ECO-DRIVING APPLICATIONS TO FREIGHT TRAINS

by

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SUMMARY

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The South African rail industry is seeking a critical measure to save energy and monitor its usage in the freight rail sector. The rail industry is experiencing increasing operational costs and is recording high energy-consuming driving along various coal lines. Eco-driving emphasises safety and fuel efficiency and is a modern and efficient driving strategy. This study provides an algorithm to find the eco-driving optimal velocity trajectory for a freight train that is hauling a load over a specific distance. The Freight Eco-Driving Energy Optimiser (FEDEO) is an algorithm that optimises the energy usage of an electric train, specifically the 19E locomotive with CCR-9 wagons, on the Ermelo-Richards Bay coal line.

A mixed-integer non-linear programming (MINLP) algorithm for the FEDEO was developed for the study. This algorithm has been used in applications such as the General Electric and Freightmiser driver advisory systems. The optimisation algorithm minimises the energy used by calculating the minimum tractive effort notch required over each interval gradient. The critical sections formulated are acceleration, cruising, coasting, and braking. The train layout consists of 8 locomotives and 200 wagons loaded with commodity goods. Route data of the section is presented as a case study, and energy efficiency is compared to the actual route simulation to illustrate the algorithm's effectiveness.

The study findings are that the FEDEO application can be used for any section of a freight line, provided the elevation and distance profiles are known. The simulation shows that the algorithm achieves significant cost savings and is achievable. The FEDEO application makes a useful research contribution in that its principles cover economic driving, prediction of the ideal trajectory, and the efficient use of the train momentum. The core objectives are to increase awareness within the freight section and provide an optimal profile for the train driver.

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LIST OF ABBREVIATIONS

19E	South African freight electric locomotive
AC	Alternating current
AI	Artificial intelligence
BE	Braking effort
CCR-9	Wagon type for 19E train consist simulation
CNES	Centre of New Energy Systems
CO	Coasting (vehicle)
CO2	Carbon dioxide
CR	Cruising (vehicle)
DAS	Driver advisory system
DC	Direct current
DP	Dynamic programming
EMF	Electromotive force
EU	European Union
EV	Electric vehicle
FEDEO	Freight eco-driving energy optimiser
GA	Genetic algorithm
GE	General Electric
GHG	Greenhouse gas
GPS	Global positioning system
Hp	Horsepower
ICE	Internal combustion engine
IoT	Internet of things
LP	Linear programming
MA	Maximum acceleration
MATLAB	Multi-paradigm programming language and numeric computing environment
MB	Maximum braking
MILP	Mixed-integer linear programming
MINLP	Mixed-integer non-linear programming
NLP	Non-linear programming
POET	Performance, operational, equipment and technology

PMP	Pontryagin’s maximum principle
QP	Quadratic programming
SQP	Sequential quadratic programming
TFR	Transnet Freight Rail
TTG	European transportation technology
UIC	International union of railways
USA	United States of America
VFD	Variable frequency drive
VSD	Variable speed drive

LIST OF SYMBOLS

A_{fr}	Locomotive frontal area, *(metres per second squared* $[m^2]$*)*
a_j	Train acceleration, *(metres per second squared* $[m^2]$*)*
C	Unit of ambient temperature, *(degrees Celsius [C])*
C_L	Drag coefficient, *(newtons [N])*
dt	Elapsed time, *(seconds [s])*
E_G	Total energy consumption, *(joules [J])*
F_{aero}	Aerodynamic resistance, *(newtons [N])*
F_j^b	Braking resistance, *(newtons [N])*
F_j^g	Gravitational resistance, *(newtons [N])*
F_j^r	Rolling + aerodynamic resistance, *(newtons [N])*
F_j^t	Locomotive traction force at the wheels, *(newtons [N])*
F_t	Locomotive/Train tractive effort, *(newtons [N])*
F_t/dB	Drawbar tractive effort, *(newtons [N])*
g	Unit of measure of gravitational constant, *(metres per second squared* $[m^2]$*)*
g/CO_2	Unit of emissions, *(grams per carbon dioxide)*
GW	Unit of measure of power (equivalent to 1 million kW), *(giga-watt)*
h_t	Height at the specific distance, *(metres [m])*
j	Counter of sampling intervals
J	Objective function for energy usage, *(joules [J])*
K_f	Torque reduction factor
kg	Unit of measure of mass, *(kilogram)*
kJ	Unit of measure of derived energy use, *(kilo-joule)*
km	Unit of measure of distance (equivalent to 1000 metres), *(kilometres)*
km/h	Unit of measure of speed, *(kilometres/hour)*
km/s	Unit of measure of speed, *(kilometres/second)*
km/s^2	Unit of measure of acceleration, *(kilometres/second squared)*
kN	Unit of measure of force, *(kilo-newton)*
kW	Unit of measure of power, *(kilo-watt)*
kWh	Unit of measure of energy, *(kilo-watt hour)*
$kWh/tonne$	Unit of measure of energy, *(kilo-watt hour/tonne)*
L	Length of the section, *(metres [m])*

m	Unit of measure of distance, *(metres)*
m/s	Unit of measure of speed, *(metres/second)*
m/s^2	Unit of measure of acceleration, *(metres per second squared* $[m^2]$*)*
N	Number of sampling intervals
N	Unit of measure of force, *(newtons [N])*
N/kN	Unit of measure of relative force, *(newton/kilo-newton* $[N/kN]$*)*
p	Air density, (kg/m^2)
P_{max}	Maximum power, *kilowatts [kW]*
P_R	Total power requirement, *(kilowatts [kW])*
R_a	Rolling resistance component independent of train speed
R_b	Coefficient used to define train resistance dependent on train speed
R_c	Streamlining coefficient used to determine train resistance
Re	Train resistance, *(newtons [N])*
θ	Angle of the slope, *(degrees)*
TE_{max}	Maximum tractive effort, *(kilo-newton [kN])*
t_s	Sampling period for the route simulation, *(seconds [s])*
u_s	Adhesion limit of the wheel-rail surface
u_j^b	Braking effort notch, *(0 to 10)*
u_j^t	Tractive effort notch, *(0 to 10)*
V	Unit of measure of potential difference, *(volts [V])*
v_j	Train speed, *(metres per second [m/s])*
V_{max}	Maximum speed, *(metres per second [m/s])*
v_{wind}	(Head) wind speed, *(metres per second [m/s])*

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CHAPTER 1 INTRODUCTION

1.1 CHAPTER OVERVIEW

This chapter introduces the study. Section 1.2 presents the problem statement, which details the context of the problem dealt with in the study: the implementation of eco-driving in rail transportation in South Africa. The gap in research regarding this problem is discussed and the solution investigated in this study introduced. Section 1.3 identifies the research objectives and questions. Section 1.4 outlines the first principle modelling approach to the study. Section 1.5 presents the research goals and Section 1.6 outlines the research contribution. Section 1.7 lists the research outputs. Section 1.8 mentions the research limitations for this study. The chapter ends by providing a summary of each chapter of the thesis in Section 1.9.

1.2 PROBLEM STATEMENT

1.2.1 Context of the problem

The South African freight industry requires a measure to optimise energy usage on freight locomotives. A high percentage of operational cost is attributed to power usage on the coal and iron ore lines. Operational changes to reduce cost aim to achieve a cost reduction to haul tonnages of iron ore, coal and manganese, which means that efficiency monitoring of the locomotive fleet is essential. The potential risks brought about by inefficient driving behaviour include possible derailment, increased running times and operating costs, and significant fatigue damage owing to poor rolling stock maintenance and in-train forces increasing in magnitude [1]. The strategy to increase efficiency starts with the driver. This study introduces and develops a freight eco-driving energy optimiser (FEDEO) algorithm that is compared and simulated for a specific section of the route, which is the Ermelo-Richards Bay line. The aim is that the FEDEO algorithm is applicable for any electrical locomotive that is hauling a load where the distance and elevation are known [2].

The coal freight section feeds both the domestic and international export markets and consists of a range of line types, with the most prominent export line being between the section between Ermelo and Richards Bay. This line serves the coalfields located in Mpumulanga Province via the coal backbone feeder network. The line is electrified to 25 kV alternating current (AC) and supports 26 tonne/axle loading. The single-track section accommodates a maximum capacity of 200-wagon export trains (16 per day) and is limited by power supply limitations. The average traction energy consumption is 263 million kWh per annum, while the regeneration energy is 89 million kWh.

The energy usage and emissions of the train depend on physical environmental factors such as weather, track condition, traction efficiency, and track stability. The driving style with continuous acceleration, braking, and speeding is the primary influence on energy consumption. Aggressive driving wastes a critical amount of energy. On a track with changing gradients, it is essential to anticipate the state of the train at intervals of the route profile to drive in an ecologically optimal manner. Traditional optimal control strategies use an acceleration-cruise-coast-brake strategy [3, 4, 5].

1.2.2 Research gap

Within the context described above the efficient driving of freight trains within the South African railway sector requires further research. Energy efficiency is a crucial aspect of rail transportation. Energy consumption within the rail network should be reduced by at least 2% per year to reduce the train journey's operational and environmental impact costs [1, 6, 7]. Around 80% of the energy from locomotive motion is used for traction, which is for powering the trains [1, 8]. Extensive research conducted in the past has focused mainly on the effects of energy-efficient optimal train control within a limited bandwidth. There are substantial forecasted savings for efficient train control in the range of 5–20% [8]. However, these savings do not apply to an entire rail network. This means that providing advice to the driver regarding the movement of the train under the route profile conditions can result in economical driving.

Along with driver behaviour, delays have been found to impact the overall energy efficiency factor. The control strategy used will affect the total output of the energy profile. Train idling is a factor that causes increased energy consumption as there is a delay when multiple trains traverse a single route. The energy required to move the train over a specific distance or section is the requirement originating from overcoming the resistances found in modelling the train. Operating long trains on the Ermelo-Richards Bay route is challenging when the train has steep changing gradients and constant speed limits. However, improving the energy profile of the train is critical to saving operational costs.

From the above, it is clear that the fundamental principles of eco-driving, including smooth driving, anticipation and prediction, efficient use of the train momentum, planning and optimising global driving style, require further study. This study develops and tests FEDEO with the key objectives of increasing awareness of eco-driving within the freight sector, embedding a culture of low-emission driving, and producing a minimal carbon footprint. The problem is that excessive energy is being consumed, which requires the formulation of a solution such as the FEDEO algorithm subject to dynamic route parameters. This study uses the FEDEO algorithm with the aim of bridging the gap in research on optimal driving of freight trains so that train personnel can have insight into and become aware of the social impact of energy-efficient driving [6, 9, 10].

1.2.3 A freight eco-driving energy optimiser

Eco-driving is a driving practice that focuses on economical, ecological and safe driving, and these factors ensure that rail transportation is an efficient mode of transport [11, 12]. This study focuses on the economical aspect of freight train energy usage by developing the FEDEO. The FEDEO algorithm aims to find the optimal eco-driving speed profile that uses minimal energy, such that the train driver can follow an optimal and guided profile. The main constraints in developing such a profile are the route profile, speed restrictions and the notches required at critical velocity regions [3]. The FEDEO solution consists of mixed control and state variable constraints that require a decision-making formulation regarding the tractive and braking effort notches.

The aim of the FEDEO algorithm is to build up acceleration on downward sections and cruise at the optimal velocity setpoint. The energy usage of the train depends on various physical factors such as track condition, weather, traction efficiency, and track stability. This study focuses on the energy optimisation of the velocity trajectory. Driving behaviours such as rapid acceleration, braking, and speeding waste considerable energy. On a track with varying slopes, it is required to drive in an economically optimal manner by anticipating the state of the train at fixed intervals of the route profile [13]. Traditional optimal methods use an acceleration-cruise-coast-brake energy optimisation strategy [14].

The FEDEO solution aims to use the lowest tractive energy possible, less stop-start driving and efficient driving. The principles of the FEDEO solution include economical driving, prediction of the ideal trajectory, and the efficient use of train momentum. The core objectives of the FEDEO are to increase awareness of eco-driving within the freight sector and provide a complete monitoring profile that the driver can use to traverse from one station to the next. Primarily, this study formulates the ideal trajectory of the train without any notch changes that would be similar to electric vehicles (EVs) with acceleration and braking [15].

Secondly, the eco-driving profile formulated from [15] is used to minimise the speed changes that the train experiences over a varying gradient. Lastly, Mixed-Integer Non-Linear Programming (MINLP) is used to solve the eco-driving problem using the MATLAB optimisation toolbox, Opti-Toolbox [11]. The train, consisting of eight 19E locomotives and 200 CCR-9 wagons, is a highly energy-consuming train. This study optimises the notch profile and simulates the optimal speed using real-time data [16].

This study incorporates several novel aspects, including:

1. The FEDEO algorithm only uses the route profile data: the elevation and distance, which can be generalised to any other routes
2. The FEDEO algorithm applies to any train or locomotive with wagons whose average, minimum and maximum speed, acceleration, train mass, time and resistance coefficients are known
3. The algorithm does not include any power-electronic related variables but focuses on driving behaviour. The tractive effort usage based on the varying notches is formulated and optimised
4. The FEDEO algorithm has an idealised trajectory using the approach in [15] and then uses a discretised approach using notches to reduce the section energy usage

The prediction of instantaneous energy usage under real-world situations is required. Previous studies have explored the relationship between the vehicle parameters and energy consumption, such as acceleration, velocity, auxiliary loads, and braking energy regeneration [17]. With eco-driving, the energy consumption can be decreased by an average of 9%, reducing travel time by 3% [18, 19, 20]. The two train movement regions where the FEDEO algorithm can be applied are the acceleration and braking regions [1]. For EVs, machine learning methods perform better when operated on complex direct real-world conditions owing to the fitness of the non-linear relationships, and the accuracy results can be significantly improved, based on iterative studies [21]. To predict the energy consumption of

EVs, two methods classified are data-driven and physical models [22, 23]. The inputs given as the driver's operation directly relate to the notch command for train motion.

Reference [22] proposed an energy consumption formulation that can be calibrated through a multi-level and typical least squares regression, based on the GPS information. For data-driven models, real-world driving conditions data in tandem with the weather, road, and traffic conditions can predict the energy consumption of EVs under complex direct conditions, based on machine-learning and statistical algorithms [24]. Many vehicles or route parameters need to be assumed (or obtained) to use the data-model-driven methods. Moreover, it becomes highly complex when the data is required for a large fleet of vehicles with many varying parameters. All the driving condition factors cannot be considered, which may affect the algorithm performance. However, methods under real-world conditions are still not common. The focus would rather be on the operation of freight trains, which falls under the specific FEDEO application that this study formulates and validates.

The FEDEO problem is based on driver behaviour, and the algorithm is based on an EV application developed in [15]. The FEDEO profile aims to reduce the traction energy usage and re-use the kinetic energy gained during de-acceleration for vehicle braking [6, 13]. Driving behaviour, however, is not the only solution for improving vehicle energy efficiency. The power electronics aboard the locomotive, such as the traction motors, braking resistors, inverter, rectifier, and alternator, contribute to the overall energy efficiency [25]. It can be concluded that the four main driving behaviour factors for a vehicle's energy usage are velocity, notch adjustments, acceleration and deceleration changes, and the magnitude of accelerations and decelerations related to the smoothness of driving [17].

Standard techniques used in optimal vehicle control have been utilised with detailed insight to solve the FEDEO problem. Train driving that requires a Driver Advisory System (DAS) has shown that the engines or motors prefer an average speed that is not majorly changing for measuring the overall energy consumption. Critical behaviours such as acceleration and deceleration are vital factors that cause a sudden increase in the train's energy consumption; therefore, aggressive driving should be avoided [26]. The two principal contexts for solving eco-driving problems are offline and online solutions. An offline solution assumes that all route profile position and characteristic dependent constraints are known; in contrast, an online solution uses real-time predictions and estimations, based on a train being in the environment. The FEDEO algorithm is an offline solution. The energy usage in the FEDEO of a train that consists of locomotives, wagons, and coaches is critical in considering energy efficiency, operational cost, and fleet reliability [18].

The topology data and the entire road profile are integrated into the hybrid electric power-train to offer a vast potential to optimise the control strategy, as noted in [27]. It is unclear whether the solutions in various papers obtain the optimal global solution. The noticeable exception is where the problem is convex, which guarantees that the globally optimal solution exists.

1.3 RESEARCH OBJECTIVE AND QUESTIONS

The objective of this study is to build an algorithm that will develop an electric locomotive's optimal energy control over a designated route, with the analysis of the study data using traction effort, train resistance, and dynamic forces as a feasible route profile solution. The algorithm design is intended for an electric train within the South African freight railway domain and as a valuable tool for visualising the route profile.

The study seeks to answer the following research questions concerning the FEDEO algorithm [4]:

- What is the magnitude of achieving improved energy savings with the FEDEO algorithm using the MINLP optimisation method?
- What is the influence of the FEDEO algorithm on reducing journey time?
- Does the FEDEO solution meet the problem of saving operational cost within the freight rail sector?
- Does the FEDEO algorithm obtain an energy-efficient solution that saves cost and optimises energy usage?
- Which algorithm is best suited for a train journey when the elevation, distance, and resistance coefficients are known, and driver decisions for notch control need to be considered?
- Has the eco-driving solution found the optimal velocity and is there speed-tracking control?
- Is the FEDEO algorithm applicable to any set of route data that provides the distance and relative elevation?
- Is there an improvement in overall efficiency and significant savings by applying FEDEO?
- Does the number of locomotives and wagons have an effect on the optimisation performance in the real-world?

- How does the FEDEO algorithm show superiority over other rule-based optimisation methods?

1.4 FIRST PRINCIPLE MODELLING APPROACH

A first principle modelling approach was used to develop the FEDEO algorithm. This approach formulates the train dynamics, as well as the changing gradients at fixed time intervals. The FEDEO approach for simulating the 19E train with CCR-9 wagons involves the following [4, 28]:

- Formulation of the longitudinal vehicle dynamics over a given trajectory and calculation of the power and energy required at fixed intervals
- Simulation of the behaviour of the train using train mass, tractive and braking effort curves, speed limits, and aerodynamic constants
- Computation of the optimal versus the actual energy usage (kWh) for the route profile
- Energy consumed during idling and in longitudinal movement
- Achievement of maximum vehicle efficiency through the continuous comparison with the optimal route profile
- Optimisation of the speed profile by reducing the tractive effort required for the journey, by using a suitable notch for the section of the route

In addition, the FEDEO speed profile shows the speed, power required, and any speed adjustments developed as the most efficient solution for train movement [29, 30, 31].

1.5 RESEARCH GOALS

The optimisation algorithm and methodology used in this study are quantitative, with the goal of investigating two areas of research: a case study of an electric vehicle with the algorithm applied to a freight train with a load.

The research goals are to:

- Assess the impact of the locomotive aerodynamics and the train's longitudinal dynamics on the overall energy consumption, performance, and power requirements of the train
- Provide an in-depth analysis of the effects of the eco-driving solution from an optimisation approach, assessing overall energy-saving potential, locomotive behaviour, and operational modes

- Validation of the eco-driving profile, cost optimisation and savings

1.6 RESEARCH CONTRIBUTION

The research will contribute by developing an eco-driving algorithm as an optimal energy-consumption algorithm for the South African freight rail network, with application to global solutions. The optimal functioning unit is the train, driver, and longitudinal dynamics and the impact on the overall energy usage of the route profile. The solution can be applied to any route, provided that the tractive effort is the sole contributor to the overall energy usage during the journey, and the distance and elevation are known. The results of this study will be used to identify possible energy savings and future rail applications, following the continuous-time formulation presented in [11].

There is a significant requirement to lower the energy usage on the sections which require commodity goods transport. The tractive effort needed to propel the train forward consumes a lot of energy, which needs to be quantified and simulated [1, 6]. The FEDEO algorithm optimises energy usage according to an optimal speed profile to determine the lowest cost for economic savings. In summary, the study will optimise freight train energy usage using a formulation technique that is usually applied to EVs [6, 9, 10]. The FEDEO algorithm has a number of factors that make it a useful contribution and a valid and widely applicable eco-driving algorithm. These are set out below.

The FEDEO algorithm represents six areas of knowledge about the system [14]:

- the initialisation of the FEDEO algorithm
- system architecture
- parameter values
- deterministic simulations
- algorithm response
- stochastic simulations

The deterministic simulations build the eco-driving profile while the stochastic simulations validate the energy consumption. Energy savings are validated by incorporating the algorithm from an EV application. The solution to obtaining the optimal route profile involves reducing energy consumption, improving driver behaviour, and maximising savings if the train journey is to be energy optimal. Several questions and validation criteria assess the feasibility of the algorithm. The FEDEO algorithm provides an in-depth analysis of the specific route profile and the savings resulting from applying the optimisation method [11].

The statements for validating the FEDEO algorithm optimisation criteria are:

- The FEDEO algorithm using longitudinal dynamics describes the actual behaviour of the train
- Parameter values that provide the optimal relation between theory and experiments are justified
- The vehicle dynamics represent the train movement
- The magnitude of the energy savings is justified when the FEDEO solution is applied
- The eco-driving solution has an influence on the overall energy efficiency
- There is a considerable effect of optimal energy-efficient train control on operational savings
- Mixing optimisation strategies on the same network affects the energy consumption
- Power, force and energy formulations for electric trains are described

The formulation methodology for the FEDEO solution consists of [5, 32]:

- Formulating a time series to profile the energy consumption over a specified distance using fixed time intervals
- Validating the FEDEO solution for train control
- Calculating overall energy efficiency for the train
- Designing the system architecture of the FEDEO algorithm
- Formulating train dynamics

Validating the accuracy of the FEDEO algorithm will take into account the following [33]:

- Energy consumption measured for the actual and optimal route profile in kWh
- Potential savings in rand
- Eco-driving speed-tracking control using decisions for traction and braking as optimal control
- Simulation of the outputs using the given inputs of the route profile

The applicable range of the FEDEO algorithm includes [34]:

- The electric class of trains required for the purposes of shunting and freight transport
- The energy required for the delivery of commodities such as coal, minerals, and goods for identifying the energy-management strategies within the freight rail sector
- Investigation of the various technical and economic conditions associated with the eco-driving solution for train movement

Recommendations for where and how the FEDEO algorithm can be applied [34, 35] are:

- The algorithm can be tested and formulated against an EV energy-optimisation algorithm
- It can be used as a driver advisory tool for real-time display and advice on how to use the FEDEO algorithm
- The FEDEO algorithm can be used for optimising the traditional energy-efficient train-control methods
- It can be used in eco-driving for freight trains as an energy-efficient solution using parameters such as route gradient, speed limits, and load demand

1.7 RESEARCH OUTPUTS

N. George, X. Ye, and L. Zhang. "Eco-driving strategy optimisation for freight trains", *Energy* journal, 2022.

1.8 RESEARCH LIMITATIONS

The research has certain limitations in terms of the scope of the study and the availability of data within the freight rail sector. The research scope was limited by the lack of sufficient route data which meant that only a single section of the route profile could be analysed as the elevation and distance profiles were considered critical to the velocity trajectory. In terms of the availability of data, research papers and knowledge about eco-driving for trains within the South African railway domain are limited . It has limited the research due to lack of previous studies, minimal record of data collection implementation methods and the scope of discussions being compromised due to a limited research database. The final limitation is a lack of data with regard to the regeneration energy that is produced from the 19E locomotive fleet. This data could significantly contribute to the cost factor and savings recommended in this study in terms of net energy consumption.

1.9 OVERVIEW OF STUDY

Chapter 1 provides the context of the study and outlines the research problem. It presents the research objective, questions and goals and describes the research contribution.

In Chapter 2, a literature review is provided on the topics of eco-driving applications, tractive and braking effort, and force profiling.

Chapter 3 discusses the methods behind the FEDEO algorithm as the primary research of this study.

In Chapter 4, the algorithm for simulating the FEDEO algorithm is explained in detail.

Chapter 5 presents the simulation results as applied to the case study of the Ermelo-Richards Bay coal line section with analysis, and the core observations are provided and described.

Chapter 6 discusses the results obtained from the simulation of the FEDEO algorithm required for energy optimisation.

In Chapter 7, final concluding remarks are made on the formation of the FEDEO solution from a cost and energy savings perspective, and recommendations are made for the validation of energy savings in eco-driving and for further research.

CHAPTER 2 LITERATURE STUDY

2.1 CHAPTER OVERVIEW

This chapter presents a review of the literature related to the eco-driving solution. Section 2.2 provides the objectives of the chapter. Section 2.3 outlines and describes the eco-driving applications globally, and presents a review of relevant research. Section 2.4 formulates the energy consumption from a performance, operational, equipment, and technology (POET) perspective. In Section 2.5, the tractive and braking effort utilisation or application is described. Section 2.6 outlines the force dynamics of the train, including the various resistance forces, driving strategies, model fitting, parameter estimation, and power electronics on board. Section 2.7 discusses optimisation strategies. Existing freight rail energy optimisation systems such as the Freightmiser and the GE trip optimiser are described in Section 2.8. Section 2.9 summarises the literature study.

2.2 CHAPTER OBJECTIVES

This chapter aims to elaborate on the research method for formulating the eco-driving solution. The first objective is to present the concepts required for the FEDEO formulation, to provide the research with information on eco-driving principles. The second objective is to identify the POET factors that play a critical role in the formulation of the solution, as these factors impact the concept to be implemented. The third objective is to present the raw data for the specific route section to be optimised, as this data can be compared to the simulated profiles for an economical comparison. The final objective is to highlight global eco-driving solutions that contribute to the study.

The algorithm developed has the aim of increasing overall fleet efficiency by [36, 37]:

- Lowering train energy consumption
- Optimising the speed trajectory of the 19E locomotive

- Enabling more coasting and cruising and less rapid acceleration and braking
- Reducing tractive effort, especially at higher speeds

2.3 ECO-DRIVING APPLICATIONS

Many scholars have investigated and studied the eco-driving strategy of trains. Solutions provided by literature use analytical methods that formalise the train dynamic properties. Pontryagin's maximum principle (PMP) is a collection of conditions that must be satisfied by solutions of a class of optimisation problems. This method involves dynamic constraints called optimal control problems. PMP was used in one study to analyse energy-efficient control regimes, which included maximum acceleration, cruising, coasting, and maximum braking [38]. In [39], Asnis *et al.* took regenerative braking and adjusted the objective function by applying PMP. Howlett [40] considered both the continuous and discrete control problem. In the eco-driving solution of the continuous algorithm, PMP was applied to find the necessary conditions on an optimal strategy to determine the optimal switching points. Kuhn-Tucker equations were used to find the optimal switching points in the eco-driving speed-tracking control case. This led to the conclusion that driving strategies obtained from the discrete control model could be used to approximate closely those found by the continuous formulation. Policymakers have used these theories to justify electric vehicles as a tool for reducing greenhouse gas (GHG) emissions.

In countries such as China and the United States of America (USA), coal-fired plants contribute critically to electricity generation, making the environmental impact of EVs higher than that of internal combustion engines (ICEs). There has been a 3% electricity usage growth rate over the last 20 years in South Africa, with 20 GW of additional generation capacity required by 2020 and up to 40 GW by 2030 [41]. Globally, the rail environment's key target should be to transition to a lower-carbon economy, and the concern in South Africa is that electricity prices are increasing while being wholly reliant on Eskom (South Africa's primary electricity supplier, generating approximately 90% of the electricity used in South Africa and approximately 30% of the electricity generated on the African continent) for the provision of baseload electricity to power operations [42]. South Africa's freight rail energy policy commitments include improving energy efficiency, proactively managing and monitoring energy usage, reducing global GHG emissions and energy constants, and improving energy security [42, 43]. The current and future energy management initiatives include train driver training to reduce energy consumption, improving energy efficiency, reducing locomotive idling, and optimising the setup of trains. The rail organisation known as Transnet Freight Rail (TFR) has the most significant energy gains as new locomotive technology is introduced into operations, specifically from regenerative braking capability on the 19E and 15E class of locomotives on the coal and iron ore export lines.

The new technology on these lines has resulted in significant efficiency gains, with the regenerated electricity used partly by the fleet of locomotives and, where possible, transmitted back into the Eskom grid [44]. South Africa has seen studies that address and formulate algorithms related to EVs' eco-driving and contribute to a greener future [6, 41]. One study includes improving route profile operational characteristics that involve changes to the train-driving behaviour, including lowering energy usage by methods such as eco-driving [45]. For EVs, an analytical state-constrained control is implemented for eco-driving control in [46, 47]. In [48], the global optimal eco-driving of EVs is solved through sequential quadratic programming (SQP) [49].

Eco-driving techniques are employed for energy saving DASs, which mainly define energy consumption as a cost function to be minimised, allowing a more considerable speed control than those commonly found in EVs. Other methods are capable of solving the problem, such as the PMP, Dynamic Programming (DP) and analytical solutions [21]. The advantages are that the PMP method will find the best possible control for taking a dynamic system from one state to another. It is computationally efficient in that the natural conditions specify a need to hold over a particular trajectory. The disadvantage of the PMP is that incorporating state constraints is not a simple task and provides the required conditions for optimality. The DP algorithm has been used to find a globally optimal solution to the end problem in [50].

DP solves a discretised version of the operational control problem. It does this by assigning independent variables to time, distance, and position, thus discretising state and control spaces. The Hamiltonian analysis in [3] shows that only particular types of control variables can be used in an optimal strategy. The choice of control is determined by the speed and the quantity of the adjoint variables such as gradient and position. The DP method has a high computational time and creates a reference trajectory for the vehicle's driver. In contrast, a few methods have attempted to derive and use closed-form speed trajectories, which provide a real-time route profile based on the behaviour of the train at each interval or time-stamp [46].

By developing the FEDEO algorithm, this study aims to provide the South African rail industry with a method for creating and identifying energy-saving route profiles for track sections [6]. For minimal energy losses during eco-driving, the driver needs to anticipate the route profile with an understanding of the traction dynamics of the train, which is challenging to attain owing to the additional training required [51]. The ideal option is to assist the driver through technology such as the DAS. The FEDEO algorithm will simulate the longitudinal movement of the train using the dynamic equations of motion [52, 53]. A locomotive requires tractive effort for propulsion and braking effort for slowing down. A large amount of power is necessary for propulsion, and the braking element outputs regeneration energy. This is the energy from the locomotive wheels to the overhead catenary that trailing locomotives can use. The FEDEO problem will search for the local minimum of the speed profile as the critical point [54].

FEDEO will formulate the dynamic parameters that will contribute to the train's operational savings over any route profile [32]. The FEDEO solution for the train-handling strategy consists of static and dynamic parameters where the static is the input (primary) data in the formulation. Route static parameters, in this case, would include the trip distance, speed restrictions, freight train parameters (force limits, adhesion curves), and gradient profile. The decision variables consist of acceleration (or tractive effort), train deceleration (or braking effort), and the speed profile from point A to B [2]. The principles that the FEDEO governs mainly include acceleration, speeding, deceleration, route choice, idling, external factors, and stopping [8]. The eco-driving principle outlined by the FEDEO narrows down to the driving behaviours or the control a driver has over a vehicle. The FEDEO uses eco-driving principles to minimise energy usage by obtaining the optimal speed v_j^* and optimising the engine's notches.

2.4 FORMULATING ENERGY CONSUMPTION IN TRAINS USING THE POET CONCEPT

The transport sector uses an estimated 27% of the total energy required in the country, with 2% of the requirement for electric trains [34, 42]. The increasing diesel price or fuel cost causes a more favourable balance towards electric trains powered by overhead catenary lines. The investment in the grid power supply depends on the future cost of electrical power and its evolution with time. The electrification of the railways requires considerable investment as it spans miles of area and has to support the vast network traffic flow. Electrification of the railways is, therefore, a clain that requires justification. The increased train speeds and freight transported elevate the power capacity, influencing productivity and capacity gains.

Typically, 85% of the railway's energy consumption is used for traction and depends on driving behaviour, especially on the heavy-haul freight lines [1, 33, 35, 37]. There have been numerous research attempts and innovative measures to reduce energy consumption within the railway network worldwide. Well-defined train-handling techniques make significant improvements in the railways' energy efficiency possible, and improved capacity utilisation of the railway stock used by the industry would reduce railway costs. The eco-driving algorithm developed is broken up into stages, where the tractive effort greater than zero is defined as a propulsion or power segment or a coasting phase of the train resistance [52].

The major areas for improving energy efficiency are performance, operational, equipment, and technology (POET) efficiency factors [4, 55, 56, 57]:

- *Performance efficiency*: This is established using an energy-efficiency calculation computed from route profile dynamics such as power requirements, vehicle dynamics, energy usage cost, and train modelling parameters. It is expressed in units such as kg, kWh, m/s, m/s^2, $kWh/tonne$ and km
- *Operational efficiency*: For this study, operational efficiency would involve a proper integration of the system architecture sections by considering the core layers required for the FEDEO algorithm. The physical layer considers the size and complexity of data inputs; time and control consider notch selection and critical speed control to improve energy efficiency and optimise train movement
- *Equipment efficiency*: For this study, this is a parameter that describes the formulation of energy usage, traction efficiency, and driver advice systems. The success factors include driving efficiency, regeneration capability, and energy performance
- *Technology efficiency*: A parameter describing the formulation of energy usage, traction efficiency and driver advice systems. The laws include driving efficiency, regeneration capability and energy performance

2.5 TRACTIVE AND BRAKING EFFORT

The limiting of the tractive effort of an electric locomotive is caused by critical system constraints. The following factors affect the electric locomotive traction system limits [1]:

- Power limiting
- Current limiting (thermal degradation) on electrical equipment

- Commutation/voltage limiting on the older AC locomotives caused by the maximum generator voltage complemented by increased electromotive force (EMF) as speed increases
- Consumed energy during the travel in *(kWh)* unit
- Total weight of the train by computation of the entire brake force in *(kWh)* unit
- The resistance of the train in *(N/kN)* units
- The distance recordings with constant speed intervals in kilometre *(km)* units

The energy formulation uses the electric locomotive's tractive and braking effort curves in question. The analysis and simulation can derive a piecewise function for the electric locomotive's effort curves. The traction control, known as a throttle notch, sets a current position for energy and speed modelling. Typically, the notch variations are not the same for electric and diesel-electric locomotives, and the topology of the control system is different. Diesel-electric trains usually have eight notches or throttle adjustments, while electric locomotives can have ten notches. The speed causes the effort to vary. The raw tractive and braking effort simulated curves of the 19E from notches 1 to 10 are shown in Figures 2.1 and 2.2.

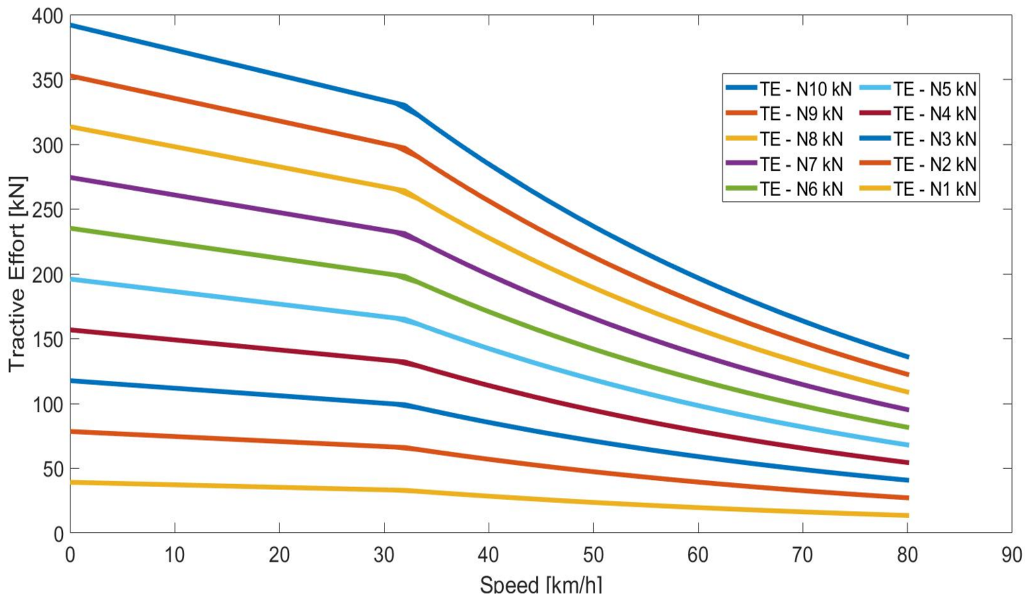

Figure 2.1. Notches of 19E tractive effort

The tractive and braking effort is controllable by the driver. When multiplied by the speed at which the train is required to run, tractive effort provides the Horsepower (Hp). The importance of the tractive effort lies in its ability to haul the train up various gradients. The tractive power limits the system bounds at higher locomotive speeds, with a lower tractive effort required at higher velocities according to the force-velocity product $P = Fv$. As the control is a current reference signal, the power curve increases by the throttle notch as the tractive effort increases [32, 58].

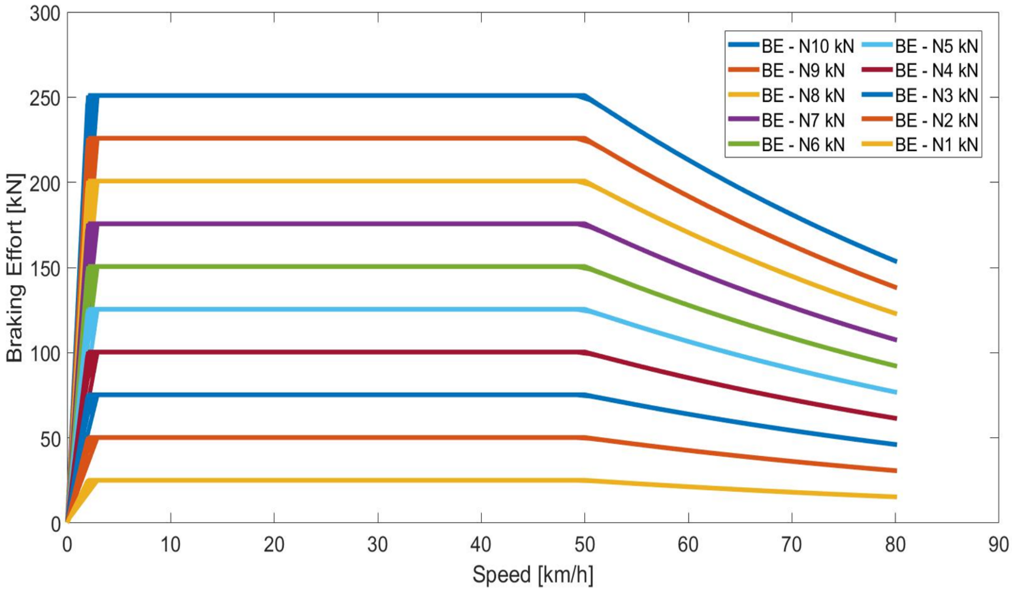

Figure 2.2. Notches of 19E braking effort

A key parameter in any discussion is the wheel adhesion, resistance coefficients, and vehicle performance. When referring to the locomotive tractive effort, modelling the tractive effort curves uses the equations presented by [32], which parameterises the torque reduction factor. In the case of the 19E locomotive with CCR-9 wagons, the power electronics topology is responsible for the maximum and minimum power required for the train's movement over a changing gradient [1, 32]. It should be noted that the resistance curve of the locomotive is included in these tractive effort curves as the testing results validate the curves. During these tests, the basic measurement technique for the tractive effort is to measure the coupler force of the locomotive. Thus, all locomotive-specific resistance forces have already been subtracted from the tractive effort to produce the coupler pull force [1]. It is not necessary to include the coupler force in the FEDEO algorithm [32]. Equation (2.1) gives the relationship between the locomotive mass, and frictional and gravitational resistance.

$$F_{t,\,max} = u_s \times m_{loco} \times g. \tag{2.1}$$

where $F_{t,max}$ is the maximum tractive effort force possible under the wheel-rail condition measured in N, u_s is the adhesion limit of the wheel-rail surface, m_{loco} is the mass of the locomotive in kg and g is the gravitational constant ($9.81m/s^2$). Under ideal conditions and with the best tractive control algorithms, the adhesion can be as high as 0.46 or 46%. Under some adverse rainy and snowy conditions, this can drop down to 0.1 or 10%. More realistic values would be 0.2-0.33 for older DC locomotives and 0.35-0.4 for newer AC locomotives [32]. The braking force is dependent on two factors, which are [1, 32]:

1. Adhesion between the wheel and the rail
2. Reaction force of the rail on the wheels during braking, and the weight factor

2.6 FORCE PROFILING

The understanding and measurement of the train resistance is a critical aspect of demonstrating energy and performance. A "pulling force" is defined for all locomotives. The speed and gradients, and load that a train can pull are determined by the tractive effort of the "pulling power" and the total resistance that the train needs to overcome to move forward. Resistances are classified as inherent and incidental. Inherent resistances apply to all the various kinds of train operations and are typically divided on tangential track. In contrast, incidental resistances occur mainly on grades, during acceleration, on curves, and in opposing winds [58]. The formula that depicts the overall vehicle force in relation to the acceleration is Newtons 2$^{\text{nd}}$ law [32, 52].

$$\sum_{j=1}^{N} F_j = ma_j = F_j^t - F_j^g - F_j^b - F_j^r. \tag{2.2}$$

In the train movement situation, the train experiences an acceleration a j with total force Fj applied in the horizontal and vertical directions. The equation governing the relationship between the train motion and driving resistances from Newton's 2^{nd} law is as follows [59]:

$$ma_j = F_j^t - (F_j^g + F_j^b + F_j^r) = F_j^t - F_j^g - F_j^b - F_j^r, \tag{2.3}$$

where:

- a_j = Train acceleration *(N)*
- F_j^t = Locomotive traction force at the wheels *(N)*
- F_j^g = Gravitational resistance *(N)*

- F_j^b = Braking resistance *(N)*
- F_j^r = Rolling + aerodynamic resistance *(N)*

The traction force at the locomotive wheel can minimise resistances to reaching the desired vehicle speed and acceleration. The driving resistance depends on the train speed, and the optimal velocity of the train must be described as the feasible solution. The resistance, in turn, affects the power requirements of the moving train and the eco-driving performance [59].

2.6.1 Aerodynamic resistance

In aerodynamic resistance, the air behind and in front of the train causes resistance to overall motion, and this resistance overcomes the total force calculation. The formula for the calculation of air resistance in train motion, according to [33, 59], is:

$$F_{aero} = 0.5 \times p \times C_L \times A_{fr}(v_j^* + v_{wind})^2, \tag{2.4}$$

where:

- F_{aero} = Total aerodynamic resistance *(N)*
- v_j^* = Train speed (*m/s*)
- v_{wind} = (Head) Wind speed *m/s*
- p = Air density *(kg/m^2)*
- C_L = Drag coefficient *(N)*
- A_{fr} = Locomotive frontal area *(m^2)*

2.6.2 Gravitational resistance

Gravitational resistance is obtained from the altitude profile, route gradients, and the mass of the train consist. Gravitational resistance is the movement of an object in a vacuum without any drag by being in free fall. At various points on the Earth's surface, the gravitational speed gain ranges from 9.764 m/s^2 to 9.834 m/s^2 depending on the latitude and altitude. A vehicle moving on a flat levelled track has a force factor perpendicular to the direction of gravity being zero. When the plane is inclined when the train moves downhill or uphill, a force component known as mgsin(θ) is developed parallel to the plane of the track. A braking force and additional identical component are found when the train goes against an upwards gradient [60]). The gradient resistance equation is [59]:

$$F_j^g = mg \times sin(\theta) = m \times g \times \frac{h_t}{L} \times 1000, \quad (2.5)$$

where:

- F_j^g = Total gravitational resistance *(N)*
- m = Total train mass (kg)
- g = Acceleration at the earth's surface due to gravity *(9.81m/s^2)*
- θ = Angle of the slope *(Degrees)*
- h_t = Height at the specific distance *(metres [m])*
- $\frac{\Delta h_t}{\Delta L}$ = Gradient of the route profile

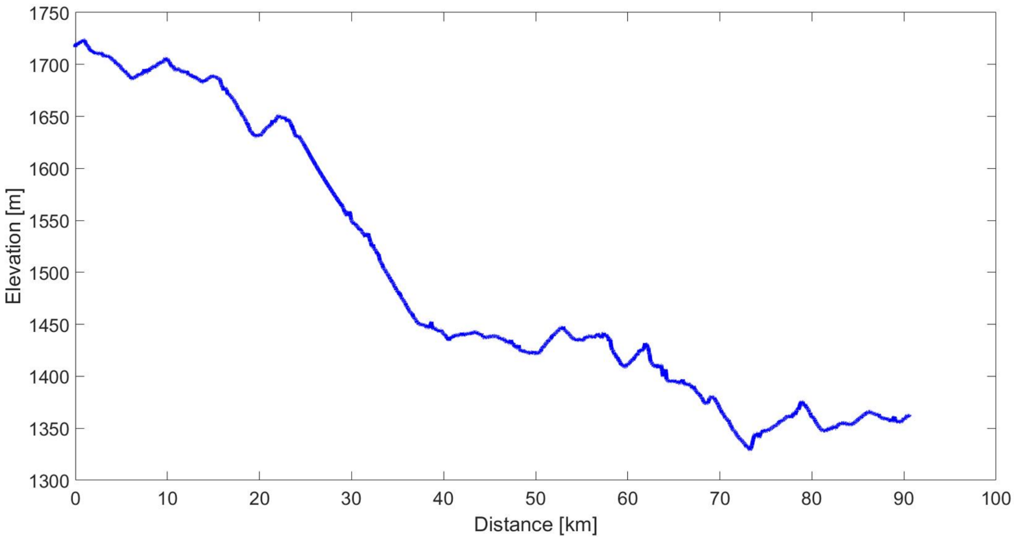

Figure 2.3. Graph of relative elevation profile section Ermelo-Richards Bay

The elevation profile of the Ermelo-Richards Bay simulated in the MATLAB route section is shown in Figure 2.3. This profile is used for the FEDEO algorithm simulation in this study. Grades are derived from section and track data plans. The gradient of the entire train is critical for analysing the energy profile against time. The steepest grades are typically 1 in 40 on most railways, meaning the line would rise every 40 m. On main lines, grades are generally 1% or less, and grades steeper than 2.2% are quite rare. For ascending grades, the resistance required for the movement of the train increases with grade variation. The route gradient would typically be in the range of -3 to 3, and any values outside this range are the result of inaccuracies in the recording of the GPS data or calibration errors. A 1 in 20 grade gives an angle of $sin^{-1}(1/20)$ = 2.866°(or 5%) and is therefore 0.05. The route used in the simulation consists of a fairly typical route profile that results in a gradient, as seen in Figure 2.4 [32, 34, 52]. The gradient profile of the Ermelo-Richards Bay route section simulated in MATLAB is shown in Figure 2.4, which is used for the FEDEO algorithm in this study.

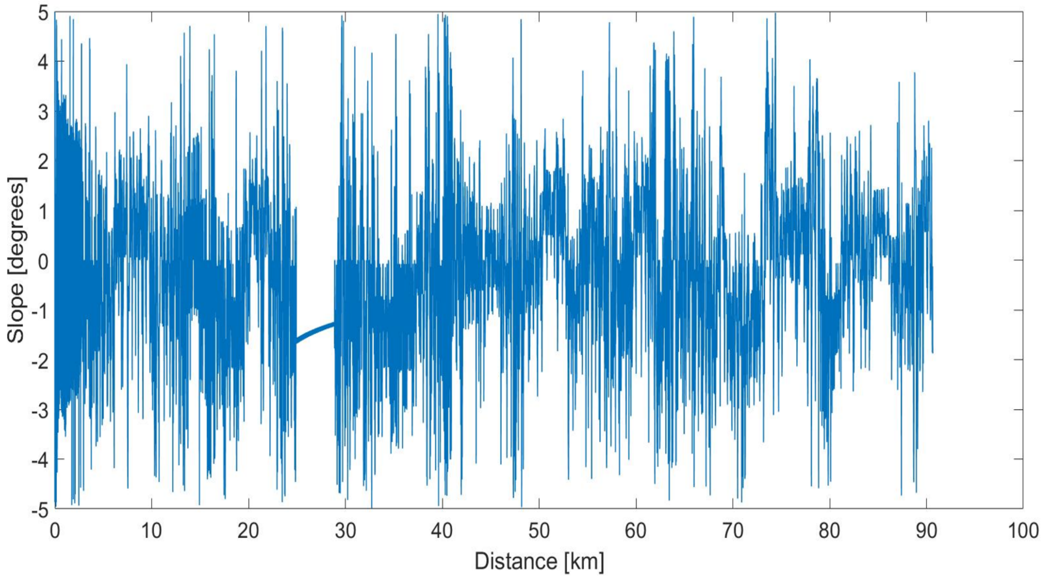

Figure 2.4. Gradient slope of section Ermelo-Richards Bay

2.6.3 Rolling resistance

Rolling resistance is the sum of the mechanical forces experienced by the locomotive (exclusive of braking and windage) that acts to obstruct the train's motion travelling in a forward direction at a constant speed on a flat track under controlled operational circumstances. Normal rolling resistance is caused by friction in the bearings, sliding within the wheel-rail interface, suspension-system energy losses, and hysteresis in the soil beneath the tracks. Different wheel radii on identical axles, hunting, wheel lift, flanging, and parasitic energy dissipation in the draft gear caused by gradient changes and train handling/movement are the most effective forms of abnormal wheel resistance. The formula presented by [59] for the computation of locomotive abnormal and normal rolling resistance is [14, 59]:

$$F_{rr} = C_{RR} \times m_{total} \times g, \tag{2.6}$$

where:

- F_{rr} = Total track resistance *(N)*

- C_{RR} = Total resistance coefficient
- m_{total} = Train mass *(kg)* (Locomotives and Wagons)
- g = Acceleration due to gravity (m/s^2)

2.6.4 Train energy calculations based on time and power

Validating the energy consumption of the simulated algorithm by utilising the equations defined in (2.2) and (2.3), the total power P_R is [59]:

$$P_R = (F_j^t - F_j^g - F_j^b - F_j^r) \times v_j^*, \tag{2.7}$$

where:

- P_R = Train power requirement *Watts (W)*
- v_j^* = Speed of train (m/s)

Integrating the power needed for the trip time obtains the train energy consumption. The energy consumption equation gives [59]:

$$E_G = \int_0^T P_R \times dt, \tag{2.8}$$

where:

- E_G = Total energy consumption *joules (J)*
- P_R = Train power requirement (kW)
- dt = Elapsed time (s)

If P_R is constant, then the energy consumption becomes $E_G = P_R \times dt$.
The time intervals impact the sections at which the speed is reduced and when the energy consumption is the highest.

2.6.5 Davis formula

The Davis equation put forward by W.J. Davis in 1926 proposed an experimental formula for computing "Tractive Resistance of Electric Locomotives and Cars" moving on a flat track which is straight and level. The proposed values were as follows [32]:

$$A = 1.3 + 29/W, \tag{2.9}$$

$$CD = Ca/WN, \tag{2.10}$$

$$B = 0.03 \; for \; locomotives, \; 0.045 \; for \; wagons. \tag{2.11}$$

$$For \; vehicles \; with \; light \; axle \; weights, \; i.e. \; less \; than \; 5 \; tonnes, \; use \; A = 9.4/\sqrt{w} + 12.5/W. \tag{2.12}$$

Davis recommended the following values for the formula [32] as set out in Table 2.1:

Table 2.1. Davis resistance coefficients for freight vehicles

Where Used	B	C	α
Locomotives	0.03	0.0024	50 ton = 9.7548 m^2
		(0.0017 – Streamlined)	70 ton = 10.2193 m^2
			100+tons = 11.1484 m^2
Freight Cars	0.045	0.0005	7.8968 m^2 – 8.82579 m^2
Passenger Cars (Vestibulated)	0.03	0.00034	11.15164 m^2
Multiple Units – Leading	0.045	0.0024	9.2903 m^2 – 10.2193 m^2
Multiple Units – Training	0.045	0.00034	9.2903 m^2 – 10.2193 m^2
Motor Cars	0.09	0.0024	2 trucks: 7.432 – 9.290 m^2
			1 truck: 6.5032 – 6.9677 m^2

The Davis equation is then summarised in (2.13) to (2.15) for the vehicles such as wagons, locomotives and low-weight freight cars. Using Table 2.1, the equations summarised for aerodynamic resistance are:

Aerodynamic resistance for wagons using average weight:

$$R = 1.3 + \frac{29}{W} + 0.045 v_j^* + \frac{0.0005 \alpha v_j^{2,*}}{WN}. \tag{2.13}$$

Aerodynamic resistance for locomotives using normal weight:

$$R = 1.3 + \frac{29}{W} + 0.03 v_j^* + \frac{0.0024 \alpha v_j^{2,*}}{WN}. \tag{2.14}$$

Aerodynamic resistance for low-weight (axle weight < 5 tons (US)) freight cars:

$$R = \frac{9.4}{\sqrt{W}} + \frac{12.5}{W} + 0.045 v_j^* + \frac{0.0005 \alpha v_j^{2,*}}{WN}. \tag{2.15}$$

The Davis resistance equation can be summarised as [32]:

$$R = A + B v_j^* + C D v_j^{2,*}. \tag{2.16}$$

Axle weight in tonnes of 19E Locomotive = 26 tonnes.

Axle weight in tonnes of CCR-9 Wagon = 26.1375 tonnes.

2.6.6 Driving strategies

The driving strategy affects the impact of the forces on the overall energy usage. Energy efficiency and financial investment are two of the key determinants of energy-efficient driving. There are a variety of benefits to eco-friendly driving with and without regenerative braking, coasting and driving, while limiting the maximum speed of the train reduces the Carbon Dioxide (CO_2) emissions and energy consumption. The increase in energy consumption is a global alarm, and the European Union (EU) is dedicated to reducing its total emissions to at least below 15% by the year 2030 [5, 35].

Within the transport sector, measures to reduce energy consumption include modal change, improved infrastructure, and planning. Eco-driving improves the energy profile in freight trains by allowing for coasting and utilising braking regeneration that generates electricity by converting the train's kinetic energy back into electricity and returning it to the supply system to be used by other lagging trains or the local utility grid [7, 9, 35, 55, 61]. The research in [61] shows the results of route energy consumption and travel times over a specific route. The eco-driving solution proposed in this study improves the energy consumption at specified time intervals of the sections between Ermelo and Richards Bay [11].

Strategies for economically friendly driving involve the following conditions, which have been applied to the optimisation strategy for the required algorithm [35]:

- Limit the maximum speed of the route section
- Accelerate the peak speed, keep the maximum speed of the vehicle, and reduce speed by coasting before each of the stations and stops where the train is required to slow down
- Coast until a speed higher than that necessary to stop is reached
- Accelerate as much as possible, then perform coasting to lose some of the vehicle speed, and, after that, brake at maximum to slow down the train before reaching the station

2.6.6.1 Model fitting and parameter estimation

The resistance equations are modelled using best-fit curves, which then creates a function for solving, plotting and manipulating symbolic math equations. The fitting of data uses the algorithm of: fitobject = fit(x,y,fitType) which generates the fit to the data in the y and x formulate ranges specified by the fit-Type. The objective of data fitting is to accurately model how the vehicle behaves and use non-parametric methods to model the acquired data. The data fitting capabilities extend to [29]:

- Fitting curves and surfaces to data using the MATLAB Curve Fitting Toolbox application. This includes nonlinear, parametric, and non-parametric formulations
- Performing constrained data fitting where parameters need to be satisfied, such as train traction, braking, accelerating, and coasting
- Creating an accurate dynamic formulation such as the FEDEO algorithm by calculating the entries of state-space matrices, dynamic models and smoothing curves

2.7 OPTIMISATION STRATEGIES

The traction system consumes the most critical part of the train's energy and is dependent on driving behaviour. Formulating the sections of driving styles such as coasting, braking, accelerating, and cruising will find the optimal speed profile. The optimal profile will consider both the operational and physical constraints such as the maximum allowable travel time, maximum allowable acceleration and braking effort. The control strategy involves a review of the non-linear and linear optimisation algorithms for energy, speed, and cost optimisation [62].

The FEDEO algorithm aims to provide an accurate prediction of the optimal energy consumption for the route profile. The electrical energy is typically divided into two parts: the traction and the braking systems. The speed and energy optimisation methods can be experimental, exact or meta-heuristic. The exact methods require revision when the route profile is unsuitable and unrealistic for real-time optimisation. The strategy for optimal energy profiling involves formulating the resistance equations to validate the optimal speed required for developing a route profile that has improved cost savings [5, 8, 14].

The optimisation algorithm using MINLP will meet the objective of the system considered in this study, which is to find the optimal eco-driving speed profile. Several transformations are required to restructure and compare the raw data obtained. The simulated data is stored in a central location such as the MATLAB workspace to extract realistic velocity profiles and to work out the optimal result required for energy savings. The method used is described in the FEDEO algorithm formulation in Chapter 4 for the optimal journey setup from Ermelo to Richards Bay. It should be noted that the algorithm's efficiency is never wholly realistic, and, therefore, certain assumptions have to be made in the process [52, 63].

The core factors from the formulation of the train kinematics that affect the vehicle energy consumption include parameters such as distance, speed, rolling resistance, and tractive and braking effort. The onboard equipment, such as the engine, traction motors, auxiliary motors, fans, and radiators, has an increased impact on the overall power usage. The critical factors required for energy usage optimisation are [8, 32, 64]:

- Gross weight *(kg)* and entire train length *(m)*
- The gradient at a specific position of the route (%)
- Gross to tare mass of the train *(kg)*)
- Driving behaviour (e.g. speed, acceleration, braking distance, reaction time) and air resistance
- Train speed (eco-driving versus speed-tracking control)
- Human accidents and calibration errors

The optimisation toolbox in MATLAB, Opti-Toolbox, provides functions for finding parameters that minimise or maximise objective functions while satisfying the constraints. The Opti-Toolbox involves solving for linear and non-linear programming (LP and MINLP), and mixed-integer quadratic programming (QP), among others. The approaches to the problem include either a problem-based optimisation or a solver-based optimisation setup. The setup of the problem requires the symbolic form of the objective function and formulation of the constraints for energy minimisation. It also involves the translation of the vehicle dynamics into matrix form with an increased number of variables. The literature discussed below describes the optimisation method used in the simulation and its application in real life [65, 66].

2.7.1 Mixed-integer non-linear programming (MINLP) algorithm

The MINLP solves the optimisation problem using mixed integers similar to the Mixed-Integer Linear Programming (MILP) optimisation method, except that non-linearity is introduced with the Davis formula and aerodynamic resistance factor. The MILP method does not have a non-linear factor, while the MINLP method uses this factor. The tractive and braking efforts are applied according to a control formulation approach where the decision variables and non-linear constraints determine the train's optimal speed profile. The optimal speed of the train is formulated using the algorithm in [11].

The syntax behind the problem is:

$$min\ f(X), \tag{2.17}$$

where f is the scalar function or the non-linear objective function, which is required for energy optimisation. The braking effort will be applied when the tractive effort is zero and vice versa, as they cannot be applied at the same time. The canonical form of (2.17) used the nonlinear continuous (*nlcon*) function of MATLAB R2021 Optimisation Toolbox. Equation (2.17) is subject to [65]:

$$AX \leq b \ \ (linear\ inequality\ constraint), \tag{2.18}$$

$$A_{eq}X = b_{eq} \ \ (linear\ equality\ constraint), \tag{2.19}$$

$$L_b \leq x \leq U_b \ \ (lower\ and\ \ upper\ bounds), \tag{2.20}$$

$$C(X) \leq 0 \ \ (nonlinear\ inequality\ constraint), \tag{2.21}$$

$$C_{eq}(X) = 0 \ \ (nonlinear\ equality\ constraint). \tag{2.22}$$

For optimal control, the vector X contains the variables requiring to be solved. The equality constraints are represented by A and b, with the lower and upper boundary constraints given as L_B and U_B. The objective function of the current FEDEO algorithm is a nonlinear mixed-integer function [67]. Hence, the *nlcon* function of MATLAB Optimisation Toolbox is also used for the global solution in [15].

2.7.2 Optimisation solver detail

Table 2.2 describes the MATLAB optimisation method used for the FEDEO algorithm regarding the 19E fleet from Ermelo to Richards Bay.

Table 2.2. MATLAB optimisation MINLP methods

Optimisation Method	Gradient and Hessian	Large Scale Optimisation	Computation Time Length	Accuracy of Results
MINLP	No, does not need Gradient and Hessian. Versatile solver that combines NLP and MNLP.	Yes, significant scale problems can be computed. Solves non-convex and non-linear constraints. Minimises constraint violation, finds optimal solution.	Takes a long time to compute, but result returns desired outcome. Computation time larger than SQP.	Result returned will be optimal for non-linear optimisation. Adjusts feasibility based on constraints.

2.7.3 19E power train parameters and application

The power flow on board the 19E locomotive as represented in Figure 2.5 and parameters outlined in Table 2.3. The driver sends a command to the onboard computer, which triggers the catenary power to switch on the locomotive. The circuit breaker interrupts the current flow if a fault is detected. This current then goes to the rectifier, which converts the AC to DC. The transformer is used to step down the large voltage from the overhead line to around 400 V so that the auxiliaries on board can be powered. The DC-Link is an electrical device that filters and controls the DC bus voltage and current in a variable frequency or speed drive (VFD/VSD). The grid consists of resistors termed "dynamic braking" when the traction motor acts as a generator to slow the vehicle down. The power generated from the traction motors then allows for control and operation of the front and rear bogies [18, 55].

Table 2.3. 19E locomotive power electronics parameters

Parameter	Value
Pantograph output power	4000 kW
Maximum brake wheel force	6250 N
Starting tractive effort 19E	392 kN
Peak electric braking effort 19E	251 kN
Coefficients of rolling resistance model	$Fr = 9.81 * (R_a + R_b * v + R_c * V_t^2) * m$
R_a	2.41538
R_b	0.03
R_c	0.00276923076

Key constraints in any train model are the wheel adhesion, resistance coefficients, and vehicle performance. The vehicle performance requires optimisation of the tractive and braking effort notches. The performance takes into account the current limiting factor, which plays a role in the initial positive gradient up to the peak. The use of the train brakes of the locomotive to decelerate the train will continue as the train dynamic changes. The efficiency of the train dynamic brakes is constrained at higher speeds by voltage, current, and commutator limits. Lower velocities achieve an ideal complete dynamic brake force. Dynamic braking controls as a continuous function moderately better than a notch, but again, some locomotives deliver discrete control points [32, 59].

The minimisation of the required energy for a section can be reasonably complex, and a single mass-point model is needed to find the optimal profile for speed measurement. While the evidence suggests that minimising energy improves the forces required for train coupling, no official steps have been taken to optimise both the energy usage and the in-train coupling forces. Optimisation literature proposes using genetic algorithm (GA) and artificial intelligence (AI) algorithms, which are unique arbitrary optimisation algorithms requiring no specialised knowledge of the problem. These algorithms require tens of thousands of function evaluations and other methods, such as ant colony optimisation or cuckoo search algorithms. Computational constraints make it currently not feasible to converge to machine accuracy, as this often results in highly unrealistic and inconsistent results [6, 68].

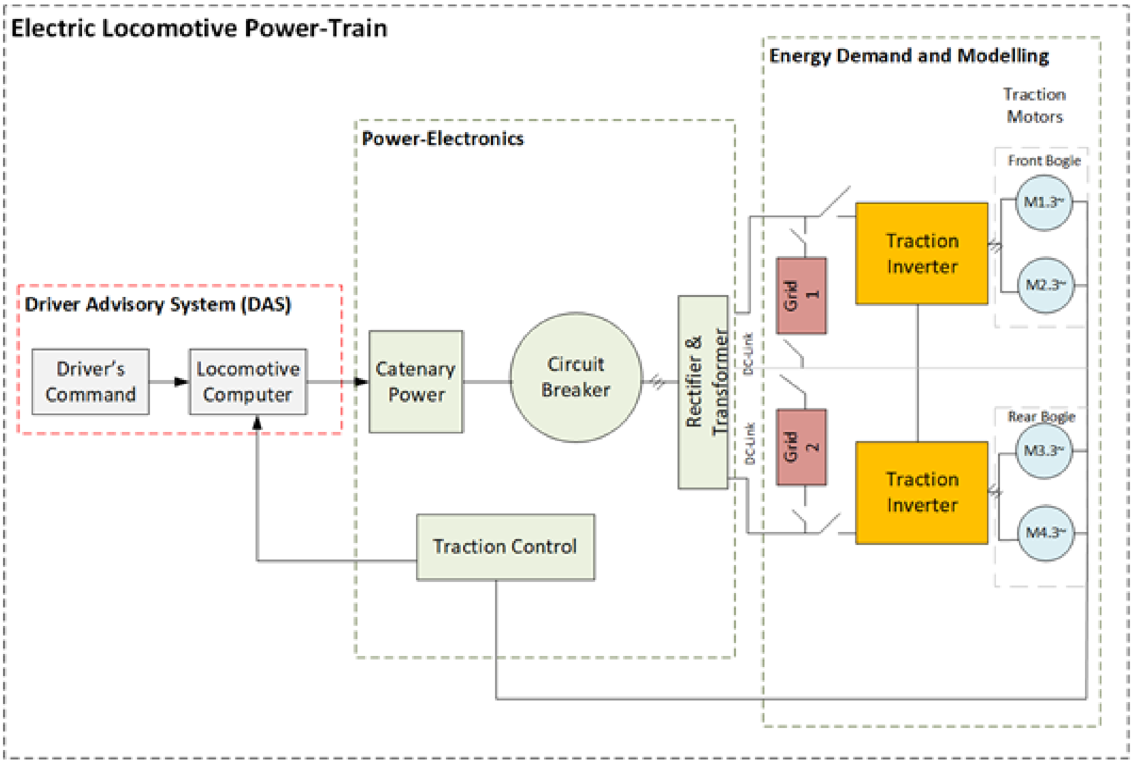

Figure 2.5. Power electronics block diagram of 19E

The vehicle dynamics to be formulated for FEDEO include the longitudinal movement of the train over a given route profile. The following points affect the route profile [60, 69]:

- The energy consumption and power required will increase with more significant gradients
- Heavy freight trains may have difficulties climbing up steep gradients
- Braking distances for high-speed and freight trains tend to rise in an uphill gradient

2.7.4 19E historical data and route information

The simulation algorithm requires information on the 19E locomotives and their vehicle parameters, such as their speed, gear ratios, mass, and resistance coefficients, which are highlighted in Table 2.4 [69].

Table 2.4. 19E electric locomotive data-set parameters and quantities

Route parameter	Value
Wheel arrangement	Bo-Bo
Track gauge	1067 mm
Designed maximum speed	120 km/h
Axle mass of locomotive	26,000 kg
Overhead supply voltage	25 kV AC and 3 kV DC (50 Hz)
Electric braking	Blended Regen/Rheostatic
Power rating, per motor continuous	750 kW at 34 km/hr
Motor rating, total continuous	3000 kW
Tractive effort start	392 kN
	Continuous: 311 kN at 34 km/h
Gear ratio	92/19
Number of traction motors	4
Electric braking – regen/rheostatic	3490 kW
Auxiliary supply	380 V – 3 Phase
Total number of vehicles in the train	208
Auxiliary supply	380 V – 3 Phase
Locomotive mass including load kg	104,000
Wagon mass including load kg	80,000
Locomotive length including coupler length	18.789 m
Number of axles	4
Wagon mass including load kg	104,550
Wagon length including coupler length	12.07
Number of axles – wagon	4
Number of locomotives	8
Number of wagons	200
Locomotive and wagon brake type	Tread

To counter these problems, significant gradients result primarily in more massive locomotives, higher locomotive power and/or reduced speed and line capacity or less freight train weight. There is also the requirement of higher braking capacity or a greater number of long (or longer) signalling distances. The algorithms such as MINLP and LP are used extensively in global optimisation products. Trip optimisers and eco-driving solutions for cars, trucks, trains, and other vehicles have an energy optimisation algorithm built into the vehicle system. Some of these optimisation products are discussed below.

2.8 GLOBAL FREIGHT RAIL ENERGY OPTIMISATION PRODUCTS

Various control systems have been designed globally to improve driving performance and the energy efficiency of the trip. The core idea is to save fuel and optimise fleet train movement, with the concept being very similar to autopilot in an aircraft. Such a system creates an eco-driving solution, parameterises the train's characteristics, creates an optimal trip profile, and controls the tractive and braking effort to reduce energy consumed and provide effective train management. The result is that trains run on time, operate more efficiently, and use fuel or electricity more proficiently, with a consequent 3-17% fuel savings and corresponding emission decrease. Apart from their role in the optimisation of train fleets, emission reductions are critical in reducing ozone depletion.

2.8.1 Freightmiser in-cab driver optimiser

The Freightmiser system is an in-cab system for long-haul train drivers that will improve timetabling to scheduled target times with increased trip optimisation while satisfying train handling, speed limits, and safe-working conditions. The idea was first envisioned in 1996 by the Scheduling Group at the University of South Australia. In consultation with European Transportation Technology (TTG), the Group developed the Freightmiser technology with funding from the Cooperative Research Centre and Australian Research Council. Paper [70] shows the prototype Freightmiser screen that displays the elevation profile where the orange lines are speed limits, and triangles indicate the current speed of the train. Using Freightmiser has enabled fuel savings of up to 12%. The application of this technology within the South African rail sector can be an excellent advantage for the drivers as well as the fleet owners [70].

The freight train is driven on a different gradient track, but where speed limits are applied. For a journey that lacks speed restrictions full-throttle speed is required for the optimal driving strategy, power, speed holding, full braking, and coasting. The solution is largely applicable to eco-driving owing to its application of incorporating the route profile to find the minimum energy usage. Modern-day technological advice for calculating competent driving during a journey is predominantly applicable to long-haul railway and suburban trips. Coasting control optimises the train path through coasting operations to ensure the lowest energy consumption under the journey time limitations. The optimisation seeks the ideal train trajectory by applying various control means such as acceleration, cruising, coasting, and deceleration [3, 5, 56].

2.8.2 General Electric (GE) trip optimiser

GE Transportation's trip optimiser fuel management system routinely controls locomotive acceleration and speed in real-time, reducing driver fluctuations for increased efficacy. The trip optimiser is an intelligent, fuel-saving cruise-control method for locomotives that optimises fuel consumption according to the train's specific makeup and the route profile. The system development is simulation-based and integrates the physical network model to calculate running times between stations and to forecast arrival times at scheduled stops independently of the planned times for the network. In offline mode, the software endorses solutions using "what-if" time and analysis schedule variation, while identifying the critical struggles that consider the customers' primacies and contractual obligations [71].

The innovative technology of the trip optimiser provides a real-time method for up to the next eight to twelve hours, forecasting the updated profile on the basis of real-time calculations. The GE trip optimiser is an auto-control tool that can be coupled to other GPS tracking and GE evolution series scheduling software of eco-friendly and energy-efficient products. Over 2000 USA freight locomotives are furnished with the trip optimiser. The additional elements of the trip optimiser are built to reduce locomotive idling, enable a smooth locomotive restart and prevent shutdown [37].

2.9 SUMMARY

This chapter summarises the application of eco-driving globally, with the formulation of energy usage required for traction and braking. The POET factors are addressed to improve energy efficiency, with the formulation of the train dynamics. The forces experienced by the locomotive are outlined, along with the resistance forces. The driving strategies required for FEDEO are highlighted, with strategies for optimisation. The optimisation solver used is described, as well as the critical parameters required for the FEDEO algorithm. Finally, the global rail energy optimisation products are described in terms of their contribution.

CHAPTER 3 METHODOLOGY

3.1 CHAPTER OVERVIEW

This chapter presents the methodology used to derive the eco-driving solution that is the focus of this study. Section 3.2 outlines the architecture used for the FEDEO algorithm, which is required for the methodology. The architecture consists of the data inputs, route profile sections, locomotive behaviour regions, optimisation constraints, train energy modelling, efficiency factors, and kinetic energy regions. Section 3.3 outlines the energy formulations for the FEDEO solution. In Section 3.4, the algorithm methodology is outlined, and Section 3.5 formulates the eco-driving solution.

3.2 FEDEO ARCHITECTURE

The validation of the FEDEO algorithm is critical to improving overall operational locomotive efficiency. At the sub-system level, the components are verified and refined through testing to meet the sub-system target specifications. The sub-system level includes the dynamic equations of motion, efficiency parameters, constraints, and raw data. The component level, which is the FEDEO algorithm, then builds the entire solution for meeting the technical target specifications required by improvement and experimentation. Experimentation involves a complete analysis of information, such as the train mass, maximum speed, tractive and braking efforts, route profile data, and train resistance coefficients, before the FEDEO algorithm is applied. The simulation is conducted once all the route information has been incorporated, and then the eco-driving solution is tested [1, 3].

The FEDEO algorithm formulation uses energy laws, dynamic equations, optimal control method analysis, and Newton's laws of motion to describe the vehicle movement. According to the methodology used by the FEDEO algorithm, potential energy-savings' opportunities need to be identified and then prioritised via optimisation through the following possible methods [14]:

- Cruising (CR) at speeds of less than the speed limit, if time allows
- Coasting (CO) when going downhill
- Reducing the amount of braking, especially at high speeds
- Maximum braking (MB) when reaching the station and maximum acceleration (MA) when leaving the station
- Minimising tractive effort required on steep gradients
- Speed trajectory optimisation to assist the driver with "economical" driving
- Modelling the train as a single mass point, with the total number of wagons and locomotives having an effect on the FEDEO model

The FEDEO architecture is based on the locomotive behaviour, efficiency, route profile, power requirements, and optimisation constraints, as shown in Figure 3.1. below. These parameters were used to model the FEDEO algorithm in MATLAB.

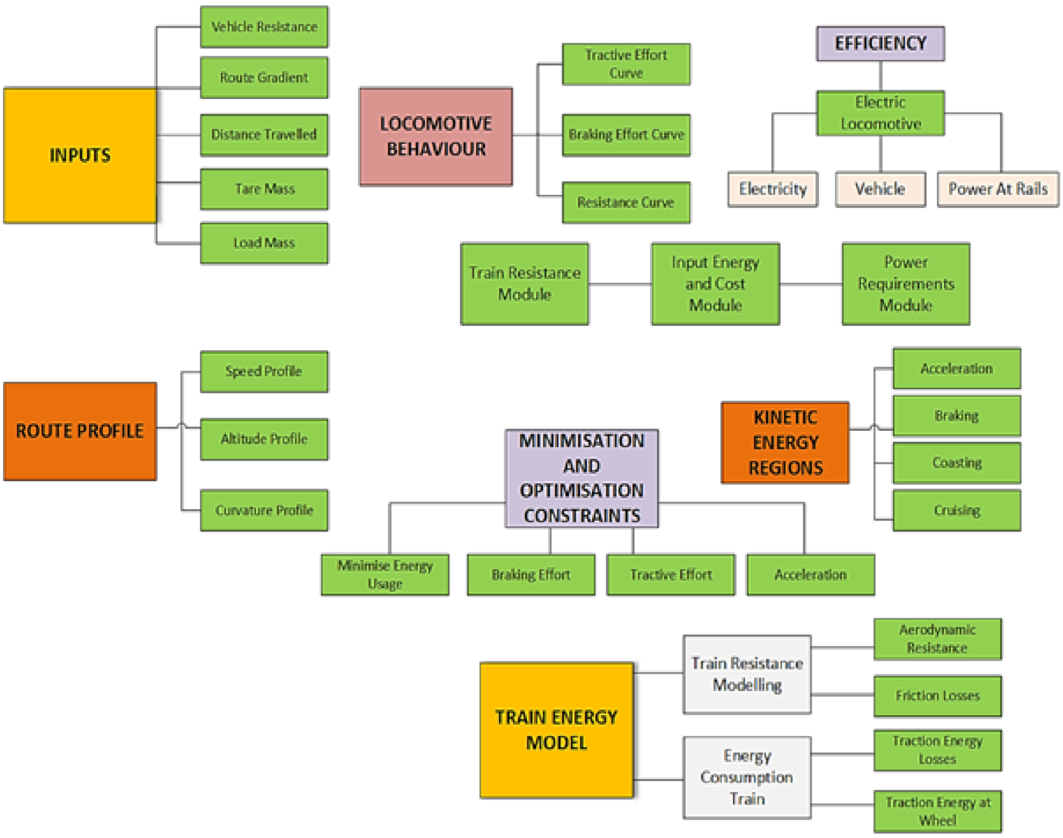

Figure 3.1. FEDEO system architecture for FEDEO optimal control algorithm

3.3 ENERGY CONSIDERATIONS

For the energy management study of the train, it is necessary to reduce the amount of energy currently used. To introduce innovations or changes, the energy use of the train must be analysed. The following points were considered: The train's average speed influences the total energy consumption and the sum of the resistance forces, taking into account the possible effects of the changes in altitude. The variations in elevation will affect the FEDEO algorithm and how the continuous profile is modelled. The data is required to be analysed in terms of journey points. The FEDEO algorithm incorporates the work taken to get the train up to the required speed. The halting and idling of the locomotive lead to energy being wasted, and hence regeneration validates the intention to recover lost energy. Additionally, energy is lost through signalling conditions, start-stop, the route gradient and altitude differences, idling, and driver behaviour. The cost savings are obtained from an economical speed profile achieved using the MINLP method [5].

3.4 ALGORITHM METHODOLOGY

The algorithm takes into consideration the mass of the train as well as the gradient at fixed time intervals, and advises the driver of the optimal notch at every gradient change. The method uses MINLP to formulate the optimal velocity trajectory. The method has been chosen on the basis of the trial and error of the optimal results. The development of the FEDEO algorithm in question requires an understanding of locomotive kinematics. The number of locomotives and wagons have an effect on the optimisation performance in the real world as it influences the single mass-point model used for formulating FEDEO. Optimising the speed of the train minimises the overall energy usage. The locomotive system is not static; i.e., its state evolves in consideration of time naturally or due to [64]:

- Input signals (vehicle effort, speed, notch commands)
- External disturbances (weather, track resistance, equipment failure)

The locomotive is a dynamic system owing to changes in [3]:

- Route profile parameters: acceleration, velocity, position, altitude, and mass
- Engine power, maximum demand, and driver behaviour
- Locomotive tractive and braking effort

A first principle formulation approach develops the overall system's mathematical representation by first principles. The mathematical formulation is for data-control purposes and simulation of the energy savings. The system in question uses a non-linear speed-varying model that optimises train resistance and mechanical and kinetic energy. The system is a non-linear velocity-varying system for which the output does not directly represent the input state. The significance of using this type of system is to deduce the system behaviour and the real-time algorithm for experimental validation. The data algorithm is utilised for analysing the system breakdown and amalgamation, feed-forward and feedback control systems. The system analysis for the FEDEO algorithm considers [52]:

- Optimal system parameters (speed, train resistance, gradients, power usage)
- Stability of the system
- Efficient speed-tracking control
- Maintaining system stability and guaranteeing disturbance rejection (robustness)
- Coasting, accelerating, braking, and cruising regions
- Power requirements of the trip
- Cost of journey and notch pattern required to reduce operational costs

The mass of the train is modelled as a single mass point model. Single-point representation is mathematically efficient, but less precise than the complex multiple and single line representations. The proposed algorithm uses a single-point representation for validating the energy consumption and the vehicle dynamics to determine the optimal speed trajectory. From an optimisation viewpoint, it is defined as a non-linear problem. The profile for speed optimisation is shown in Figure 3.2 below.

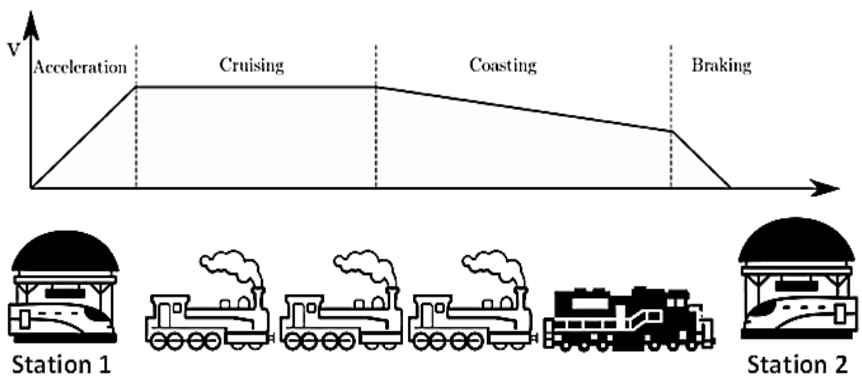

Figure 3.2. FEDEO optimal profile for section Ermelo-Richards Bay

The coasting phase seen in Figure 3.2 starts with a traction force equal to zero. The traction command reduces the overall energy consumption, meaning that achieving minimal cost means lengthier cruising and coasting times. A coasting period is then obtained as a trade-off between the travelling time and energy consumption. The last phase is braking to ensure that the locomotive reaches the destination at zero speed. The FEDEO algorithm developed analyses the speed profile and minimises the consumed energy [57].

3.4.1 Route profile data formulation

The achievement of the FEDEO solution means that improving the overall efficiency of the route profile is critical to reducing energy usage. In formulating the route profile data, the FEDEO algorithm simulates the longitudinal movement of the train using the dynamic equations of motion. The main functions for the FEDEO algorithm to be parameterised are the velocity, distance, and acceleration. The hurdles for freight operation include derailment, increased running times and operating costs, more significant fatigue damage due to inefficient rolling stock maintenance, and increased in-train forces. These hurdles are not included in the FEDEO algorithm setup. Only the critical factors for the formulation of FEDEO have been utilised [18, 52].

A locomotive requires tractive effort for propulsion and braking effort for slowing down. The two train movement regions where the optimisation algorithm is applied are the acceleration and braking regions. A large amount of power is required for propulsion, and the braking element produces regeneration energy. This is the energy that moves from the wheels to the overhead catenary that trailing locomotives can use. The solution for the train-handling strategy includes static and dynamic parameters, where static represents the input (primary) data in the FEDEO algorithm. Static parameters, in this case, would be the trip distance, speed restrictions, train characteristics (force limits and adhesion curves) and elevation profile. The decision or proxy variables include or consist of acceleration (or tractive effort), deceleration (or braking effort), notches and the speed profile from point A to point B [5, 7, 54, 64]. This data is required for the route profile analysis and setup.

The eco-driving principle narrows down to the driving behaviours or control that a driver has over a train during a journey that can influence energy consumption. The typical factors that eco-driving principles govern include acceleration, speeding, deceleration, route choice, idling, and vehicle accessories (other factors). Advisory train driving has globally shown that the engines or motors prefer an average speed that does not change vastly for optimal energy usage.

Critical behaviours of eco-driving, such as acceleration and deceleration, are vital factors that can cause a sudden increase in the train's energy consumption. Therefore, aggressive driving should be avoided. The track type, aerodynamic drag, and grade influence the train's performance over a specific distance. The equipment on board the train, such as air-conditioners, compressor, lighting, and electrical appliances, also contributes to the energy usage. The route profile conditions include the requirements listed below. The train layout is shown in Figure 3.3 [14, 26, 32, 55].

- The train stops once the station is reached for rest and refuelling or maintenance purposes
- A velocity of 0 km/h is the final speed on reaching the station
- Tractive effort is only applied when the braking effort = 0 and vice versa
- The route elevation is used to determine where the tractive effort needs to be applied (on inclines) and where the gravitational force will be greater (on declines)
- Curve resistance has not been used for resistance calculation as it is minimal, but instead the Davis resistance formula (aerodynamic, friction, and rolling) has been used
- The ideal profile is the eco-driving solution, in which the optimal profile is created by applying the speed-tracking control

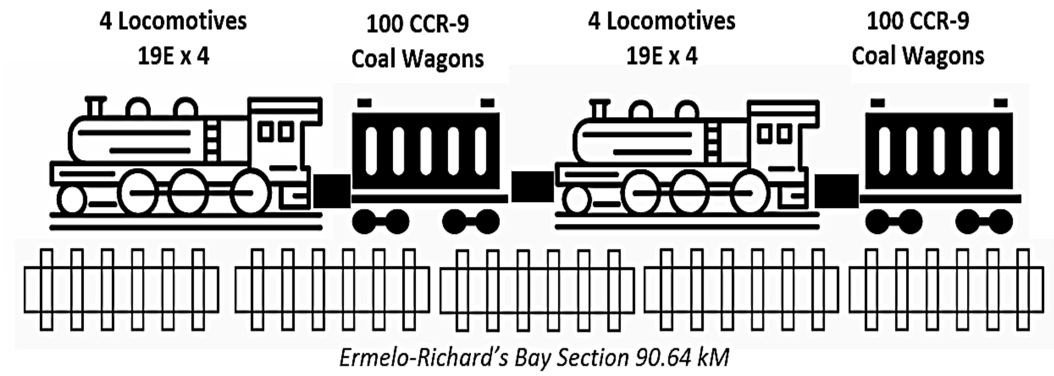

Figure 3.3. Test configuration for section Ermelo-Richards Bay

The operation of the train along the route path must follow the equations of speed and motion restrictions. Four main operating regimes are commonly used: acceleration, deceleration, constant speed, and stop. The train velocity and net force sections in each of the four regimes are shown in Table 3.2.

The three operating modes that are the focus of this study are described in Table 3.1 [69].

Table 3.1. Train driving modes for three operating areas

Train operating mode		Tractive effort condition	
		$F_j^t = 0$	$F_j^t > 0$
Brake force condition	$F_j^b = 0$	Coasting mode	Powering mode
	$F_j^b > 0$	Braking mode	——

Table 3.2. Inter-vehicle force and speed conditions for four operating regimes

Operating regimes	Net force (N)	Speed/velocity (m/s)
Stop	$F_j^t - F_j^r(v_j^{*,v,i,\Upsilon}) - F_j^b = 0$	$v_j^* = 0$
Acceleration	$F_j^t - F_j^r(v_j^{*,v,i,\Upsilon}) - F_j^b = 0 > 0$	$0 \leq v_j^* \leq v_j^{*,max}$
Steady/constant speed	$F_j^t - F_j^r(v_j^{*,v,i,\Upsilon}) - F_j^b = 0$	$v_j^* > 0$
Deceleration	$F_j^t - F_j^r(v_j^{*,v,i,\Upsilon}) - F_j^b = 0 < 0$	$0 \leq v_j^* = 0 \leq v_j^{*,max}$

The force and velocity conditions shown in Table 3.2 are based on:

- F_j^t = Tractive effort of the train *(N)*
- F_j^r = Total train resistance *(N)*
- F_j^b = Braking force of the train *(N)*
- v_j^* = Train velocity *(km/h)*
- i = Gradient or slope of the route (%)
- Υ = Curve radius of the track *(m)*

There is no formal relationship between the train driving modes and the operating regimes described in Tables 3.1 and 3.2 respectively. Energy optimisation involves finding the minimum cost of the function from point A to point B. This consists of finding the control u(t) moving system from A to B in time [0, t_s] with the lowest possible cost. For a railway to operate competently, its locomotives should have enough control to accelerate their trains to the maximum speed, and the braking force or effort should be able to bring the locomotive to a complete stop at a signal, station, or even at extreme gradients [2, 14]. Brake and tractive effort notches follow Tables 3.3 and 3.4 for load power [1].

3.4.2 19E class tractive and braking effort parameterisation

The MINLP method uses the decision variables U_j^t and U_j^b for the tractive and braking effort notches, ranging from 1 to 10. The energy required J from tractive F_j^t effort applied for FEDEO requires formulation of the locomotive notches as shown in (3.1) to (3.3) below, while the locomotive effort regions for the 19E are shown in Table 3.5 [8, 72].

$$U_j^t \in \{0,\ldots,10\} \ \ (1 \leq j \leq N), \tag{3.1}$$

$$U_j^b \in \{0,\ldots,10\} \ \ (1 \leq j \leq N), \tag{3.2}$$

$$U_j^t \times U_j^b = 0. \tag{3.3}$$

Table 3.3. Load versus tractive notch position

Tractive throttle notch position	% Load (kW)
Tractive notch 1	10%
Tractive notch 2	20%
Tractive notch 3	30%
Tractive notch 4	40%
Tractive notch 5	50%
Tractive notch 6	60%
Tractive notch 7	70%
Tractive notch 8	80%
Tractive notch 9	90%
Tractive notch 10	100%

During operation of the train, only one of either U_j^b or U_j^t can be applied. All the train efforts will be zero when the locomotive is idle or to save energy when on a decline. This means that U_j^t and U_j^b is zero. The reason for the tractive effort U_j^t solely contributing to the energy usage is that the braking effort energy is fed back into the overhead line as regeneration energy. In regeneration, the torque reduces the motor speed and generates the electrical power. The energy that is regenerative will be converted by power electronic equipment into electrical energy that is fed back into the overhead line. Globally, trains that incorporate regeneration of energy have a high capacity for eco-driving and for being economical, based on the driver behaviour. The incorporation of the tractive and braking effort requires the vehicle dynamics that are discussed in Section 3.4.3.

Table 3.4. Load versus braking notch position

Braking throttle notch position	% Load (kW)
Braking notch 1	10%
Braking notch 2	20%
Braking notch 3	30%
Braking notch 4	40%
Braking notch 5	50%
Braking notch 6	60%
Braking notch 7	70%
Braking notch 8	80%
Braking notch 9	90%
Braking notch 10	100%

Table 3.5. Tractive and braking effort decision regions

Velocity (km/h)	Tractive effort (kN)	Braking effort (kN)
$0 \leq v_j^* < 2$	$(\frac{-31}{16} \times v_j^*) + 392$	$125.5 \times v_j^*$
$2 \leq v_j^* < 32$	$(\frac{-31}{16} \times v_j^*) + 392$	251
$32 \leq v_j^* < 50$	$595.793 \times (0.982)^{v_j^*}$	251
$50 \leq v_j^* < 80$	$595.793 \times (0.982)^{v_j^*}$	$568.036 \times (0.984)^{v_j^*}$

3.4.3 Problem formulation

The problem originates with the high energy required for freight trains to traverse the South African Ermelo-Richards Bay coal line. Electricity usage is costly in South Africa, especially for freight operation. The route profile force diagram is shown in Figure 3.4 below. The traction motors on board the electric locomotive are mainly responsible for the propulsion of the train, where the trailing wagons carry the freight (coal). The braking element or rheostat contributes to the energy regeneration parameter. The FEDEO algorithm optimises the energy usage of the train using only the route elevation, gradient angle profile, and distance travelled. The FEDEO algorithm aims to lower the energy consumption J by optimising the travel speed of the train and determining the tractive and braking effort U_j^t and U_j^b notches based on this optimal speed. The notches and power $P_R(t)$ represent the control variables. The state variables are the train acceleration a_j and speed v_j^*. The initial parameters refer to the train setup, such as the train mass, speed, and the resistance coefficients for the route simulation. The FEDEO problem is presented separately in both continuous time and discrete time. The main target of the eco-driving solution is to optimise the velocity profile, with the motion limited by longitudinal dynamics; lateral dynamics are not considered.

3.5 FEDEO FORMULATION FOR ECO-DRIVING SOLUTION

This section formulates the FEDEO algorithm as outlined by [11] for the continuous optimal route profile. The energy optimisation is based on J_1 and J_2 shown in (3.4) and (3.5), with the critical route profile parameters described in Section 2.5. A continuous-time formulation of the FEDEO algorithm is provided for a single-mass point model; the algorithm aims to optimise the tractive force $u(t)$ and velocity profile $v(t)$ that minimises the energy or the integral of the power usage P by the train over a time period $t_s \in [t_0,\ t_f]$ over a given trajectory $s(t) \in [s_0,\ s_f]$ with known geographical parameters such as gradient angle profile α [11, 15, 73, 74].

$$\min_{v(t),\ u(t)} \quad J_1 = \int_{t_0}^{t_f} P(v(t), u(t))\, dt. \tag{3.4}$$

Equation (3.5) further develops (3.4), where $f(v,s)$ is subject to the gravitational constant g from [15]. The gravity constant, g, is 9.8 m/s^2, where t_s is the length of the sampling interval. In (3.4), (3.5), and (3.8), m represents the total mass of the train in kg; c_r represents the rolling resistance coefficient of the route section, aerodynamic drag is represented by $\sigma_d = \frac{1}{2} c_d \rho_a A_f$ with c_d being the drag coefficient, in which ρ_a denotes the air density in kg/m^3; and A_f is the frontal area of the locomotive in m^2. The continuous-time optimal control problem is provided by (3.4) [2, 11, 75].

$$J_2 = \min_{v(t), u(t)} \int_{t_0}^{t_f} P(v(t), ma(t) + f(v(t), s(t)))\, dt, \tag{3.5}$$

Equation (3.5) is subject to:

$$\frac{dv}{dt} = a(t), \tag{3.6}$$

$$\frac{ds}{dt} = v(t). \tag{3.7}$$

Equation (3.8) has been simplified in reference to [11], where a, s and v are the critical parameters required for optimisation.

$$\int_{t_0}^{t_f} P(v, ma + f(v,s))\, dt \;=\; \int_{t_0}^{t_f} P_R(a,\ v,\ s)\ dt. \tag{3.8}$$

$$f(v,s) = \sigma_d v(t)^2 + c_r mgcos(\alpha(s)) + mgsin(\alpha(s)). \tag{3.9}$$

Figure 3.4 describes the gradient angle derivations shown in (3.9). The given gradient angle profile is $\alpha(s)$: $[s_0, s_f]$ -> $[\frac{-\Pi}{2}, \frac{\Pi}{2}]$, where $\alpha(s)$ is the gradient angle profile at position $s(t)$; while being subject to longitudinal vehicle dynamics, non-negative velocity bounds of the route profile $v(t) \in [v_{min}, v_{max}]$ where v_{min} = 0 at rest and boundary conditions on the position and velocity. The inclination angle $\alpha(s)$ has been based on the height difference, *dh*, versus the distal difference, *ds*. *H(s)* is the elevation profile and $s'(t)$ represents the horizontal projection of $s(t)$.

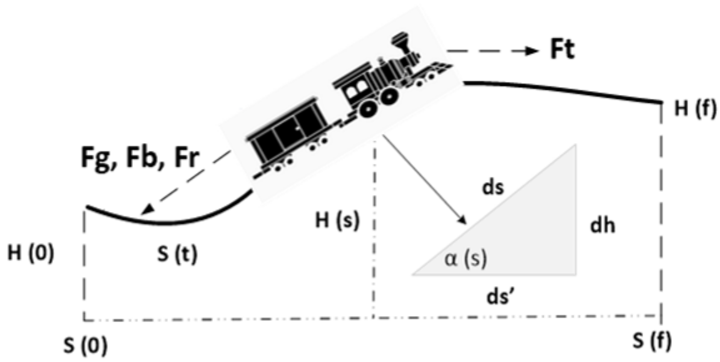

Figure 3.4. Locomotive force diagram against route characteristics

Equation (3.10) is an approximation of (3.9) for electric motors because friction losses, energy usage and ohmic losses are captured by the terms $\beta_0 v^2$, $\beta_1 vu$ and $\beta_2 u^2$, respectively. It has been assumed to be a quadratic function of the form [11, 15]:

$$P_R(a,\ s,\ v) \;=\; \beta_0 v^2 + \beta_1 vu + \beta_2 u^2. \tag{3.10}$$

The reformulation of the problem outlined in Chapter 4 focuses on discrete-time approximations where the non-convexity is introduced in (4.1). Equation (3.11) for obtaining the train's energy usage is further derived from (3.1) to (3.4) as:

$$\begin{aligned}P_R(a,\,s,\,v) = {} & \beta_0 v^2 + \beta_1 \sigma_d v^3 + \\ & 2\beta_2 m^2 ga(sin(\alpha(s)) + c_r cos(\alpha(s))) + \beta_2(ma)^2 + \\ & \beta_2(mg\sin(\alpha(s)) + \sigma_d v_j^{2,*} + c_r mgcos(\alpha(s)))^2,\end{aligned} \tag{3.11}$$

where:

1. $P_R(a,\,s,\,v)$ is the power requirement of the train *(kW)*
2. m is the mass of the train including load *(kg)* and g is the acceleration caused by gravity *(m/s^2)*
3. σ_d is the aerodynamic force constant and c_r is the rolling resistance coefficient for wheel on steel
4. a *(m/s^2)*, s *(km)* and v *(m/s)* are the train's acceleration, distance and speed at time t_s
5. β_0, β_1 and β_2 are the friction loss coefficient for the traction motor, braking loss coefficient and the ohmic loss coefficient of the brake resistors, respectively, of which the constants are given in Table 4.1

The FEDEO algorithm solves the eco-driving problem using MINLP in the Opti-Toolbox solver from MATLAB as the problem to be optimised is non-linear owing to the use of the Davis resistance factor. Chapter 4 describes the train dynamics, with the aim of lowering energy consumption by optimising the train notches. The initial formulation of FEDEO is provided by the eco-driving algorithm in [11], which is discretised by incorporating the train notches, tractive and braking efforts, and parameter bounds. Minimum energy usage is calculated through a search of the local minima using the points where the energy usage is the lowest.

CHAPTER 4 FEDEO SIMULATION ALGORITHM

4.1 CHAPTER OVERVIEW

Chapter 4 presents the formulation considerations and equations used to create a FEDEO simulation algorithm. Section 4.2 sets out the algorithm used for FEDEO, which includes elements such as the objective function shown in Section 4.2.1 with its constraints and bounds. Section 4.3 provides a summary of the chapter.

4.2 FEDEO ALGORITHM FORMULATION FOR SIMULATION MODEL

Creating a FEDEO simulation algorithm involves choosing an optimisation objective, which for this study is to complete the required distance between the two endpoints with the minimum energy required and at an optimal speed where less tractive effort is needed for the 19E locomotive. The time required should be computed without knowing the recorded value. The decision variables, in this case, would be the tractive and resistive notches of the vehicle, the optimal speed variable, and the time and distance of the journey travelled. Modern optimisation methods include simulated annealing, GAs, particle swarm optimisation, ant colony optimisation, neural network-based optimisation, and fuzzy logic. The method this study uses is MINLP. Common examples of optimisation applied are optimal (minimum) trajectories for space vehicles, shortest route, and design of aircraft for minimum weight.

The traction system consumes the most critical part of the train's power. The tractive power depends on driving behaviour. Improving the driving style such as through coasting, braking, accelerating, and cruising will find the optimal speed profile. The optimised profile considers both the operational and physical constraints such as the maximum allowable travel time, maximum allowable acceleration, and speed constraints per section. The objective function, which aims to reduce energy usage, is built on the MINLP approach. The default solver used is BONMIN, which is explained at the basis node of the problem. BONMIN is an open-source solver for mixed-integer nonlinear programming

(MINLPs), implementing branch-and-bound, branch-and-cut, and outer approximation algorithms. The speed-profile optimisation methods can also be experimental, exact, or meta-heuristic. It is, however, challenging to find a correct solution for the model. The objective function is where the energy is optimised regarding the train speed and where the cost savings are measured from [63]. Figure 4.1 outlines the flow-diagram for the simulation of the FEDEO algorithm.

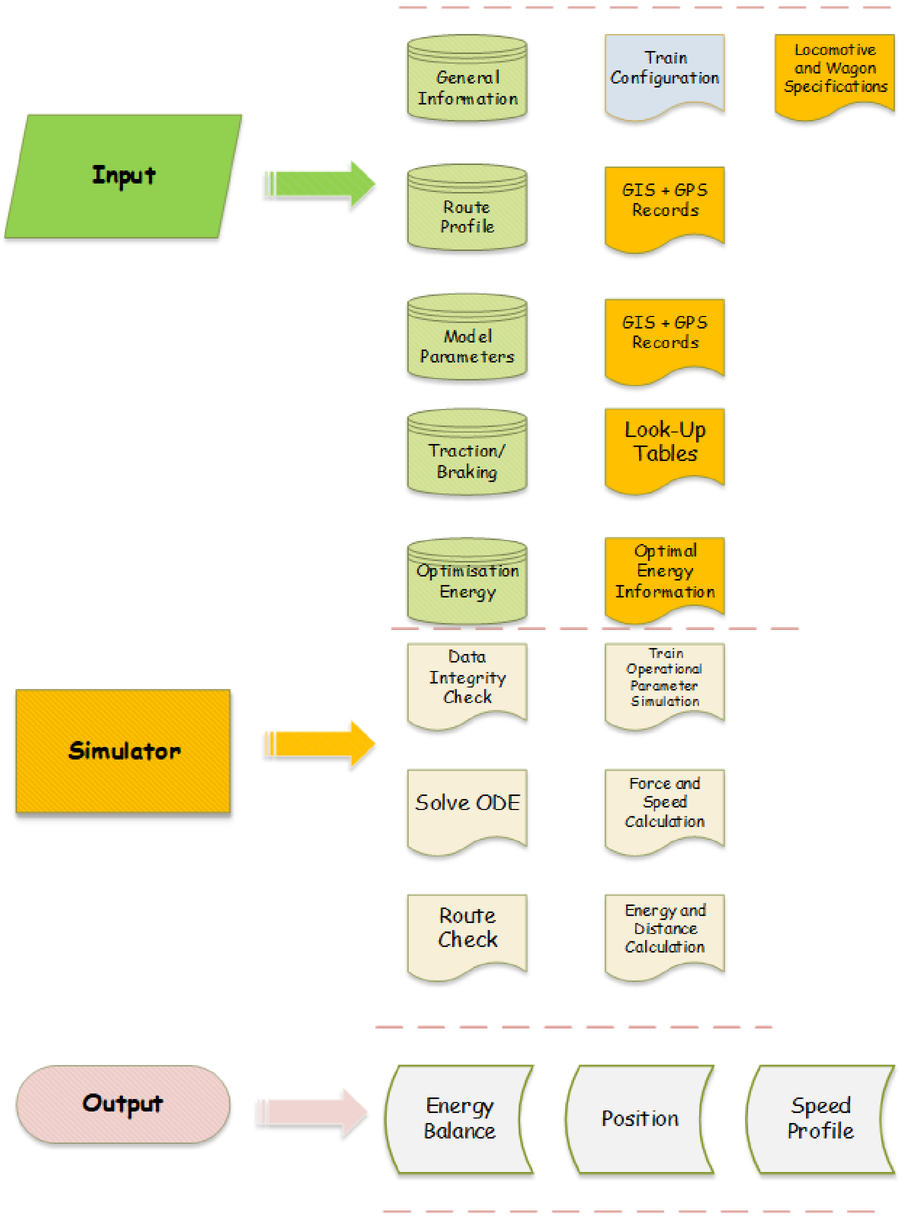

Figure 4.1. Model structure of the FEDEO algorithm

The algorithm aims to find the most energy-efficient speed profile using onboard collected data. A formulation is required to clean and reorganise the raw data obtained. The data is stored in a central location such as the MATLAB workspace. The eco-driving speed optimisation problem formulated in Section 3.5 has been discretised to make it solvable [52, 63]. The eco-driving speed optimisation problem does not include the tractive and braking effort notches, and the reason for discretisation is to transfer the continuous function, models, variables, and equations derived in Section 3.5 into discrete counterparts. The route profile parameters are shown in Table 4.1, which summarises the critical information required for the FEDEO simulation.

Table 4.1. FEDEO simulation route profile parameters

Parameter	Value
Minimum speed	0 km/h
Maximum speed	80 km/h
Cruising speed	70 km/h
Acceleration (maximum)	2.03 m/s^2
Acceleration (minimum)	-2.87 m/s^2
Starting point	0 km
Final distance	90.64 km
Train mass	21,742,000 kg
Acceleration due to gravity	9.81 m/s^2
Rolling resistance coefficient (Crr)	0.001
Drag coefficient (Cd)	1.8
Friction loss coefficient (β_0)	0.2
Braking loss coefficient (β_1)	0.9
Ohmic loss coefficient (β_2)	0.00602

4.2.1 Objective function

The objective of the algorithm is to minimise the energy usage of the train as a single-mass point model within the route profile parameter bounds. In this section, v_j is the train's optimal velocity, and v_j^* is the eco-driving speed of the train determined by incorporating tractive and braking effort notches and the discrete modelling approach. The results from the simulation of the parameters in the objective function shown in (4.1) are used to represent the optimal outputs and results and are described in Chapter 5.

$$J = \sum_{j=1}^{N} P_R(a_j, s_j, v_j^*) \times U_j^t \times \Delta t_s, \tag{4.1}$$

where:

1. J is the energy usage (kWh), also known as the objective function of the eco-driving problem

2. Δt_s is the sampling period for the route simulation
3. U_j^t is the tractive effort notch of the 19E locomotive respectively (0.1 to 1)
4. a_j (m/s^2), s_j (km) and v_j^* (m/s) are the acceleration, distance, and optimal speed of the train at time t_s
5. N is the number of samples and j is the counter of sampling intervals

4.2.1.1 FEDEO constraints

The constraints used for FEDEO are based on the acceleration and tractive and braking decisions. The objective function in (4.1) is subject to the constraints and bounds shown in (4.2) to (4.10). The acceleration difference for the eco-driving solution has been calculated from the computed force $\sum F_j$ and vector a_j. FEDEO is formulated based on the tractive force F_j^t, braking force F_j^b, gravitational force F_j^g and the resistance force F_j^r over N sampling intervals shown in (4.3) with the train profile shown in Figure 3.3. The sum of the forces is given as $\sum_{j=1}^{N} F_j$, while the braking force or F_j^b is dependent on two factors, based on the train dynamics suggested by [32]:

1. Adhesion between the wheel and the rail
2. Reaction force of the rail on the wheels during braking (hence on weight per braked wheel)

$$\frac{\sum_{j=1}^{N} F_j}{m} - a_j = 0, \tag{4.2}$$

$$\sum_{j=1}^{N} F_j = ma_j = F_j^t - F_j^g - F_j^b - F_j^r. \tag{4.3}$$

- $\sum_{j=1}^{N} F_j$ is the sum of the forces in kN where equations of the forces are provided in Section 4.2.1.2.

The objective function in (4.1) is subject to the constraints:

$$U_j^t \in \{0,\ldots,10\} \ (1 \leq j \leq N), \tag{4.4}$$

$$U_j^b \in \{0, \ldots, 10\} \ (1 \leq j \leq N), \tag{4.5}$$

$$U_j^t \times U_j^b = 0. \tag{4.6}$$

$$v_j^{*,min} \leq v_j^* \leq v_j^{*,max}. \tag{4.7}$$

$$s_j^{min} \leq s_j \leq s_j^{max}. \tag{4.8}$$

$$a_j^{min} \leq a_j \leq a_j^{max}. \tag{4.9}$$

$$h_j^{min} \leq h_j \leq h_j^{max}. \tag{4.10}$$

where the decision 1 or 0 is the state of movement of the train, and h_j is the elevation profile. The MINLP method uses the decision variables U_j^t and U_j^b for optimisation. The optimisation is updated every j^{th} sampling interval [8, 72].

4.2.1.2 Algorithm to solve the FEDEO formulations

FEDEO aims to minimise $f^T X$ subject to the equality constraints $(A_{eq}X = b_{eq})$ and upper and lower boundaries of the control variables $(L_B \leq X \leq U_B)$. The control variables are U_j^t and U_j^b, while A_{eq} and B_{eq} are the equality matrices, and L_B, U_B, *and* f are vectors represented below in (4.11) and (4.12). The independent variables are tractive and braking effort forces F_j^t and F_j^b, dependent variables are the train acceleration a_j and continuous velocity v_j and the core state variables are the distance s_j and optimal velocity v_j^* [76]. The objective function is solved using the canonical form in (4.1) as the vector $f^T X$ [6, 77]:

$$\boldsymbol{min\, f^T X} \tag{4.11}$$

subject to:

$$\left\{ \begin{array}{ll} A_{eq}X = b_{eq} & (linear\ equality\ constraint) \\ L_B \leq X \leq U_B & (upper\ and\ lower\ bounds) \end{array} \right\}. \tag{4.12}$$

Vector **X** contains all the state and independent variables. Let matrix $A_{eq}X$ and $b_{eq}X$ be:

$$A_{eq} = \begin{bmatrix} A_{eq1} \\ A_{eq2} \\ A_{eq3} \end{bmatrix}_{(2N+4)\times(5N+2)}, b_{eq} = \begin{bmatrix} b_{eq1} \\ b_{eq2} \\ b_{eq3} \end{bmatrix}_{(2N+4)\times(1)} \tag{4.13}$$

The vector f^T in the canonical form shown in (4.14) can be obtained from (4.1) to calculate the power required for every route section's sampling period.

$$f^T = [P_R(1) \quad \ldots \quad P_R(N)]_{1\times(5N+2)}. \tag{4.14}$$

The linear matrix for A_{eq1} is:

$$A_{eq1} = [U_j^t,\, U_j^b,\, A_1,\, A_2,\, A_3]_{N\times(5N+2)}. \tag{4.15}$$

The dynamic equation in its continuous form is discretised for use in A_{eq1} as:

$$V_j^{i,*} - V_j^{f,*} + (a_j \times dt) = 0. \tag{4.16}$$

The equality matrices required for A_{eq1} are shown in (4.17) to (4.21):

$$U_j^t = U_j^b = 0_{N \times N}. \tag{4.17}$$

$$A_1 = \begin{bmatrix} v_j^{i,*} & -v_j^{f,*} & 0 & \dots & 0 \\ 0 & v_j^{i,*} & -v_j^{f,*} & \dots & 0 \\ 0 & 0 & \ddots & \ddots & 0 \\ 0 & 0 & 0 & v_j^{i,*} & -v_j^{f,*} \end{bmatrix}_{N \times (N+1)}, \tag{4.18}$$

$$A_2 = \begin{bmatrix} a_j \times dt & 0 & \dots & 0 \\ 0 & a_j \times dt & \dots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & a_j \times dt \end{bmatrix}_{N \times N}, \tag{4.19}$$

$$A_3 = S_j = 0_{N \times (N+1)}, \tag{4.20}$$

$$b_{eq1} = 0_{N \times 1}. \tag{4.21}$$

Equation (4.22) is the unknown vector we are trying to solve for using the FEDEO algorithm.

$$\boldsymbol{X} = \begin{bmatrix} U_{j,0}^t \\ \vdots \\ U_{j,N}^t \\ U_{j,0}^b \\ \vdots \\ U_{j,N}^b \\ v_{j,0}^* \\ \vdots \\ v_{j,N+1}^* \\ a_{j,0} \\ \vdots \\ a_{j,N} \\ s_{j,0} \\ \vdots \\ s_{j,N} \end{bmatrix}_{(5N+2) \times 1}. \tag{4.22}$$

The linear matrix for A_{eq2} is:

$$A_{eq2} = [U_j^t, U_j^b, A_5, A_6, A_7]_{N\times(5N+2)}. \tag{4.23}$$

The longitudinal movement in its continuous form must be discretised as shown below for use in A_{eq2}:

$$s_j^i - s_j^f + (\frac{1}{2} \times a_j \times dt^2) = 0. \tag{4.24}$$

$$(v_j^{i,*} \times dt) - s_j^i = 0. \tag{4.25}$$

The equality matrices required for A_{eq2} are shown in (4.26) to (4.29):

$$A_5 = \begin{bmatrix} dt \times v_j^{i,*} & 0 & \dots & 0 \\ 0 & dt \times v_j^{i,*} & \dots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & dt \times v_j^{i,*} \end{bmatrix}_{N\times(N+1)}, \tag{4.26}$$

$$A_6 = \begin{bmatrix} \frac{1}{2}a_j \times dt^2 & 0 & \dots & 0 \\ 0 & \frac{1}{2}a_j \times dt^2 & \dots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & \frac{1}{2}a_j \times dt^2 \end{bmatrix}_{N\times N}, \tag{4.27}$$

$$A_7 = \begin{bmatrix} s_j^i & -s_j^f & 0 & \dots & 0 \\ 0 & s_j^i & -s_j^f & \dots & 0 \\ 0 & 0 & \ddots & \ddots & 0 \\ 0 & 0 & 0 & s_j^i & -s_j^f \end{bmatrix}_{N\times(N+1)}, \tag{4.28}$$

$$b_{eq2} = 0_{N\times 1}. \tag{4.29}$$

The equality matrices required for A_{eq3} are formulated as:

$$v_j^{i,*} = v_j^{f,*}, s_j^i = 0km, s_j^f = 90.64\,km. \tag{4.30}$$

The linear matrices for A_{eq3} are shown below in (4.31) to (4.34) :

$$A_{eq3} = [U^t_{j(4\times N)}, U^b_{j(4\times N)}, A_8, a_{j(4\times N)}, A_9]_{4\times(5N+2)}. \tag{4.31}$$

$$A_8 = \begin{bmatrix} v_j^{i,*} & 0 & \dots & 0 \\ v_j^{f,*} & 0 & \dots & -v_j^{f,*} \\ 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \end{bmatrix}_{4\times(N+1)}, \tag{4.32}$$

$$A_9 = \begin{bmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ s_j^i & 0 & \dots & 0 \\ 0 & 0 & \dots & s_j^f \end{bmatrix}_{4\times(N+1)}, \tag{4.33}$$

$$b_{eq3} = \begin{bmatrix} v_j^{i,*} \\ v_j^{f,*} \\ s_j^i \\ s_j^f \end{bmatrix}_{4\times 1}. \tag{4.34}$$

The lower bounds (L_B) and upper bounds (U_B) are shown in (4.35) to (4.36). The simulation results shown in Chapter 5 using the MATLAB Opti-Toolbox are used to validate the FEDEO algorithm.

$$\begin{aligned} L_B = {} & [0,\dots 0,\, 0,\dots 0, -2.87,\dots -2.87,\, 0,\dots \\ & 0,\, 0,\dots 0]^T_{(5N+2)\times 1}, \end{aligned} \tag{4.35}$$

$$\begin{aligned} U_B = {} & [10,\dots 10,\, 10,\dots 10, 2.03,\dots 2.03,\, 80,\dots \\ & 80,\, 90.64,\dots 90.64]^T_{(5N+2)\times 1}. \end{aligned} \tag{4.36}$$

4.3 SUMMARY

The FEDEO algorithm using MINLP makes continuous iterations to find the global minimum and not the local minima for the energy consumption profile. When simulated in MATLAB, these points are called nodes and aim to find a unique global optimal solution under mild and realistic conditions outlined by the route profile. Application of the tractive and braking effort notches at the critical points of the journey is essential to reduce overall energy usage and maintain an ideal trajectory for the section of 90.64 km considered in the study. The speed profile simulation describes a trajectory that does not regularly accelerate and brake, but rather performs more cruising and coasting. A description of the route profile simulations is presented in Chapter 5.

CHAPTER 5 FEDEO SIMULATION RESULTS

5.1 CHAPTER OVERVIEW

This chapter presents the FEDEO simulation results. Section 5.2 validates the superiority of the algorithm versus other global rule-based methods. Section 5.3 outlines the route profile used for FEDEO. Section 5.4 presents the results of the [0, 90.64 km] profile. The entire simulated section is 90.64 km, with a smaller section of 20.64 km to check the FEDEO algorithm speed-tracking solution. Section 5.5 then shows the results of [70, 90.64 km] with start and end speed at 0 km/h and Section 5.6 shows the results of the same profile with the start and end speed at 60 km/h.

5.2 GLOBAL RULE BASED METHODS VERSUS FEDEO

There are numerous methods used currently to optimise energy usage for electric vehicles. The methods require an increased amount of computation time, and do not necessarily give you the global optimal solution [11]. In [3], Howlett *et al.* uses the Hamiltonian analysis to consider the full range of possible control transitions at the end of each regular phase of optimal control. The Pontryagin principle is then incorporated to use the position as the independent variable. The method uses multi-point boundary conditions with partial derivatives and continuous functions and is therefore best applied to a multiple-mass-point model. This is due to each vehicle being considered for in-train forces, but this becomes extremely complex and skewed when you have a train with different types of locomotives and wagons [4].

The approach of MPC has to take into account all physical and operational constraints, which becomes extremely complex for a route with changing conditions and route profile. The disadvantage of MPC lies on its complex algorithm that generally needs longer time than other controllers. All present studies schedule a train according to its current running condition, including position, velocity and track information. It is desirable to optimise the train's operation during a longer travel period, rather than at a specific position, such that the future states are accounted for. The FEDEO algorithm does this by predicting the optimal behaviour of the train over the route profile. The FEDEO algorithm adopted from [15] optimises the train's operation over a long journey. The control manipulates the traction/braking forces required by optimising the notches required. At each time when a control is required, the FEDEO control predicts the future states of the train, according to information available, for a specific time interval t_s [36]. The FEDEO algorithm is superior to other approaches due to its computational efficiency, cost effectiveness and energy savings.

5.3 FEDEO ROUTE PROFILE

The FEDEO algorithm is simulated from Ermelo to Kempton Park. From these stations, the 200 loaded wagons from more than 46 coal sidings are shared into a 200-wagon train for the export market. Ermelo handles AC, DC and diesel traction, which are used to power the trains. The Ermelo-Richards Bay route was built in 1976 and trains have to overcome a height difference of 1700 metres on their journey. The loaded trains have to endure significant gradients of around 6.25%, while empty trains travelling uphill have to endure an estimated 6.25% gradient. This can contribute to a substantial amount of energy consumption. On average, 48 trains can run on the 25 kV route powered by AC. But, owing to the limited power supply, the trains can only follow each other every hour. A complete trip along the entire Ermelo-Richards Bay route takes about 17 hours. The 200 car trains are usually approximately 2.5 metres long and weigh an estimated 20,800 tonnes [12, 70].

A case study of the 19E train profile with CCR-9 wagons has been investigated to validate the optimisation algorithm. The assumption is that the maximum travel time in the present work is 1.45 hours, divided into sampling period t_s or dt, of 1.05 minute, which is 62.70 seconds, yielding total samples of N is $(1.45 \times 60/1.05) = 83$. The average time between data points is 1.05 minute or 62.70 seconds. This data is based on existing route profile data, where trains have traversed the Ermelo-Richards Bay section route profile. The FEDEO parameters are shown in Table 4.1. The optimal velocity profile between Ermelo and Richards Bay is shown in Figure 3.2. A maximum of 3000 kN tractive effort is expected with an 80 km/h speed limit [1, 11, 17].

The FEDEO algorithm performs a discrete iteration to find the global minimum, as shown in Figure 5.2. Figure 5.2 shows that the train will try to accelerate rapidly, then cruise for a distance, coast, and finally apply the brakes at the stop. Figure 5.4 follows a similar trajectory as the mass is used to determine the force experienced by the train. Figure 5.5 shows cumulative energy usage of the train.

The elevation smoothing profile is used to incorporate a data set that is simplified for the FEDEO algorithm to optimise energy use. The actual speed data was obtained from the black box located within the locomotive cab. The data was recorded during March 2015 between the stations of Ermelo and Kempton Park.

5.4 ECO-DRIVING SOLUTION FOR [0, 90.64 KM]

This section presents a simulation of the FEDEO algorithm for the entire section of the route from Ermelo to Kempton Park. The profile is the entire section of simulated track that will be analysed to validate the energy savings and velocity optimal trajectory.

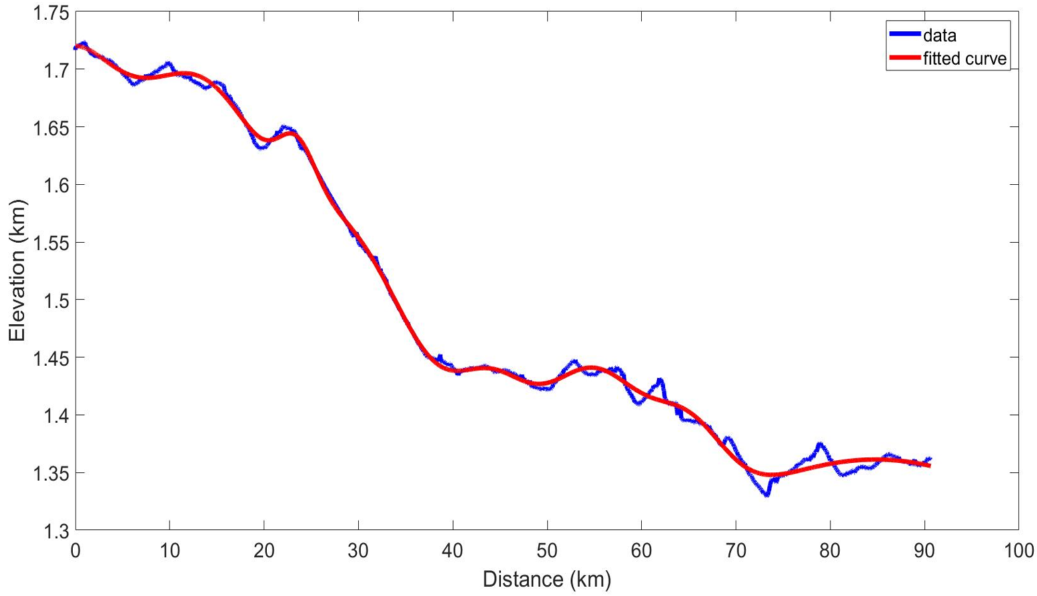

Figure 5.1. Elevation smoothing profile for [0, 90.64 km]

The tractive effort force of the train shown in Figure 5.3 indicates a maximum value of 2839 kN, while the braking effort is significant because it is required for regeneration. Ft represents the tractive force, Fg is the gravitational force, Fb represents the braking force, Fr is the rolling resistance force, $Fnet$ is the net force or summation of all the forces and Route Profile is the elevation profile. The train comes to a stop at the 40 km point as this is a security checkpoint. The power used for the 90.64 km section is 11,369 kW, which explains the optimal energy usage (kWh) shown in Table 6.1. The MA is also lower at 0.4739 m/s^2 for the 90.64 km section.

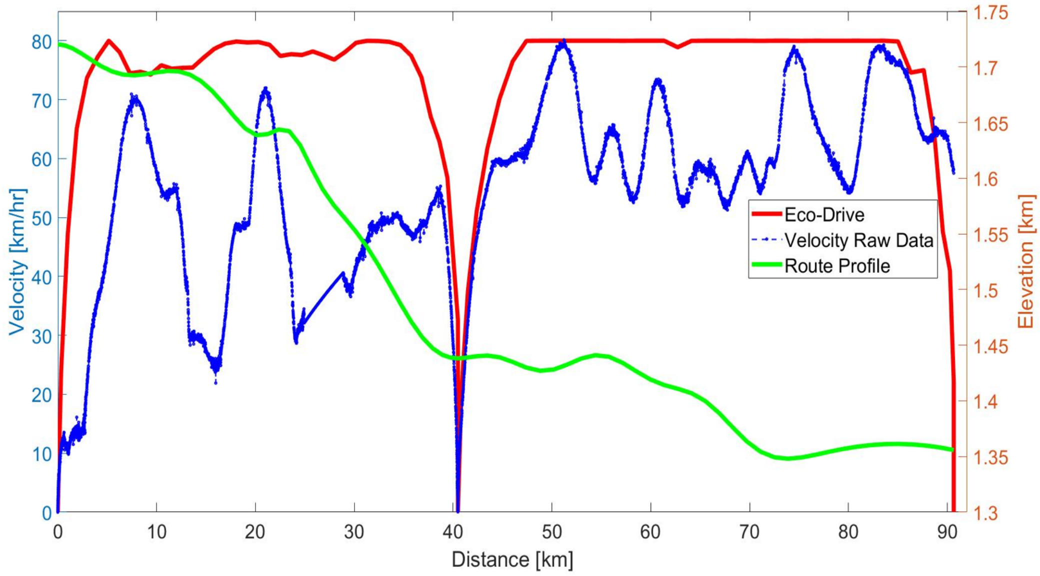

Figure 5.2. Speed profile for Ermelo-Richards Bay section [0, 90.64 km]

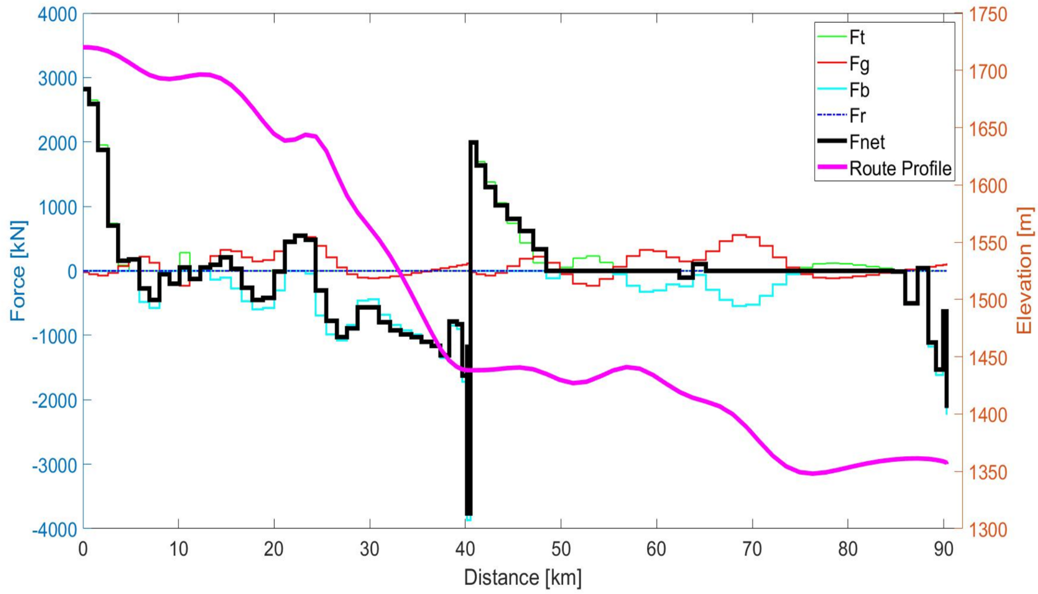

Figure 5.3. Route profile against forces for [0, 90.64 km]

The net force, $Fnet$, shown in Figure 5.3 varies according to the route profile and the magnitude of the force is dependant on the change in gradient. This will allow the driver to predict where a large magnitude of tractive or braking effort is require to propel the train. The braking force will significantly contribute to the regeneration energy savings, but this study will require more data and a multiple-mass-point model to accurately calculate the energy savings of the train.

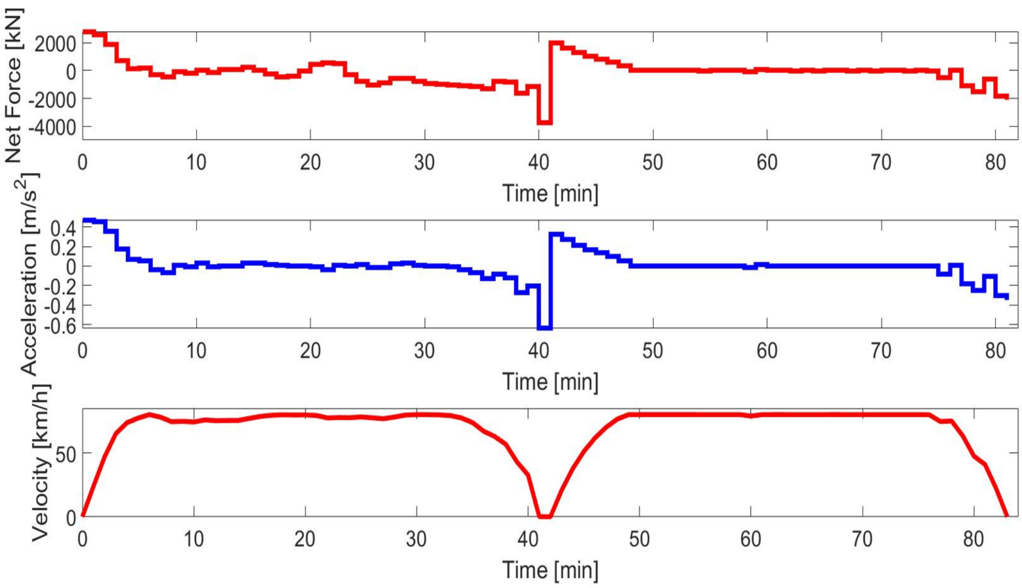

Figure 5.4. Net force, acceleration, and velocity simulation for [0, 86.74 minutes]

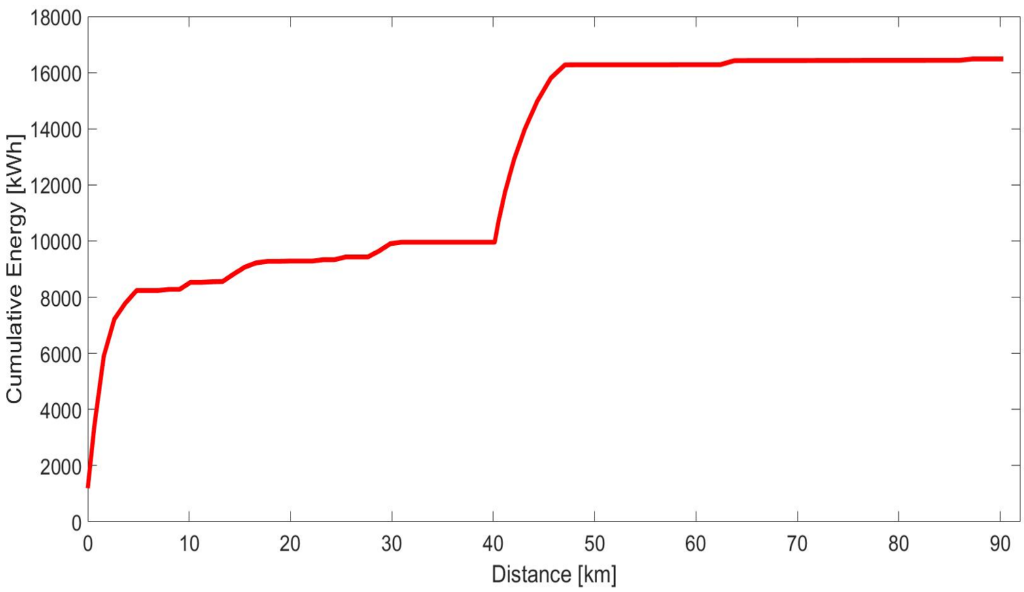

Figure 5.5. Cumulative energy plot for [0, 90.64 km]

5.5 ECO-DRIVING SOLUTION FOR [70, 90.64 KM] WITH START AND END SPEED AT 0 KM/H

This section presents the results of applying the FEDEO algorithm over a specific distance of 20.64 km, which is the last part of the route from 70 km to 90.64 km. The plots shown in Figures 5.6 to 5.10 simulate the speed at the start to be 0 km/h and the final speed to be 0 km/h.

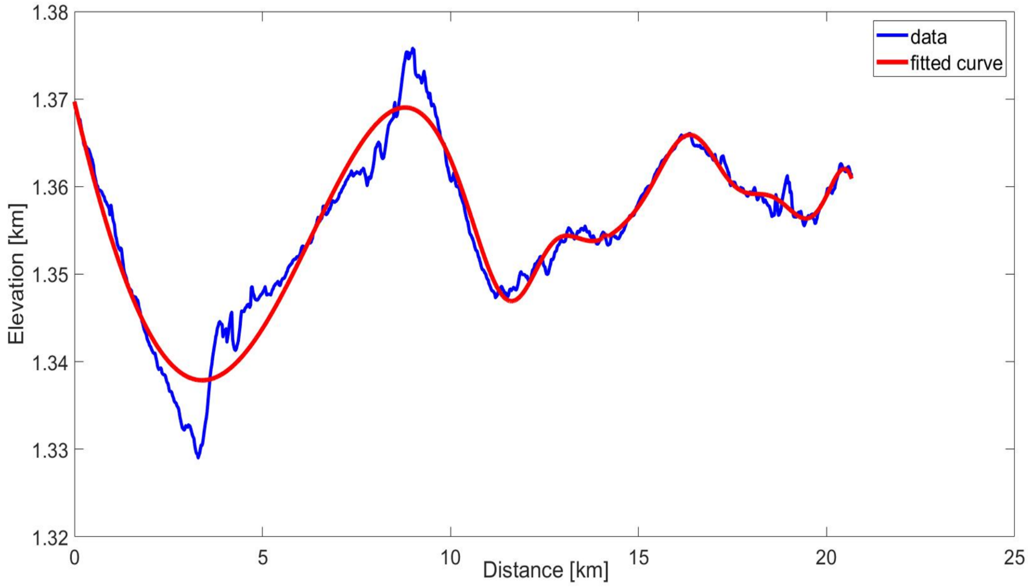

Figure 5.6. Elevation smoothing profile for [70, 90.64 km]

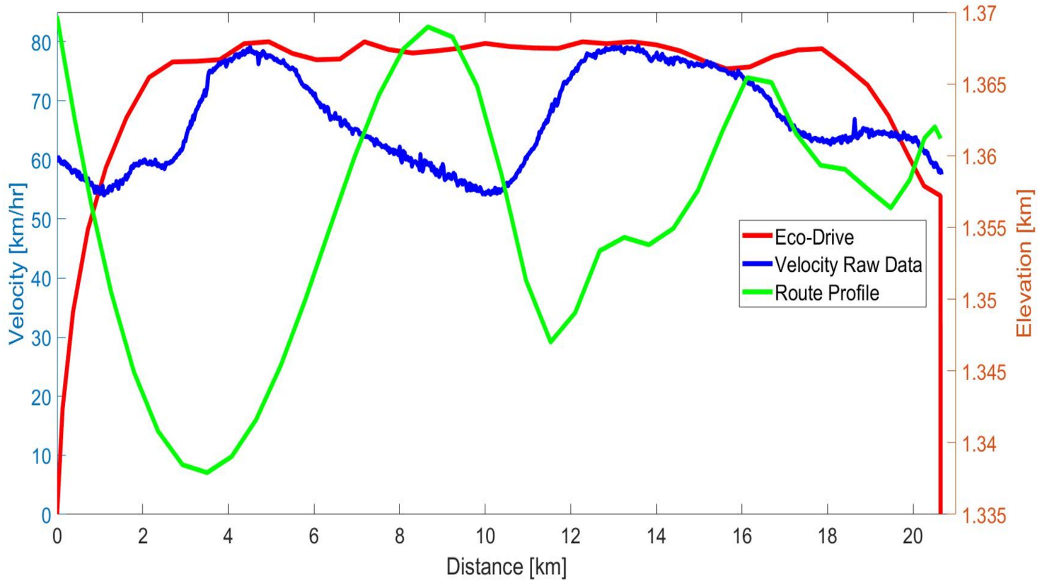

Figure 5.7. Speed profile for [70, 90.64 km]

The energy consumption for the section [70, 90.64 km] with start and end speed at 0 km/h is higher than the measured route energy usage owing to the train speed being required to start and end at 0 km/h. The forced start and end speed simulated in MATLAB makes the energy usage 47% higher. The time taken for the optimised route profile is 6.37% less than the actual time. The optimal route profile validates that energy can be saved if there is less acceleration and braking, and more cruising and coasting. This can be seen in the speed profile shown in Figure 5.7.

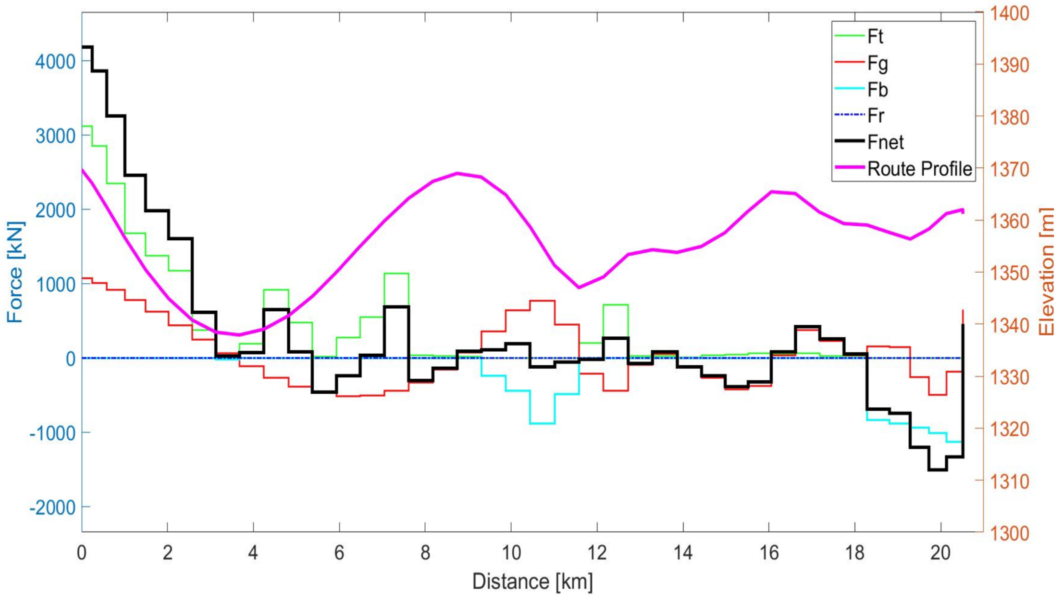

Figure 5.8. Route profile against forces for [70, 90.64 km]

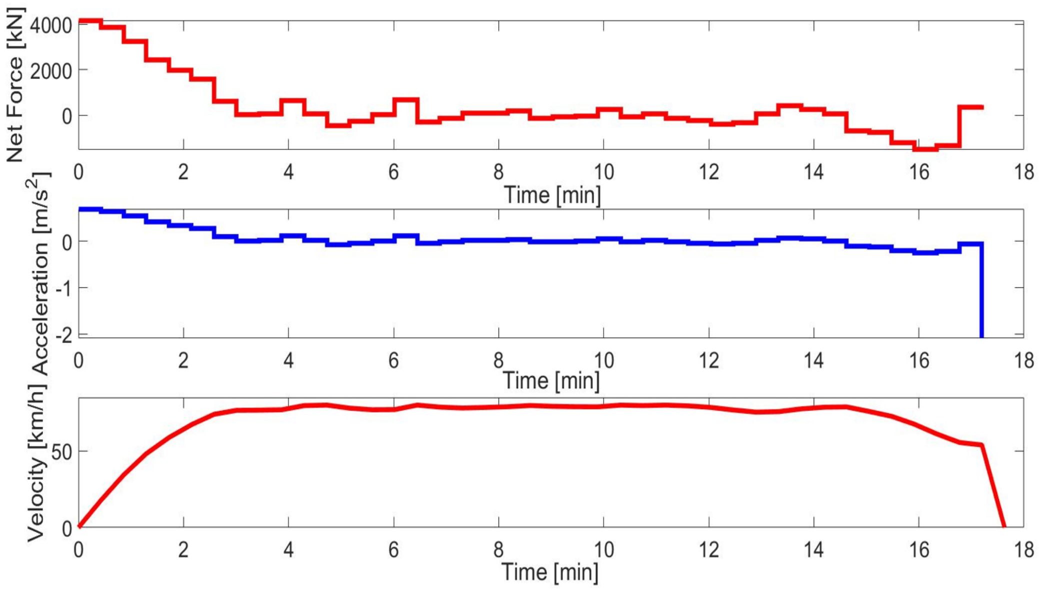

Figure 5.9. Net force, acceleration, and velocity simulation for [0, 17.63 minutes]

The force profiles shown in Figure 5.8 describe the adjustments to the train trajectory with regard to the tractive and braking forces as the elevation changes. The optimal energy usage of 7448.9 kWh is higher than the actual 5097 kWh used. The true representation of this optimal trajectory is presented in Section 5.6, where the FEDEO algorithm is applied. The duration of the optimal trip is lower than the actual trip because of sudden changes in acceleration and braking.

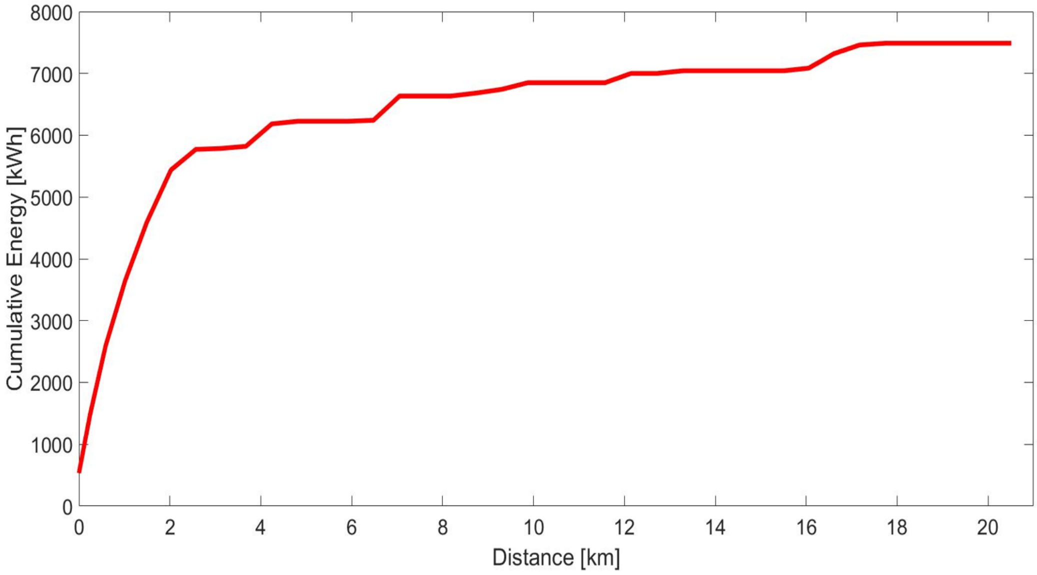

Figure 5.10. Cumulative energy plot for [70, 90.64 km]

5.6 ECO-DRIVING SOLUTION FOR [70, 90.64 KM] WITH START AND END SPEED AT 60 KM/H

In this section, results for [70, 90.64 km] are presented with a simulated train speed that starts at 60 km/h and ends at 60 km/h.

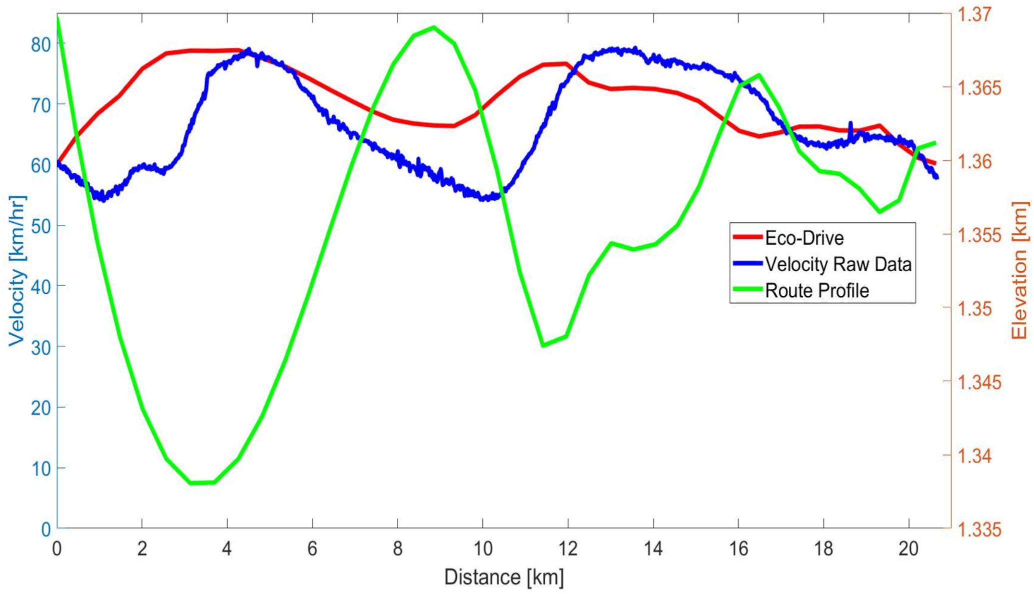

Figure 5.11. Speed profile for [70, 90.64 km]

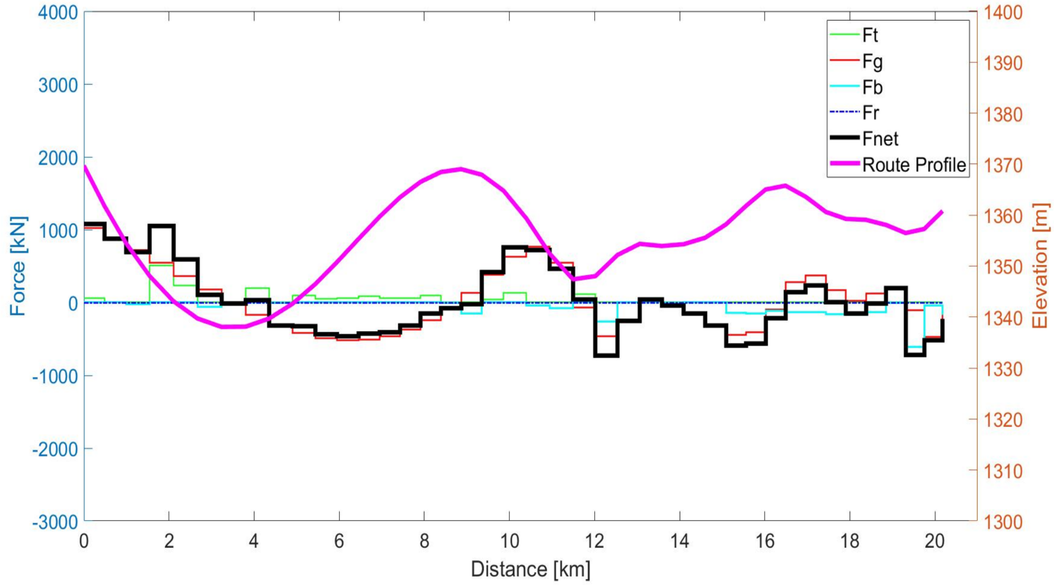

Figure 5.12. Route profile against forces for [70, 90.64 km]

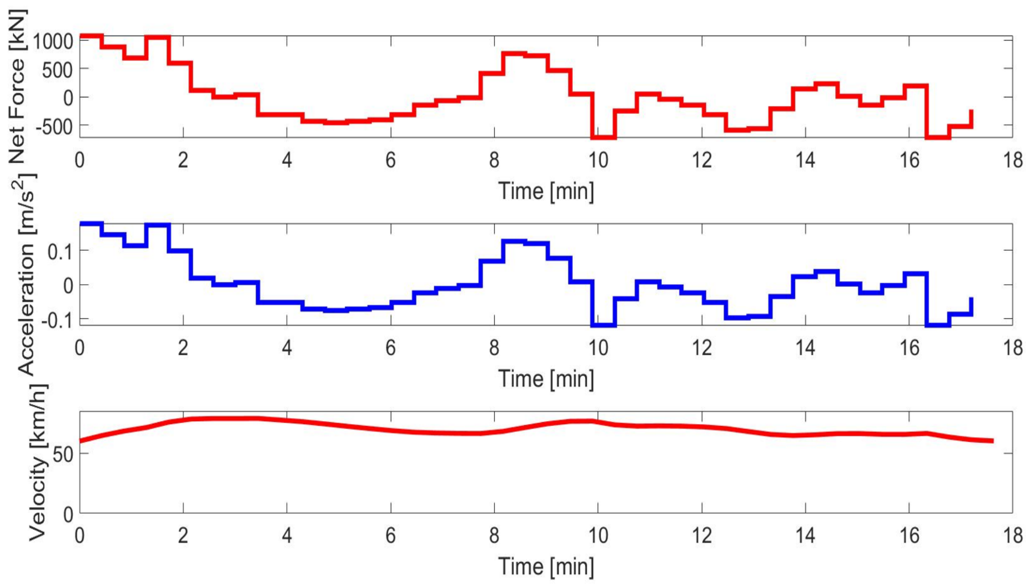

Figure 5.13. Net force, acceleration, and velocity for [0, 17.63 minutes]

The energy consumption reduces by 25.17% compared to the measured route profile. The energy usage calculated is based on the acceleration $a(t)$ in m/s^2, power $P(t)$ in $Watts(W)$ or $N.m/s$ and energy $E(t)$ measured in Wh. The negative acceleration is braking, and acceleration that is positive is used for traction.

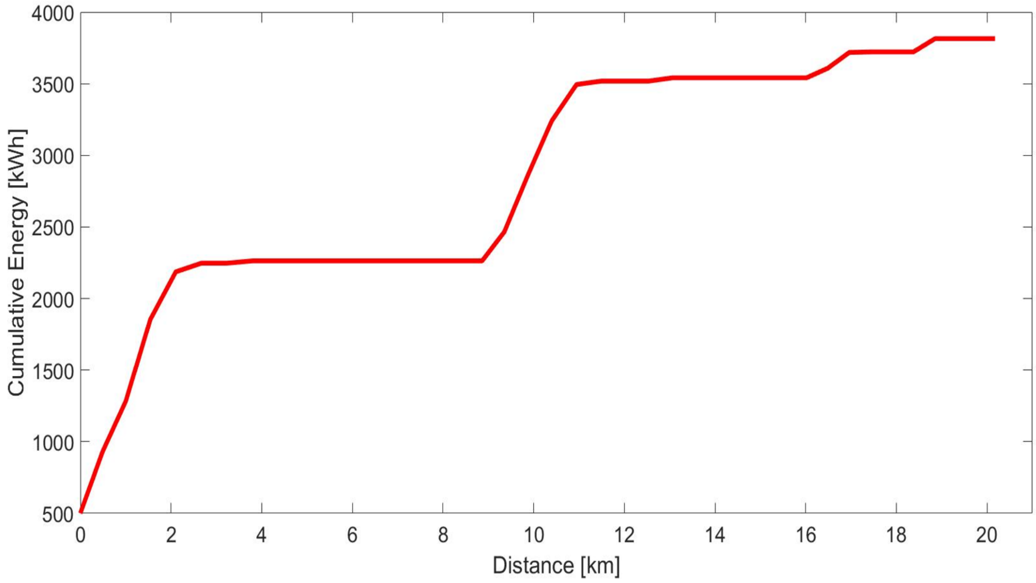

Figure 5.14. Cumulative energy plot for [70, 90.64 km]

$$\frac{dv}{dt} = a(t)\ ,\ Force\ F(t) = ma(t), \tag{5.1}$$

$$P(t) = F(t)\ x\ v(t), \tag{5.2}$$

$$E(t) = P(t) \times dt. \tag{5.3}$$

The results were plotted according to the theoretical algorithms presented in Chapter 4. Figures 5.1 to 5.14 describe the results of the FEDEO optimisation after the speed-tracking control is applied. The results presented in this chapter are interpreted and discussed in Chapter 6, where the optimised sections of the route profile are presented and the savings achieved described.

CHAPTER 6 DISCUSSION

6.1 CHAPTER OVERVIEW

This chapter answers the research questions posed in Chapter 1 in Section 6.2, and discusses the results of the FEDEO algorithm simulation in Section 6.3. In this discussion it presents a summary of the cost and energy-saving figures and discusses how these can be achieved in the scenario of the 19E train on the specific Ermelo to Richards Bay section of the coal line.

6.2 RESEARCH QUESTIONS FEEDBACK

The study sought to answer ten research questions concerning the FEDEO algorithm [4]:

- What is the magnitude of achieving improved energy savings with the FEDEO algorithm using the MINLP optimisation method?
- What is the influence of the FEDEO algorithm on reducing journey time?
- Does the FEDEO solution meet the problem of saving operational cost within the freight rail sector?
- Does the FEDEO algorithm obtain an energy-efficient solution that saves cost and optimises energy usage?
- Which algorithm is best suited for a train journey when the elevation, distance, and resistance coefficients are known, and driver decisions for notch control need to be considered?
- Has the eco-driving solution found the optimal velocity and is there speed-tracking control?
- Is the FEDEO algorithm applicable to any set of route data that provides the distance and relative elevation?
- Is there an improvement in overall efficiency and significant savings by applying FEDEO?
- Does the number of locomotives and wagons have an effect on the optimisation performance in the real-world?

- How does the FEDEO algorithm show superiority over other rule-based optimisation methods?

The research questions posed in Chapter 1 sought to establish whether the FEDEO solution meets the requirements of an eco-driving solution. The magnitude of achieving energy savings has been validated as a 34.76% result indicates significant cost reduction. This ensures that the FEDEO algorithm searches for the optimal velocity trajectory. The influence of the FEDEO algorithm on reducing journey time is significant as there is more cruising and coasting, as well as less acceleration and braking at various intervals of the route section. The FEDEO solution meets the problem of saving operational cost within the freight rail sector, by creating an energy optimal route profile speed trajectory. The result of the FEDEO solution optimises energy usage through its objective function, which uses the optimal notch for an efficient velocity trajectory. The FEDEO algorithm has proven that this solution will exist for any solution where the elevation, distance, and train coefficient parameters are known.

The eco-driving solution has found the optimal velocity and implements a speed-tracking control based on the locomotive dynamics and longitudinal movement of the train. The results shown in Table 6.1 indicate an increase in overall efficiency and significant savings through implementing FEDEO. The number of locomotives and wagons definitely has an effect on the optimisation performance in the real-world as the single-mass-point model is used. In [36], it is highlighted that using a single-mass-point model in a long train leads to unreasonable power distribution throughout the train and results in unacceptable in-train forces. This is because a portion of the train will be over the hill, and a portion of the train behind the hill. The FEDEO algorithm is superior compared to other approaches due to its cost effectiveness, energy savings, robustness and performance shown in this study.

6.3 DISCUSSION OF FEDEO SIMULATION RESULTS

The first finding of the study is that the FEDEO algorithm shows results with a signficant reduction in energy usage over the complete journey, which is affected by train acceleration, speed, and gradient constraints. This means it has achieved energy savings using the MINLP method, which leads to improvement in overall efficiency. The profile prediction horizon of the eco-driving solution was broken down into N intervals within the discretised prediction horizon in the FEDEO algorithm. An EV will realistically follow the continuous algorithm since the route profile will follow a continuous path. However, in the case of the 19E electric locomotive with regeneration, the simulation has shown that driving can be improved at gradients requiring higher speeds and substantial energy savings can be achieved by the simple application of the train notch decisions. The braking force combines the mechanical and electrical braking, and the braking force is low when the train runs at high speed owing to the reliance on coasting for movement.

The second finding is that the FEDEO algorithm utilises the optimal notch at each time interval of the journey. This means that the best suited algorithm has been found when distance and elevation are known. It also allows more braking as this force is responsible for regenerative energy. The typical gradient varies from -3 to +3% for the route profile regarding freight sections globally; this is because freight trains cannot carry an excessive load over specific gradients for reasons such as possible stalling, loss of cargo, higher energy usage required to overcome higher gradients, and onboard power electronics of the locomotive not having the required traction. The algorithm developed using MINLP can allow the train control centre to advise the driver about which route profile behaviour to follow regarding the train at gradients with a high energy usage requirement [11, 72].

The third finding is that the FEDEO algorithm utilises more coasting and cruising, and fewer changes in the acceleration and braking. The specific eco-driving solution introduced in this study uses a significant acceleration in the beginning, lower gradient resistance in the middle of the section (coasting), and fast braking at the end of the section. The FEDEO algorithm reduces journey time, finds the optimal velocity and implements speed-tracking control. The train requires the traction energy to achieve the gravitational energy on sections that are uphill and uses the gravitational energy on downhill sections. The quality of the trip is optimised by using minimal traction energy on the middle sections of the route. The eco-driving solution depends on the train mass, acceleration and speed limitations, and the gradient profile of the route.

The fourth finding is that the solution can be used for any freight train, provided that the route profile and train coefficient parameters are known. The maximum speed limits also have a critical impact on the optimal route profile and the energy savings. The static parameters such as the gradient profile, speed and acceleration limits, and train mass cannot be modified. However, dynamic parameters have been optimised using the MINLP algorithm or eco-driving. The formulation reduces the difference in the trajectory the train would follow if it were to traverse a continuous profile, compared to the discrete case, which incorporates notches as demonstrated by the MINLP algorithm. The FEDEO algorithm has shown reduced energy usage and distinct savings, as summarised in Table 6.1 [6, 11, 72].

The final finding is that the eco-driving solution applied to EVs can also be applied to freight trains by incorporating the train coefficient parameters. The discrete objective function obtained is for the speed greater than 0 with the train moving forward. In the ideal problem case, the tractive and braking energy both contribute to the route profile energy consumption. However, in the discrete eco-driving approach described in Section 4.2, the 19E locomotive only requires energy consumption from the tractive effort. The energy used during braking is fed back into the overhead line as regeneration energy. The eco-driving example is applied to a hybrid EV, as outlined by Khalik *et al.* [11]. In this study, this approach has been applied to the scenario of the 19E train on the specific Ermelo to Richards Bay section. A variable speed has been proposed with an eco-driving strategy where the train speed changes between the given bounds of the route profile. The comparison between the actual and optimal eco-driving energy costs and the time taken is shown in Table 6.1 [15, 52, 72, 74].

Table 6.1. Energy usage comparison of the FEDEO simulated sections

Simulated Section (FEDEO)	Actual energy usage (kWh)	Optimal energy usage (kWh)	Actual time (minutes)	Optimal time (minutes)
[0, 90.64 km]	25,629.48	16,485.00	122.97	86.74
[70, 90.64 km] $[0\ km/h, 0\ km/h]$	5097.79	7488.9	18.83	17.63
[70, 90.64 km] $[60\ km/h, 60\ km/h]$	5097.79	3814.9	18.83	17.63
Savings (%)				
[0, 90.64 km]	-	34.763	-	29.46
[70, 90.64 km] $[0\ km/h, 0\ km/h]$	-	- 46.905	-	6.373
[70, 90.64 km] $[60\ km/h, 60\ km/h]$	-	25.166	-	6.373

CHAPTER 7 CONCLUSION

7.1 SUMMARY

In conclusion, the optimisation of the energy utilising MINLP by making calculated decisions using the tractive and braking effort significantly reduces the overall energy consumption of the train by exactly 34.76% for the entire route section and 25.17% for the smaller section of 20.64 km. Non-linear vehicle dynamics formulate the general train control problem from the traction and train resistance forces as a function of speed and route elevation changes. The route is partitioned into stations of varying gradients and speed. The problem formulated is a multiple phase problem where each section of the route depends on the load being hauled, the gradient, and the train's ability to coast, cruise, brake, and accelerate during inclines and declines. Owing to the nature of the 19E train, which utilises regenerative braking, the focus is on the train's tractive effort, acceleration, and speed for optimisation. The modelling of the eco-driving solution has shown that intelligent driving over large gradients can significantly save cost and improve the train trajectory over the route profile.

This study has reviewed the energy optimisation (FEDEO) algorithm for reducing energy consumption and costs for the 19E train using CCR-9 wagons on the Ermelo-Richards Bay coal line. Energy-efficient train control is a requirement for the operational sector of freight transport. Any optimisation model used needs to be analysed and set out methodologically to obtain the required performance and accuracy. The algorithm in this study has optimised the solution of eco-driving within the freight rail sector of South Africa and globally.

7.2 RECOMMENDATIONS FOR FUTURE RESEARCH

The following recommendations are made for future research regarding the eco-driving of trains:

- A networking model element could be incorporated where a timetable is required for the optimisation of energy as and when the trains arrive and depart
- A driver advisory solution that incorporates the energy optimisation algorithm for improving driving behaviour and train movement could be analysed
- Different sections of the South African freight route such as the iron-ore and manganese transport lines could be analysed and compared to the findings of this study
- The regeneration energy savings could be remodelled
- Incorporating a cascaded or multiple-mass-point model for future studies to obtain accurate in-train forces and power distribution

7.3 PRACTICAL RECOMMENDATIONS FOR ECO-DRIVING

The following practical recommendations are made for the validation of energy savings:

- Internet of Things (IoT) devices should be installed on board a freight train to record route data, and a comparison study made with the FEDEO algorithm
- A driver should follow the route profile generated by the FEDEO algorithm to check whether the solution can improve the driving style over this route
- A practical solution should be implemented where this solution could be incorporated as a sub-system of the driver cab screen and real-time data inputted as the train is in motion or stationary
- Energy usage data on board the train should be monitored through energy meters
- A platform with electronic components should be utilised to measure the actual regeneration energy obtained from braking, to compare to the FEDEO algorithm calculated usage

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