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SPATIAL REGRESSION MODEL ANALYSIS OF TRAFFIC VOLUME AND SPEED IN KEDIRI CITY

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Abstract

Urban development is often accompanied by traffic challenges, particularly the increasing volume of vehicles that is not commensurate with the capacity of road infrastructure. This study aims to evaluate the effect of spatial heterogeneity of vehicle volume and type on vehicle speed at four main intersections in Kediri City: Alun-Alun, Semampir, Bandar Alim, and Kawi. A quantitative approach was used through direct observation, floating car method, and linear regression analysis and ANOVA. The results show that intersections with high vehicle volume tend to have lower speeds, especially when dominated by heavy vehicles. Alun-Alun intersection has the highest R-Square value for vehicle volume (0.847), while Bandar Alim intersection recorded the highest R-Square for vehicle speed (82%). T-test and ANOVA indicate a significant effect of vehicle direction and type on speed, especially at Semampir and Bandar Alim. These findings demonstrate the importance of integrating volume and speed in traffic management, as well as the need for a data-driven and spatial approach in developing intelligent transportation systems. Therefore, it is necessary to discuss further in the objectives and body of the research regarding the causal relationship between vehicle volume, vehicle type composition, travel direction, and spatial variations between intersections, so that the research results can provide a stronger scientific basis for adaptive traffic management policies to the specific conditions of each intersection.

Keywords: Kediri City Intersections, Spatial Heterogeneity, Vehicle Speed, Vehicle Volume

Introduction

The development of cities in developing countries often faces major challenges in the transportation sector, particularly related to the rapid increase in the number of motorized vehicles that is not proportional to the capacity of road infrastructure (Allam et al., 2022; Reza et al., 2022). This imbalance gives rise to various problems such as traffic congestion, longer travel times, and a decline in the quality of life for urban communities (Mueller & Weiler, 2023). The impacts are not only felt on transportation efficiency but also extend to social, economic, and environmental aspects (Bittencourt et al., 2025; Ahmed Alkaissi, 2024). In developing cities, traffic patterns are often spatially uneven (Lin et al., 2024). Some areas, particularly economic activity centers, experience extremely high vehicle density, while others remain less congested (Chatzinikolaou, 2025; Prasetya et al., 2024). This condition reflects spatial heterogeneity in the distribution of vehicle density and volume, which has a direct effect on travel time (Guo et al., 2023; Lopes et al., 2025). The problem is further exacerbated by rapid urbanization that is not accompanied by comprehensive transportation planning (Wang et al., 2019; Xu et al., 2019).

This rapid urbanization ultimately drives the increasing potential for traffic congestion. The growth of population and vehicles that is not aligned with improvements in road infrastructure capacity leads to a range of negative consequences. Traffic congestion brings wide-ranging impacts, including high fuel consumption, increased economic costs, and reduced productivity (Saadi et al., 2025; Ji et al., 2023). Commuting times are often much longer than the actual travel distance (M. Li et al., 2025; Yang & Qian, 2019). In addition, developing cities often face limitations in collecting accurate, real-time traffic data, such as vehicle volumes and community movement patterns, even though these data are crucial for analysis and for developing appropriate solutions (Wu et al., 2025; Meng et al., 2025). Although studies on the relationship between traffic density, vehicle volume, and travel time have been widely conducted in developed cities, the results are not necessarily relevant to the conditions of developing cities (Z. Wu et al., 2024; T. Li et al., 2025). Developed cities generally have more established transportation systems and advanced technologies, such as intelligent transportation systems, while developing cities still face specific challenges, such as unequal infrastructure development and dependence on private vehicles (Qian et al., 2024; Ahmed et al., 2019).

The urgency to understand the factors that influence travel time has increased, as these factors affect not only transportation efficiency but also the environment (Ma & Chiu, 2025; Kirimtat et al., 2020). Traffic congestion contributes to higher carbon emissions, worsening air pollution, and greenhouse gases (Nian et al., 2021; Wisetjindawat et al., 2019). Therefore, research that maps the spatial heterogeneity of traffic factors is essential to help governments identify high-density areas that require priority intervention (Putra G et al., 2019; Zhong et al., 2021). Uncertain travel times also affect public productivity, increase logistics costs, and reduce satisfaction with the existing transportation system, ultimately undermining public trust in government policies (Huang & Xu, 2021; Herdian Bayu Ash Siddiq et al., 2024).

This study aims to evaluate how the spatial heterogeneity of traffic factors, such as vehicle density and volume, affects travel time in developing cities (Zhang et al., 2022; Gao et al., 2024). A spatial analysis approach will be applied to map the distribution of traffic factors, providing a more comprehensive understanding of transportation dynamics (Tong et al., 2021; Betkier, 2025). This research is expected to provide a significant contribution to understanding transportation patterns in developing cities and to serve as a scientific basis for more effective policymaking (J. Wu et al., 2023; Hairrudin & Suroso, 2025). By adopting a data-driven approach, this study can support governments and stakeholders in minimizing the negative impacts of traffic, creating more efficient transportation systems, and promoting sustainability in transportation management (Murakami & Seya, 2022; Yu & Krstic, 2021; Cheng et al., 2020).

Research Methods

This research uses a quantitative approach with a cross-sectional design and a spatial analysis perspective (Haydari & Yilmaz, 2022). The research was conducted from January to March 2025 at four main intersections in Kediri City: Alun-Alun, Semampir, Bandar Alim, and Kawi intersections (Hidayati & Rarasati, 2023). The research locations were selected based on the criteria of intersections with high traffic volumes and representative of urban traffic conditions in Kediri. The four intersections were chosen because:

1. Alun-Alun Intersection: Center of Commercial and Government Activities
2. Semampir Intersection: Main Connecting Route for South Java
3. Bandar Alim Intersection: Densely Built-up Commercial and Residential Area
4. Kawi Intersection: Access Route to Educational and Industrial Areas

The population of this study is all motorized vehicles passing through four main intersections in Kediri City, namely Alun-Alun Intersection, Semampir Intersection, Bandar Alim Intersection, and Kawi Intersection, which include light vehicles (motorcycles, passenger cars, public transportation) and heavy vehicles (buses, trucks, goods vehicles) (Prasetyo et al., 2022; Betkier & Oszczypała, 2024; Putra G et al., 2019). Samples were taken using a systematic sampling method with a 15-minute time interval for 12 full hours of observation (06.00–18.00 WIB) at each intersection to capture variations in traffic flow during peak and non-peak hours (Cheng et al., 2020). Primary data was obtained through continuous video recording to record all intersection arms, manual counting using a tally counter to verify vehicle volume and type, and travel time measurements using the Floating Car Method (FCM) with a survey vehicle that repeatedly crossed the route at various hours to produce the actual average traffic speed (Cahyono et al., 2023; J. Wu et al., 2023). Secondary data was obtained from the Kediri City Transportation Agency in the form of a road network map connecting major intersections, as well as intersection geometric data from field surveys including the number of intersection arms, the number and width of lanes, queue lengths, the presence of road medians, and passenger boarding and alighting points (Murakami & Seya, 2022; Haydari & Yilmaz, 2022). All of this data was used in an integrated manner to analyze the relationship between volume, vehicle type, direction of travel, and vehicle speed at each intersection (Prasetya et al., 2024; Tong et al., 2021; Tang et al., 2019).

$$Y= \beta_0+ \beta_0 X_i \ldots (1)$$

where:
Y = Vehicle volume
X = Peak hours data
$\beta0$ = Intercept (constant)
$\beta1$ = Regression coefficient for the peak hour variable

In the second stage, an analysis was conducted on the vehicle speed data. First, a determination coefficient (R-Square) test was conducted to measure how much variation in vehicle speed can be explained by the independent variables used (Lubis et al., 2023). The R^2 value is in the range of 0.00 to 1.00 where the value closer to 1 indicates that the regression model provides a stronger contribution in explaining the dependent variable (Tio Purnomo et al., 2024). Next, a T-test was conducted to determine the significant effect of each independent variable, namely the intersection arm (west, south, east, north) and vehicle type (bus, motorcycle, car, truck), on the dependent variable, namely vehicle speed. To determine the combined effect of the intersection arm and vehicle type simultaneously on vehicle speed, Two-Way ANOVA was used. In this analysis, a multiple linear regression model was used with the following equation:

$$Y=\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\beta_4 X_4 + \beta_5 X_5+ \beta_6 X_6+ \beta_7 X_7+\beta_8 X_8 \ldots (2)$$

Where:
Y = Vehicle Speed
X1 = West Approach
X2 = South Approach
X3 = East Approach
X4 = North Approach
X5 = Bus Vehicles
X6 = Motorcycles
X7 = Cars
X8 = Trucks
βi = Regression coefficient of each independent variable (i=1,2,...,8)

This model is used to determine the contribution of each independent variable to vehicle speed, either partially or simultaneously.

Research Results and Discussion

Regression Analysis on Vehicle Volume Data

To determine the contribution of the time variable (rush hour) to vehicle volume at each intersection, a simple linear regression analysis was conducted using the coefficient of determination (R-square). The R-square value indicates the proportion of the variation in vehicle volume that can be explained by the time variable at each intersection arm (North, South, East, and West). The closer the value is to 1, the stronger the relationship between the two variables, indicating that the time variable plays a significant role in explaining fluctuations in vehicle volume. The analysis was conducted at four major intersections in Kediri City: Alun-Alun, Semampir, Kawi, and Bandar Alim intersections. The results of the R-square calculations for each intersection arm are presented in Table 1 below.

Table 1. R-square Test Results at All Intersections

R Square	North	South	East	West	Mean
Alun-Alun Intersection	0.92572711	0.90174939	0.792625376	0.77155184	**0.847913**
Semampir Intersection	0.860307315	0.835550702	0.83913807	0.767052254	**0.825512**
Kawi Intersection	0.855932357	0.60424796	0.727264607	0.439047422	**0.656623**
Bandar Alim Intersection	0.839248415	0.878387177	0.833390878	0.765154723	**0.829045**

Source: Author's Processed Results (2025)

Based on the R Square value, the Alun-Alun intersection shows the strongest correlation (average 0.847) between directions, followed by the Bandar Alim intersection (0.829), the Semampir intersection (0.825), and the lowest is the Kawi intersection (0.656). This indicates that the stability of the relationship between traffic volume and travel time is highest at the Alun-Alun intersection, while the Kawi intersection requires special attention. Therefore, the intelligent transportation system should be implemented in stages, starting from the intersection with the highest correlation.

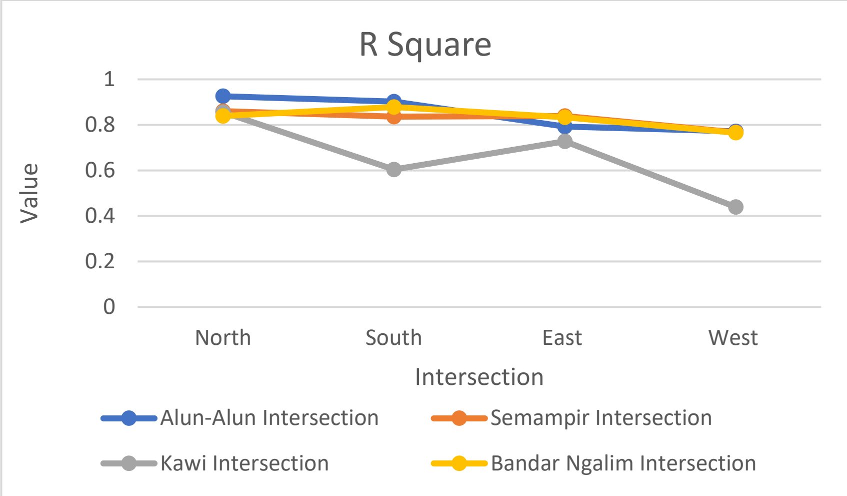

Figure 1. R Square Test Graph at All Junctions

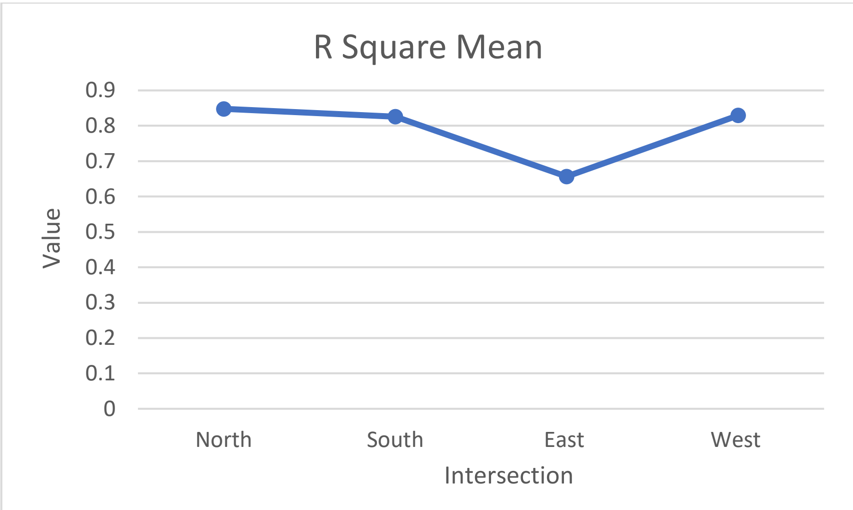

Figure 2. R Square Test Graph Averaged at All Junctions

The highest average R Square value is found at the Alun-Alun Intersection at 0.848, followed by the Bandar Alim Intersection (0.829), Semampir Intersection (0.826), and the lowest at the Kawi Intersection (0.657). This indicates that the relationship pattern between traffic variables at Alun-Alun is more consistent than at other intersections. The higher the average value, the more reliable the intersection is in representing traffic behavior. Therefore, the priority for developing an intelligent transportation system in Kediri City should start from the intersection with the highest average value.

Table 2. Results of the T-test (Partial) at All Intersections

Intersection	Alun-Alun Intersection	Semampir Intersection	Kawi Intersection	Bandar Alim Intersection
North	16.6	11.64	11.43	10.72
South	14.2	10.57	5.80	8.93
West	12.5	8.51	4.15	8.47

Intersection	Alun-Alun Intersection	Semampir Intersection	Kawi Intersection	Bandar Alim Intersection
East	9.2	10.71	7.66	10.51
Mean	**13.13**	**10.36**	**7.26**	**9.66**

Source: Author's Processed Results (2025)

Based on vehicle volume data per direction, Simpang Alun-Alun recorded the highest figures in all directions with dominant volumes from the North (16.6) and South (14.2), indicating that this intersection is the main meeting point for vehicle flows in the city center. Simpang Semampir and Simpang Bandar Alim showed a relatively balanced but lower traffic distribution, while Simpang Kawi recorded the lowest volumes, especially from the West (4.15) and South (5.80), indicating less traffic activity.

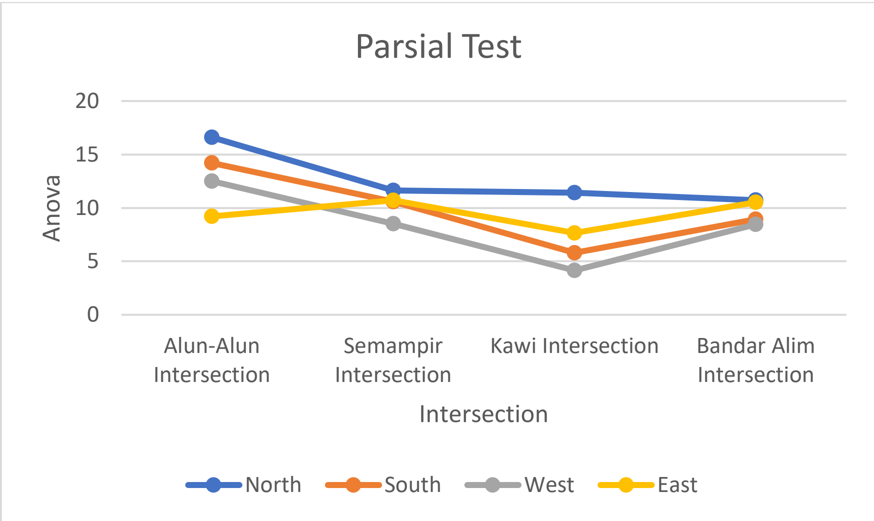

Figure 3. T (Partial) test graph at All Junctions

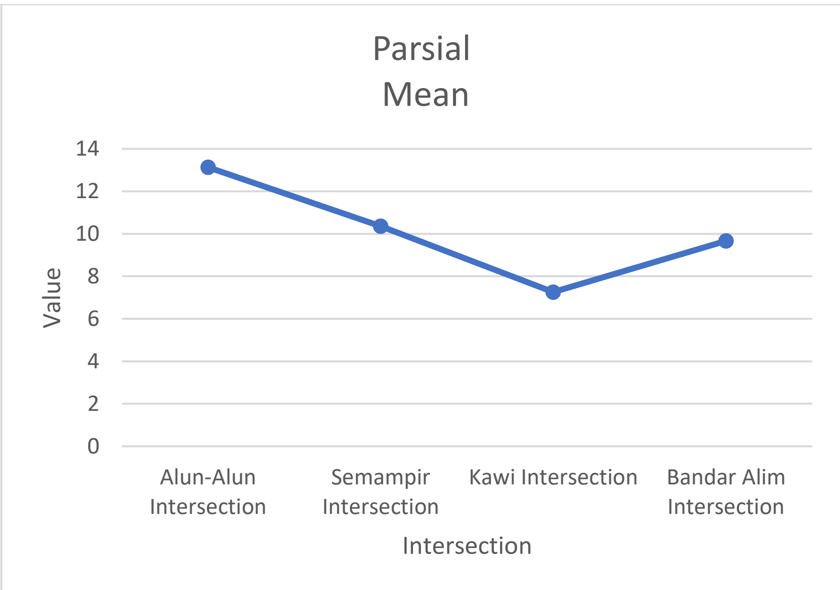

Figure 4. Partial T-Test Average Graph for All Intersections

The average (mean) value, Alun-Alun Intersection ranks first with 13.13, followed by Bandar Alim (9.66), Semampir (10.36), and Kawi Intersection with the lowest score at only 7.26. This average value reflects the overall intensity of intersection use. Therefore, transportation system development in Kediri City should prioritize intersections with the highest average volume as control centers, particularly Alun-Alun Intersection, which has significant potential for technology-based traffic management.

Table 3. F-Test Results (ANOVA) for All Intersections

Intersection	Alun-Alun Intersection	Semampir Intersection	Kawi Intersection	Bandar Alim Intersection
North	274.20	135.49	130.71	114.86
South	201.92	111.78	33.59	79.79
West	157.09	72.44	17.22	71.68
East	84.09	114.76	58.66	110.46
Mean	**179.33**	**108.62**	**60.05**	**94.20**

Source: Author's Processed Results

Based on daily traffic volume data, Simpang Alun-Alun recorded the highest traffic volume from all directions, particularly from the North (274.20) and South (201.92), indicating that this intersection is a major traffic hub in Kediri City. Simpang Semampir was in second place with a significant traffic volume from the East (114.76), while Simpang Kawi showed the lowest traffic volume, particularly from the West (17.22) and South (33.59). This indicates that traffic distribution between intersections varies considerably depending on their location and function.

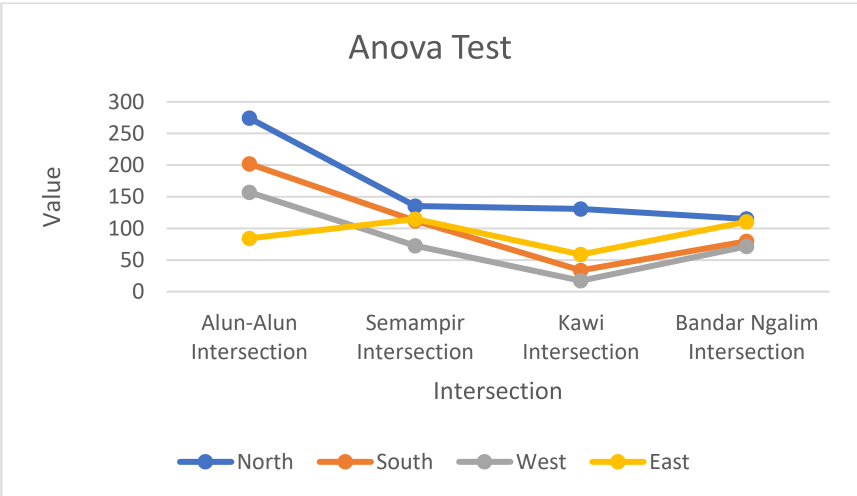

Figure 5. Test F (ANOVA) Graph at All Junctions

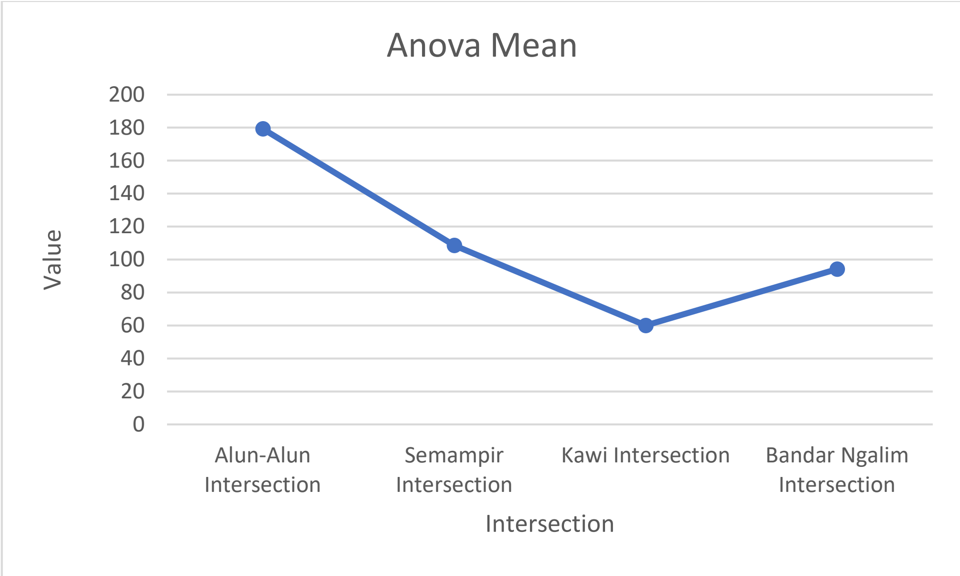

Figure 6. Average F-Test Graph (ANOVA) at All Intersections

Judging from the average (mean) value, the Alun-Alun Intersection again holds the highest position with 179.33 vehicles per direction, followed by Semampir (108.62), Bandar Alim (94.20), and Kawi (60.05) the lowest. These values reinforce the fact that Alun-Alun is a strategic traffic node. Therefore, the implementation of an intelligent transportation system in Kediri City is strongly recommended to begin at the intersection with the highest average volume for a more significant impact on overall traffic efficiency.

Regression Analysis on Vehicle Speed Data

Regression analysis was conducted on vehicle speeds at four intersections. The tests performed included the R-square, T-test, ANOVA, and the mathematical model of the regression.

Table 4. R-Square Results for Average Vehicle Speed at All Intersections

Intersection	R	R-sq
Alun-Alun	0.797280	60.54%
Semampir	0.878418	77.03%
Kawi	151.454	65.20%
Bandar Alim	132.598	82.00%

Source: Author's Processed Results

Based on the regression analysis results, the highest R-Square value was found at the Bandar Alim intersection at 82.00%, followed by Semampir (77.03%), Kawi (65.20%), and Alun-Alun (60.54%). This indicates that the variables used in the model are adequately able to explain variations in vehicle speed, especially at Bandar Alim and Semampir. Therefore, this regression model is suitable for speed prediction, especially at intersections with high R-Square values.

Table 5. Results of the Partial T-Test: Average Vehicle Speed at All

Intersection	T-Value Mean	P-Value Mean
Alun-Alun	1.7	0.409

Intersection	T-Value Mean	P-Value Mean
Semampir	2.14	0.164
Kawi	1.55	0.1783
Bandar Alim	5.67	0.035

Source: Author's Processed Results

The results of the t- and p-tests show that Simpang Bandar Alim has the highest t-value (5.67) and the lowest p-value (0.035), indicating that the influence of the independent variable on vehicle speed at this intersection is statistically significant. Meanwhile, Alun-Alun, Semampir, and Kawi have p-values above 0.05, so they are not statistically significant. Based on this, regression modeling is most appropriate to be applied first to Simpang Bandar Alim as a priority for developing a data-based transportation system..

Equation Alun-Alun Intersection

$$Speed = 8.860 + 0.132\, Location\ Alun - West\ Alun\ Intersectio + 0.310\, Location\ Alun - South\ Alun\ Intersection - 0.585\, Location\ Alun - East\ Alun\ Intersection + 0.143\, Location\ Alun - North\ Alun\ Intersection - 0.590\, Vehicle\ Type_{Bus} + 0.484\, Vehicle\ Type\_MC + 0.804\, Vehicle\ Type\_Car - 0.699\, Vehicle\ Type\_Truck \ldots \text{(3)}$$

Regression Equation Semampir Intersection

$$Speed = 10.655 + 0.923\, West\ Semampir\ Location - 0.763\, South\ Semampir\ Location - 0.862\, East\ Semampir\ Location + 0.702\, North\ Semampir\ Location + 0.627\, Bus\ Vehicle\ Type + 0.901\, MC\ Vehicle\ Type - 0.139\, Car\ Vehicle\ Type - 1.388\, Truck\ Vehicle\ Type \ldots \text{(4)}$$

Regression Equation Kawi Intersection

$$Speed = 10.957 + 1.524\, West\ Kawi\ Location + 0.671\, South\ Kawi\ Location - 1.013\, East\ Kawi\ Location - 1.181\, North\ Kawi\ Location - 1.000\, Bus\ Vehicle\ Type + 1.668\, MC\ Vehicle\ Type + 0.149\, Car\ Vehicle\ Type - 0.817\, Truck\ Vehicle\ Type \ldots \text{(5)}$$

Regression Equation Bandar Alim Intersection

$$Speed = 8.831 + 1.536\, West\_Bandar\ Location - 3.258\, South\_Bandar\ Location + 1.948\, East\_Bandar\ Location - 0.226\, North\_Bandar\ Location + 0.674\, Bus\_Vehicle\ Type + 0.289\, MC\_Vehicle\ Type\ b - 0.164\, Car\_Vehicle\ Type - 0.799\, Truck\_Vehicle\ Type \ldots \text{(6)}$$

The vehicle speed regression model at four intersections shows variations in the influence of location and vehicle type. At the Alun-Alun intersection, speed is positively influenced by the southbound direction (0.310) and cars (0.804), but negatively by the eastbound direction (-0.585) and trucks (-0.699). At the Semampir intersection, the westbound direction (0.923) and motorcycles (0.901) increase speed, while the eastbound direction (-0.862) and trucks (-1.388) decrease it. At the Kawi intersection, motorcycles (1.668) and the westbound direction (1.524) have the strongest positive effects, while the northbound direction (-1.181) and buses (-1.000) have a negative impact. Meanwhile, at the Bandar Alim intersection, the eastbound direction (1.948) and westbound (1.536) have a significant positive impact, while the southbound direction (-3.258) and trucks (-0.799) decrease speed. This coefficient variation is important as a basis for developing traffic engineering policies tailored to the characteristics of each intersection.

Table 6. ANOVA Test Results for Average Vehicle Speeds at All Intersections

Intersection	Source	F-Value	P-Value	Decisions
Alun-Alun	Location	1.00	0.436	Not Influential
	Vehicle Type	3.60	0.059	Not Influential
Semampir	Location	4.62	0.032	Influential
	Vehicle Type	5.45	0.021	Influential
Kawi	Location	3.02	0.087	Not Influential
	Vehicle Type	2.60	0.117	Not Influential
Bandar Alim	Location	12.75	0.001	Influential
	Vehicle Type	0.91	0.473	Not Influential

Source: Author's Processed Results

The results of the analysis showed that at Simpang Semampir, the variables of Location and Type of Vehicle had a significant influence on vehicle speed. This is evidenced by the significance value (P-Value) for the Location variable of 0.032 and for the Vehicle Type variable of 0.021, both of which are smaller than the significance limit of 0.05 ($P < 0.05$). Thus, it can be concluded that changes in location and vehicle type statistically contribute to speed variations at the intersection. Meanwhile, at Simpang Bandar Alim, the Location variable was also proven to significantly affect the speed of vehicles with a P-Value of 0.001 which is far below the threshold of 0.05. This indicates that the location factor has a strong influence on the speed of traffic at the Bandar Alim intersection.

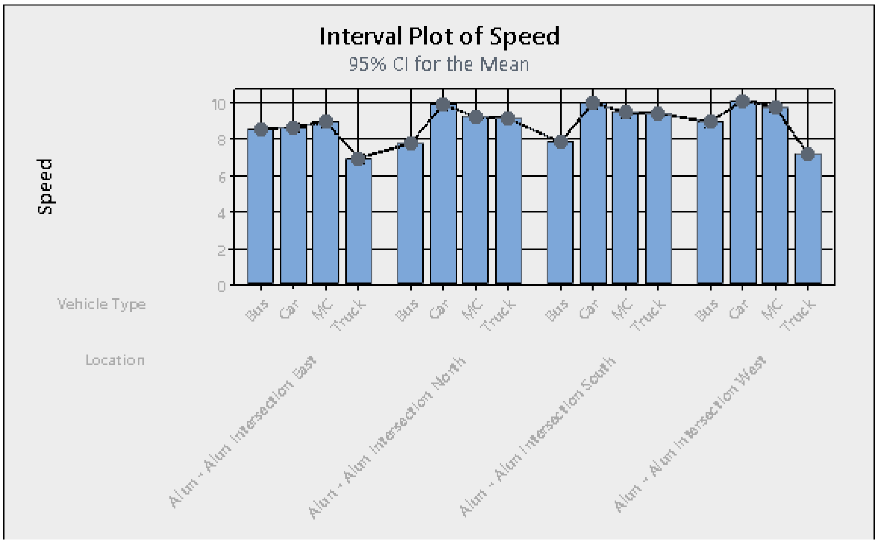

Figure 7. Interval Plot of Speed (95% Confidence Interval for the Mean) in Alun-Alun Intersection

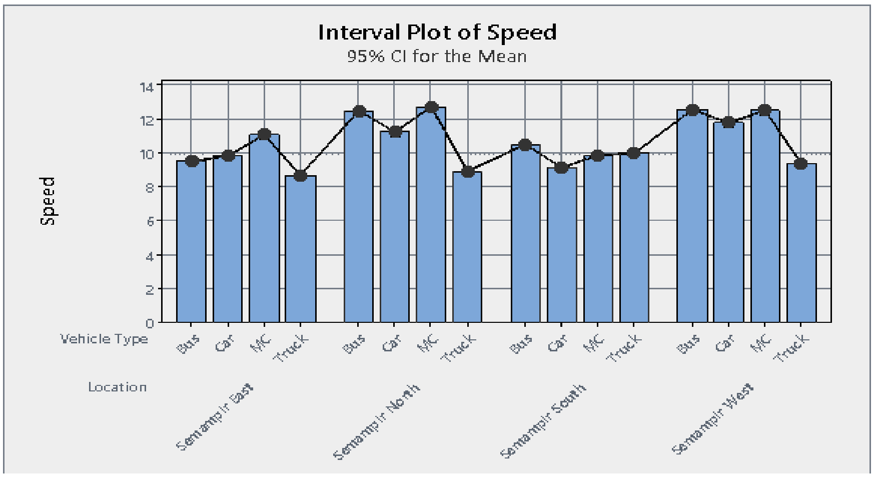

Figure 8. Interval Plot of Speed (95% Confidence Interval for the Mean) in Semampir Intersection

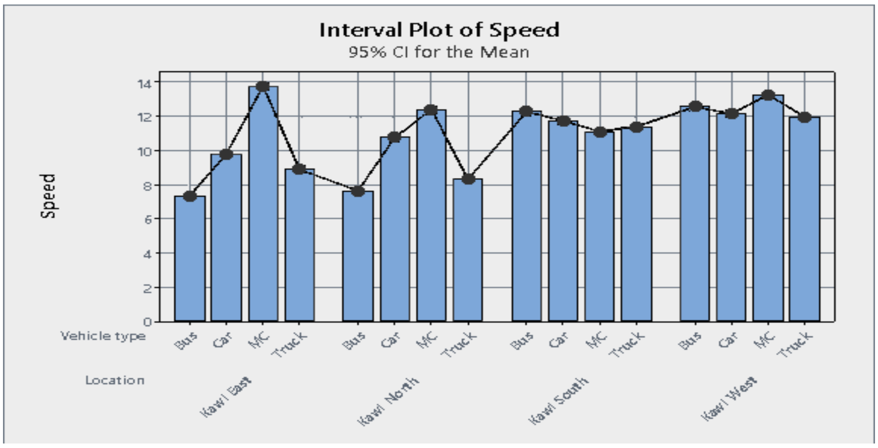

Figure 9. Interval Plot of Speed (95% Confidence Interval for the Mean) in Kawi Intersection

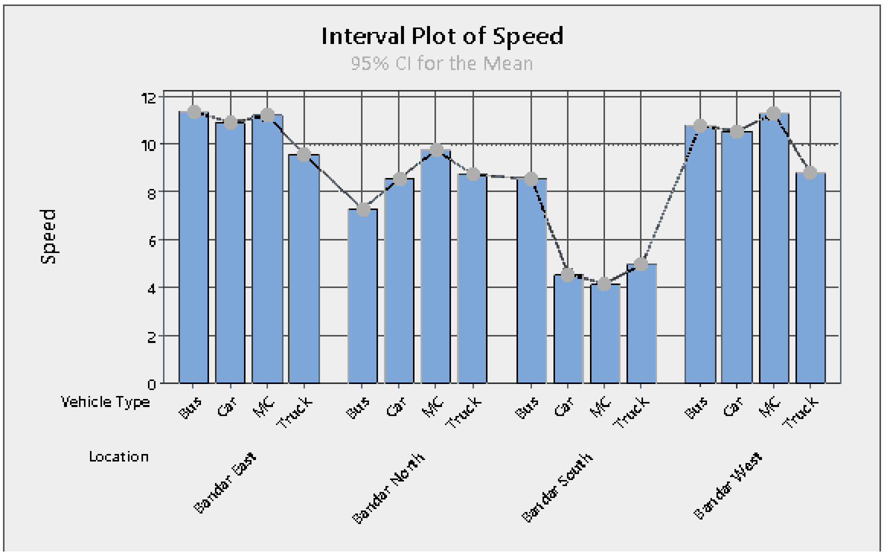

Figure 10. Interval Plot of Speed (95% Confidence Interval for the Mean) in Bandar Intersection

Integration of Vehicle Volume Regression Parameters with Vehicle Speed

The integration between volume regression and vehicle speed provides a comprehensive picture of traffic conditions in Kediri City. The results of the analysis showed that intersections with a high volume of vehicles, such as Alun-Alun and Bandar Alim, tended to have lower vehicle speeds, mainly due to the dominance of heavy vehicles such as trucks and buses. The high R-Square values in both regression models at multiple intersections indicate that peak times and vehicle types strongly influence traffic behavior. Therefore, the simultaneous utilization of these two parameters is important to design more effective traffic management strategies, such as traffic signal management, heavy vehicle management, and the implementation of location- and time-based intelligent transportation systems.

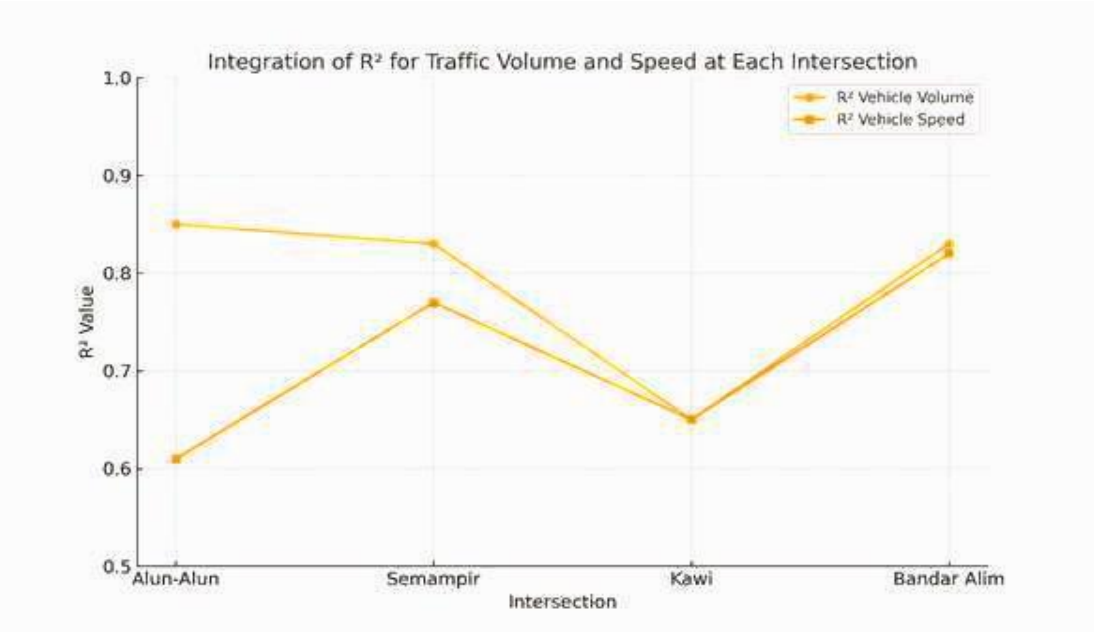

Figure 11. R^2 Integration Line Graph of Vehicle Volume and Speed at Each Intersection

Discussion

The results of this study indicate a significant relationship between vehicle volume and speed at major intersections in Kediri City. The linear regression approach used indicates that increased vehicle volume, particularly during peak hours and for heavy vehicles such as trucks and buses, is directly correlated with decreased vehicle speed. This finding is consistent with the results of a study by Alkaissi (2024), which used a Fuzzy Inference System (FIS) approach and GIS-based spatial data to detect congestion levels based on speed and speed ratio parameters. The study emphasized that reduced speed is a dominant indicator in identifying congestion points, supporting the validity of the integrated volume and speed approach used in this study. Furthermore, the relevance of a multivariate regression approach that considers spatial factors is also supported by the study by Lin et al. (2024) through the application of Mixed Geographically Weighted Regression (MGWR) to analyze intercity traffic volume. They found that the influence of factors such as time, weather, and location is spatially heterogeneous. This strengthens this study's approach, which differentiates regression models at each intersection, considering the differing traffic characteristics between locations. Another study by Lin et al. (2022) also confirmed that trip frequency and weather conditions significantly contribute to variations in vehicle travel time. These findings align with the speed regression results in this study, which show that speeds decrease significantly at intersections with high traffic volumes and a predominance of heavy vehicles. Furthermore, a study by Zhong et al. (2020) confirmed that built environment variables, such as distance from intersections and the number of bus stops, influence vehicle travel timeThis study confirms that built environment variables, such as intersection spacing and the number of bus stops, influence vehicle travel time. One of the intersections with the most significant influence is Simpang Semampir, where T-test and ANOVA results indicate that travel direction and vehicle typ. E have a significant impact on speed variations. This is due to its strategic role as a major connecting intersection with dense mixed traffic, including heavy vehicles from goods distribution routes and private vehicles from residential areas. This condition strengthens the finding that speed reduction is influenced not only by traffic volume, but also by vehicle composition and movement patterns. Thus, Simpang Semampir is an important representation in understanding traffic dynamics in Kediri City and a top priority in urban traffic management policies.

Conclusion

The results show that vehicle speeds tend to decrease as volume increases, particularly when heavy vehicles dominate during peak hours. The regression approach used in this study provides a new way to examine the influence of time, direction, and vehicle type on traffic conditions at each intersection, a factor that has not been widely discussed previously. A key finding of this analysis is that a significant effect was identified only at Semampir Intersection, where direction of travel and vehicle type were shown to play a significant role in speed variations, while other intersections showed no significant impact. This confirms Semampir Intersection's strategic role as an intersection with complex mixed flows, making it a top priority in urban traffic management. These findings can also form the basis for more adaptive policies, such as adjusting traffic signal timings to reflect real-world conditions or restricting heavy vehicles to specific hours. In the future, this approach can be further developed by incorporating spatial analysis to make transportation planning more accurate and tailored to the characteristics of each location.

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