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**DEVELOPMENT OF A RAILWAY NOISE MODEL FOR  
SRI LANKA**

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Degree of Master of Science in Civil Engineering

Department of Civil Engineering

University of Moratuwa

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Thesis/Dissertation submitted in partial fulfilment of the requirements for the degree  
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## **Abstract**

Railway noise poses a significant environmental concern in many countries. With the expansion of railway networks and increased train transportation for passengers and goods, the issue has been aggravated. Railway noise can have various adverse health impacts, and the lack of noise-related impairment data highlights the issue, emphasizing the need for more research and attention to mitigate the noise pollution's impact. Understanding the factors influencing railway noise is crucial for developing precise noise models and finding effective noise management strategies. Existing noise models have been developed to align with regional contexts and infrastructure, with different models considering varying sets of factors. However, many of these models lack compatibility with unique local conditions, such as those in Sri Lanka, where factors like braking systems, track characteristics, bridge effects, and maintenance variations play a significant role in railway noise generation and propagation. This study aims to develop a model predicting railway noise levels, incorporating distinctive elements. Key factors considered are speed, engine type, brake system, working principle, locomotive operational years, locomotive maintenance details, sleeper type, track alignment, environment type, distance, and the influence of bridge or level crossing. The model is tested using data from Sri Lanka and noise levels adjacent to railway lines were measured using a noise level meter. The analysis of pre-processed data through one-hot encoding, multicollinearity analysis and multiple regression analysis has revealed significant insights into the varying contributions of different factors to railway noise. The study has identified factors with substantial impact as well as those with minimal influence on the railway noise levels. Locomotive type, brake system type, working principle, bridge, track alignment, distance and speed exert a substantial impact on railway noise levels compared to other considered factors such as locomotive operational years and locomotive maintenance details. Using this mathematical model, a noise dispersion map for the coastal railway line was developed with ArcMap, providing a visual representation of noise impact in adjacent areas. The study's findings emphasize the need for targeted noise mitigation measures, including prioritizing the use of quieter Diesel Multiple Units (DMUs), speed regulations in noise-sensitive areas, and infrastructure modifications such as noise barriers and smoother track designs in critical zones like curved railway lines and bridge crossings. These measures aim to guide railway operators in implementing sustainable noise management strategies, ultimately improving the quality of life for communities near railway lines.

Keywords: Railway noise, Noise model, Noise mitigation

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# 1 INTRODUCTION

## 1.1 Background

Railway noise is a significant environmental concern in many countries (Brons et al., 2003; Micheli & Farné, 2016). As the world's population continues to grow, the consequent urbanization and economic development have led to an upsurge in transportation requirements (Pucher et al., 2007). Railway noise pollution is becoming a more pressing issue with the expansion of railway networks and the increasing use of trains for transporting passengers and goods (Chen & Haynes, 2015; Watson et al., 2018). Railway noise causes challenges for both passengers and residents living or working in proximity to railway lines and infrastructure (Peris et al., 2016). Passengers are subjected to the discomfort and disturbance of noise pollution during their journeys, which can affect their overall travel experience (Pahalavithana & Sonnadara, 2009). Residents and workers near railway stations and tracks endure periodic disturbances, often linked to train schedules (Brink et al., 2019). Consequently, it disrupts daily routines, causes stress, and potentially leads to long-term health and well-being issues.

Road traffic noise and railway noise exhibit remarkable differences (Moehler et al., 2000). Railway noise typically possesses a distinct and rhythmic character, often likened to the rolling of wheels on tracks, creating a rhythmic noise (Fields & Walker, 1982). In contrast, road traffic noise tends to be more variable and irregular in its sound patterns (Subramani et al., 2012). Additionally, railway noise is characterized by a lower frequency spectrum, producing deeper and more resonant tones which can penetrate into the buildings more effectively than higher-frequency traffic noise, making it more intrusive to residents (He et al., 2023; Moehler et al., 2000). While railway noise and traffic noise exhibit distinct characteristics, the discussion on which is more annoying remains complex due to numerous influencing factors. However, studies suggest that railway noise is often perceived as more annoying than road traffic noise, particularly with the increase in the number of trains (G-GUNNARSSON,

2011). Furthermore, the combination of noise and vibration from the railway amplifies the overall perception of annoyance and discomfort (Maigrot et al., 2020).

Railway noise, a prominent environmental concern, can lead to multiple health issues, such as sleep disturbances, annoyance, cardiovascular problems, hearing damage and mental health issues such as depression, anxiety, cognitive decline, and dementia among nearby residents (Eriksson et al., 2012; Hegewald et al., 2020; Petri et al., 2021). Noise pollution can decrease property values in areas close to railway tracks, affecting residents' financial well-being (Thiel, 2022; J. K. Walker, 2016). Noise distractions compromise safety protocols at workplaces and affect the workers' ability to perform their tasks effectively ("Workplace Safety," 2017). Furthermore, it disrupts natural habitats and wildlife, altering their behavior, migration patterns, and overall well-being (Dorsey et al., 2015; Watson et al., 2018). Managing and mitigating railway noise is crucial to safeguard both human health and the delicate balance of ecosystems in affected areas.

Railway noise is categorized into four primary categories based on its sources. Rolling noise arises from wheel-rail interaction, traction noise results from engine and motor sounds, aerodynamic noise originates from the train's movement through the air, and other noises include track irregularities, brakes, and miscellaneous factors (Pahalavithana & Sonnadara, 2009; Talotte et al., 2003; Yoon & Pyo, 2019). Railway noise generation is influenced by internal factors, including train speed, track characteristics, train and locomotive characteristics and their braking systems (Fields & Walker, 1982; J. Walker, 1977). These elements directly affect the noise produced by the train itself. In contrast, external factors, such as ground and terrain conditions, atmospheric factors, and the urban or rural environment, influence how the noise propagates and its impact on surrounding areas (ISO, 1996; Salomons et al., 2011). Both internal and external factors play crucial roles in understanding railway noise levels.

In Sri Lanka, there are diesel locomotives, some of which date back to the 1990s. As these locomotives are relatively old, it suggests that rolling and traction noise are the

predominant sources of noise generators. Older locomotives often exhibit increased mechanical wear and noise emissions (Pahalavithana & Sonnadara, 2009). Comprehensive knowledge of various railway noise sources and influencing factors is crucial for developing accurate noise models, whether analytical or numerical. These models enable the prediction of noise levels and serve as a foundation for designing effective noise management strategies (Van Leeuwen, 2000; J. Walker, 1977). By incorporating data on locomotive types, track conditions, and environmental variables, these models empower authorities to make informed decisions, reduce the health and environmental impacts of railway noise, and enhance the overall quality of life for nearby communities.

## **1.2 Problem statement**

Railway noise threatens the health of residents near tracks and passengers, impacting their quality of life, sleep, and overall well-being. Prolonged exposure to high noise levels raises stress, blood pressure, and cardiovascular risks. Disturbed sleep leads to fatigue, irritability, and cognitive impairment. Continuous exposure to railway noise negatively affects mental health, causing anxiety, depression, and decreased well-being. The lack of specific and tailored models for accurately predicting and evaluating railway noise levels within the Sri Lankan context and similar countries further compounds this issue.

Existing models often fail to account for the unique factors and sources of noise pollution that are specific to countries like Sri Lanka, thereby limiting their applicability and effectiveness in addressing this pressing concern. Given these challenges, it is crucial to develop specific and tailored models that consider the distinctive aspects of the railway noise problem. These models should account for factors such as train speed, locomotive and track characteristics, as well as variations in the environment. By incorporating these unique elements, predictive models can provide more accurate assessments of noise levels and assist in the formulation of effective noise reduction strategies.

### **1.3 Objectives**

1. Identify the factors influencing railway noise levels and determine the relative contribution of each factor to the overall noise levels.
2. Assessment of current noise levels and development of a mathematical model to estimate railway noise levels using the above-identified influential factors.
3. Provide recommendations for noise management strategies for Sri Lanka's railway system.

## **2 LITERATURE REVIEW**

Railway noise is a significant environmental issue that can have negative impacts on passengers and nearby communities (Fields & Walker, 1982). Railway noise modeling has emerged as an important tool for predicting and mitigating the effects of railway noise. There are some significant differences between road traffic noise and railway noise. Railway noise typically has a higher frequency content than road traffic noise, with more energy in the higher frequency ranges. This is due to the relatively high speeds of trains and the nature of the noise sources (Moehler et al., 2000). Railway noise has the directivity property, which distinguishes it from other sources of environmental noise. Directional property refers to due to the location of the noise sources on the sides of the train; railway noise is highly directional, with the highest noise levels radiating perpendicular to the tracks (Zhang et al., 2019). Individuals are more highly annoyed by railway noise compared to road traffic noise. (Brink et al., 2019).

### **2.1 Health impacts of railway noise**

Railway noise has a continuous impact on passengers during their travel time and periodic impacts on residents and workers living or working near railway lines or stations. Compared to railway lines, railway stations cause more impacts on residents and workers due to the time spent waiting, acceleration and deceleration of the train (Kanakasabai et al., 2005). Railway noise can have a significant impact on public health, with potentially harmful effects on physical and mental well-being. Exposure to high levels of railway noise over an extended period has been linked to a range of negative health outcomes, such as auditory effects (noise-induced hearing loss, tinnitus) sleep disturbance (Wrótny & Bohatkiewicz, 2020), blood pressure, hypertension (Petri et al., 2021), cardiovascular disease (increased blood pressure, ischemic heart disease) (Eriksson et al., 2012) and negatively impacts mental health (nervous complaints, anxiety, emotional stress, effects on residential behaviour and annoyance) (Hegewald et al., 2020).

## **2.2 Railway noise sources**

Railway noise sources can be classified into four main types based on their noise generation: Rolling noise: This is the sound created by the wheels of the train rolling over the rails (Yoon & Pyo, 2019). It is one of the most significant sources of railway noise. traction noise: is the noise generated by the train's engines (Pahalavithana & Sonnadara, 2009; Yoon & Pyo, 2019) and transmissions, including the sound of the motor, gearbox, and cooling system. aerodynamic noise: When a train moves through the air, it creates a turbulent flow of air that produces aerodynamic noise (Talotte, 2000). The level of aerodynamic noise can increase when passing other vehicles, too. For example, when 2 vehicles are moving in opposite directions on adjacent tracks. In this case, the relative speed of the vehicles is higher and huge turbulences may occur (Leštinský & Zvolenský, 2019). There are other noises generated due to horns and irregularities, such as joints & switches. As the speed of the train increases, the noise generated by the movement of air around the train, known as aerodynamic noise, becomes more prominent. Conversely, at lower speeds, the rolling noise and traction noise, caused by the wheels rolling on the tracks and the train's engine, respectively, are the dominant sources of noise (Talotte, 2000; Thompson & Gautier, 2006; Yoon & Pyo, 2019; Zhang et al., 2019).

## **2.3 Railway noise modelling**

Railway noise modelling is an important technique used to anticipate and manage the impacts caused by railway operations. It uses analytical or numerical models to simulate the sound produced by trains and predict the noise levels at different locations (Jónsson, 2007; Lei, 2020). This approach helps railway noise modelling to develop strategies for noise reduction, select appropriate mitigation measures, and design quieter railway systems. Developing accurate and reliable noise models is crucial for effective management of railway noise and its effects on people and the environment. Railway noise modelling involves considering several factors that can influence the noise generated by the railway system. Railway noise generation is influenced by internal factors such as speed, track type, train condition and brake systems (J. Walker, 1977). On the other hand, railway noise propagation is influenced by external factors

such as ground conditions, terrain conditions, atmospheric conditions and urban or rural area conditions (ISO, 1996). By considering these internal and external factors noise models can be developed to predict the railway noise levels for different instances. Different countries use unique noise models based on their acoustical priorities, regulations, and infrastructure. Sri Lanka lacks a model tailored to its specific factors, elements, and development context.

## 2.4 Analytical models

An analytical railway noise model is a mathematical model that uses equations and theoretical principles to predict noise generated by railway systems. The model typically involves simplifying assumptions and considers the required factors. One of the primary advantages of analytical railway noise models is that they require relatively low computational resources and are straightforward to implement. If we see the general setup of the prediction model, the basic relationship between sound pressure level and sound power level can be expressed as follows (Van Leeuwen, 2000):

$$L_p = L_w + \sum \Delta_{propagation\ factors} \text{ in dB}$$

where  $L_p$  is the calculated noise level,  $L_w$  is the sound power level of the source and  $\sum \Delta_{propagation\ factors}$  is the summation of the total of all the attenuation and corrections due to propagation. A prediction model can be divided into two primary components. The first part focuses on the source description, encompassing a comprehensive account of essential factors related to the source's position or sources, such as the type of train and its speed, and the construction of the track, etc. The second part provides detailed explanations and descriptions of various models employed to analyze the spread and transmission of noise, considering factors such as distance, terrain characteristics, atmospheric conditions, and other relevant parameters (Van Leeuwen, 2000).

Among analytical models, ISO 9613 is a standard model developed by the International Organization for Standardization (ISO) for the calculation of sound

attenuation. ISO 9613-1 provides general guidance for outdoor environments, ISO 9613-2 provides more specific guidance for outdoor environments, and ISO 9613-3 provides guidance for enclosed spaces such as buildings or tunnels. Geometrical divergence, atmospheric absorption, ground effect and obstacle characteristics were considered in this model development (ISO, 1996; Jang et al., 2017).

ISO 9613-2 provides a framework for calculating sound attenuation in outdoor environments, considering factors such as spherical spreading (geometrical divergence), atmospheric absorption, ground effects, meteorological corrections, and screening effects (ISO, 1996). While the model incorporates detailed equations and tables for these factors, it lacks specific guidelines for noise sources, especially for railways. As a generalized model for outdoor environments, ISO 9613-2 does not address the unique characteristics of railway noise sources, such as the directivity of train engines or braking systems, resulting in reduced accuracy for these sources. The ISO 9613-2 model does not include correction terms for factors such as track characteristics or bridge effects, which are essential for accurately modelling noise propagation (Jang et al., 2017).

The Schall-03 method is a noise prediction model developed by the German Federal Railway Authority (EBA) for predicting railway noise levels. The model is designed to consider a range of factors that affect noise propagation from railway sources including rolling noise and aerodynamic noise. The basic relationship is given as,

$$L = 10 \log \left[ \sum 10^{(0.1 \cdot (51 + D_{Fz} + D_D + D_L + D_s))} \right] + D_{Tt} + D_{Br} + D_{Lc} + D_{Ra}$$

The Schall-03 method accounts a range of factors that affect noise propagation including train length ( $D_L$ ), speed ( $D_s$ ), brake effect ( $D_d$ ), track geometry, and the surrounding environment. For surrounding environment,  $D_{Br}$  correction considered bridges and their effect on noise (+3 dB). The correction  $D_{Lc}$  is +5 dB in the case of a railway junction and the  $D_{Ra}$  correction is a correction for an annoying squeaking sound that occurs when a trainset passes on a track with a small radius of curvature (from 0 dB to 8 dB) (Němec et al., 2015, 2020, 2021). However, the Schall-03 method

is specifically developed for use in Germany and is structured according to German and European standards. As Sri Lankan railway infrastructure, train types, and track conditions differ significantly from European standards, this model is not suitable for direct application in Sri Lanka. Moreover, the model does not account for parameters specific to newer train technologies and track conditions, which limits its applicability for modern railway noise prediction in diverse contexts (Moehler et al., 2008).

The MPVHD model is specifically designed for railway noise prediction and incorporates a broader range of factors compared to the Schall-03 method. It considers train or engine type, traction noise, instantaneous speed, and the number of wagons in a train, offering a more detailed framework for estimating noise levels (Němec et al., 2015, 2020). Similarly, the Harmonoise model, developed by the European Union's Harmonoise project, provides a comprehensive approach for assessing railway noise. Notably, it introduces advancements in modelling the transition region and the effects of atmospheric refraction, which distinguishes it from other models (Salomons et al., 2011). The Reken-en Meetvoorschrift Railverkeerslawaai (RMR) method, a Dutch standard, offers guidelines for calculating and measuring railway traffic noise. It evaluates noise levels by considering train characteristics, track conditions, speed, distance, and environmental factors, accounting for rolling noise as well as propulsion and aerodynamic noise (Mezitis et al., 2020).

While these models incorporate several critical parameters for noise prediction, they exhibit significant gaps. Many of these models are designed for specific regions, such as Europe, and are tailored to infrastructure, train technologies, and operational conditions that differ from local contexts, such as those in Sri Lanka. The MPVHD and RMR methods, for example, do not adequately account for variations in track conditions, train maintenance levels, and noise perceptions unique to non-European settings. These limitations highlight the need for a more adaptable and context-sensitive noise prediction model that reflects the unique characteristics of local railway systems.

Other than these railway noise models there are noise models which are used for traffic noise modelling. In different contexts, several traffic noise models are utilized, including the CoRTN model, RLS 90 model, NMPB-Routes-2008 model, ASJ RTN-Model 2008 (De Lisle, 2016), and Son Road model (Garg & Maji, 2014). However, these models are not applicable to estimate noise from rail locomotives.

## **2.5 Numerical models**

A numerical railway noise model is a computer simulation that uses complex algorithms and models to predict noise generated by railway systems. This model considers more detailed and realistic representations of the train and track system, including factors such as rail roughness, wheel-rail interaction, and atmospheric conditions, and produces more accurate and detailed noise predictions. Numerical models are computationally intensive and require significant computational resources but are more accurate than analytical models. CadnaA, SoundPLAN (Puckeridge et al., 2019) and FE-SEA (Lei, 2020) methods are most commonly used numerical models in railway noise modelling.

## **2.6 Sri Lankan noise level standards**

Noise regulations and guidelines vary from country to country, as each jurisdiction sets its own standards based on local conditions, needs, and priorities. These regulations and guidelines establish permissible noise levels, define noise assessment methodologies, and outline measures to mitigate the impacts of noise.

In Sri Lanka, A set of noise standards has been developed which specify the maximum permissible noise levels for various types of environments, including residential, commercial, and industrial areas. Central Environmental Authority's rail transit system noise standards specify that the maximum  $L_{AF, max}$  (The maximum Sound Level with 'A' frequency weighting and "Fast" Time weighting during the measurement period) should not exceed 85 dB under various conditions, including residential and commercial areas, as well as day and night times (Mawatha, 2018). The  $L_{Aeq, T}$  (Equivalent continuous sound level) levels should fall less than 60dB and 50dB

for the residential areas during the day and night times and less than 65dB and 55dB for the commercial land use during the day and night times (Mawatha, 2018). These standards can be used as a reference for evaluating the noise impacts of railway projects and for setting noise limits for railway operations. Other than this, areas categorized as silent zones or sensitive land uses such as courthouse, hospital, public library, school, sacred areas and areas set apart for recreation or environmental purposes should have  $L_{Aeq,T}$  lesser than 50dB. (Mawatha, 2018). Collected data revealed that the noise levels in residential and commercial areas closer to the coastal railway lines are exceeding these noise level standards. Therefore, it is crucial to identify the factors contributing to railway noise in these areas. By understanding these factors, appropriate measures can be implemented to control them and effectively reduce the noise levels. These standards can be used as a reference for evaluating the noise impacts of railway projects and for setting noise limits for railway operations. But it is important to consider factors such as the frequency and duration of noise exposure when making decisions regarding these noise levels.

Regulations related to construction boundaries also differ from country to country. Sri Lanka Survey department states that no land should be used for any construction purposes within 40m distance from the railway lines other than it is approved by railway department (*Departmental Survey Regulations, Sri Lanka, 2020*). However, in Sri Lanka, there are both authorized and unauthorized constructions within 40m of railway lines. As a result, the noise levels from railway lines cause harmful health impacts for the people who live or work in these areas.

### **3 METHODOLOGY**

This chapter presents the detailed methodological framework and techniques employed in the development of a railway noise model. Key factors influencing railway noise were identified through a literature review and discussions with railway authorities. These factors fall into three main categories: train characteristics (including speed, locomotive type, brake system, working principle, year of manufacture, and maintenance details), track infrastructure (such as track alignment, sleeper type, and presence of bridges or level crossings), and environmental conditions (surrounding land use such as urban or suburban and distance). Factors such as air absorption and ground attenuation, mentioned in the literature (Ingård, 1953) as having minimal impact within 250 meters, were excluded. Even though factors like exhaust systems and cooling systems have a considerable amount of influence on the noise level, they were excluded, since they are uniform across all train types in Sri Lanka.

The required data and information were gathered from the Sri Lankan Railway Department, primarily focusing on locomotive specifications and operational data. Noise level assessments were conducted at strategic locations bordering diverse railway settings. The collected data was cleaned and processed to prepare it for modelling. The most significant variables for predicting railway noise levels in Sri Lanka were identified, and Microsoft Excel and the Python language were used for model development. The accuracy of the new model was validated using collected data in comparison to existing models for predicting railway noise levels. The following sections will explain the specific details of the methodology, data collection, study area, noise assessment strategies, noise model development procedures, data analysis techniques, constraints and limitations encountered during this study.

#### **3.1 Data collection and pre-processing**

The purpose of the study is to analyse the system and examine the interactions between selected variables to develop a method that will identify the variables influencing the noise produced by trains. Data collection for this study occurred in two distinct phases. Initially, essential data concerning locomotives and their operations was gathered

directly from the Sri Lanka Railway Department. Subsequently, noise level readings were obtained in proximity to the railway lines utilizing a dedicated noise level meter.

### **3.1.1 Locomotive and operational data collection**

This data collection encompassed comprehensive details on locomotive and carriage specifications, encompassing engine specifics such as engine types, engine classes, brake systems, number of axles, number of cylinders, combustion cycle, exhaust systems / air compressor and cooling systems physical dimensions, manufacturing details, maintenance details, and distinctive features. Operational data delved into usage patterns, including typical routes, and frequency of operations. Due to the absence of digitized records, the collection of this data necessitated referencing physical drawings and engaging in consultations with railway authorities. From the collected data, various factors influencing noise levels were identified and explored for their impact within the railway environment.

The collected dataset summarises diverse categories within each influential factor contributing to noise levels along railway lines. Engine types were classified into distinct categories such as diesel-electric, diesel multiple units, and diesel-hydraulic, highlighting variations in propulsion systems. The engine classes, designated as M class, S class, W class, and Y class, each denote distinct locomotive characteristics. Additionally, numerical numbering within these classes further explains specific sets of locomotive attributes. Brake systems were categorized as air, vacuum and air & vacuum based on their operational mechanisms, while the number of axles, combustion cycle variations and no of cylinders details were gathered into respective classes to ascertain their influence on noise emissions. From the discussions with railway authorities, it was initially highlighted that exhaust systems, air compressors, and cooling systems also held significant impact over noise emissions. However, through discussions with railway authorities, it was revealed that identical air compressor, exhausters, and cooling systems are utilized across all locomotive types in Sri Lanka. Therefore, these uniform factors were not considered within the scope of this study. Details of physical dimensions of both locomotives and carriages were

gathered for the calculations of the train speed. Information regarding the specific routes served by trains of various types and classes, along with the underlying reasons, was obtained through discussions held with railway authorities. The manufacturing years of collected locomotives ranged from 2019 to 1990, reflecting a broad temporal spectrum within the dataset. These diverse classifications of other factors provided a nuanced understanding of how specific design elements within locomotives contribute to the overall noise environment in railway settings. Initially, the number of axles was considered a potential factor influencing noise levels. However, it was later determined that the number of axles is consistent across different types of compartments and varies only in locomotives. As a result, the number of axles does not significantly impact average noise levels when considering the railway system (locomotives and compartments) as a whole. Due to this limited influence, the number of axles was excluded from the final analysis.

The locomotive-related data collected for this study is summarized in the Table 01:

Table 1: Summarized locomotive details collected from SLR

<b>Train No</b>	<b>Locomotive Class</b>	<b>Locomotive type</b>	<b>Brake system</b>	<b>No of Axle</b>	<b>No of Cylinders</b>	<b>Combustion cycle</b>	<b>Length (mm)</b>
569 - 573	M2	Diesel Electrical	Vacuum Air	4	12 V	2 Stroke	13,107
591 - 593	M2A	Diesel Electrical	Vacuum Air	4	12 V	2 Stroke	13,107
594 - 595	M2B	Diesel Electrical	Vacuum Air	4	12 V	2 Stroke	13,107
626 - 627	M2C	Diesel Electrical	Vacuum Air	4	12 V	2 Stroke	13,107
628 - 629	M2D	Diesel Electrical	Vacuum Air	4	12 V	2 Stroke	13,107
743 - 756	M4	Diesel Electrical	Vacuum Air	6	12 V	4 Stroke	17,774
769,	M5A	Diesel Electrical	Vacuum Air	4	12 V	4 Stroke	16,143
768, 772, 777, 778	M5B	Diesel Electrical	Vacuum	4	12 V	4 Stroke	16,143
767, 771, 775, 776, 779, 781, 782	M5C	Diesel Electrical	Vacuum Air	4	16 V	4 Stroke	16,143
783 - 798	M6	Diesel Electrical	Vacuum Air	6	12 V	2 Stroke	16,600
799 - 814	M7	Diesel Electrical	Vacuum Air	4	8 V	2 Stroke	12,800
841 - 848	M8	Diesel Electrical	Vacuum Air	6	16 V	4 Stroke	17,145
877 - 878	M8A	Diesel Electrical	Vacuum Air	6	12 V	4 Stroke	16,500
864 - 873	M9	Diesel Electrical	Vacuum Air	6	12 V	4 Stroke	19,200
914 - 916	M10	Diesel Electrical	Vacuum Air	6	12 V	4 Stroke	17,350
940 - 945	M10A	Diesel Electrical	Vacuum Air	6	12 V	4 Stroke	17,350
949 - 958	M11	Diesel Electrical	Air	6	12 V	4 Stroke	21,000
650, 657, 658	W1	Diesel Hydraulic	Vacuum	4	12 V	4 Stroke	13,300
704, 715	W2	Diesel Hydraulic	Vacuum	4	16 V	4 Stroke	13,180
631, 636, 638, 647, 659, 665, 666, 667, 669, 673	W3	Diesel Hydraulic	Vacuum	4	12 V	4 Stroke	13,300
675 - 702	Y	Diesel Hydraulic	Vacuum Air	3	8 V	4 Stroke	8,912

717 - 720	S5	Diesel Multiple Unit	Vacuum Air	4	8 V	4 Stroke	17,878
733 - 742	S6	Diesel Multiple Unit	Vacuum Air	4	12 V	4 Stroke	20,805
757 - 766	S7	Diesel Multiple Unit	Vacuum Air	4	12 V	4 Stroke	20,805
821 - 840	S8	Diesel Multiple Unit	Air	4	12 V	4 Stroke	20,805
849 - 863	S9	Diesel Multiple Unit	Air	4	12 V	4 Stroke	20,955
879 - 893	S10	Diesel Multiple Unit	Air	4	12 V	4 Stroke	20,955
894 - 913	S11	Diesel Multiple Unit	Air	4	16 V	4 Stroke	21,462
917 - 939	S12	Diesel Multiple Unit	Air	4	12 V	4 Stroke	16,383
959 - 970	S13	Diesel Multiple Unit	Air	4	12 V	4 Stroke	20,000
993 - 996	S13A	Diesel Multiple Unit	Air	4	12 V	4 Stroke	20,000
971 - 988	S14	Diesel Multiple Unit	Air	4	12 V	4 Stroke	15,800
989 - 992	S14A	Diesel Multiple Unit	Air	4	12 V	4 Stroke	15,800

As part of the data collection process, detailed information on the manufactured year and maintenance history of locomotives was obtained from Sri Lanka Railways (SLR). Scheduled repairs for locomotives are typically carried out based on time intervals, mileage, or machine working hours whichever threshold is reached first. For example, the M11 class locomotive follows a structured maintenance schedule with repairs occurring at intervals of 92 days, 184 days, 1 year, 2 years, 3 years, and at extended cycles such as 6, 7.5, 10, 12, and 18 years. The major scheduled repair at the 3-year mark is done by the earliest occurrence of one of the following: a time interval of 3 years, a running distance of 480,000 km, or 7,500 machine working hours (MW hrs).

A review of the maintenance manuals revealed that each type of scheduled repair involves a different set of mechanical and electrical maintenance tasks. Based on these technical documents and consultations with railway authorities, the major scheduled repair milestones for each locomotive type considered in this study were identified. Table 2 below summarizes the manufactured year and the corresponding major scheduled repair criteria for the locomotives considered in the study:

Table 2: Summarized details of locomotive’s manufactured details and major scheduled repairs

Locomotive Class	Manufactured year	Major scheduled repair
M4	1975	7500 MW hrs
M5C	1979Re 2002*	7500 MW hrs
M8	1998	7500 MW hrs
M8A	2001	7500 MW hrs
M11	2018	7500 MW hrs
M10A	2012	7500 MW hrs
S8	1991	W6 (24000 MW hrs)
S9	2000	W6 (24000 MW hrs)
S10	2009	QL4 (30000 MW hrs)
S11	2012	12000 MW hrs
W3	1998	12000 MW hrs

\* M5C locomotives were originally built in 1979; however, some units were rebuilt around 2002 and are still in operational use.

The collected data showed that M4 class locomotives, which are still in active use, were manufactured in 1975 and have been in operation for over 40 years. Such long service periods underscore the importance of regular and well-documented maintenance in managing operational efficiency and minimizing excessive noise generation. Furthermore, the scheduled repair records, including the last repair date, repair type, and locomotive number, were also collected from SLR. These scheduled repair details help to determine the maintenance interval for each locomotive, specifically by identifying the time elapsed between the last major scheduled repair and the point of noise level data collection.

### **3.1.2 Noise levels data collection**

The second phase involved collecting noise level readings along the railway line. Because of the extensive nature of the railway network in Sri Lanka, it was not feasible to collect data at every point along the railway lines. The scope of data collection for this study was confined to the coastal railway line, spanning from Colombo Fort to Panadura. A systematic approach was employed to define specific data collection locations within the study area. To define the data collection locations, several factors were taken into consideration. The study incorporated considerations for noise variations attributed to factors such as bridges and track alignment. When it comes to variations in alignment, there are straight lines and curves in railway lines. The selection of noise assessment locations took these factors into account. The selection of noise assessment locations took into consideration variations across urban, suburban, and rural areas.

#### **3.1.2.1 Noise level measuring instrument**

TECPEL DSL-332 sound level meter with internal calibrator was used for the noise level measurement. The specific model employed complied with the IEC 61672-1 Class 2 and ANSI S1.4 Type 2 standards, ensuring accuracy and reliability in data collection (International Electrotechnical Commission, 2013) . This noise level meter was equipped with frequency weightings A and C, as well as time weightings including

Slow, Fast, and Impulse settings, allowing for comprehensive analysis of varying noise characteristics. With a broad measurement range spanning from 35 to 130 decibels, the device accommodated diverse noise intensities commonly encountered in the study area. Additionally, the meter featured inbuilt calibration functionality and a windshield, enhancing the accuracy of measurements taken under varying environmental conditions (*Sound Level Meter Instruction Manual*, 2014).

### **3.1.2.2 Data collection methodology**

At each selected location, noise readings were taken at a specific distance. Readings were taken at distances between 10m - 100m perpendicular to the railway line. Readings were taken at representative distances such as 10 m, 30 m, 40 m, 60 m, and 90 m, depending on the specific site layout and observational feasibility during each train pass-by event. For safety purposes, it is recommended to maintain a minimum distance of 10 meters from the railway track when conducting noise measurements (Sethunga et al., 2014). A maximum distance of 100 meters is typically chosen for noise measurements to ensure accurate and representative data. Noise measurements were taken on both sides perpendicular to the railway line at different distances. The noise measurement instrument was placed at a height of 1.5 m from the ground to overcome the effect of the 0.3 m elevation of the railway track (Sethunga et al., 2014). At each time, two readings were taken to understand the difference between the noise level at normal time and the time of the train passing. Hot sunny days were used for measurements. Rainy days were avoided to disregard the additional noise caused by rain. Measurements were conducted during the day to capture typical noise levels experienced by nearby communities.

Apart from the above considerations, other environmental factors, such as wind, air absorption and ground attenuation, are known to contribute to railway noise levels. However, these factors were not included in this study. Regarding air absorption and ground attenuation, as highlighted in the literature, their influence becomes significant only at distances greater than 250 m, where factors such as temperature, relative humidity, and ground conditions play a more prominent role (Ingård, 1953). Since this

study focused on distances of up to 100 m, these variables were deemed irrelevant to the current analysis. Wind was not considered in this study as the literature indicates that calm weather conditions, with wind speeds below 5 m/s, have negligible effects on noise levels (Attenborough & Van Renterghem, 2021). To ensure this criterion was met, wind speeds at the data collection locations and times were verified using Google weather reports, confirming that all data measurements were conducted under calm conditions. Additionally, the noise measurement instrument used in this study was equipped with a windshield, further mitigating any potential wind effects during data collection.

Due to the absence of data logging capabilities in the noise level meter used, alternative methods were employed to capture critical information. Video recordings were utilized during noise measurements, allowing for subsequent detailed analysis. Through this approach, instantaneous noise level measurements were derived. Moreover, the videos facilitated the extraction of essential train details, including locomotive number, locomotive class, the count of engines and compartments, and the duration taken by trains to traverse specific locations.

### **3.1.3 Video analysis**

Due to the absence of data logging capabilities in the noise level measurement instrument, videos were collected and analysed. Graphs were generated for each train passing incident based on this analysis. Locomotive numbers were successfully identified from the videos and subsequently used to retrieve additional locomotive details from the data acquired by the railway department. Train type and compartment details were gathered from the videos, and the total length of the train was calculated with the details collected from SLR. By utilizing the timing recorded for the train to traverse a particular point along with the total length of the train, the train's speed at that specific location was calculated. Utilizing the gathered data, it was feasible to determine both the maximum noise level and the average noise level during a specific train passing incident.

### **3.1.4 Data pre-processing**

Once the data on noise levels along the railway line has been collected, it is essential to conduct pre-processing procedures before moving forward with the development of the noise model. The pre-processing stage involves several steps designed to enhance the quality and usability of the collected data. This includes activities such as data cleaning to remove any outliers or errors, data normalization to ensure consistency and comparability, and data aggregation or interpolation to achieve uniformity across the dataset. Additionally, any missing or incomplete data points may be addressed through appropriate imputation techniques. By undertaking these pre-processing steps, the data becomes more reliable, consistent, and suitable for further analysis and model development, ultimately leading to more accurate predictions and insights into railway noise in Sri Lanka.

### **3.1.5 Short-term equivalent train pass by noise levels**

In the investigation of train pass-by noise levels, obtaining precise measurements requires a comprehensive approach considering both noise intensity and its exposure time. While only the maximum noise level can be directly determined from graphical representations, additional calculations are necessary to derive more nuanced metrics of train pass-by noise levels. While recognizing the availability of both short-term and long-term equivalent noise levels, this study exclusively prioritizes the short-term equivalent noise level. The rationale behind this choice lies in the study's primary aim: capturing the immediate impact of train pass-by events.

In this study, two short-term equivalent noise levels were used to evaluate the railway noise:  $L_{Aeq, T}$  and  $L_{Aeq, Tp}$ . The  $L_{Aeq, T}$  represents the equivalent continuous noise level over a specified time period, typically determined within a timeframe encompassing noise levels lower than 20 dB from the maximum level. On the other hand, the  $L_{Aeq, Tp}$ , also known as the Transit Exposure Level (TEL), accounts for the duration of the train's passage over the buffers, offering a more refined evaluation of noise exposure during the entire pass-by event. Given below are the equations of the Transit Exposure Level ( $L_{Aeq, Tp}$ ) and  $L_{Aeq, T}$ .

$$L_{Aeq, T_p} = 10 \log_{10} \left\{ \frac{1}{T_p} \int_{t_1}^{t_2} \frac{p^2(t)}{p_{ref}^2} dt \right\}$$

$$L_{Aeq, T} = 10 \log_{10} \left\{ \frac{1}{T} \int_{t_1}^{t_2} \frac{p^2(t)}{p_{ref}^2} dt \right\}$$

where  $p(t)$  is the pressure at the considered time,  $p_{ref}$  is the reference pressure,  $T$  is the time range which is taken for less than 20dB from the maximum level and  $T_p$  is the time taken for the length of the train over the buffers. The main difference between these two is the exposure time considered. Literature states that, for a train of similar vehicles, the TEL ( $L_{Aeq, T_p}$ ) serves as a standardized method for quantifying the 'average' noise level during the pass-by event. Because equivalent levels across the -10 or -20dB points account for the complete pass-by duration but yield a lower level than the  $L_{Aeq, T_p}$ , and are sensitive to the duration incorporated into the average (Thompson, 2008). With the collected data a comparative analysis between  $L_{Aeq, T}$  and  $L_{Aeq, T_p}$  was conducted to examine their suitability in representing average noise levels during train pass-by events.

### 3.2 One-hot encoding

To develop a robust mathematical model from the collected dataset, which encompassed a mix of qualitative and quantitative data, the application of one-hot encoding is crucial. One-hot encoding is a pivotal technique in data analysis that transforms categorical variables into a numerical format, facilitating their effective integration into models (Lopez-Arevalo et al., 2020). This method converts categorical data into a binary format, assigning a unique binary representation to each category within the variable. In this study, the qualitative data underwent one-hot encoding, thereby enabling the incorporation of categorical features into the mathematical model. Through this process, each distinct category within the qualitative data was converted into binary vectors, ensuring compatibility, and enhancing the model's ability to interpret and utilize this information efficiently. Consequently, each categorical variable was segmented into its distinct categories. Engine type was categorized as

diesel multiple units, diesel-electric, and diesel-hydraulic (rehabilitated). Similarly, the working principle was classified as 12 V 4 stroke and 16 V 4 stroke, while brake system was divided into air, vacuum, and a combination of air and vacuum. Sleeper type was categorized as wooden, concrete, and no sleeper, and environmental condition was segmented into urban and suburban categories.

### **3.3 Multicollinearity**

In this study, regression analysis was used to investigate the relationship between railway noise levels and the influencing factors. Multicollinearity, in regression analysis, refers to the high correlation between independent variables included in the model. Its presence can pose challenges in accurately interpreting the regression coefficients and lead to inflated standard errors, thereby affecting the reliability of the model estimates. Detecting multicollinearity is crucial as it ensures the robustness of the regression model and aids in identifying variables that may need to be modified or excluded (Shrestha, 2020). In our analysis, multicollinearity was assessed using Excel, employing correlation matrices technique. Since the categorical variables were converted into binary variables using one-hot encoding, all variables in the dataset became numerical (either continuous or binary). This conversion made it possible to use Pearson's correlation coefficient to examine pairwise linear associations among the variables. Although Pearson's correlation was originally designed for continuous data, it is widely applied to binary (0/1) variables in regression analysis, as it provides a meaningful measure of association. Therefore, its use was considered appropriate for detecting potential multicollinearity in this study. Examining correlation matrices helps identify pairs of variables exhibiting high correlation coefficients, warranting attention in subsequent model development steps.

### **3.4 Multiple regression analysis**

Multiple regression analysis is a statistical method employed to examine the relationship between a dependent variable and two or more independent variables. It allows for the prediction of the dependent variable's outcome based on the variations in the independent variables. This analysis extends the principles of simple linear

regression, accommodating several predictors to understand how they collectively influence the noise level. Consequently, multiple regression analysis was utilized in this study to construct a mathematical model for the average noise level (TEL). 80% of the collected data is allocated for training the model. This subset is used to teach the model patterns and relationships between railway noise levels and variables considered. By incorporating locomotive data alongside other relevant factors, this method enabled the exploration of how various variables collectively contribute to and predict the observed noise levels. Multiple regression analysis is being used to understand the basic connectivity between the considered factors and the noise levels. Also, multiple regression analysis can identify the outliers of the collected data.

Initially, Microsoft Excel was utilized to develop multiple regression for its ease of use and familiarity. However, due to the complexity and increasing number of variables involved in the model, a transition to Python and its libraries was made to enhance computational efficiency and flexibility. The transition from Excel to Python for multiple regression analysis offered enhanced computational efficiency, flexibility in handling complex datasets, and the capability to incorporate a larger number of variables.

Prior to model development, an assessment of multicollinearity among the selected independent variables was conducted to mitigate potential issues such as inflated standard errors and unreliable regression coefficient estimates. This assessment involved generating a correlation matrix of the independent variables to identify those that were highly correlated, which were subsequently removed. Additionally, transformations were explored for continuous variables, such as considering logarithmic decay for distance, deemed more suitable for the model. Following these preparatory steps, the model was constructed using multiple regression analysis in Python.

### **3.5 Model validation**

The validation process aimed to assess the accuracy and reliability of the predictive model in forecasting railway noise levels within Sri Lanka. Approximately 80% of the collected dataset was allocated for training the model, while the remaining 20% was reserved as an untouched testing set. This division ensured that the model encountered unseen data during training, maintaining its ability to generalize to new, unfamiliar instances. Performance Metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared, Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are used to evaluate the model performance (Chicco et al., 2021). MSE and RMSE captured the average squared and square-rooted differences between predicted and actual noise levels. Lower values of MSE and RMSE indicate a closer alignment between predictions and observed values. R-squared offered insights into the proportion of variance in noise levels explained by the model's predictors, providing a measure of goodness of fit. A higher R-squared suggests that the model adequately captures the relationships between predictors and noise levels. MAE computed the average absolute differences between predicted and actual values, while MAPE represented these differences in percentage terms, aiding in understanding relative prediction accuracy.

### **3.6 Development of the Noise Dispersion Map**

To better understand how railway noise propagates into the surrounding environment, noise dispersion maps were developed for the study area. This map provides a spatial and visual representation of noise exposure levels, which is essential for identifying zones with varying degrees of noise impact. For the noise dispersion map development, the variables influencing railway noise levels were categorized into two groups: variables with constant values for a specific train pass-by event and variables with values that vary during the event. For a given train pass-by event, certain factors such as locomotive type, brake system, braking principle, years in use, and maintenance gap remain constant since only one type of locomotive is used per event. On the other hand, variables such as the speed of the train vary along the railway line. However, for the purpose of developing the sound dispersion map, it was assumed that

the train travels at a constant speed throughout the route. Literature reveals that Fort to Ratmalana has an average speed of about 24 km/h (*CSRP | Colombo Suburban Railway Project - Sri Lanka*, 2018; Rowan Marcus, 2015). Since this map focuses on the segment from Fort to Moratuwa, the average speed of 24 km/h for the Ratmalana–Fort section has been considered for this noise map development.

Additional varying factors that influence noise levels were identified, including the presence of curves, bridges, concrete sleepers, and urban or suburban conditions. Curved railway lines were determined using the 'Bearing' feature in ArcMap, as well as Google Earth and the World Imagery basemap. Bridges were identified using a combination of Google Maps, Google Earth, and the World Imagery basemap available in ArcMap. Urban and suburban areas were defined based on specific contextual criteria. For example, areas with high-rise buildings close to the railway line and multiple noise sources, such as nearby roads, were categorized as urban due to the reflection of noise waves by high-rise structures. In contrast, areas with three- or four-story buildings and the absence of other significant noise sources were categorized as suburban. These environmental conditions were also identified using Google Maps, Google Earth, and the World Imagery basemap in ArcMap. Concrete sleepers were identified as the predominant type along the railway line, with the exception of bridges. Based on the mathematical model, the Diesel Multiple Unit (DMU), which produces less noise than other locomotives, was selected for mapping. Key factors such as the Air brake system, 12 V 4-stroke working principle, years in use, and maintenance gap were aligned with the operational characteristics of DMUs, using average values from existing units.

A map of the coastal railway line from Fort Railway Station to Moratuwa Railway Station was developed, and the varying variables were added as attributes to the map. Based on the noise reduction factor with distance, identified through the mathematical model, a noise dispersion map was created using ArcMap. This map delineated noise level zones such as 100–90 dB, 90–80 dB, and 80–70 dB, providing a clear representation of noise level dispersion along the railway line.

## 4 RESULTS AND DISCUSSION

This section presents a detailed discussion of the study's analysis and the significant findings that have emerged.

### 4.1 Graphical analysis of train passing incidents

As mentioned in the methodology chapter, graphs were drawn with the collected videos for each train passing incident. Graphs showed how the noise levels varied during a train's passing. Graphs provided in Figure 01 and Figure 02, which are drawn for a diesel electric locomotive (M10A) and a diesel multiple unit locomotive (S9). In these figures, "Train Enter" refers to the moment when the foremost point of the train passes perpendicularly in front of the noise level measurement point, and "Train Exit" refers to when the rear end of the train passes the same measurement point. These markers help indicate the duration of the pass-by event and highlight how noise levels fluctuate from entry to exit.

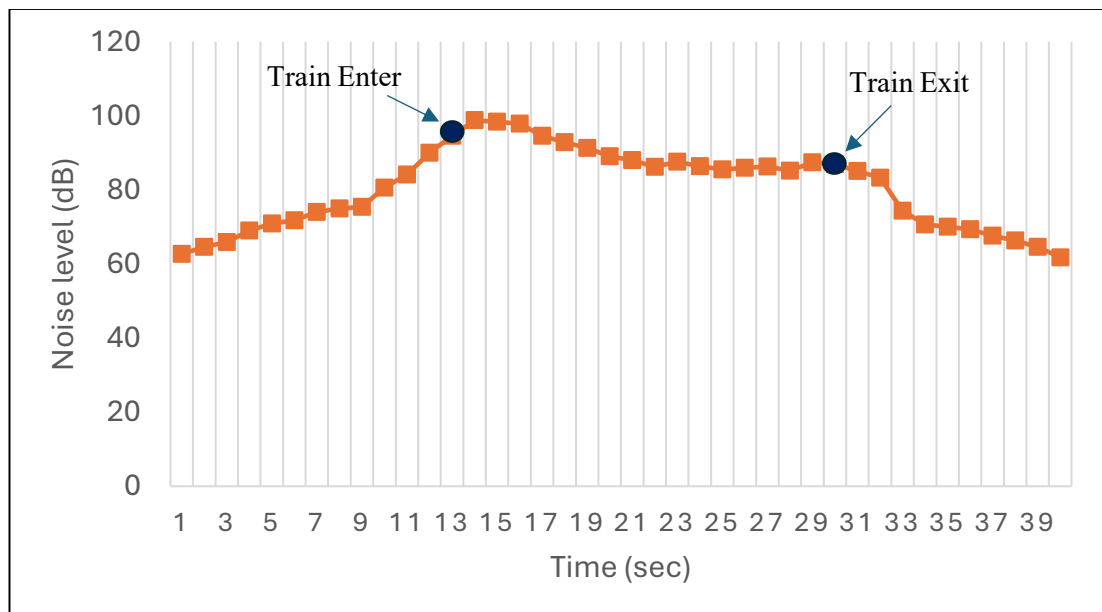


Figure 1: Instantaneous readings taken for the M10A class train at 10m distance

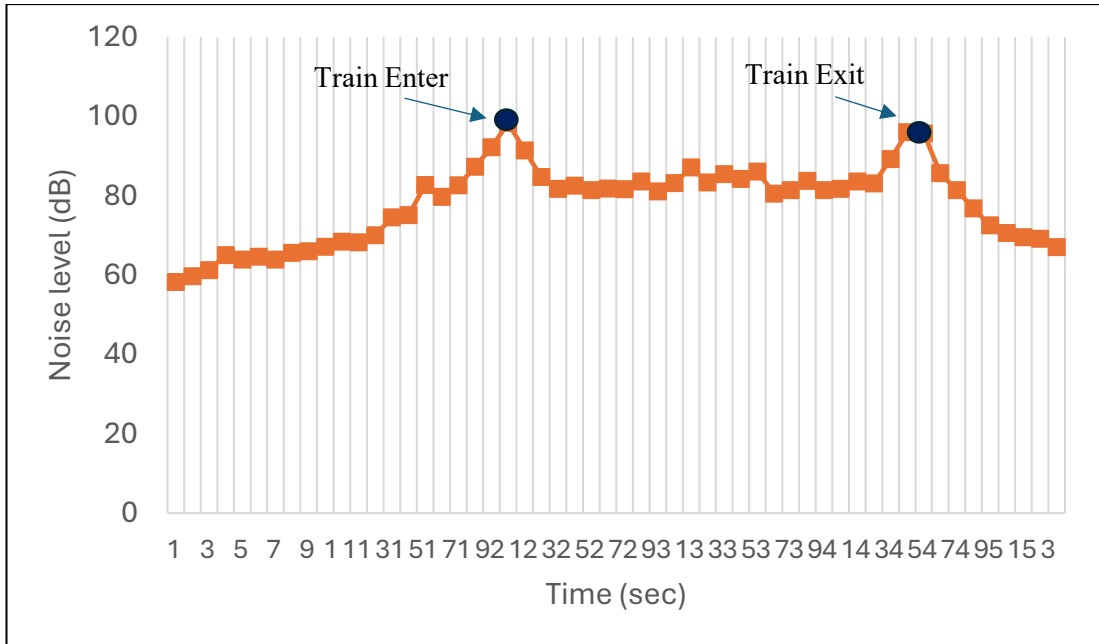


Figure 2: Instantaneous readings taken for S9 class train at 10m distance

Analysis of the graphs revealed that the peak noise level coincides with the locomotive's closest proximity to the noise measuring point. The initial graph of diesel electric locomotive depicts a single peak noise level corresponding to a train equipped with a single locomotive at the front. Conversely, the second graph of diesel multiple unit locomotive displays dual peak noise levels, indicative of a train featuring locomotives positioned on both ends.

During the train passing events, the maximum instantaneous noise levels reached approximately 100 dB as the locomotives passed directly in front of the measurement point, while the noise levels during the remainder of the pass-by event varied between 80 and 90 dB. These maximum noise level readings substantially exceed the maximum permissible limit of 85 dB ( $L_{AF, max}$ ) as defined by the Central Environmental Authority's standards for rail transit systems in Sri Lanka. Noise levels during the pass-by event are likely to exceed the  $L_{Aeq, T}$  thresholds of 60 dB during the daytime and 50 dB at night for residential zones and may also surpass the commercial limits of 65 dB (day) and 55 dB (night).

## 4.2 Measurement of train pass by noise levels

The two types of short-term equivalent noise levels have been discussed, and through a comprehensive review of existing literature, the Transit Exposure Level (TEL) has been identified as a more formalized means of measuring the 'average' level during pass-by events. To provide further clarity, a sample calculation for a train pass-by event has been conducted to clarify the differences in short-term equivalent measurements. Tables 3 and 4 below show the parts of the sample calculations done for a train pass by event to identify a more formalized method of measuring the average noise level.

Table 3: Part of sample calculation of train pass by event

Time	dB	Pressure level (P)	(P/P_ref)^2 )	Remarks
1	75.1	0.79893617	1595747510	
2	82.7	0.879787234	1935063943	
3	79.7	0.84787234	1797218764	
4	82.6	0.878723404	1930387053	
5	87.3	0.928723404	2156317904	Train Enter
6	92.2	0.980851064	2405172024	
7	98.3	1.045744681	2733954844	
8	91.4	0.972340426	2363614758	
9	84.7	0.90106383	2029790063	
10	82.5	0.877659574	1925715822	
11	81.6	0.868085106	1883929380	
12	83.6	0.889361702	1977410593	
13	81.1	0.862765957	1860912743	
14	83.2	0.885106383	1958533273	
15	87.1	0.926595745	2146449185	
16	83.3	0.886170213	1963244115	
17	85.4	0.908510638	2063478950	
18	86.1	0.915957447	2097445111	
19	81.4	0.865957447	1874705749	
20	83.7	0.890425532	1982144070	
21	81.7	0.869148936	1888549683	
22	83.6	0.889361702	1977410593	
23	83.1	0.884042553	1953828090	
24	89.2	0.94893617	2251199638	
25	96	1.021276596	2607514713	Train Exit
26	95.7	1.018085106	2591243210	
27	85.7	0.911702128	2078001924	

28	81.4	0.865957447	1874705749	
29	76.8	0.817021277	1668809416	
		<b>Total at Tp 20s</b>	<b>44101321299</b>	
		<b>Total at T 29s</b>	<b>59572498868</b>	

Table 4: Calculated short-term equivalent noise levels

Maximum Noise Level	98.3
Passing time	20
SEL (Sound Exposure level)	107.750458
$L_{(Aeq, T)}$	94.7401582
$L_{(Aeq, Tp)} - TEL$	93.4342161

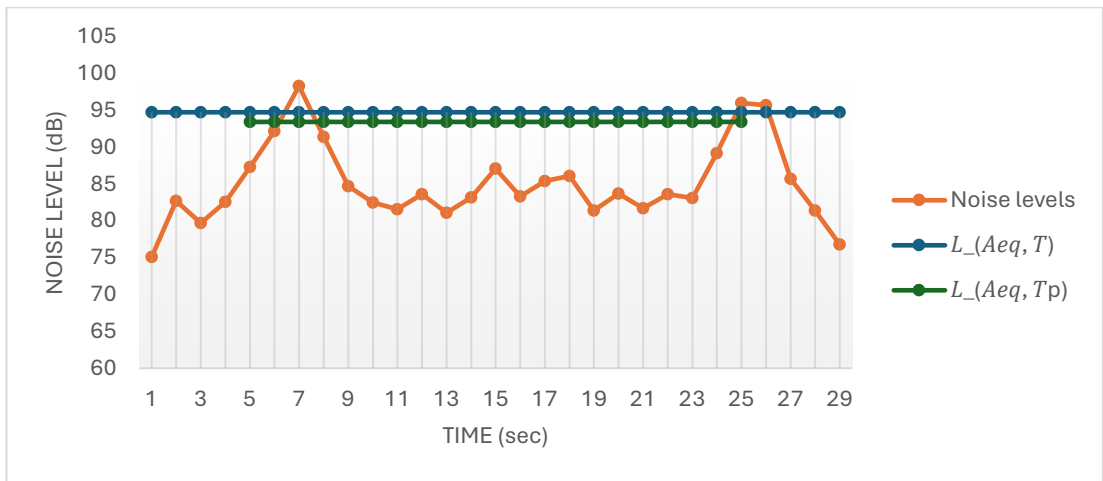


Figure 3: Instantaneous and short-term equivalent noise levels

From the sample calculation done for a train pass-by event, a minimal deviation between  $L_{Aeq, T}$  and  $L_{Aeq, Tp}$  was observed, as illustrated in Figure 03 and shown by the numerical values presented in Table 04 for the corresponding train pass-by event. Consequently, in accordance with the findings in the literature, TEL was regarded as the average level of noise during the train pass-by event.

### 4.3 Distance analysis

In the literature, various approaches to incorporating distance into noise models have been documented, including direct consideration or logarithmic decay. Moreover, different formulations such as  $10\lg[4\pi r^2]$ ,  $10\lg[2\pi r^2]$ ,  $10\lg[d]$ ,  $10\lg[d/10]$ , and  $10\lg[d/25]$  have been explored for logarithmic decay, where  $r$  and  $d$  represent the

distance between the rail line and the noise data collection point. Given this variability, it became essential to determine the most suitable method for implementing distance in the developing model. To address this, a separate analysis was conducted, concurrently considering other factors. Utilizing multiple regression analysis in Excel, distinct models were developed by treating distance as  $d$ ,  $10\lg[4\pi r^2]$ ,  $10\lg[2\pi r^2]$ ,  $10\lg[d]$ ,  $10\lg[d/10]$  and  $10\lg[d/25]$ . Subsequently, each model was evaluated based on metrics including Multiple R, R Square, Adjusted R Square, Standard Error, and Significance F, to ascertain their efficacy in capturing the relationship between distance and noise levels (Table 05).

Table 5: Output of distance analysis

	Regression Statistics					
	$d^*$	$10\lg[4\pi r^2]^*$	$10\lg[2\pi r^2]^*$	$10\lg[d]^*$	$10\lg[d/10]^*$	$10\lg[d/25]^*$
Multiple R	0.94	0.95	0.95	0.95	0.95	0.95
R Square	0.88	0.91	0.91	0.91	0.91	0.91
Adjusted R Square	0.69	0.73	0.73	0.73	0.73	0.73
Standard Error	2.77	2.38	2.38	2.38	2.38	2.38
Significance F	3.38E-20	6.30E-23	6.30E-23	6.30E-23	6.30E-23	6.30E-23
Coefficients	-0.37	-1.30	-1.30	-2.60	-2.60	-2.60
* “d” and “r” represent the distance (in meters) between the railway track and the noise measurement point. “d” represents direct linear distance between the railway line and the noise measurement point, without transformation. The expressions $10\lg[4\pi r^2]$ and $10\lg[2\pi r^2]$ represent spherical and cylindrical sound propagation models, while $10\lg[d]$ , $10\lg[d/10]$ , and $10\lg[d/25]$ are simplified logarithmic decay functions.						

Higher values were observed for Multiple R, R square, and adjusted R square in the case of logarithmic decay compared to direct application, while the standard error and significance F exhibited lower values. These findings suggest that utilizing distance as logarithmic decay is more suitable than using it directly. Remarkably, despite the implementation of different methods within logarithmic decay, identical results were obtained in terms of these metrics. For the ease of interpretation and implementation distance was utilized as  $10\lg[d]$  in the model. Negative values were observed in the coefficients from these models, indicating a proper relationship between noise level and the distance from the source. This suggests that as the distance from the noise source increases, the noise level tends to decrease.

#### 4.4 Multicollinearity

Multicollinearity provides critical insights into the interrelationship between independent variables in this regression analysis. Correlation between each pair of independent variables was assessed using Excel and a correlation matrix of independent variables was developed in Excel using Pearson's correlation as shown in Table 6. The matrix was adjusted by setting values between mutually exclusive categorical variables to zero, as these correlations do not reflect actual relationships and may mislead interpretation.

According to the matrix developed (Table 06), a higher correlation was observed between certain independent variables. Literature suggests that a correlation coefficient greater than 0.7 between predictor variables is a critical threshold, beyond which multicollinearity may significantly distort model estimation and prediction (Dormann et al., 2013). Based on the findings from the correlation matrix, variable pairs with coefficients exceeding 0.7 were identified and evaluated for relevance to the study. Variables deemed less necessary for the context of the analysis were excluded to mitigate the effects of multicollinearity and enhance the robustness of the regression model. For example, even though Locomotives and Brake systems have a higher correlation as they are more important to the context, no changes were made for those two independent variables. But the Bridge and sleeper types showed a significant correlation because in Sri Lanka, wooden sleepers were provided only at the bridges. Therefore, the 'wooden sleeper' variable was removed from the considered variables. Similarly, a considerable correlation was identified between level crossing and sleeper type. This is because no sleepers have been placed at the level crossings in Sri Lanka. In this case, considering the level crossings scenario directly implies that there is no sleeper placed at this location. Therefore, the 'no sleeper' variable was removed from the considered variables. Following these adjustments, the independent variables considered for this study include diesel multiple units, diesel-electric, diesel-hydraulic (rehabilitated), 12 V 4 Stroke, 16 V 4 Stroke, air, vacuum, air vacuum, bridge, curve, level crossing, concrete, urban, suburban, years in use, distance, maintenance gap, and speed (km/h).

Table 6: Correlation matrix of the Independent Variables

<b>Diesel multiple unit</b>	0.00	0.00	0.00	-0.22	0.22	<b>0.91</b>	-0.27	<b>-0.82</b>	-0.14	0.07	0.11	0.05	-0.14	0.11	0.07	-0.07	<b>-0.52</b>	0.04	-0.08	0.06
<b>Diesel - electric</b>	0.00	0.00	0.00	0.17	-0.17	<b>-0.80</b>	-0.16	<b>0.90</b>	0.13	-0.02	-0.08	-0.07	0.13	-0.08	-0.02	0.02	<b>0.52</b>	0.07	-0.07	-0.03
<b>Diesel - Hydraulic (Rehabilitated)</b>	0.00	0.00	0.00	0.14	-0.14	<b>-0.30</b>	<b>1.00</b>	-0.15	0.01	-0.12	-0.08	0.04	0.01	-0.08	-0.12	0.12	0.03	<b>-0.25</b>	<b>0.35</b>	-0.07
<b>12 V 4 Stroke</b>	<b>-0.22</b>	0.17	0.14	0.00	0.00	<b>-0.17</b>	0.14	0.11	0.04	<b>-0.15</b>	0.02	-0.05	0.04	0.02	<b>-0.15</b>	0.15	<b>0.42</b>	<b>-0.10</b>	0.00	0.12
<b>16 V 4 Stroke</b>	0.22	<b>-0.17</b>	-0.14	0.00	0.00	0.17	-0.14	-0.11	-0.04	0.15	-0.02	0.05	-0.04	-0.02	0.15	<b>-0.15</b>	<b>-0.42</b>	0.10	0.00	-0.12
<b>Air</b>	<b>0.91</b>	<b>-0.80</b>	<b>-0.30</b>	-0.17	0.17	0.00	0.00	0.00	-0.06	0.10	0.08	0.01	-0.06	0.08	0.10	-0.10	<b>-0.66</b>	0.12	-0.08	0.04
<b>Vaccum</b>	<b>-0.27</b>	-0.16	<b>1.00</b>	0.14	-0.14	0.00	0.00	0.00	0.01	-0.12	-0.08	0.04	0.01	-0.08	-0.12	0.12	0.03	<b>-0.25</b>	<b>0.35</b>	-0.07
<b>Air Vaccum</b>	<b>-0.82</b>	<b>0.90</b>	-0.15	0.11	-0.11	0.00	0.00	0.00	0.06	-0.05	-0.05	-0.03	0.06	-0.05	-0.05	0.05	<b>0.67</b>	-0.01	-0.07	-0.01
<b>Bridge</b>	-0.14	0.13	0.01	0.04	-0.04	-0.06	0.01	0.06	0.00	<b>-0.37</b>	<b>-0.25</b>	<b>-0.77</b>	<b>1.00</b>	<b>-0.25</b>	<b>-0.37</b>	0.37	0.13	0.07	<b>0.35</b>	0.31
<b>Curve</b>	0.07	-0.02	-0.12	-0.15	0.15	0.10	-0.12	-0.05	<b>-0.37</b>	0.00	-0.21	<b>0.48</b>	<b>-0.37</b>	<b>-0.21</b>	<b>0.58</b>	<b>-0.58</b>	-0.13	0.15	<b>-0.59</b>	<b>-0.68</b>
<b>Level crossing</b>	0.11	-0.08	-0.08	0.02	-0.02	0.08	-0.08	-0.05	<b>-0.25</b>	<b>-0.21</b>	0.00	<b>-0.43</b>	<b>-0.25</b>	<b>1.00</b>	<b>-0.21</b>	0.21	0.03	0.09	-0.02	0.21
<b>Concrete</b>	0.05	-0.07	0.04	-0.05	0.05	0.01	0.04	-0.03	<b>-0.77</b>	<b>0.48</b>	<b>-0.43</b>	0.00	0.00	0.00	<b>0.48</b>	<b>-0.48</b>	-0.14	-0.12	<b>-0.31</b>	<b>-0.43</b>
<b>wood</b>	-0.14	0.13	0.01	0.04	-0.04	-0.06	0.01	0.06	<b>1.00</b>	<b>-0.37</b>	<b>-0.25</b>	0.00	0.00	0.00	<b>-0.37</b>	0.37	0.13	0.07	<b>0.35</b>	0.31
<b>No sleeper</b>	0.11	-0.08	-0.08	0.02	-0.02	0.08	-0.08	-0.05	<b>-0.25</b>	<b>-0.21</b>	<b>1.00</b>	0.00	0.00	0.00	<b>-0.21</b>	0.21	0.03	0.09	-0.02	0.21
<b>Urban</b>	0.07	-0.02	-0.12	-0.15	0.15	0.10	-0.12	-0.05	<b>-0.37</b>	<b>0.58</b>	<b>-0.21</b>	<b>0.48</b>	<b>-0.37</b>	<b>-0.21</b>	0.00	0.00	-0.13	0.15	<b>-0.59</b>	<b>-0.68</b>
<b>Sub urban</b>	-0.07	0.02	0.12	0.15	-0.15	-0.10	0.12	0.05	<b>0.37</b>	<b>-0.58</b>	<b>0.21</b>	<b>-0.48</b>	<b>0.37</b>	<b>0.21</b>	0.00	0.00	0.13	-0.15	<b>0.59</b>	<b>0.68</b>
<b>Years in use</b>	<b>-0.52</b>	<b>0.52</b>	0.03	<b>0.42</b>	<b>-0.42</b>	<b>-0.66</b>	0.03	<b>0.67</b>	0.13	-0.13	0.03	-0.14	0.13	0.03	-0.13	0.13	0.00	-0.16	0.11	0.00
<b>Maintenance gap (Months)</b>	0.04	0.07	<b>-0.25</b>	-0.10	0.10	0.12	<b>-0.25</b>	-0.01	0.07	0.15	0.09	-0.12	0.07	0.09	0.15	-0.15	-0.16	0.00	<b>-0.35</b>	0.14
<b>10lg[d]</b>	-0.08	-0.07	<b>0.35</b>	0.00	0.00	-0.08	<b>0.35</b>	-0.07	<b>0.35</b>	<b>-0.59</b>	-0.02	<b>-0.31</b>	<b>0.35</b>	-0.02	<b>-0.59</b>	<b>0.59</b>	0.11	<b>-0.35</b>	0.00	0.20
<b>Speed (km/h)</b>	0.06	-0.03	-0.07	0.12	-0.12	0.04	-0.07	-0.01	<b>0.31</b>	<b>-0.68</b>	0.21	<b>-0.43</b>	<b>0.31</b>	0.21	<b>-0.68</b>	<b>0.68</b>	0.00	0.14	0.20	0.00
	<b>Diesel multiple unit</b>	<b>Diesel - electric</b>	<b>Diesel - Hydraulic (Rehabilitated)</b>	<b>12 V 4 Stroke</b>	<b>16 V 4 Stroke</b>	<b>Air</b>	<b>Vaccum</b>	<b>Air Vaccum</b>	<b>Bridge</b>	<b>Curve</b>	<b>Level crossing</b>	<b>Concrete</b>	<b>wood</b>	<b>No sleeper</b>	<b>Urban</b>	<b>Sub urban</b>	<b>Years in use</b>	<b>Maintenance gap (Months)</b>	<b>10lg[d]</b>	<b>Speed (km/h)</b>

#### 4.5 Scatter Plots - Continuous variables vs Noise level (TEL)

Drawing scatter plots before developing a mathematical model is essential for visualizing the relationship between variables and identifying patterns, trends, and outliers. This preliminary step helps assess whether the data meet the assumptions required for regression and guides model specification.

The scatter plot provided in Figure 04 presents the relationship between the number of years locomotives have been in use and the corresponding noise level, measured in decibels (dB). The number of years locomotives have been in use spans a range of 0 to 50 years. The dotted trend line suggests a slight positive correlation, indicating that noise levels tend to remain relatively stable over time, with a reasonable increase over a number of years. This stability implies that the equipment maintains a consistent noise output throughout its lifecycle.

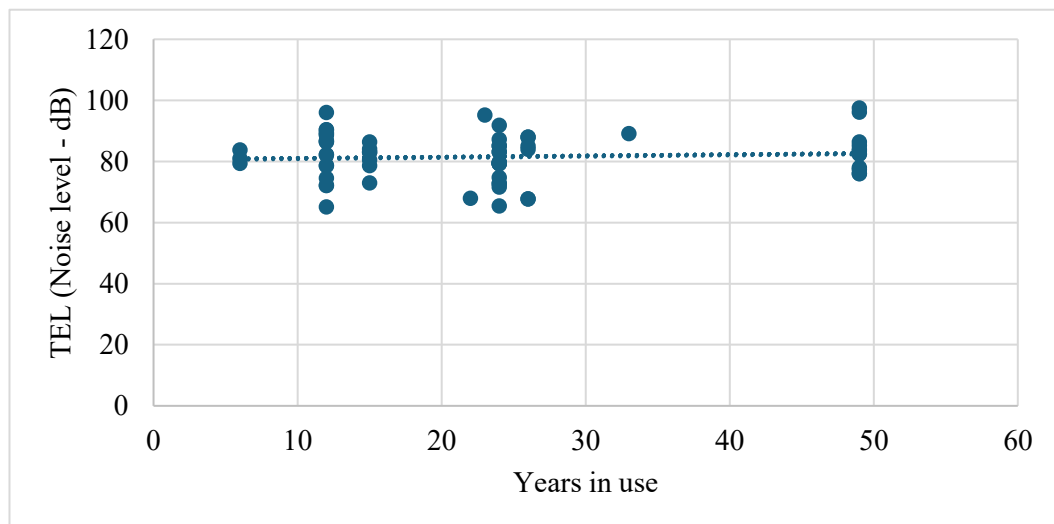


Figure 4: Years in use (locomotive) vs Noise level (TEL)

The scatter plot in Figure 05 illustrates the relationship between the interval between the last major scheduled maintenance repair, measured in months, and the noise level (TEL), expressed in decibels (dB). The maintenance interval in months spans from 0 to 60 months. The trend line shows an upward slope, suggesting an increase in noise levels as the maintenance interval lengthens. This trend indicates potential wear and tear or decreased efficiency over time.

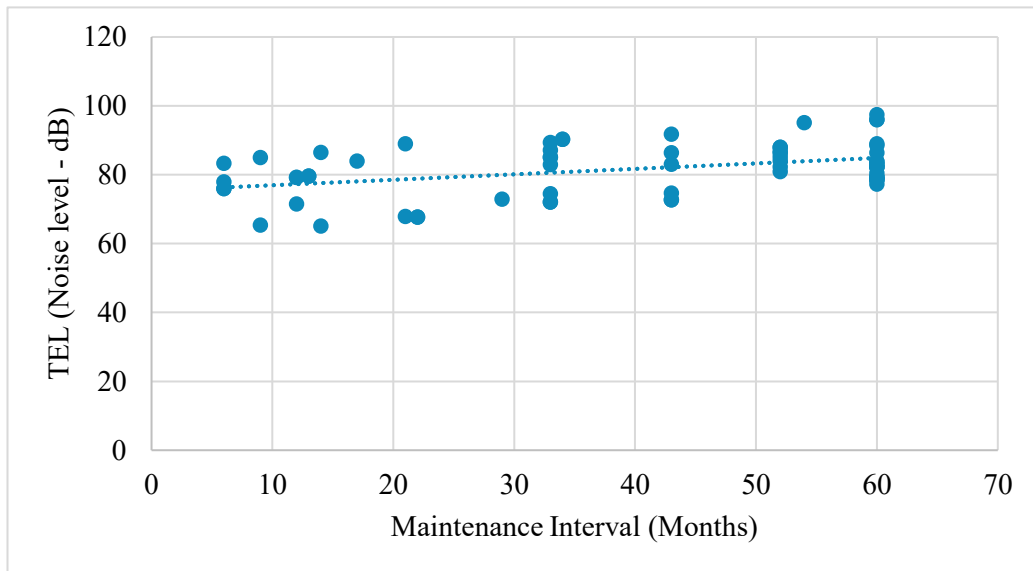


Figure 5: Scatter plot in between Maintenance interval (Months) vs Noise level (TEL)

This graph in Figure 06 explores the relationship between the logarithmic scale of distance (represented as  $10\log[d]$ ) and the noise level (TEL), measured in decibels (dB). The dotted trend line indicates a negative correlation, suggesting that as distance from the railway line increases or in other words distance from the noise source increases, the noise levels tend to decrease.

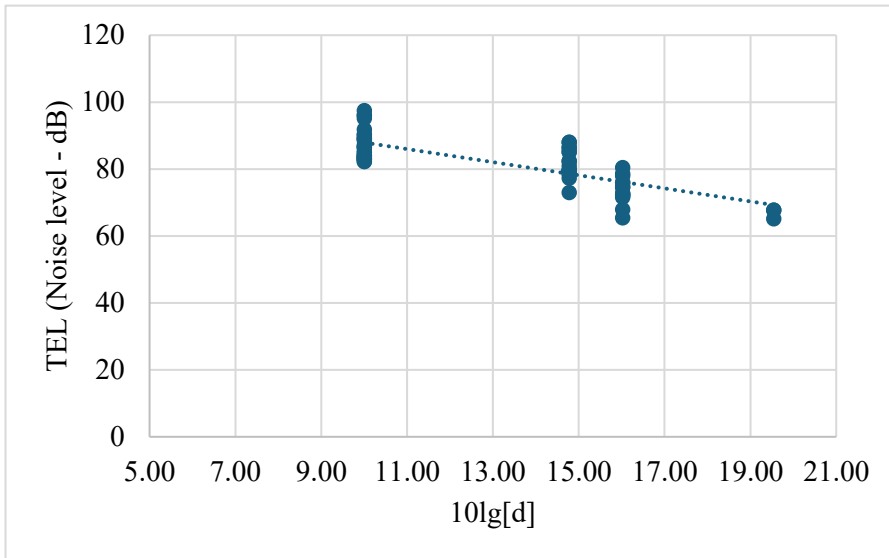


Figure 6: Scatter plot in between 10lg[d] vs Noise level (TEL)

This scatter plot (Figure 07) illustrates the correlation between vehicle speed and noise level (TEL). The data points suggest a weak or no apparent relationship between speed and noise level. But the trend line suggests a weak positive relationship between Noise levels and train speed. The above graphs and the findings from the graphs align with theoretical expectations between noise and the factors considered, such as the distance, speed, maintenance interval and years in use.

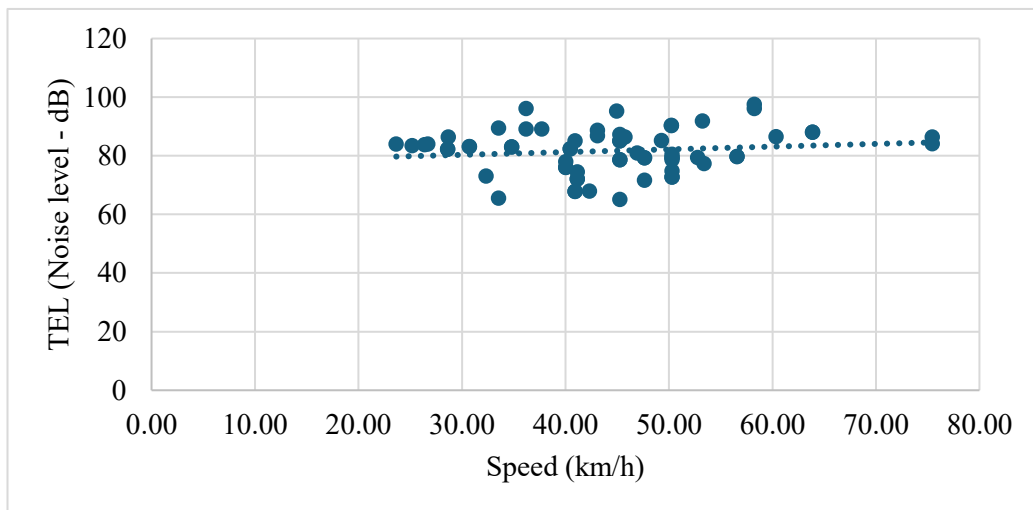


Figure 7: Scatter plot in between Speed (km/h) vs Noise level (TEL)

#### 4.6 Model development

Due to the number of independent and dependent variables, multiple regression analysis has been employed for model development. To avoid overfitting, the sample dataset has been divided into 80% for training data and 20% for testing data. The model was developed using only the training data to ensure unbiased evaluation during testing. Table 07 provides the constant, coefficients, standard error, and P values of the developed mathematical model.

Table 7: Constant, coefficients, standard error and P values of the developed mathematical model

<b>Variables</b>	<b>Coef.</b>	<b>Std. Err.</b>	<b>P value</b>
Constant	33.21	1.50	0.00
Diesel multiple unit	9.73	1.41	0.00
Diesel – electric	10.91	1.25	0.00
Diesel - Hydraulic (Rehabilitated)	12.57	1.01	0.00
12 V 4 Stroke	15.67	0.96	0.00
16 V 4 Stroke	17.55	0.98	0.00
Air	9.41	1.48	0.00
Vacuum	12.57	1.01	0.00
Air Vacuum	11.23	1.71	0.00
Bridge	12.79	1.00	0.00
Curve	11.18	0.51	0.00
Level crossing	11.24	1.05	0.00
Concrete	9.19	0.75	0.00
Urban	22.18	0.51	0.00
Sub urban	11.03	1.47	0.00
Years in use	0.05	0.06	0.41
Maintenance gap (Months)	0.02	0.03	0.35
10lg[d]	-2.33	0.22	0.00
Speed (km/h)	0.18	0.06	0.00

The constants and coefficients of the developed model indicate the baseline noise level and the magnitude and direction of the impact of each variable, respectively. Positive coefficients suggest an increase in noise level with an increase in the variable, while negative coefficients suggest a decrease. From the values of the Table 2, only the distance variable shows a negative coefficient, while all other independent variables

have positive coefficients. The negative coefficient for the distance variable is consistent with the well-established principle that noise levels decrease as the distance from the source increases.

Compared to qualitative variables, quantitative variables like years in use, maintenance gap, distance, and speed have comparatively smaller coefficients. However, due to the different scales of numerical inputs, these quantitative variables demonstrate varied impacts. Among the quantitative variables, distance and speed have a significant impact, while years in use and maintenance gap have a lesser impact on the model. Standard errors reflect the precision of the coefficient estimates, with smaller values indicating more precise estimates. The p-values assess the statistical significance of each coefficient, with values less than 0.05 indicating a significant impact.

Table 08 presents the regression results derived from the training dataset, including values for R-squared, adjusted R-squared, F-statistic, and standard error. These metrics, computed using only the training data, reflect how well the model fits the training data and indicate that the developed regression model has a good fit and is statistically significant. Table 09 presents the actual and predicted TEL (dB) values from the testing dataset, along with the corresponding absolute and percentage errors for each observation. To validate and assess the model's predictive performance, performance metrics such as mean squared error, root mean squared error, mean absolute error, and mean absolute percentage error were used on an untouched test dataset. These performance indicators, also included in Table 09, confirm that the model provides satisfactory predictive accuracy.

Table 8: Performance metrics from multiple regression analysis

<b>Statistic</b>	<b>Value</b>
Multiple R	0.9083
R-squared	0.8251
Adjusted R-squared	0.7769

Standard Error	3.2201
Observations	64
F-statistic	17.1497
Prob (F-statistic)	7.701E-12

Table 9: Actual Noise levels and Predicted Noise Levels from the testing data set and Performance metrics from testing data set

Actual TEL (dB)	Predicted TEL (dB)	Absolute Error	Percentage Error (%)
65.11	64.02	1.09	1.67
71.59	71.34	0.25	0.35
74.50	75.42	0.92	1.23
76.67	78.19	1.52	1.98
78.61	72.35	6.26	7.96
79.67	81.19	1.52	1.91
80.46	77.55	2.91	3.62
82.98	84.94	1.96	2.36
85.57	83.33	2.24	2.62
89.41	86.01	3.4	3.80
90.17	87.69	2.48	2.75
90.34	88.65	1.69	1.87
90.78	87.85	2.93	3.23
91.40	96.11	4.71	5.15
91.83	86.34	5.49	5.98
97.50	96.03	1.47	1.51
Mean Squared Error (MSE)			9.96
Root Mean Squared Error (RMSE)			3.16
Mean Absolute Error (MAE)			2.55
Mean Absolute Percentage Error (MAPE)			2.99

The developed multiple regression model effectively estimates railway noise levels (TEL in dB) based on a combination of locomotive types, brake systems, engine cylinder configurations, track features (such as bridges, curves, and level crossings), and operational parameters including train speed and distance from the source. The model demonstrates strong predictive capability, as evidenced by model fitting parameters and satisfactory values of performance metrics on the independent test dataset.

The developed railway noise model yielded the following coefficient values: Diesel-Hydraulic (Rehabilitated) locomotives exhibited the highest coefficient among locomotive types (12.57), while Diesel Multiple Units had the lowest (9.73). This indicates that Diesel-Hydraulic (Rehabilitated) locomotives produce higher noise levels compared to other locomotive types, whereas Diesel Multiple Units generate significantly less noise.

Among brake systems, vacuum brakes showed the highest coefficient (12.57), indicating a greater noise contribution compared to air (9.41) and air-vacuum brakes (11.23). Data from the railway revealed that Diesel-Hydraulic locomotives are predominantly equipped with vacuum brake systems. This combination suggests that the higher noise levels are primarily driven by the interaction between Diesel-Hydraulic locomotives and vacuum brake systems. Conversely, Diesel Multiple Units, which use air brake systems, produce lower noise levels, further emphasizing the benefits of this locomotive-brake combination.

In terms of engine configuration, the coefficients for 12 V 4-stroke (15.67) and 16 V 4-stroke engines (17.55) indicate that an increase in the number of cylinders is associated with higher noise levels. Additionally, the model reveals a positive relationship between train speed and noise, as indicated by the coefficient for speed (0.18). This implies that higher train speeds contribute to increased noise levels. Overall, these findings offer valuable insights into the factors that influence railway noise levels. The results highlight specific locomotive and brake system combinations,

engine configurations, and operational factors such as speed that can be addressed to reduce noise levels near railway lines.

#### 4.7 Noise Dispersion Map

A noise dispersion map was developed using ArcMap to visualize noise propagation during train pass-by events along the coastal railway line. Figure 8 illustrates a section of the developed noise dispersion map, highlighting the division of noise level zones.



Figure 8: Part of noise dispersion map

Figure 9 illustrates the noise dispersion close to Fort railway station, highlighting the significant influence of curvature on noise generation. The curved sections of the railway line result in an increase of approximately 11 dB in noise levels. Due to the logarithmic decay of noise, the affected area expands significantly near the curved railway lines, emphasizing the pronounced impact of curvature on the extent of noise dispersion.



Figure 9: Noise dispersion map closer to Fort railway station (Curved railway lines)

Figure 10 depicts the variation in noise dispersion caused by the presence of bridges along the railway line. The developed mathematical model indicates that bridges contribute to an increase in noise levels by approximately 13 dB, demonstrating their significant impact on noise generation and propagation.



Figure 10: Noise dispersion closer to bridges (Dehiwala & Wellawatta bridges)

By overlaying the noise dispersion maps with land-use data, it becomes evident that a significant portion of the affected zones particularly those exceeding 70 dB intersect with densely populated residential and commercial areas, especially around Fort Railway Station and other urban segments. According to the Central Environmental Authority (CEA) guidelines, the  $L_{Aeq,T}$  should not exceed 60 dB during the day and 50 dB at night in residential areas, and 65 dB during the day and 55 dB at night in commercial areas. Although the CEA provides these standards based on long-term equivalent noise levels, this study focuses on short-term equivalent noise levels. Therefore, while a direct comparison is limited, the short-term noise levels observed often exceeding these thresholds highlights potential risks, especially in noise-sensitive areas along the coastal railway line.

In order to visually evaluate the impact of locomotive type on railway noise propagation, two separate noise dispersion maps were developed for Diesel Multiple Unit (DMU) and Diesel Hydraulic locomotives. These maps were generated by varying locomotive-specific parameters, such as locomotive type, working principle, brake system, years in use and maintenance interval, while keeping all other influencing factors constant. This approach enables a direct comparison of the noise dispersion patterns attributable solely to the type of locomotive used, thereby highlighting the relative contribution of each locomotive to noise impact. The resulting maps are presented in Figure 11 (diesel multiple unit) and Figure 12 (Diesel Hydraulic). The comparison reveals that Diesel Hydraulic locomotives result in a significantly larger affected area due to their higher noise emissions. For instance, the noise impact zone for 70 dB expands from approximately 140 meters for the DMU to nearly 320 meters for the Diesel Hydraulic locomotive. This considerable increase is primarily because of logarithmic decay, where even modest increases in noise levels lead to disproportionately larger spatial impacts.

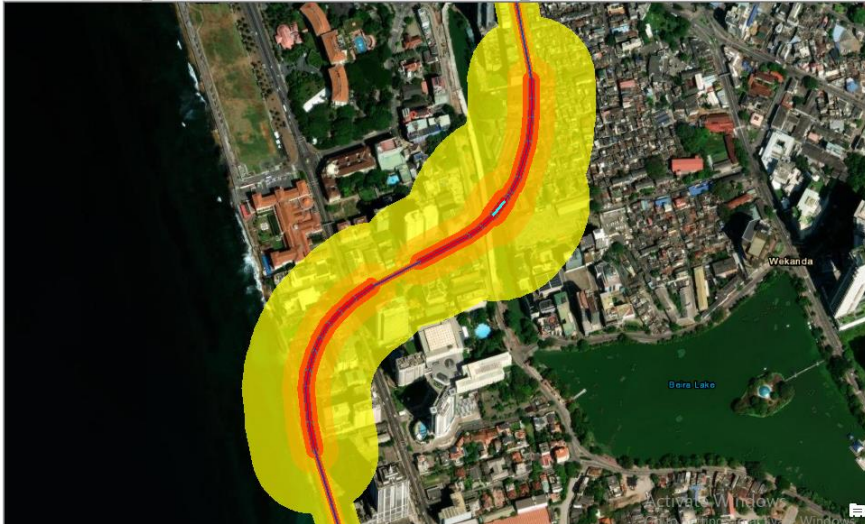


Figure 11: Noise Dispersion Map of Diesel Multiple Unit locomotive

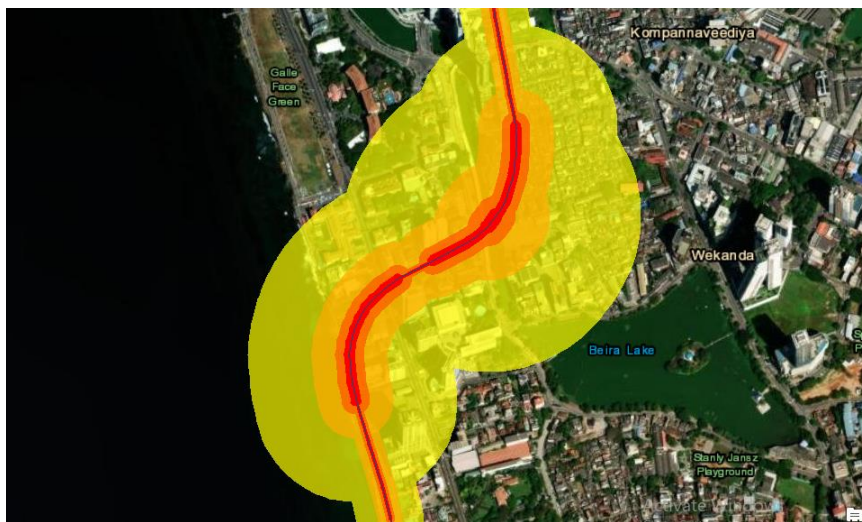


Figure 12: Noise Dispersion Map of Diesel Hydraulic Locomotive

The noise dispersion maps, and the identified impact zones underscore the need to establish minimum clearance distances when planning or upgrading railway lines. Field observations and land use maps reveal that a significant number of households currently exist within these noise-affected zones, and some of them even fall within designated railway reservation boundaries. In certain instances, these constructions are unauthorized, raising serious concerns about regulatory enforcement and public health protection. Therefore, at least in noise-sensitive areas such as schools, hospitals, and densely populated residential zones, a minimum clearance distance equivalent to the

70 dB impact zones derived from this study should be maintained, rather than commonly adopted 40-meter clearance guideline provided by the Survey Department. For example, the noise maps reveal that Uyana Primary School in Lunawa, Moratuwa, is located less than 50 m from the railway line, placing it well within the high-impact noise zone. Similarly, St. Sebastian's Girls' School in Moratuwa, situated approximately 70 m from the railway line, also lies within an affected area. These findings highlight the direct exposure of educational institutions to railway noise along this corridor. While these are specific examples, the noise maps further indicate numerous other locations where schools and densely populated residential buildings are situated adjacent to the tracks, reflecting broader exposure to elevated noise levels.

According to the results, the 70 dB noise impact distance for Diesel Multiple Unit (DMU) operations is approximately 35 meters on straight track segments is below the standard clearance but for Diesel Hydraulic locomotives, the distance extends to 75 meters. On curved railway sections, which intensify noise propagation due to track geometry the 70 dB zones extend up to 104 meters for DMUs and up to 225 meters for Diesel Hydraulic locomotives. These findings indicate that clearance guidelines must be adjusted based on locomotive type and track geometry. A clearance of approximately 200 meters is recommended for curved sections where Diesel Hydraulic locomotives operate frequently.

## **5 CONCLUSION AND RECOMMENDATIONS**

### **5.1 Conclusion**

This study has identified several key factors influencing locomotive noise levels. Upon analysis, Diesel-Hydraulic (Rehabilitated) locomotives were found to be significant contributors to noise due to their design characteristics, including the incorporation of vacuum-type brake systems, which generate more noise compared to air-type brake systems. In contrast, Diesel Multiple Units (DMUs), which utilize quieter air-type brake systems, represent a preferable alternative for operations in noise-sensitive areas (schools, hospitals, and densely populated residential zones) adjacent to railway lines.

The study further reveals a direct correlation between locomotive noise and the number of cylinders, highlighting that locomotives with more cylinders tend to produce higher noise levels. This finding suggests that the design and mechanical specifications of locomotives play a critical role in noise generation. Moreover, the analysis shows that factors such as the years a locomotive has been in use and the intervals between maintenance have a minimal impact on noise levels, emphasizing the predominance of other variables, such as locomotive type and speed, in influencing noise.

Additionally, the study identifies train speed as a significant contributor to increased noise levels, underscoring the need for speed regulation, particularly in proximity to noise-sensitive environments. Other environmental factors, including bridge crossings, curves, and level crossings, have also been pinpointed as notable sources of railway noise. The developed noise dispersion map reveals that curved railway lines have a significantly higher noise impact on adjacent areas compared to other locations along the railway line, affecting a larger surrounding area due to the amplified noise generation in these sections. This highlights the need for prioritizing noise mitigation measures in curved railway sections over other areas along the railway line.

The study also emphasizes the planning implications of locomotive noise, particularly regarding appropriate clearance distances near railway lines. The analysis of noise dispersion patterns has demonstrated that current standard clearances may be

insufficient in certain operational contexts. These insights serve as a strong basis for updating spatial planning guidelines in railway development, especially for routes operating high-noise locomotives and in complex track geometries like curves.

Regarding the limitations, this study was limited to the coastal railway line, and results may differ for other railway lines in Sri Lanka due to variations in environmental and terrain conditions, as well as additional locomotive-related factors. Only 80 observations were taken due to time and resource constraints, which may affect reliability. While efforts were made to minimize the influence of external noise sources, slight interference may have influence while taking measurements at longer distances from the railway lines. Employing more advanced instruments and additional readings closer to the tracks could further enhance the accuracy of the study.

Overall, this comprehensive analysis provides valuable insights into the factors that significantly impact locomotive noise levels and underscores the need for targeted strategies to mitigate noise in railway operations.

## **5.2 Recommendations**

Based on the findings of this study, several recommendations can be made to mitigate railway noise and improve the quality of life for communities living near railway lines. Given that Diesel Multiple Units (DMUs) are quieter due to their use of air-type brake systems, railway operators should prioritize the use of DMUs over Diesel-Hydraulic (Rehabilitated) locomotives in noise-sensitive areas (schools, hospitals, and densely populated residential zones). This shift would significantly reduce noise levels and is particularly relevant for railways running through residential or urban zones. Additionally, the high noise levels associated with Diesel-Hydraulic locomotives, especially those with vacuum-type brake systems, suggest that reducing their use or phasing them out in favour of quieter alternatives could be an effective noise mitigation strategy.

Another key recommendation involves optimizing locomotive design. The direct correlation between the number of cylinders and noise levels indicates the need for careful consideration of locomotive design features. Future procurement and design of locomotives should prioritize models that balance performance with noise reduction, potentially by limiting the number of cylinders or employing noise-dampening technologies. Alongside design considerations, speed regulation is also crucial. Implementing speed limits, particularly in noise-sensitive areas, could help reduce overall noise levels.

The findings from the noise maps provide clear evidence of the implications for noise sensitive areas. For example, Uyana Primary School in Lunawa, Moratuwa, located less than 50 m from the railway line, and St. Sebastian's Girls' School in Moratuwa, situated approximately 70 m away, are both directly exposed to high noise levels. These cases highlight the importance of stricter speed regulation in such environments and the reconsideration of existing clearance distance policies, which are often inadequate. While these are specific examples of schools, the noise maps also indicate several other locations where schools and densely populated residential buildings are positioned adjacent to the railway line, reflecting a broader exposure to elevated noise levels and emphasizing the necessity for targeted mitigation strategies.

Based on the study's findings, minimum clearance distances must be reconsidered, especially in noise-sensitive zones. The commonly adopted 40-meter guideline is inadequate in many cases. Therefore, relevant authorities should revise clearance policies to reflect these differences in locomotive types and track configurations. At locations where implementing full recommended distances is not feasible particularly in densely built urban areas alternative noise mitigation solutions should be adopted.

Infrastructure modifications present a practical and necessary approach in such constrained environments. Engineering solutions such as noise barriers, sound-absorbing materials, and smoother track designs could help mitigate noise in these areas. Finally, rail operators should develop and implement comprehensive noise management plans that incorporate the study's findings. These plans should include

regular noise monitoring, community engagement, and adaptive strategies to effectively address noise complaints and emerging noise issues.

By adopting these recommendations, railway operators can significantly reduce noise pollution, contributing to a quieter, more sustainable environment for communities living near railway lines. The implementation of these strategies requires a collaborative approach involving railway authorities, government agencies, and community stakeholders to ensure effective and sustainable outcomes.

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