Impact of Side Friction Parameters to Road Performance, A Study of Road Side Activities to Jend. A Yani Road, Purbalingga

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Abstract. Traffic flow on city roads is greatly affected by side friction elements, like parking on the street, pedestrian crossings, and non-motorized vehicles (NMVs), mainly in areas with mixed traffic. This study looks at these effects on Jenderal A. Yani Road in Purbalingga, Indonesia, which is an important industrial route that links key manufacturing sites and sees a lot of vehicle and foot traffic. The goals of the research are to (1) find the side friction factor that most impact vehicle space mean speed (SMS), (2) use multivariate regression to understand the link between side friction and SMS, and (3) determine which traditional traffic flow model—Underwood, Greenshield, or Greenberg—best fits the observed flow patterns in mixed-traffic situations. Early results indicate that stopped vehicles are the biggest friction element that lowers SMS, while pedestrian crossings and NMVs also lead to delays during busy times. The Underwood model, which shows how speed decreases exponentially with increasing density, is the most accurate for depicting traffic dynamics on Jenderal A. Yani Road, with a critical density of 9.75 vehicles per km suggesting the start of congestion. These findings are useful for creating plans that improve traffic flow in urban-industrial areas. By addressing side friction and using the right traffic models, the research aids in developing data-informed approaches to enhancing the Level of Service (LOS) on roads with high friction, especially in developing nations facing similar traffic challenges. This work helps in managing urban traffic by laying the groundwork for planning that accommodates mixed traffic and lessens congestion.

1 Introduction

The way cars and other vehicles move on city roads is greatly affected by outside issues called side friction. Side friction covers many roadside actions like parking, people walking, and non-motorized vehicles (NMVs). These activities disrupt the normal traffic flow, lowering how many cars the road can handle effectively and affecting the space mean speed (SMS) of vehicles. It is important to understand how side friction relates to vehicle speeds for better managing urban roads, especially where there is a lot of business and industrial activity.

Jenderal A. Yani Road in Purbalingga, Indonesia, serves as an important example for this study because it connects three industrial areas. This road has three major manufacturers—PT Boyang Industrial, PT Indokores Sahabat, and PT Yuro Mustika—employing around 17,000 people. These factories make Jenderal A. Yani Road a vital route for business and industrial traffic, especially during busy times like shift changes. This leads to a notable rise in both vehicle and pedestrian traffic. The large number of workers and movement of goods and people cause a lot of side friction, which lowers the road's Level of Service (LOS) and increases delays and time travel during busy hours.

In addition, the road features mixed traffic, with various types of vehicles including motorcycles, cars, trucks, and NMVs like bicycles and three-wheelers. This varied traffic makes conditions on this divided urban road, as it is shown in Fig.2., even trickier. Mixed traffic, typical in many urban areas of developing nations, creates more issues as vehicles travel at different speeds and use varying amounts of road space. Research has indicated that the presence of slow-moving NMVs can greatly slow down motorized vehicles, reduce road capacity, and heighten congestion (Biswas, S., Chandra, S., & Ghosh, 2021; Purohit, Chattaraj, & Panda, 2014).

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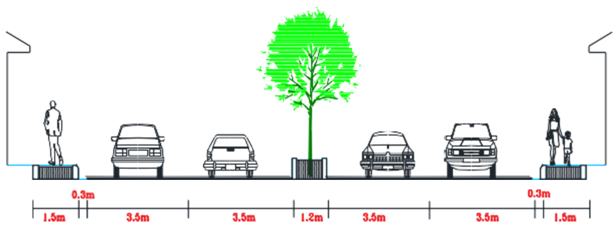

Fig.1. Jenderal A. Yani Road Cross Section

Key side friction factors influencing Jenderal A. Yani Road include on-street parking, which narrows the effective road space; pedestrian crossings, which often interrupt traffic flow, especially near business and industrial areas; and NMVs, which move slower and hinder attempts to pass other vehicles. These side friction aspects lead to marked drops in vehicle speeds during peak traffic times. The road's undivided design worsens these problems as vehicles must often stop behind NMVs or go around parked cars, adding to delays and creating complicated traffic situations (Hardini, 2010).

This study, recognising the mixed traffic and side friction challenges of Jenderal A. Yani Road, has several main goals. First, it wants to find out which side friction variable most affects vehicle space mean speed. By examining how on-street parking, pedestrian activity, and NMVs impact traffic speed, the study aims to pinpoint the most significant factor. Second, the research will apply multivariate regression analysis to understand the connection between side friction and changes in vehicle speed. This method will offer a numerical framework to estimate how shifts in side friction affect vehicle speed, providing a solid foundation for predicting speed reductions under various traffic conditions. Lastly, the study will assess the degree of speed reductions during peak hours, the busiest times, due to combined industrial and commercial activities.

Furthermore, this study looks to identify and analyse the traffic flow patterns along Jenderal A. Yani Road, determining which traditional traffic flow models—like Underwood's, Greenshield's, or Greenberg's—best fit the observed data flow situations. These models give a basic view of how vehicle speed, density, and flow work together in different traffic situations, especially in busy city areas (Roess, R. P., Prassas, E. S., & McShane, 2004). Figuring out which model best shows the flow behaviour on this road will help understand the traffic traits of roads with significant side friction and mixed vehicle types.

This study adds value by presenting real-world data and modelling the side friction effects in a mixed-traffic setting found on urban roads in developing countries. By measuring how these factors affect vehicle speed and finding the best traffic flow models for high-friction roads, this research gives useful information for city traffic management and planning. This can help reduce congestion and enhance the level of service (LOS) on similar roads.

2 Methodology

To reach the research goals and understand how side friction impacts vehicle space mean speed (SMS) and traffic flow on Jenderal A. Yani Road, a clear and organised method is needed. This part covers the main steps in gathering data, modelling traffic flow, and analysing regression. It also includes assessing traffic flow patterns using basic models like Greenshield's, Underwood's, and Greenberg's. All these methods will help find the most important side friction factors and how they affect traffic speed and flow, especially during busy times. The following methodology will direct the study, making sure each goal is met in an orderly way.

2.1 Study Area and Data Collection

The study is conducted on Jenderal A. Yani Road in Purbalingga, Indonesia, which is a major urban road that experiences significant traffic volumes due to its proximity to commercial and industrial zones. Data collection will occur at the industrial entrance along this road. These areas have high-level side friction activities nearby.

To fulfil the research objectives, traffic data will be collected through a combination of manual and automated methods. The following types of data will be gathered:

- Time travel and volume
  This data, collected using video cameras, will be used to monitor and analyse traffic flow and vehicle types, especially during peak and off-peak periods.
- Speed data
  This data will be compiled from all sources (radar guns, video recordings, and manual observations). Inconsistencies such as outliers (e.g., anomalously high or low speeds) will be removed, and missing data points will be addressed to ensure clean datasets for analysis.
- Side friction variables.
  Data is observed to record the frequency and intensity of side friction activities:
  a) On-Street Parking, this data includes the number and position of parked vehicles along the road. On-street parking density is quantified based on the number of vehicles per unit length of the road.
  b) Pedestrian Movements, this data covers the frequency of pedestrian crossings, particularly in proximity to industrial and commercial zones.
  c) Non-Motorised Vehicles (NMVs), data covers the number and types of NMVs (e.g., bicycles, three-wheel cycles). It is recorded along with their interaction with motorised vehicles.
- Road Geometry.
  This data is measured and documented to account for their impact on vehicle speeds and capacity.

2.2 Field Survey

The field survey was conducted in two phases: a pre-survey and a main survey. These phases ensured that data collection occurred during the peak traffic period, capturing the most relevant traffic and side friction conditions.

2.2.1 Pre-Survey

The pre-survey was conducted to identify the peak traffic day and hours. Observations were made over multiple days, Tuesday to Thursday, and it was determined that the highest traffic volumes occurred on weekdays during factory shift changes. The peak traffic hours were identified as 4:45 – 5:45 p.m. on Wednesday.

2.2.2 Main Survey

During the main survey, data were collected at peak hours using a combination of video cameras and manual observations. The data collection focused on:

- Traffic Volume, the number of vehicles, including motorcycles and MPUs (Motorized Public Utility vehicles), was recorded and counted.
- Vehicle Speeds, video recordings were used to measure the time taken by vehicles to travel over a set distance, allowing for the calculation of space mean speed (SMS) for motorcycles and MPU.
- Side Friction Factors, included on-street parking density (the number of parked vehicles per kilometre), Pedestrian Crossing Frequency (the number of pedestrians crossing the road at both designated and undesignated locations per hour), and non-motorized vehicle (NMV) Presence (the percentage of NMVs e.g., bicycles, three-wheels cycle in the traffic stream).

2.3 Data processing

2.3.1 Calculation of SMS

For every observation time (15-minute slots), the space mean speed (SMS) of vehicles will be figured out using the speeds of all seen vehicles over a certain distance. SMS represents the average speed of all vehicles moving along a road segment, measured in kilometres per hour (km/h). Calculations were performed by averaging the time taken by vehicles to cover a fixed distance within each segment. The SMS speed will be figured for each type of vehicle (such as bikes, cars, trucks, and NMVs) and then added together to show the total average for mixed traffic.

2.3.2 Traffic Flow Models

SMS data will be fitted into classical traffic flow models (Greenshield's, Underwood's, and Greenberg's) to evaluate which model best describes the traffic conditions on Jenderal A. Yani Road. Model performance will be evaluated using statistical measures such as the coefficient of determination (R^2) to determine the most accurate model for this urban road with high side friction.

2.3.3 Multivariate Regression Analysis:

The calculated SMS will serve as the dependent variable in the multivariate regression analysis, which will explore the relationship between the dependent variable (space mean speed/SMS) and independent variables (various side friction factors such as on-street parking, pedestrian movements, and NMVs). This will allow us to quantify the extent to which each side friction variable affects the space mean speed of vehicles.
The general form of the regression model is:

$$y = \beta 0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon \tag{1}$$

Where:

Y	: Space Mean Speed (SMS)
$\beta 0$	: Intercept
β_1, β_2, β_3	: Coefficients for side friction variables
x_1	: Parking Density
x_2	: Pedestrian Crossings
x_3	: NMV
ϵ	: Error term

2.4 Model Fit and Statistical Testing

2.4.1 Model Fit

The regression model's fit was looked at using the R-squared (R^2) statistic. This statistic shows how much of the change in the dependent variable (SMS) is explained by the independent variables (side friction factors). A higher R^2 value means a better model fit, indicating that side friction factors explain a good amount of the variation in vehicle speed.

It is expected that the R^2 value would be high if side friction factors strongly affect SMS. For example, if the R^2 value is 0.75, this means that parking density, pedestrian crossings, and NMV presence explain 75% of the change in vehicle speed.

2.4.2 Significance Testing

The regression model's significance and the individual coefficients were examined using ANOVA (Analysis of Variance) and t-tests (Field, 2017).

- ANOVA checks if the model is overall significant by testing the null hypothesis that it explains nothing (meaning all coefficients are zero). If the F-statistic from ANOVA is significant (p-value < 0.05), this means the model is overall significant and that the side friction variables help explain the changes in vehicle speed.
- T-tests were done to check the significance of each coefficient one at a time. A significant t-statistic (p-

value < 0.05) for a coefficient shows that the related side friction variable (like parking density) significantly impacts SMS (space mean speed).

2.4.3 Regression Coefficients

The regression coefficients (β1, β2, β3) show how much each side friction variable affects vehicle speed:
- β1 (Parking Density Coefficient) shows the change in speed (km/h) for each extra parked vehicle per kilometre. A negative value means that more parking leads to slower vehicle speeds.
- β2 (Pedestrian Crossing Coefficient) indicates how the number of pedestrian crossings affects speed. A negative value implies that more pedestrian crossings result in slower speeds.
- β3 (NMV Presence Coefficient) relates to how non-motorized vehicles affect speed. A negative number indicates that a greater share of NMVs in traffic leads to reduced speeds.

2.4.4 Expected Results

The multivariate regression analysis is expected to show that side friction variables such as parking density, pedestrian crossing frequency, and NMV presence have a significant negative impact on vehicle space mean speed. The model fit, as indicated by the R^2 value, is anticipated to show that these side friction factors explain a substantial proportion of the variance in vehicle speed. The regression coefficients will provide insight into the relative importance of each side friction variable in contributing to speed reductions along Jl. Jend. A. Yani, with NMV presence likely having the largest effect due to the slow speeds of these vehicles.

By providing a clear quantitative relationship between side friction and SMS, the results will offer valuable guidance for improving traffic flow and reducing congestion on urban roads with similar characteristics.

3 Result and Discussion

3.1. Traffic Behaviour

In this part, we look at how well three traffic flow models—Greenshield, Greenberg, and Underwood—work by matching them to the data we collected on traffic volume and speed. We use their mathematical formulas to understand how speed relates to density and check how well they fit the data using the coefficient of determination (R^2).

The traffic flow data was gathered over one hour and divided into 15-minute segments to see changes in traffic conditions. Table 1 shows the data we observed, which includes time intervals, traffic volume in passenger car units per hour (pcu/h), average speed (Us) in km/h, and density (D) in vehicles per kilometre. This data is what we use to examine if the Greenshield, Greenberg, and Underwood models are suitable for explaining the connection between speed and density in different traffic situations.

Table 1. Traffic Data.

Time Interval	Volume (pcu/h)	Speed, Us (km/h)	Density, D (veh/km)
16.45 – 17.00	197.05	13.74	14.341
17.00 – 17.15	211.55	31.44	6.729
17.15 – 17.30	178.4	34.39	5.188
17.30 – 17.45	139.05	43.11	3.225

3.1.1. Greenshield Model

The Greenshield model assumes a linear relationship between speed and density as follows, represented by equation (Davis, Ji, Liu, & Levinson, 2020)

$$Us = a + b \cdot D \qquad (2)$$

Linear regression of the data produced a slope b =−1.853 and intercept a=54.41, resulting in the following model

$$Us=54.41-1.853 \cdot D$$

The free flow speed occurs when D = 0, so

$$FFSGreenshield = a = 54.41 \ km/h$$

In the Greenshield model, the relationship is linear, and the critical density (k_{crit}) occurs at half the jam density k_j. At this density, the flow reaches its maximum (flow capacity), and speeds start to decline more significantly. It is formulated as follows

$$k_{crit} = \frac{k_j}{2} \qquad (3)$$

The estimated critical densities (early onset congestion) of 7.17 vehicles/km. This model achieved an R^2 value of 0.9819, indicating a strong fit but with limitations in capturing the speed decline at higher densities, as linear models may not adequately represent congestion effects.

3.1.2. Greenberg Model

The Greenberg model assumes a logarithmic relationship between speed and density, expressed as Us=a+b·ln (D). It is performing a regression analysis on the logarithmic transformation of density values yielded coefficients a=57.18 and b=−15.86, giving the model:

$$Us=57.18-15.86 \cdot ln(D)$$

To find the free flow speed, we consider the limit as D approaches a very small positive value (close to zero). In this case:

$$FFSGreenberg = a = 57.18 \ km/h$$

The logarithmic term vanishes as D as 0, leaving only the constant a as the free flow speed.
In Greenberg's model, the speed-density curve shows a logarithmic decrease, with congestion typically setting in at higher densities. The critical density for maximum flow is generally calculated as

$$k_{crit} = \frac{k_j}{e} \quad (4)$$

Resulting from the equation above, early onset congestion for the Greenberg model is 11.11 vehicles per km.
This model showed an improved R^2 value of 0.9883, suggesting a slightly better fit than the Greenshield model, particularly at lower densities. However, the logarithmic nature may still underrepresent the rapid speed decrease at high densities.

3.1.3. Underwood Model

The Underwood model posits an exponential relationship between speed and density, given by:

$$Us = a \cdot e^{b \cdot D} \quad (5)$$

By taking the logarithm of speed, we linearise the model as:

$$\ln(Us) = \ln(a) + b \cdot D \quad (6)$$

Regression on the transformed data provided values ln (a)=3.745 (or a=42.36) and b=−0.1095, resulting in the exponential model:

$$Us = 42.36 \cdot e^{-0.1095 \cdot D}$$

When D=0, the exponential term $e^{b \cdot D}$ becomes 1, so:

$$FFS_{Underwood} = a = 42.36 \text{ km/h}$$

The Underwood model's exponential relationship suggests congestion onset as speeds decline sharply after a certain density level. In this model, the critical density is often close to

$$k_{crit} = \frac{1}{|b|}$$

Here, b is the decay coefficient from the Underwood model's speed equation $Us = vf \cdot e^{-b \cdot k}$. The early onset of congestion is 7.17 vehicles per km.
The Underwood model achieved the highest R^2 value of 0.9944, indicating it is the best fit among the three models. The exponential form captures the sharp decline in speed with increasing density, particularly in congested conditions.

3.1.4. Comparative Analysis
From the traffic behaviour analysis shown earlier and in **Fig. 2**, it is clear that the Underwood model does better than the Greenshield and Greenberg models. This is because it has an exponential relationship that gives the highest R^2 value (0.9944) and reflects the quick drop in speed as density goes up. This strong fit shows that the Underwood model is best at representing traffic behaviour in both low and high-density situations, including when congestion starts. The Greenberg model does a decent job with a moderate fit (R^2=0.9883) and works well for less congested traffic, where speed decreases slowly, but it does not perform well under high-density conditions. On the other hand, the Greenshield model has the lowest R^2 value (0.9819) and provides a simpler linear relationship that estimates general traffic flow, but it is not accurate in congested situations because it cannot handle sudden drops in speed. Therefore, the Underwood model shows the best performance with the data provided.

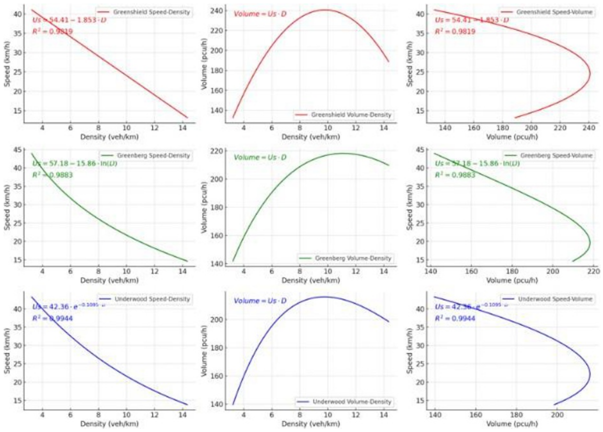

Fig.2. Traffic Model

The analysis shows that the Underwood model works best for explaining traffic behaviour on the roadway examined. Its exponential link between speed and density effectively highlights the quick drop in speed as traffic density rises, which makes it useful for forecasting traffic flow and handling congestion. The model's findings about the quick start of congestion and the elevated free-flow speed are significant for traffic planning and infrastructure upgrades.

3.2. Speed Change Analysis

3.2.1. Motor Cycle

The regression model has a fair fit, with an R^2 of 0.439. This indicates that side friction factors, such as pedestrian crossings, NMV, and stopping vehicles, account for 43.9% of the changes in motorcycle speed (Y_{MC}). There is still some variance that is not explained, which implies that additional factors might influence vehicle speeds. Nonetheless, the model offers useful information regarding the effect of side friction factors on traffic behaviour. The standard error of 11.55 shows a moderate degree of accuracy in the predictions made by the model.

Table 1. Model Summary MC.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.662[a]	0.439	0.425	11.55057

a. Predictors: (Constant), Ped_crossing, UM, Stopping_veh
b. Dependent Variable: YMC

The ANOVA results (Table 3) indicate that the overall regression model is highly significant (p-value = 0.000). The independent variables (Pedestrian Crossing, UM, and Stopping Vehicles) together explain a significant portion of the variation in the dependent variable

(YMC). The F-statistic of 30.763 is large, suggesting that the variation explained by the model is much greater than the unexplained variation, which strengthens the validity of the model.

The significant p-value (< 0.05) confirms that the side friction factors analysed (Pedestrian Crossing, UM, Stopping Vehicles) are important predictors of vehicle space mean speed (YMC), and the regression model provides a strong statistical foundation for understanding their impact.

Table 3. Anova Motor Cycle.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12312.919	3	4104.306	30.763	.000[b]
	Residual	15743.048	118	133.416		
	Total	28055.967	121			

a. Dependent Variable: YMC
b. Predictors: (Constant), Ped_crossing, UM, Stopping_veh

Based on the coefficients from Table 4, the formula of the regression equation that predicts the dependent variable (YMC) based on the independent variables (Stopping Vehicles, UM, and Pedestrian Crossings) is

Y_{MC}=54.702−1.320(Stopping Vehicles) + 2.773 (NMV)−0.064(Pedestrian Crossings)

Explanation:

- Intercept (54.702): When all independent variables (Stopping Vehicles, UM, and Pedestrian Crossings) are zero, the predicted YMC is 54.702 units.
- Stopping Vehicles (-1.320): For each additional stopping vehicle, YMC decreases by 1.320 units.
- NMV (2.773): For each unit increase in UM, YMC increases by 2.773 units. However, keep in mind that this variable was not statistically significant.
- Pedestrian Crossings (-0.064): For each additional pedestrian crossing, YMC decreases by 0.064 units.

- **Table 4.** Model Coefficients MC.

Model		Unstandardized B	Unstandardized Std.	Standardized Beta	t	Sig.
1	(Constant)	54.702	2.306		23.722	0.000
	Stopping_veh	-1.320	0.541	-0.318	-2.439	0.016
	UM	2.773	2.986	0.091	0.929	0.355
	Ped_crossing	-0.064	0.017	-0.421	-3.698	0.000

a. Dependent Variable: YMC

Thus, this regression formula can be used to estimate vehicle space mean speed based on the number of stopping vehicles, UM, and pedestrian crossings. However, as noted earlier, the UM variable was not statistically significant, so its impact on YMC may not be reliable.

3.2.2. UMP

Model Fit

As shown in Table 5, the R value of 0.709 indicates a moderate to a strong positive correlation between the predictors (Pedestrian Crossing, Non Motorised Vehicles, and Stopping Vehicles) and the dependent variable. This suggests that the predictors have a significant relationship with the outcome variable R (Correlation Coefficient). The R square value shows that 50.3% of the variance in the dependent variable can be explained by the model. This implies that the predictors account for just over half of the variability in the outcome, demonstrating a reasonably strong explanatory capability, though there is still room for improvement. Also, an Adjusted R Square value of 0.488 indicates that 48.8% of the variance in the dependent variable is explained after adjusting for the predictors, which further supports a moderate model fit. The Standard Error of the Estimate is 9.00142, reflecting the average difference between predicted values and observed values. A lower standard error suggests that the model's predictions are close to the actual values, giving an idea of its precision. In terms of significance, the model shows a very strong level of significance with a p-value of 0.000 (p < 0.001), which supports the overall validity of the model.

Table 5. Model Summary.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Sig. F Change
1	.709[a]	0.503	0.488	9.00142	0.000

a. Predictors: (Constant), Ped_Crossing, UM, Stopping_Veh
b. Dependent Variable: Ympu (space mean speed of MPU)

Predictor Significance

The ANOVA results in Table 6 show that the model, which includes Pedestrian Crossing, UM, and Stopping Vehicles as predictors, is important for explaining the changes in mpu speed (Ympu). With a notable F-ratio (F = 33.448, p < 0.001), the model finds significant trends in the data, indicating that these predictors work together to affect the dependent variable. However, the large residual sum of squares (8021.533) suggests that while the model accounts for a good amount of variance, other factors might also influence Ympu. This points to the need for further studies to add more relevant variables to enhance the model's accuracy.

Table 6. Anova MPU

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8130.435	3	2710.145	33.44	.000[b]
	Residual	8021.533	99	81.026		
	Total	16151.968	102			

a. Dependent Variable: Ympu
b. Predictors: (Constant), Ped_Crossing, UM, Stopping_Veh

Model coefficients

Table 7. Model Coefficient MPU.

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Stand. Coeff Beta	t	Sig.
1	(Constant)	45.842	1.844		24.863	0.000
	Stopping_Veh	-2.418	0.461	-0.643	-5.241	0.000
	NMV	3.951	2.348	0.158	1.683	0.096
	Ped_Crossing	-0.018	0.014	-0.143	-1.259	0.211

a. Dependent Variable: Ympu

Based on the coefficients provided in the SPSS output in Table 7, the regression model for predicting Ympu (SMS) can be expressed as:

$$Ympu=45.842-2.418\cdot Stopping\_Veh+3.951\cdot UM-0.018\cdot Ped\_Crossing +3.951\cdot UM-0.018\cdot Ped\_Crossing$$

Where:

- 45.842 is the intercept (constant), representing the baseline level of Ympu when all predictors are zero.
- Stopping_Veh has a coefficient of -2.418, indicating that each additional unit increase in stopping vehicles is associated with a decrease of 2.418 units in Ympu.
- UM has a coefficient of 3.951, suggesting that an increase in UM is associated with an increase of 3.951 units in Ympu, though this effect is not statistically significant.
- Ped_Crossing has a coefficient of -0.018, showing a minor and statistically insignificant negative association with Ympu.

This model is statistically significant overall, but the primary influential predictor is Stopping Vehicles, as the other predictors do not significantly impact Ympu in this context.

4. Conclusion

Traffic delay on Jl. Jend. A. Yani in Purbalingga's industrial area is a big problem for movement and efficiency. These issues are mainly due to regular traffic disruptions from side friction. This study tried to solve these problems by (1) looking at traffic flow patterns using basic traffic models—Underwood, Greenshield, and Greenberg—to find the model that best matches the actual traffic situation, and (2) figuring out which side friction factor most impacts vehicle space mean speed. The results showed the Underwood model is the best fit for traffic on Jl. Jend. A. Yani, with a high R^2 value of 0.9944. This indicates it accurately captures how speed decreases as traffic density goes up. This model found that congestion starts early, at a critical density of 9.75 vehicles per km, making it useful for understanding speed and density in urban industrial areas. Looking at side friction factors, the analysis revealed that Stopping Vehicles is the most important factor that affects vehicle space mean speed, showing a strong negative impact that is statistically significant ($p<0.001$, Beta = -0.643). This means that vehicle stops mainly cause reduced traffic flow efficiency, while other factors, like UM and Pedestrian Crossings, have little effect. These findings emphasize the need for specific measures to reduce stoppages, offering valuable information for enhancing traffic flow in industrial areas like Jl. Jend. A. Yani.

To make traffic better on Jl. Jend. A. Yani in Purbalingga's industrial area, we suggest creating no-stop zones and setting up designated places for loading and unloading. This will help limit stops by vehicles, which cause congestion. Improving pedestrian crossings, potentially with overpasses or underpasses, along with real-time traffic monitoring, can also help traffic move better in this area. Moreover, planning industrial activities during less busy times and encouraging public transit or carpooling can lessen the number of vehicles. These actions will help traffic flow smoother, enhance mobility, and meet the industrial area's needs effectively.

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