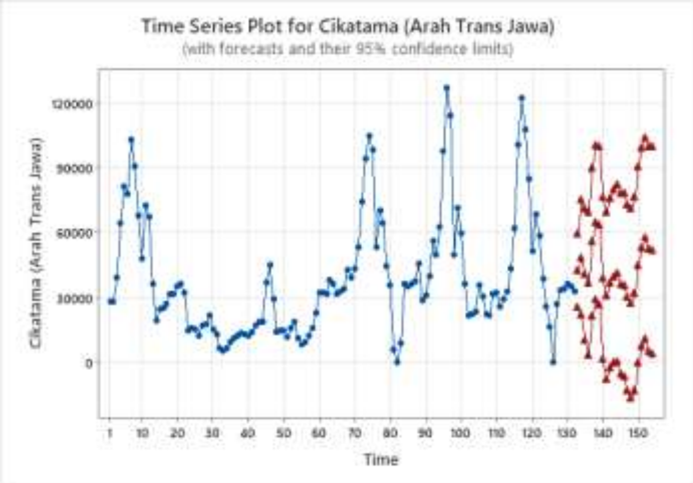

Figure 11. Best parameter prediction graph for sarima (1,1,2) (2,1,2) [22] number of vehicles through the cikatama toll gate (Trans Java flow)

The data pattern of the SARIMA model SARIMA (1,1,2) (2,1,2)[22] is similar to the prediction using the previous decomposition model. However, the SARIMA model was better than the decomposition model.

b. Stationarization of Data on the Number of Vehicles Passing Through the Cikatama Toll Gate (Entrance to Jakarta)

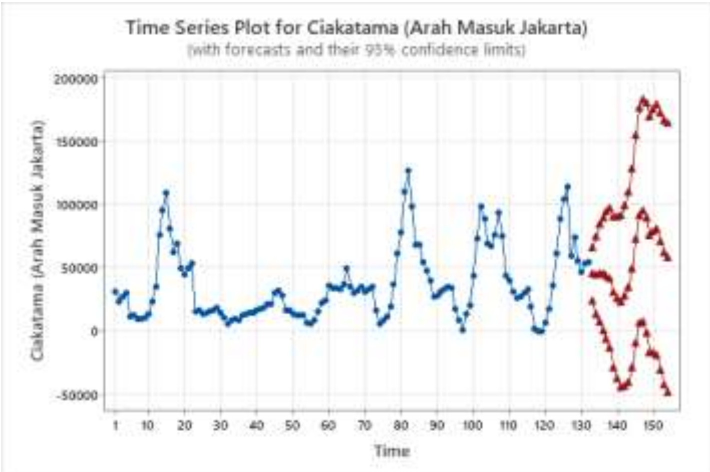

Figure 12. Best prediction graph sarima (2.1.0)(1,1,2)[22] number of vehicles passing through the cikatama toll gate (entry direction to Jakarta)

The number of vehicles entering Jakarta ten days after Eid al-Fitr was predicted to increase significantly. The SARIMA model results are more reasonable than those of the decomposition model because they can capture patterns of increases and fluctuations (high, medium, and low), although they still have limitations in capturing external factors that influence the data.

4.1.4 VCR Data Analysis of the Number of Vehicles Passing the Cikatama Toll Gate in 2019 – 2024 (Daily)

Table 3. Basic Capacity of Toll Roads

JBH (Toll Road) Type	Alineman Road Type	C_0 ((SMP/Hour/Lane)
JBH4/2 and JBH 6/2	Flat	2500
	Hill	2350
	Mountain	2200

The daily prediction table for vehicle flow at the Cikatama Toll Gate exit (Trans Java) uses an assumed capacity of 60,000 vehicles/day based on the 2023 Indonesian Road Capacity Guidelines. The calculation of toll road capacity (freeway) is an average of 2,350 vehicles/h, so the daily capacity obtained is 24 × 2,350 = 56,400, which is rounded to 60,000 vehicles per day.

Table 4. VCR calculation prediction of the number of vehicles passing through the Cikatama toll gate (entrance direction to Jakarta) in 2025 (daily)

Year	Day	Vehicle Prediction (V) Trans Java Direction	Maximum Capacity (C)	VCR (V/C)
2025	H-10	42,256	60,000	0.70
2025	H-9	48,097	60,000	0.80
2025	H-8	40,304	60,000	0.67
2025	H-7	36,003	60,000	0.60
2025	H-6	55,445	60,000	0.92
2025	H-5	64,345	60,000	1.07
2025	D-4	63,024	60,000	1.05
2025	H-3	38,657	60,000	0.64
2025	H-2	30,348.2	60,000	0.51
2025	H-1	36,284.3	60,000	0.60
2025	H1	39,268.5	60,000	0.65
2025	H2	40,838.3	60,000	0.68
2025	H+1	35,908.2	60,000	0.60
2025	H+2	35,223.9	60,000	0.59
2025	H+3	29,663.7	60,000	0.49
2025	H+4	26,731.6	60,000	0.45
2025	H+5	31,318.2	60,000	0.52
2025	H+6	44,760.1	60,000	0.75
2025	H+7	52,996.3	60,000	0.88
2025	H+8	57,155.8	60,000	0.95
2025	H+9	52,356.8	60,000	0.87
2025	H+10	51,741.9	60,000	0.86

The calculation results showed that heavy traffic (VCR > 1.00) occurred on D-5 and D-4, indicating a high risk of congestion. Most days have VCR < 0.85, indicating that traffic is still smooth, especially from D+3 to D+5, which are very quiet (VCR < 0.55). Days with potential congestion (VCR 0.85–1.00) occurred on D-6, D+7, D+9, and D+10, approaching the maximum capacity of the toll road.

Table 5. VCR calculation prediction of the number of vehicles passing through the cikatama toll gate (entrance direction to Jakarta) in 2025 (daily)

Year	Day	Vehicle Prediction (V) Direction of Entry to Jakarta	Maximum Capacity (C)	VCR (V/C)
2025	H-10	43,831.8	60,000	0.73
2025	H-9	42,980.0	60,000	0.72
2025	H-8	44,614.3	60,000	0.74
2025	H-7	44,048.7	60,000	0.73
2025	H-6	42,753.6	60,000	0.71
2025	H-5	40,652.7	60,000	0.68
2025	D-4	30,059.5	60,000	0.50
2025	H-3	25,121.9	60,000	0.42
2025	H-2	21,948.0	60,000	0.37
2025	H-1	26,927.6	60,000	0.45
2025	H1	33,313.6	60,000	0.56

2025	H2	48,564.9	60,000	0.81
2025	H+1	71,717.5	60,000	1.20
2025	H+2	90,425.4	60,000	1.51
2025	H+3	94,537.8	60,000	1.58
2025	H+4	88,230.0	60,000	1.47
2025	H+5	74,935.7	60,000	1.25
2025	H+6	77,746.5	60,000	1.30
2025	H+7	79,192.5	60,000	1.32
2025	H+8	69,935.4	60,000	1.17
2025	H+9	60,879.6	60,000	1.01
2025	H+10	57,318.5	60,000	0.96

Based on the calculations, high congestion (VCR > 1.00) occurs from D+1 to D+9, indicating the peak return flow with vehicle volume exceeding the toll road capacity. Smooth traffic (VCR < 0.85) occurred from D-10 to D-1 before the return flow began. Days with the potential for high density (VCR 0.85–1.00) occurred on D+10, approaching the maximum capacity but not yet congested.

4.2 Discussion

4.2.1 Analysis of Homecoming Traffic Patterns Based on Historical Data

An analysis of historical data on the Jakarta-Cikampek Toll Road shows significant traffic spikes occurring five to two days before the Eid exodus (homecoming traffic) and two to six days after the Eid return (returning traffic), with a consistent seasonal pattern each year. Vehicle volumes have consistently increased since 2019, except in 2020–2021, owing to the COVID-19 pandemic, which reduced the density by up to 50%. Time series prediction models (including ARIMA/SARIMA) were used to anticipate traffic spikes and were validated using the ADF and Ljung-Box tests. These results can be used for mitigation strategies, such as traffic engineering, increasing toll capacity, and distributing travel times.

4.2.2 Evaluation of Congestion and Service Efficiency with VCR Indicators

The Volume, Capacity, and Ratio (VCR) indicator shows that during the peak exodus (D-5 to D-2) and return flows (D+4 to D+6), the VCR value exceeds 1, indicating congestion due to the vehicle volume exceeding the road capacity. On normal days, the VCR was lower, indicating smoother traffic. To improve toll road efficiency, recommended strategies include travel time management, increasing infrastructure capacity (such as road widening and contraflow), and implementing smart technology to monitor and predict vehicle flow. VCR evaluation can form the basis for more effective transportation policies.

4.2.3 External Factors That Influence Traffic Congestion

Traffic congestion during the homecoming period is caused not only by vehicle volume but also by external factors such as the increasing number of cars in DKI Jakarta, West Java, and Central Java, extreme weather conditions (rain, fog, flooding), traffic accidents, and one-way and odd-even traffic policies. Other factors include large-scale activities, logistics distribution, and undisciplined driver behavior, such as using hard shoulders and stopping for long periods in rest areas. Anticipatory strategies include infrastructure development, such as continuous toll systems, data-based traffic management, driving education, and improvements in public transportation.

4.2.4 Integration of Prediction Models in Long-Term Planning

The traffic flow prediction model in this study can be integrated into long-term planning to support smooth exodus traffic and improve the Level of Service (LOS) on the Jakarta-Cikampek Toll Road. This model helps policymakers anticipate changes in traffic patterns and optimize infrastructure capacity, transaction systems, and policies. Using methods such as ARIMA, SARIMA, or machine learning, planning can become more proactive. Predictive data also support decisions regarding road widening, lane addition, and scheduling maintenance outside peak exodus/return traffic.

4.2.5 Traffic Flow Management at Rest Areas

One of the main challenges during homecoming traffic is congestion in rest areas, which often triggers traffic jams on toll roads because of the simultaneous entry and exit of vehicles. The contributing factors include limited capacity, irregular parking durations, and inefficient access patterns. Mitigation solutions include organizing parking zones, limiting stopover times, and utilizing technology, such as digital signage and AI-based CCTV, to monitor rest area capacity in real time. Improving facilities such as restrooms and gas stations, as well as developing multilevel rest areas, is recommended to reduce queues and parking times.

4.2.6 Implementation of Prediction Models for Traffic Engineering Strategies

A predictive model based on historical traffic flow data is very helpful for the Indonesian National Police Traffic Corps (Korlantas Polri) in designing traffic engineering strategies, such as contraflow, one-way, and odd-even systems. This model allows the identification of vehicle movement patterns, estimation of traffic surges, and adjustment of road capacity, toll gates, and other areas. Data analysis from 2019 to 2024 showed a significant increase in vehicle volume during peak exodus and return flows, with peak density occurring four to two days before Eid al-Fitr and two to four days after Eid al-Fitr. Historical data also show a post-pandemic surge in traffic, with significant fluctuations in vehicle volume. A predictive model using decomposition indicated that the vehicle volume in 2025 is expected to increase compared to that in the pandemic years. Although the current model shows a high error (MAPE of 151%), this underscores the need for improvements, including the consideration of external factors, such as government policies and infrastructure changes. Peak return flow occurs two to four days before Eid al-Fitr, requiring attention in traffic engineering planning to avoid such congestion. Solutions such as limiting vehicle types, implementing one-way traffic, and optimizing public transportation can help reduce congestion at the Cikatama Toll Gate.

5. Conclusions

5.1 Conclusion

Based on the analysis and implementation of the predictive model in the traffic engineering strategy, several conclusions can be drawn. First, the peak of homecoming traffic occurs between D-5 and D-1, whereas the peak of return traffic occurs between D+2 and D+5. Second, traffic flow prediction using the SARIMA method has been proven to produce more accurate patterns than the ARIMA model because it can capture seasonal patterns that occur every year. Third, the results of the Volume Capacity Ratio (VCR) calculation show that during the peak periods of homecoming and return trips, the VCR value approaches or even exceeds 1.0, indicating saturated traffic conditions and is prone to long-term congestion. Fourth, the predictive model based on historical data has proven effective in anticipating traffic surges; therefore, it can be integrated into long-term infrastructure-planning. Fifth, the analysis results show that the remaining areas are crucial factors that influence the smooth flow of traffic. Finally, the regular evaluation of the predictive model is crucial for ensuring the accuracy and relevance of the results produced when dealing with changing traffic conditions in the future.

5.2 Research Limitations

The study primarily relied on historical traffic data for its predictions, which may not fully account for external factors, such as sudden changes in government policies, unexpected weather conditions, or other disruptions that could influence traffic flow during the homecoming period. Additionally, the model's prediction accuracy is limited by the quality and completeness of the data, and the high variability in traffic patterns from year to year. Although the SARIMA and ARIMA models performed well, they still face challenges in capturing all the complexities and real-time dynamics of traffic flow. The results may also be less applicable in the case of significantly unforeseen events, such as natural disasters or sudden large-scale restrictions, which could drastically affect mobility. Future research could explore more adaptive models that incorporate real-time data and external variables to improve prediction accuracy.

5.3 Suggestion Suggestions and Directions for Future Research

Based on the conclusions of this study, several suggestions have been made to enhance traffic management and improve the accuracy of future prediction models. First, authorities should optimize the management of homecoming and return traffic by implementing strategies such as contraflow, one-way systems, and adaptive restrictions on heavy vehicles from D-5 to D+5 to reduce extreme congestion. Second, the SARIMA prediction model, which has proven to be more accurate than ARIMA, should be sustainably used as the primary reference in seasonal traffic planning and simulations, integrating real-time data from sensors or CCTV systems. Third, the government must prioritize increasing road capacity and improving congestion-prone areas, particularly in sections with high VCR, and focus on the development of alternative routes and the widening of critical sections. Fourth, rest area management should be improved by regulating entry and exit access, limiting maximum stopping times, and providing additional temporary areas during peak travel times. Fifth, the Ministry of Transportation and toll road operators should integrate predictive models into national transportation planning to develop long-term policies that support sustainable transportation. Lastly, regular updates and evaluations of the prediction models are essential to incorporate changes in travel patterns, weather conditions, and new infrastructure developments, ensuring that the models remain relevant and accurate in the future.

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