

ASSESSING THE IMPACT OF LEVEL CROSSINGS ON VEHICLE EMISSIONS FOR SUSTAINABLE URBAN TRANSPORTATION

Mira Lestira Hariani¹, Yackob Astor², Ikhlas Maddinah Pradana¹

¹Civil Engineering Department, University Swadaya Gunung Jati, Indonesia

²Politeknik Negeri Bandung, Indonesia

E-mail: mira.hariani0103@ugj.ac.id

Received 5 March 2026, Accepted 26 April 2026

ABSTRACT

Level crossings are a persistent source of traffic congestion and vehicular emissions in many urban areas, particularly in mid-sized cities where road and rail networks intersect at grade. This study investigates the impact of level crossing operations on vehicle CO₂ emissions by analyzing traffic delays caused by train movements at nine crossings in Cirebon City, Indonesia. Using field observations, four traffic-related variables were collected: train frequency (crossings/day), average waiting time (seconds), queue length (meters), and idle vehicle count (vehicles/day). Emissions were estimated using the IPCC Tier 1 methodology, and a multiple linear regression model was developed to assess the relationship between traffic conditions and daily CO₂ emissions. The results show that train frequency and idle vehicle count are statistically significant predictors of emissions, with each additional train and idle vehicle contributing substantially to total CO₂ output. While waiting time and queue length were less significant, their influence was observed to be moderated by vehicle type and traffic density. The regression model explains 99.6% of the variance in emissions (Adjusted R² = 0.996), underscoring the strength of the identified predictors. This study highlights the need for localized emission mitigation strategies, such as optimizing train schedules, improving traffic flow near crossings, and accounting for vehicle composition in emission control policies. The methodology and findings provide a practical framework for traffic-environmental assessments in similar urban settings.

Keywords : Level crossing, CO₂ emissions, Urban traffic delay, Idle vehicles, Regression analysis.

INTRODUCTION

Land transportation is a major contributor to global greenhouse gas emissions, particularly in densely populated urban areas, and poses a significant challenge to efforts aimed at mitigating climate change. The transportation sector plays a critical role in the global emission of carbon dioxide (CO₂), accounting for approximately 24% of total global emissions attributable to human activities. This substantial contribution to greenhouse gases is primarily due to automobiles, trucks, and other forms of transportation that largely rely on fossil fuels for energy, leading to significant emissions during combustion (Sari & Sofwan, 2021). For instance, the transportation sector's emissions are expected to triple by 2050 if current trends persist, which poses a severe threat to sustainability efforts globally (Taqi et al., 2023). The urban transportation element is increasingly scrutinized, as cities are responsible for about 80% of global greenhouse gas emissions (Ma et al., 2015). This phenomenon is exacerbated in high-density urban areas where transportation systems are primarily characterized by extensive reliance on personal vehicles and outdated technologies, leading to substantial environmental degradation (Sari & Sofwan, 2021).

The rapid growth in urban populations further intensifies the demand for transportation, increasing energy consumption and CO₂ emissions at an unprecedented rate. A clear example is Cairo, where the intense daily activity of its 4.5 million vehicles results in about 11,500 tons of CO₂ emissions per day (Hassan & Ageed, 2024). This pattern serves as a microcosm of the challenges faced by urban centers worldwide. There is also a direct correlation between urbanization and transport emissions. A recent study indicates that a 1% rise in urbanization can lead to an approximately 2.67% increase in CO₂ emissions from the transport sector (Solaymani, 2022). This nexus illustrates the complexities urban planners and policymakers must navigate in their quest for sustainable development. Understanding this connection is vital in formulating effective solutions, including technological innovations that enhance energy efficiency and systemic changes that reduce dependence on fossil fuels. Addressing CO₂ emissions from the transportation sector is not merely an environmental imperative but a critical element in the broader push towards sustainable cities.

In the context of Indonesia, level crossings between railway lines and public roads are often a major source of traffic congestion, particularly in small and medium-sized cities. Providing users with information about train arrival times and available safety features can help alleviate congestion in these areas. Utami and Widyastuti explains that queuing conditions at level crossings without gates are closely related to the length and speed of passing trains (Utami & Widyastuti, 2019). Their findings indicate that each additional train carriage contributes to a longer closure duration at the crossing, which in turn increases traffic congestion. Vehicles approaching these crossings often face delays due to traffic signals, barriers, or the presence of trains, leading to increased idling times and fuel consumption during these waits. Research has shown that idling vehicles are a considerable source of air pollution, including pollutants such as nitrogen oxides (NO_x) and particulate matter (PM) (Ernwati et al., 2022). By understanding the factors contributing to congestion, decision-makers can design better infrastructure plans around level crossings to reduce bottlenecks, enhance overall transportation efficiency, and ensure smoother traffic flow.

Train frequency significantly impacts traffic flow at level crossings, which directly affects vehicle emissions. According to Li et al, intersections and crossings are critical areas for understanding vehicle energy consumption and emissions, as the frequency of trains can create substantial delays for road traffic (T. Li et al., 2023). When trains pass through these intersections, vehicles must stop, leading to an increase in idling time. This idle time translates to higher emissions of harmful gases, including CO₂ and other pollutants, as vehicles release emissions during stop-and-go conditions. If planning does not adequately account for these interactions, it could exacerbate emissions and diminish air quality in surrounding areas. The length of vehicle queues at crossings also plays a crucial role in determining overall emissions. Extended queues due to delays caused by train crossings result in higher levels of emissions from prolonged idling and repeated acceleration once traffic resumes (Jang et al., 2023). Research by Jang et al. underscores the importance of accurately estimating road traffic emissions for a more comprehensive understanding of pollution levels. Long vehicle queues, particularly during peak hours, create a considerable burden on air quality, as vehicles continue to emit pollutants while waiting to proceed, indicating an urgent need for strategies to mitigate these delays.

Traffic volume is another critical variable in this study. Higher traffic volume typically correlates with increased emissions due to congestion. As noted by Gan et al,

effective carbon control strategies during transportation planning rely heavily on understanding how varying traffic volumes affect emissions (Gan et al., 2020). In urban areas with high traffic density, frequent stopping and starting lead to greater fuel consumption and higher emissions. Thus, failing to consider traffic volumes in relation to train frequency and queue lengths could result in ineffective transport policies that do not adequately address emission levels. The synergistic effect of train frequency, queue lengths, and traffic volume is paramount. Research indicates that poor coordination between rail and road traffic can lead to significant environmental degradation (Radhakrishnan et al., 2024). For instance, without considering how frequent train arrivals impact vehicle queues and traffic flow, urban planners may overspend on infrastructure improvements that fail to effectively reduce emissions. This interconnectedness suggests that an integrative approach to modeling traffic at crossings is essential for accurately predicting emissions and improving urban air quality.

To guide effective urban transport policy, understanding the dynamics of these variables is essential. Urban policies must account for the impact of increased train frequencies and traffic volumes on vehicle emissions (Mueller et al., 2017). Effective policies can enhance traffic management systems, such as through normalized signal timings and improved public transit integration to reduce waiting times at level crossings. Such proactive measures can contribute to substantial reductions in congestion and associated emissions, leading to healthier urban environments. The development of a comprehensive emissions model that considers these three factors will be invaluable. As Kholod et al argue, understanding the vehicle fleet composition and level of emissions control is imperative for developing effective pollution mitigation strategies (Kholod et al., 2016). Creating a nuanced model that incorporates train frequency, queue lengths, and traffic volumes will provide a robust framework for assessing emissions at level crossings. This model can assist local authorities in informing transport policies, prioritizing infrastructure investments, and enhancing overall urban sustainability.

The lack of local studies quantifying the impact of level crossings on vehicle emissions often leads to urban transportation policies overlooking their potential contribution to air pollution. Often, these crossings where roads intersect railway lines are overlooked in broader transport policy discussions, despite their

significant potential contributions to air pollution levels. It is essential to understand that level crossings are intrinsically linked to traffic congestion and resultant emissions. The gaps in research surrounding emissions from level crossings emphasize a critical need for data-driven policymaking. As illustrated in Cheng et al.'s work, urban transportation management policies need rigorous evaluation and data collection to accurately capture their effects on emissions (Cheng et al., 2015). This need is particularly pressing in developing urban areas in Indonesia, where the rapid pace of growth often outstrips the ability to conduct thorough environmental assessments. Further, local studies are integral to understanding how practices in urban transportation can adapt to mitigate emissions.

Without a thorough understanding of the relationship between level crossings and vehicle emissions, urban infrastructure planning and environmental policies risk being ineffective or even exacerbating air pollution issues in the future. This lack of comprehension can lead to several significant consequences that collectively undermine efforts to promote sustainable urban environments, such as increased air pollution levels, inefficient urban planning, missed opportunities for policy implementation, escalating public health issues, public awareness and engagement deficiencies, environmental justice concerns, failure to meet regulatory standards and increased financial burden. Ignoring the emissions generated at level crossings can result in unaddressed air quality issues in urban areas. As vehicles slow down at crossings, they tend to idle or accelerate more frequently, contributing to an increase in harmful emissions such as PM_{2.5}, nitrogen oxides (NO_x), and volatile organic compounds (VOCs) (W. Wang et al., 2022). Wang et al highlight that urban traffic emissions primarily stem from congestion, and failure to recognize and mitigate these emissions can perpetuate high pollution levels, ultimately increasing health risks associated with air quality degradation (W. Wang et al., 2022). As highlighted by Wang et al, poor design around crossings can exacerbate traffic congestion, leading to increased emissions (W. Wang et al., 2022). Consequently, infrastructure investments may not yield the intended environmental benefits, limiting the potential for cleaner transport networks. Failure to acknowledge the pollution problem at intersections may lead to a greater prevalence of health issues within communities. As reported by Kulick et al., long-term exposure to air pollution can negatively affect cognitive function and exacerbate chronic health conditions (Kulick et al., 2020). Regions experiencing inadequate traffic management around level crossings may particularly suffer, as heightened emissions can lead to increased hospitalizations for respiratory and

cardiovascular conditions. Without accurate data, health officials may struggle to draw connections between traffic emissions and health outcomes, thereby impeding effective public health responses.



Figure 1. Traffic Phenomena at Level Crossing

The research study aims to assess the influence of train frequency, vehicle queue lengths, and traffic volume on vehicle emissions at nine level crossing points in Cirebon City. This inquiry is essential for informing sustainable urban transportation planning. Given the findings from the study, several recommendations can be made for ensuring effective urban transportation planning. The interaction between train frequency, vehicle queue lengths, and traffic volume significantly influences vehicle emissions at level crossings in Cirebon City. This research emphasizes the need for localized studies to appropriately inform urban transport policies and infrastructure planning, ultimately contributing to more effective solutions for minimizing emissions and enhancing urban air quality. By integrating these findings into transportation planning, local authorities can better address the challenges posed by increasing urbanization and traffic congestion while ensuring sustainable practices in urban areas.

METHODS

Research Flow Diagram

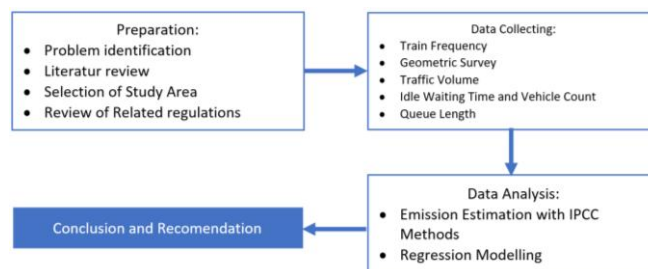


Figure 2. Research Flow Diagram

The overall steps of this research are summarized in the flowchart shown in Figure 2. The process begins with the preparation phase, including problem identification, literature review, selection of the study area, and review of relevant regulations. The second stage involves collecting traffic and geometric data, specifically train frequency, traffic volume, idle waiting time, vehicle count, and queue length. These data form the basis for the emission analysis in the next stage, where the IPCC Tier 1 method is applied to estimate CO₂ emissions. Finally, multiple linear regression modeling is conducted to determine the influence of each traffic variable on total emissions. The results are then synthesized into conclusions and recommendations for urban transportation policy and emission mitigation strategies.

Study Area

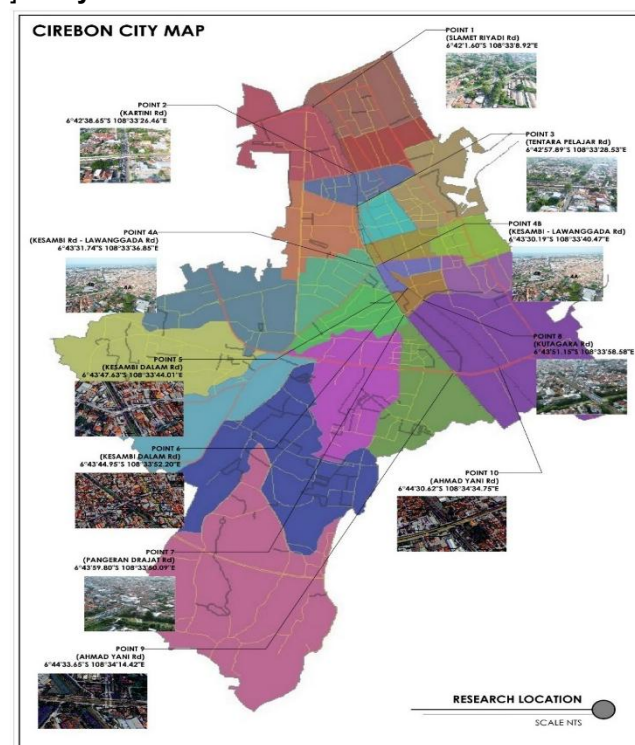


Figure 3. Study Area

This study was conducted in Cirebon City, a mid-sized urban center in West Java, Indonesia. The city features nine active level crossings that are integrated within the

primary urban road network. These crossings regularly experience congestion due to frequent train schedules, making them suitable sites for analyzing the relationship between traffic delay and vehicle emissions. These crossings were selected based on varying train frequencies, traffic volumes, and their strategic location on arterial roads, making them representative of typical urban traffic conditions in Indonesian cities.

Data Collection

Traffic and operational data were collected through direct field observations and video recording over a 12-hour period during typical weekdays. Four key variables were recorded at each of the nine crossings:

1. Train Frequency: The number of train crossings at each site over a 12-hour period (times/day).
2. Queue Length: Observed average queue length (in meters) during the closure of each crossing.
3. Waiting Time: The average duration (in seconds) for which vehicles remain idle during each gate closure.
4. Idle Vehicle Count: Number of vehicles that were stopped during gate closure, directly observed and counted based on the queue length at the time of the survey.

Observers positioned at each site recorded data using stopwatch measurements, wheel distance counters, and manual vehicle counts. Queue lengths were cross-validated using drone footage to ensure consistency and accuracy.

Emission Estimation Method

Vehicle CO₂ emissions were estimated using the Intergovernmental Panel on Climate Change (IPCC) Tier 1 method, which is suitable when detailed fleet composition or fuel usage data are limited. The formula used is:

$$E = A \times EF \times T \quad (1)$$

Where:

E = Total CO₂ emissions (grams)

A = Number of idle vehicles (vehicles)

EF = Emission factor (grams CO₂ per vehicle per second of idling), based on IPCC default values

T = Total idling time per vehicle (seconds)

The idle vehicle count was derived directly from survey data of vehicles observed in the queue during crossing closures. Idling time was calculated by multiplying the average wait time by the number of train events. The emission factor used was 0.0023 kg CO₂/sec per vehicle.

Statistical Analysis

To assess the impact of traffic-related variables on vehicle emissions, a multiple linear regression model was developed with the following structure:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon(2)$$

Where :

X₁ = Train frequency (crossings/day)

X₂ = Average waiting time (seconds/train)

X₃ = Queue length (meters)

X₄ = Number of idle vehicles (vehicles/day)

β₀ = Intercept

β₁–β₄ = Regression coefficients for each predictor

ε = Error term

Regression analysis was conducted using SPSS version 25.0. The model's assumptions were tested through:

1. Multicollinearity diagnostics (Variance Inflation Factor)
2. Normality of residuals (Q-Q plots, Shapiro-Wilk test)
3. Homoscedasticity (scatterplots)
4. Linearity and independence (Durbin-Watson statistic)

The analysis aimed to determine which variables significantly influenced emissions and to quantify their respective contributions. The adjusted R² value, p-values, and standardized coefficients were used to interpret the strength and significance of the predictors.

RESULTS AND DISCUSSION

Overview Observed Data

The observed train frequency across the nine level crossings in Cirebon City showed notable variation. The number of train crossings recorded over a 12-hour observation period ranged from 20 to 51 times per day, with an average of 32 times per day for 9 level crossings. This variation reflects the differing intensities of rail activity at each location, which in turn influences traffic conditions during gate closures. Locations with higher train frequency typically experienced more frequent interruptions to road traffic, resulting in longer cumulative waiting times for vehicles. These findings suggest that train scheduling is an important factor in shaping traffic flow and the extent of vehicle accumulation at level crossings.

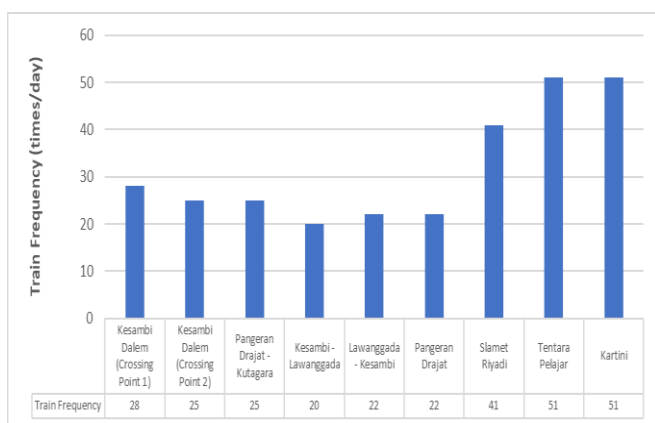


Figure 4. Train Frequency

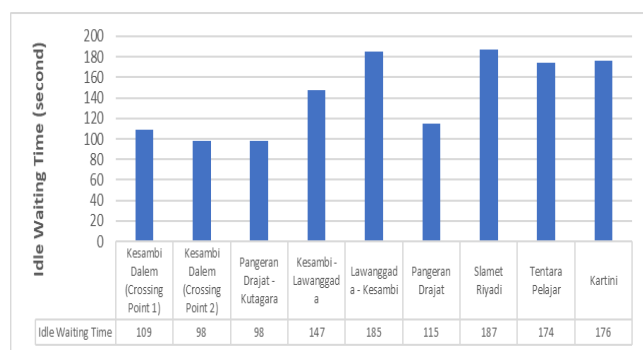


Figure 5. Idle Waiting Time

Idle waiting time refers to the duration for which vehicles remain stationary during gate closures at level crossings. Observations across the nine sites revealed that average waiting times varied depending on the length of each train and the frequency of closures. The recorded idle times ranged from 98 to 187 seconds per closure, with an overall average of 143,4 seconds. These variations were influenced by differences in train speed, number of railcars, and crossing gate response times. Prolonged waiting times contribute to extended vehicle idling, which increases fuel consumption and potential emissions. Crossings with longer average wait durations tended to exhibit greater vehicle accumulation and more pronounced traffic delays, underscoring the importance of gate operation efficiency in minimizing environmental and traffic impacts.

Queue length was measured as the average length of vehicle buildup (in meters) occurring during each gate closure at the level crossings. The observed queue lengths across the nine locations ranged from 11,32 to 154,25 meters, with a mean queue length of approximately 84,05 meters. These variations were influenced by several factors, including traffic volume, road geometry, and train closure durations. Longer

queues were typically observed at crossings located on major arterial roads or in areas with high vehicle flow during peak periods. In some locations, limited road space and the absence of advance warning systems exacerbated the extent of queue formation. The accumulation of vehicles in queues not only indicates traffic congestion but also signifies potential increases in vehicle idling and emissions, especially when closures occur repeatedly within short intervals.

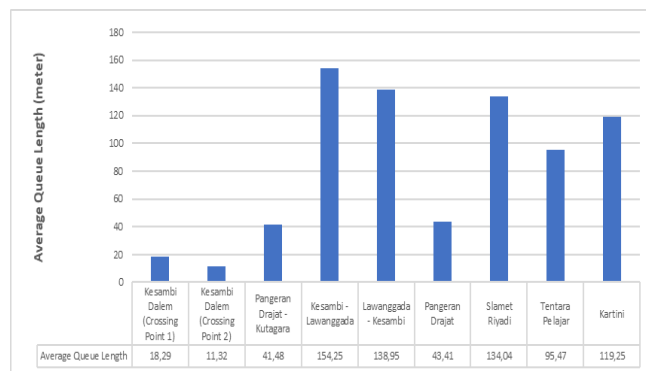


Figure 6. Average Queue Length

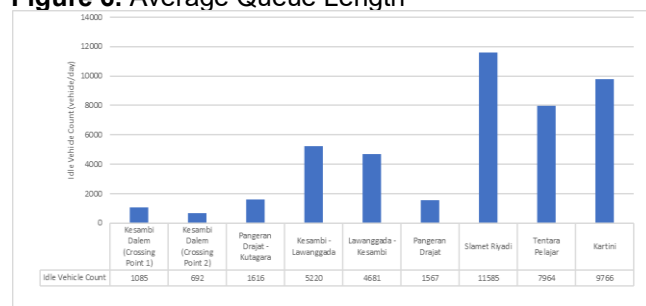


Figure 7. Idle Vehicle Count

Idle vehicle count represents the number of vehicles that were observed to be stationary in a queue during each gate closure at the level crossings. This variable was recorded directly through field surveys, using queue length observations and visual confirmation. The number of idle vehicles per day ranged from 692 to 11585 vehicles, with an average of 4908 vehicles observed across the nine locations. Higher idle counts were typically found at crossings with longer queues and more frequent train activity. These figures reflect the scale of traffic disruption caused by level crossings and serve as a critical input for estimating total vehicle emissions. The presence of a large number of idle vehicles, even over short time periods, can lead to significant cumulative emissions, particularly in locations with high daily train frequency.

The total CO₂ emissions per level crossing in Cirebon City exhibit substantial variation. Based on emission estimations using the IPCC Tier 1 method, the calculated values range from 241.95 kg/Tj to 17,256.09 kg/Tj, with an average emission of 5,371.96 kg/Tj and a standard deviation of 6,466.20 kg/Tj. This high level of dispersion is further reflected in the wide interquartile range, where

50% of the sites fall between 672.96 kg/Tj (Q1) and 8,256.17 kg/Tj (Q3). Such disparity highlights the differing conditions and characteristics across the nine observation points. This variation in emissions is primarily influenced by the operational and geometric differences between crossings. For instance, crossings located on high-volume arterial roads with frequent train schedules, such as Kartini and Tentara Pelajar, exhibited significantly higher emissions due to greater idle vehicle accumulation and prolonged waiting times. Conversely, minor crossings with lower train frequency and lighter traffic, such as Kesambi Dalem Point 2, generated substantially lower emissions.

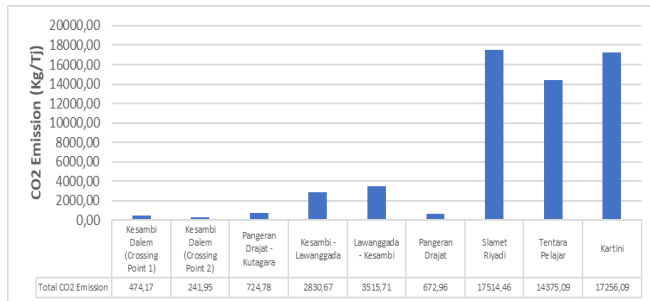


Figure 8. Total CO2 Emission

Tabel 1. Statistic Data of Total CO2 Emission

Statistic	Value (kg/Tj)
Minimum	241.95
Quartile 1 (Q1)	672.96
Median (Q2)	2830.69
Quartile 3 (Q3)	8256.17
Maximum	17256.09

Tabel 2. Result of Regression Model

Independent Variable	Koefisien (B)	Std. Error	Beta Standar	t	Sig.	VIF
(Constant)	-6,225.544	1,319.916	—	-4.739	0.009	—
Train Frequency (x_1)	173.239	36.201	0.285	4.785	0.009	6.754
Waiting Time (x_2)	11.854	13.501	0.060	0.878	0.429	8.793
Queue Length (x_3)	-26.526	10.035	-0.194	-2.643	0.057	10.251
Idle Vehicle Count (x_4)	1.569	0.159	0.837	9.884	0.001	13.604
$R^2 = 0.998$ Adjusted $R^2 = 0.996$ $F = 473.575$ Sig. = 0.000 Durbin-Watson = 1.909						

The regression equation is expressed as:

$$\text{CO}_2 \text{ Emission} = -6225.544 + 173.239 X_1 + 11.854 X_2 - 26.526 X_3 + 1.569 X_4 \quad (3)$$

Statistic	Value (kg/Tj)
Mean	5371.96
Standard Deviation	6466.20

The data distribution clearly indicates that vehicle emissions at level crossings are highly site-specific. This reinforces the need for localized traffic management strategies, rather than one-size-fits-all policies, when addressing urban emissions. Additionally, the presence of outlier values, particularly at crossings with extreme traffic densities does not diminish data quality but rather emphasizes the real-world diversity of traffic scenarios in Indonesian urban contexts. This descriptive pattern underscores the importance of further analysis using regression modeling to quantify the specific influence of variables such as train frequency, waiting time, queue length, and idle vehicle count. The regression model thus serves to explain the underlying mechanisms contributing to this wide range of emissions and to identify which traffic factors should be prioritized in mitigation efforts.

Result of Regression Model

The multiple linear regression analysis was performed to evaluate the relationship between four independent variables such as train frequency, average waiting time, queue length, and idle vehicle count and the dependent variable, total CO₂ emissions (kg/Tj). The resulting model exhibited an R^2 value of 0.998 and an adjusted R^2 of 0.996, indicating that the model explains 99.6% of the variability in emissions among the observed sites. The overall model was statistically significant ($F = 473.575$, $p < 0.001$), suggesting a very strong predictive capacity.

Among the predictors, train frequency and idle vehicle count emerged as the most significant contributors, both showing strong positive coefficients and statistically significant p-values ($p = 0.009$ and $p = 0.001$, respectively). This confirms that the more frequent the train crossing and the greater the number of vehicles idling, the higher the resulting CO₂ emissions. Although queue length was not statistically significant at the 5% level ($p = 0.057$), its negative coefficient suggests a potentially complex interaction in congested environments that may require further investigation. Waiting time, with a p-value of 0.429, was not a significant predictor in this model, possibly due to collinearity effects—especially with idle vehicle count, which may have captured overlapping effects.

The Durbin-Watson value of 1.909 indicates no serious autocorrelation in the residuals, supporting the model's validity. However, high VIF values (particularly for idle vehicle count = 13.604) suggest the presence of multicollinearity, which will be further addressed in the discussion section. Overall, this model provides a robust quantitative basis for understanding how specific traffic and operational variables at level crossings influence CO₂ emissions, offering a foundation for targeted emission reduction strategies.

Model Interpretation

The regression model reveals several important findings regarding the relationship between traffic characteristics at level crossings and vehicle CO₂ emissions.

First, train frequency ($B = 173.239$, $p = 0.009$) has a strong positive and statistically significant effect on emissions. This means that each additional train crossing per day is associated with an increase of approximately 173.2 kg of CO₂ emissions. This confirms that frequent train operations lead to more frequent interruptions in traffic flow, causing increased idling time and, consequently, higher emissions. This result is in line with research by Utami and Widyastuti which shows that increasing vehicle volume at level crossings contributes to congestion, which together with train time closures, increases CO₂ emissions in the area (Utami & Widyastuti, 2019). In addition, Marsa et al highlighted that busy level crossings with tight train schedules tend to cause longer vehicle waiting times, thus worsening the surrounding air emission conditions (Marsa et al., 2023).

Second, idle vehicle count is the strongest individual predictor in the model ($B = 1.569$, $p = 0.001$). For each additional vehicle that stops at the crossing, emissions are predicted to rise by around 1.57 kg of CO₂. This result underscores the direct impact of vehicle accumulation

during gate closures, particularly in high-density urban areas where many motorized vehicles rely on fossil fuels. This result are in line with Zhang et al who indicate that idle speed significantly contributes to vehicle emissions, particularly under stop-and-go conditions typical of urban intersections where vehicles experience prolonged idling (Zhang et al., 2022). Their work supports the claim that as more vehicles accumulate at traffic signals or crossings, emissions rise due to the extended periods of idling.

Interestingly, the variable queue length shows a negative coefficient ($B = -26.526$) and is marginally significant ($p = 0.057$). While counterintuitive at first glance, this may suggest that longer queues do not always result in proportionally higher emissions. One plausible explanation is that queue length reflects the physical space occupied, but not necessarily the number or type of vehicles within it. For example, a queue dominated by smaller motorcycles (which are common in Indonesia) may occupy a similar length as a shorter queue with larger vehicles like trucks or SUVs. Because emission intensity varies significantly by vehicle type, especially between two-wheelers and heavy-duty vehicles, queue length alone may not be a sufficient proxy for emission volume. This points to the importance of combining vehicle composition data with physical traffic metrics when modeling emissions. This result are in line with Konečný et al who discuss that emission factors are influenced by various vehicle characteristics, such as size and type. Their research indicates that larger vehicles, such as trucks, typically have higher emission levels compared to smaller vehicles like motorcycles. Thus, a longer queue might consist predominantly of smaller vehicles, leading to comparatively lower emissions despite the physical space occupied (Konečný et al., 2020). This supports the idea that queue length alone may not be a proxy for emission volume. Pryciński et al. provide insight into the emission characteristics of different vehicle types. They confirm that passenger cars and light-duty vehicles contribute differently to emissions compared to heavy-duty vehicles, reinforcing the understanding that longer vehicle queues may not correspond to a proportional increase in emissions (Pryciński et al., 2023). Jo and Kim explore how different vehicle compositions affect emissions in their model, emphasizing the importance of including different vehicle types when assessing total emissions. Their findings suggest that vehicle mix can significantly alter expected emissions from traffic, supporting the claim that queue length alone does not provide a complete picture (Jo & Kim, 2021).

Lastly, average waiting time ($B = 11.854$, $p = 0.429$) was not statistically significant in this model. Although theoretically relevant, its explanatory power may have

been diluted due to collinearity with train frequency and idle vehicle count. In practical terms, this suggests that the duration of each closure contributes less to emission variance than the number of vehicles affected and the frequency of closures.

The model demonstrates that emissions are driven more by volume and frequency-related variables than by spatial or temporal metrics alone. The findings highlight the role of vehicle type and operational characteristics in shaping emission outcomes at level crossings. This has important implications for urban emission control strategies: targeting locations with high train frequency and dense traffic may offer the greatest potential for CO₂ reduction.

Comparison With Previous Study

The results of this study support and extend existing research on the environmental impacts of traffic disruptions at level crossings. The statistically significant influence of train frequency and idle vehicle count aligns with findings from Zhao et al, who demonstrated that traffic interruptions, particularly those associated with frequent train operations substantially increase vehicle emissions due to prolonged idling and repeated stop-and-go cycles (Zhao et al., 2019). Similarly, Sitati et al observed that vehicle emissions tend to peak during congestion periods, especially in urban intersections that experience frequent delays (Sitati et al., 2022).

The dominant effect of idle vehicle accumulation in this study reinforces the role of traffic density in shaping emission profiles. This is consistent with Anjos and Meier, who emphasized that traffic volume and the number of vehicles affected by stoppages are more predictive of emissions than waiting time alone (Anjos & Meier, 2025). The current study contributes further by providing localized empirical evidence from an Indonesian urban setting, demonstrating that idle vehicle count is not just statistically significant but also practically impactful, especially in areas with high motorcycle and private vehicle usage. Nkosi et al. highlighted that while their study focused on PM₁₀ emissions, heavy traffic and idling conditions at intersections were recognized as contributing to increased overall emissions, reinforcing the idea that high vehicle counts lead to higher pollution levels (Nkosi et al., 2023). Wang et al. discussed how various factors, including vehicle composition and traffic demand, affect CO₂ emissions during traffic disruptions. Their study revealed that emissions spiked as vehicles idling during delays, supporting the relationship between idling and CO₂ emissions (Y. Wang et al., 2024). Leong and Shafie found that reducing delay time at intersections is critical to minimizing air pollutants. Their study showed that emissions were strongly influenced by idling time,

which is directly related to the number of vehicles queuing for clearance (Leong & Shafie, 2024). This highlights the correlation between greater vehicle accumulation and increased emissions during idling period. Jamal et al. argued that vehicle emissions are significant due to queues and waiting times at traffic intersections. Their findings suggest that large volumes of idling vehicles can drastically increase pollutant emissions as the number of vehicles waiting at traffic lights increases (Jamal et al., 2020).

The negative coefficient found in queue length presents a nuanced insight and suggests that vehicle composition not just spatial queue metrics plays a crucial role. As previously reported by Ernwati et al, two-wheelers such as motorcycles contribute lower CO₂ emissions per unit of space compared to four-wheelers or heavy vehicles (Ernwati et al., 2022). In Indonesia, the high presence of motorcycles may cause long queues without corresponding high emissions, thereby explaining the inverse relationship observed in the model. This finding highlights the need for future emission models to consider vehicle-type weighting for more accurate estimation. Previous research conducted by Caviades et al who highlighted how traffic fleet composition affects emissions. They noted that urban areas often experience varying emissions due to differences in the proportion of light versus heavy vehicles. This suggests that longer queues with light vehicles may lead to different emission profiles compared to shorter queues with heavier vehicles, supporting the assertion that queue length is inadequate as a stand-alone measure of emissions (Caviades et al., 2016). Li et al. emphasized that emission factors can vary significantly based on vehicle type and environmental context. Their findings support the claim that the presence of lighter vehicles (such as motorcycles) can mitigate the expected increase in emissions due to longer queues (X. Li et al., 2020). They advocate continued monitoring and consideration of vehicle type when modeling emissions in urban environments.

The insignificance of waiting time as a standalone predictor, despite its theoretical importance, reflects overlapping influence with other variables such as train frequency and idle vehicle count. Previous studies such as Yang and Wang also observed that real-time traffic conditions can diminish the isolated effect of average delay, especially in systems where delay duration is highly synchronized with flow intensity (Yang & Wang, 2024).

In terms of policy implications, these results underscore the importance of targeting crossings with high idle vehicle accumulation and frequent train activity. While engineering improvements to crossing infrastructure may be costly, strategic solutions such as optimizing gate

operation timing, rerouting traffic during peak train hours, or disseminating real-time train arrival information to drivers may reduce vehicle idle time and emissions more cost-effectively. Additionally, policy interventions that consider vehicle composition such as emission controls for high-polluting vehicles at specific crossings could be more effective than blanket regulations.

This study, while limited to nine crossings within Cirebon City, offers methodological insights for broader application. The combination of field-based observations and IPCC-based emission modeling provides a replicable framework for other cities facing similar emission challenges due to mixed traffic and level crossings. Moreover, the observed variations in emission levels across sites demonstrate the importance of localized transport planning, where interventions must be tailored to the characteristics of each crossing.

Policy Implication

The findings of this study carry significant implications for urban transportation and environmental management, particularly in mid-sized cities where level crossings remain prevalent and contribute heavily to traffic congestion and vehicle emissions. The strong influence of train frequency and idle vehicle count on CO₂ emissions suggests that any emission mitigation strategy must prioritize interventions that reduce the frequency, duration, or impact of train-induced traffic stoppages.

One policy direction involves the optimization of train scheduling, particularly during peak road traffic hours. While modifying rail timetables may be complex due to operational constraints, better coordination between road and rail transport agencies could help minimize the overlap between high train activity and peak vehicular flows. At the very least, advance warning systems and real-time digital signage informing road users of approaching trains could enable drivers to reroute or adjust their travel time, reducing idle accumulation at the crossings.

Another practical strategy is the implementation of traffic management systems that redistribute traffic flows away from heavily congested crossings. This could include dynamic rerouting, prioritizing alternate roads during gate closures, or restructuring public transport routes to avoid crossings with high emissions. For example, public buses and paratransit routes could be adjusted to reduce idle time near level crossing with high daily emissions.

The results also support infrastructure-based interventions, such as building flyovers or underpasses at crossings with persistently high idle vehicle counts and emissions. While such projects are capital-intensive, this

study provides a quantitative justification for prioritizing certain crossings over others based on emission profiles. Furthermore, the observed negative coefficient on queue length possibly reflecting the predominance of low-emission two-wheelers suggests that vehicle composition should be considered in policymaking. Targeted regulations for high-emission vehicles (e.g., delivery trucks, old diesel buses) near sensitive or congested crossings may be more effective than uniform emission restrictions. In the long term, promoting modal shift toward low-emission vehicles or electric motorcycles in cities like Cirebon could also support emission reduction efforts at ground level.

Lastly, policy development should emphasize data-driven planning. The methodology in this study integrating queue analysis, waiting time, and real-world emission estimation can serve as a replicable framework for other cities experiencing similar challenges. By focusing on site-specific traffic dynamics, local governments can develop prioritized, context-sensitive solutions that reduce both congestion and emissions simultaneously.

CONCLUSION

This study explored the relationship between traffic characteristics at level crossings and vehicular CO₂ emissions in the urban context of Cirebon City, Indonesia. By integrating field-observed data on train frequency, waiting time, queue length, and idle vehicle count with the IPCC Tier 1 emission estimation method and multiple linear regression analysis, the study successfully quantified the extent to which each factor contributes to emissions.

The results revealed that train frequency and idle vehicle count are the most significant predictors of CO₂ emissions, highlighting the critical role of traffic interruption frequency and vehicle accumulation in shaping emission outcomes. Although waiting time and queue length were less statistically influential, their roles remain relevant, particularly when considered alongside vehicle composition and traffic flow conditions. The negative coefficient associated with queue length suggests the need to further consider vehicle types within emission modeling, as long queues composed primarily of motorcycles may produce fewer emissions than shorter queues of larger vehicles.

This research provides empirical evidence to support localized traffic and environmental management policies. It demonstrates that emission impacts at level crossings are site-specific and must be addressed through targeted interventions in scheduling, infrastructure design, and traffic management. The model developed herein also offers a practical framework for similar studies in other

urban settings facing congestion and air quality challenges due to road-rail intersections.

However, several limitations should be acknowledged. First, the sample size was limited to nine level crossings, which, while sufficient for initial modeling, may not fully capture broader network-wide variations. Second, the study did not account for dynamic traffic flow, vehicle type differentiation, or meteorological factors that can also influence emission dispersion and accumulation. Additionally, multicollinearity among predictor variables—particularly idle vehicle count, queue length, and waiting time—presents a challenge in isolating the individual effects of each factor.

For future research, expanding the study to include more crossing points and incorporating vehicle classification data (e.g., car, truck, motorcycle) will enhance the precision of emission modeling. Furthermore, real-time traffic simulations and integration of air quality monitoring data can offer a more comprehensive view of the environmental impacts of level crossings. Lastly, exploring nonlinear or machine learning models such as Partial Least Squares (PLS-SEM) or regression trees may help better address multicollinearity and improve predictive power. This study reinforces the need for evidence-based, site-specific transport planning and presents a replicable approach to understanding and mitigating traffic-related emissions at level crossings in growing urban areas.

REFERENCES

- Anjos, M., & Meier, F. (2025). Zooming Into Berlin: Tracking Street-Scale CO₂ Emissions Based on High-Resolution Traffic Modeling Using Machine Learning. *Frontiers in Environmental Science*, 12. <https://doi.org/10.3389/fenvs.2024.1461656>
- Caviedes, Á., Bigazzi, A., & Figliozzi, M. (2016). Modeled Effects of Traffic Fleet Composition on the Toxicity of Volatile Organic Compound Emissions. *Transportation Research Record Journal of the Transportation Research Board*, 2570(1), 118–126. <https://doi.org/10.3141/2570-13>
- Cheng, Y.-H., Chang, Y., & Lu, I. J. (2015). Urban Transportation Energy and Carbon Dioxide Emission Reduction Strategies. *Applied Energy*, 157, 953–973. <https://doi.org/10.1016/j.apenergy.2015.01.126>
- Ernwati, H., Bindar, Y., Purqon, A., & Srigutomo, W. (2022). Prediction of Carbon Monoxide Concentration With Variation of Support Vector Regression Kernel Parameter Value. *Journal of Mathematical and Fundamental Sciences*, 54(1), 39–53. <https://doi.org/10.5614/j.math.fund.sci.2022.54.1.3>
- Gan, J., Li, L., Xiang, Q., & Ran, B. (2020). A Prediction Method of GHG Emissions for Urban Road Transportation Planning and Its Applications. *Sustainability*, 12(24), 10251. <https://doi.org/10.3390/su122410251>
- Hassan, N. E., & Ageed, S. (2024). Assessing the Impact of CO₂ Emissions From Transport and Power on Health and Environment in Duhok, Kurdistan Region, Iraq. *Ijamrs*, 4(5), 704–707. <https://doi.org/10.62225/2583049x.2024.4.5.3313>
- Jamal, A., Rahman, M. T., Al-Ahmadi, H. M., Ullah, I., & Zahid, M. (2020). Intelligent Intersection Control for Delay Optimization: Using Meta-Heuristic Search Algorithms. *Sustainability*, 12(5), 1896. <https://doi.org/10.3390/su12051896>
- Jang, S., Song, K. H., Kim, D., Ko, J., Lee, S. M., Elkosantini, S., & Suh, W. (2023). Road-Section-Based Analysis of Vehicle Emissions and Energy Consumption. *Sustainability*, 15(5), 4421. <https://doi.org/10.3390/su15054421>
- Jo, H., & Kim, H. (2021). Developing a Traffic Model to Estimate Vehicle Emissions: An Application in Seoul, Korea. *Sustainability*, 13(17), 9761. <https://doi.org/10.3390/su13179761>
- Kholod, N., Evans, M., Gusev, E., Yu, S., Malyshev, V., Tretyakova, S., & Barinov, A. S. (2016). A Methodology for Calculating Transport Emissions in Cities With Limited Traffic Data: Case Study of Diesel Particulates and Black Carbon Emissions in Murmansk. *The Science of the Total Environment*, 547, 305–313. <https://doi.org/10.1016/j.scitotenv.2015.12.151>
- Konečný, V., Gnap, J., Settey, T., Petro, F., Skrúcaný, T., & Figlus, T. (2020). Environmental Sustainability of the Vehicle Fleet Change in Public City Transport of Selected City in Central Europe. *Energies*, 13(15), 3869. <https://doi.org/10.3390/en13153869>
- Kulick, E. R., Wellenius, G. A., Boehme, A. K., Joyce, N. R., Schupf, N., Kaufman, J. D., Mayeux, R., Sacco, R. L., Manly, J. J., & Elkind, M. S. (2020). Long-Term Exposure to Air Pollution and Trajectories of Cognitive Decline Among Older Adults. *Neurology*, 94(17). <https://doi.org/10.1212/wnl.0000000000009314>
- Leong, L. V., & Shafie, S. A. M. (2024). Traffic Emissions Before and After Development Based on Traffic Impact Assessment. *Iop Conference Series Earth and Environmental Science*, 1368(1), 12012. <https://doi.org/10.1088/1755-1315/1368/1/012012>
- Li, T., Gong, B., Peng, Y., Nie, J., Wang, Z., Chen, Y., Xie, G., Wang, K., & Zhang, H. (2023). Analysis and Comparative Study of Signalized and Unsignalized Intersection Operations and Energy-Emission Characteristics Based on Real Vehicle Data. *Energies*, 16(17), 6235.

- <https://doi.org/10.3390/en16176235>
- Li, X., Dallmann, T. R., May, A. A., & Presto, A. A.** (2020). Seasonal and Long-Term Trend of on-Road Gasoline and Diesel Vehicle Emission Factors Measured in Traffic Tunnels. *Applied Sciences*, 10(7), 2458. <https://doi.org/10.3390/app10072458>
- Ma, J., Mitchell, G., & Heppenstall, A.** (2015). Exploring Transport Carbon Futures Using Population Microsimulation and Travel Diaries: Beijing to 2030. *Transportation Research Part D Transport and Environment*, 37, 108–122. <https://doi.org/10.1016/j.trd.2015.04.020>
- Marsa, R. R. M., Linggasari, D., & Angkat, H. R.** (2023). Studi Keselamatan Di Perlintasan Sebidang JPL No. 5a Km 2 + 285 Jalan Hadiah. *JMTS Jurnal Mitra Teknik Sipil*, 1025–1034. <https://doi.org/10.24912/jmts.v6i3.24907>
- Mueller, N., Rojas-Rueda, D., Basagaña, X., Cirach, M., Cole-Hunter, T., Dadvand, P., Donaire-González, D., Foraster, M., Gascón, M., Martínez, D., Tonne, C., Triguero-Mas, M., Valentín, A., & Nieuwenhuijsen, M.** (2017). Urban and Transport Planning Related Exposures and Mortality: A Health Impact Assessment for Cities. *Environmental Health Perspectives*, 125(1), 89–96. <https://doi.org/10.1289/ehp220>
- Nkosi, N., Burger, R., Pauw, C., Ayob, N., & Piketh, S.** (2023). The Impact of Vehicle Parameters on Road PM10 Vehicle Resuspended Emissions: A Case in South African Low-Income Settlement. *Clean Air Journal*, 33(2). <https://doi.org/10.17159/caj/2023/33/2.15497>
- Pryciński, P., Wawryszczuk, R., Korzeb, J., Pielecha, P., & Murawski, J.** (2023). Selected Vehicle Emissivity Assessment Issues in Passenger Transport Services. *Combustion Engines*. <https://doi.org/10.19206/ce-169806>
- Radhakrishnan, R., Ajimon, M. A., Bose, S., Surya, S., Pillai, V. G., & Sandeep, U. P.** (2024). Unscrambling Traffic Congestion and Increasing Sustainability in Special Urban Intersection. *E3s Web of Conferences*, 529, 4011. <https://doi.org/10.1051/e3sconf/202452904011>
- Sari, E. G., & Sofwan, M.** (2021). Carbon Dioxide (CO2) Emissions Due to Motor Vehicle Movements in Pekanbaru City, Indonesia. *Journal of Geoscience Engineering Environment and Technology*, 6(4), 234–242. <https://doi.org/10.25299/jgeet.2021.6.4.7692>
- Sitati, C., Oludhe, C., Oyake, L., & Mbandi, A.** (2022). A Street-Level Assessment of Greenhouse Gas Emissions Associated With Traffic Congestion in the City of Nairobi, Kenya. *Clean Air Journal*, 32(1). <https://doi.org/10.17159/caj/2022/32/1.12546>
- Solaymani, S.** (2022). CO2 Emissions and the Transport Sector in Malaysia. *Frontiers in Environmental Science*, 9. <https://doi.org/10.3389/fenvs.2021.774164>
- Taqi, M., Zainab, F., Anwar, S., & Zia, A.** (2023). Nexus Between Carbon Emission Per Capita and Urbanization. *Journal of Economics Management & Business Administration*, 1(2), 15–26. <https://doi.org/10.59075/jemba.v1i2.116>
- Utami, A., & Widyastuti, H.** (2019). Model Panjang Antrian Kendaraan Pada Perlintasan Sebidang Tanpa Palang Pintu (Studi Kasus: Perlintasan Sebidang Jl. Gayung Kebonsari Surabaya). *Jurnal Aplikasi Teknik Sipil*, 17(1), 27. <https://doi.org/10.12962/j2579-891x.v17i1.4693>
- Wang, W., Yang, S., Yin, K., Zhao, Z.-D., Ying, N., & Fan, J.** (2022). Network Approach Reveals the Spatiotemporal Influence of Traffic on Air Pollution Under COVID-19. *Chaos an Interdisciplinary Journal of Nonlinear Science*, 32(4). <https://doi.org/10.1063/5.0087844>
- Wang, Y., Lv, C., Nie, Q., & Liu, H.** (2024). Analyzing the Impact of Road Accidents on Carbon Dioxide Emissions in Freeway Traffic: A Simulation and Statistical Modeling Approach. *Sustainability*, 16(5), 2168. <https://doi.org/10.3390/su16052168>
- Yang, J., & Wang, P.** (2024). Multi-Segment Variable Speed Predictive Control Strategy for Eliminating Traffic Bottlenecks in Emergency Cases on Super-Long-Span Bridges. *Applied Sciences*, 14(24), 11644. <https://doi.org/10.3390/app142411644>
- Zhang, Y., Zhou, R., Peng, S., Mao, H., Yang, Z., André, M., & Zhang, X.** (2022). Development of Vehicle Emission Model Based on Real-Road Test and Driving Conditions in Tianjin, China. *Atmosphere*, 13(4), 595. <https://doi.org/10.3390/atmos13040595>
- Zhao, H., Geng, G., Zhang, Q., Davis, S. J., Li, X., Liu, Y., Peng, L., Li, M., Zheng, B., Huo, H., Zhang, L., Henze, D. K., Mi, Z., Liu, Z., Guan, D., & He, K.** (2019). Inequality of Household Consumption and Air Pollution-Related Deaths in China. *Nature Communications*, 10(1). <https://doi.org/10.1038/s41467-019-12254-x>