POLITECNICO DI TORINO

Master of Science
in Automotive Engineering

Master's Thesis

Modular Model to Generate Drive Cycles for Estimating the Energy Consumption and Fuel Consumption of Heavy-Duty Vehicles

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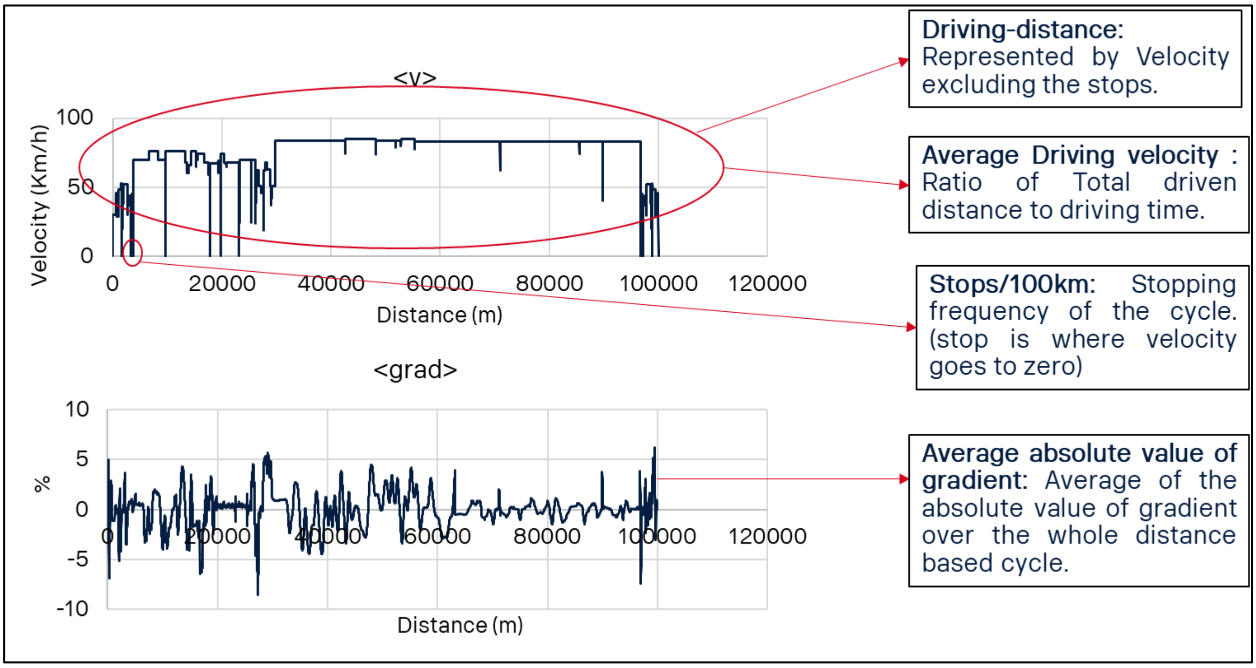
ABSTRACT

The present work proposed in the thesis aims at developing a new methodology for generating artificial distance-based drive cycles and their validation for the sales tool. The sales tool is called Calculation and visualization applications (CAVA) which is used for the energy and fuel consumption calculation of heavy-duty vehicles (HDV's) based on the inputs from the customers.

CAVA needs a new tool for the energy consumption calculation. Therefore, the idea is to generate artificial drive cycles based on three coefficients: Average driving velocity, stop frequency (stops per 100Km), average absolute value road gradient. These three coefficients are the ones which will be input from the customers for CAVA. The idea is to pre-process all the data to create drive cycles which are sufficient to accurately estimate energy and fuel consumption. The stated three coefficients can be derived from operational data or existing drive cycles.



The methodology described in the thesis uses the operational data logged from Scania vehicles running all over the world. The range of useful node points for average velocity, stops per 100 km and average absolute value of road gradient are processed from this operational data by statistical analysis. Gradient profiles are generated using a power spectral density approach and autocorrelation principles for randomly generated data sets for given average absolute values of road gradient. The velocity profile is constructed from a basic cycle followed by entering the desired number of stops and alteration of the final velocity profile according to the given acceleration and deceleration curves. The generated cycles are validated with a vehicle model against Vehicle energy calculation tool (VECTO) cycles and operational data to check the applicability of the methodology. The validation is performed in a simulation tool that uses longitudinal vehicle dynamics to simulate the desired vehicle model.

The validation results for fuel and energy consumption of generated cycles against VECTO cycles and operational data show a deviation nearly within $\pm 10\%$ for most of the cases. Some of the cases lie outside the scope of operational data limits and hence the deviations are more than $\pm 10\%$. It was analyzed that the deviation depends on the energy content of the cycles given by characteristic acceleration if stop frequency of cycles in comparison is same. The characteristic acceleration shows the transient nature of the cycle by taking into account kinetic, potential energy and number of stops. The energy content of a cycle is kinetic and potential energy over the complete cycle. The energy content is dependent on the velocity and gradient profile of cycles. It was also analyzed and reported that the base cycle design is a major factor for reducing the deviation in fuel and energy consumption of the generated cycle from VECTO cycles and operational data.

Contents

List of Figures

List of Tables

Nomenclature

Abbreviations

HDV	Heavy Duty Vehicle
VECTO	Vehicle Energy Calculation Tool
CAVA	Calculation and Visualisation Application
CVV	Customer Value Vehicle

Notations

Symbol	Description	Unit
a	Vehicle acceleration	$[\frac{m}{s^2}]$
A_F	Cross sectional area	$[m^2]$
c_d	Air drag coefficient	[-]
g	Acceleration due to gravity	$[\frac{m}{s^2}]$
f_{RR}	Rolling resistance coefficient	[-]
F_{Trac}	Traction force	$[N]$
F_{Air}	Air drag force	$[N]$
F_{Roll}	Rolling resistance force	$[N]$
F_{Acc}	Acceleration force	$[N]$
$F_{Gradient}$	Gradient force	$[N]$
F_0	Road load coefficient (constant)	$[N]$
F_1	Road load coefficient (linear)	$[N\frac{s}{m}]$
F_2	Road load coefficient (quadratic)	$[N\frac{s^2}{m^2}]$

Symbol	Description	Unit
I	Rotational inertia	$[kgm^2]$
I_{RP}	Rotational inertia mass related to drive axle	$[kgm^2]$
m_v	Vehicle mass	$[kg]$
P	Power	$[W]$
P_{Trac}	Traction power	$[W]$
$P_{Loss,Friction}$	Losses due to Friction	$[W]$
r_{wheel}	Radius wheel	$[m]$
$s(t)$	Driven distance at time t	$[m]$
t	Current time	$[s]$
$t_{closing}$	Time to close the coupling	$[s]$
tq	Torque	$[Nm]$
$tq_{Inertia}$	Torque required to accelerate component with inertia I	$[Nm]$
v	Vehicle speed	$[\frac{m}{s}]$
v_{rel}	Relative vehicle speed	$[\frac{m}{s}]$

1 Introduction

This chapter includes an explanation about the background and purpose along with the outline of the work done during the thesis.

1.1 Background and Theory

Scania is a manufacturer of commercial vehicles and engines, mainly within heavy trucks and buses. Scania deals in various HDV segments but long haulage trucks are the main segment for the company as shown in Figure 2.1.

A drive cycle is a set of data points of vehicle speed versus time or distance and the gradient profile, which are used for vehicle simulation. Drive cycles are traditionally used for certification test procedures. There are various newly proposed methods generating driving cycles from large amounts of operational data [1].

In order to maintain a level of pollutants, the automotive field has its legislation where defined emission limits have to be followed by every carmaker. Pollutant emissions are strictly related to engine operating conditions. Thus, there is a need for emission limits in combination with test procedures determining the engine operating points. For all the vehicles certain drive cycles have been established trying to reproduce the operating conditions [2].

The current trend of using drive cycles for vehicle design, especially in tuning the powertrain system for emissions control and diagnostics has lead to the importance of capturing real-world driving [1]. There are a lot of models developed in the past to estimate the emissions and fuel consumption which are categorized as either a travel-based model or a fuel-based model. The fuel-based models are based on fuel use data from the traffic database to estimate emissions with the factor expressed in grams per unit fuel consumed (emission factor). A travel-based model makes use of the emission factors in certain regions with its travel data generating certain emission inventories for emission estimations [14]. Drive cycles are representative of travel-based model which are used for various purposes such as setting up the emission standards, for traffic management purposes and also to determine the travel time [3].

1.2 Purpose of the Thesis

The aim of the thesis was to generate a modular model based on three input coefficients, average driving velocity, stops per 100 Km, average absolute value of road gradient, to generate different artificial distance-based drive cycles for predicting the energy and fuel consumption of HDV's. The model could be later used for initial preprocessing of data to generate drive cycle in Scania's energy consumption tool CAVA.

CAVA is a sales tool being developed by Scania. The tool will be used for the estimation of energy and fuel consumption for heavy-duty vehicles. The principle behind CAVA is that a sales engineer will take the input, of the same three coefficients mentioned in this section earlier, from the customer and simulate an equivalent vehicle model on the particular drive cycle.

The idea with the current drive cycle generation methodology is to preprocess all the operational data to generate artificial drive cycles for the Energy consumption module in CAVA. In the current thesis we focused majorly on validating the mechanical work and fuel consumption of the generated cycles against VECTO cycles and operational data.

1.3 Thesis Outline

The thesis is organized as follows:

Chapter 2 explains the statistical analysis of HDV operational data. The relevance of this statistical analysis as a starting point of the thesis is objectified. The drive cycle coefficients also used later as an input to our model are defined and the analysis methodology with an example of an HDV class is explained.

Chapter 3 explains the theory of Power spectral density, autocorrelation and how these concepts have been developed to generate the gradient profile of the drive cycle.

Chapter 4 mentions the strategy for the generation of the velocity profile of the drive cycle from the base cycle with the method followed for entering the stops in the drive cycle. The idea behind the alteration of velocity profile according to the limit acceleration-deceleration curves and average driving velocity is also explained.

Chapter 5 provides information about the simulation tool and the theory of longitudinal vehicle dynamics behind it. The chapter also explains information about the validation parameters and the validation strategy to be followed.

Chapter 6 presents all the valuable results and discussion related to the validation strategy mentioned in the previous chapter. It also presents the importance of base cycle design in the current methodology.

Chapter 7 reports the most important conclusions developed during the thesis and also indicates suggestions for the future work for the improvement of the current thesis.

2 Statistical Analysis

In this chapter, the statistical analysis of some Scania HDV operational data is discussed. The relevance of this statistical analysis as a starting point of the thesis is objectified. The drive cycle coefficients also used later as an input to our model are defined and the analysis methodology with an example of an HDV class is explained.

2.1 Objective

The statistical analysis of Scania HDV operational data was an important step in order to filter down the data. The large amount of data collected from Scania nowhere provides any information about the drive cycle coefficients and how to use them in order to yield a drive cycle for particular HDV. In order to generate relevant drive cycles capable of estimating the energy consumption of HDV, it was very important to know the relevant velocity, stop frequency and average absolute gradient ranges for particular HDV segments. Thus, it narrows down the data to yield the required range of drive cycle coefficients for each HDV market segment as shown in Figure 2.2 and eliminates the need for large pre-processing capabilities of the drive cycle generator to some extent. Also, the analysis provides us with the strategy to input the relevant stops according to the real-world trends without using heavy mathematical models. Furthermore, the gradient analysis was important to keep the road profiles within the acceptable limits of real-world altitude values. For this data-driven methodology to work it was very important to understand the data structure and dominance of certain ranges for particular vehicle segments.

2.2 Drive Cycle Coefficients

The drive cycle coefficients termed in this thesis are basically the averages of a given set of operational data or a drive cycle. These include average driving velocity, stop frequency and average absolute road gradient shown in Figure 2.1. These averages can be distance-based or time-based. A time-based data can be easily converted into distance-based using the distance, speed and time relationship.

In our model, we used the distance-based averages except for time based average driving velocity. This is because the position based drive cycle is vehicle independent. The driver model in the simulation tool limits current velocity with a position look ahead to reach demanded velocity if used without limit curves which helps to follow the expected drive cycle [10]. The simulation tool is explained further in Chapter 5.

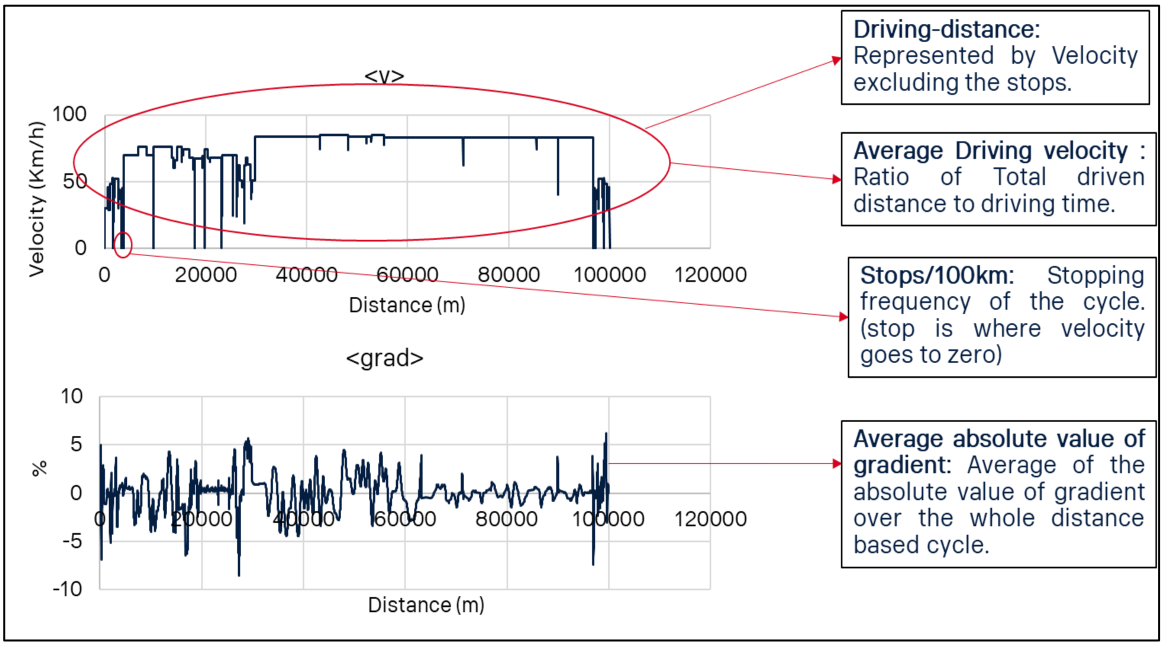


Figure 2.1: Drive-cycle Coefficients

2.2.1 Average Driving Velocity

It is defined as the ratio of the total driven distance to driving time. The velocity is zero during a stop. The stops are defined as the position where the velocity of the vehicle goes to zero. There should be a deacceleration profile before the zero velocity and acceleration profile after the zero velocity in order to define a stop.

2.2.2 Stop Frequency

The stop frequency is defined as the number of times the vehicle performs a stop over a 100 Km distance range of the drive cycle. The stop frequency is also termed as Stops per 100 km of the given cycle.

2.2.3 Average Absolute Value of Gradient

The gradient provides information about the slope characteristics of the road. It can have both positive and negative values and it is a dimensionless quantity expressed in percentage. Thus the average absolute gradient is defined as the average of the absolute value of gradient over the whole distance-based cycle.

2.3 Analysis Methodology

2.3.1 Operational Data Analysis

A total data of 186,004 Scania HDV running all over the world in 2015,2016 and 2017 was downloaded and analyzed. In the first step, all the data were filtered according to the market segments of HDV. Thus, the share of HDV's in the different market segment as entered by sales was obtained and plotted as shown in Figure 2.2.

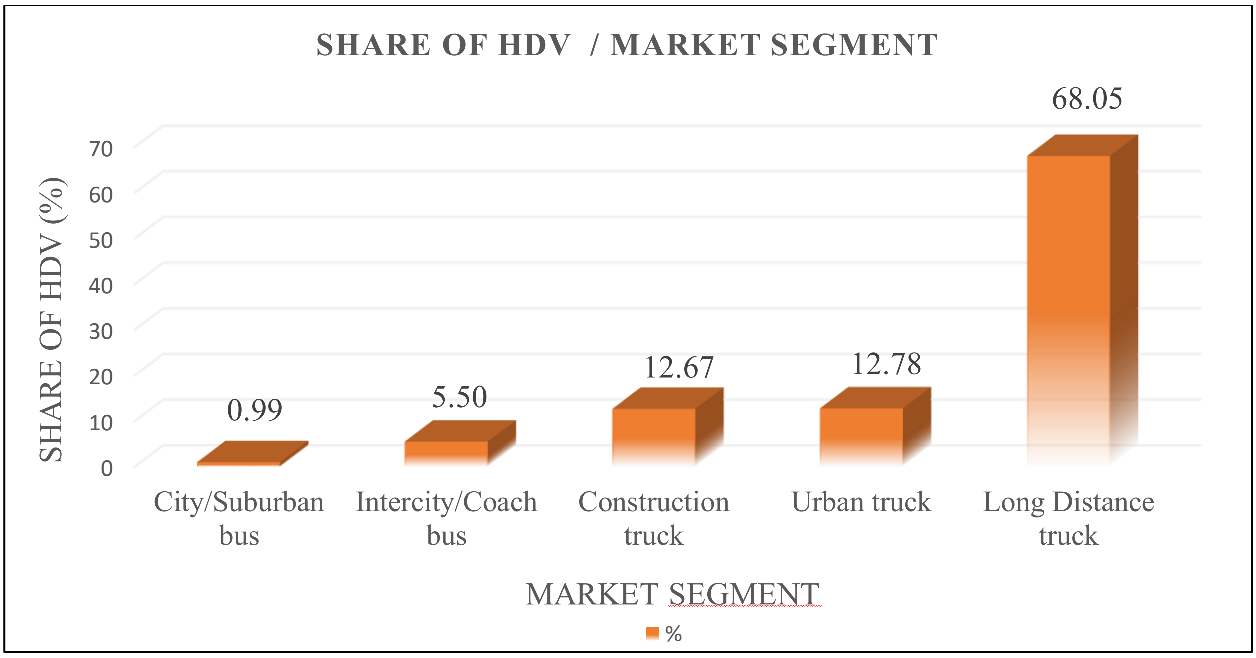


Figure 2.2: Share of HDV's in the different market segment [8]

From Figure 2.2 most HDV's are concentrated in the Long-Distance market segment and the least ones are in the City/Suburban segment. This step was important to get a general perspective for developing the methodology. We focused on two totally different market segments of Long-distance trucks and City/suburban buses and later tried to verify that the results are valid for other market segments too. In the later part of the analysis, we divided the data in each market segment into different velocity classes. For each of the market segments, the relevant velocity classes with the highest share of HDV's and corresponding stop frequency, the average absolute value of road gradient range is chosen. The lower and upper 2.5 percentile of data was omitted before choosing the range of data just to filter out the relevant information for the generation of drive-cycles. An example of Long-distance statistical analysis is shown in Figure 2.3.

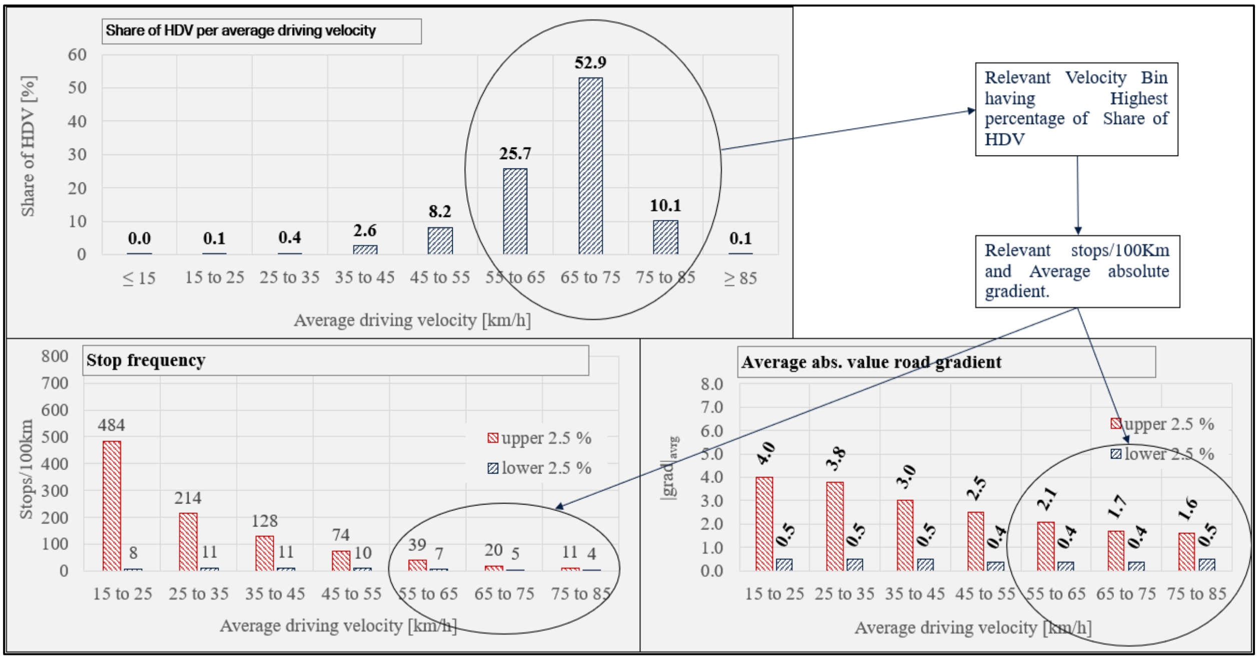


Figure 2.3: Long Distance Statistical Analysis

2.3.2 Stop Frequency Analysis

The data collected provided a deeper understanding of the real-world driving conditions. Thus, it was important to understand the relation between the stop frequency and average driving velocity in order to work with the velocity profile generator for inputting Stops. The HDV's data was plotted on a graph between Stops per 100 km and Average driving velocity in order to see their dependence on each other. Considering a large amount of data we had to generate a trendline using Microsoft Excel trendline feature as shown in Figure 2.4. It provided us the information that the stop frequency was decreasing with an increased average driving velocity approximately estimated according to the Eq. 2.1.

$$y = 781.22e^{-0.061x} \tag{2.1}$$

Where: y – stop frequency [1/100 Km], x – average driving velocity [Km/hr].

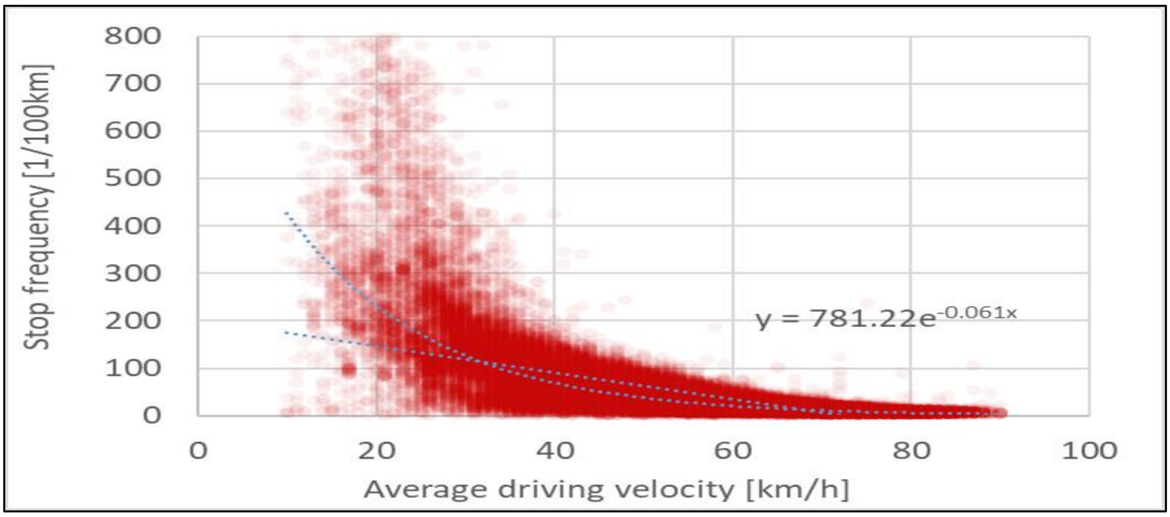


Figure 2.4: Stops per 100 Km vs Average driving velocity [16]

2.3.3 Gradient Crest Frequency analysis

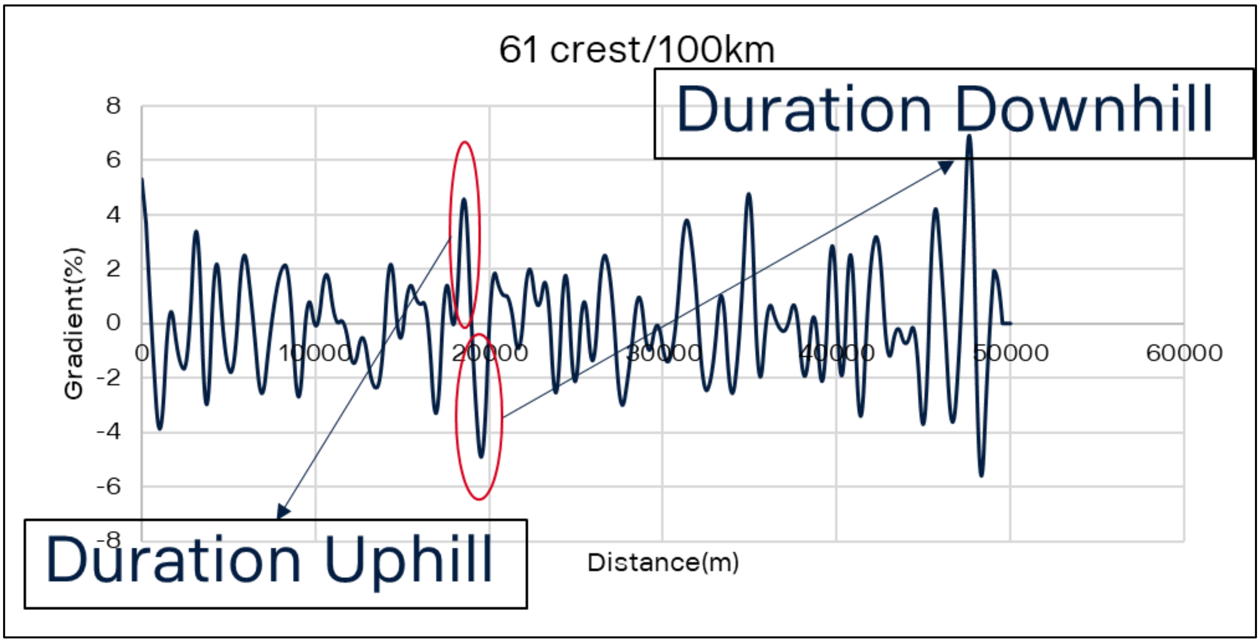


Figure 2.5: Road profile for uphill/downhill duration with 61 crest/100 Km

The word crest is taken from the wave theory. In a wave the crest is the highest region. If we simplify a road profile and just look at a particular section, it represents a trigonometric wave having the crest as the highest altitude of the road profile. The region between the two crests is a valley here since we are talking about road profile. The crest frequency here is thus defined as the number of times it repeats in a 100 km distance. It was important to analyze the crest frequency because it provides us with a duration of downhill and uphill traveled distance as shown in Figure 2.5.

3 Gradient Profile Generation

In this chapter, the concepts of stochastic random process and power spectral density are explained. The methodology of generation of gradient profile using autocorrelation and power spectral density approach is also mentioned.

3.1 Literature

3.1.1 Stochastic Random Process

The concept of stochastic random process explains that a random variable is the function that assigns number to each possible outcome of experience [4]. There are two kinds of random variables; continuous and discrete. Farhang Jalilian explains the concept of random variable with a simple example. Assuming the experiment of rolling a dice once, the outcome of the experiment can be any integer value between 1 to 6. Thus, defining a continuous random variable $x(\zeta)$that takes on the value of 1 for odd and 0 for even [4].

$$x(\zeta) = \begin{cases} 1 & for\ \zeta = 1,3,5 \\ 0 & for\ \zeta = 2,4,6 \end{cases} \tag{3.1}$$

Where, $x(\zeta)$ is a continuous random variable.
The stochastic process assigns every ζ a function x (t, ζ). In this case, the position of a vehicle at any point of interest on a random road is given by stochastic process.

3.1.2 Wide Sense Stationary Random Process and Autocorrelation

A random process is called as wide sense stationary process if its mean function and correlation function does not change over time interval. Autocorrelation is defined as the correlation between two values separated over the time interval [19].
Thus, the autocorrelation of wide sense stationary discrete random process x[n] is given by [19]

$$R_{xx}[k]=E(x[n]*x[n-k]) \tag{3.2}$$

Where, $R_{xx}[k]$	Autocorrelation function
x[n]	Random variable at n data point
x[n-k]	Random variable at n-k data point

3.1.3 Power Spectral Density

The concept of Power spectral density (PSD) is used for random signal analysis. The road surfaces are not very deterministic. If we measure a road elevation for certain distance the ground profile will be irregular. The average we expect on this signal is given by [5]:

$$E(z) = \frac{1}{L}\int_0^L z(x)dx = 0 \tag{3.3}$$

Where,

E(z)	Average of road elevation (m)
L	Distance (m)
z(x)	Road elevation at x (m)

But we cannot use averages to quantify the irregularity of the surface as on a broader scale the path randomness average will be always zero including the elevations and depressions in road profile. Thus, squaring the signals is a better option [5].

$$E(z^2) = \frac{1}{L}\int_0^L z^2(x)dx \tag{3.4}$$

Squaring the signals allow the positive and negative contributions to be added up and hence it will not be zero. This quantity is called mean square value. PSD is just defined as the Fourier transform of Mean square value in frequency domain and is represented as follows [5]:

$$\int_0^\infty G(f)df = E(z^2) \tag{3.5}$$

Thus, it tells us how the Mean square value is distributed in frequency domain. In the present thesis the Mean square value is related with the average absolute value of road gradient through simple mathematics.

The PSD of road profile as a function of elevation v/s distance and PSD of elevation v/s wave number can be plotted as shown in Figure 3.1 [6].

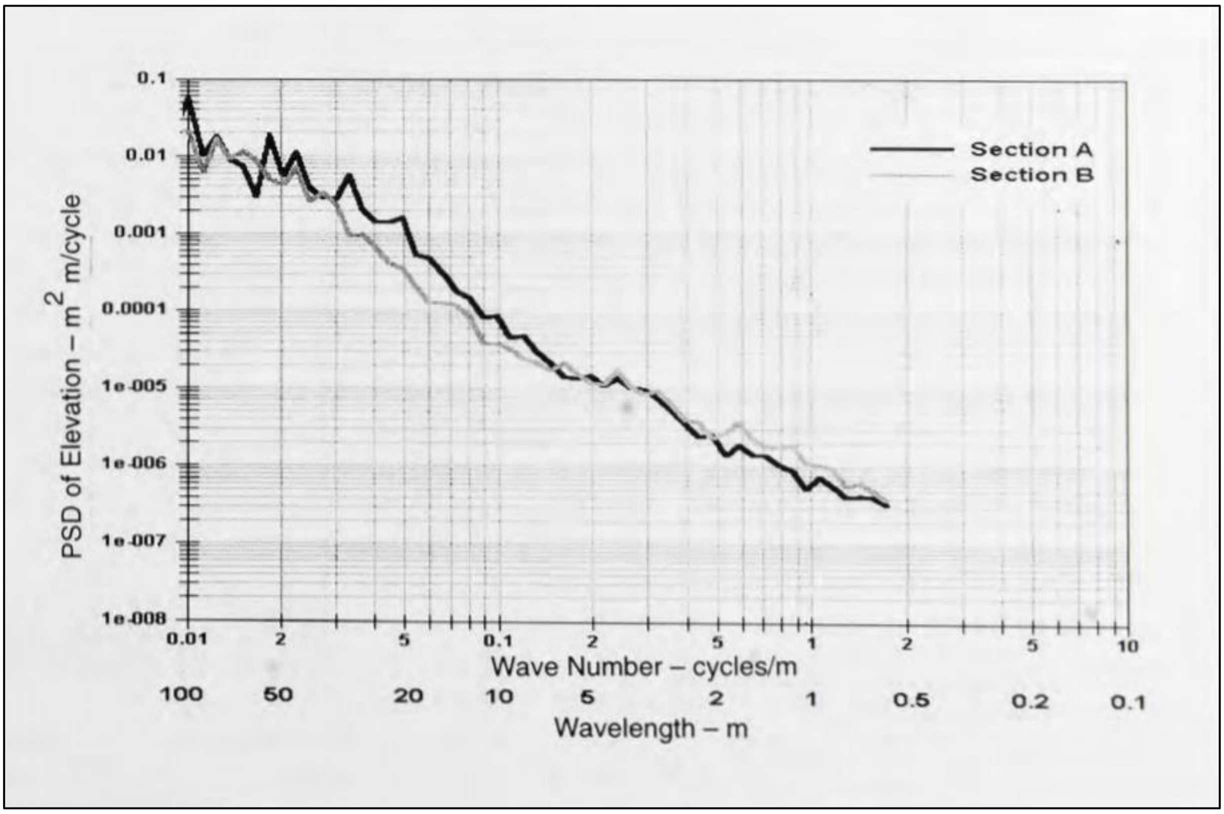


Figure 3.1: PSD of profile elevation plot.

As seen from figure 3.1 the amplitude for long wavelength are higher than for short wavelength. Thus to generate a gradient profile PSD road surfaces is considered on macro level not focussing on the roughness of the road. This means longer length of road profiles which was decided to be 50 Km by Scania Cv Ab for the drive cycle generator and high wavelength and low wavenumber. The wave number or waviness is the frequency of the wave that corresponds to the gradient crest freqency analysis in our case and is set to 3 cycles/m by hit and trial method for having a required crest frequency of 61 crests per 100 km which was decided by taking the average of the crest frequency of real world cycles [8]. Thus the road profile can be represented by PSD function given by [7]:

$$G_d(n) = G_d(n_0).(\frac{n}{n_0})^{-w}$$

where G_d is the displacement PSD in m3 , n is the spatial frequency, n_0 = 0.1 cycles/m is the reference spatial frequency, $G_d(n_0)$ is the PSD value at the reference spatial frequency n_0 (usually identified as C), and w is the exponent of the fitted PSD (also known as waviness).
The altitude variation with crest frequency is also shown in Figure 3.2.

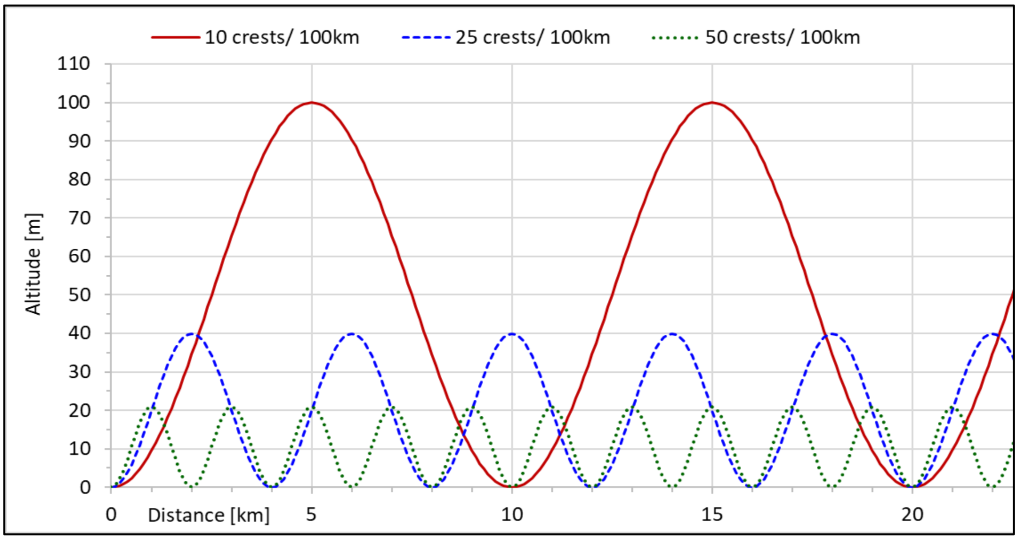


Figure 3.2: Altitude V/s crest frequency of sinusoidal waves.

From Figure 3.2 we can analyse that the altitude increases with decrese in crest frequency. The crest frequency corresponds to wavelength as it is the distance between two crests of a wave. Thus the concept of roughness of road profile was transformed into a gradient profile generation with PSD taking larger values of wavelength and Length of the road making it a real random road profile evaluation problem.

3.2 Gradient Profile Generation Methodology

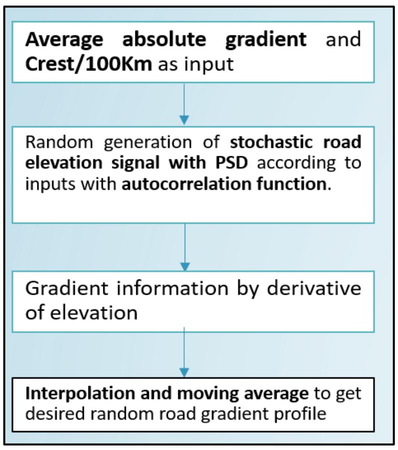


Figure 3.3: Gradient generation methodology flowchart.

The gradient profile generation methodology is based on average absolute gradient and crest frequency as input. The methodology is developed to generate gradient profiles of average absolute value of road gradient between 0.25 and 6 % along with crest frequency between 25 and 95 crest/100km. The Power spectral density approach mentioned in the Literature is used to generate stochastic road elevation signals with the help of autocorrelation function. The gradient is derivative of road elevation profile. The gradient signal achieved here is very transient because of randomness in generating the road elevation profile. The interpolation and moving average mathematical techniques are used to smoothen the signal and obtain final gradient profile of required average absolute value.

4 Velocity Profile Generation

This chapter explains the strategy for the generation of the velocity profile of the drive cycle. The information regarding the terminology of the base cycle, its generation are mentioned. The chapter also explains the method followed for entering the relevant number of stops into the drive cycle. The idea behind the alteration of velocity profile according to the limit acceleration-deacceleration curves and average driving velocity is mentioned at the end of the chapter.

4.1 Base-Cycle

The term base-cycle was coined specifically for this thesis by Mr. Antonius Kies at the YDMC department of Scania CV AB. Base-cycle is nothing but a simple velocity profile having a random mix of acceleration, constant velocity and deceleration sections without any maximum value curve limits. A base-cycle can have any velocity profile depending upon the design capabilities of the designer. There should not be any stops in a base cycle. Basically, it is a velocity profile that looks rectangular without any stop and maximum acceleration-deceleration limits.

4.1.1 Design Aspects of Base-cycle Generation

For this research work it was decided by Scania CV AB that the drive cycle should be 50 Km long. Also, The maximum speed limit for HDV's in Europe is 110 Km/hr for buses and 90 Km/hr for trucks. In order to follow these decisions and yet keep the drive cycle generation methodology modular for future drive cycle generations, the base-cycles were designed for a length of 25 Km and with a maximum velocity of 110 Km/hr. The maximum velocity of the base cycle can be modified so as to obtain the velocity profile needed for various drive cycles. In order to modify the maximum velocity in base-cycle all the velocity values greater than the specified maximum limit are reassigned to the limit value thus lowering the maximum velocity sections in the drive cycle.

For the velocity profile generation, the velocity bins in the range chosen from statistical analysis were taken. The node points were taken as the mid-points of the velocity bins just to keep the methodology simple. Hence, we generate base-cycle for different average driving velocity node points. For instance, if the relevant average driving velocity bin was 15-25Km/h in statistical analysis, the base cycle was generated for an average driving velocity of 20 Km/h. An example of a base-cycle with an average driving velocity of 70 Km/h is shown in Figure 4.1.

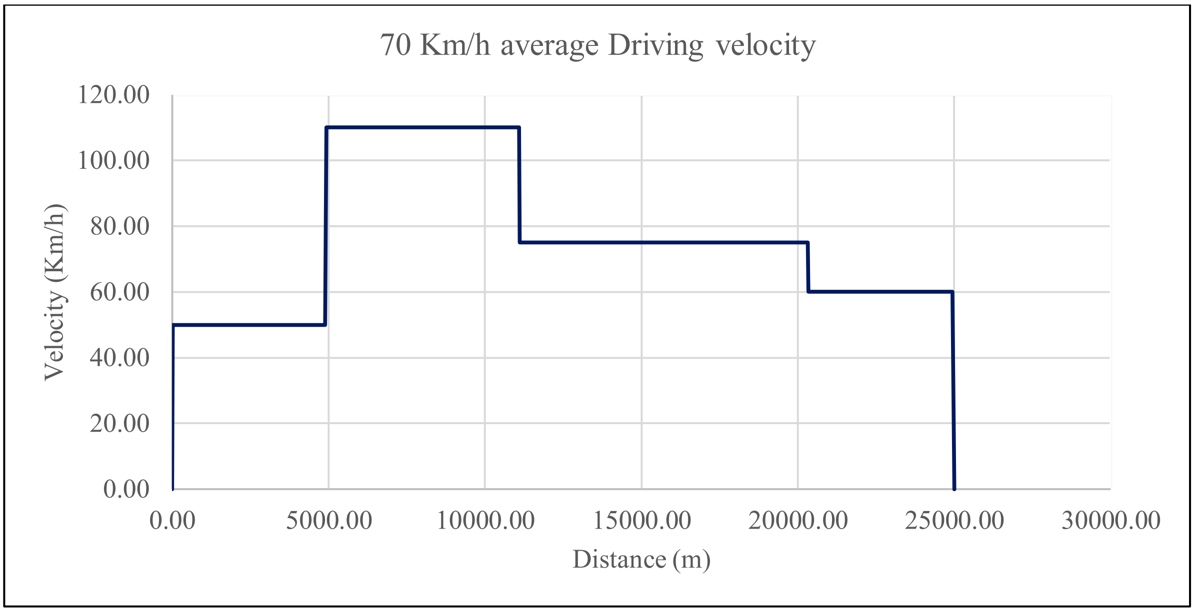


Figure 4.1: Base-cycle for average driving velocity of 70 Km/h

4.2 Stop Strategy

The stops were generally placed with a strategy that when the drive cycle is simulated in the simulation model, it should be able to follow the demanded velocity at any load conditions. It was tried to keep the velocity profile least transient. Thus, the idea behind the stopping strategy is to place the stops first at all acceleration and deceleration sections. The algorithm checks for the velocity changes at each next data point and if there is a change in velocity it places a stop according to the Eq. 4.1 & Eq. 4.2.

$$\begin{gathered} v(n+1) = v(n) \quad \forall \ \mathrm{n} = 2, \dots \dots .., \mathrm{n}-2 \\ v(n+1) = v(n+1) \end{gathered} \tag{4.1}$$

$$\begin{gathered} v(n+1) \neq v(n) \quad \forall \ \mathrm{n} = 2, \dots \dots .., \mathrm{n}-2 \\ v(n+1) = 0 \end{gathered} \tag{4.2}$$

Where, v(n)- velocity [Km/hr] , n-data points.

In the next step, stops are placed from least velocity sections to higher velocity sections according to the Eq. 4.3. This equation is derived from the relationship mentioned in Eq. 2.1 in chapter 2. Eq.2.1 shows the relationship between stop frequency and Average driving velocity of Scania HDV operational data.

$$v\left(n + \frac{1}{(781.22e^{-0.061x}) \times 100}\right) = 0 \quad \forall \ \mathrm{n} = 1, \dots \dots .., \mathrm{n} - \frac{1}{(781.22e^{-0.061x}) \times 100} \tag{4.3}$$

Where, x – velocity of the section where the stop is being placed.

The number of stops placed is tracked and counted regularly during all the steps and if the required number of stops is reached the algorithm stops the execution of the strategy. An example of base-cycle with placed stops is shown in Figure 4.2.

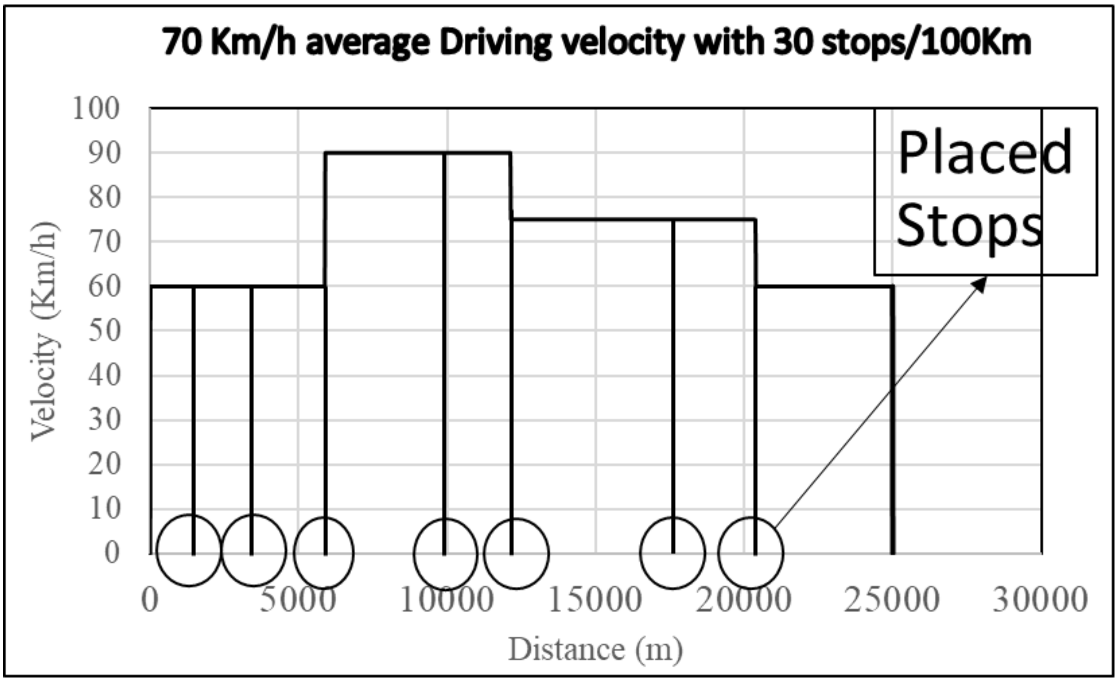


Figure 4.2: Base-cycle with stops.

4.3 Alteration of Velocity Profile

The base cycle velocity profile is altered according to limit acceleration-deceleration curves and average driving velocity of base-cycle which is explained in sections 4.3.1 and 4.3.2 respectively. The final altered cycle is repeated to obtain a 50 Km cycle desired by Scania CV AB.

4.3.1 Alteration according to Limit Acceleration-Deceleration Curves

The simulation tool mentioned in Chapter 5 is based on VECTO functionality. In VECTO the drive-cycles are specified keeping acceleration and deceleration limits which are based on the vehicle type and should be followed by the desired vehicle [10]. These acceleration-deceleration limit curves are provided by Scania for both buses, trucks and are shown in Figure 4.3. As noticed from Figure 4.3 both bus and truck have different acceleration-deceleration limit curves and they are designed according to the safety and comfort level of the occupants. Thus, to generate a drive-cycle for each vehicle type the acceleration-deceleration curves related to that type were used. Following the VECTO strategy, the initial base cycle with stops becomes the target velocity and the new demanded velocity which is the altered velocity profile is calculated based on limit acceleration-deceleration curves.

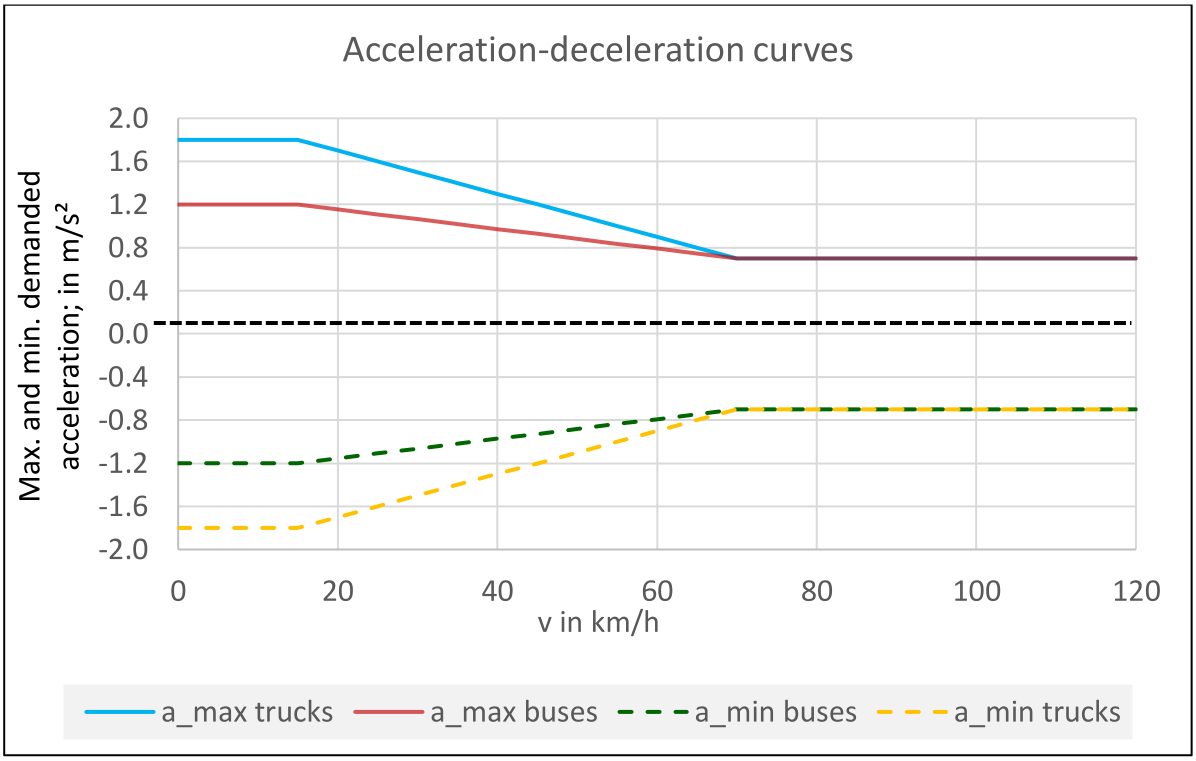


Figure 4.3: Acceleration-deceleration curve for Trucks and Buses[16]

4.3.2 Alteration according to the average driving velocity of base-cycle

Following the alteration according to limit curves and induction of stops in the base-cycle the average driving velocity reduces. This results in a final velocity profile of the drive cycle having different average driving velocity than specified. Thus, to obtain the desired average driving velocity in the drive cycle the current base-cycle with reduced average is multiplied with a factor. This consolidating factor is a variable factor which is developed in a way that it does not affect the maximum velocity of the drive cycle but raises the lower velocity sections. The compensation factor (k) values are shown in Figure 4.4.

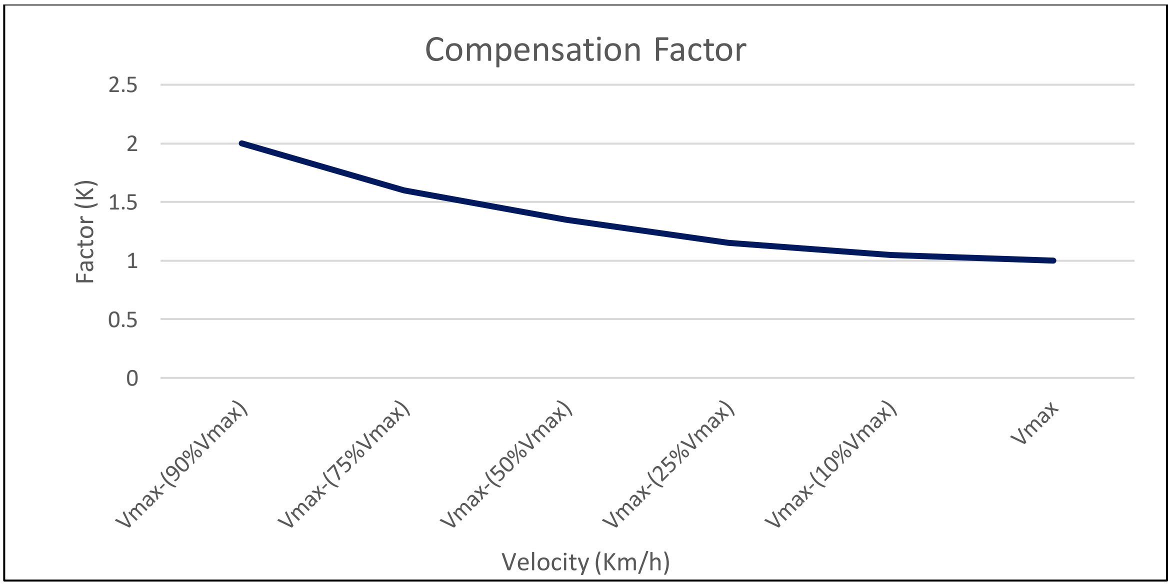


Figure 4.4: Compensation Factor(k) for velocity profile.

In Figure 4.4 the V_{max} represents the maximum velocity of the desired drive cycle. The factor increases approximately exponentially for the lower velocity sections. The final velocity profile obtained after all the alterations is repeated to obtain the 50 Km cycle. An example of final velocity profile is shown in Figure 4.5.

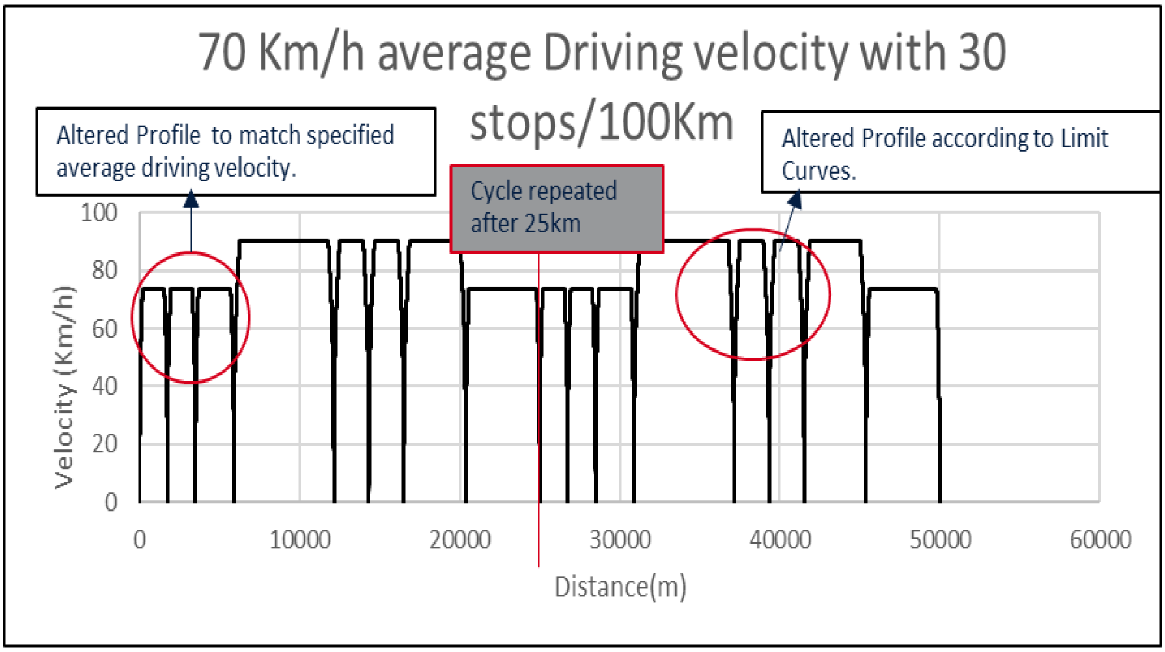


Figure 4.5: Final Generated Velocity Profile.

4.4 Adding Idling Phase to the final drive-cycle

Idling is a condition when engine is running but vehicle is at rest. This condition is represented by a stop in a drive-cycle. All the stops placed in our cycle with the strategy mentioned in section 4.2 are for one second. The idling percentage of VECTO cycles was calculated from the cycle data. The percentage of idling phase data was also available to us in the Scania HDV operational data. For adding idling phase to the final generated drive cycle the last stop was extended in such a way that idling in our generated drive cycle is equivalent to the VECTO cycle or the operational data.

5 Simulation and Validation Strategy

This chapter provides information about the simulation tool used in this thesis for the calculation of the energy consumption of HDV's. The concept related to Longitudinal vehicle dynamics for the simulation model is also described. The later part of the chapter explains the various parameters used for validation and the expected strategy for validation.

5.1 Simulation Tool

The simulation tool used in this thesis for the energy consumption of HDV's was developed by Mr. Johan Holmberg from the YDMV department in Scania CV AB as a thesis project [10]. The model was created using MATLAB/SIMULINK. The simulation tool was created according to the VECTO functionalities added with the Scania proposed gearshift algorithm. The tool is based on longitudinal vehicle dynamics as explained in section 5.1.1.

5.1.1 Longitudinal Vehicle Dynamics

The longitudinal vehicle dynamics explain the vehicle's longitudinal motion with the help of backward and forward models, quasistatic and dynamic as explained in the referenced literature [17]. For the backward simulation, velocity and road-gradient profiles are always given and the calculation flow is from wheels to the engine. The power at the wheels is estimated by evaluating various forces shown in Figure 5.1 [17].

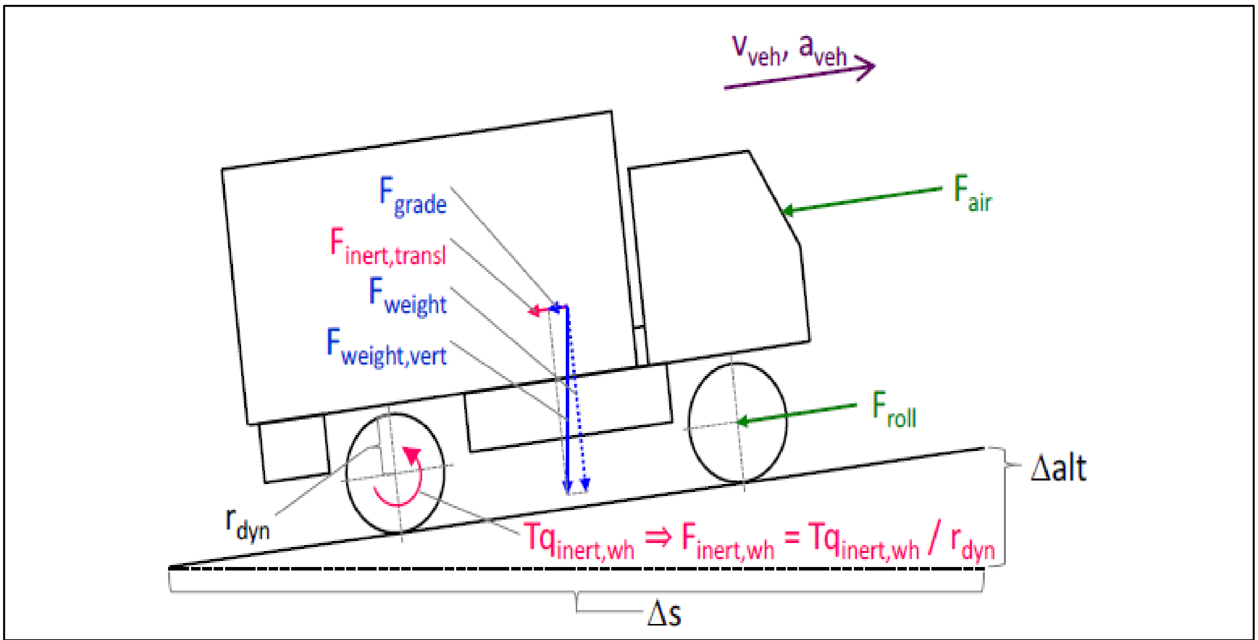


Figure 5.1: Longitudinal forces acting on the driving vehicle. [9]

Using Newton's 2nd law, the equilibrium of forces for defining the wheel force to overcome the longitudinal forces is shown in equation 5.1.

$$F_{wh} = F_{roll} + F_{grade} + F_{air} + (F_{inert,transl} + F_{inert,wheel}) \quad (5.1)$$

Where:	F_{wh}	Tractive forces at the wheels.
	F_{roll}	Rolling resistance forces of tires.
	F_{grade}	Gravitational forces acting on the vehicle.
	F_{air}	Air drag force acting on vehicle.
	$F_{inert,transl}$	Inertia force of translationally accelerated vehicle mass.
	$F_{inert,wh}$	Equivalent inertia force of all rotating wheels.

The above equation can be rewritten as a complex expression and simplified into a final expression as shown in Equation 5.2.

$$F_{wh} = \left(\frac{\Delta alt}{\Delta s} + RRC\right) * (m_{curb} + m_{payl}) * g + C_d * A_{cr} * \frac{\rho_{air}}{2} * v_{veh}^2 + (m_{curb} + m_{payl} + m_{rot,eq,wh}) * a_{veh} \quad (5.2)$$

Where:	$\Delta\, alt$	Difference in altitude at the road section
	$\Delta\, s$	Horizontal distance at the road section
	RRC	Rolling resistance coefficient of tires
	m_{curb}	Curb mass of the vehicle
	m_{payl}	Mass of payload
	g	Gravity coefficient (9.81 m/s2)
	C_d	Drag coefficient
	A_{cr}	Cross sectional area of vehicle
	ρ_{air}	Air density
	V_{veh}	Velocity of vehicle
	$m_{rot,eq,wh}$	Equivalent mass of rotating wheels
	a_{veh}	Acceleration of vehicle in long. direction

Hence Power at the wheels is calculated by equation 5.3.

$$P_{wh} = (F_{wh} * r_{dyn}) * \left(\frac{V_{veh}}{r_{dyn}}\right) = (F_{wh} * V_{veh}) = (Tq_{wh} * \omega_{wh}) \quad (5.3)$$

where:	ω_{wh}	Angular speed of propelled wheel, here in rad/s
	P_{wh}	Power at wheel hubs to drive or brake the vehicle
	Tq_{wh}	Sum torque at hubs of driven wheels

This power is supplied by the internal combustion engine for the conventional vehicles and for the future electric powertrains may be supplied by electric motor. The flow of calculations is shown by Mr. Antonius Kies in Figure 5.2 [9].

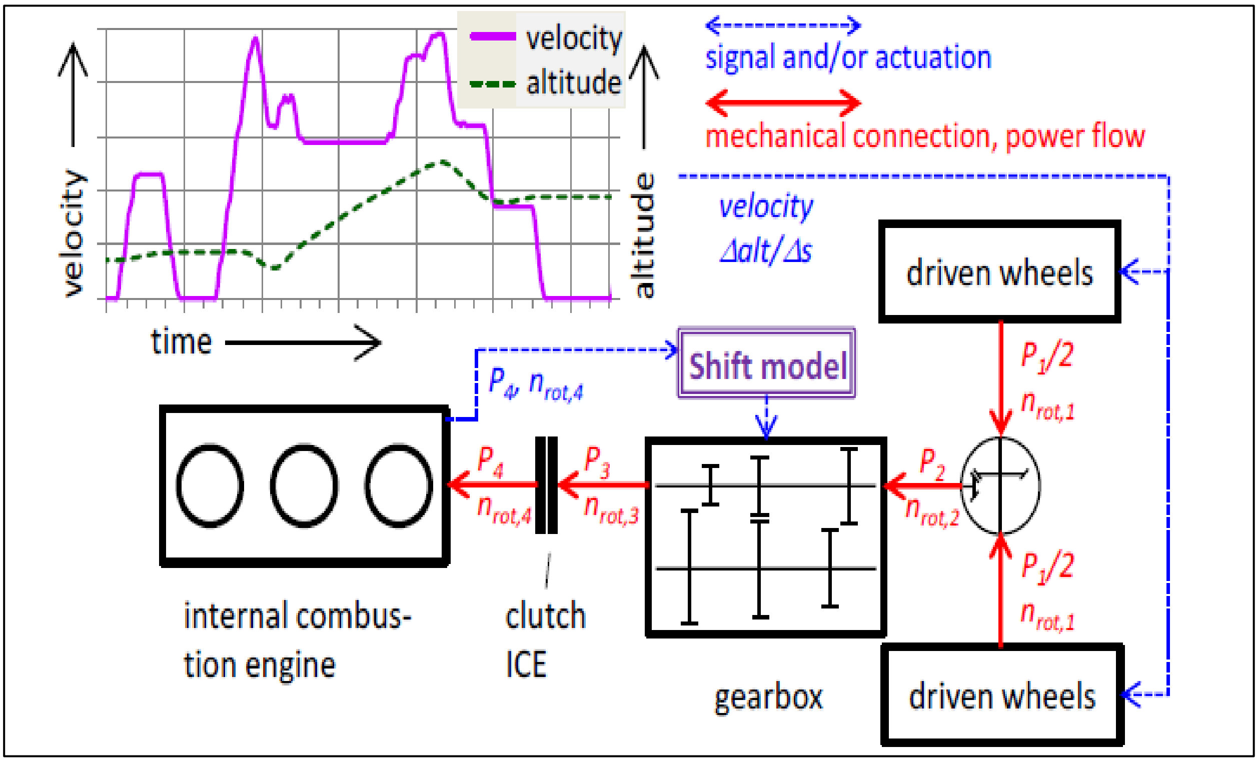


Figure 5.2: Calculation flow of backward simulation[9]

The forward simulation model works in the opposite way to the backward simulation. The calculation flow is from the engine to the wheels. A virtual controller called the driver model uses input values of velocity and desired acceleration-deceleration limits and generate signals for accelerator and brake pedal. The calculation scheme for forward simulation is also discussed in the same paper of Mr. Antonius Kies as shown in Figure 5.3 [9].

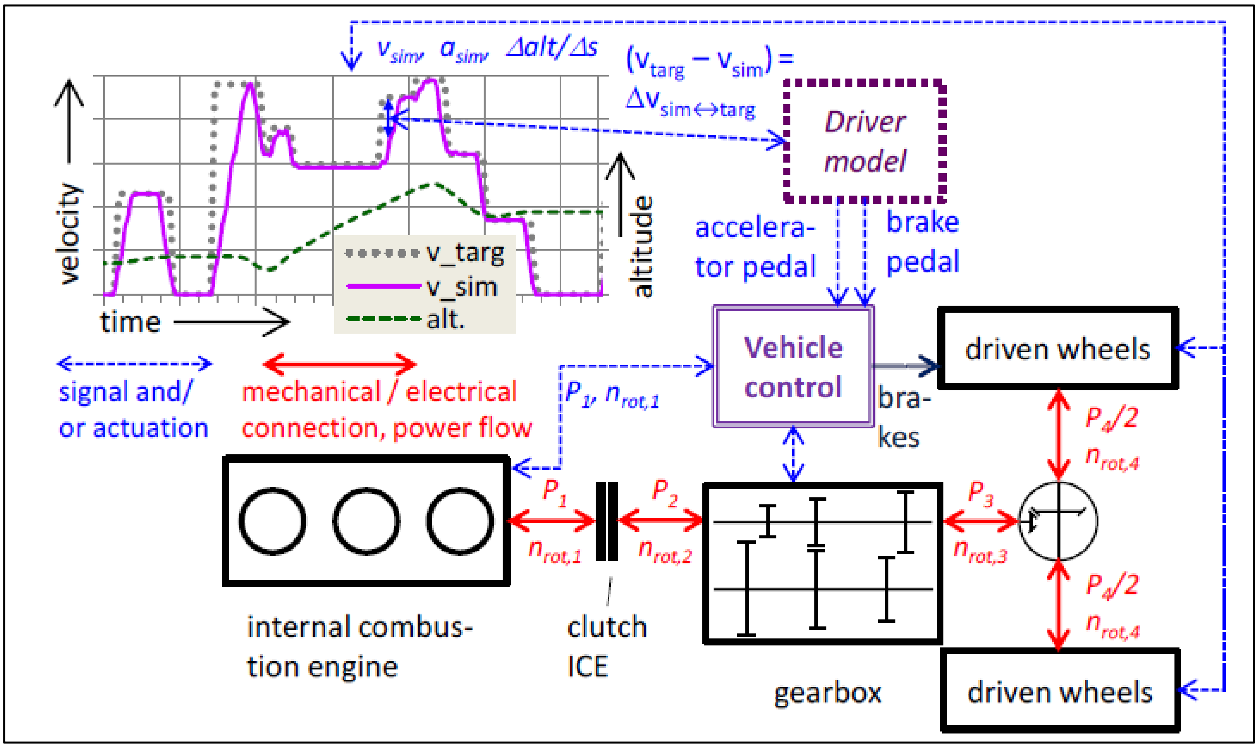


Figure 5.3: Calculation flow of forward simulation[9].

5.1.2 Simulation Principle

The simulation principle of the tool used is similar to VECTO tool. There are various sub models which help the simulation tool work as expected. The working principle is explained by Mr. Johan Holmberg in his thesis paper [10]. The calculation flow is from engine to wheels and the model requires more processing and calculation capabilities as engine torque needs to be regulated to reach desired acceleration. This type of calculation flow is called forward simulation model and is followed in this simulation tool. A new gear shift algorithm was included in this simulation tool just to make sure that the selected gear would not result in very high or low engine speed [10].

5.2 Validation Parameters

These parameters were used for comparing the drive cycle generated with this methodology to the VECTO drive cycles and real-world data. The parameters provide a general understanding of vehicle behavior over a given drive cycle. The characteristic acceleration, fuel consumption and energy consumption were used as validation parameters which explain the energy content of a given drive cycle. The energy content of a cycle is kinetic and potential energy over the complete cycle.

5.2.1 Characteristic Acceleration

Characteristic Acceleration shows the transient nature of the cycle. Higher value of characteristic acceleration means higher unsteadiness and higher mass forces during the drive cycle. It takes into account both kinetic and potential energy thus the higher value explains either the velocity is fluctuating more or the gradient profile is fluctuating more. Higher values of characteristic acceleration generally also indicates more stops and hence more opportunity for higher energy[11]. If the number of stops of two cycles is the same the cycle characteristics like velocity distribution and gradient profile play an important role in deciding the cycle with higher energy. Ideally, the overall energy content of the cycle will always be a function of characteristic acceleration. This does not mean that both positive and negative energy will be higher. It means the sum of both will result in higher energy than the cycle with less characteristic acceleration. The positive and negative energy will still be dependent on cycle velocity and gradient profiles and hence needs to be evaluated to understand the results.

An expression of characteristic acceleration is shown in equation 5.4 [18].

$$\tilde{a} = \frac{\sum_{q=1}^{q=q_{max}^{-1}} max\{0;[0.5*(v_{q+1}^2 - v_q^2) + g*(alt_{q+1} - alt_q)]\}}{s_{max}} \tag{5.4}$$

Where: $\tilde{a}$ Characteristic acceleration

v Velocity in m/s

alt Altitude in meters

5.2.2 Fuel Consumption and Energy Consumption

Fuel consumption is measured in Liters per 100 km and it explains about the Fuel consumed over the cycle. The fuel consumed over the cycle depends upon the type of cycle. If the cycle has higher velocity and acceleration demands the cycle is said to have more positive and negative energy because the cycle operates at higher load points of the engine as discussed by Claudio Cubito in his Ph.D. thesis [13]. Thus the vehicle running on the energy-demanding cycle has more Energy consumption and as a result more fuel consumption. Also, the forces at the wheel also called as road load, due to various resistances to motion like tire rolling resistance, driveline losses, and aerodynamic drag have a high effect on the fuel consumption and energy consumption of a vehicle [13]. Thus, the road profile has a major contribution to the positive and negative energy of the vehicle. This is a very important parameter to explain the difference between different drive-cycle. An example of calculating positive and negative energy at the wheel is explained in Figure 5.4.

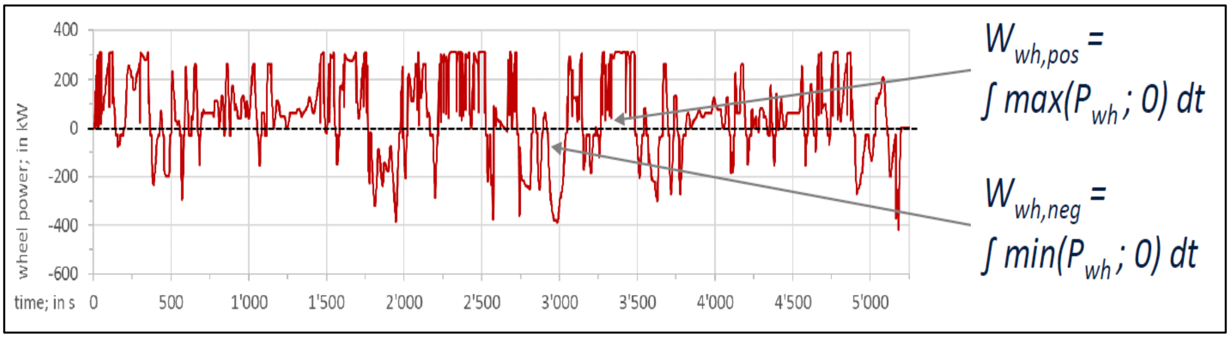


Figure 5.4: Positive and negative energy at the wheels [16]

5.3 Validation Strategy

The validation is performed in order to check if the developed methodology works for estimating energy and fuel consumption or not. The validation was done using the simulation tool explained in section 5.1. The payload was considered to be zero (0 tons), half (15 tons) and full (30 tons) for simulation of different VECTO cycles. For operational data, the payload was considered as mentioned in the datasheet for the particular set used in simulation. The vehicle model of a tractor-trailer was used for different VECTO drive-cycles. The vehicle model of the Customer value vehicle (CVV) R450 truck was used for long haulage operational data validation. The CVV vehicle on an average represents the typical Scania Long haulage trucks. The vehicle model of P280 typical delivery truck was used for urban delivery operational data validation. The validation is performed with the following scenarios:

1) Comparison of generated cycles with VECTO drive-cycles.
2) Comparison of generated cycles with long haulage Operational data.
3) Comparison of generated cycles with urban delivery operational data.
4) Comparison modifying the velocity distribution of base-cycle to match velocity distribution of chosen operational data.

Before the validation is performed the generated drive cycles are checked for plausibility which means to check the maximum velocity and acceleration-decelerations in order to make sure the drive-cycle is realistic. The drive cycle is also checked for the altitude relative to the starting point of the drive-cycle. If there is a change in altitude relative to the starting point the vehicle has gained potential energy which is not favorable[14]. This change in altitude can cause deviations in Fuel consumption estimation and should be corrected by applying altitude error correction so that there is no delta change in altitude over the cycle.

6 Results and Discussion

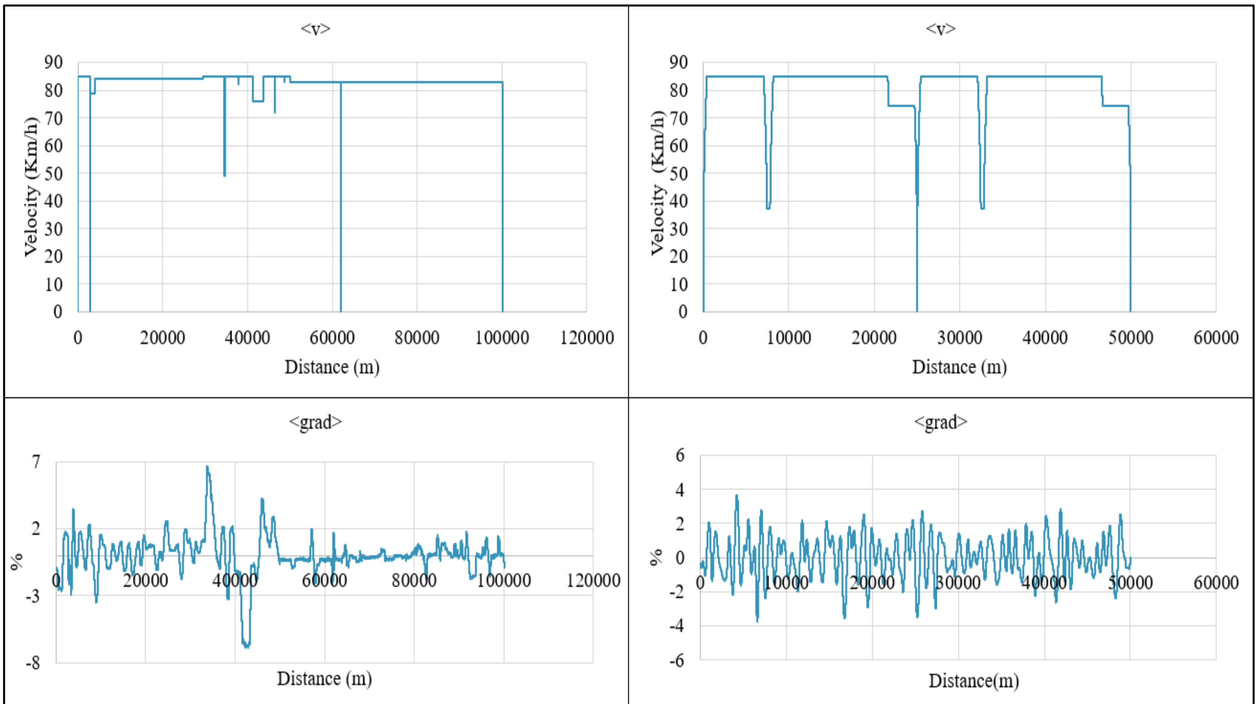
In the present chapter, the results related to the validation of drive-cycle methodology are reported. The comparison of drive cycle generator with VECTO drive-cycles, long haulage operational data, and urban delivery operational data are presented. The deviations are reported and analyzed for successful implementation of the methodology. A solution to reduce deviations is also reported and analyzed.

6.1 Comparison of Generated Drive-cycles with VECTO Drive-cycles

For this comparison, the equivalent drive cycles are generated with the methodology mentioned in the thesis for every VECTO drive cycle. The generated drive cycles and VECTO drive cycles are exposed to the simulation strategy mentioned in Chapter 5 and hence the results for Fuel and energy consumption are obtained and analyzed. The vehicle model of a tractor-trailer was used for different VECTO drive-cycles. The results for only VECTO long haulage, inter-urban, and their equivalent generated drive-cycles are reported for reference in section 6.1.1 and 6.1.2. The other results are shown in the Appendix.

6.1.1 Long Haulage Drive Cycles

As discussed in the methodology the average driving velocity, stops per 100 Km and average absolute road gradient values are calculated from VECTO long Haulage drive cycle. These values were used as an input to generate an equivalent long haulage drive cycle with the methodology mentioned in the thesis. The VECTO cycle and the generated cycle are shown in Figure 6.1.



Average Abs Grad	V avg in m/s	V avg in Km/h	Charact_Acc (m/s^2)	stops/100 km
0.95	22.72	81.81	0.055	3

Vecto Cycle

Average Abs Grad	V avg in m/s	V avg in Km/h	Charact_Acc (m/s^2)	stops/100 km
1	22.22	80	0.062	3

Drive Cycle Generator Cycle

Figure 6.1: Long haulage VECTO drive cycle v/s generated cycle.

In order to compare the cycles mentioned in Figure 6.1 characteristic acceleration of both the cycles was calculated. The characteristic acceleration of the generated cycle was 0.062 m/s^2 which is more than the VECTO drive cycle characteristic acceleration reported as 0.055 m/s^2. Hence as mentioned in section 5.2.1 the generated long haulage cycle is more transient having more energy density which should result in more fuel and energy consumption. The results reported in Figure 6.2 obtained with the simulation model attest to this claim.

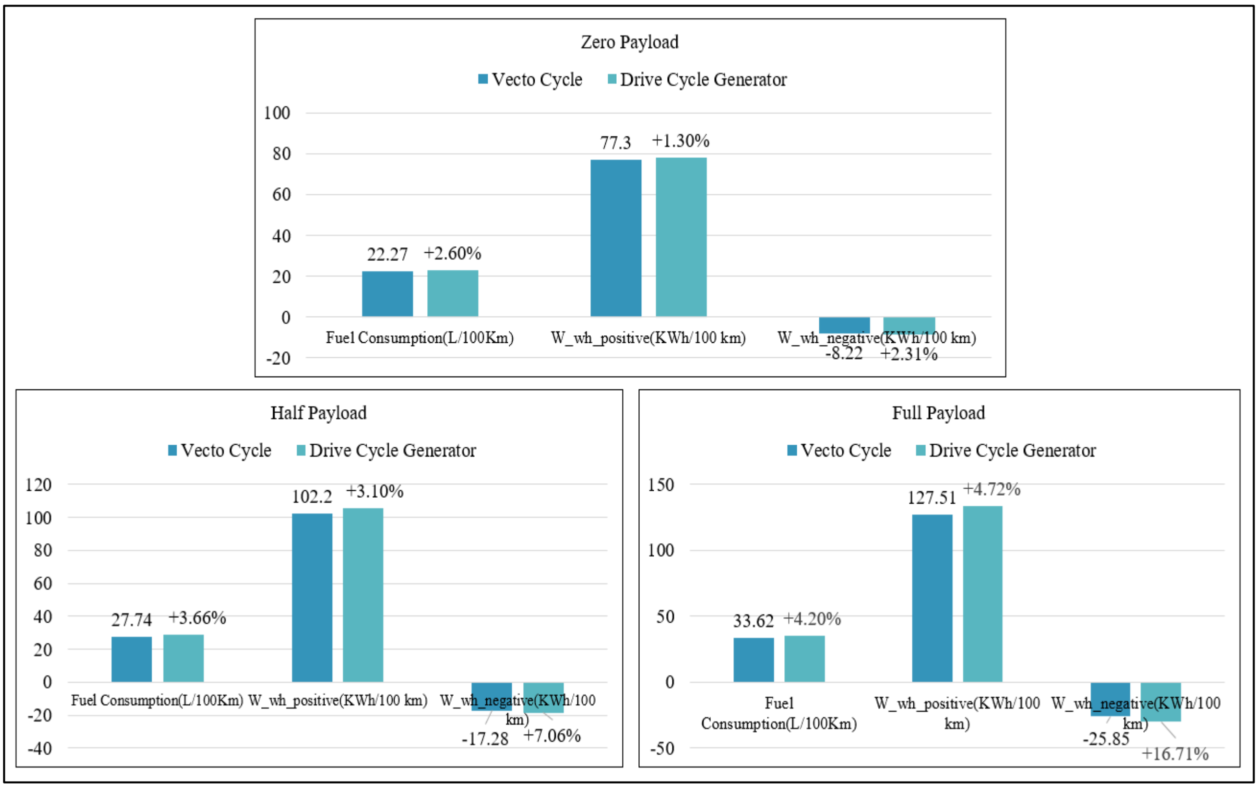


Figure 6.2: Long Haulage cycles simulated results for fuel and energy consumption.

The high characteristic acceleration generally indicates higher mass forces and a transient cycle but since the stops per 100 Km of both the cycle are the same we need to analyze the velocity and road profile distribution to understand the high energy and fuel consumption of the generated cycle.

As shown in Figure 6.2 the fuel and energy consumption reported on the generated cycle is more as compared to the VECTO drive cycle in the range of+2 to +7% for most of the cases. This is because the generated cycle has a more stringent gradient and velocity distribution as compared to the VECTO cycle shown in Figure 6.3. At full payload, there is +16% more negative energy. This is because of the fact that at high loads the simulated model has to brake more considering the profile of the generated drive cycle creating more braking force. Also, due to the velocity and gradient profile distribution in higher range as shown in Figure 6.3 this creates high load points on the engine which results in even higher energy and fuel demands.

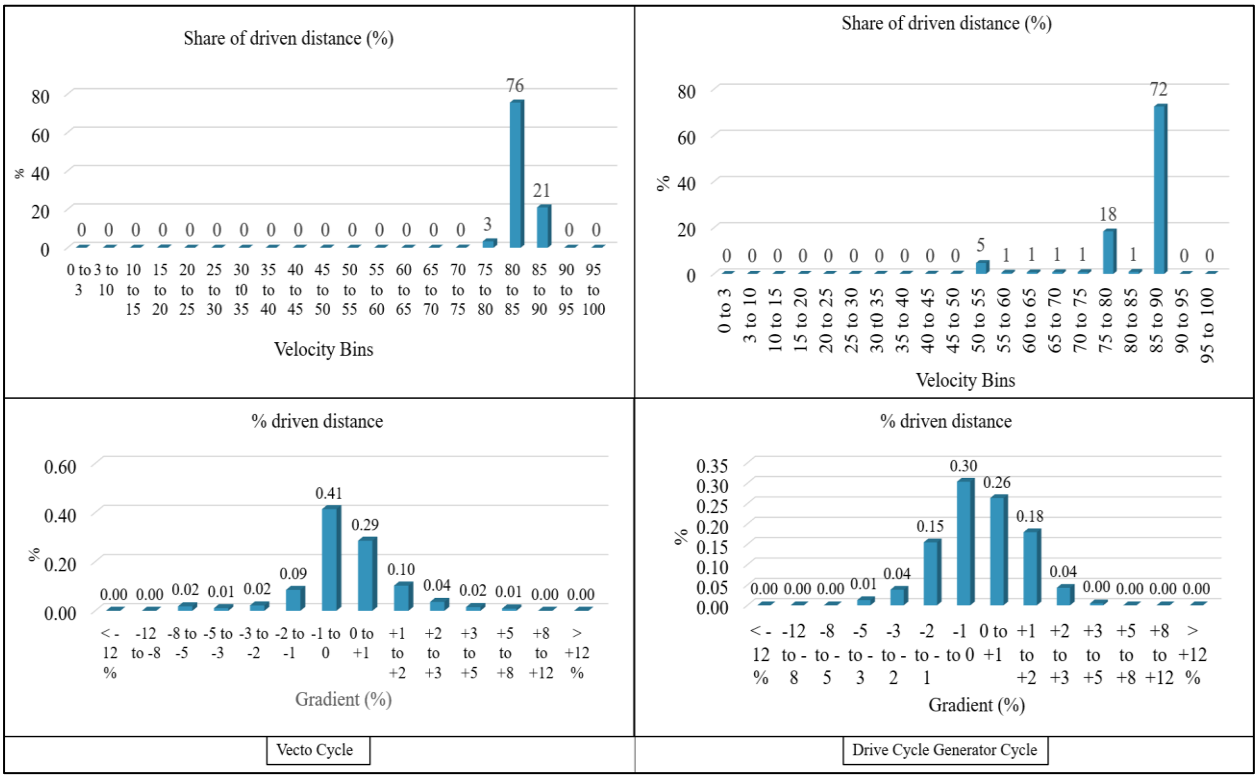
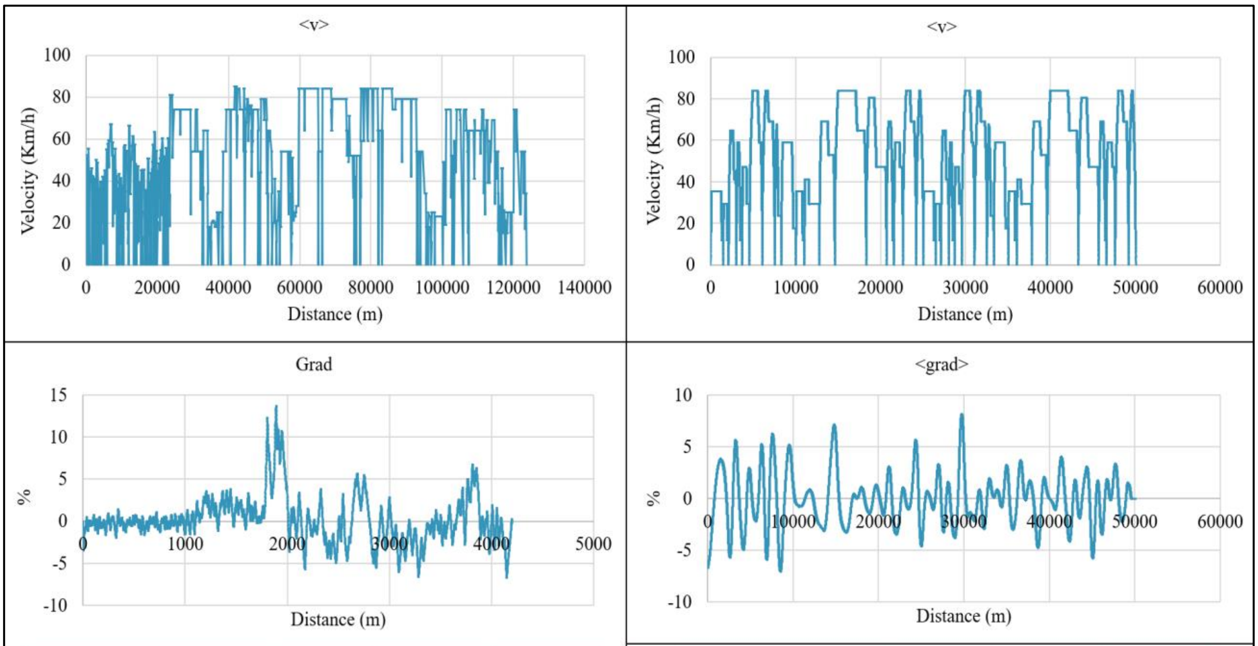


Figure 6.3: Long Haulage cycles velocity and Gradient Profiles

6.1.2 Bus Inter-Urban Drive Cycle

The VECTO equivalent bus inter-urban drive cycle was generated with the same methodology mentioned in the thesis and simulated. The VECTO and the equivalent generated cycle are shown in Figure 6.4.



Average Abs Grad	V avg in m/s	V avg in Km/h	Charact_Acc (m/s^2)	stops/100 km
1.8	11.11	40	0.18	70

Vecto Cycle

Average Abs Grad	V avg in m/s	V avg in Km/h	Charact_Acc (m/s^2)	stops/100 km
2	11.11	40	0.17	70

Drive Cycle Generator Cycle

Figure 6.4: Bus Inter-Urban VECTO drive cycle v/s generated cycle.

As shown in Figure 6.4 both generated cycle and VECTO drive cycle has urban and suburban sections in the velocity profile. Also, the stops per 100 Km and characteristic acceleration are nearly the same. This provides evidence that the three input parameters mentioned in section 2.2 are more than enough for the methodology to generate drive cycles. The results of the simulation for both VECTO cycle and generated equivalent cycle are reported in Figure 6.5.

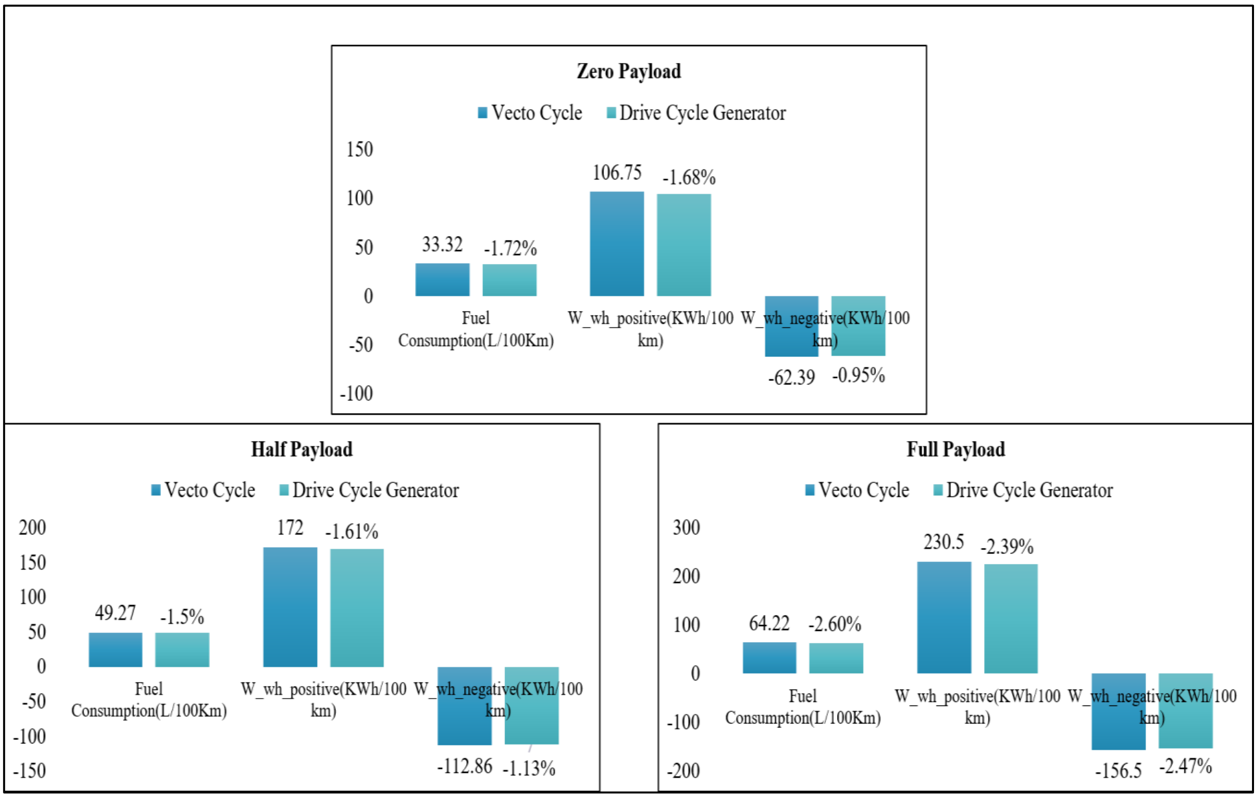


Figure 6.5: Bus Inter-urban cycles simulated result for Fuel and energy consumption.

From Figure 6.5 we can see that the simulations of both the cycles gave us a result for fuel and energy consumption mostly within 2.5% deviation. This is because the characteristic acceleration of the cycles was quite near explaining that both the cycles were having nearly equal energy demand. The characteristic acceleration of the generated cycle was lower which explains the reason for the underprediction of fuel and energy consumption in the simulation tool. Since the stops per 100 Km were the same the characteristic acceleration is a factor of velocity and gradient profile shown in Figure 6.6.

Analysing the gradient distribution of both the VECTO cycle and the equivalent generated cycle we can see that the VECTO cycle has distribution clearly in a higher range. Talking about the velocity distribution, the VECTO cycle has 37% share of driven distance lying above 70 Km/hr velocity scale compared to only 22% of the generated cycle. Also, the generated cycle has 5% more share of driven distance in the highest velocity distribution scale which tries a little to compensate for the previous point but still the effect of the last point is large. Hence the VECTO cycle has higher load points on the engine in this case and as a result more fuel and energy consumption.

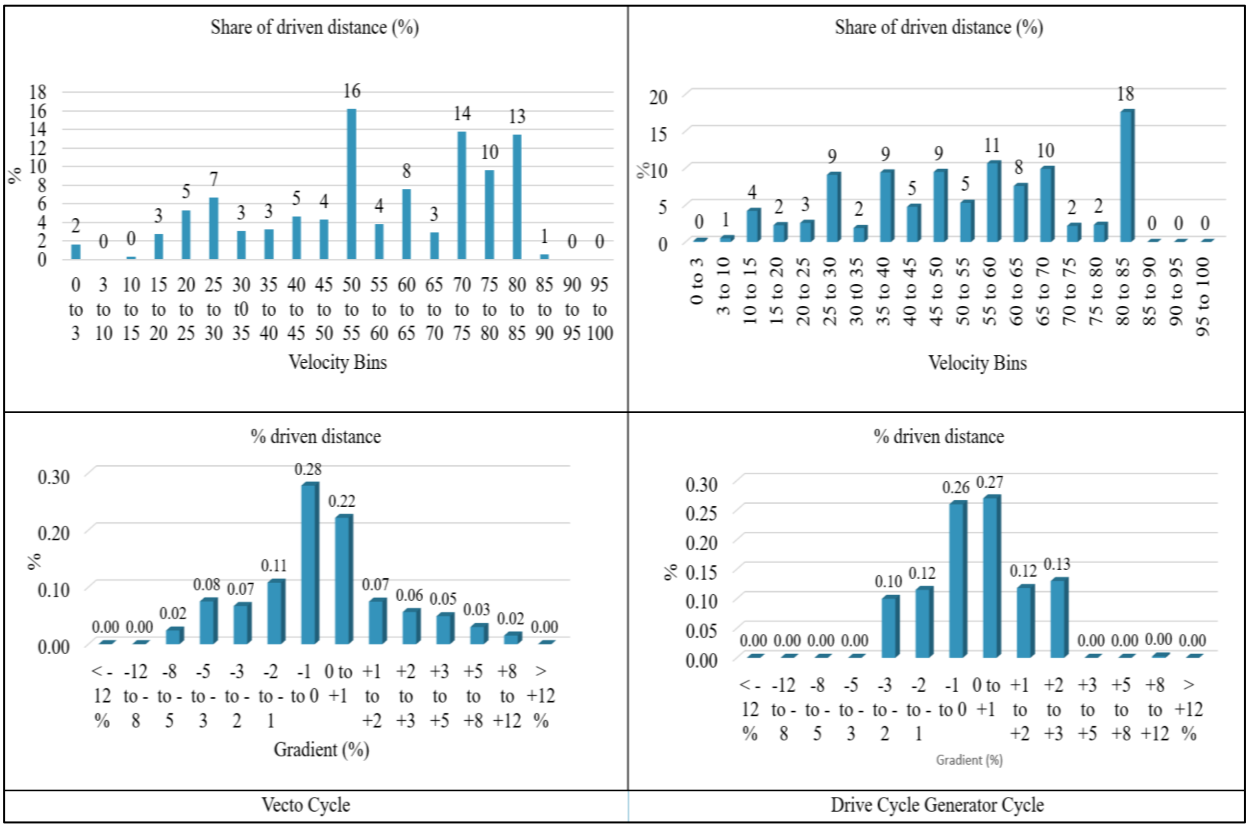


Figure 6.6: Bus Inter-urban cycles velocity and gradient profiles.

6.2 Comparison of Generated Cycles with Long Haulage Operational Data

In order to check the methodology of generating drive cycles, it was important to validate the equivalent drive cycle simulation results of fuel consumption with the long haulage operational data. Since the methodology is based on the inputs from operational data analysis we expect methodology to work for real-world drive cycle generation. Two sets of Operational data and their generated equivalent cycles are reported in this section. The vehicle model of the Customer value vehicle (CVV) R450 truck was used for long haulage operational data validation. Table 6.1 and 6.2 show the coefficients related to the operational data and the generated equivalent cycle. Figure 6.7 and 6.8 show the generated drive cycles.

Table 6-1: Long haulage operational data set 1 V/s equivalent generated cycle

	Operational Data	Drive Cycle Generator
Average Velocity (Km/h)	66	70
Stops/100km	10	10
Total Mass(Kg)	28000	28000
Average Absolute Gradient(%)	**0.83**	**0.83**

Table 6-2: Long haulage operational data set 2 v/s equivalent generated cycle

No.368	Operational Data	Drive Cycle Generator
Average Velocity (Km/h)	73	70
Stops/100km	4	7
Total Mass(Kg)	35000	35000
Average Absolute Gradient(%)	0.91	0.91

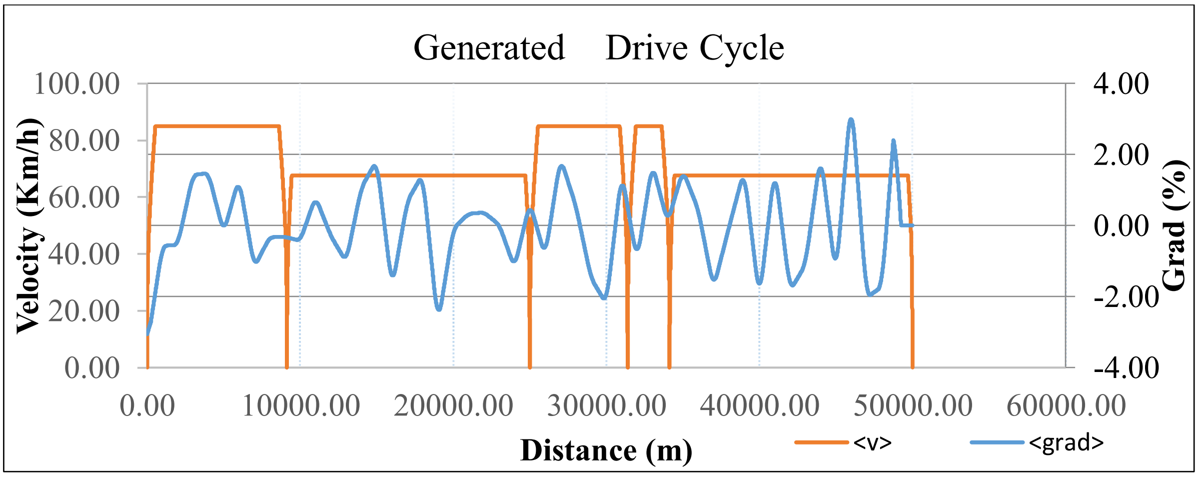


Figure 6.7: Long haulage operational data set 1 equivalent generated cycle.

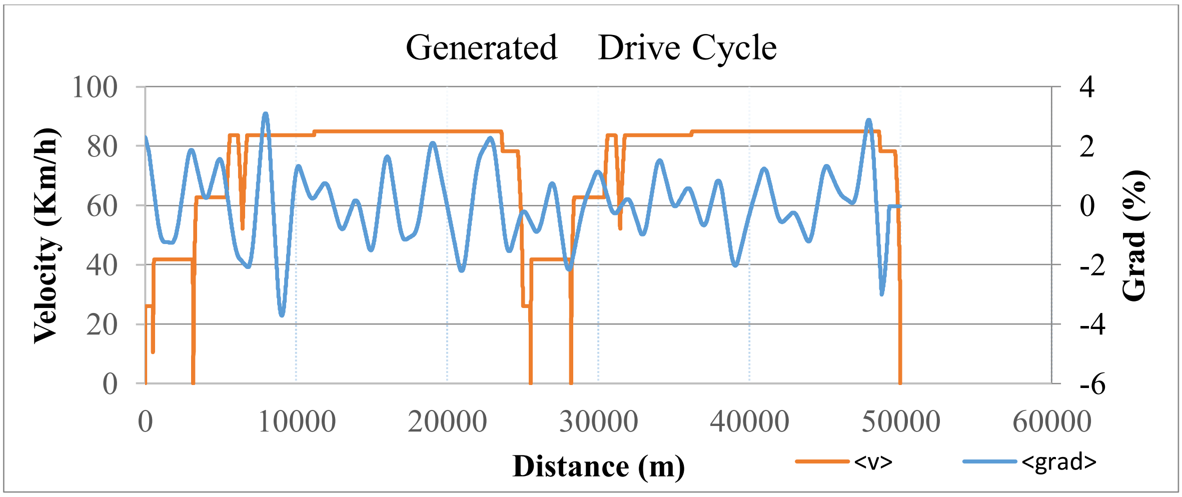


Figure 6.8: Long haulage operational data set 2 equivalent generated cycle.

All the data for long haulage operational trucks like fuel consumption, gradient, and velocity distribution, etc. was already recorded and made available by Scania from the real word data loggers. The equivalent drive cycle is generated and simulated to record the fuel consumption results. The fuel consumption of both operational data and generated cycle for two sets of operational data are reported in Figures 6.9 and 6.10 respectively.

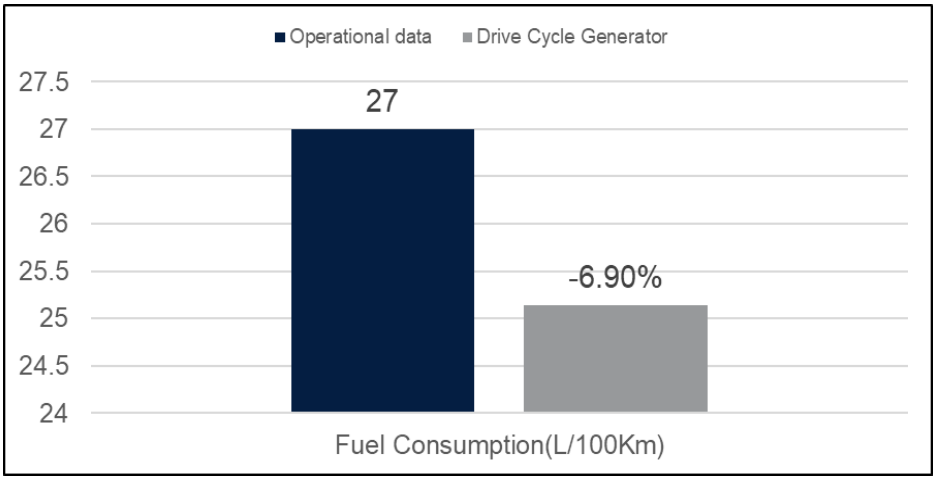


Figure 6.9: Long haulage operational data set 1 v/s generated cycle fuel consumption.

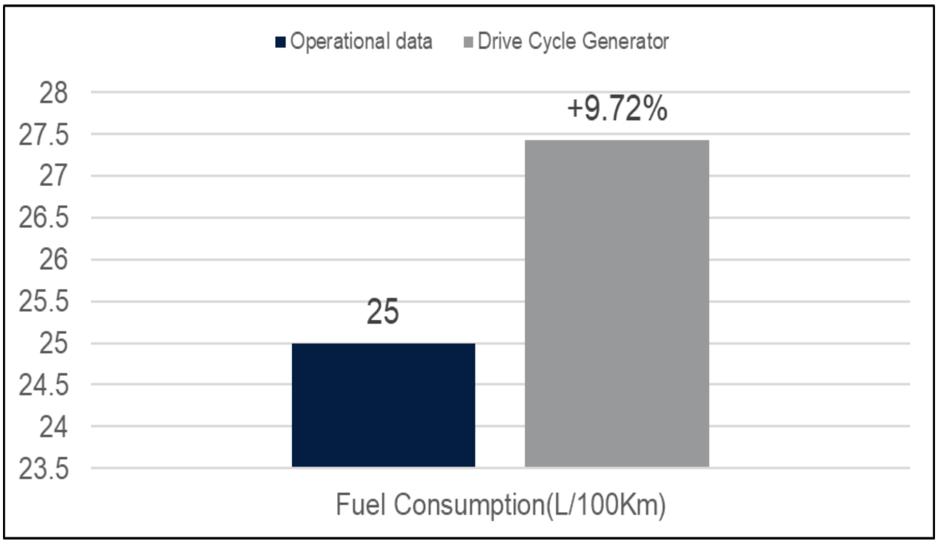


Figure 6.10: Long haulage operational data set 2 v/s generated cycle fuel consumption.

The results show that we have a low fuel consumption with the equivalent cycle for first data set whereas in the second case we have more fuel consumption but both the results lie within ±10%. To understand the deviations velocity and gradient profile shown in figurer 6.11 and 6.12 need to be analyzed.

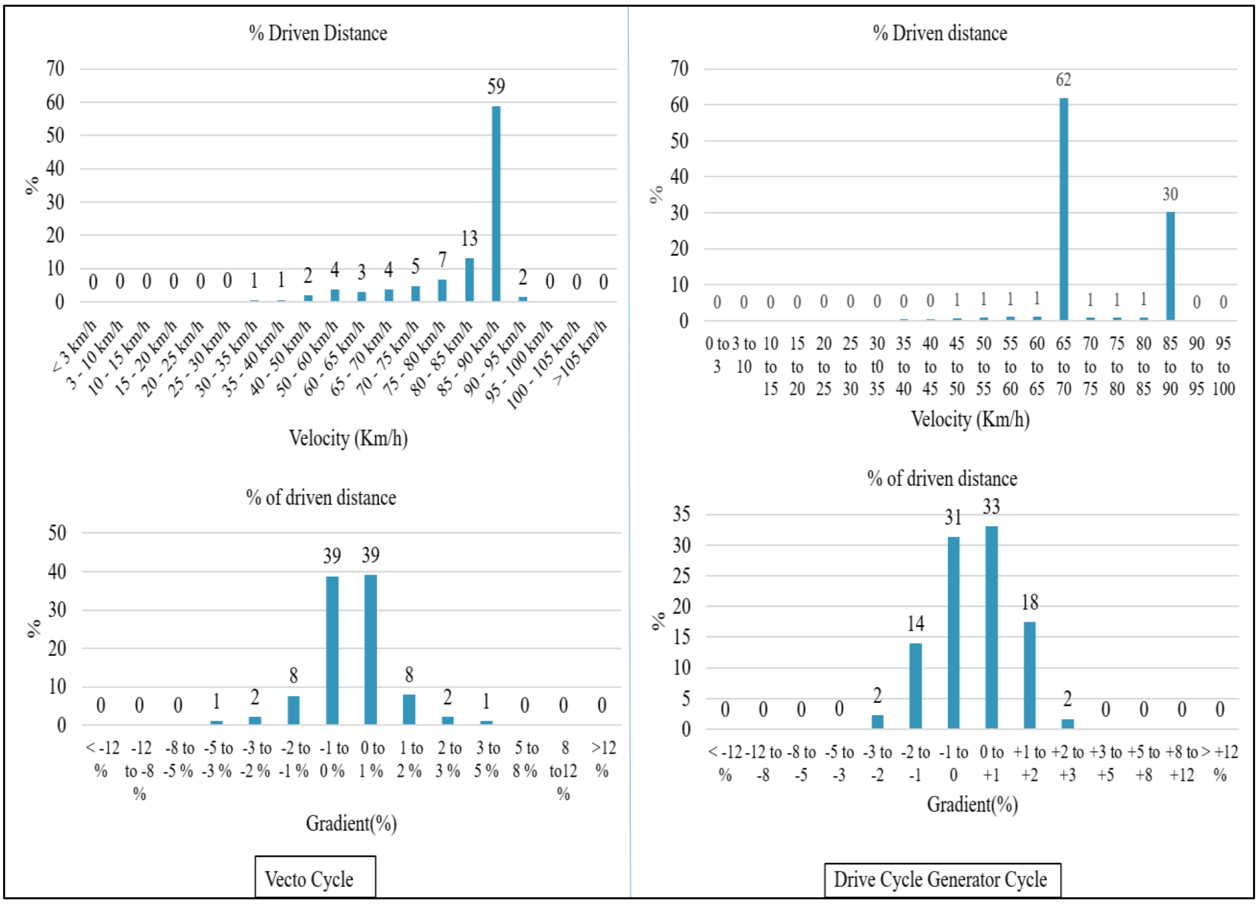


Figure 6.11: Long haulage operational data set 1 v/s generated cycle velocity and gradient distribution.

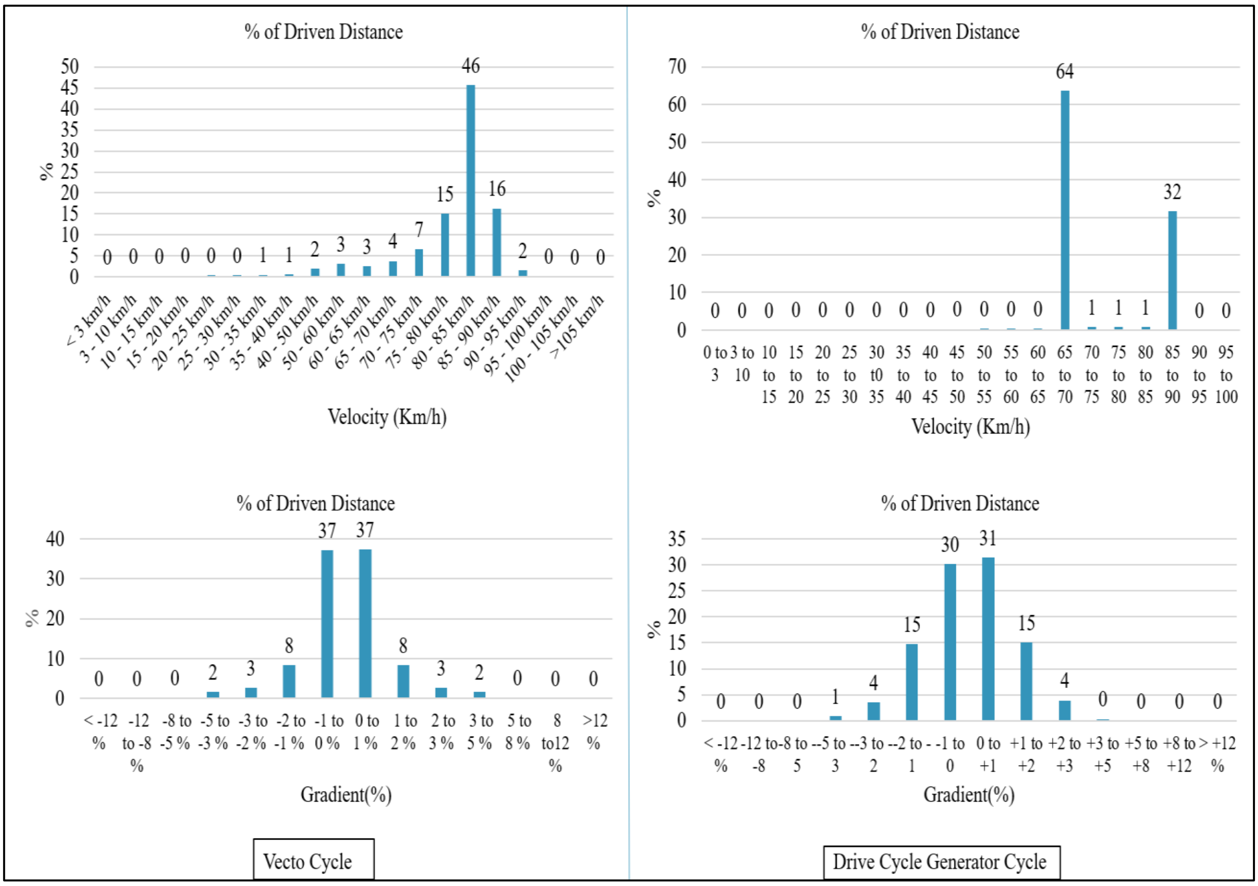


Figure 6.12: Long haulage operational data set 2 v/s generated cycle velocity and gradient distribution.

From the velocity and gradient distribution for the operational data set 1, we can see that for operational data the distribution is on the higher range compared to the generated cycle which results in high load points on engine and as a result more fuel consumption. For the operational data set 2, the generated cycle has more fuel consumption but the distribution of velocity and gradient is not on the higher range. This is again explained by a small concept mentioned in section 5.2.1. The cycle with more stops have greater characteristic acceleration and in turn greater energy content. The more energy-demanding cycles have high fuel consumption. Here, for data set 2 the generated cycle had more stops/100 Km than the operation data hence it resulted in more fuel consumption. Also various vehicle data values like Road rolling coefficient (RRC), Auxilliary power, drag coefficient, Area of crossection of vehicle etc. are estimated and are different from real operational data. The operational data does not provide any such values and hence it increases the uncertainity.

6.2.1 Comparison with modification of Base cycle

The results stated in section 6.2 are within $\pm10\%$ deviation but still it is a large value. In order to reduce the deviation and to check if the base cycle has an imposing effect on the final fuel consumption, the base cycle profile is modified in a way that the final velocity distribution is very close to the operational data set 1 velocity distribution. The velocity distribution and results obtained after modifying the base cycle profile is shown in Figure 6.13 and 6.14 respectively.

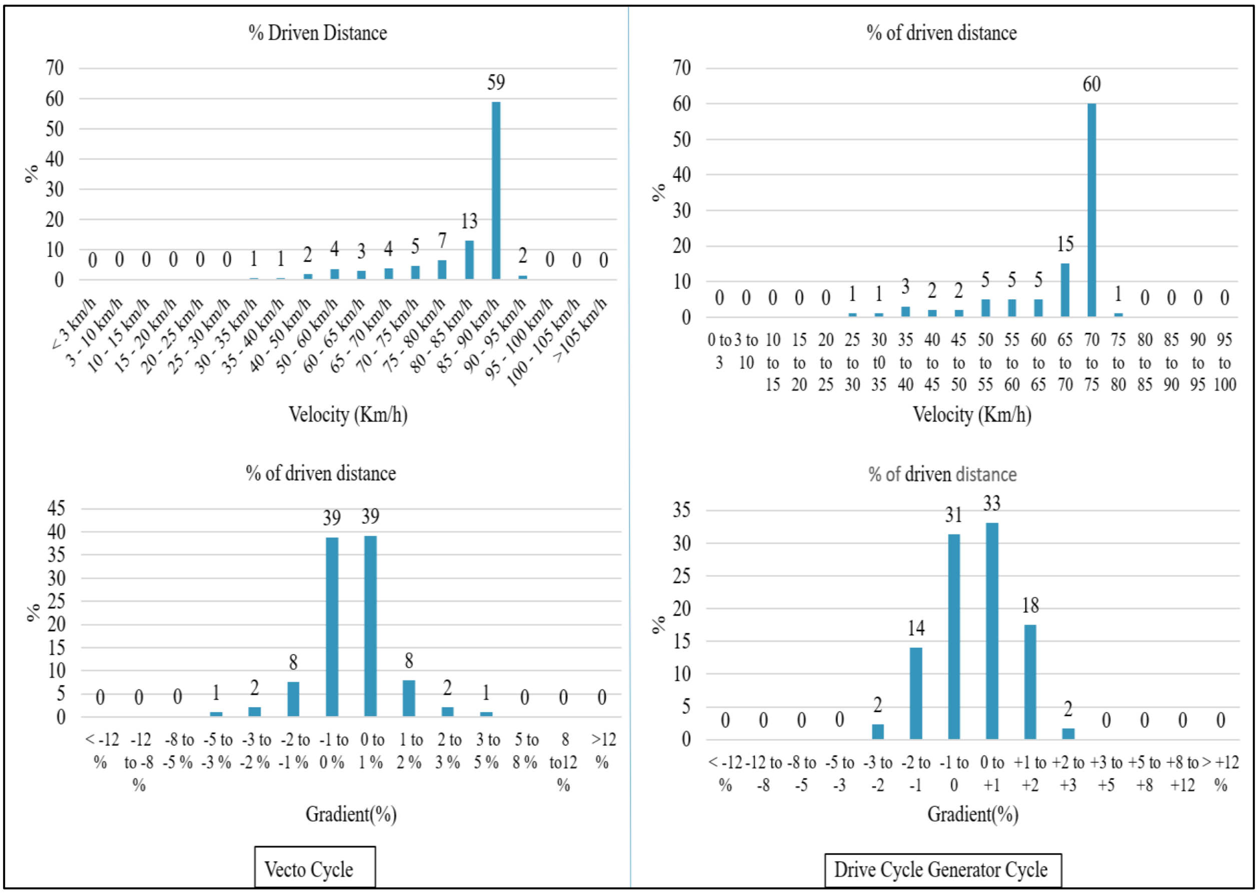


Figure 6.13: Long haul operational data set 1 v/s generated cycle with modified base cycle.

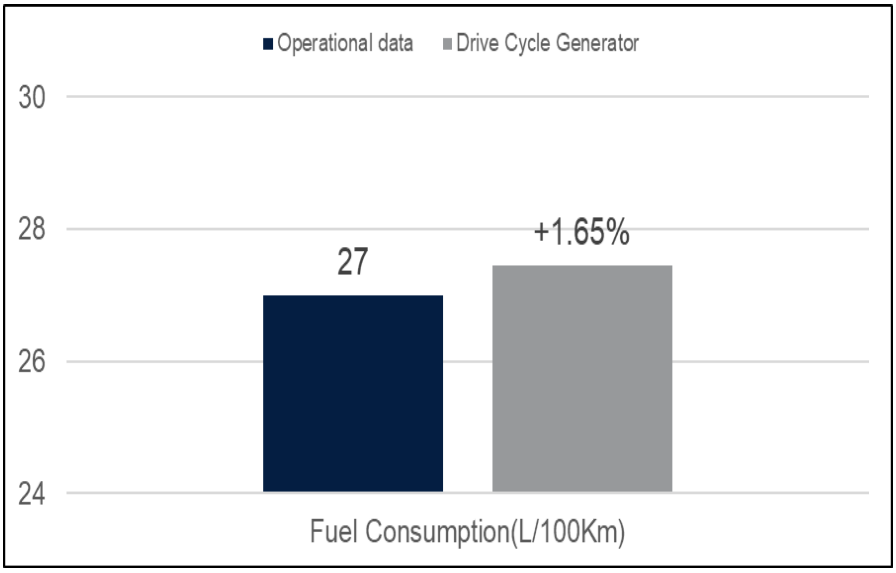


Figure 6.14: Long haul operational data set 1 v/s generated cycle with modified base cycle fuel consumption.

As shown in Figure 6.14 the fuel consumption deviation of the generated cycle is brought to +1.65% from -6.90% by just modifying the base cycle profile. The modification of the base cycle resulted in a very similar velocity distribution of the final drive cycle to the operational data set 1 but the vehicle data values shown in section 6.2 were still unknown. In order to confirm the importance of base cycle the modification is also checked with urban delivery operational data in section 6.3 later.

6.3 Comparison of Generated Cycles with Urban Delivery Operational Data

The last comparison of the methodology was performed against Urban delivery operational data to check its capability for predicting fuel and energy consumption for any real-world driving scenario. One set of Operational data and generated equivalent cycle results are reported in this section. The vehicle model of P280 typical delivery truck was used for urban delivery operational data validation. Table 6.3 and Figure 6.15 shows the coefficients related to the operational data and the generated equivalent cycle respectively.

Table 6-3: Urban Delivery operational data set V/s equivalent generated cycle

No.10	Operational Data	Drive Cycle Generator
Average Velocity (Km/h)	36	40
Stops/100km	112	100
Total Mass(Kg)	15000	15000
Average Absolute Gradient(%)	**1.29**	**1.29**

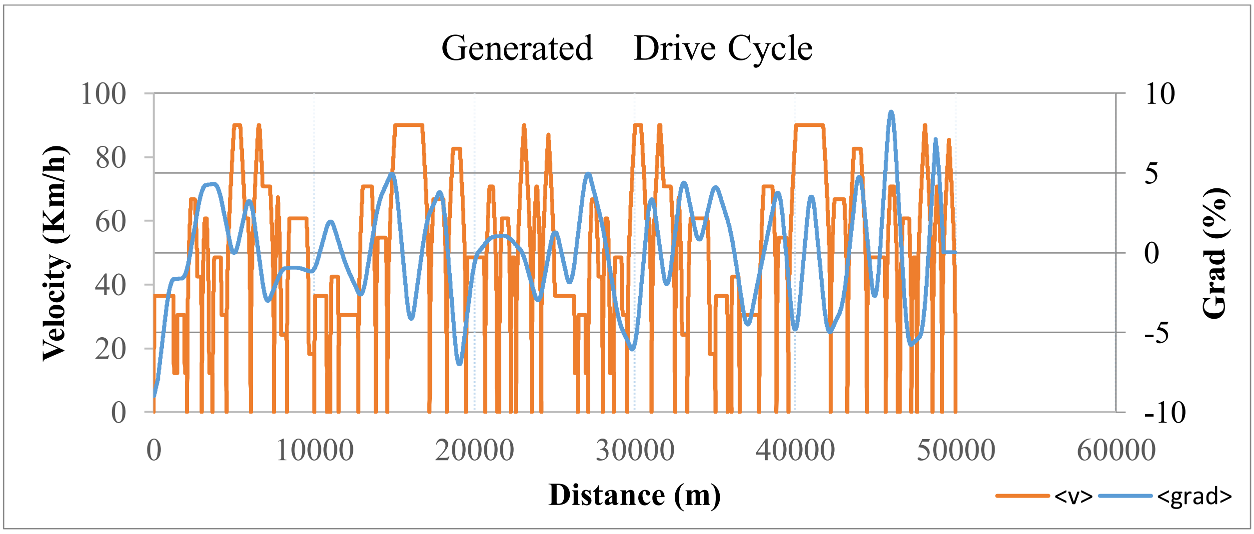


Figure 6.15: Urban Delivery operational data set equivalent generated cycle

The equivalent drive cycle generated was simulated again in the same simulation tool with the strategy mentioned for urban delivery trucks in section 5.3. The simulation results for fuel consumption are reported in Figure 6.16.

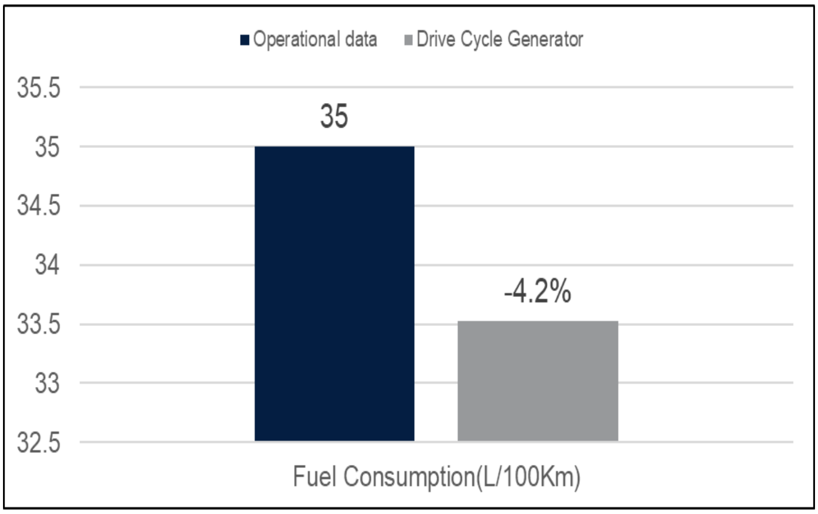


Figure 6.16: Urban delivery operational data set v/s generated cycle fuel consumption.

The results show a deviation of -4.2% for the generated cycle because it has fewer stops per 100 km and as suggested in section 5.2.1 this means we have a cycle with low energy content and hence low fuel consumption. This is a limitation of the methodology that we cannot generate the exact same number of stops to the operational data. We can only generate stops per 100 km equal to the node points decided from the statistical analysis in Chapter 2. Thus, in this case, we generated the nearest node point for stops per 100 km which is less than the operational data set used.

6.3.1 Comparison with modification of Base cycle

The base cycle of the generated equivalent cycle for the urban delivery operational data set was modified in order to get a velocity distribution equivalent to the operational data. This was done in order to confirm the importance of the base cycle profile shown in section 6.2.1. The modified drive cycle velocity and gradient distribution is shown in Figure 6.17.

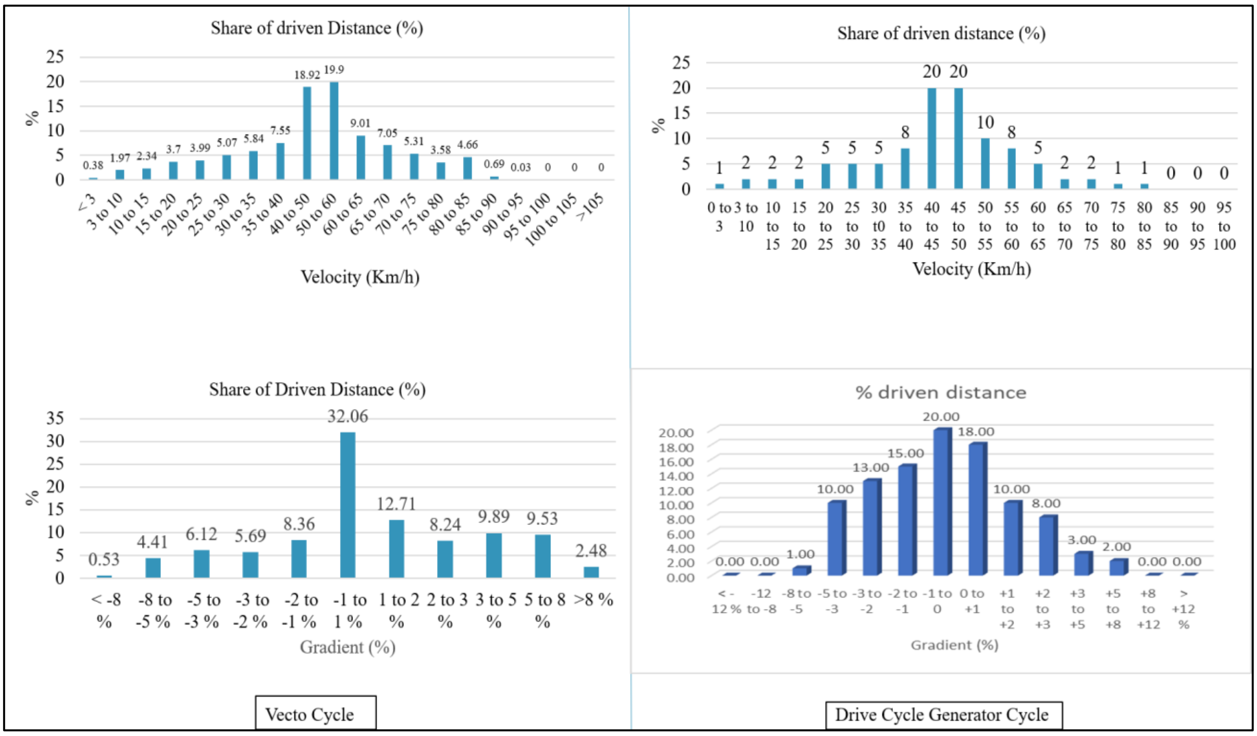


Figure 6.17: Urban delivery operational data set v/s generated cycle with modified base cycle.

The modified drive cycle was simulated, and the results obtained are shown in Figure 6.18.

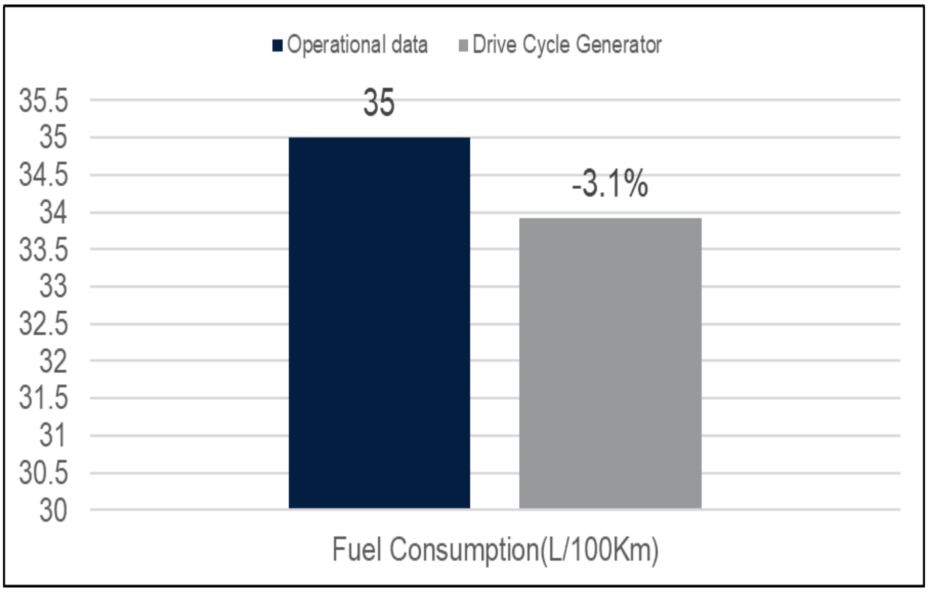


Figure 6.18: Urban delivery operational data set v/s generated cycle with modified base cycle fuel consumption.

As shown in Figure 6.18 the deviation in fuel consumption calculation between operational data and generated equivalent cycle was brought down to -3.1% by just modifying the base cycle velocity profile design in order to match the velocity profile of operational data. The present deviation is because of the more stops per 100 Km in operational data and the estimated vehicle data not equivalent to real operational vehicle. Hence this proves the significance of base cycle design in the methodology and just because of time constraints was not worked on in this thesis. Also, the stops per 100 km have a significant effect. If the stops per 100 Km have been similar the results would have been closer in this case.

7 Conclusions & Future Recommendations

In this thesis, work has been carried out on a modular methodology to generate drive cycles for the calculation of energy consumption of HDV's. This modular model is developed to be integrated into the future energy consumption tool called CAVA in Scania. The aim was to develop a reliable tool to preprocess all the data and generate artificial drive cycles for CAVA. The modular model was tested for application and integration in EC CAVA and the following conclusions were made:

1. The methodology for generating drive cycle tends to work for VECTO drive cycles, having a range of deviations in fuel and energy consumption calculations within $\pm 10\%$ for most of the cases analyzed.
2. It was not possible to analyze the deviations in generated cycles from operational data because of the unavailability of real vehicle data.
3. The range of deviations is less if the characteristic acceleration and stops per 100 Km of the original cycle and it's equivalent generated cycle are the same.
4. For different stops per 100 Km, the average velocity and gradient profile distribution are responsible for the deviations between the two compared cycles.
5. There is a positive deviation in fuel and energy consumption calculation if the generated drive cycle has a velocity and gradient distribution in the higher range compared to the original cycle or the operational data and vice versa.
6. The base cycle design has a major impact on the deviations. If the base cycle is designed in a way that the final generated cycle has a velocity distribution similar to the original cycle or operational data, the deviations could be significantly less.
7. The three input coefficients used in the thesis to generate an artificial drive cycle proved significantly enough and capable of producing drive cycles for predicting fuel and energy consumption within an expected range of $\pm 10\%$.

For future work, it can be suggested to validate the developed methodology with the battery-electric vehicle model to predict the energy consumption demands of BEV's. It can be recommended to work on the base cycle design methodology to further reduce the deviations in the model. Also, it is recommended to study the autocorrelation and power spectral density principles to further validate a better frequency coefficient in relation to the crest frequency of the real-world driving cycles for a more realistic gradient profile development.

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Appendices

Appendix A1: HDV Vehicle data

- **CVV R450 Truck vehicle data:**

Type	Tractor 4×2
Application	Long Haulage
Engine Model	DC13148
Engine	13L- 6 cyl.- 450HP- EU6
Gearbox	12 speed AMT, 11.32-1.00
Axle Gear	Single reduction axle,2.59
Wheels	315/70 R22.5
Average vehicle mass	26.79 tons
Lost maps certified	EU-2017-2400

- **P280 typical delivery truck vehicle data:**

Type	Rigid truck 4x2
Application	Delivery truck
Engine Model	DC09113
Engine	9 L- 6 cyl.-280HP-EU6
Gearbox	8 speed AMT,9.173-1.00
Axle Gear	Single reduction, 3.070
Wheels	315/80 R22.5
Average vehicle mass	25 tons
Lost maps certified	EU-2017-2400

Appendix A2: Comparison results of Generated cycles with VECTO cycles.

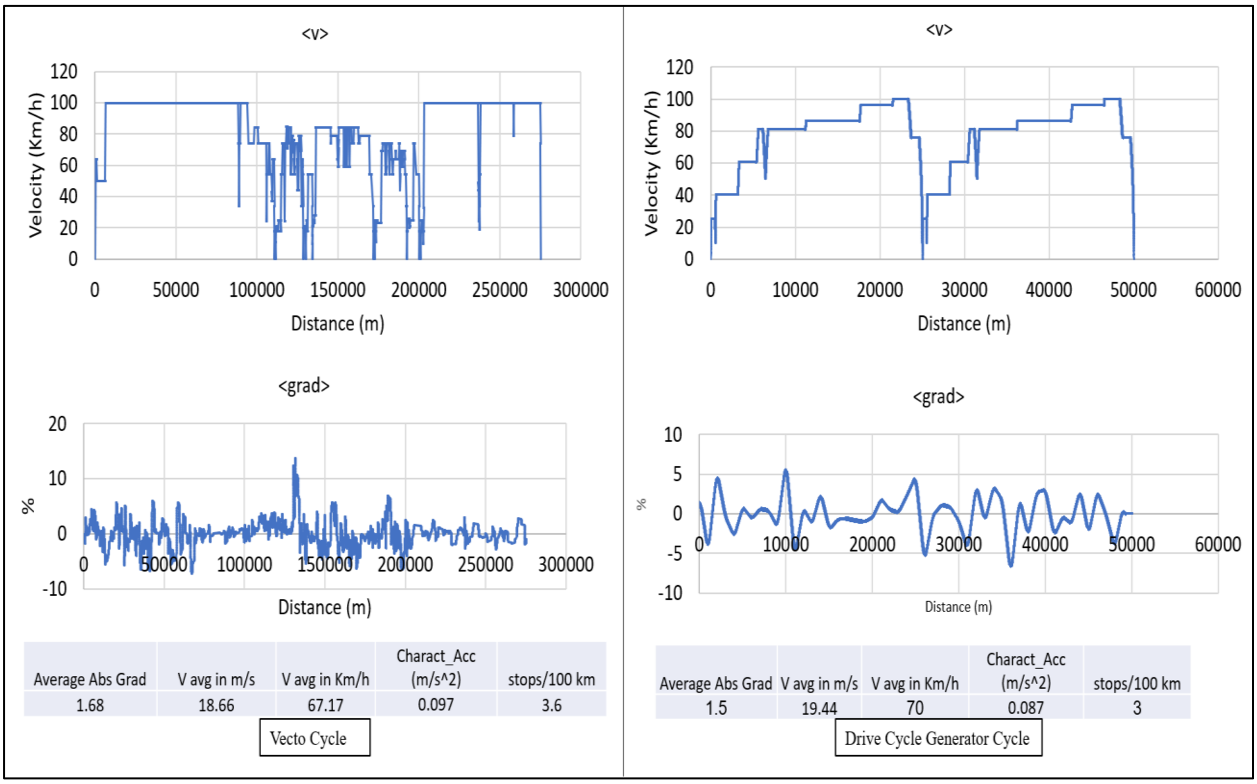

Figure A.1: Coach Bus VECTO V/s equivalent cycle

Table A.1: Coach Bus VECTO V/s equivalent cycle results

ZERO PAYLOAD	Vecto Cycle	Drive Cycle Generator
Average Velocity After Simulation	67.61	69.72
Fuel Consumption(L/100Km)	27.41	-11.60%
W_wh_positive(KWh/100 km)	95.02	-10.73%
W_wh_negative(KWh/100 km)	-18.78	-8.4%

HALF PAYLOAD	Vecto Cycle	Drive Cycle Generator
Average Velocity After Simulation	66.38	69.22
Fuel Consumption(L/100Km)	35.94	-10.4%
W_wh_positive(KWh/100 km)	131.98	-9.06%
W_wh_negative(KWh/100 km)	-40.28	-7.59%

	Vecto Cycle	Drive Cycle Generator
Average Velocity After Simulation	64.31	68.03
Fuel Consumption(L/100Km)	44.82	-9.48%
W_wh_positive(KWh/100 km)	168.66	-8.57%
W_wh_negative(KWh/100 km)	-61.98	-7.82%

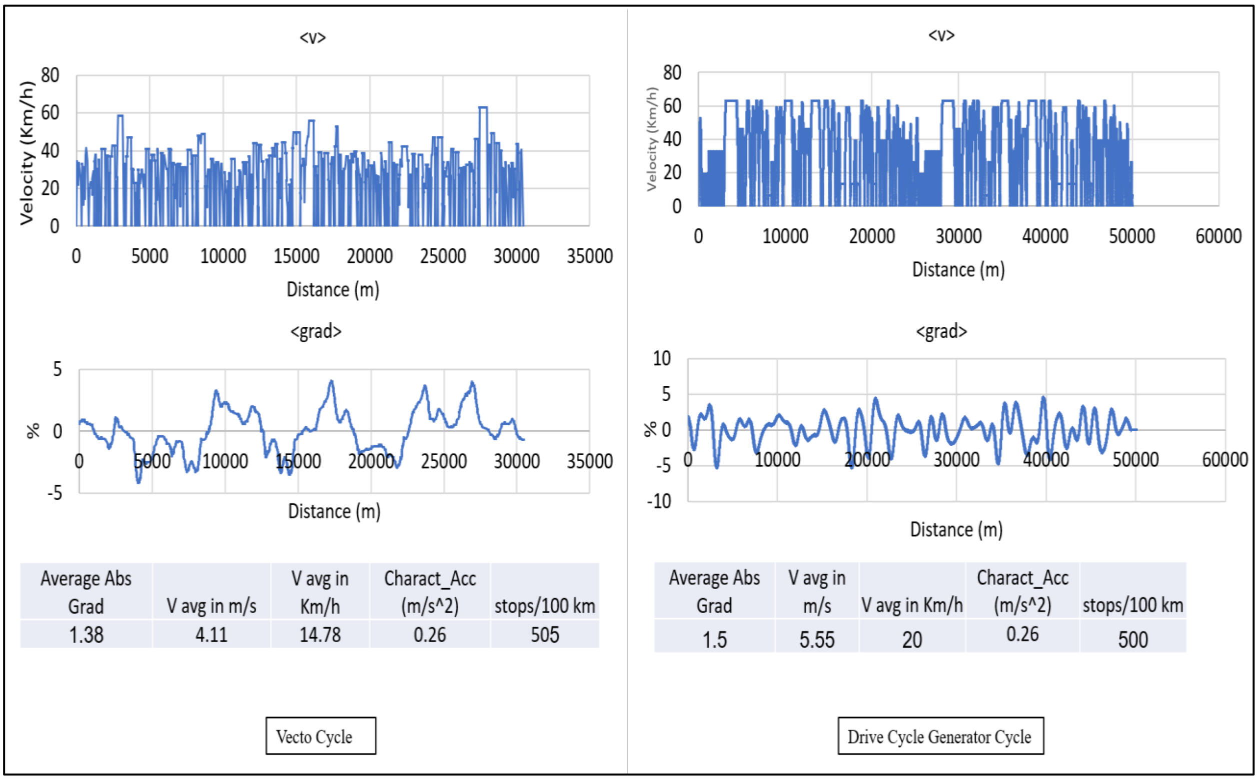

Figure A.2: Bus heavy Urban VECTO V/s equivalent cycle.

Table A.2: Bus heavy Urban VECTO V/s equivalent cycle results.

ZERO PAYLOAD	Vecto Cycle	Drive Cycle Generator
Average Velocity After Simulation	21.43	18.90
Fuel Consumption(L/100Km)	54.48	-11.06%
W_wh_positive(KWh/100 km)	129.34	+2.64%
W_wh_negative(KWh/100 km)	-106.93	-3.44%
HALF PAYLOAD	**Vecto Cycle**	**Drive Cycle Generator**
Average Velocity After Simulation	21.09	18.65
Fuel Consumption(L/100Km)	78.50	-9.7%
W_wh_positive(KWh/100 km)	224.127	-1.7%
W_wh_negative(KWh/100 km)	-189.34	-6.76%
FULL PAYLOAD	**Vecto Cycle**	**Drive Cycle Generator**
Average Velocity After Simulation	20.47	18.21
Fuel Consumption(L/100Km)	101.57	-11.56%
W_wh_positive(KWh/100 km)	313.31	-6.16%
W_wh_negative(KWh/100 km)	-265.46	-11.33%

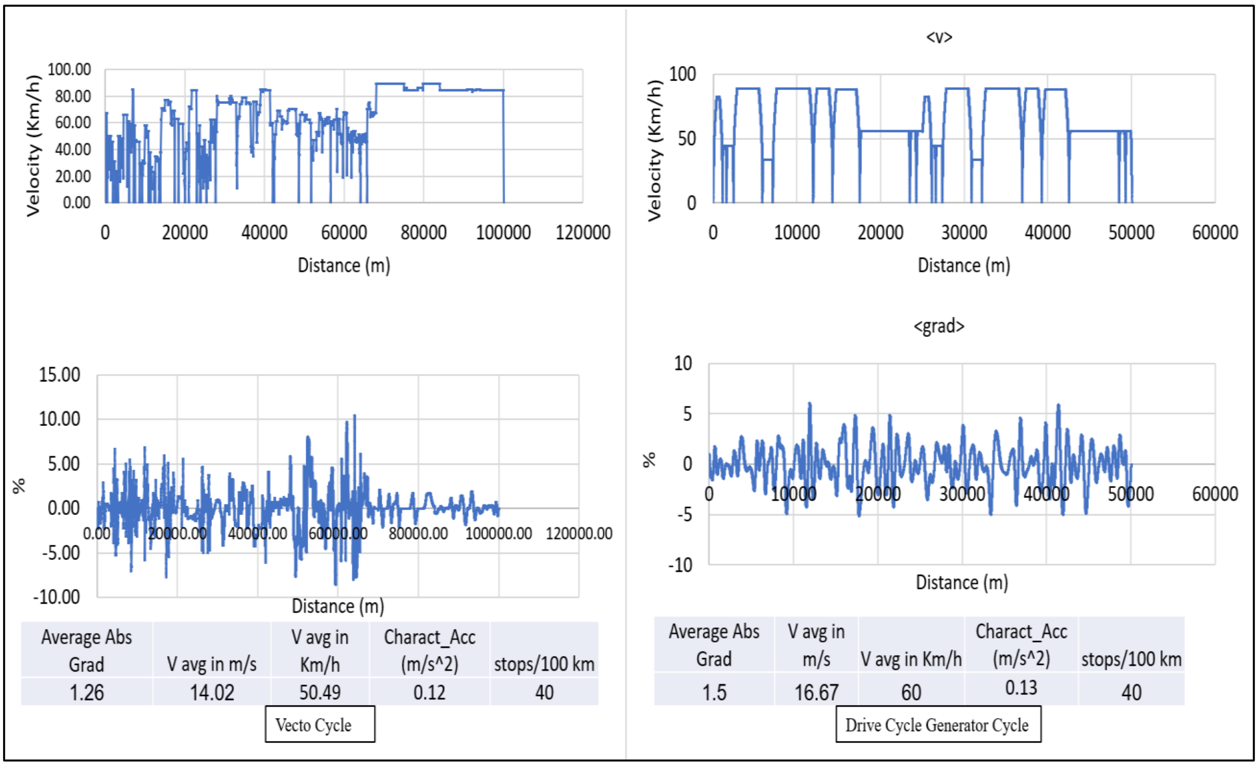

Figure A.3: Truck Construction VECTO V/s equivalent cycle

Table A.3: Truck Construction VECTO V/s equivalent cycle results.

ZERO PAYLOAD	Vecto Cycle	Drive Cycle Generator
Average Velocity After Simulation	53.37	57.39
Fuel Consumption(L/100Km)	28.90	-3.77%
W_wh_positive(KWh/100 km)	94.71	+1.33%
W_wh_negative(KWh/100 km)	-39.61	-2.70%
Characteristic_acceleration	0.12	0.13
HALF PAYLOAD	**Vecto Cycle**	**Drive Cycle Generator**
Average Velocity After Simulation	52.49	55.92
Fuel Consumption(L/100Km)	40.54	-2.86%
W_wh_positive(KWh/100 km)	143.76	+1.33%
W_wh_negative(KWh/100 km)	-72.49	+2.06%
FULL PAYLOAD	**Vecto Cycle**	**Drive Cycle Generator**
Average Velocity After Simulation	51.31	54.17
Fuel Consumption(L/100Km)	51.72	-2.49%
W_wh_positive(KWh/100 km)	189.64	+0.65%
W_wh_negative(KWh/100 km)	-102.43	+2.79%

Appendix A3: Comparison results of Generated cycles with Operational Data.

Table A.4: Urban Delivery operational data v/s equivalent cycle result.

	Operational Data	Drive Cycle Generator
Average Velocity (Km/h)	53	60
Fuel Consumption(L/100Km)	27	-4.5%
Stops/100km	38	40
Total Mass(Kg)	15000	15000
Average Absolute Gradient(%)	**1.67**	**1.67**

	Operational Data	Drive Cycle Generator
Average Velocity (Km/h)	41	50
Fuel Consumption(L/100Km)	30	+3.32%
Stops/100km	82	80
Total Mass(Kg)	15000	15000
Average Absolute Gradient(%)	2.05	2.05

Table A.5: Long Haulage operational data v/s equivalent cycle result.

	Operational Data	Drive Cycle Generator
Average Velocity (Km/h)	70	70
Fuel Consumption(L/100Km)	31	-4.7%
Stops/100km	20	20
Total Mass(Kg)	30000	30000
Average Absolute Gradient(%)	**0.79**	**0.79**

	Operational Data	Drive Cycle Generator
Average Velocity (Km/h)	69	70
Fuel Consumption(L/100Km)	31	-3.35%
Stops/100km	8	10
Total Mass(Kg)	29000	29000
Average Absolute Gradient(%)	**1.71**	**1.71**