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Statistical Modelling of Traffic Noise Using Smart PLS-SEM in Urban Roads

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Abstract
The objectives of this study are to assess the traffic noise levels in Shah Alam, Selangor, Malaysia, and to propose traffic noise model among influential factors. Five factors and 20 attributes were measured at three locations using a sound level meter and analyzed using the PLS-SEM approach. The results of this study showed that high traffic noise levels on urban roads exceeded the maximum permissible limit of 60 dBA during the day, according to Malaysian guidelines. However, the integrated traffic noise prediction model approach has specific indirect effects: built environment -> climate conditions -> traffic flow.

Keywords: Traffic noise; Modelling; Urban Roads; PLS-SEM

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1.0 Introduction

Urban microclimate, resident activities, and morphological urban patterns are only a few of the variables that urban planning and design are closely related to and play a critical role in (Bherwani et al., 2020). According to Zhang et al. (2023), traffic noise is the second-biggest environmental concern worldwide. It has been shown to impact people's health and productivity at work (Jafari et al., 2019). From 51% in 1985 to 71% in 2010, urbanization in Malaysia is expected to reach 80% by 2030. The higher standard of life and employment prospects in cities are the main factors driving migration. This tendency puts more pressure on sustainable urban development to make it easier to build the facilities and infrastructure that are required while also making sure that the use of carbon resources stays within sustainable bounds. By improving the road, rail, aviation, and maritime sectors and their interconnectedness, the National Transport Policy 2019–2030 will be able to advance the country's logistical efforts and assist Malaysia in achieving its goal of being a Regional Distribution Hub. By expanding the road and rail arteries to facilitate the movement of people and products, Malaysia has consistently constructed and improved its transportation network (NTP, 2019). However, there will be a large number of new metropolitan cities and a strong demand for transport, which could increase the number of vehicles on the road, traffic congestion, and increased traffic noise pollution. This indicates that future traffic noise-related issues are anticipated to become more serious (Haron et al., 2019).

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Road traffic noise is a major environmental annoyance and threat to human health. Traffic noise is known to aggravate people, cause sleep disturbances, increase the risk of cardiovascular disease, and have negative impacts on mental health (Morawetz et al., 2024). There are several negative health implications of prolonged noise exposure, with noise irritation being one of the more common ones. Road traffic, railroads, aeroplanes, and construction noise are among the many environmental noise pollution that disproportionately affect those living in highly populated urban areas. The issue of noise pollution for city dwellers has been made worse by the fast expansion and densification of the urban regions (Eggenschwiler et al., 2022).

Numerous parameters categorized under general factors, including road characteristics, traffic characteristics, climate conditions, built environment, etc., are shown in the literature to considerably impact traffic noise near highways (Gilani & Mir, 2021). One example of a traffic characteristics factor is the percentage of heavy vehicles, traffic volume, speed, honking, etc. Carrierway width, road surface, median width, road gradient, and other significant influencing factors are the primary components of the road characteristics factor (Khajehvand et al., 2021). Climate conditions take temperature, wind speed, and relative humidity into account (Hamad et al., 2017). Finally, the built environment factors investigated qualities include land use, building height, density, and unauthorized street parking (Gilani & Mir, 2021).

Numerous research has attempted to examine the direct impact of different variables on traffic noise. However, some evidence from the literature suggests that noise characteristics might be related to one another, and that their relationship to traffic noise would not always be direct but rather occasionally indirect (Chen et al., 2023). Despite some indications, the intricate linkages between noise attributes and their inherent (direct and indirect) effects on traffic noise have not received much research. Therefore, conducting a thorough and systematic investigation of traffic noise relationships is essential. Therefore, this study aims to determine the level of noise and propose statistical modelling of urban roads using the PLS-SEM approach

2.0 Literature Review

2.1 Attribute Factors of Traffic Noise

According to Fallah-Shorshani et al. (2022), traffic noise modelling evaluates and forecasts traffic noise using a wide range of field-measured parameters. The most critical factors influencing traffic noise are speed, road geometry, and traffic volume. Furthermore, certain studies have revealed the impact of context-specific characteristics on traffic noise, including weather and seasons, street characteristics, honking, and city dwellers (Shi et al., 2023). Urban sprawl, population growth, and rising car ownership may all contribute to an increase in the volume and frequency of traffic noise (Duan et al., 2024). However, recognizing the roadway factors is essential to understanding the dynamics of traffic noise and subsequently supporting the creation of noise models (Gilani & Mir, 2021). Noise modelling usually takes into account the origin of the noise and the distance to the destination, taking into account a number of contributing factors, primarily the traffic conditions (i.e., the flow of traffic, the percentage of traffic flow, the type of pavement, the width and gradient of the roadway, and the speed of the vehicle) as well as non-roadway factors like weather and barriers (buildings, shrubs, and trees). As a result, it is feasible to calculate, assess, and forecast traffic noise levels concerning urban descriptors (Ibili et al., 2022).

2.2 Traffic Noise Modelling

The European-Common Noise Assessment Methods (CNOSSOS-EU), the Australian Burgess model and the UK-specific Calculation of Road Traffic Noise (CORTN) model all take traffic volume, heavy vehicle percentage, receiver distance from the carriageway, road gradient, and other factors into consideration when analysing the influencing attributes used in conventional traffic noise models (Kephalopoulos et al., 2014). Similar to the Federal Highway Administrative (FHWA) model, the Italian Consiglio Nazionale delle Ricerche (CNR) model, the German Richtlinien für den L¨armschutz a Straben-90 (RLS 90) model, and the Japanese Acoustical Society of Japan-Road Traffic Noise (ASJ-RTN) model, the primary attributes of these models include traffic volume, speed, the distance of the sound level metre from the carriageway centerline, the surface type between the source and the receiver, the angle of road segment length where the primary characteristics are the barrier and the weather (Sakamoto, 2020).

Techniques for structural equation modelling (SEM) are helpful in determining essential elements, putting complex hypothetical relationships to the test, and assessing how strongly links between factors hold (Hair et al., 2021). These methods allow researchers to use a structured model with many items and constructs to investigate the net impact of predictor factors on the outcome variable. PLS-SEM is a method that relies on ordinary least squares (OLS) regressions but requires fewer assumptions about the distribution of the data (Sarstedt et al., 2022). It is especially useful when attempting to evaluate a theoretical framework from the standpoint of prediction and when the study's goal is to advance established theories to understand complex relationships (Sarstedt et al., 2022).

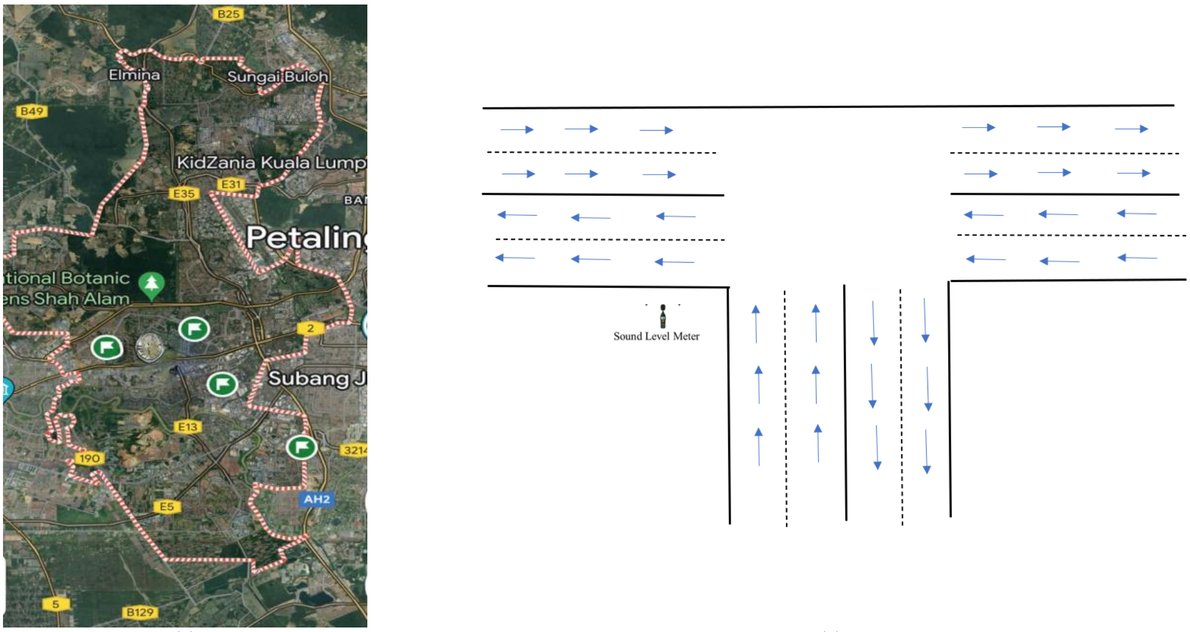
3.0 Methodology

3.1 Study Location

This research was carried out across Shah Alam, Selangor, Malaysia (Fig. 1 (a)). A smart and sustainable city is currently the top priority on local governments' urban strategy agendas across the globe. This is particularly true in developed nations where rapid urbanisation has made a growing number of intricate social and infrastructure problems possible. In the centre of Selangor, Shah Alam grew and flourished over the course of two decades, and today it is ranked as the state's most urbanised metropolis. Shah Alam is ready for an urban renewal that will turn it into a worldwide metropolis with top-notch amenities, supported by a vibrant group of city authorities, the unshakeable backing of the populace, and the necessary political will. Being the most ecologically friendly city in Malaysia is one of Shah Alam's long-term objectives. This aligns with international commitments and objectives including the Sustainable Development Goals (SDGs) and the New Urban Agenda (NUA) (Voluntary Local Review, 2021).

3.2 Data Collection

Hourly equivalent noise level (Leq, one h) and associated parameters (traffic flow, road geometry, climate, and built environment components) have all been measured at each research location. Fig. 1 (b) showed A sound level meter (SLM), tape, and tripod stand were used to calculate the continuous equivalent noise level and associated characteristics at intersections. SLM was mounted to a tripod stand and placed adjacent to the building line at 1.2 meters above the floor. The geometric distances of roads were measured with a measuring wheel and tape. At the same time, meteorological data is used to record temperature, relative humidity, and wind speed.



(a) (b)

Fig. 1. (a) Study location; (b) Data collection

3.3 Data Descriptive

The continuous equivalent noise level is extracted using sound level meters. Since it is difficult to distinguish between the noise contribution from other sources and the noise caused by road traffic, this study assumes that the measured continuous equivalent noise level matches the equivalent traffic noise level during the modelling phase. The hourly average of the climate conditions is used to calculate its properties. The current study then classified the measured characteristics into five predefined categories: traffic volume, road geometry, built environment, climate conditions, and equivalent traffic noise (LAeq).

3.4 Methodological Approach

The current study develops a traffic noise model on urban roads using a PLS-SEM technique. This method assesses potential relationships between observable and invisible components while maximizing the explained variation in the dependent variable. Two models are created during the process: a measurement and structural models. Confirmatory factor analysis, which enables researchers to validate and confirm the relationship patterns of constructs and their underlying indicators put forth based on earlier theory/knowledge, is genuinely taken into consideration in the measuring model. Furthermore, the structure model—an inner model—clarifies the connections between the constructions.

All validity and reliability requirements, including internal consistency, indicator, convergent, and discriminant validity, are met by the evaluation of the measurement model. The structural component of the PLS-SEM model is further evaluated by utilizing the parameters of the degree of significance, coefficient of determination (R^2), and size effect (f^2). By calculating the total influence of exogenous (independent) constructions on the endogenous (dependent) construct, the R^2 number indicates the explanatory strength of the model. R^2 has a value that ranges from 0 to 1. According to Hair et al. (2021), the model's substantial, moderate, and modest prediction accuracy is represented by R^2 values of 0.75, 0.50, and 0.25, respectively.

4.0 Findings

4.1 Level of Noise at Urban Roads

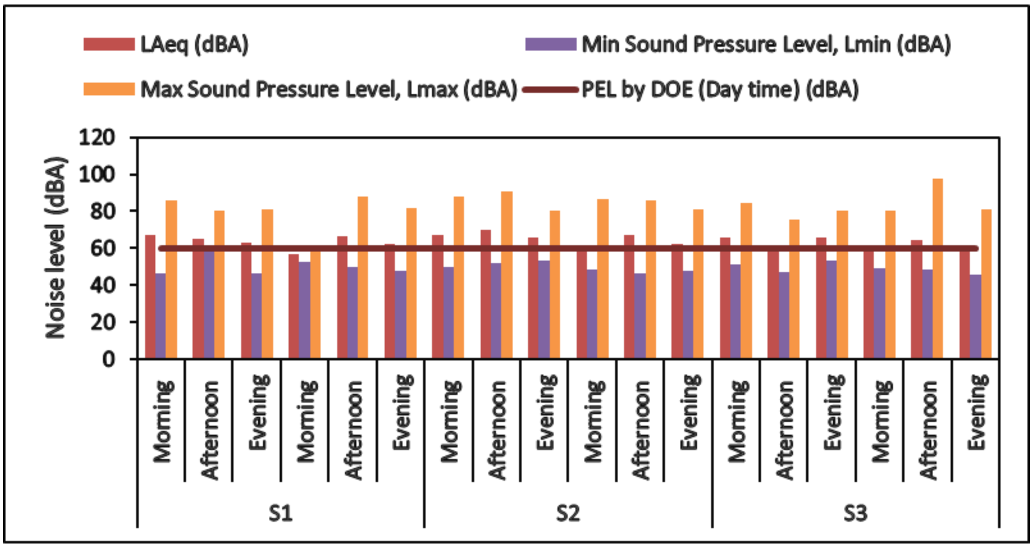


Fig. 1. Noise level comparison result

Fig. 1 shows the mean LAeq value stands at 63.8 dBA with the average noise level of 66.9 dBA at Sampling Point 1 as well as Sampling Points 2 and 3 continued to exhibit traffic-related noise, with Point 3 notably experiencing higher levels. The noise level surpassed the maximum permissible limit of 60 dBA set by the Department of Environment (DOE), ranging from 60.5 dBA to 85.9 dBA.

4.2 Statistical Modelling of Traffic Noise

To evaluate and analyse the exploratory model, the current study deploys the investigated correlations among the components to create a PLS-SEM structural (path) model in SmartPLS 4.0 software. Twenty underlying qualities and a set of five constructs make up the developed PLS-SEM model. The structural model also evaluates the path relations among the constructs. The evaluated path relations, particular factors' effects on equivalent traffic noise, the structural model's goodness-of-fit, and the model's validity and reliability are covered in the ensuing subsections.

4.2.1 Assessed Path Relations

The results of the structural path model are shown in Table 1. A path coefficient larger than 0.2 at a 95% confidence interval is typically used to indicate the degree of influence of the assessed path link among the components (Hair et al., 2021). At a significance threshold of 0.001, the table reveals that only the built environment -> traffic flow has a path link that has achieved significant path coefficients.

Table 1. The structural path model results

Traffic Noise Factor	Path coefficients
Built environment -> LAeq	-0.193
Built environment -> climate conditions	-0.922
Built environment -> road geometry	-0.104
Built environment -> traffic flow	0.280
Climate conditions -> traffic flow	-0.376
Road geometry -> traffic flow	-0.199
Traffic flow -> LAeq	-0.423

4.2.2 Effect of Each Factor on Equivalent Traffic Noise

Table 2 depicts the indirect effect of each factor on equivalent traffic noise. Their influence on traffic noise is visible indirectly through other factors. It has a negative direct influence on equivalent traffic noise such as built environment -> traffic flow -> LAeq; built environment -> climate conditions -> traffic flow -> LAeq and built environment -> road geometry -> traffic flow -> LAeq. While other specific indirect effects attained for some path relations have positive effects. It implies that most path relations have a significant specific indirect effect at a 0.001 significance level, with the highest indirect effect built environment -> climate conditions -> traffic flow (0.346) followed by climate conditions -> traffic flow -> LAeq (0.159).

Table 2. Specific indirect effect factor of Equivalent traffic noise

Traffic Noise Factor	Specific indirect effects

Built environment -> road geometry -> traffic flow	0.021
Built environment -> climate conditions -> traffic flow	0.346
Built environment -> traffic flow -> LAeq	-0.118
Built environment -> climate conditions -> traffic flow -> LAeq	-0.146
Climate conditions -> traffic flow -> LAeq	0.159
Built environment -> road geometry -> traffic flow -> LAeq	-0.009
Road geometry -> traffic flow -> LAeq	0.084

4.2.3 Goodness-of-fit of the Structural Model

To ensure that collinearity does not skew the regression results, it must be investigated before evaluating the structural correlations. From the result of the VIF value (Table 3), built environment -> LAeq; built environment -> climate conditions; built environment -> road geometry; road geometry -> traffic flow; traffic flow -> LAeq show ideal formative model. According to Hair et al., (2021) VIF values should ideally be around three or less.

Table 3. VIF value of traffic noise modelling

Traffic Noise Factor	VIF
Built environment -> LAeq	1.718
Built environment -> climate conditions	1.000
Built environment -> road geometry	1.000
Built environment -> traffic flow	7.338
Climate conditions -> traffic flow	7.700
Road geometry -> traffic flow	1.174
Traffic flow -> LAeq	1.718

As a measure of the explanatory power of the model, the variance is measured by the R^2, which is explained by each of the endogenous constructs. R^2 values of 0.75, 0.50, and 0.25 are generally considered significant, moderate, and weak (Hair et al., 2021). Based on the result depicted in Fig. 2, climate conditions have substantial variance, with R^2 0.849 followed by a moderate value of 0.500 traffic flow, while equivalent traffic noise (LAeq) has weak power at 0.322.

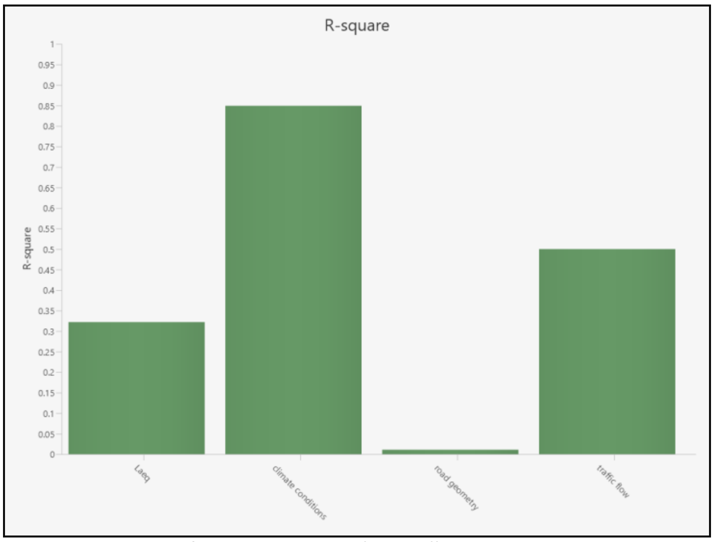


Fig. 2. R-square result of the traffic noise model

The magnitude of the path coefficients and this metric, the f^2 effect size, are a little redundant. More specifically, when comparing the size of the path coefficients and the f^2 effect sizes, the rank order of the predictor constructs' relevance in explaining a dependent construct in the structural model is frequently the same. According to Hair et al., (2021), values greater than 0.02, 0.15, and 0.35 often represent modest, medium, and large f^2 effect sizes. Table 4 shows that built environment -> climate conditions have the highest path coefficient in contrast with others that show an f^2 value of 0.01-0.06, considered a small effect size. Only traffic flow -> LAeq has a medium f^2 value at 0.154.

Table 4. The f^2 effect size of traffic noise modelling

Traffic Noise Factor	f-square
Built environment -> LAeq	0.032
Built environment -> climate conditions	5.631
Built environment -> road geometry	0.011
Built environment -> traffic flow	0.021
Climate conditions -> traffic flow	0.037
Road geometry -> traffic flow	0.068
Traffic flow -> LAeq	0.154

4.2.4 Reliability and Validity of the Model

The findings of the PLS-SEM measurement model are shown in Table 5. Standard loading levels larger than 0.5 are seen in most indications, indicating sufficient indicator dependability. Additionally, the constructs yielded positive and negative composite reliability (CR) values, and Cronbach's Alpha and Average Variance Extracted (AVE) values are more significant than 0.5, indicating the trustworthiness of the model's internal consistency and Each construct's strong convergent validity.

Table 5. PLS-SEM measurement model results

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Built environment	-2.950	0.999	0.996	0.999
Climate conditions	-0.736	0.837	0.171	0.376
Road geometry	0.924	1.067	0.961	0.926
Traffic flow	0.068	0.924	0.569	0.561

Furthermore, for every assessed indicator, the Heterotrait-Monotrait (HTMT) values are primarily greater than 0.5 (Hair et al., 2021). It confirms that there is adequate discriminant validity between the model's constructs. In order to predict traffic noise, the association between five components and their 20 underlying qualities was therefore established by the measurement model findings. In this sense, the research topic of traffic noise variables and the characteristics that go along with them is addressed.

Table 7. Heterotrait- Monotrait (HTMT) values of the model

	Built environment	LAeq	Climate conditions	Road geometry	Traffic flow
Built environment					
LAeq	0.467				
Climate conditions	0.986	0.530			
Road geometry	0.107	0.529	0.587		
Traffic flow	0.663	0.597	0.901	0.412	

5.0 Discussions

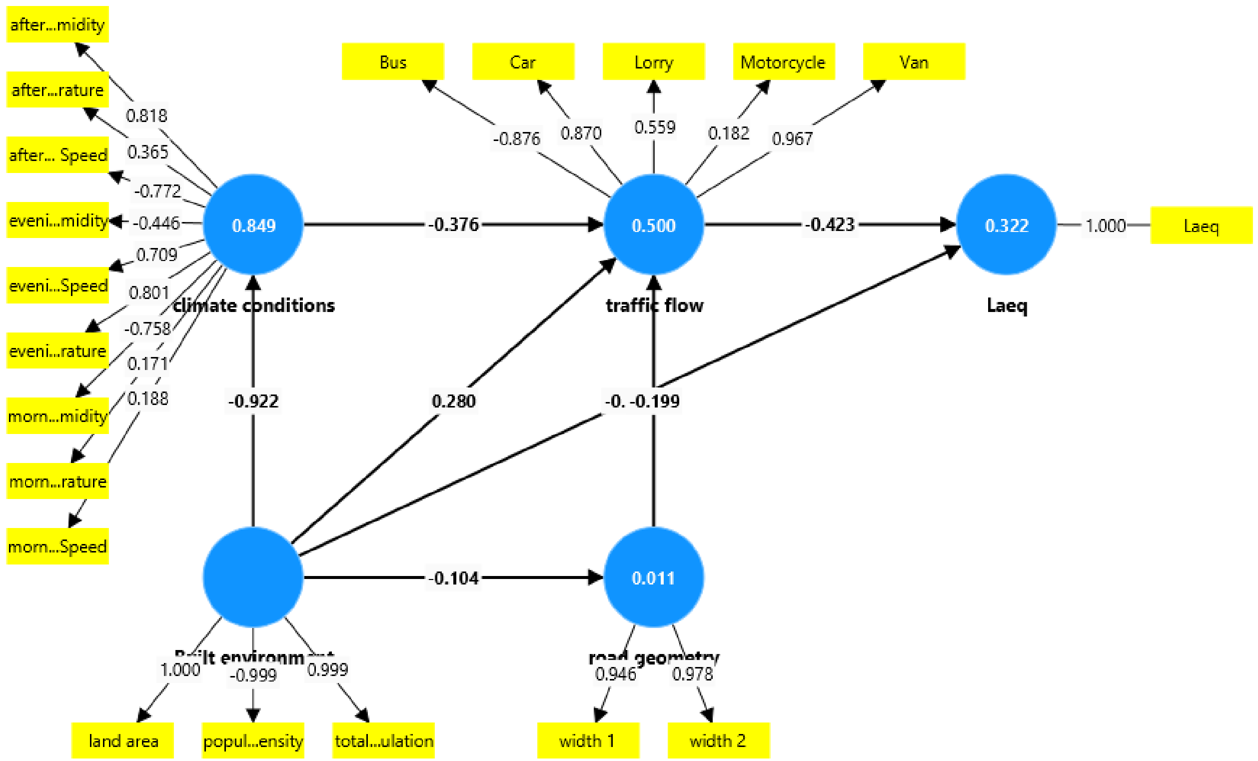


Fig. 3. Traffic noise modelling

The Guidelines for Environmental Noise Limits and Control, Third Edition, released in 2019 by the Department of Environment under the Ministry of Energy, Science, Technology, Environment, and Climate Change (MESTECC), is the document that governs traffic noise in Malaysia (Haron et al., 2019). The guidelines offer recommendations and guidance for ambient noise standards to reduce environmental disruption. Additionally, it draws attention to the noise restrictions placed on new construction and projects in order to shield the general population from loud noises. It outlines the methods or policies for determining, evaluating, and reducing noise pollution in the surroundings. These recommendations, in general, address all common forms of environmental noise pollution. The Department of environment ministry of energy, science, technology (2019) states that the permissible noise level limit for residential areas, which includes low-, medium-, and high-density regions, is between 55 and 65 dBA during the day and between 50 and 60 dBA at night. Results from Fig. 1 align with previous studies indicating that heavy vehicles, like lorries and buses, are significant contributors to excessive noise emissions (Nayan et al., 2022). As a result, the evaluation of road traffic noise levels correctly represented the level of noise pollution in the neighbourhood. According to Hegewald et al., (2020), the findings made it possible to determine the preservation strategies that would lessen the irritation that traffic noise causes in residential areas.

Using a PLS-SEM technique, the current work has created a traffic noise model at road crossings that illustrates the correlations between the contributing components. In the end, it is discovered that this methodology is reliable and suitable for revealing the intriguing and obscure interactions between the influencing elements within and with Equivalent traffic noise.

PLS-SEM surprisingly shows that all possible links are present. Furthermore, Fig. 3 displays the finished traffic noise model with significant path interactions. The results show only the built environment directly improves traffic flow; the other four elements negatively impact both traffic flow and related noise, in contrast with the result conducted by Yadav et al. (2022), where traffic flow is realized as the most dominant factor affecting traffic noise positively. In summary, with this investigation the developed model can be applied effectively for forecasting traffic noise levels at urban roads and accordingly deployed noise mitigation measures.

6.0 Conclusion & Recommendation

The main contributor to urban noise pollution is traffic noise. Planners worldwide have been focussing on measurement and the creation of traffic noise prediction models due to the severity of noise pollution. The equivalent noise level assessment result is above the 60 dBA threshold imposed by Malaysia's Department of Environment in 2019. Nevertheless, legislators and planners working to address this issue by positive means must comprehend the precise interactions between significant elements that contribute to and are influenced by traffic noise. The current work creates a traffic noise model for an urban road that illustrates the interactions between the key parameters that affect traffic noise. PLS-SEM confirmed a plausible fit for creating the traffic noise model at urban road for five factors and twenty underlying attributes. Determining the direct and indirect effects of influencing factors on traffic noise has been made easier with the help of the integrated method. In order to increase the prediction accuracy of traffic noise, the research should explore and construct interrelationships among the affecting elements.

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Paper Contribution to Related Field of Study

The proposed model is a crucial resource for effectively controlling noise pollution, improving the quality of life in cities, ensuring regulatory compliance, protecting public health, and assisting in decision-making.

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