DEVELOPMENT OF AN EMISSION ESTIMATION MODEL FOR TRAINS USING DRIVING CYCLE CONCEPT

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(209584P)

Degree of Master of Engineering

Department of Civil Engineering

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Thesis submitted in partial fulfillment of the requirements for the Master of Engineering in Civil Engineering

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Declaration, copyright statement and the statement of the supervisor

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Dr H L K Perera

Abstract

This study develops an emission estimation model for the route having the highest emission, using the Driving Cycle concept to analyze the train emissions in Sri Lanka, aiding policy development by determining threshold values to meet future emission reduction targets. Selection of the route for the highest emission is selected based on the vertical alignment of the railway track. The onboard measurement method collected train speed data, analyzed using Python. The micro trip-based method was chosen to develop a driving cycle, as it is most suitable for emission estimation purposes.

Analysis of slow and express trains, including locomotive and power-set types, reveals that slow trains have significantly higher idling times due to frequent stops. In contrast, express trains allocate more time to acceleration and cruising. When developing driving cycles (DCs), the mean relative difference (MRDi) factor was considered, using averages of acceleration, deceleration, speed, and running speed. The MRDi values for selected DCs were 1.246% for locomotive express, 1.191% for power-set express, 0.105% for locomotive slow, and 0.179% for power-set slow trains. Express trains showed higher MRDi values due to a smaller pool of micro trips for their combinations compared to slow trains, highlighting differences in operational characteristics between the two train types.

After developing driving cycles for all train types, a connection between speed and smoke density (k) was determined. To derive this relationship, correlations were first developed between RPM (revolutions per minute) and speed, as well as between RPM and smoke density (k). These correlations were then used to determine the relationship between speed and smoke density (k). Comparing the emissions to the diesel engine threshold (k=4) indicated that locomotive trains should adhere to the 81st percentile regulation, while power-set trains already conform to Sri Lanka's existing emission standards. If the threshold smoke density values are further lowered to enforce stricter emission regulations without enhancing train engine performance, it has been observed that the travel distance decreases at nearly the same rate.

In summary, this study facilitates future studies on emission estimation economically and collaborates with the proposed emission factors. It will help to make a policy decision for measuring, regulating and imposing restrictions on the emission of trains.

Keywords: Emission, Driving cycle, Train, Smoke density

Acknowledgement

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CHAPTER 1 - INTRODUCTION

1.1 Introduction

Greenhouse gas emissions have become a critical global challenge with significant implications for climate change and sustainability. In 2019, worldwide emissions were about 57 gigatons of CO_2 equivalent, with electricity and heat generation contributing 34%, industry 24%, agriculture, forestry, and other land use 22%, transportation 15%, and buildings 6% (Dhakal, Minx, & L. Toth, 2022). In response to these emission levels, the Paris Agreement, adopted in 2015 by nearly 200 countries, is a landmark international treaty aimed at combating climate change and its impacts. One of its core objectives is to limit the rise in global average temperatures to well below 2°C above pre-industrial levels, with a strong emphasis on pursuing efforts to restrict warming to 1.5°C. To meet this goal, the Paris Agreement mandates that global greenhouse gas emissions must peak before 2025, meaning that emissions should stop increasing and begin to decline. Following this peak, emissions must be reduced by approximately 43% by 2030 compared to 2019 levels (United Nations, 2016) (United Nations Framework Convention on Climate Change, n.d.). Similarly, in the Sri Lankan context, sectors like energy, transport, agriculture, industry, forestry, and waste management generate significant greenhouse gas emissions, resulting in a per capita emission of approximately 1.02 tonnes per person (Ratnayake, et al., 2023). In 2010, the energy and transport sectors accounted for 64.1% of total emissions. To address this, the Ministry of Environment of Sri Lanka has set a target to reduce emissions from these sectors, among others, by 14.5% by 2030 (Ratnayake, et al., 2023).

Among the key contributors to emissions in Sri Lanka, the transport sector stands out, with road and rail transport relying heavily on fossil fuels for operation. The majority of vehicles in Sri Lanka run on fossil fuels, primarily auto diesel and petrol. While some vehicles are electric, most rely on petroleum, and the entire rail network in Sri Lanka operates using auto diesel (Ratnayake, et al., 2023). Rail is an efficient way to move people and freight (Jaffe, et al., 2014). However, the combustion of diesel fuel in train engines releases pollutants such as nitrogen oxides (NO_x) and particulate matter (PM), and it has a significant impact on air quality due to the emission of gases (Ratnayake, et al., 2023). Many railway lines around the world run through densely populated urban areas, where the emissions from trains can significantly impact human health (Jaffe, et al., 2014). These emissions not only affect individuals living near the tracks but also pose risks to commuters, as the exhaust plume can infiltrate the interior, especially when the locomotive pulls the train (Andersen, et al., 2019). Consequently, both train staff and passengers are regularly exposed to emission. Prolonged exposure to diesel exhaust is linked to an increased risk of lung cancer and cardiovascular diseases (Andersen, et al., 2019). From an environmental perspective, PM degrades air quality, contributes to haze and smog, and exacerbates climate change by accelerating snow and ice melting through black carbon deposition (Bond, et al., 2013). However, currently, there is insufficient information to assess the effects of rail transport on air quality (Jaffe et al., 2014).

Given this reliance on rail transport, understanding the types of trains operating in Sri Lanka is essential for assessing their environmental and operational impacts. In the Sri Lankan context, there are primarily two types of trains: locomotive trains and power set trains. These types are categorized based on their method of power supply for propulsion. A comparison between locomotive trains and power set trains used in SL is provided in Table 1.1, and general details of each locomotive train and power set train currently operating in Sri Lanka are shown in Tables 1 and Table 2 of Appendix B, respectively (Herath, 2020). According to these Tables in Appendix B, most operational locomotive trains were imported prior to the year 2000. In contrast, powerset trains were imported after the year 2000, with the majority being newer models compared to the locomotive trains. Table 1.1 below provides a comparison between Power set trains and Locomotive trains in terms of design, propulsion and flexibility.

Table 1.1 Comparison between Power-set trains and Locomotive trains

	Locomotive-Hauled Trains	**Power Set (Multiple Unit) Trains**
Design	These trains have a separate locomotive unit that houses the engine. The locomotive is responsible for pulling or pushing the train's compartment.	These trains have multiple powered units distributed throughout the train, with each carriage potentially having its own set of motors.
Propulsion	The locomotive provides all the power needed to move the train. (In Sri Lankan context, Diesel powered the locomotives)	The propulsion system is spread out across several or all of the train's carriages. This can also be diesel or electric. (It's diesel in Sri Lanka)
Flexibility	Locomotive-hauled trains are versatile and can easily have carriages added or removed.	These trains are less flexible than locomotive-hauled trains in terms of modifying the train's length.

These diesel locomotives can be categorized into three main types according to power transmission method.

1. Diesel Electrical Locomotives
2. Diesel Hydraulic Locomotives
3. Diesel Mechanical Locomotives

The majority of diesel locomotives currently used in Sri Lanka are diesel-electric locomotives. In diesel-electric locomotives, drivers can control both the direction and speed of the train by adjusting the current in the traction motor. The motor's axle is connected to the axles of the bogies. This motor is powered by electricity generated from converting kinetic energy. Essentially, the traction motor is connected to an alternator, which is, in turn, linked to the engine's crankshaft.

Understanding the emissions generated by different transport systems requires considering factors beyond the type of vehicle or train, such as speed, route design, traffic volume, flow, and driving patterns (Pouremeaili, Aghayan, & Taghizadeh, 2017). Based on changes in vehicle speed and changes in speed (acceleration and deceleration), environmental engineers calculate the number of pollutants produced in urban streets by vehicles (Pouremeaili, Aghayan, & Taghizadeh, 2017). Standard speed-time variation curves (Driving Cycles) in developed countries are used to create an emission estimation model and estimated emission factors for sustainable transportation planning (Tzeng & Chen 1998).

According to (Ratnayake, et al., 2023), it is projected that long-distance trains in Sri Lanka will emit approximately 71,000 tonnes of carbon dioxide (CO2) annually by 2050. Despite this projection, there is still no mechanism for emission regulation methods to regulate train emissions in Sri Lanka. However, Globally, emissions from trains are measured through specific methodologies designed for rail transport. According to (Johnson, et al., 2013), they have conducted a study to measure the emission of locomotive trains using the mobile laboratory by locating a mobile laboratory adjacent to the railway line. Emission factors published by the Environmental Protection Agency (EPA) are used to calculate the emissions (E) caused by loco motive trains in Turkey (Environmental Protection Agency, 1991) & (Dincer & Elbir, 2007).

Evaluation of vehicle performances from an air quality point of view plays a basic role in modelling emission estimation models (Abo-Qudais & Abu Qdais, 2005). Among the approaches used for modeling emission estimation, traffic simulation models are built upon vehicle speed, acceleration, and deceleration. The driving cycle is the speed-time profile for a vehicle driving under a specified condition, usually selected to represent a glimpse of a real-life situation (Tong & Hung, 2010). It denotes the driving behavior of a specific region pertaining to the travelling route, road infrastructure, traffic management mechanism, traffic flow, topography, land use, driving condition, and vehicle type. The driving cycle can be used for both legislative and non-legislative purposes, such as the development of emission inventory and the determination of fuel consumption. However, driving cycles are influenced by factors such as driver behavior, traffic conditions, and road characteristics. As a result, the developed driving cycle for one specific region cannot be directly applied as it is to another region. (Gamalath, Fernando, Galgamuwa, Perera, & Bandara, 2012). This means that although driving cycles for trains have been developed in other countries, using them to estimate emissions in Sri Lanka would not be appropriate, and it’s most suitable to develop a driving cycle for Sri Lanka.

Rather than placing a gas analyzer near the railway track to measure emitted gases, the driving cycle-based emission estimation model represents the whole journey for emission estimation. The usage of a gas analyzer for emission estimation provides results limited to that specific location and fails to represent emissions for the entire journey. Therefore, the driving cycle-based method for emission estimation is focused here on emission regulations because it represents the driving behavior along the whole selected route.

Once the appropriate driving cycle is finalized for emission estimation, the standard procedure typically involves placing the vehicle on a chassis dynamometer (controlled testing platform that simulates road conditions) and following the speed-time profile of the selected driving cycle (Dukulis & Pirs, 2009). However, this method is not feasible for large vehicles like train engines due to several key limitations. Chassis dynamometers are specifically designed for road vehicles and cannot accommodate the size, weight, and unique operational characteristics of trains. Additionally, setting up a dynamometer for trains would be impractical, prohibitively expensive, and operationally challenging. Therefore, in this study, an alternative emission estimation method is essential to address these constraints while providing a scalable, cost-effective, and realistic solution tailored to the unique requirements of train engines.

After determining the alternative method for emission estimation, the light absorption coefficient (k) was chosen as the primary metric to assess the opacity of exhaust emissions from diesel vehicles, representing the concentration of particulate matter in the exhaust. Many countries have established varying permissible k-value limits based on their environmental policies and air quality standards. According to the gazettes (Ministry of Environmnet & Natural Resources, 2008), Sri Lankan emission standard for diesel vehicles is set at a comparatively high k-value of 4.0 m^{-1}, allowing for greater exhaust opacity. In contrast, stringent standards are implemented in other regions, such as the European Union, where the maximum permissible k-values are 2.5 m^{-1} for naturally aspirated engines and 3.0 m^{-1} for turbocharged engines (Dartoy, et al., 2006). Similarly, countries like India, Australia, Singapore, Malaysia, and South Africa adopt k-value limits of 2.5 m^{-1} to 3.0 m^{-1}, aligning closely with European norms. Japan enforces some of the most stringent regulations, with k-values generally capped at 2.0 m^{-1}, depending on vehicle type and engine specifications. These variations highlight Sri Lanka's more lenient emission thresholds, allowing higher levels of particulate emissions compared to the stringent controls in other countries.

1.2 Problem Statement

The train population in Sri Lanka is ageing and growing exponentially, which causes a consistent rise in air pollution levels and negative environmental impact. Therefore, in order to achieve the target emission levels, set in various protocols (2050 Carbon Net Zero, Parris), establishment of emission standards for trains is highly desirable.

1.3 Aims and Objectives of the Study

1. Development of a Driving Cycle (DC) for Trains
    - Collecting data (Speed Vs. time)
    - Driving Cycle Formulation for the Maximum Emission Route
    - Assessment and validation of the developed DC

2. Development of a model for emission estimation of trains for maximum emission route in Sri Lanka using the Driving Cycle.
    - Find out an economical and alternative method
    - Comparison between standard driving cycle emission factors (Smoke density “k”)

CHAPTER 2 - LITERATURE REVIEW

2.1 Economical Driving Cycle

The driving cycle represents the typical driving behavior in a specific city or region, characterized by speed and acceleration patterns. It includes a series of various vehicle operation conditions, such as idling, acceleration, deceleration, and cruising. The driving cycle is regarded as a distinctive indicator of the driving characteristics of that area. (Kamble, Mathew, & Sharma, 2009). Developed driving cycles can be divided into two categories: legislative driving cycles and non-legislative driving cycles. Legislative driving cycles are considered to be broadly representative of the driving conditions within their respective jurisdictions. They are provided to governments for motor vehicle emissions controls. The US 75 cycle, ECE cycle and Japan 10–15 mode cycles are examples of driving cycles currently used as legislative driving cycle (Tong & Hung, 2010). Non legislative driving cycles are broadly used for emission estimation and fuel consumption analysis (Gebisa, Gebresenbet, Gopal, & Nallamothu, 2021).

When developing a driving cycle, it is important to follow cost-effective methods due to limited resources. However, these methods must remain accurate and executable. According to (Galgamuwa, Perera, and Bandara, 2016), data collection can be made more economical by using chase car and on-board techniques, depending on their suitability for the area being studied.

2.2 Steps for Economical Driving Cycle

When developing a driving cycle, five key factors must be considered: the percentages of acceleration, deceleration, idling, cruising, and the average speed (Nesamani & Subramanian, 2011). These parameters are used to develop a driving cycle which is close enough to the on-road driving condition and test vehicle emissions. The already developed driving cycle in the world can't be applied as it is to another region or road section. Because the already developed driving cycle for another section does not represent the actual traffic condition of the given section. Therefore, developing exclusive driving cycles is a compulsory requirement to enable better estimation of emissions (Nesamani & Subramanian, 2011). There are four basic steps that have been followed for driving cycle construction; those steps can be expressed as route selection, driving data collection, formation of the driving cycle and assessment of the developed driving cycle (Galgamuwa, Perera, & Bandara, 2015). These steps are used in every driving cycle development.

2.2.1 Route Selection

Route selection is one of the paramount steps in driving cycle construction. The selection of a route for data collection should truly represent the actual traffic condition of the region; otherwise, the collected data for constructing the driving cycle will be biased, and the driving cycle developed from this data will not accurately reflect the region's actual traffic conditions. There are several factors to be considered for route selection, and it depends on the driving cycle's development purpose. Vertical alignment is crucial for developing a driving cycle intended for emission estimation or fuel consumption assessment (Galgamuwa, Perera, & Bandara, 2015). Another important consideration for route selection is the density of traffic light-controlled junctions and the posted speed limits of the chosen route (Freij & Ericsson, 2005). In addition to the previously mentioned parameters, factors such as land use patterns, population density, topography, and altitude are commonly considered in the route selection process for driving cycle construction. However, some factors may be excluded from route selection due to their inapplicability. For instance, population density and land use patterns were not considered in the development of the driving cycle for the Southern Expressway in Sri Lanka, as these factors do not influence traffic behavior on expressways due to their limited access. (Galgamuwa, Perera, & Bandara, 2016).

2.2.2 Data Collection

Data collection is the second crucial step in driving cycle development. The two primary methods for gathering speed-time data are the on-board measurement method and the chase car method. In addition to these two main methods, there is a hybrid method derived from the previously mentioned techniques for data collection. Each method has its own inherent advantages and disadvantages, so it is important to weigh the pros and cons of each to select the most suitable method for data collection. (Tong & Hung, 2010).

The chase car method is more cost-effective than other methods and is ideal for monitoring true driving behavior, as it requires fewer resources and provides real-time traffic conditions. However, it can sometimes be complicated due to the target vehicle's behavior, making it difficult for the chase car to follow the target vehicle smoothly. If the target vehicle's driving behavior is aggressive, it becomes challenging to chase, making the process time-consuming, less cost-effective, and less accurate (Gamalath, Fernando, Galgamuwa, Perera, & Bandara, 2012). On the other hand, the chasing cars would easily be confused about which vehicle should be chosen according to the target vehicle random selection procedure, especially when the chase car enters a new roadway or at high volume traffic conditions, which can also be considered a disadvantage of the chase car method. (Tong & Hung, 2010). During the construction of the Pune driving cycle, the chase-car method was used to gather speed-time data. Vehicles were randomly selected for chasing, and this process was repeated to compile a large dataset. The chase-car method was employed during both peak and off-peak hours to capture varying traffic conditions (Kamble, Mathew, & Sharma, 2009). The data collection method for the Sydney driving cycle also utilized the chase-car technique, similar to the Pune driving cycle. An instrumented vehicle was driven along selected routes to gather the data (Kent, Allen, & Rule, 1977).

Considering the instrumentation cost of the vehicle used for the on-board measurement method, it's relatively high, which is why the on-board measurement method is rarely used for large-scale studies. However, the on-board measurement method has several advantages over other methods, such as eliminating delays caused by driver response time and preventing the overestimation of hard accelerations and decelerations (Tong & Hung, 2010). When developing the driving cycle for Colombo - Sri Lanka, handheld GPS devices were utilized by (Galgamuwa, Perera, & Bandara, 2016) for the on-board measurement method due to the availability of the limited budget. These handheld GPS devices were used to record every one-second speed data on road segments with ±7m tolerance maximum estimated error. However, despite these two distinct methods, researchers can use the combination of the on-board measurement method and the chase car method according to the study's requirement and their limitations. This combined method is called the hybrid data-collecting method (Tong & Hung, 2010).

2.2.3 Cycle Development

After gathering travel data from the selected route or region, this data is used for driving cycle development. When developing a driving cycle, several methods can be followed, such as the micro trip-based method, segment-based method, driving pattern classification method, and model-based driving cycle construction method. The selection of a suitable method of driving cycle construction depends on the purpose of the driving cycle. According to (Seers, Nachin, & Glabus., 2015), developing driving cycles serves three main purposes: estimating emissions, supporting traffic engineering, and estimating vehicle fuel consumption.

As suggested by its name, the micro trip-based method relies entirely on the extracted micro trips from the base data (Tamsanya, Aibulpatana, & Chokchai, 2009). These extracted micro trips can be selected in three ways: the random selection method, the best incremental method, or a hybrid of both approaches. After the selection of micro trips from a pool of micro trips, these selected micro trips are combined and checked to determine whether their target parameters closely match the parameters of base data or not (Dai, Niemeier, & Eisinger, 2008). When developing a driving cycle for specific purposes such as emission estimation, traffic engineering, or fuel consumption estimation, it is important to consider the advantages and disadvantages of each method used. If the micro trip-based method is chosen for driving cycle development, it effectively addresses each stop-and-go condition of traffic flow. Therefore, it is most suitable for emission estimation purpose-based driving cycle development. Because each stop–and–go condition causes higher fuel consumption and higher emissions. (Galgamuwa, Perera, & Bandara, 2015).

A segment-based method for driving cycle development is also close enough to a micro trip-based method for driving cycle development. However, in this case, trips were separated considering the actual traffic condition of the road, physical characteristics of the road and LOS of road sections (Dai, Niemeier, & Eisinger, 2008). Therefore, the segment-based driving cycle development method is more suitable for traffic engineering purposes than driving cycle development for emission estimation purposes.

There are inherent pros and cons of this segment classification method. One of the major drawbacks of this method is that adopting this method at an early stage of driving cycle development requires more information to divide collected data into kinematic sequences and classify the routes, hence making it time-consuming. However, this method has the ability to capture the traffic pattern on the road and could closely represent the actual behavior on a road, region or country (Galgamuwa, Perera, & Bandara, 2015).

Pattern classification method-based driving cycle development is highly depending on the statistics. In this method, the whole trip was classified into several categories by considering the kinematic sequence. When developing the driving cycle, the succession probability of activity classes was considered (Galgamuwa, Perera, & Bandara, 2015).

Markov Chain theory is the basic concept behind the Model driving Cycle Construction method. In this method, real-world driving data were divided into four events: acceleration, deceleration, cruise and idling. It was assumed that the likelihood of a particular modal event depended only on the previous modal event. There are four steps to be followed for Modal driving cycle construction. At the beginning collected driving data is divided into sub-elements based on accelerations, and then sub-elements are assigned into bins using the maximum likelihood clustering method, which considers the average, minimum, and maximum speeds and acceleration. After that, acceleration rates and average speed were used to define the modes, and then a transition matrix was developed for succession probabilities between different modes. Finally, the Markov chain method is used to chain sub-elements into one cycle, considering the transition probability matrix until it achieves the target length of the driving cycle.

2.2.4 Cycle Assessment

Assessment of the developed driving cycle is the final step of the driving cycle development procedure. This step is the crucial step, because of it checks whether the developed driving cycle is truly representing the actual driving pattern or not for particular region or route. There are a number of assessment criteria for driving cycle assessment that can be categorized under maximums and minimums, time proportions, averages, standard deviations, percentiles and some specific parameters for emission such as Root Mean Square Acceleration (RMS), Vehicle Power (P) and Positive acceleration Kinetic Energy (PKE). The table 2.1 describes the assessing parameters and its relevant subcategory for each (Galgamuwa, Perera, & Bandara, 2015) (Galgamuwa, Perera, & Bandara, 2016).

Table 2.1 Relevant Assessing Parameters and its Subcategory

Subcategory	Traffic-Related Parameters
Maximum and minimums	Speed, acceleration, deceleration, acceleration rate
Percentages	Idle time, acceleration time, deceleration time, cruise time, creeping time
Means and averages	Average speed, average running speed, average acceleration and average deceleration, mean length of a driving period, average number of acceleration deceleration changes within one driving period
Standard deviations and percentiles	Speed standard deviation and acceleration standard deviation, speed at the 95th percentile, acceleration/deceleration rate at the 95th percentile
Other relevant parameters	Root means square acceleration, Positive acceleration Kinetic Energy, Speed Acceleration Probability Distribution (SAPD) or Speed Acceleration Frequency Distribution

Among the parameters mentioned above, driving characteristics and the smoothness of the driving pattern in Manila City are represented using the speed-acceleration joint probability density function (JPDF) graph. In the methodology used to develop a driving cycle for tricycles in Manila, the joint probability density function (JPDF) is used to evaluate the developed driving cycles (Abuzo, Sigua, & Vergel, 2004). Figure 2.1 shows the developed driving cycle for tricycles in Manila city; Figure 2.2 shows the joint probability density function (JPDF) for the target driving cycle. Figure 2.3 shows the joint probability density function (JPDF) for the developed driving cycle.

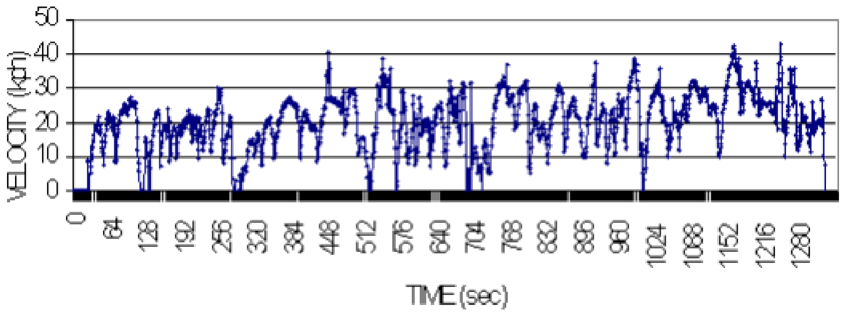

Figure 2.1 Developed candidate driving cycle for Tricycle of Manila City

Likewise, to create a driving cycle for Galle Road in Colombo, Sri Lanka, three candidate driving cycles were compared using the Speed Acceleration Frequency Distribution (SAFD) graph, and the best candidate driving cycle was chosen.

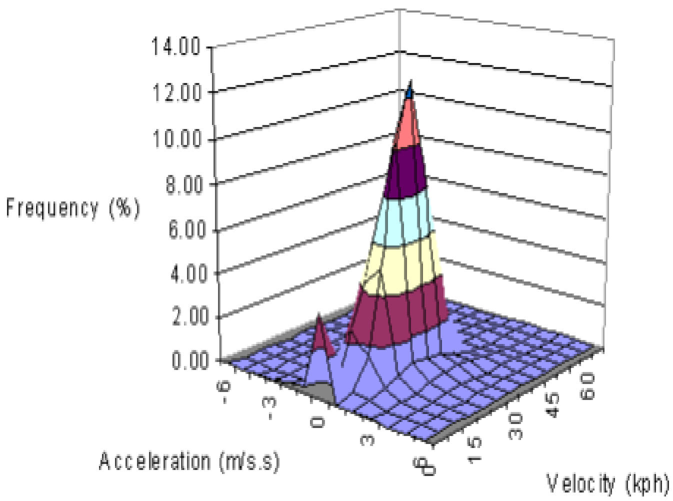

Figure 2.2 Joint Probability Distribution Function for Target Cycle

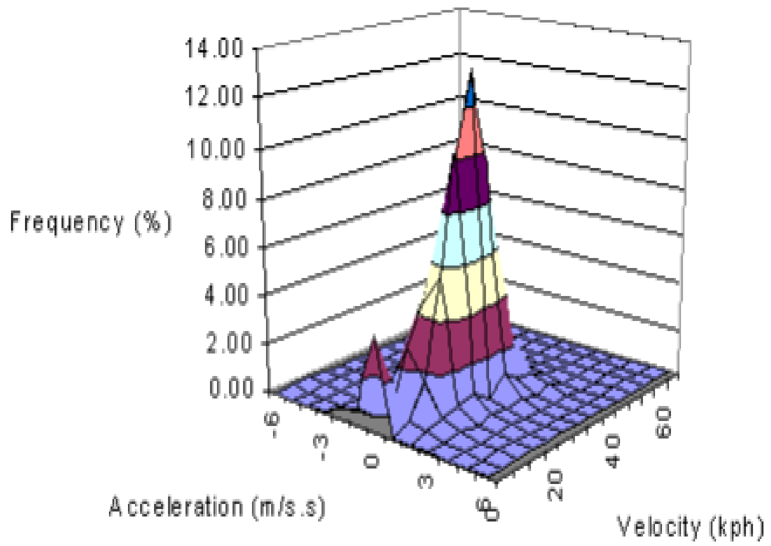

Figure 2.3 Joint Probability Distribution Function for Candidate cycle

(Gamalath, Fernando, Galgamuwa, Perera, & Bandara, 2012). Performance Value (PV) is also a popular factor of evaluation used by many researchers to evaluate their driving cycles. The cycle with the lowest PV value can be chosen as the typical driving cycle. For the calculation of performance value, the target parameter was calculated for population and candidate driving cycles. Then, the percentage of deviation of the target parameter is calculated for population and candidate driving cycles.

Finally, consider the values that are taken from the per cent deviation multiplied by values by weightage. This weightage is given according to the relevance of those parameters to the purpose of the driving cycle. (Galgamuwa, Perera, & Bandara, 2015).

2.3 Emission Estimate from Driving Cycles

Various factors, such as particulate matter, carbon monoxide, carbon dioxide, ozone, and air toxics, are employed to assess the emission levels of vehicles. Of these, particulate matter (PM) stands out as the most critical component in diesel exhaust emissions. PM is the solid particles and liquid droplets present in the air. The particulate matter emission value was experimentally determined using the EEC 13-modes test. (Dai, Niemeier, & Eisinger, 2008).

Typically, vehicles undergo emission tests in a laboratory using chassis dynamometers, following standardized driving cycles. While this method has a clear benefit, the testing conditions may not accurately reflect real-world driving. It has been found that emissions measured during real-world driving cycles are generally higher than those recorded in laboratory conditions. (Tong, Hung, & Cheung, 2000). Additionally, the parameters of real-world driving cycles significantly differ from legislative cycles; for example, the average speed is 46% different from that of Indian Driving Condition (IDC) cycles, and the maximum speed varies by 58% from IDC cycles (Sithananthan, Kumar, Maheshwari, & Saxena, 2022).

According to (Tamsanya, Aibulpatana, & Chokchai, 2009), a close analysis of the Economic Commission of Europe (ECE) driving cycle reveals that it does not accurately reflect urban traffic conditions. Despite this, the ECE cycle is currently used in Bangkok to test vehicles for compliance with national emission standards.

2.4 Methods of Emission Estimated

2.4.1 On Board Emission Estimation

On-board measurement method is the one of the most accurate measurement methods of measuring exhaust emissions. Because of this method engaged with the real time traffic characteristics and the geometric design provides, therefore this method provides an accurate estimate of the emission rates (Gao & Checkel, 2007).

When fixing the apparatus to the vehicle for on-board emission estimation, the gas filter was connected to the gas analyzer and the fuel flow meter was connected to the fuel supply pipe. After connecting all this equipment to the vehicle, the vehicle was driven by a well-experienced driver (Gao & Checkel, 2007) (Tong, Hung, & Cheung, 2000).

2.4.2 Chassis Dynamometer

Chassis dynamometer is commonly used for testing purposes of light-duty vehicles. The engine test bench is the method normally used to test heavy-duty vehicles (Pelkmans & Debal, 2006). For light-duty vehicles, A chassis dynamometer is calibrated to replicate the inertia of a testing vehicle and road load (aerodynamic and rolling resistances). Using a Positive Displacement Pump (PDP) and the Constant Volume Sampling (CVS) technology of the chassis dynamometer, the exhaust stream was continuously diluted with ambient air during the driving cycle. As shown in Figure 2.4; sample of the entire diluted flow was collected in sample collecting bags during the test to evaluate the average amounts of pollutants; a second sample of diluted gas was measured in every second using the gas analyzer. This gas analyzing system includes a NDIR (Non-Dispersive Infrared) detector to measure CO and CO2, a CLD (Chemiluminescence Detector) to measure NOx, and an FID (Flame Ionization Detector) to measure THC (total hydro carbon) (Costagliola, Costabile, & Prati, 2018).

The output results of the testing process can be generated in various format files like Word, Excel, or PDF, and it can be saved, updated, and printed. The test process can be loaded either automatically or manually, and the test results can generate customized test reports, curve charts, etc. Because of the test system's interface is straightforward, upgradable, manageable and user-friendly (Tamsanya, Aibulpatana, & Chokchai, 2009)

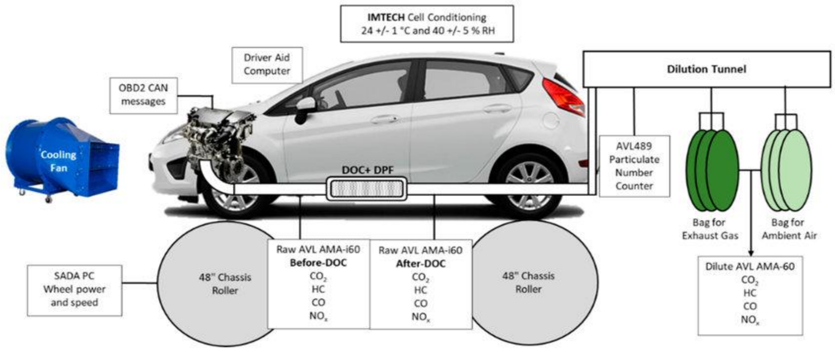

Figure 2.4 The schematic of the chassis dynamometer test facility

2.4.3 Comprehensive Modal Emission Modal (CMEM)

Model emission modelling is a better approach to evaluating the effect of vehicular emissions associated with transportation operations. CMEM was originally developed at the University of California, Riverside, along with researchers from the University of Michigan and Lawrence Berkeley National Laboratory. At the initial stage of modelling, the vast majority of the models of emission models have been developed for light vehicles due to the availability of a larger body of light-duty vehicle emission data than heavy-duty vehicles. Therefore, there are very few models for heavy-duty diesel vehicles, because the development of a model for heavy-duty trucks is part of a larger comprehensive model emission modelling (CMEM).

CMEM uses a physical power-demand modal modelling approach based on a parameterized analytical representation of emissions production. In such a physical model the entire emissions process is broken down into different segments that relevant to physical process associated with operation of vehicle and emissions production.

After that, each segment is modelled as an analytical representation consisting of various parameters (Barth, Scora, & Younglove, 2004).

2.5 Emission Policies

Considering the current Sri Lankan standard values on vehicle emissions, the smoke density ("K" value) is used to measure the emission state of diesel vehicles. Considering the present emission standard values for diesel vehicles in Sri Lanka, they can't be compared with the global emission standard values. Because most other countries don't use the smoke density (K) value to measure the emission of diesel vehicles, as shown in Table 2.2 (CleanCo Lanka Limited, 2021). The values of emission factors, China and Sri Lanka use very basic unit’s percentages and volume to volume ratios respectively as shown in Table 2.2. But majority of other countries use g/km. It is the way of standard emission factors represent.

Table 2.2 Emission standards of various countries.

Country	**Effectivity**	**Vehicle Type**	**CO**	**HC**	**Smoke Density (k)**
India	2000	2 & 4 Stroke	2.0 g/km	-	-
	2005	2 & 4 Stroke	1.5 g/km	-	-
	2005	3-wheel gas	2.25g/km	-	-
	2005	3-wheel diesel	1.0 g/km	-	-
Sri Lanka	2016	Motor Bikes/Three-wheeler	4.0 % v/v	6000ppm	-
		Other Petrol Vehicle	3.0% v/v	1000ppm	-
		Diesel Vehicles	-	-	4
China		2 & 4 Stroke	4.00%	6000ppm	-
	2004	2 & 4 Stroke	3.00%	2000ppm	-
Thailand	2000	2 & 4 Stroke	4.5 g/km	3.0g/km	-
	2003	2 & 4 Stroke	3.5 g/km	-	-
	2004	2 & 4 Stroke	3.5 g/km	-	-
Vietnam	2004	2 & 4 Stroke	4.5 g/km	-	-
	2007	2 & 4 Stroke	3.5 g/km	-	-
	2007	2 & 4 Stroke	1.0 g/km	-	-
	2007	2 & 4 Stroke	3.5 g/km	-	-

CHAPTER 3 - METHODOLOGY

3.1 Methodology Flow Chart

The flow chart shown in Figure 3.1 illustrates the sequence of methodological steps, including data collection, processing, and analysis, ensuring a coherent understanding of the research design.

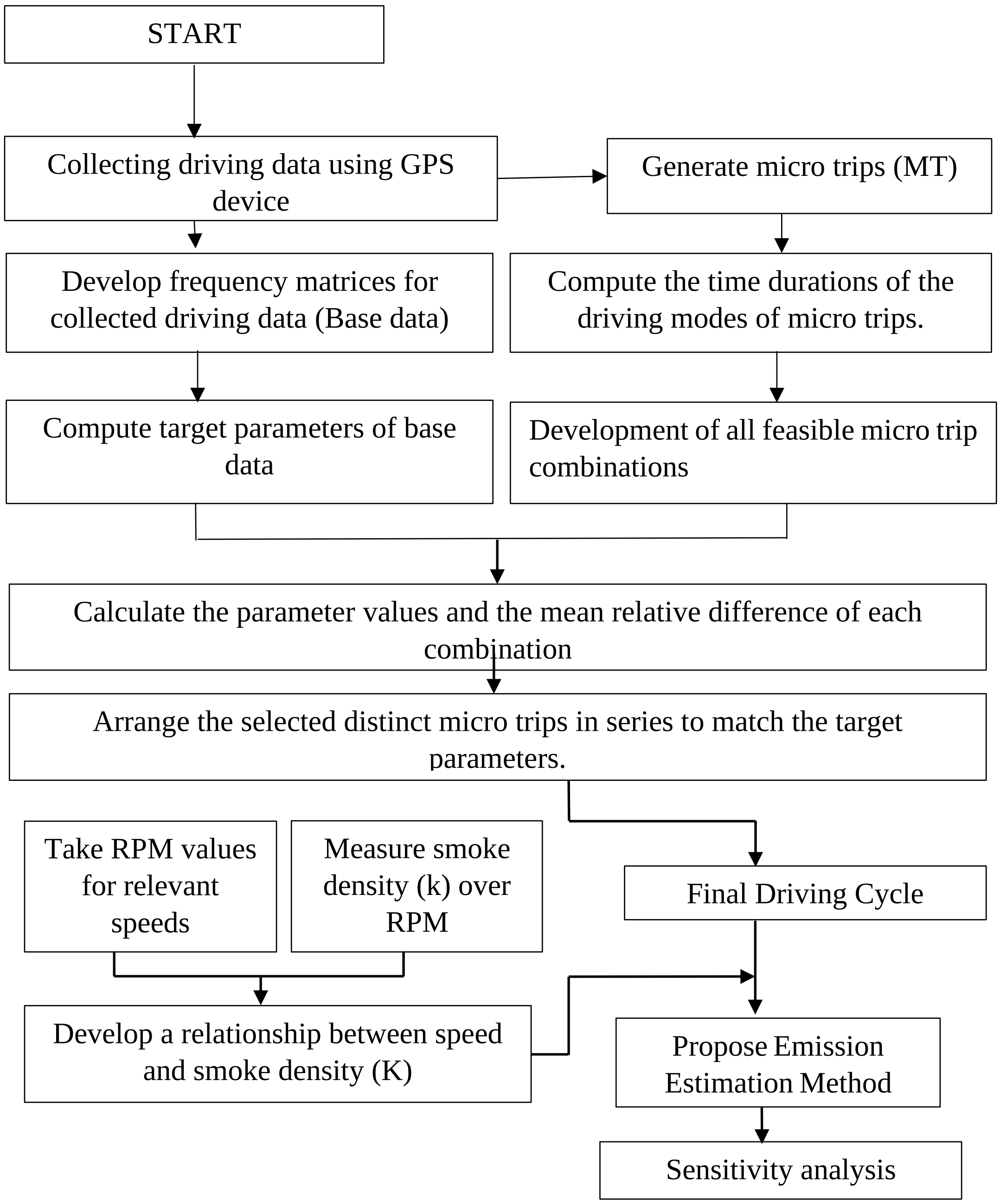

Figure 3.1 Methodology Flow Chart

The flow chart in Figure 3.1 presents a structured method for developing an emission estimation model. The process starts with collecting train driving data (Speed vs. Time) using a GPS device and generating micro trips (MT). This data is processed to create frequency matrices for the base data, while the time durations of driving modes (acceleration, deceleration, idling, and cruising) are calculated for the micro trips. Key target parameters, including the time percentages of these driving modes acceleration, deceleration, idling, and cruising (Pab, Pdb, Pcb, Pib) and the average velocity of base data (Vavg), are determined. Then, feasible micro trip combinations are generated within a 1500-second total running time limit, and their driving mode time percentages are computed. These combinations are evaluated using the value of their mean relative difference factor (MRDi), which factor compares the target and calculated parameters. After computing MRDi values for all micro trips, micro trips with the lowest MRDi value are selected as the final driving cycles. Simultaneously, RPM values for relevant train speeds are recorded, and smoke density (k) is measured at specific RPMs. This data helps establish a correlation between speed and smoke density, which is incorporated into the final driving cycle to develop an emission estimation method. This systematic approach ensures precise emission modelling based on realistic train driving behavior.

3.2 Route Selection

When determining the optimal route for data collection, it is essential to consider factors such as the vertical alignment of the railway track, the number of level crossings, the distance between stations, and delays caused by signals. These factors influence train speeds. Among them, vertical alignment is the most critical factor for train speed due to the significant self-weight of trains. Steep gradients slow trains uphill by increasing traction demands and require frequent braking downhill to maintain stability, leading to lasting operational inefficiencies. Unlike level crossings, station spacing, or signal delays (issues that are situational and often addressed through modern solutions like grade separations or advanced signaling) vertical alignment has a continuous impact that is challenging and costly to rectify after construction. As a result, optimizing vertical alignment during the design phase is essential for maximizing train speed and achieving efficient, sustainable rail operations.

Considering the current railway network in Sri Lanka as shown in Figure 3.2, five major railway tracks were identified to represent the whole network of Sri Lanka and identified the railway track which can have the maximum emission for data collection. These selected routes are Colombo fort to Peradeniya, Colombo fort to Gal Oya, Colombo fort to Puttalam, Colombo fort to Anuradhapura and Colombo fort to Galle. These routes encompass various terrain types, such as flat, rolling, and mountainous terrains. While most routes traverse on flat terrain, the Colombo Fort to Peradeniya railway track passes through all flat, rolling and hilly terrain. Another reason for choosing these routes is that they represent the majority of train travel across Sri Lanka.

Figure 3.2 Map of Railway Tracks in Sri Lanka

Then, summation of the gradient of railway track multiplied by relevant railway track length along the considered railway track is calculated following the equation 01 shown below. Railway track with the highest gradient factor was selected as the route for data collection. Because a higher gradient factor of the chosen route means the train has to travel a longer distance through sections with steeper vertical alignment.

$$\text{Gradient Factor} = \sum_{k=0}^{n} [(\text{Gradient of track}) \times (\text{Track Length})] \text{ ……………….. (1)}$$

k = Considered section for gradient and track length

n = Total number of sub sections of particular route

3.3 Data Collection

Considering economic constraints, time and accuracy of the data collection, a portable GPS (Qstarz BT - Q1000XT) devise, as shown in Figure 3.3, was used for data collection following an on-board data collection method. Likewise, the route from Colombo Fort to Peradeniya junction is given the highest gradient factor among the selected gradient factors, and it was selected as the data-collecting route to obtain the maximum emission among the selected routes. When evaluating suitable data collection methods for trains, the chase car method is deemed impractical for gathering real-time driving data. Consequently, the on-board measurement method was employed to collect driving data along the selected route. The GPS device utilized for data collection is affordable and was manufactured in the recent year of 2021. According to (Tavel Recorder XT), the level of accuracy is quite high, with an average error of 3 meters when the device is used in a moving vehicle. Another notable feature of the device is its data recording interval, the device has the capability of recording longitude and latitude for every second. And also, the data logger is capable of collecting more than four hundred thousand data points on a single charge. The GPS device can export this data as a CSV file, a sample snippet is shown in Table 3.1, making it easier to save and manage large datasets. The traveling path of the GPS device and speed fluctuation of the device are also given by the device, as shown in Figure 3.4.

Figure 3.3 GPS Device

Trains in operational conditions in Sri Lanka can be categories as; express trains and slow trains. All these trains run by pre-announced timetable, and all stops are also predefined by the railway department of Sri Lanka. When collecting driving data of trains, both slow & express trains running in Colombo – Peradeniya route (selected route) are covered separately to collect considerable data set as base data (Population data).

Table 3.1 Sample Data Recorded in GPS Device

Index	UTC Date	UTC Time	Local Date	Local Time	M/S	VALID	Latitude	N/S	Longitude	E/V	Height	Speed
13107	2024/03/23	02:38:00	2024/03/23	08:08:00	0	DGPS	6.93352206	N	79.85085834	E	-72.589 M	0.229 km/h
13108	2024/03/23	02:38:01	2024/03/23	08:08:01	0	DGPS	6.93352206	N	79.85085855	E	-72.593 M	0.255 km/h
13109	2024/03/23	02:38:02	2024/03/23	08:08:02	0	DGPS	6.93352199	N	79.8508587	E	-72.596 M	0.146 km/h
13110	2024/03/23	02:38:03	2024/03/23	08:08:03	0	DGPS	6.9335219	N	79.85085893	E	-72.598 M	0.321 km/h
13111	2024/03/23	02:38:04	2024/03/23	08:08:04	0	DGPS	6.93352178	N	79.85085928	E	-72.600 M	0.471 km/h
13112	2024/03/23	02:38:05	2024/03/23	08:08:05	0	DGPS	6.93352174	N	79.85085959	E	-72.605 M	0.295 km/h
13113	2024/03/23	02:38:06	2024/03/23	08:08:06	0	DGPS	6.93352172	N	79.85085999	E	-72.612 M	0.452 km/h
13114	2024/03/23	02:38:07	2024/03/23	08:08:07	0	DGPS	6.93352172	N	79.85086135	E	-72.618 M	0.735 km/h
13115	2024/03/23	02:38:08	2024/03/23	08:08:08	0	DGPS	6.93352185	N	79.8508635	E	-72.628 M	1.130 km/h
13116	2024/03/23	02:38:09	2024/03/23	08:08:09	0	DGPS	6.93351829	N	79.85088315	E	-72.949 M	1.471 km/h
13117	2024/03/23	02:38:10	2024/03/23	08:08:10	0	DGPS	6.93351667	N	79.85090187	E	-72.953 M	1.796 km/h
13118	2024/03/23	02:38:11	2024/03/23	08:08:11	0	DGPS	6.93351511	N	79.85092009	E	-72.927 M	2.185 km/h
13119	2024/03/23	02:38:12	2024/03/23	08:08:12	0	DGPS	6.93351482	N	79.85093633	E	-72.904 M	2.446 km/h

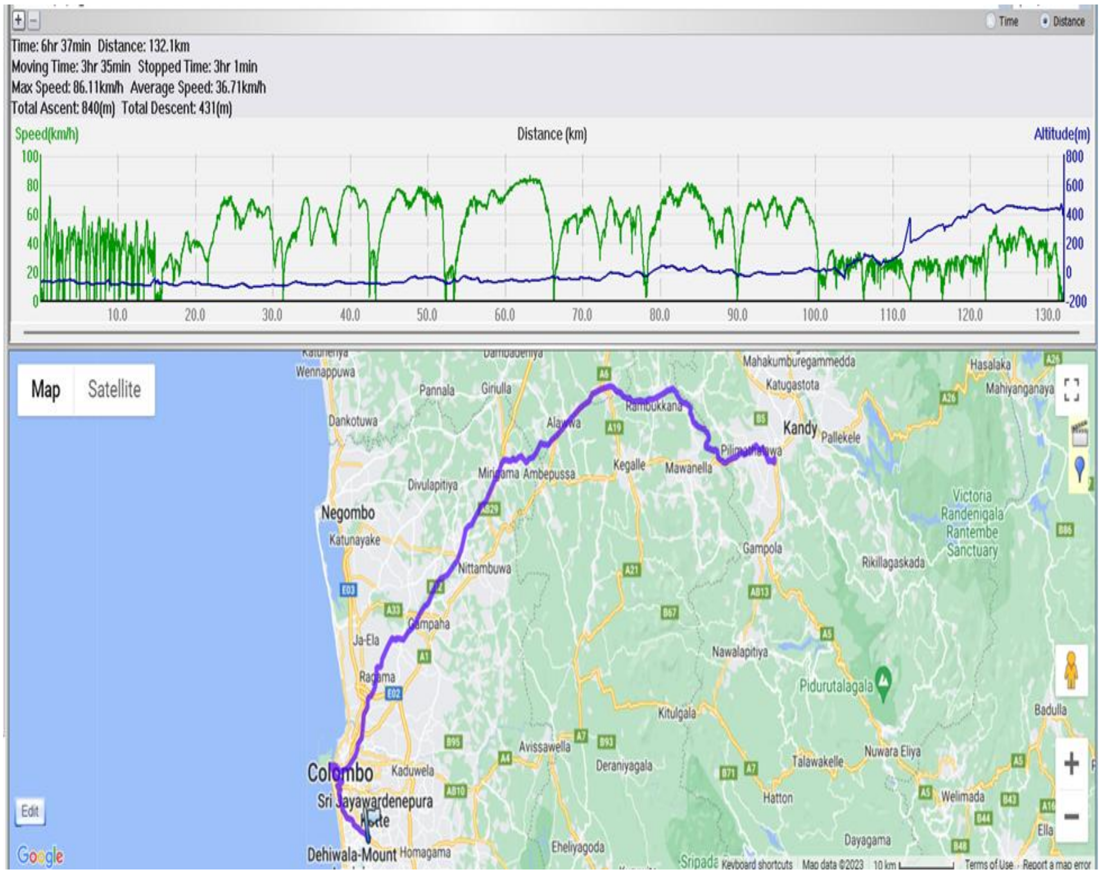

Figure 3.4 Route & Speed fluctuations given by GPS device

3.4 Data Filtration

Although the GPS device is considerably accurate, occasional errors may occur during data recording such as false zero speeds. It means, sometimes train may not move, but devise gives the small value as velocity of the train. Therefore, filtering process is required to be obtained most accurate data.

According to (Gu, 2013), any observation with a speed less than 1 mph (1.61 km/h) speed is labelled as an idling observation. This study followed the same principle, but labelled any observations with a speed less than 2.5 km/h as idling observations, considering the maximum recorded speed at the idle stage during the data collecting. This indicates that the speed data recorded under idling conditions (Idling at the stations) were analyzed, revealing that the maximum speed observed during idling was very close to 2.5 km/h. As a result, all speed values below 2.5 km/h were filtered and adjusted to zero prior to the extraction of micro-trips. A sample of corrected speed is shown in as shown in sample Table 3.2.

Table 3.2 Sample adjustment of false zero speeds – Case 01

Local date	**Local Time**	**Speed**	**Adjusted Speed**
202309/23	12:43:21	1.604 km/h	0.000 km/h
202309/23	12:43:22	1.547 km/h	0.000 km/h
202309/23	12:43:23	1.290 km/h	0.000 km/h
202309/23	12:43:24	0.947 km/h	0.000 km/h
202309/23	12:43:25	1.412 km/h	0.000 km/h
202309/23	12:43:26	1.194 km/h	0.000 km/h
202309/23	12:43:27	1.406 km/h	0.000 km/h
202309/23	12:43:28	1.073 km/h	0.000 km/h
202309/23	12:43:29	1.368 km/h	0.000 km/h
202309/23	12:43:30	1.030 km/h	0.000 km/h
202309/23	12:43:31	1.240 km/h	0.000 km/h
202309/23	12:43:32	1.064 km/h	0.000 km/h
202309/23	12:43:33	1.569 km/h	0.000 km/h
202309/23	12:43:34	1.615 km/h	0.000 km/h
202309/23	12:43:35	2.044 km/h	0.000 km/h
202309/23	12:43:36	3.045 km/h	3.045 km/h
202309/23	12:43:37	3.765 km/h	3.765 km/h
202309/23	12:43:38	5.702 km/h	5.702 km/h
202309/23	12:43:39	8.610 km/h	8.610 km/h
202309/23	12:43:40	9.690 km/h	9.690 km/h
202309/23	12:43:41	12.233 km/h	12.233 km/h
202309/23	12:43:42	9.928 km/h	9.928 km/h
202309/23	12:43:43	11.674 km/h	11.674 km/h
202309/23	12:43:44	13.955 km/h	13.955 km/h
202309/23	12:43:45	13.369 km/h	13.369 km/h

3.5 Analyzing the Filtered Data

Literature suggests that this micro trip-based method is widely employed globally in driving cycle development to examine the emission-related behaviors of vehicles. Since this micro trip-based cycle development covers each stop-go driving pattern and it will be a most suitable approach for emission purpose and estimation of fuel consumption.

After filtration of the recorded GPS data, entire speed time data was put into a single bin and then calculated the idling time in percentage for population data. Basically, idling time for trains means stopping time at railway stations for passenger transit and halting due to signal issues. After the calculation of the idling time in percentage, all the micro trips included in the base data are extracted. Calculated acceleration for every second of these extracted micro trips are adjusted according to the assumption made for cruise mode. Because of high sensitivity of the GPS devise has a speed fluctuation in each and every second. Therefore, it’s not possible to identify the cruise mode in the original data set given by the GPS device. Therefore, acceleration values between -0.5 km/h/s and 0.5 km/h/s are assumed as zero acceleration, and relevant speeds for this acceleration range are classified as cruise mode.

3.6 Development of Driving Cycle for Trains

Extracted micro trips from base data are combined to develop a candidate driving cycle. During this process, the total duration of the driving cycle is targeted to be around 1,500 seconds, aligning with similar driving cycles used for vehicle emission estimation in previous studies (Kamble, Mathew, & Sharma, 2009), considering effectively capturing of the key aspects of train operations, including acceleration, deceleration, cruising, and idling. Since typical station-to-station travel times range from about 4 to 8 minutes, a 1,500-second cycle covers multiple such short trips. A computer program was developed using Python language to randomly combine the extracted micro trips under the previously mentioned time limitation to have all possible combinations and to select the most suitable combination of micro trips because there are massive numbers of generated micro trip combinations to check the compatibility with base data.

Large number of possible candidates driving cycles are developed using this Python code. The code is attached as Appendix A. The Python code randomly distributes all micro trips into four bins during each run. Subsequently, it generates all feasible combinations of micro trips within these bins while adhering to a time constraint of 1,500 seconds. Normally, each iteration gives nearly 5,000 possible micro-trip combinations. It means running more and more gives all the possible combinations of micro trips for the candidate driving cycle.

3.7 Cycle Assessment

The driving cycle must accurately reflect the typical driving behavior observed in that specific region or country. Therefore, cycle assessment is one of the major & compulsory steps for validating the candidate cycle. Among those large number of driving cycles developed by executions of python code, the best candidate driving cycles are selected in this study by considering the following assessment criteria,

- Percent time in Acceleration
- Percent time in Deceleration

- Percent time in Cruise of the entire population and candidate driving cycle

Then, the assessment parameters of the generated candidate driving cycle should be close enough to the above assessment parameters of population data. Also, to select the best representative driving cycle among them, the mean relative difference for each driving cycle is calculated.

$$MRD_i = \frac{\sum_{j=1}^{n} [(^*CP_i - CP_i)/CP_i]}{n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

- $^*CP_i$ = Characteristic Parameters of Developed DC
- CP_i = Target Parameters of Base Data
- n = Number of parameters considered for relative difference
- i = i th Developed DC

3.8 Propose Emission Estimation Method & Emission Policies

Many researchers have noted that on-board emission measurements are more precise than laboratory measurements when studying emission estimations. When measuring the emission of trains, measuring equipment (Opacimeter) and sensors are attached to trains while the train is stable in idling mode. An opacimeter is chosen because it is easy to handle, takes less time, and is readily available.

To create an emission estimation model based on the driving cycle, it's necessary to establish a relationship between the train's speed and the corresponding emissions. This process begins by developing correlations between RPM (Revolution per Minute) vs speed and RPM vs smoke density (k), as shown in Figure 3.5. Smoke density (k) refers to the concentration of particulate matter in the exhaust gases. To develop a relationship between RPM and smoke density; the RPM of the train engine is gradually increased, and the smoke density value ("k") is measured at specific RPM values using the opacimeter (MAHA-MDO2 LON). After measuring the smoke density of several trains, a graph is plotted to show the relationship between RPM and smoke density (k) for the trains. After plotting the graph, drew the best-fitted curve with given data points and developed an equation for the best-fitted curve using RPM value as the independent variable and smoke density as the dependent variable. Likewise, the relationship between RPM and speed was also developed using RPM as the independent variable and speed as the dependent variable.

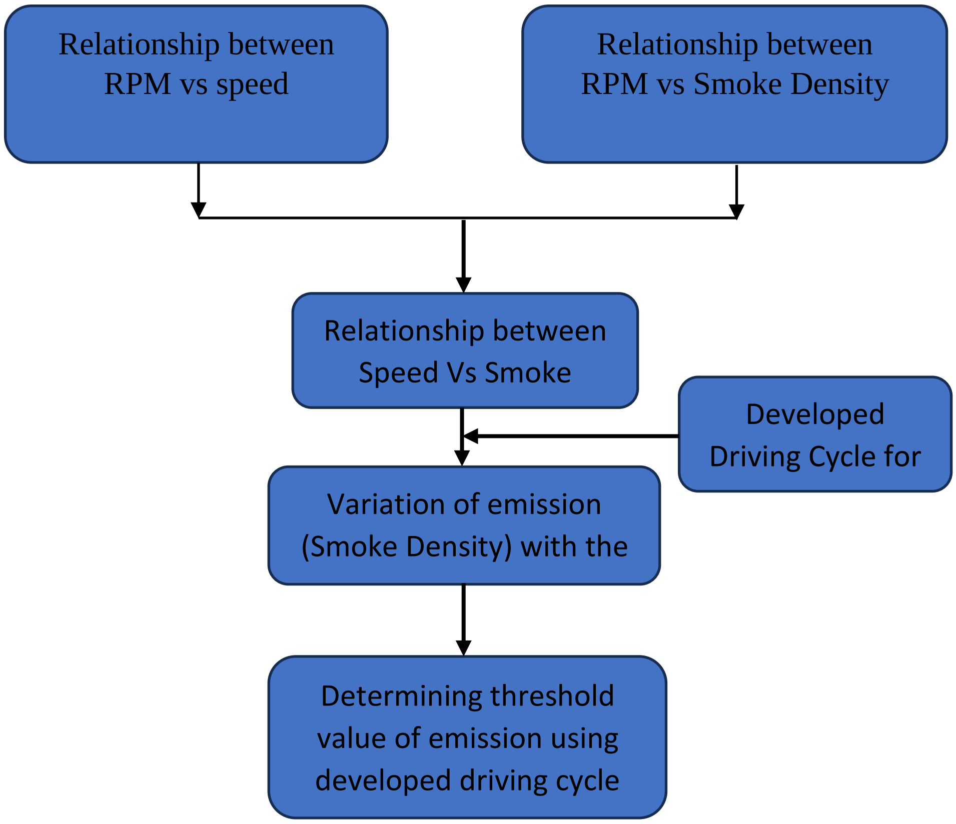

Figure 3.5 Procedure for developing emission variation over time

As stated by the (Society of Automotive Engineers (SAE), 1996), an opacimeter determines smoke density (k) values based on the standard pipe opening size with a diameter of 127 mm. Consequently, when measuring smoke density for tailpipes with different opening sizes, the opacimeter's readings must be adjusted to account for the tailpipe's specific opening size. Therefore, it is required to make an adjustment to the given "k" value by the opacimeter by considering the effective optical path length (Lm) as directed by (the Society of Automotive Engineers (SAE), 1996) using the below equations.

$$T=e^{-kl} \quad \text{..........} \quad (3)$$

$$N(\%)=100*(1-T) \quad \text{..........} \quad (4)$$

$$k = -\left(\frac{1}{Lm}\right) *\left(\ln\left(1-\left(\frac{Nm}{100}\right)\right)\right) \quad \text{..........} \quad (5)$$

Transmittance (T) = The fraction of light transmitted from a source which reaches a light detector

Smoke Density (k) = A fundamental means of quantifying the ability of a smoke plume or a smoke-containing gas sample to prevent the passage of light.

Effective Optical Path Length (L) = The length of the smoke-obscured optical path between the smoke meter light source and light detector.

Effective Optical Length (Lm) = Effective optical path length

Opacity (N) = The percentage of light transmitted from a source which is prevented from reaching a light detector.

To develop an emission estimation model for trains, it's crucial to establish a relationship between speed and smoke density. This relationship is important because the driving cycle that has been created will be used in the emission estimation model.

There are two relationships that need to be developed to develop a relationship between speed and smoke density (k) of trains

1. Relationship between RPM and Speed of the train.

   In accordance with (Abid, 2019), RPM Vs speed variation of vehicles behave linearly, as shown in Figure 3.6. The variation of RPM with speed depends on the engine's gear ratio; therefore, this relationship is linear for trains also as shown in Figure 3.6.

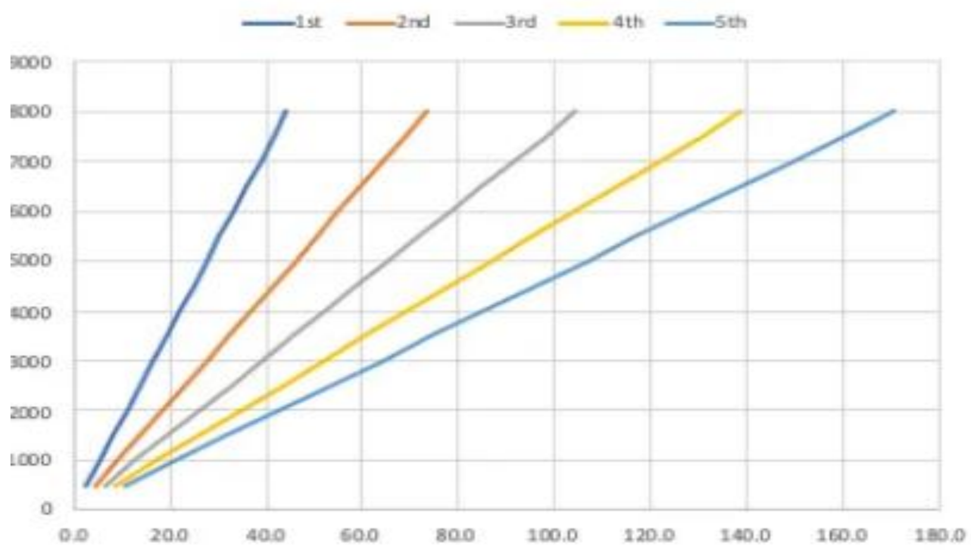

Figure 3.6 Variation of RPM vs Speed (Abid, 2019)

2. Relationship between RPM and Smoke density (k).

   Once the relationships between RPM and speed, as well as RPM and smoke density (k), are established, they can be combined into a model linking speed directly to smoke density. This involves replacing RPM in the smoke density equation with an expression derived from the RPM-speed relationship, thereby linking smoke density directly to speed.

   Equation of the final model will provide a direct relationship between speed and smoke density (k):
   k= f (speed)

Then, the driving cycle, which includes speed profiles over time, can be applied to the derived speed-smoke density relationship to estimate emissions over a given journey. This allows for the calculation of smoke density (k) at each time step of the driving cycle.

Completing these steps will develop an emission estimation model that effectively links speed to smoke density, providing a critical tool for assessing and mitigating train emissions.

3.9 Sensitivity Analysis for Emission Estimation Model Developed

Developed emission estimation models for all four categories of trains were utilized to analyze the sensitivity of emission with respect to threshold values. In this analysis, emission values obtained from the models of express and slow trains of both locomotives and power-sets were grouped into two groups: emission values of locomotive trains and power-se trains. The corresponding emissions in mg/m³ for smoke density (k) were computed every second for both locomotive and power-set trains. The average emission value in mg/m³ was then determined separately. This average was subsequently multiplied by the total annual fuel consumption (in liters) of all engines for each train type, along with the emission factor (mg/m³) per liter of fuel. Following this, higher emission values than threshold values are adjusted to specific value considering the emission threshold values. All smoke density values exceeding “4” were adjusted to “4”, and the corresponding mg/m³ values were also modified accordingly since the current emission threshold for diesel vehicles is “4”. The average mg/m³ value was recalculated, and the relevant emissions in mg/m3 were determined. A similar adjustment was then made for the maximum smoke density value (k), which was adjusted to 2.5. The value of 2.5 was selected because it is stricter than the current threshold, and countries like India also use 2.5 (65HSU) as their threshold value (Akbar & Kojima, 2002). After calculating emissions in “mg” for the above-mentioned three statuses, percentages of emission deductions are calculated from the current emission state to each other state.

CHAPTER 4 - RESULTS AND DISCUSSION

4.1 Selected Route for Data Collection

The gradient factors of the five selected railway tracks are calculated as shown in Table 4.1 for comparison and to select the most suitable route for data collecting.

Table 4.1 Gradient Factors of the Selected Routes

Route	Gradient Factor
Colombo-Peradeniya	34.13
Colombo-Anuradhapura	7.47
Colombo – Gal Oya	7.61
Colombo - Puttalam	3.92
Colombo – Galle	Records of the railway track's vertical alignment are unavailable. However, the track is situated on nearly a flat terrain and does not pass through mountainous areas. Hence, the expected gradient factor would be low compared to Colombo-Peradeniya route.

Considering the values given in Table 4.1, the Colombo – Peradeniya route was selected because it gives the highest emission than other railway tracks due to its higher value of gradient factor. Since this route consist of both rolling and flat terrains it covers a wide spectrum of conditions with one go.

When assessing the gradient of the railway track between stations, it was found that the section from Colombo to Polgahawela is flat terrain, while the sections beyond Polgahawela station feature rolling terrain, as shown in Table 4.2. Therefore, when developing the driving cycle, it is necessary to select micro trips that represent both terrains.

Table 4.2 Gradient of railway track segment between two consecutive stations

Railway Station	District	Elevation (m)	Distance Between Colombo Fort (km)	The Gradient Between Two Consecutive Stations (%)(m/km)
Colombo Fort	Colombo	4.87	0	
Maradana	Colombo	5.46	2.08	0.283653846
Dematagoda	Colombo	3.05	4.54	-0.979674797
Kelaniya	Gampaha	3.96	7.72	0.286163522
Wanawasala	Gampaha	3.25	9.42	-0.417647059
Hunupitiya	Gampaha	3.04	10.84	-0.147887324
Ederamulla	Gampaha	3.18	12.58	0.08045977
Horape	Gampaha	3.52	14.98	0.141666667
Ragama Junction	Gampaha	3.65	16.42	0.090277778
Walpola	Gampaha	4.25	19	0.23255814
Batuwaththa	Gampaha	4.3	20.08	0.046296296
Bulugahagoda	Gampaha	8.05	21.64	2.403846154
Ganemulla	Gampaha	9.45	23.44	0.777777778
Yagoda	Gampaha	9.99	25.28	0.293478261
Gampaha	Gampaha	10.97	28.4	0.314102564
Daraluwa	Gampaha	11.05	30.8	0.033333333
Bemmulla	Gampaha	12.25	32.78	0.606060606
Magalegoda	Gampaha	14.75	35.03	1.111111111
Heendeniya Pattiyagoda	Gampaha	14.89	36.5	0.095238095
Veyangoda	Gampaha	18.59	38.3	2.055555556
Wadurawa	Gampaha	19.31	40.14	0.391304348
Keenawala	Gampaha	20.75	42.36	0.648648649
Pallewela	Gampaha	27.42	44.7	2.85042735
Ganegoda	Gampaha	27.43	46.98	0.004385965
Wijaya Rajadahana	Gampaha	30.83	49.32	1.452991453
Meerigama	Gampaha	50	51.04	11.14534884
Wilwatta	Gampaha	53.69	52.86	2.027472527
Botale	Gampaha	51.37	54.9	-1.137254902
Ambepussa	Gampaha	55.48	56.98	1.975961538
Yaththalgoda	Kurunegala	56.37	60.58	0.247222222
Bujjomuwa	Kurunegala	56.98	62.66	0.293269231
Alawwa	Kurunegala	57.92	66.48	0.246073298
Walakumbura	Kurunegala	56.52	70.52	-0.346534653

Polgahawela Junction	Kurunegala	74.39	73.92	5.25588
Panaliya	Kurunegala	74.11	77.5	0.956258065
Tismalpola	Kegalle	76.71	79.74	1.160714286
Yatagama	Kegalle	77.06	82.02	0.153508772
Rambukkana	Kegalle	88.42	85.14	3.641025641
Kadigamuwa	Kegalle	194.81	90.14	21.278
Gangoda	Kegalle	151.21	94.42	-10.18691589
Ihala Kotte	Kegalle	210.57	96.74	25.5862069
Balana	Kandy	428.35	101.66	44.26422764
Kadugannawa	Kandy	515.24	106.1	19.56981982

4.2 Target Parameters for Driving Cycle

Initially, speed-acceleration matrices were created for each sub-category of the collected data, including locomotive express trains, power set express trains, locomotive slow trains, and power set slow trains. A sample of the developed speed-acceleration matrix is presented in Table 4.3. This table illustrates the distribution of the available data based on speed and acceleration. This distribution is used to calculate the percentage values for acceleration, deceleration, and cruising, which are then utilized as target parameters. The point to highlight is in this sample the combined cruise & idling phases account for 36.03%, 37.14%, and 26.83%, respectively.

Table 4.3 Sample of Speed-Acceleration Base Matrix for Locomotive Trains

Speed (kmph)	**Acceleration (Km/h/s)**														
	-10	-9	-8	~~~	-3	-2	-1	0	1	2	3	~~~	8	9	10
0-5	0	0	0	~~~	35	89	247	8020	513	78	28	~~~	2	0	5
5-10	0	0	0	~~~	86	158	407	313	499	220	95	~~~	4	0	4
10-15	1	0	1	~~~	129	267	561	355	621	254	145	~~~	3	3	5
15-20	4	0	3	~~~	153	315	655	0	813	377	155	~~~	5	4	5
	~~	~~~	~~~	~~~	~~~	~~~	~~~	~~~	~~~	~~~	~~~	~~~	~~~	~~~	~~~
85-90	1	1	1	~~~	35	47	102	72	76	22	14	~~~	0	0	0
90-95	1	0	0	~~~	1	6	0	3	1	1	0	~~~	0	0	0
90-100	0	0	0	~~~	0	0	0	0	0	1	0	~~~	0	0	0
100-105	0	0	0	~~~	0	0	0	0	0	0	0	~~~	0	0	0
Total	7	1	5	~~~	439	882	1972	8763	2523	953	437	~~~	14	7	19
Total (Percentage)	0.01%	0.00%	0.01%	~~~	0.62%	1.24%	2.78%	12.34%	3.55%	1.34%	0.62%	~~~	0.02%	0.01%	0.03%
	36.03%							26.83%	37.14%						
	Percentage in Deceleration							% in Cruise	Percentage in acceleration						

Tables 4.4 display the target parameters of population data obtained from the Speed Acceleration matrix for locomotive express trains, power set express trains, locomotive slow trains, and power set slow trains, as shown below. The data clearly shows that the idling time for slow trains is significantly higher compared to express trains. Similarly, Table 4.4 highlights that express trains (both locomotive and power set) allocate more time to acceleration and cruising, whereas slow trains spend a greater proportion of time in idle and deceleration modes, reflecting their frequent stops and slower overall operations.

Table 4.4 Target Parameters of Population Data for Trains

Target Parameters of Population Data	**Train Type**			
	Locomotive Express	**Power-set Express**	**Locomotive Slow**	**Power-set Slow**
Percent time in Acceleration (Pab)	29.9%	32.7%	30.7%	30.7%
Percent time in Deceleration (Pdb)	30.9%	32.0%	26.6%	26.8%
Percent time in Cruise (Pcb)	31.4%	20.8%	21.8%	23.1%
Percent time in Idle (Pib)	7.81%	14.5%	20.9%	19.5%

4.3 Developed Candidate Driving Cycles

After executing the Python code once, an excel file is generated containing approximately ten thousand micro trip combinations, which are randomly combined micro trip combinations within specified time constraints of less than 1500 sec. Repeating the execution of Python code gives more and more combinations of micro trips. Moreover, Python code is developed to get the percentage of the mean relative difference in the same excel file at once, as shown in Table 4.8

Table 4.5 Sample of Excel File Given by Python Code Executions

Subset	Average Acceleration	Average Disseleration	Average Cruise Speed	Absolute Difference (Acceleration)	Absolute Difference (Deccelera tion)	Absolute Difference (Cruise)	Relative Difference in Acceleration	Relative Difference in Decceleration	Relative Difference in Acceleration	MRDi
78, 56, 105, 93, 99	1.555779	-1.84492141	30.76082	0.0022206	0.000921	0.012816	0.142530392	-0.049967962	-0.04168167	0.060838
31, 37, 18, 57, 15, 56, 3	1.55389	-1.84278803	30.76991	0.0041096	0.001212	0.021908	0.263777222	0.065725058	-0.07125173	0.105285
108, 12, 4, 51, 106	1.561783	-1.84272039	30.77385	0.0037834	0.00128	0.025846	-0.24283587	0.06939291	-0.08405798	0.107368
13, 105, 94, 18, 101, 74	1.558547	-1.85211579	30.77286	0.0005473	0.008116	0.024862	-0.0351312	-0.440118735	-0.08085609	0.146523
25, 44, 91, 9, 75, 64	1.560914	-1.84682292	30.81636	0.0029144	0.002823	0.068364	-0.18705724	-0.153086587	-0.2223371	0.183469
13, 105, 94, 27, 18, 74	1.558252	-1.85489974	30.72132	0.0002523	0.0109	0.026675	-0.01619479	-0.591091982	0.08675407	0.207895
31, 37, 18, 15, 56, 3	1.556269	-1.83339385	30.78069	0.0017309	0.010606	0.03269	0.111095263	0.575170567	-0.10631617	0.212003
30, 47, 25, 101, 50, 15	1.556243	-1.83853754	30.8308	0.0017573	0.005462	0.082799	0.112789213	0.296228984	-0.26928338	0.224154
50, 11, 29, 97, 42, 49	1.546726	-1.84538044	30.73891	0.011274	0.00138	0.009087	0.723622494	-0.074861213	0.02955172	0.227101
85, 54, 35, 69, 11	1.559486	-1.82977666	30.75184	0.0014858	0.014223	0.003836	-0.09536834	0.771330885	-0.0124765	0.229384
13, 105, 50, 77, 101	1.558743	-1.86203395	30.75325	0.0007425	0.018034	0.005248	-0.0476603	-0.977979968	-0.01706672	0.26912

Below shows a sample calculation for mean relative difference (MRDi) for one of the micro trip combinations. Micro trips are numbered for ease of handling and identification, and a group of these numbers is used to indicate the micro trip sub-set. Table 4.6 shows the selected micro trip combination and its percentage values.

Table 4.6 Details of Sample Micro Trips Combination

Micro Trip Subset	**Total Duration (sec)**	**Acceleration (%)**	**Deceleration (%)**	**Cruise (%)**
23,59,33,41	1,179	37.1	36.1	16.1

Calculated parameters for population data (Target Parameters) are shown in Table 4.7

Table 4.7 Target Parameters

Target Parameters	**Value**
Percent time in Acceleration (Pab)	37.14%
Percent time in Deceleration (Pdb)	36.03%
Percent time in Cruise (Pcb)	16.13%
Percent time in Idle (Pib)	10.70%
Average Velocity (Vavg)	35.59 km/h

Sample calculation for Mean Relative Difference (MRDi) of selected micro trip combination is shown in Table 4.8

Table 4.8 Sample calculation for MRDi

Parameter	**Calculation**	**Result**	**Absolute Value**
Relative Difference in Acceleration	$\frac{(37.14089\ -\ 37.14\ ) * 100}{37.14}$	0.000886%	0.000886%
Relative Difference in Deceleration	$\frac{(36.06173 -\ 36.03\ ) * 100}{36.03}$	0.031732%	0.0317328%
Relative Difference in Cruise	$\frac{(16.09738 - 16.13\ ) * 100}{16.13}$	-0.032618%	0.032618%
	Mean Relative Difference of Absolute Value.	=	0.021746%

Table 4.9 - 4.12 show the extracted best micro trip combinations for locomotive express trains, power-set express trains, locomotive slow trains and power-set slow trains, respectively, after the Python code executions in number of times; the best combinations of each execution are tabulated in the tables below. The five combinations with the lowest mean relative difference (MRDi) among all executions are identified as the best ones.

The lowest MRDi value for locomotive slow trains is 0.258%**,** indicating that this driving cycle is the best representation for this train type. For the other train types, the best MRDi values are 0.41% for power-set slow trains, 0.814% for power-set express trains, and 2.51% for locomotive express trains. Among these, the MRDi for locomotive express trains is significantly higher than the best MRDi values for the other train types. Overall, the MRDi values for express trains are higher compared to slow trains. This difference could be attributed to the fact that the micro trip combinations for slow trains are created from a larger pool of micro trips compared to the micro trip pool for express trains.

Table 4.9 Developed candidate driving cycles for locomotive express trains

Combination Number	Population Parameters (Percentage In)	Parameter Values of Combinations (Percentage Values (%))			Mean Relative Difference (MRDi)
		Acceleration	Deceleration	Cruise	
Combination 01	Acceleration: 29.88% Deceleration: 30.87% Cruise: 31.44%	30.27%	29.59%	32.33%	2.764%
Combination 02		30.13%	29.51%	32.55%	2.93%
Combination 03		30.50%	29.18%	32.51%	3.65%
Combination 04		30.15%	29.15%	32.51%	2.88%
Combination 05		30.34%	29.71%	32.14%	2.51%

Table 4.10 Developed candidate driving cycles for power set express trains

Combination Number	Population Parameters (Percentage In)	Parameter Values of Combinations (Percentage Values (%))			Mean Relative Difference (MRDi)
		Acceleration	Deceleration	Cruise	
Combination 01	Acceleration: 32.72% Deceleration: 31.97% Cruise: 20.79%	32.66%	32.59%	20.25%	0.954%
Combination 02		32.36%	32.36%	20.76%	0.814%
Combination 03		32.36%	32.36%	20.76%	0.814%
Combination 04		32.36%	32.36%	20.76%	0.814%
Combination 05		32.36%	32.36%	20.764%	0.814%

Table 4.11 Developed candidate driving cycles for locomotive slow trains

Combination Number	Population Parameters (Percentage in)	Parameter Values of Combinations (Percentage Values (%))			Mean Relative Difference (MRDi)
		Acceleration	Deceleration	Cruise	
Combination 01	Acceleration: 30.71% Deceleration: 26.61% Cruise: 21.77%	30.23%	26.64%	21.94%	0.751%
Combination 02		30.71%	26.73%	21.65%	0.327%
Combination 03		30.54%	26.59%	21.96%	0.492%
Combination 04		30.62%	26.72%	21.76%	0.258%
Combination 05		30.75%	26.87%	21.47%	0.830%

Table 4.12 Developed candidate driving cycles for power set slow trains

Combination Number	**Population Parameters (Percentage In)**	**Parameter values of Combinations (Percentage Values (%))**			**Mean Relative Difference (MRDi)**
		Acceleration	**Deceleration**	**Cruise**	
Combination 01	Acceleration: 30.78% Deceleration: 26.62% Idle: 23.55%	30.68%	26.82%	23.11%	0.98%
Combination 02		30.59%	26.58%	23.44%	0.41%
Combination 03		30.41%	26.50%	23.70%	0.76%
Combination 04		30.33%	26.85%	23.43%	0.93%
Combination 05		30.80%	26.59%	23.22%	0.52%

4.4 Assessment of Developed Driving Cycle

When selecting the most suitable candidate driving cycle among all micro trip combinations generated by Python code, the percentages of acceleration, deceleration, and cruising for both the micro trip combinations and the population data are considered. Then, the mean relative differences of all combinations are calculated, and those with lower mean relative differences are extracted. When selecting micro trip combinations with lower mean relative difference values, it is necessary to choose the combinations that represent micro trips in both flat and mountainous terrain. In this case, the Colombo to Polgahawela section was considered as flat terrain and beyond the Polgahawela station was considered as mountainous terrain.

After extracting the best micro trip combinations for locomotive express trains, power-set express trains, locomotive slow trains and power-set slow trains as shown in Table 4.9, Table 4.10, Table 4.11 and Table 4.12 respectively, based on the previously mentioned parameters (percentages of acceleration, percentages of deceleration and percentage of cruise). The final driving cycles for these types of trains are determined by considering average speed, average running speed, average acceleration, and average deceleration values of previously selected micro trip combinations and population data as shown in Table 4.13, Table 4.14, Table 4.15 and Table 4.16 for locomotives and power-sets of express trains and slow trains respectively.

Table 4.13 Summary of assessment of DC for loco motive express trains.

Combination Number	**Population Parameters (in Average)**	**Parameter Values of Candidate DC**				**Mean Relative Difference (MRDi)**
		Average Acceleration (km/h/s)	**Average Deceleration (km/h/s)**	**Average Speed (km/h)**	**Average Running Speed (km/h)**	
Combination 01	Acceleration: 1.877 km/h/s Deceleration: -1.962 km/h/s Speed: 42.516 km/h Running Speed: 46.943 km/h	1.819	-1.959	42.532	46.136	1.246%
Combination 02		1.824	-1.953	42.973	46.614	1.261%
Combination 03		1.819	-1.957	43.008	46.651	1.280%
Combination 04		1.820	-1.952	42.905	46.539	1.322%
Combination 05		1.822	1.949	43.152	46.807	1.329%

Table 4.14 Summary of assessment of DC for power set express trains.

Combination Number	**Population Parameters (in Average)**	**Parameter Values of Candidate DC**				**Mean Relative Difference (MRDi)**
		Average Acceleration (km/h/s)	**Average Deceleration (km/h/s)**	**Average Speed (km/h)**	**Average Running Speed (km/h)**	
Combination 01	Acceleration: 1.949 km/h/s Deceleration: 1.996 km/h/s Speed: 39.921 km/h Running Speed: 45.251 km/h	1.938	-1.975	38.98	45.605	1.191%
Combination 02		1.978	-1.999	38.78	45.365	1.196%
Combination 03		1.978	-1.999	38.78	45.365	1.196%
Combination 04		1.978	-1.999	38.78	45.365	1.196%
Combination 05		1.978	-1.999	38.78	45.365	1.196%

Table 4.15 Summary of assessment of DC for loco motive slow trains.

Combination Number	**Population Parameters (in Average)**	**Parameter Values of Candidate DC**				**Mean Relative Difference (MRDi)**
		Average Acceleration (km/h/s)	**Average Deceleration (km/h/s)**	**Average Speed (km/h)**	**Average Running Speed (km/h)**	
Combination 01	Acceleration: 1.558km/h/s Deceleration: 1.844km/h/s Speed: 30.748km/h Running Speed: 38.897km/h	1.553	-1.843	30.77	38.77	0.105%
Combination 02		1.562	-1.843	30.77	38.91	0.107%
Combination 03		1.559	-1.852	30.77	38.91	0.147%
Combination 04		1.557	-1.838	30.72	38.84	0.152%
Combination 05		1.554	-1.844	30.81	39.96	0.161%

Table 4.16 Summary of assessment of DC for loco motive slow trains.

Combination Number	**Population Parameters (in Average)**	**Parameter Values of Candidate DC**				**Mean Relative Difference (MRDi)**
		Average Acceleration (km/h/s)	**Average Deceleration (km/h/s)**	**Average Speed (km/h)**	**Average Running Speed (km/h)**	
Combination 01	Acceleration: 1.553km/h/s Deceleration: 1.844km/h/s Speed: 32.11km/h Running Speed: 39.851km/h	1.547	-1.849	32.08	39.84	0.179%
Combination 02		1.555	-1.852	32.08	39.84	0.190%
Combination 03		1.558	-1.854	32.09	39.85	0.220%
Combination 04		1.561	-1.839	32.08	39.84	0.221%
Combination 05		1.556	-1.843	32.21	40.00	0.238%

Considering the mean relative difference value of each of the above combinations for all locomotives and power sets of express and slow trains, candidate driving cycle relevant to micro trip combination 01 of Table 4.13, Table 4.14, Table 4.15 and Table 4.16 are selected respectively as the most representative Driving Cycles for locomotives and power sets of express and slow trains for the route having highest emission in this study. Because of these combinations, they give lesser value as mean relative difference value. The graphs in Figure 4.1, Figure 4.1, Figure 4.3 and Figure 4.4 present the developed driving cycles, which were created using selected micro trip combinations for locomotive express trains, power-set express trains, locomotive slow trains and power-set slow trains, respectively.

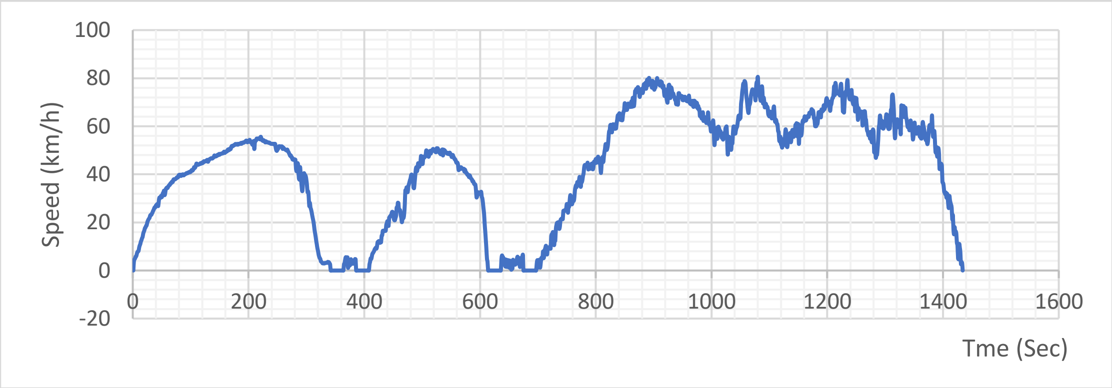

Figure 4.1 Selected Driving Cycle for Locomotive Express Trains

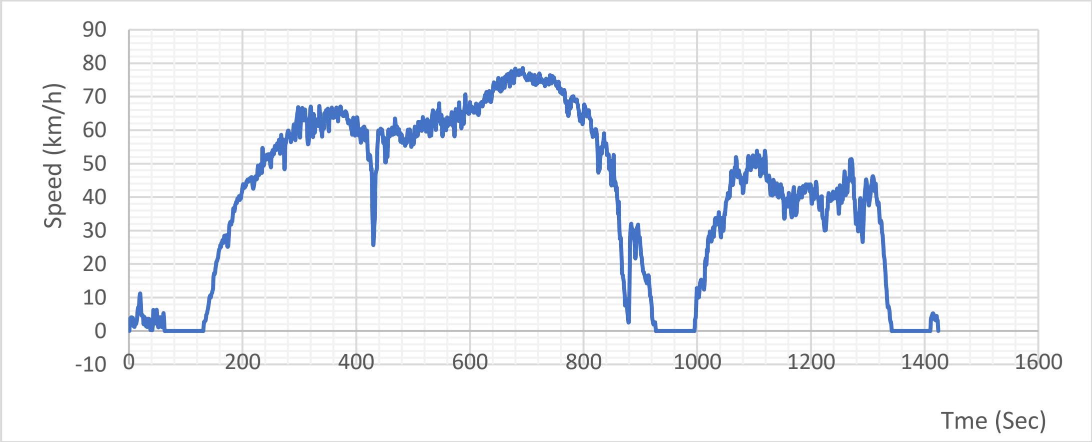

Figure 4.2 Selected Driving Cycle for Power-Set Express Trains

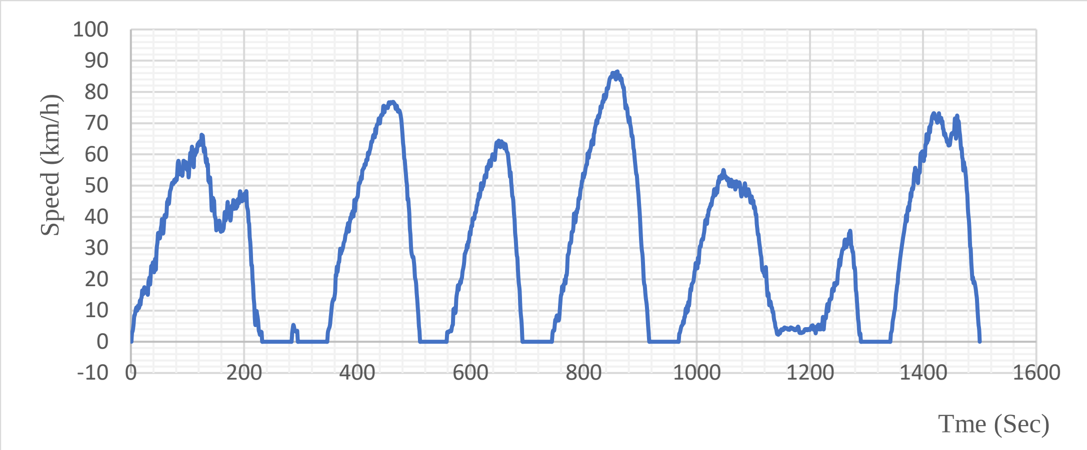

Figure 4.3 Selected Driving Cycle for Locomotive Slow Trains

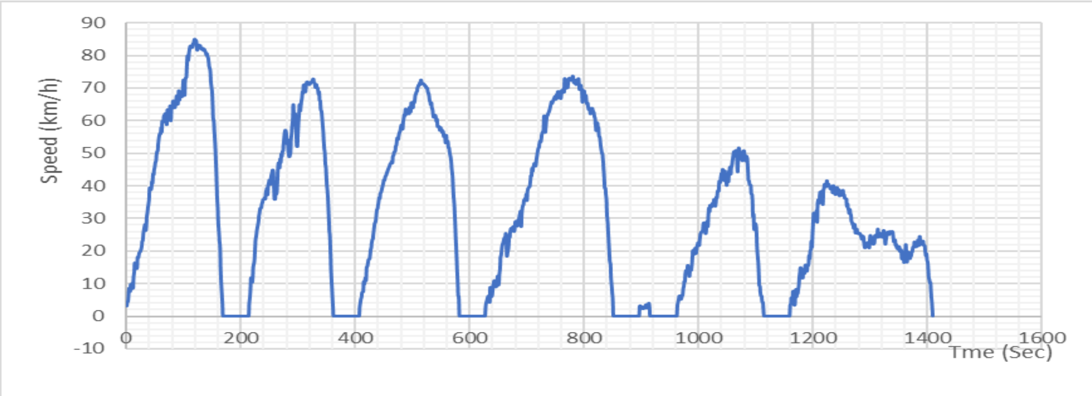

Figure 4.4 Selected Driving Cycle for Power-Set Slow Trains

Based on the analysis and observations from the graphs in Figures 4.1 to 4.4, there are common characteristics observed across all four types of trains studied. One of these is the micro trips, which have a very short duration and a significantly lower maximum speed compared to other micro trips in each driving cycle. Under real-world conditions, this behavior can be attributed to train movements caused by signaling issues. Specifically, when a train encounters a signaling problem, it experiences this characteristic.

The second common characteristic is the maximum running speed of the trains and its fluctuations, which range between 80±5 km/h for both express and slow trains. In addition to the previously mentioned characteristics, the driving cycle of express trains indicates that they attempt to maintain a steady cruising speed between two railway stations. However, in the case of slow trains, most of the micro trips do not exhibit a nearly constant speed between stations. When trains travel from origin to destination, some stations are bypassed without stopping for transit. This occurrence can also be observed in Figures 4.1 to 4.4. It suggests that when a train is running at high speed and needs to pass a station without stopping, its speed is reduced slightly until it has passed the station. This situation is more common for express trains than for slow trains, as express trains skip more stations compared to slow trains.

4.5 Parameters of Selected Driving Cycle and Population Data for Trains

4.5.1 Locomotive Express Trains

Table 4.17-Parameter comparison of locomotive express train

Parameters	**Target Values (Population Data)**	**Values of Developed DC**
Average Speed (km/h)	42.5 km/h	42.5 km/h
Average Running Speed (km/h)	46.9 km/h	46.1 km/h
Average Acceleration (km/h/s)	1.877 km/h/s	1.819 km/h/s
Average Deceleration (km/h/s)	-1.962 km/h/s	-1.959 km//h/s
Idle percentage (%)	7.81%	7.81%
Cruising percentage (%)	31.44%	32.33%
Acceleration percentage (%)	29.88%	30.27%
Deceleration percentage (%)	30.87%	29.59%

4.5.2 Power Set Express Trains

Table 4.18 Parameter comparison of power-set express train

Parameters	**Target Values (Population Data)**	**Values of Developed DC**
Average Speed (km/h)	39.921 km/h	38.98 km/h
Average Running Speed (km/h)	45.251 km/h	45.605 km/h
Average Acceleration (km/h/s)	1.949 km/h/s	1.938 km/h/s
Average Deceleration (km/h/s)	-1.996 km/h/s	-1.975 km//h/s
Idle percentage (%)	14.81%	14.81%
Cruising percentage (%)	20.79%	20.25%
Acceleration percentage (%)	32.72%	32.66%
Deceleration percentage (%)	31.97%	32.59%

4.5.3 Locomotive Slow Trains

Table 4.19 Parameter comparison of locomotive slow train

Parameters	Target Values (Population Data)	Values of Developed DC
Average Speed (km/h)	30.70 km/h	30.77 km/h
Average Running Speed (km/h)	38.90 km/h	38.77 km/h
Average Acceleration (km/h/s)	1.558 km/h/s	1.553 km/h/s
Average Deceleration (km/h/s)	-1.844 km/h/s	-1.843 km//h/s
Idle percentage (%)	20.91%	21.20%
Cruising percentage (%)	21.77%	21.94%
Acceleration percentage (%)	30.71%	30.23%
Deceleration percentage (%)	26.61%	26.63%

4.5.4 Power-Set Slow Trains

Table 4.20 Parameter comparison of power-set slow train

Parameters	Target Values (Population Data)	Values of Developed DC
Average Speed (km/h)	32.11 km/h	32.08 km/h
Average Running Speed (km/h)	39.85 km/h	39.84 km/h
Average Acceleration (km/h/s)	1.558 km/h/s	1.547 km/h/s
Average Deceleration (km/h/s)	-1.844 km/h/s	-1.849 km//h/s
Idle percentage (%)	19.47%	19.47%
Cruising percentage (%)	23.55%	23.11%
Acceleration percentage (%)	30.78%	30.68%
Deceleration percentage (%)	26.62%	26.82%

4.6 Estimated Emission Model

After selecting the most representative driving cycles for all considered types of trains, the developed driving cycles are used to derive the relationship between speed and smoke density (k). Two relationships are required to create this relationship: RPM vs. speed and RPM vs. smoke density. To establish the relationships, a S10 Powerset engine and a M10 Locomotive engine have been selected. Their selection for emissions estimation in Sri Lanka is based on their year of importation, with the S10 introduced in 2008 and the M10 in 2012 (Herath, 2020). These models fall into the mid-range age category among the currently operational train engines in the country. As they are neither too old nor too new, they provide a balanced representation of Sri Lanka's existing train fleet. Consequently, these engines offer the most accurate and relevant interpretation of train-related emissions in Sri Lanka (Herath, 2020).

1. Relationship between RPM and Speed of the train.

   To develop the relationship between RPM and speed, RPM and the associated speed are recorded while the train is in operation, as illustrated in Table 4.17 and Table 4.18 for locomotives and power-sets. Then, the best-fitted curves are developed, as shown in Figures 4.5 and 4.6. As shown in Figure 4.5 and Figure 4.6, unlike the multi-line reference figure 3.6, this graph 4.6 and 4.7 behaves linearly due to the nature of the train's transmission system. The trains used for data collection is a diesel-electric type, where torque and speed are controlled electrically, without discrete mechanical gear changes. This results in a smooth and continuous RPM vs. speed relationship throughout the trip. The equation of the linear relationship is "y = 6.8817x + 418.99" for locomotive trains, and its constant value is 418.99, and its gradient is 6.8817; likewise, "y = 12.159x + 918.79" for power-set trains, and its constant value is 918.79, and its gradient is 12.159.

Table 4.21 Speed & relevant RPM values for locomotive trains

Speed (km/hr)	0	5	10	15	20	25	30	40	50	60	70
RPM	440	450	480	540	620	560	595	650	740	820	910

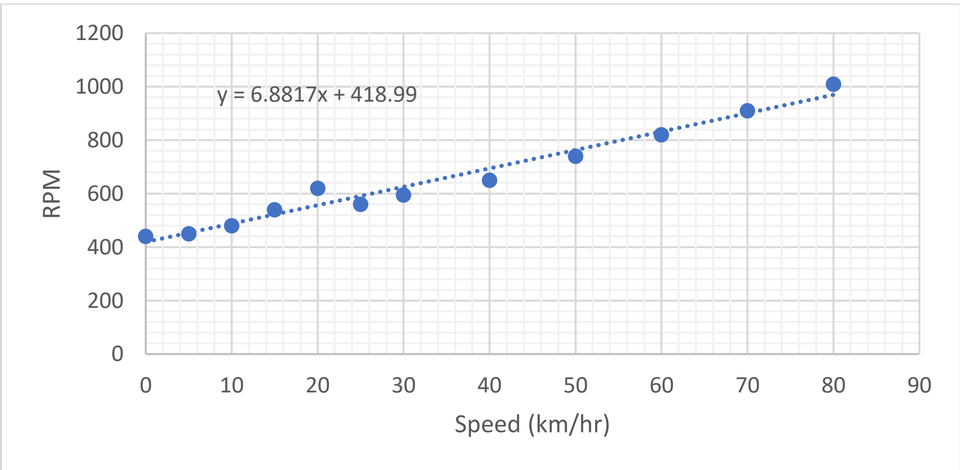

Figure 4.5 Graph of RPM Vs Speed for

Table 4.22 Speed & relevant RPM values for Power-set trains

Speed (km/hr)	0	5	10	15	20	25	30	40	50	60	70
RPM	890	930	970	1050	1180	1320	1450	1360	1590	1640	1730

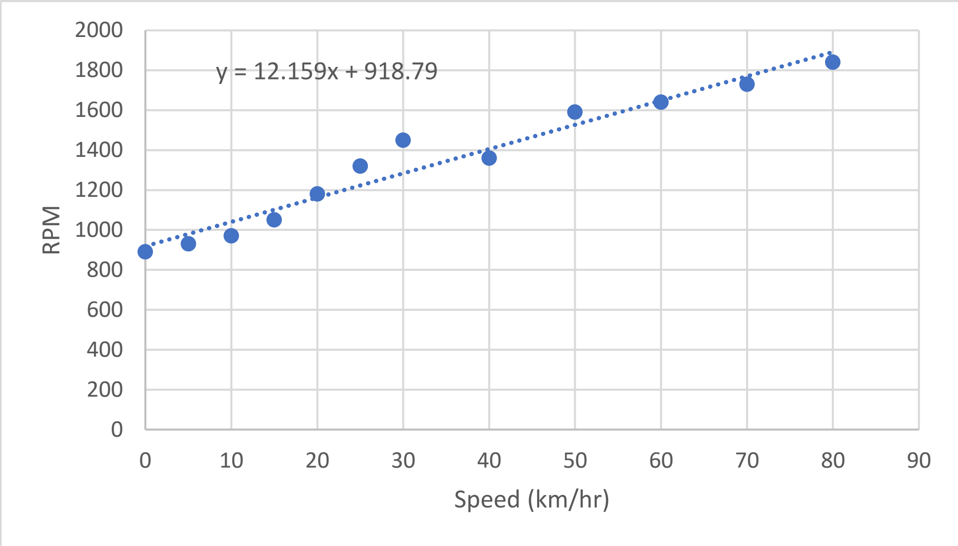

Figure 4.6 Graph of RPM Vs Speed for Powerset Trains

2. Relationship between RPM and Smoke density (k)

Graphs of smoke density (K) Vs RPM values and its best-fitted curves are shown in the below graphs in Figure 4.7 & Figure 4.8 for locomotives and power-sets, respectively. As shown in Figure 4.7 & Figure 4.8, the relationship between RPM & speed can be identified as a linear relationship.

The equation of the linear relationship is "y = 0.0009x – 3.642" for the locomotive trains, and "y = 0.0033x – 2.8927" for the power-set trains. Its constant values are 3.642 & 2.8927 and its gradients are 0.009 & 0.0033 for locomotives and power-sets respectively. The equation of the best-fitted curve given in Figure 4.7 and Figure 4.8 are only valid for the RPM values greater than 440 RPM & 890 RPM, respectively. This is due to the minimum RPM of the train engines which were used for data collection.

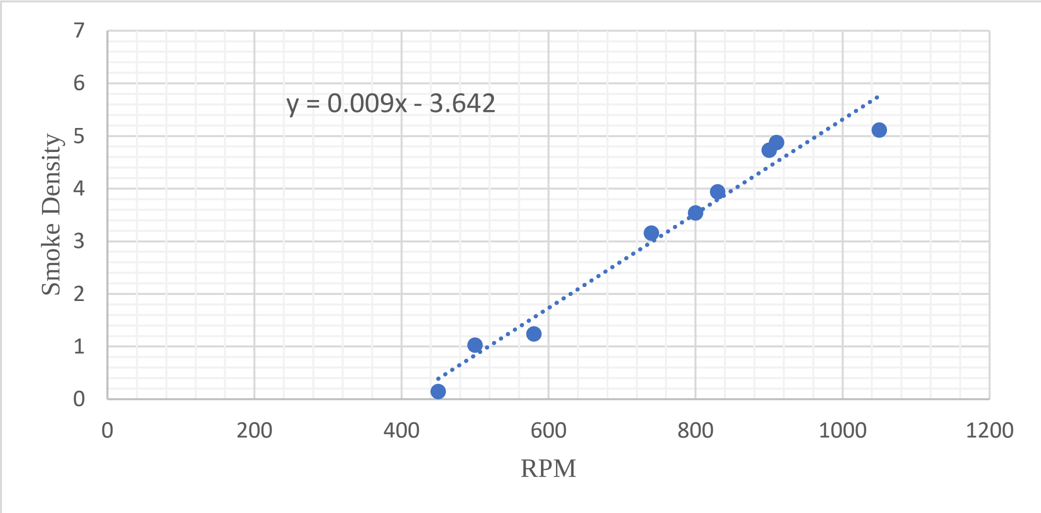

Figure 4.7 Graph of RPM Vs Speed for

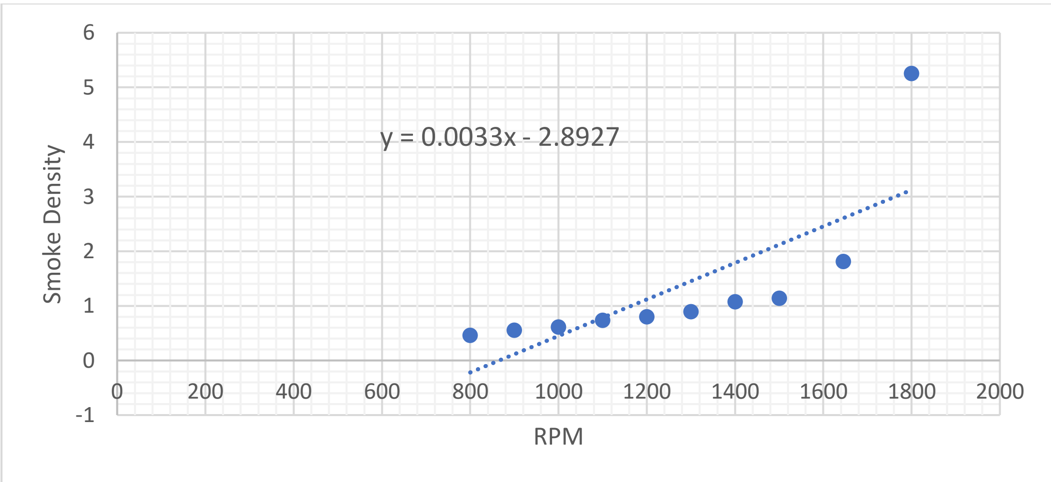

Figure 4.8 Graph of RPM vs Speed for Powerset Trains

Then, obtaining the relationships of RPM vs Speed and RPM vs Smoke density, speed fluctuations according to the developed driving cycles are used to derive the relevant smoke density (k) variations along the driving cycles, as shown in Figure 4.9, Figure 4.10, Figure 4.11 and Figure 4.12 for all considered types of express trains and slow trains, respectively.

After analyzing the emission variation graphs for both express trains and slow trains, the threshold for smoke density was determined using percentile values. According to the (Enforcement, 2021) study, the 97th percentile values were recommended to calculate the emission thresholds.

However, when discussing emission thresholds, there are two distinct types used to estimate the emission of vehicles in Sri Lanka. One is the usage emission factor, which is used to measure the emission of petrol vehicles. Usage of smoke density (k) is the second type, and it is used for diesel vehicles. Although, currently, Sri Lanka does not regulate train emissions, and there are no existing limits on such emissions. Therefore, it is worthwhile to determine whether the current regulations for diesel vehicles can be applied to control train emissions.

In this study, the observations from Figures 4.9, 4.10, 4.11, and 4.12 clearly show that the smoke density of locomotive emissions is significantly higher compared to that of power-set emissions during operation. From the relationships illustrated in Figures 4.5, 4.6, 4.7, and 4.8, it is evident that when a locomotive train and a power-set train operate at the same speed, the emissions from the locomotive train are greater than those from the power-set train. Further analysis shows that locomotive trains attain a smoke density value of "4" at a speed of 63 km/h, while power-set trains can reach the same smoke density at a higher speed of 96 km/h. Therefore, same percentile value can't be applied for both types; it means 97th percentile value for locomotive trains is 4.87 and it's higher than "4" although power-set trains give 3.17 and 3.36 values as "k" values for express and slow trains respectively and these values are less than the "4".

Hence, using the same percentile value to establish the emission threshold for both express and slow trains is not appropriate. It is essential to determine the specific percentile that corresponds to a smoke density value of four for each train type separately. According to the (Ministry of Environment and Natural Resources, The Gazette of the Democratic Socialist Republic of Sri Lanka 1887/20, 2014), a smoke density of four is the current emission limit for diesel vehicles in Sri Lanka. Analysis of the data series used to develop the driving cycles for both locomotive and powerset trains reveals that only locomotive trains produce smoke density values exceeding this threshold. In contrast, all measured emissions from powerset trains remain below the limit. As a result, only locomotive train data were considered when identifying the percentile value that aligns with a smoke density of four since other train types already meet the regulatory standard. This analysis indicated that the 81st percentile is the appropriate regulatory threshold for locomotive trains complying with the current threshold value. For powerset trains, all observed smoke density (k) values fall below four, confirming compliance with existing Sri Lankan emission standards.

According to the gazettes (Ministry of Environmnet & Natural Resources, 2008) and (Ministry of Environment and Natural Resources, 2014), the smoke density (K) emission threshold for diesel vehicles was set at "8" in 2008. However, six years later, in 2014, this threshold was revised to "4." This means that while power-set trains currently meet the existing emission standards, they might fail to comply with stricter standards (e.g.: k=3) in the future.

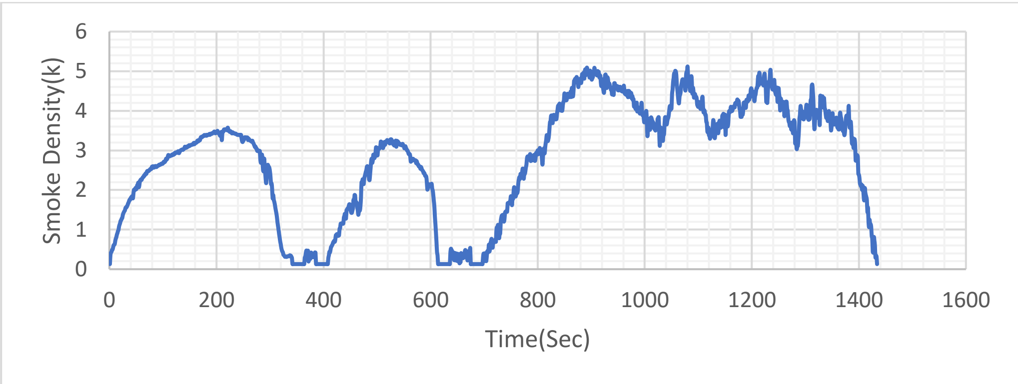

Figure 4.9 Variation of Smoke Density (k) vs Time for Locomotive Express Trains

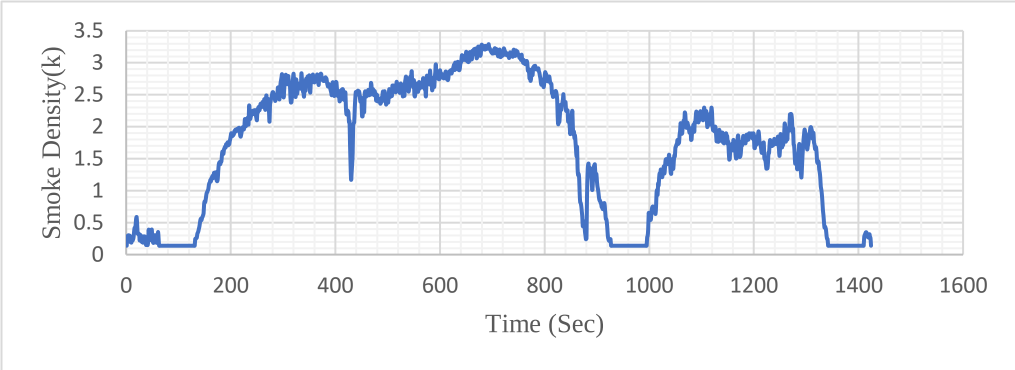

Figure 4.10 Variation of Smoke Density (k) vs Time for Power-set Express Trains

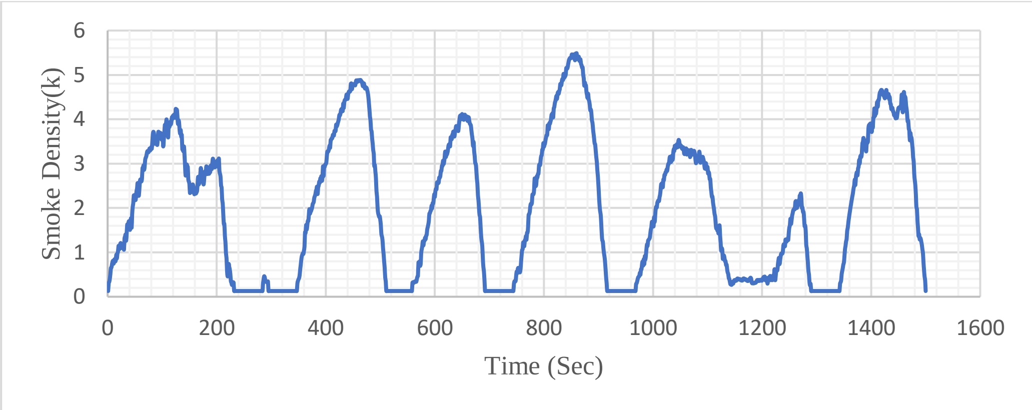

Figure 4.11 Variation of Smoke Density (k) vs Time for Locomotive Slow Trains

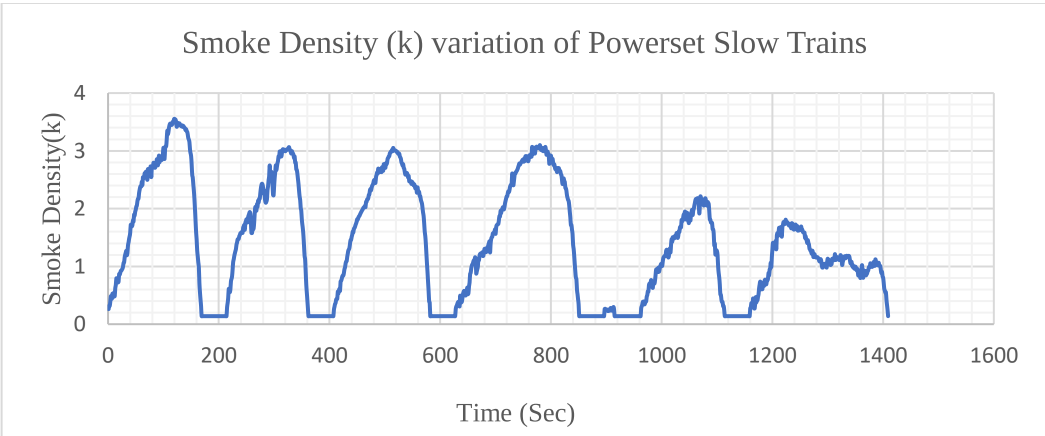

Figure 4.12 Variation of Smoke Density (k) vs Time for Power-set Slow Trains

When examining the concept of smoke density for emission estimation, there are two main methods like usage of Hartridge Smoke Units (HSU) and light absorption coefficient (K) (CleanCo Lanka Limited, 2021) & (National Environmental Agency of Singapore, 2013). While both measure exhaust smoke opacity, they do so in different ways. HSU, expressed as a percentage, indicates the proportion of light blocked or obscured as it passes through the exhaust smoke. In contrast, K represents the rate at which light intensity diminishes per unit length as it travels through the smoke. Higher values of either HSU or K signify denser smoke with greater particulate matter content.

According to (Ministry of Science,Technology and the Environment, 2000), Malaysia, the permissible smoke opacity limit for diesel engines is set at 50 Hartridge Smoke Units (HSU). This standard is enforced through the Environmental Quality (Control of Emission from Diesel Engines) Regulations 1996, which were amended in 2000 to tighten the allowable smoke density from the previous limit of 60 HSU to the current 50 HSU (equal to 1.61 in k terms). It's noteworthy that Malaysia's threshold aligns with standards in other countries within the region. For instance, Indonesia, Thailand, Hong Kong, and Singapore have similar or slightly varying HSU limits for diesel vehicles (DTE Staff, 2015). As stated by (CleanCo Lanka Limited, 2021), the threshold value for the light absorption coefficient (k) for diesel engine emissions in Sri Lanka is 4. When converted to Hartridge Smoke Units (HSU), this value corresponds to 82 (Dodd & Holubeki, 1965).

4.7 Sensitivity of Emissions

In Sri Lanka, emission regulations are enforced for diesel vehicles based on smoke density with a threshold value of k = 4**.** Although there are numbers stipulated on the books, train emissions are not regulated at present. Analyzing emission models derived from driving cycles for locomotive and power-set trains revealed that k value exceeds this threshold at some instances. If train emissions were regulated under the prevailing standards, any k value above four would need to be reduced to 4 or lower. Adjusting these higher values to 4 resulted in a 3.8% reduction in emissions. This can be done in two ways and respective consequences are as follows. One way would be to use the existing engines as it is and lower the k values by means of lowering the speeds (speed correlated to RPM and k) to match the set k value, which have an impact on the total trip time. The total trip time for locomotive trains is expected to increase by 2.56%, while powerset trains will remain unaffected since they already comply with the current regulation (k=4). Second way is to purchase more energy efficient engines where required speed can be achieved at lower k value than required. However, this option is quite expensive and further analysis on benefit vs cost is required before making such decision. However, such analysis is also out of the scope of this study and can be considered separately in the future.

Since emission reduction targets agreed in various protocols are challenging, this study has looked into further reduction of emissions by means of reducing the k value further and a summary of the outcomes are presented in Table 4.23. Figures 4.14 and 4.15 depicts the impact on k value reduction on travel distance in a graphical manner. According to the Table 4.23, tightening the smoke density threshold to k = 2.5 would lead to a 25.78% emissions reduction in locomotive trains and 5.73% emissions reduction in power-set trains in rail transport emissions. This threshold value of k = 2.5 was considered because India, a neighboring country, also applies k = 2.5 (65 HSU) as the emission regulation limit for diesel vehicles (DTE Staff, 2015).

Table 4.23 Impact of Regulatory Threshold (K) on Emissions and Travel Distance for Trains

Regulated Value	**Locomotive Trains**		**Power-set Trains**	
	Reduction in Emissions	**Reduction in Travelling Distance**	**Reduction in Emissions**	**% of Reduction in Travelling Distance**
Present	-	-	-	-
K=4	3.80%	4.34%	0.00%	0.00%
K=3.5	8.68%	9.82%	0.00%	0.00%
K=3.0	15.92%	17.86%	0.75%	0.88%
K=2.5	25.78%	28.58%	5.73%	6.45%

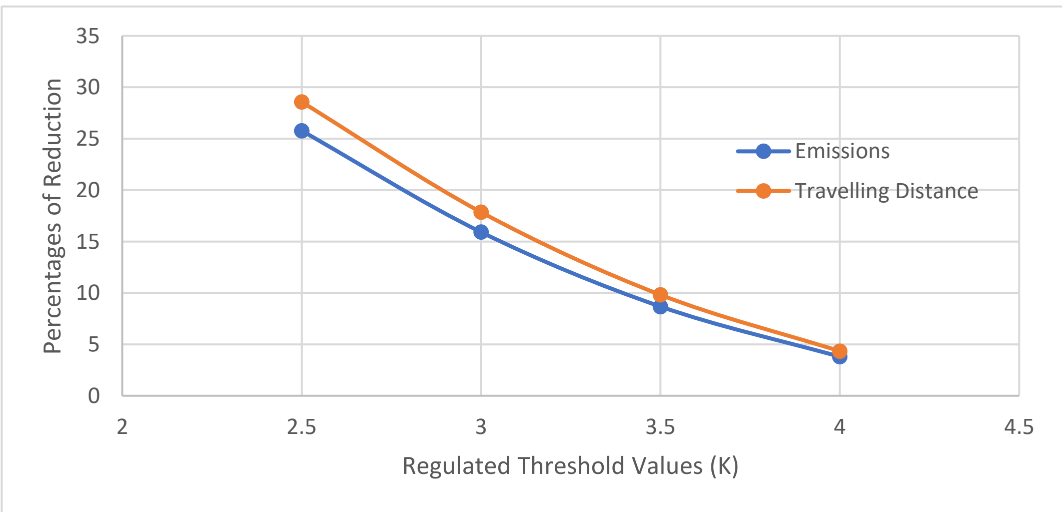

Figure 4.13 Impact of Regulated Threshold Values (K) on Emissions and Travel Distance for Locomotive Trains

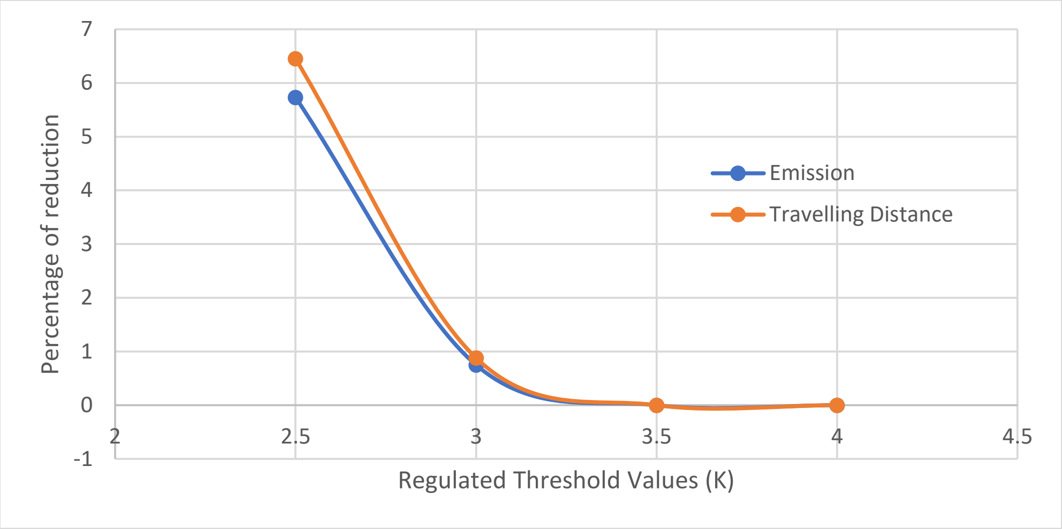

Figure 4.14 Impact of Regulated Threshold Values (K) on Emissions and Travel Distance for Power-Set Trains

The graphs illustrated in Figure 4.13 and Figure 4.14 indicate a clear trend: as the threshold value decreases, both emissions and travel distance are reduced. This sensitivity analysis is crucial in understanding the trade-offs involved in implementing stricter emission regulations.

The impact of reducing the regulatory threshold (K) differs between power-set and locomotive trains. Power-set trains remain unaffected at K = 4 and show minimal changes at K = 3.5. However, at K = 3.0, emissions decrease by 0.75% and travel distance by 0.88%, with a more noticeable reduction at K = 2.5 (5.73% emissions drop and 6.45% travel distance decrease). This suggests power-set trains experience minor efficiency losses under stricter regulations.

In contrast, locomotive trains are significantly affected by tighter thresholds. At K = 4, emissions drop by 3.8% and travel distance by 4.34%, indicating they already exceed this limit and require adjustments. More stringent thresholds (K = 3.5 and K = 3.0) lead to steeper reductions, with the most severe effects at K = 2.5, where emissions fall by 25.78% and travel distance by 28.58%. This highlights that locomotives face greater operational constraints under stricter regulations, requiring speed reductions or more efficient engines to comply.

Unlike power-set trains, which are largely unaffected at higher K values, locomotive trains show a clear and immediate response to regulatory changes. The non-linear reduction pattern suggests that as K values are tightened, locomotive performance is increasingly restricted, leading to substantial reductions in both emissions and travel distance. This indicates that stricter regulations would require either a decrease in speed or investment in more efficient engines, both of which have significant operational and economic consequences.

CHAPTER 5 - CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Among all the primary railway routes in Sri Lanka, the Colombo – Peradeniya route is primarily chosen due to its considerably higher gradient factor of track. Moreover, this selected route represents both flat and rolling terrains. Power-sets and locomotive trains are represented in the selected route, and both types of trains are used for data collection. Micro trip-based cycle development is the simplest and most appropriate method basically for emission estimation purposes rather than traffic engineering-related purposes. Generating micro trip combinations and finding the most representative driving cycle by using a developed Python program is less time-consuming and the easiest method. Cycle duration was set to 1500 s, which sufficiently captured the total running duration from the Colombo – Peradeniya junction. However, after selecting the sets of micro trips close enough to the candidate driving cycles, cycle assessment is done for the selected driving cycles to select the most suitable one.

The average speed of both types of express trains falls between 39 and 43 km/h, while slow trains, whether locomotive or power-set, have an average speed of 30 to 32 km/h. Generally, locomotive express trains are about 11 km/h faster than locomotive slow trains, whereas power-set express trains are approximately 7 km/h faster than slow trains. Considering the average running speeds, locomotive and power-set express trains operate at 45±1 km/h, while slow trains run at an average speed of 39±1 km/h. This means the running speed of express trains is 6 km/h faster than that of slow trains. The percentage of time spent idling is nearly the same for both types of slow trains. However, power-set express trains spend significantly more time idling than locomotive express trains. This difference arises from a reduction in cruising time for power-set express trains while maintaining a higher percentage of time spent in acceleration and deceleration compared to locomotive express trains.

This study recommended using On-board measurement methods to analyze the emissions by developing the relationship between speed vs RPM and RPM vs. Smoke density of trains. Using the on-board measurement method in this case does not cover the real environmental conditions. These developed driving cycles have been used to set emission standards according to the tested emission results. This study determined that the current diesel engine threshold (k=4) is reached at the 81st percentile of emission values for locomotive trains, based on data derived from the driving cycle. However, all smoke density values (k) derived from driving cycles for power-set trains are below 4, indicating that power-set trains comply with the current emission threshold for smoke density (k=4). The objective of this study is to develop a driving cycle for trains and develop an emission estimation model using this developed driving cycle. As a result of the study, a model for smoke density variations of emission gas has been developed and marginal values are identified. Considering currently available regulation parameters for diesel vehicles in Sri Lanka, emission of trains also can be regulated.

Based on the sensitivity analysis results, it is highlighted that aligning rail transport with Sri Lanka's existing diesel vehicle emission regulations could lead to an approximate 4.0% reduction in emissions from locomotive trains. However, power-set trains are already compliant with the current threshold value (k = 4), so no additional measures are needed for them. To enhance emission control effectively, it is recommended to gradually lower the emission threshold values. The most suitable approach is a step-by-step reduction, starting with enforcing k = 4, followed by a future adjustment to k = 3.5 after an adequate transition period. Since power-set trains already meet or fall below the k = 3.5 threshold, this adjustment would primarily impact locomotive trains without affecting power-set trains.

5.2 Recommendations

To enhance the accuracy and representativeness of emission estimations, future studies should consider selecting a broader range of train engines, covering various import years. The current study focuses on a locomotive engine imported in 2012 and a power-set engine imported in 2008, which may not fully capture the emission variations across Sri Lanka's railway fleet. Since the government railway operates engines imported between 1954 and 2020, older engines may exhibit higher emissions due to wear and outdated technology, while newer engines may have better emission control systems. Expanding the selection to include both older and newer engines would provide a more comprehensive understanding of train emissions and improve the applicability of findings for policy development and emission control strategies.

Another thing is the RPM vs smoke density (K) relationship; It was derived under engine idling conditions, where the load on the engine is minimal. Under operational (loaded) conditions, the smoke density at a given RPM may increase due to higher fuel demand and combustion dynamics. Therefore, the linear equations derived here may underestimate smoke density in real-world operations, and further investigation under loaded conditions is recommended for more comprehensive modeling.

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APPENDIX A – Python code for micro trip combining & calculations

```
'''import csv'''
import numpy as np
import pandas as pd
from itertools import chain, combinations, product
import math
import openpyxl
import random

'''Constant Values'''
target_acc = 37.14
target_dis = 36.03
target_cur =  16.13
idle_time = 0

all_trips = pd.read_csv('AllTrips.csv')

# Create a new Excel workbook and select the active sheet
workbook = openpyxl.Workbook()
sheet = workbook.active

def powerset(iterable):
    s = list(iterable)
    return chain.from_iterable(combinations(s, r) for r in range(len(s)+1))

def get_all_subsets(matrix):

    mt_array = np.array([matrix['MT'].values])
```

```
df =  pd.DataFrame(matrix)
data_matrix = df.values

m, n = mt_array.shape
#elements = list(mt_array.flatten())

#randon shuffle of the list and break the list into 4 ists
all_mts = list(mt_array[0])
print(all_mts)

# Randomly shuffle the list
random.shuffle(all_mts)

# Calculate the size of each sublist
sublist_size = len(all_mts) // 4

# Split the list into 4 separate lists
sublist1 = all_mts[:sublist_size]
sublist2 = all_mts[sublist_size:2 * sublist_size]
sublist3 = all_mts[2 * sublist_size:3 * sublist_size]
sublist4 = all_mts[3 * sublist_size:]

# Print the sublists
print("Sublist 1:", sublist1)
print("Sublist 2:", sublist2)
print("Sublist 3:", sublist3)
print("Sublist 4:", sublist4)

sheet.append(sublist1)
```

```
    sheet.append(sublist2)
    sheet.append(sublist3)
    sheet.append(sublist4)

    sublists = [sublist1,sublist2,sublist3,sublist4]
    sheet.append(['subset','Total Duration', 'avg_acc', 'avg_dis', 'avg_cr', 'diff_acc', 
'diff_dis', 'diff_cr', 'abs_diff_acc', 'abs_diff_dis', 'abs_diff_cr', 'sum_diff','rel_acc', 
'rel_dis', 'rel_cr', 'mean_rel_diffs'])

    for sublist in sublists:

        print(sublist)
        #print(list(powerset(sublist))[1:])
        for subset_indices in list(powerset(sublist))[1:]:
            subsets_with_diffs = []
            #print(list(subset_indices))

            subset = list(subset_indices)
            ##subsets.append(subset)
            ##Instead of inserting into a new list , write to a file
            if(len(subset)>=3): #check whether this is needed
                result_list = get_avg_subset_values(subset,data_matrix)
                subset_str = ', '.join(str(num) for num in subset)
                subsets_with_diffs.append(subset_str)
                subsets_with_diffs.extend(result_list)

                # Write data to the Excel file only if the total duration of a subset is less 
than 1500 s
                if (result_list[0]<=1500):
                    sheet.append(subsets_with_diffs)
```

```
        # Save the workbook to a file
        workbook.save('example.xlsx')


def get_avg_subset_values(subset,data_matrix):

    df =  pd.DataFrame(data_matrix)
    np_data_matrix = df.values

    acc_arr = []
    dis_arr = []
    cr_arr = []

    for s in subset:
        acc_arr.append(np_data_matrix[s-1,2])
        dis_arr.append(np_data_matrix[s-1,3])
        cr_arr.append(np_data_matrix[s-1,4])

    #Create arrays with Accelaration, Discelaration and Cruise
    np_acc_arr = np.array(acc_arr)
    np_dis_arr = np.array(dis_arr)
    np_cr_arr = np.array(cr_arr)

    #Calculate Total Durations
    total_acc = np.sum(np_acc_arr)
    total_dis = np.sum(np_dis_arr)
    total_cr = np.sum(np_cr_arr)
```

```
#Total duration of select micro trips without idle time(tdt_no_x)
tdt_no_x = total_acc + total_dis + total_cr

#Calculating idle time of selected set of micro trips(x)
x = tdt_no_x * (0.107/0.893)

#Calculating Total Duration of the selected mirco trips
total_dura = x + tdt_no_x

#Calculating Average Values
if(total_dura != 0):
    avg_acc = (total_acc / total_dura)*100
    avg_dis = (total_dis / total_dura)*100
    avg_cr = (total_cr / total_dura)*100
else:
    avg_acc = np.nan
    avg_dis = np.nan
    avg_cr = np.nan

#Comparing Average values with target values
if(avg_acc != np.nan):
    diff_acc = target_acc - avg_acc
if(avg_dis != np.nan):
    diff_dis = target_dis - avg_dis
if(avg_cr != np.nan):
    diff_cr = target_cur - avg_cr


#Get Absolute value of diffs
```

```
    abs_diff_acc = abs(diff_acc)
    abs_diff_dis = abs(diff_dis)
    abs_diff_cr = abs(diff_cr)

    #Get sum of Absolute values
    sum_diff = abs_diff_acc + abs_diff_dis + abs_diff_cr

    #Get Relative differences, absolute values and its sum
    rel_acc = (diff_acc /target_acc)*100
    rel_dis = (diff_dis /target_dis)*100
    rel_cr = (diff_cr/target_cur)*100

    abs_rel_acc = abs(rel_acc)
    abs_rel_dis = abs(rel_dis)
    abs_rel_cr = abs(rel_cr)

    mean_rel_diffs =   (abs_rel_acc +  abs_rel_dis + abs_rel_cr)/3

    #Append the calculated values to the subset list
    subset_list = subset
    calc_avg_list = [avg_acc, avg_dis, avg_cr]
    diff_list = [diff_acc, diff_dis, diff_cr]
    abs_diff_list = [abs_diff_acc, abs_diff_dis, abs_diff_cr]
    final_list = [total_dura, avg_acc, avg_dis, avg_cr, diff_acc, diff_dis, diff_cr,
abs_diff_acc, abs_diff_dis, abs_diff_cr, sum_diff, rel_acc, rel_dis, rel_cr,
mean_rel_diffs]

    return final_list

def print_calc_avarage_of_subsets(matrix):
```

```
    get_all_subsets(matrix)
    print("\nResults are written to an excel file--------")

# Sample Data
matrix = all_trips
print_calc_avarage_of_subsets(matrix)
```

APPENDIX B – Details about Train Engines

Table 1 Details about the Locomotives Currently Operating in Sri Lanka

Class		Details
M2		• Manufactured in Canada • Imported -1954-1956 • Sub-classes - M2,M2a,M2b,M2c.M2d • Power output -1425hp • Axel arrangement -A1A • Weight 79 tons • Maximum speed - 112kmph
M6		• Built-in Germany • Imported in 1979 • Engine type -V12 two-stroke diesel • Power output-1650 hp • Maximum speed - 90kmph • Axel arrangement A1A-A1A • Weight-60-70tons
M8		• Built-in India • Sub-classes -M8A • Imported in 1996 and 2001(m8a) • Engine type -M8(V16) ,M8A(V12) • Power output- 2800hp(M8) ,2200hp(M8A) • Maximum speed- 120kmph • Axel arrangements -Co-Co • Weight -112 tons

M10		• Built-in India • Sub-classes - M10A • Imported in 2012 • Engine type- V12 four-strokes • Power output -2300hp • Maximum speed - 120kmph • Axel arrangement - Co-Co • Weight- 117tons
M11		• Built-in India • Imported in 2018-19 • Engine type -EMD 12-710G 3C • Power output -3000hp • Maximum speed - 120kmph • Axel arrangement- Co-Co • Weight -130tons

Source: (Herath, 2020)

Table 2 Details about the Power Sets, Currently Operating in Sri Lanka (Herath, 2020)

Class		Details
S9		• Built-in China • Imported in 2000. • Engine Type -V12 • Power output -1580hp • Maximum speed -100kmph • Weight -73 tons • Axel Arrangement -B-B
S10		• Built-in China • Imported in 2008 • Engine type MTU V12 4000R41 • Power output-1950hp • Maximum speed 100kmph • Axel arrangement -Bo-Bo • Weight- 76tons
S11		• Built-in India • Imported in 2011 • Engine type -KTA50L V16-EFI • Power output -1350-1800 hp • Maximum speed-110kmph • Axel arrangement -Bo-Bo • Weight- 100tons
S12		• Built-in China • Imported in 2012 • Engine type -MTU V12 4000R1 • Power output -1950hp • Maximum speed-100kmph • Axel arrangement -Bo-Bo • Weight- 76tons

S13		• Built-in India • Imported in 2018-19 • Power output -1800hp • Maximum speed-120kmph • Axel arrangement -Bo-Bo • Weight- 76tons
S14		• Built-in China • Imported in 2019 • Power output -1950hp • Maximum speed-120kmph • Axel arrangement -Bo-Bo • Weight- 74tons