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Performance quantification of signal interfaces in hybridized long vehicle combinations

Comparative Analysis of Energy Management Allocation Strategies: A Study on Model Predictive Control (MPC) vs. Rule-Based Control Under Information-Reduced Conditions

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Cover:A modern electrically converter dolly (e-dolly) with a streamlined design and unique tyres and connections.

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Abstract

This study develops a predictive control algorithm for hybrid trucks operating under reduced information exchange conditions. In these conditions, the signal interface of an electric converter dolly (E-dolly) transmits limited vehicle state and control signals. This e-dolly connects the first and second trailers in an A-double vehicle combination. The study compares fuel consumption across different power split strategies. Simulation results showed that lower fuel consumption was achieved by formulating nonlinear optimal control problem and solving it using sequential linear programming (SLP). In addition, a grid search method was used in rule-based hybrid truck model to adapt it to different topography and speed limits. The study also introduces the real-time iterative (RTI) method for updating in real time, which achieves lower fuel consumption compared to grid search. This study not only verifies the effectiveness of SLP in dealing with nonlinear programming (NLP) problems, but also explores the potential for real-time updates. This is particularly relevant in scenarios with reduced information exchange through the signal interface. Based on these methods, optimal energy allocation strategies can be provided for different external environments.

Keywords: long combination trucks, fuel consumption, sequential linear programming, predictive energy management, nonlinear model predictive control(NMPC), Real-Time Iteration.

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Yao Wang & Tianyi Zhang, Gothenburg, June 2024

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ADS	Automated Driving Systems
ADS–DV	Automated Driving Systems-Dedicated Vehicle
AGV	Automated Guided Vehicle
BEHV	Battery Electric Heavy Vehicle
CHV	Conventional Heavy Vehicle
COG	Center of Gravity
DAE	Differential Algebraic Equations
EM	Electric Motor
EMS	Energy Management Strategy
ICE	Internal Combustion Engine
LCV	Long Combination Vehicle
LHV	Longer Heavier Vehicle
LP	Linear Program
LTI	Linear Time-Invariant
LTV	Linear Time-Varying
MINLP	Mixed Integer Nonlinear Programs
MPC	Model Predictive Control
NLP	Nonlinear Programs
NMPC	Nonlinear Model Predictive Control
NOCP	Nonlinear Optimal Control Problem
OCP	Optimal Control Problem
ODE	Ordinary Differential Equations
PEM	Predictive Energy Management
RTI	Real-Time Iteration
SLP	Sequential Linear Programming

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1
Introduction

1.1 Background

It is often anticipated that the demand for road transport will continue to grow to address increasing transportation needs. On December 1, 2023, Sweden enacted a landmark and groundbreaking legislation allowing truck combinations of 34 meters in length and a maximum total weight of 74 tons[1]. This strategic measure aims to improve transportation efficiency by increasing the carrying capacity of vehicles. Previous analyses of similar legislation in Sweden, allowing longer and heavier vehicles (LHVs), have shown improvements in transport efficiency and emissions reduction [2].

To improve overall vehicle combination cost and efficiency, The HELPED Project aims to integrate the propulsion capabilities of e-dollies with those of existing long-combination vehicles (LCVs). However, achieving optimal power distribution between the ICE and the dolly's electric motor is a significant challenge, especially in complex real-world driving scenarios. This challenge can be addressed effectively by formulating it as a nonlinear optimal control problem (NOCP) and solving it to achieve optimal performance.

The best performance of these vehicles rely on the communication of key operating data such as speed, acceleration, and power usage between different vehicle units. Reducing this data communication may result in sub-optimal energy utilization because the system may not be able to make fully intelligent decisions about propulsion and braking. Therefore, to study the specific impact of information loss on and signal interfaces between vehicle units, this project will compare the simulation results of specific methods such as a rule-based hybrid truck model, off-line NMPC, and on-line NMPC, and obtain a large amount of optimization and simulation data by setting different conditions. This can help users designing different energy allocation strategies according to given transportation tasks and limits of data communication and signal interfaces between vehicle units.

1.2 Aim

The central objective of this study is to meticulously evaluate the influence of signal interferences on performance outcomes. We place a special emphasis on energy consumption metrics. This analysis considers diverse mission profiles and investi-

gates the implications of varied power split control strategies. The ultimate goal is to optimize performance when there is a reduced information exchange between long-combination vehicle (LCV) units.

1.3 Limitations

A simulated plant model of the vehicle is used to generate data under various conditions. This data supports the design of energy allocation strategies for different tasks. Therefore, the uncertainty that may exist in the transportation task is ignored in this project. The parameters such as the prescribed reference curve generated by nonlinear optimization do not take into account unexpected changes in the environment. At the same time, the vehicle model used for motion control in this paper is derived based on assumptions.

The results of this thesis are based on simulations, and the proposed control algorithm has not been experimentally verified, the mathematical model of the vehicle used is obtained based on experimental data. At the same time, it is necessary to assume that the surrounding environment information and feedback signals are partially missing, and then study how e-dolly will set a reasonable energy allocation strategy based on the current situation when the signal is missing.

1.4 Main Research Questions

The main research questions to be answered in this project are summarized as follows:

1. How is the energy-saving performance influenced by reduced signal exchange between the vehicles of the combination?
2. How can the signal interface investigation be made independent on the power-split control strategy?
3. How can the signal interface investigation be made agnostic to the mission characteristics, such as topography, speeds etc.?

2

Methodology and Problem Formulation

This chapter provides a comprehensive overview of the methodology used in this study. We introduced an electric converter dolly (E-dolly) in a long combination truck, detailing our choice of the battery model for the E-dolly and fitting the torque curve of the electric motor and internal combustion engine. This approach improved energy efficiency, reduced fuel consumption, and enhanced road safety [3]. Additionally, we developed control strategies to optimize fuel consumption, designed to function effectively even with information reduced on the E-dolly interface between vehicle units. Furthermore, we discuss a real-time solution to nonlinear optimization problems to maximize vehicle performance and efficiency under these challenging conditions.

To validate the proposed methodology and design, we simulated how the vehicle model performed under different road conditions and control strategies, which generated a large amount of fuel consumption data. By comparing this data, we identified the best parameter settings and control strategy for optimal truck model perform. This approach provides valuable insights into optimizing energy allocation strategies and braking force distribution when introduce E-dollies to LCVs in practical applications.

2.1 Architecture

The aim of the project is to compare the fuel consumption of a vehicle combination with hybrid propulsion, controlled by a rule-based powertrain management system, to that of a predictive energy management (PEM) controlled vehicle for a given task. Additionally, the project seeks to determine the optimal energy allocation strategy under reduced information conditions. The study is based on road data provided by Volvo Group and the research process is as follows:

– First, simulation is performed using a conventionally powered truck model with known road information (e.g. topography, speed limit, etc.). Parameters such as travel time and fuel consumption of the vehicle are calculated, considering factors such as engine power and gear shifting. The simulation of the conventionally powered truck model provided a reference for subsequent analyses to ensure a consistent comparison.

– Subsequently, based on the vehicle's fuel consumption parameters, environmental constants, dynamics parameters, states, and road data, several simulations were performed to ensure that the vehicle operated according to the expected behaviour during the simulation. These simulations are used to generate the initial guess to solve the nonlinear optimal control problem (NOCP). This step lays the foundation for the subsequent solution of the optimisation problem.

– After gathering the necessary data, Sequential Linear Programming (SLP) and real-time iteration are used to solve the nonlinear problem. The effectiveness of the optimization was validated by comparing the fuel consumption generated by the simulation with the baseline results. The SLP solver and RTI methods provide different optimization approaches for fuel consumption. Their effectiveness is evaluated by comparing the results from these two approaches.

– The optimal speed derived from the SLP solver is used as the reference speed for the rule-based hybrid truck model. Further simulations were carried out to calculate the fuel consumption for different energy distribution strategies (varying power distribution ratio of internal combustion engine and electric motor) and different allocations of braking energy between regenerative energy to electric motor and friction braking. The best energy distribution strategy and regenerative braking efficiency are determined by comparing the results. This process helps us to optimize the fuel efficiency of rule-based hybrid trucks in different road conditions (e.g. different topographies and speed limit), aiming to achieve near-optimal energy distribution strategy without solving NLP. This is valuable in scenarios with reduced data communication between vehicle units, where simpler, yet effective, strategies are crucial for maintaining performance.

– Finally, a real-time control strategy using the Real-Time Iteration (RTI) method is introduced. This strategy provides real-time control inputs for energy distribution and regenerative braking ratios based on current vehicle information and future road data. In situations where the communication between vehicle units is reduced, this strategy uses control inputs from the previous sampling interval. The RTI scheme is designed to ensure nominal closed-loop stability, even if few optimizer iterations are applied per control step [23]. This makes RTI suitable for applications with limited communication, as it can still maintain system stability and control performance under these conditions [4]. This study employs a SLP-based RTI instead of a the SQP-based RTI method used in [4] for small-scale quadrotor systems. The shift to sequential linear programming (SLP) is motivated by the increased complexity of long combination trucks, whose dynamics and computational demands make sequential quadratic programming (SQP) unsuitable for real-time iteration. This distinction is further introduced in subsequent sections. Consequently, real-time iteration has a better performance than a rule-based hybrid truck under re-

duced information conditions.

Through the above research process, we are able to determine the best energy distribution strategy and regenerative braking efficiency of for hybrid vehicle combinations, particularly in scenarios with limited communication between vehicle units. This finding improves the fuel efficiency and provides theoretical and practical support for the real-world application of hybrid vehicle combinations, when introducing electrical dolly propelled.

2.2 Optimization problems

The first is the construction of a non-linear optimization problem. Optimization problems generally consist of three elements:

1. Decision variables: $x = (x_1, x_2, \ldots, x_n)^T \in \mathbb{R}^n$, represents the variables we want to solve in the optimization problem.
2. Objective function: $f : \mathbb{R}^n \to \mathbb{R}$, represents an expression that needs to be maximized or minimized.
3. Constraint conditions: $c_i : \mathbb{R}^n \to \mathbb{R}^m$, Indicates the equality condition or inequality condition that needs to be satisfied.

The basic form of the optimisation problem is shown below:

$$\begin{array}{ll} \text{find} & \mathbf{x} \in \mathbb{R}^n \\ \text{minimize} & f(\mathbf{x}) \\ \text{subject to} & g_i(\mathbf{x}) \leq 0,\ i = 1, \ldots, m \\ & h_j(\mathbf{x}) = 0,\ j = 1, \ldots, n \end{array} \tag{2.1}$$

Where $\mathbf{x}$ is the decision variable, $f(\mathbf{x})$ denotes the cost function, and $g_i(\mathbf{x}) \leq 0$ and $h_j(\mathbf{x}) = 0$ represent a set of inequality and equality constraints, respectively, for constructing the optimisation problem.

Depending on the decision variables, the cost function, and the constraints, the approach to solving the optimisation problem varies. The problems addressed in this thesis have the following characteristics:

1. In EMS optimisation problems, the constraints usually contain integer variables (discrete variables) and continuous variables. These problems are essentially nonlinear programming problems (MINLP) with integer constraints. This type of optimisation problem is more complex and challenging to solve because it involves both discrete and continuous decision variables.

2. In the simplified energy management problems where gear selection decision variable is removed, optimisation problems involving continuous decision variables and nonlinear and smooth cost functions and constraints are known as nonlinear programming (NLP).

2.3 Sequential linear programming

Sequential programming is an effective method for solving complex nonlinear optimisation problems by progressively approximating the optimal solution by decomposing the original problem into a series of simpler subproblems. Ghandriz et al. applied Sequential Linear Programming (SLP) to mixed-integer nonlinear optimization problems in their research, demonstrating its advantages in speed compared to Sequential Quadratic Programming (SQP) [6]. Sequential Linear Programming (SLP) and Sequential Quadratic Programming (SQP) are two specific implementations of sequential programming. SLP transforms a nonlinear problem into a series of linear programming problems and SQP transforms it into a series of quadratic programming problems.

Sequential Linear Programming (SLP) is especially suitable for cases where the objective and constraint functions can be better approximated by linear functions. The basic idea is to decompose a complex nonlinear programming problem into a series of easy-to-solve linear programming problems by linearising the nonlinear functions. Specifically, SLP first linearises the objective function and constraint functions at the current solution point in each iteration step, and then solves the linearised linear programming problem to obtain a new solution point. This process is repeated, and each iteration improves the accuracy of the solution through the linearised approximation, gradually approximating the optimal solution of the nonlinear problem.

The specific implementation process of SLP can be summarised in the following steps. Firstly, an initial point $x^{(0)}$ is chosen to ensure that it lies in the feasible domain. Then, set the tolerance error ϵ and the maximum number of iterations N_{max}. In each iteration, the objective and constraint functions are first linearised at the current solution point $x^{(k)}$, i.e., the nonlinear function is approximated as a linear function using the first order term of the Taylor expansion. Next, the linearised linear programming problem described above is solved to obtain a new solution point $x^{(k+1)}$. Then, check the convergence of the solution, if the change between the new solution point and the current solution point is less than the set tolerance error ϵ, or the number of iterations reaches the maximum number of iterations N_{max}, stop the iteration, and the final solution is the optimal solution, or else the new solution point is used as the initial point for the next iteration, and the iterative process continues.[5]

Overall, SLP is an effective method of sequential programming, which can effectively approximate the optimal solution of a nonlinear problem by linearising and solving linear programming subproblems step by step. In contrast, Sequential Quadratic Programming (SQP) works better when dealing with nonlinear constraints and objective functions of quadratic terms, while SLP performs particularly well when the objective and constraint functions can be linearly approximated well. In this thesis, the SLP method is used to gradually approximate the optimal solution of the nonlinear problem by approximating the cost function and constraints with a linear (affine) function in each iteration.The following is the solution procedure for SLP.

Algorithm 1 Sequential Linear Programming (SLP) for Optimal Control

Input: Initial state $\hat{x}$, Initial control input $u_0(s)$, tolerance ϵ
Output: Approximate optimal control inputs $u^*(s)$
Initialization: $k \leftarrow 0$, $x^k(s) \leftarrow \hat{x}$, $u^k(s) \leftarrow u_0(s)$
while $|J^{k+1} - J^k| < \epsilon$ **do**
    Linearize the objective function and constraints:
        Gradient of the terminal cost: $\nabla_u C_t(x^k(s_f), s_f)$
        Gradient of the stage cost: $\nabla_u L(x^k(s), u^k(s), s)$
        Gradient of the dynamic constraints: $\nabla_u g$
        Gradient of the inequality constraints: $\nabla_u h$
    Solve the linear optimization problem to obtain the increment $\Delta u^k(s)$
    Update the control input: $u^{k+1}(s) \leftarrow u^k(s) + \Delta u^k(s)$
    Update the state: $x^{k+1}(s) \leftarrow x^k(s) + \int_{s_0}^{s} f(x^k(\tau), u^{k+1}(\tau), \tau)\, d\tau$
    Calculate the value of the objective function J^{k+1}
    $k \leftarrow k + 1$
end while
Return: $u^*(s) \leftarrow u^k(s)$

2.4 Nonlinear optimal control

Nonlinear optimal control aims at determining the best control strategy for a dynamic system to minimise the cost function. The problem studied in this thesis belongs to the nonlinear category, which is due to the fact that the cost function and its constraints contain a large number of nonlinear functions. Therefore, solving such problems requires sophisticated mathematical methods and algorithms to effectively deal with the nonlinear features and optimise the control performance.[5]

In this thesis, we study a nonlinear optimisation problem whose constraints are not based on the time dimension but on the spatial dimension. Specifically, we consider four roads with different flatness but the same length. To simplify the problem, it is assumed that these roads are continuous curves on a two-dimensional plane. In this way, we can define the optimisation problem as a nonlinear problem on a spatial domain:

$$\min_{u(s)} \left[C_t(x(s_f), s_f) + \int_{s_0}^{s_f} L(x(s), u(s), s)\, ds \right] \tag{2.2}$$

Subject to:
1. Dynamic system constraints:

$$g\left(x(s), \frac{dx(s)}{ds}, u(s), s\right) = 0 \tag{2.3}$$

2. Inequality constraints:

$$h\left(x(s), \frac{dx(s)}{ds}, u(s), s\right) \leq 0 \tag{2.4}$$

3. Initial state condition:

$$x(0) = \hat{x} \tag{2.5}$$

where C_t is the terminal cost, L denotes the stage cost, g denotes the dynamic system, $u(s)$ and $x(s)$ represent the inputs and states, respectively, h denotes the inequality constraints, $\hat{x}$ is the initial state, and s_0 and s_f represent the start and final distance. The nonlinear optimal control problems (NOCP) related to energy management involve various factors, such as fuel consumption, battery usage, and vehicle dynamics. These factors have been widely studied in vehicle energy management optimization [5, 6].

2.5 Nonlinear model predictive control

Nonlinear Model Predictive Control (NMPC) is a model-based control strategy widely used to deal with dynamic systems with nonlinear characteristics.[5] The core idea is to predict the future behaviour of the system by solving an optimisation problem at each sampling moment and to determine the current control inputs based on the prediction results.The NMPC approach can be divided into the following key steps:

1. **Model Predictive**: The basic principle of NMPC is to use a dynamic model of the system to predict future system behaviour [8]. This model is usually non-linear and can be of one of the following forms:
   - **Continuous time model**: Differential equations describing the state of a system over time.
   $$\dot{x}(t) = f(x(t), u(t)) \tag{2.6}$$
   - **Discrete time model**: Difference equations describing the change of state of a system at discrete space points.
   $$x_{k+1} = f(x_k, u_k) \tag{2.7}$$
2. **Prediction of the temporal or spatial domain**: Choose a prediction time domain or spatial domain T_p&S_p, i.e. the length of a future period of time or space (discrete time points). Predicted future states and control inputs are represented as vectors:
   - **State prediction vector**: $\{x^i_{k|k-1}, x^i_{k+1|k}, \ldots, x^i_{k+N|k+N-1}\}$
   - **Control Input Vector**: $\{u^i_{k|k-1}, u^i_{k+1|k}, \ldots, u^i_{k+N|k+N-1}\}$
3. **Optimisation problem building**: In the prediction time or spatial domain, an optimisation problem is created with an objective function that usually consists of the following two parts:

- **Tracking error**: Bring the system state as close as possible to the desired trajectory.

$$J_{\text{tracking}} = \sum_{j=0}^{N} \|x_{k+j} - x_{k+j}^{\text{ref}}\|_Q^2 \tag{2.8}$$

  where x_{k+j}^{ref} is the desired state and Q is the weight matrix.

- **Controlling costs**: Amount of change in control input

$$J_{\text{control}} = \sum_{j=0}^{N-1} \|u_{k+j-1} - u_{k+j-1}^{ref}\|_R^2 \tag{2.9}$$

  where R is the weight matrix.

In this thesis, for the convenience of expression, a variable z is defined as:

$$z_k^i = \begin{bmatrix} x_k^i \\ u_{k-1}^i \end{bmatrix} \tag{2.10}$$

Then the overall objective function is:

$$J = \sum_{j=0}^{N-1} \|z_{k+j}^i - z_{k+j}^{\text{ref},i}\|^2 = \sum_{j=0}^{N-1} \frac{1}{2} \begin{bmatrix} x_{k+j}^i - x_{k+j}^{\text{ref},i} \\ u_{k+j-1}^i - u_{k+j-1}^{\text{ref},i} \end{bmatrix}^\top \mathbf{W}_k^i \begin{bmatrix} x_{i,k} - x_{i,k}^{\text{ref},i} \\ u_{i,k} - u_{i,k}^{\text{ref},i} \end{bmatrix} \tag{2.11}$$

This represents a quadratic cost function. Although it is formulated as quadratic expression, this form can be used to represent the nonlinear programming by approximating nonlinear cost functions locally around a reference trajectory, provided that the stage cost is positive (semi-)definite [14]. Furthermore, the cost function can also include linear terms for linear approximations, such as:

$$J = \sum_{j=0}^{N-1} \frac{1}{2} \begin{bmatrix} x_{k+j}^i - x_{k+j}^{\text{ref},i} \\ u_{k+j-1}^i - u_{k+j-1}^{\text{ref},i} \end{bmatrix}^\top \mathbf{H}_k^i \begin{bmatrix} x_{k+j}^i - x_{k+j}^{\text{ref},i} \\ u_{k+j-1}^i - u_{k+j-1}^{\text{ref},i} \end{bmatrix} + \mathbf{Jf}_k^i \sum_{j=0}^{N-1} \begin{bmatrix} x_{k+j}^i - x_{k+j}^{\text{ref},i} \\ u_{k+j-1}^i - u_{k+j-1}^{\text{ref},i} \end{bmatrix} \tag{2.12}$$

Where $\mathbf{H}$ is the Hessian matrix of the quadratic approximation and $\mathbf{Jf}$ is the Jacobian matrix of the cost function. This cost function form is particularly useful in quadratic and linear programming methods that approximate solutions to nonlinear programming problems.

4. **Constraint condition**: The optimisation problem also needs to consider the constraints of the system, including:
   - **Equality constraint**: Ensure that the system dynamic and other strict conditions are met

$$g(x_{k+1}^i, x_k^i, u_k^i) = 0 \quad k = 0, \ldots, N-1, \tag{2.13}$$

   - **Inequality constraint**: Ensure that the state variables and control inputs are within the permissible range

$$h(x_{k+1}^i, x_k^i, u_k^i) \leq 0, \quad k = 0, \ldots, N-1, \tag{2.14}$$

Then The whole optimizition problem for each sample instant i has the form of:

$$\begin{aligned} \mathrm{NLP}(\hat{x}^i, x^{\mathrm{ref},i}, u^{\mathrm{ref},i}) = \arg\min_{x,u} & \sum_{k=i}^{N-1} \frac{1}{2} \begin{bmatrix} x_k^i - x_k^{\mathrm{ref},i} \\ u_k^i - u_k^{\mathrm{ref},i} \end{bmatrix}^\top \mathbf{W}_k^i \begin{bmatrix} x_k^i - x_k^{\mathrm{ref},i} \\ u_k^i - u_k^{\mathrm{ref},i} \end{bmatrix} \\ \text{s.t.} \quad & x_0^i = \hat{x}^i, \\ & g(x_{k+1}^i, x_k^i, u_k^i) = 0 \quad k = i, \ldots, N-1, \\ & h(x_{k+1}^i, x_k^i, u_k^i) \leq 0, \quad k = i, \ldots, N-1, \end{aligned} \tag{2.15}$$

5. **Application Control Inputs**: In the prediction time or space domain, the control input $u_{i,k}$ and state prediction $x_{i,k}$computed at the current moment during the optimisation process is actually applied and the control inputs at future moments are sent back to the optimizer as new reference trajectories. Then, the prediction and optimisation are re-run at the next sampling moment.

6. **Rolling time or space domain optimisation**: NMPC adopts a rolling time domain optimisation (Receding Horizon Control, RHC) strategy, i.e., predictions and optimisations are re-run at each sampling moment. This can dynamically respond to changes in the system state and external perturbations to maintain the real-time and effectiveness of the control strategy.

Overall, NMPC achieves effective control of nonlinear dynamic systems by solving an optimisation problem at each sampling moment that encompasses multiple future moments. The key is to compute the optimal control inputs in real time through accurate system modelling and optimisation problem solving to ensure that the system operates according to the desired trajectory.

2.6 Discretization and Linearization

In this thesis, a decision variable is introduced, gears γ, which is discrete. In order to avoid the mixed integer problem during gear optimization, we employ a constraint-based discrete optimization approach to maximize fuel efficiency while satisfying physical constraints (e.g., torque and RPM ranges). Additionally, we update the gear settings only if the new option significantly reduces fuel consumption. With this approach, we ensure that the problem is solved more accurately while the gears will not shift too frequently.

We employ the fourth-order Runge-Kutta (RK4) method to discretize the dynamic equations of the system. The RK4 method efficiently approximates the numerical solutions to ordinary differential equations (ODEs) [7]. For a dynamic system described by $\dot{x}(s) = f(s, x(s), u(s))$, the RK4 method is given by:

$$x_{k+1} = x_k + \frac{h}{6}(k_1 + 2k_2 + 2k_3 + k_4) \tag{2.16}$$

where:

$$k_1 = f(s_k, x_k, u_k) \tag{2.17a}$$

$$k_2 = f\left(s_k + \frac{h}{2}, x_k + \frac{h}{2}k_1, u_k\right) \tag{2.17b}$$

$$k_3 = f\left(s_k + \frac{h}{2}, x_k + \frac{h}{2}k_2, u_k\right) \tag{2.17c}$$

$$k_4 = f(s_k + h, x_k + hk_3, u_k). \tag{2.17d}$$

In these equations, x_k is the state vector at distance s_k, h is the integration step size, and f represents the system dynamics. By considering multiple intermediate slopes (k_1, k_2, k_3, k_4) within each integration step, the RK4 method is able to accurately approximate the dynamic properties of the system. In model predictive control (MPC), the update of the system state at each time or distance step is achieved by solving this type of discretized ODE [8]. This method provides a way for the controller to predict the system response.

Sequential Linear Programming (SLP) is the mainly used optimization techniques to deal with the nonlinear problems in this thesis. The SLP method simplifies the structure of the problem by linearizing the constraints and objective functions of the model around the trajectories generated in the previous iteration [9]. In each iteration step, the nonlinear functions are approximated by their first-order Taylor series expansions. The linearized problem is then solved to obtain an improved solution, and this process is repeated iteratively to converge quickly to a feasible solution.

For the nonlinear optimization problem defined by 2.1, the linearization at iteration i around the current guess trajectories $\mathbf{z}_i$ is given by:

$$J(\mathbf{z}) \approx J(\mathbf{z}_i) + \nabla J(\mathbf{z}_i)^\top (\mathbf{z} - \mathbf{z}_i) \tag{2.18a}$$

$$g(\mathbf{z}) \approx g(\mathbf{z}_i) + \nabla g(\mathbf{z}_i)^\top (\mathbf{z} - \mathbf{z}_i) = 0 \tag{2.18b}$$

$$h(\mathbf{z}) \approx h(\mathbf{z}_i) + \nabla h(\mathbf{z}_i)^\top (\mathbf{z} - \mathbf{z}_i) \leq 0 \tag{2.18c}$$

Where $\nabla J(\mathbf{z}_i)$, $\nabla g(\mathbf{z}_i)$, and $\nabla h(\mathbf{z}_i)$ are the gradients of the objective function and constraints evaluated at $\mathbf{z}_i$. By solving the linearized problem, we obtain a search direction for updating the variables:

$$\mathbf{z}_{i+1} = \mathbf{z}_i + \alpha \mathbf{d}_i \tag{2.19}$$

where $\mathbf{d}_i$ is the solution of the linearized problem, and α is the step size.

This approach is particularly suitable for dealing with large-scale and complex optimization problems, as it effectively reduces the computational effort while providing real-time updates to the solution. SLP is widely used in Nonlinear Model Predictive Control (NMPC) applications where real-time performance is critical [11].

2.7 Real-Time Iteration

In the previous section, we introduced optimization algorithms applied to model predictive control (MPC) systems for offline planning. These algorithms are able to optimize trajectories using predictive energy management policies when the information on the signal interface of the e-dolly is available. However, when the information exchanged between vehicle units is reduced—for example, due to communication constraints or data losses—the system shifts to a rule-based policy instead of predictive energy management. To address the challenge of maintaining optimal performance under such conditions, this section presents an online MPC framework that aims to improve the system's adaptability to information changes. Specifically, the system will use the results of the previous optimization to continue operations on road sections where vehicle information is lost; and once vehicle information is restored, the system restarts the real-time optimization process.

To achieve this goal, we need an approach with a more rapid optimization response. Here, we introduce the Real-Time Iteration (RTI) method, which was first proposed by Diehl et al. (2002)[15] to improve the computational efficiency of online MPC.

The RTI method greatly reduces the computational burden by performing the linearization or quadratic programming solution steps only once per control cycle, allowing the algorithms to be run under tight real-time constraints. In addition, this approach allows the system to quickly adjust the control decisions after receiving new measurement information, thus providing more flexibility to respond to changes in the dynamic environment.

In the study of real-time iterative (RTI) methods, the nominal stability has been verified and proved by Diehl et al. in 2005 [23]. Traditional real-time iterative methods mainly use the sequential quadratic programming (SQP) strategy with a single Newton iteration. However, considering the execution efficiency of the code, this study mainly employs Sequential Linear Programming (SLP) with full Newton steps, rather than Sequential Quadratic Programming (SQP) with a single Newton iteration.

When we approximate the original nonlinear programming 2.15 using SLP, The optimizition problem at guess $(x^{\text{guess}}, u^{\text{guess}})$ for each sample instant i has the form of:

$$\begin{aligned} \mathrm{LP}_{\mathrm{NOCP}}(\hat{x}^i, x^{\text{guess},i}, u^{\text{guess},i}) = \arg\min_{x,u} & \sum_{k=0}^{N-1} \mathbf{Jf}_k^i \begin{bmatrix} x_k^i \\ u_k^i \end{bmatrix} \\ \text{s.t.} \quad & x_0^i = \hat{x}^i, \\ & \tilde{\mathbf{A}}_{eq}^{\ i} \begin{bmatrix} x_k^i \\ u_k^i \end{bmatrix} = \mathbf{b}_{eq}^i, \quad k = 0, \ldots, N-1, \\ & \tilde{\mathbf{A}}^{\ i} \begin{bmatrix} x_k^i \\ u_k^i \end{bmatrix} \leq \mathbf{b}^i, \quad k = 0, \ldots, N-1, \end{aligned} \tag{2.20}$$

Where:

$$\tilde{\mathbf{A}}_{eq}^{i} = \frac{\partial g(x_k^i, u_k^i)}{\partial z_k^{i-1}}, \quad \mathbf{b}_{eq}^{i} = -g(x_k^{i-1}, u_k^{i-1}) + \tilde{\mathbf{A}}_{eq}^{i} z_k^{i-1} \tag{2.21}$$

$$\tilde{\mathbf{A}}^{i} = \frac{\partial h(x_k^i, u_k^i)}{\partial z_k^{i-1}}, \quad \mathbf{b}^{i} = -h(x_k^{i-1}, u_k^{i-1}) + \tilde{\mathbf{A}}^{i} z_k^{i-1} \tag{2.22}$$

$$z_k^i = \begin{bmatrix} x_k^i \\ u_{k-1}^i \end{bmatrix} \tag{2.23}$$

2.7.1 Embedding Initial Value

In this thesis, we developed a hybrid long combination truck model in Matlab to simulate truck fuel consumption with e-dolly propulsion. Beyond simulating fuel consumption, this model also serves as a plant model in the real-time iterations of nonlinear Model Predictive Control (NMPC). Specifically, it provides the measurement output $\hat{x}$ required for control optimization. This measurement output reflects the model's response to the latest changes and road conditions at a particular sampling distance.

Assuming that our system states are represented by vectors x_t and that the control inputs are u_t, the model can be formalized as the following state-space model:

$$x_{t+1} = f(x_t, u_t) + w(t) \tag{2.24}$$

where f denotes the system dynamics and $w(t)$ denotes the process noise.

At each sampling interval $ds = 15m$, the system updates its state estimate based on the latest measurement $\hat{x}$ obtained from the hybrid model. This measurement includes the vehicle's response to the last sampling interval and forms the starting state of the optimization problem. The the Embedding Initial Value method is using the measurement $\hat{x}^i$ at the end of each sampling interval as the initial state for the next optimization problem, which we can represent as:

$$(x^{i+1}, u^{i+1}) = \mathrm{LP}_{\mathrm{NOCP}}(\hat{x}^{i+1}, x^{\mathrm{guess},i}, u^{\mathrm{guess},i}) \tag{2.25}$$

$$\hat{x}^{i+1} = x_{i+1|i} \tag{2.26}$$

The optimization problem is then solved to find the optimal trajectories (x, u) for the next sampling interval. Embedding initial value is repeated as new measurements arrive, ensuring that the optimization algorithm uses the latest available information.

2.7.2 Warm Start and Shift Strategy

When exploring solution strategies for a series of consecutive optimization problems, the initial guess is crucial, especially in situations where fast convergence is sought. A common practice is to use a reference trajectory as the initial guess. However, in

real-time control systems, the reference trajectory may not be a good initial guess, especially when the system is disturbed and has a trajectory that is not near the reference trajectory. When we move from one optimization problem to the next, an alternative strategy in this case is to use a warm-start technique. This strategy is to use the solution (or partial solution) from the previous optimization problem as an initial guess for the optimization problem in the new calculating cycle.

$$(x^{\text{guess},i}, u^{\text{guess},i}) = \text{LP}_{\text{NOCP}}(\hat{x}^{i-1}, x^{\text{guess},i-1}, u^{\text{guess},i-1}) \tag{2.27}$$

The shift strategy is to "shift" part or all of the optimization solution obtained in the previous optimization cycle to the optimization problem in the next cycle as the initial guess for the new problem. This is done by shifting the final elements or state variables of the solution by one position to align with the new optimization cycle. For instance, if the solution in the optimization problem at distance s is

$$s = ([x_1, x_2, ..., x_{N-1}], [u_0, u_1, ..., u_{N-2}])$$

the initial guess trajectory at distance $s + 1$ then is

$$s + 1 = ([x_2, x_3, ..., x_N], [u_1, u_2, ..., u_{N-1}])$$

where the new value x_N, x_{N-1} in this paper is taken by directly keeping the last value in its place:

$$x_N = x_{N-1}, \quad u_{N-1} = u_{N-2}$$

Consequently, this methodology allows us to build the initial guess:

$$(x_k^{\text{guess},i}, u_k^{\text{guess},i}) = \text{LP}_{\text{NOCP}}(\hat{x}^{i-1}, x_{k+1}^{\text{guess},i-1}, u_{k+1}^{\text{guess},i-1}), \quad k = i, \ldots, N + i \tag{2.28}$$

In this way, the information from the previous problem is allowed to be used to speed up the solution process of the subsequent problem, thus converging quickly to the solution. The only requirement for warm-start is that the Nonlinear Optimal Control Problem(NOCP) does not change too much from one distance interval to the next. Therefore, the shorter the sampling distance interval is, the better the performance.

Alternatively, the last new value can also be derived by solving the Ordinary Differential Equation(ODE) in the last distance interval to get the last new value:

$$\mathbf{x}^{guess,s} = ODE(\mathbf{x}^{s-1}, \mathbf{u}^s)$$

so that the problem's feasibility is still guaranteed. However, using the ODE solution as the guess trajectory means that the endpoint and subsequent trajectory values will align with the ODE solution, potentially leading to deviations from the desired endpoint constraints.

In this thesis we mainly use the first method of keeping the last values directly, because of the strong constraints on the endpoint in the Nonlinear Optimal Control Problem(NOCP) of this thesis. Moreover, it is also because of the shrinking horizon method used in this paper, instead of the moving horizon, which we will introduce in the next section

2.7.3 Shrinking Horizon

Traditional model predictive control uses moving horizon control, where the controller continuously solves a fixed-length optimization problem, typically covering a prediction horizon from the current position s to $s+N$, where N is the number of steps in the prediction, and the starting point of that problem moves as advances. In this case the horizon for next optimization is $[s_{i+1}, s_{i+1}+N] = [s_i+\delta_s, s_i+N+\delta_s]$, where δ_s is the sampling distance interval.

Predictive energy management (PEM) often employs long prediction horizons, typically spanning 5–20 km, to optimize fuel consumption over extended distances. In this study, the total length of operating cycle is 8 km. Near the end of the operating cycle, the remaining travel distance becomes shorter than the prediction horizon. In such cases, maintaining a fixed-length horizon can lead to computational inefficiencies and less relevant predictions. In contrast, our real-time iterative approach using a reduced horizon. The horizon for next optimization is $[s_{i+1}, s_i+N] = [s_i+\delta_s, s_i+N]$, which means that the horizon length of the optimization problem is progressively reduced as vehicle move forward. Then in sampling interval $s_i+\delta_s$ the original optimization problem can be rewritten as:

$$\mathrm{LP}_{\mathrm{NOCP}}(\hat{x}^i, x^{\mathrm{guess},i}, u^{\mathrm{guess},i}) = \arg\min_{\Delta x, \Delta u} \sum_{k=i}^{N-1} \mathbf{Jf}_k^i \begin{bmatrix} x_k^i \\ u_k^i \end{bmatrix} \tag{2.29a}$$

$$\text{s.t.} \qquad x_0^i = \hat{x}^i, \tag{2.29b}$$

$$\tilde{\mathbf{A}}_{eq}^{\,i} \begin{bmatrix} x_k^i \\ u_k^i \end{bmatrix} = \mathbf{b}_{eq}^i, \quad k = i, \ldots, N-1, \tag{2.29c}$$

$$\tilde{\mathbf{A}}^{\,i} \begin{bmatrix} x_k^i \\ u_k^i \end{bmatrix} \leq \mathbf{b}^i, \quad k = i, \ldots, N-1, \tag{2.29d}$$

The horizon of optimization problem is progressively shortened from N steps to a smaller value as a specific distance or the end of the task is approached. In the shrinking horizon optimization problems, if the system is undisturbed, the optimization result obtained at distance s_i remains optimal up to distance s_{i+1}. Combined with the warm-start and shifting strategies introduced in the previous section, the computational burden is greatly reduced and the responsiveness of the control is improved. This is because the optimization focus on states close to the current location s to the endpoint, rather than a farther horizon.

Algorithm 2 Sequential Linear Programming (SLP) for Real-time iteration

Input: Initial state $\hat{x}$, Initial guess ($x^{guess}(s)$,$u^{guess}(s)$), tolerance ϵ
Output: Approximate optimal control inputs $u^*(s)$ and states $x^*(s)$
Initialization: $j \leftarrow 0$, $x^j(s) \leftarrow x^{guess}(s)$, $u^j(s) \leftarrow u^{guess}(s)$
while $|x^{j+1}(s) - x^j(s)| > \epsilon$ **do**
    Linearize the objective function and constraints around guess trajectories:
        Gradient of the cost function: $\nabla_{[x;u]}(L(x^j(s), u^j(s), s) + C_t(x^j(s_f), s_f))$
        Gradient of the dynamic constraints: $\nabla_{[x;u]}g$
        Gradient of the inequality constraints: $\nabla_{[x;u]}h$
    Solve the LP 2.29 to obtain ($x(s)$,$u(s)$)
    Update the guess trajectories:
        $(x^{j+1}(s), u^{j+1}(s)) \leftarrow (x^j(s), u^j(s)) + \alpha[(x^j(s), u^j(s)) - (x(s), u(s))]$
    Stepsize α decrease
    $j \leftarrow j + 1$
end while
Return: $(x^*(s), u^*(s)) \leftarrow (x^j(s), u^j(s))$

3
Methods

The aim of this chapter is to compare the fuel consumption of a conventionally powered truck model with that of a hybrid truck model under different energy allocation strategies. This comparison is conducted to determine the optimal energy allocation strategy in scenarios where incomplete information is available on e-dolly's interface. This study uses Nonlinear Model Predictive Control (NMPC) with Sequential Linear Programming (SLP) and real-time iteration (RTI) as optimization methods to assess the feasibility of achieving minimum fuel consumption under different external environmental conditions.

The study is divided into two parts. Firstly, the fuel consumption of a conventionally powered truck model is analysed under known external environments, and the information obtained is used as a reference for sequential linear programming (SLP). Secondly, the SLP and real-time iteration (RTI) methods are used to optimise the energy allocation strategy of the hybrid truck. The optimisation results are used as inputs to the model to adjust the engine and electric motor to work together in order to minimise the fuel consumption.

The effectiveness of different energy allocation strategies is evaluated by comparing the fuel consumption of hybrid trucks under specific conditions where there is incomplete information exchange on signal interface, and the optimal strategy is determined. The ultimate goal is to find a control strategy that is effective in reducing fuel consumption when introducing an e-dolly to an A-double long combination vehicle. This study provides an important reference for the design and optimisation of hybrid trucks and lays the foundation for the development of highly efficient and low-emission vehicle control systems.

3.1 Comparison between Conventional Powered Truck and Hybrid Truck

The fuel consumption of hybrid heavy-duty vehicles, including long combination vehicles, can be made lower than that of conventional internal combustion engine vehicles in specific traffic scenarios [17]. The key to achieving this is the use of simple and efficient control strategies that optimise gear selection and total power distribution between electric and conventional power to minimise fuel consumption [6].

Optimisation of energy management first requires an in-depth study of mathematical models for conventional and hybrid electric vehicles, which model the behavior of different components such as engine, electric motor, gearbox, and battery [18]. Based on these models, it is necessary to optimize the combined speed profile and power distribution for hybrid vehicles to achieve better energy efficiency. In addition, braking energy recovery for hybrid vehicles is one of the key factors. In conventional vehicles, the kinetic energy during braking is dissipated as heat. Through regenerative braking, the kinetic energy during deceleration can be recovered and converted into electrical energy, which is then stored in the battery to further reduce energy consumption [19].

Specifically, the fuel efficiency and energy utilisation of vehicles can be significantly improved by designing and implementing different control strategies [6, 16, 17, 19]. For example, the use of electric power in a certain proportion under appropriate working conditions can reduce the workload of the internal combustion engine (ICE), thereby reducing fuel consumption and emissions [20]. At the same time, an optimal gear selection strategy can ensure that the engine always works in the high efficiency range, further optimising fuel utilisation [21]. Moreover, regenerative braking technology, which recovers energy during deceleration and braking, can significantly improve overall energy efficiency.

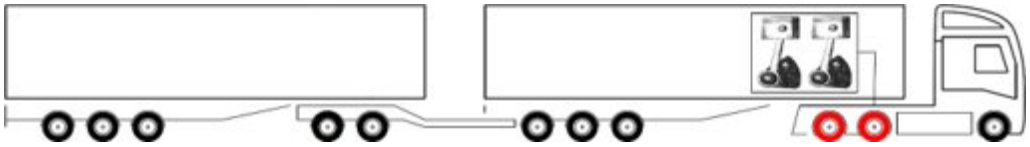
In this thesis, the consideration of the surrounding environment focuses on the impact of topography variations and traffic speed limits on energy management. On flatter roads, significant fuel savings can be realised in the hybrid truck model by employing predictive energy management strategies. Specifically, by combining regenerative braking and optimal speed profiles solved using on Sequential Linear Programming (SLP) method, fuel savings of about 13% can be achieved [3].

The benefits of the hybrid truck model's predictive energy management strategy are even more pronounced in hilly or very hilly road conditions. In such topographies, power demand and energy regeneration potential fluctuate more dramatically, and overall fuel efficiency and energy utilisation can be further improved through refined energy distribution and speed control. It is shown that in hilly topography, the optimised hybrid truck model can make full use of the energy recovered from regenerative braking to achieve higher energy savings [3].

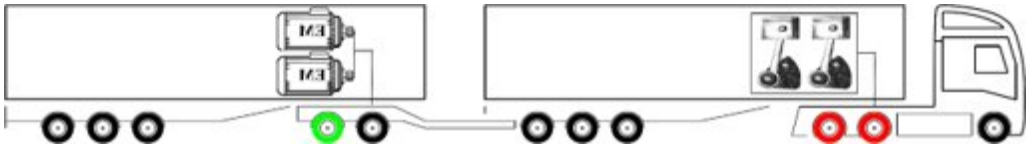
In this study, the vehicles used in both the conventionally powered truck model and the hybrid truck model are A-double heavy-duty trucks. The main difference between the two is that the hybrid truck model includes a distributed propulsion system across the axles. A distributed propulsion system means that the truck is equipped with several different power sources, i.e., an internal combustion engine (ICE) and electrically propelling trailers or the converter dolly (e-dolly). These power sources work together to drive the vehicle.

Specifically, in the hybrid truck model, each axle can be independently configured with a power unit such as an electric motor or an internal combustion engine to

achieve distributed power management. This configuration allows for more flexible regulation of the power output between different power sources, thereby optimising the energy utilisation efficiency and driving performance of the entire vehicle. In the study, examples of the hybrid and distributed propulsion vehicles assumed are shown in the following figure 3.1.



(a) Conventional truck model



(b) Rule-based hybrid truck model

Figure 3.1: Conventional truck model and rule-based hybrid model

The application of distributed propulsion systems not only improves the fuel economy of the vehicle but also enhances its adaptability in complex topography and changing traffic conditions. Through a rational power distribution strategy, high fuel efficiency can be achieved on flat roads, while maximising regenerative braking energy recovery in hilly or very hilly roads, thus reducing fuel consumption.

3.2 Powertrain modeling

In this section, we derive the dynamics equations of the hybrid powertrain and describe the associated equations for evaluating energy consumption metrics such as fuel consumption and battery state of charge. The powertrain system model is the basis for estimating the fuel consumption and the Nonlinear Optimal Control Problem (NOCP) for energy management in this thesis. By accurately modelling the energy flow of the hybrid powertrain, we are able to better predict the energy consumption and economy of the vehicle in real-world operation, thus providing theoretical support for optimal control strategies.

First, we study the combined force acting on the wheels. The force acting on the wheels at time t caused by propulsion and/or braking can be expressed by the following equation [5]:

$$F_w(t) = m\dot{v}_x(t) + F_g(s(t)) + F_{\text{roll}}(s(t)) + F_{\text{air}}(v_x(t)) \tag{3.1}$$

where m is the total mass or equivalent total mass of the vehicle, $s(t)$ is the distance travelled at time t, F_g, F_{roll}, and F_{air} denote the road gradient, the rolling resistance

(modelled as the body force), and the air drag, respectively, which are defined below:

$$F_g(s(t)) = -mg \sin \lambda_p(s(t)) \tag{3.2a}$$
$$F_{\text{roll}}(s(t)) = mgf_r \cos \lambda_p(s(t)) \tag{3.2b}$$
$$F_{\text{air}}(v_x(t)) = 0.5\rho_a A_f c_d v_x(t)^2 \tag{3.2c}$$

where g, λ_p, f_r, ρ_a, A_f and c_d stand for the gravitational acceleration constant, the road gradient, the rolling resistance coefficient, the air density, the equivalent front windward area of the vehicle, and the coefficient of air resistance, respectively.

In this thesis, we mainly consider the effect of the gradient of the road on the vehicle dynamics. We ignored all the forces caused by the steering force and articulation angle due to the road curvature. We also neglect all forces related to the rotational moment of inertia. These forces are zero when the vehicle is traveling along a straight path. Therefore, the longitudinal dynamics equations depend only on a single state variable v_x.

The total wheel power required to accelerate the vehicle and overcome resistance $P_w(t)$ is expressed as:

$$P_w(t) = F_w(t)v_x(t) \tag{3.3}$$

The energy flow (i.e., power transfer) between the different powertrain subsystems is shown in figure, which describes in detail the interaction and energy exchange between the subsystems.

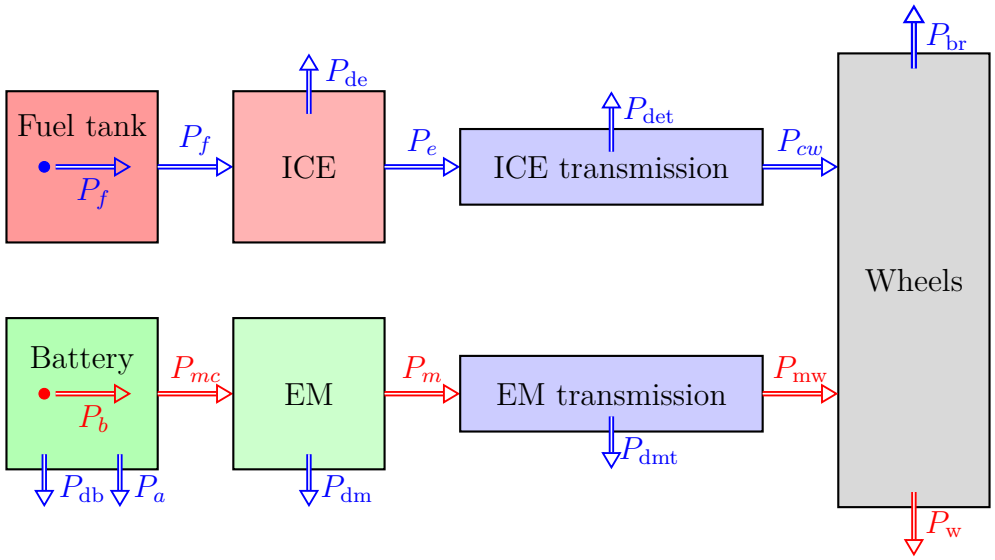


Figure 3.2: The energy flow between the different powertrain subsystems

As shown above, in this thesis, we assume that for a given time interval, let P_f, P_e, P_{de}, P_{ew} and P_{det} denote, respectively, the fuel power in the hybrid model, the output power of the internal combustion engine (ICE), the power consumed by the ICE, the power transmitted by the ICE, and the power power consumed during transmission. This section is also applicable in the conventionally powered truck model.

Compared to the conventionally powered truck model, the hybrid truck model adds an electric propulsion component. In the figure, we defined:

Table 3.1: Power Symbols and Descriptions

Symbol	Description
P_b	Power supplied by or stored in the batteries
P_{br}	Friction braking power at the wheels
P_{db}	Power dissipated in the batteries
P_a	Power used for auxiliary other equipments in the truck
P_{mc}	Power consumed or regenerated by the electric motor
P_{dm}	Power dissipated in the electric motor
P_m	Power output or input to the drivetrain in the electric motor
P_{dmt}	Power consumed during transmission from the electric motor to the drivetrain
P_{mw}	Actual power input at the wheels
P_w	Actual power output at the wheels

For the sake of uniformity, the power outflow from each subsystem is specified to be positive, as shown in the figure 3.2 for all consumption terms. The power balance equations for the two subsystems are given below [5].

$$P_e + P_{de} - P_f = 0 \tag{3.4a}$$
$$P_{ew} + P_{det} - P_e = 0 \tag{3.4b}$$
$$P_w + P_{br} - P_{ew} - P_{mw} = 0 \tag{3.4c}$$
$$P_{mw} + P_{dmt} - P_m = 0 \tag{3.4d}$$
$$P_m + P_{dm} - P_{mc} = 0 \tag{3.4e}$$
$$P_{mc} + P_{db} + P_a - P_b = 0 \tag{3.4f}$$

In (3.4), we ignored the inertia of rotating components and the energy loss caused by tire slip in the function parameters. These factors were not considered in the system, which simplified the dynamic analysis of the truck model. However, these simplified assumptions may introduce a certain degree of error in practical applications, which needs to be further explored and corrected in a more refined model.

3.3 Battery model selection

Selecting the appropriate battery system is crucial for the performance and efficiency of the electric propelled dolly (e-dolly). Based on data provided by the Volvo Group, there are two battery systems available for consideration. The main parameters of these battery systems are shown in table 3.2:

Table 3.2: Battery Systems

Battery system name	1pPopt	1pEopt
Number of packs	1	1
Battery price (Euro)	14500	10472.85
Battery energy capacity (kWh)	9.657	24.642
Battery mass (kg)	200	180
Battery energy capacity (J)	34765200	88711200
Min battery power (W)	-1.50E+05	-5.00E+04
Max battery power (W)	1.50E+05	5.00E+04
Number of cells per pack	200	180
Pack mass (kg)	200	200
Nominal voltage (V)	3.3	3.7
Cell resistance (Ohm)	**0.003**	**0.004**
Nominal cell capacity (Ah)	14	37
Cell capacity (Amp seconds)	50400	133200
Specific cell energy (kWh/kg)	0.13	0.13
Number of cycles low power	4.00E+03	2.00E+03
Number of cycles moderate power	9.00E+03	4.20E+03
Number of cycles high power	1.00E+03	1.00E+03

Analysing the data in the table above, it can be concluded that the 1pPopt battery system is significantly better in terms of power output than the 1pEopt. Specifically, the 1pPopt system offers significantly higher maximum and minimum power ratings compared to the 1pEopt. For the e-dolly, which is designed to assist in propelling heavy loads and provide regenerative braking for long combination trucks, the ability to deliver and absorb large amounts of power ensures that the e-dolly can handle the demanding requirements of acceleration and deceleration in hilly and very hilly operating cycles. The superior power capabilities of the 1pPopt make it well-suited to meet these needs.

In addition, from a battery cycle life perspective, the 1pPopt has double the cycle life at low and moderate power compared to that of the 1pEopt. Considering that the e-dolly is primarily used to assist in propelling or braking the trucks, it will spend the majority of its operating time in low and moderate power cycling, which makes the 1pPopt superior in terms of both longevity and reliability. Therefore, choosing the 1pPopt reduces the maintenance requirements and operating costs over its service life.

In this thesis, the operating cycle does not include plug-in charge for the e-dolly. While the 1pEopt has a higher total energy capacity, the e-dolly does not require such a large storage capacity for regenerative braking. This is because the amount of energy recovered during braking is not substantial enough to take advantage of the extra capacity provided by the 1pEopt. Therefore, higher energy capacity of the 1pEopt does not offer a significant advantage for this specific application.

In summary, considering the critical factors of battery power output, cycle life and suitability for this study's operating cycle, the 1pPopt battery system is the optimal choice, especially for e-dolly application scenarios. Therefore, when researching and modeling the e-dolly system in this thesis, the 1pPopt is chosen as the battery system, to ensure that it has efficient power support and long service life in practical operation. This choice aligns with the goals of this study to develop an effective hybrid truck model withe optimized energy allocation strategies.

3.4 Fitting Torque

Accurate modeling of the torque limit of the internal combustion engine (ICE) and the electric motor (EM) is essential for constructing the nonlinear optimal control problem addressed in this thesis. In order to accurately capture the range of torque, we need to either graph the data from consistent measurements or use nonlinear fitted curves for modeling and analysis.

The figure 3.3 presents the measured torque limits as functions of speed for the ICE and EM. The black lines represent the raw measurement data. These measurements provide torque outputs at different velocities, revealing highly nonlinear relationships inherent to the powertrain components. The blue lines represent the fitted curves that model the torque limits of the ICE and EM. These fitted curves define the torque limits that the ICE and EM can provide at any given angular velocities. The functions obtained that model the torque limits are critical constraints in the optimization problem.

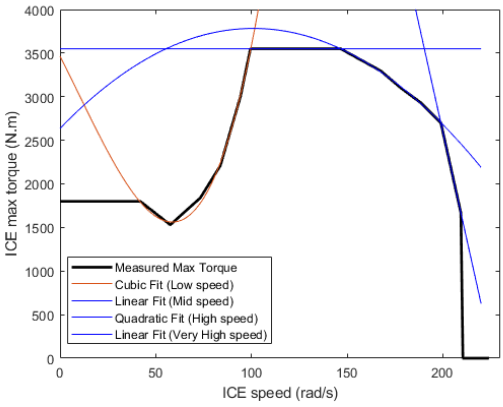
The torques and angular velocities of the ICE and EM at any given time are calculated based on their power outputs and the vehicle speed. The following equations define these relationships [6]:

$$\omega_e(t) = \frac{r_e\left(\gamma_e(t)\right)}{R_w} v_x(t), \quad T_e(t) = \frac{1}{\omega_e(t)} P_e(t) \tag{3.5}$$

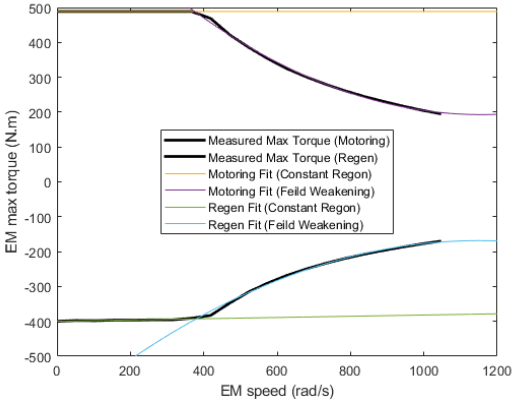
$$\omega_m(t) = \frac{r_m\left(\gamma_m(t)\right)}{R_w} v_x(t), \quad T_m(t) = \frac{1}{\omega_m(t)} P_m(t) \tag{3.6}$$

where:

- $\omega_e(t)$ and $\omega_m(t)$: Angular velocities (in rad/s) of the ICE and EM, respectively.
- $T_e(t)$ and $T_m(t)$: Torques (in N·m) of the ICE and EM, respectively.



(a) Relationship between ICE torque limit and speed



(b) Relationship between EM torque limit and speed

Figure 3.3: Relationship between torque limit and speed after experimental measurements and fitted curves

- $P_e(t)$ and $P_m(t)$: Power outputs (in W) of the ICE and EM, respectively.
- r_e and r_m: Transmission ratios of the ICE and EM, respectively.
- $\gamma_e(t)$ and $\gamma_m(t)$: Current gear ratio of the ICE and EM, respectively.
- R_w: Wheel radius (in m).
- $v_x(t)$: Speed of the vehicle (in m/s).

These equations enable the calculation of the torque and angular velocity. Using the fitted torque limit functions, we can express the torque constraints For the ICE and EM as:

$$T_e(t) \leq T_{e,1}(\omega_e(t)) \tag{3.7a}$$
$$T_m(t) \leq T_{m,1}(\omega_m(t)) \tag{3.7b}$$

Where $T_{e,1}(\omega_e(t))$ and $T_{m,1}(\omega_m(t))$ are the torque limits obtained from the fitted

curves in Figure 3.3. The polynomial curve fittings of degree n are given by [5]:

$$T_{e,\mathrm{l}}(\omega_e(t)) = \sum_{j=0}^{n} b_{e,ij}(\omega_e(t))^j, \quad i = 1,...,4 \tag{3.8a}$$

$$T_{m,\mathrm{l}}(\omega_m(t)) = \sum_{j=0}^{n} b_{m,ij}(\omega_m(t))^j, \quad i = 1,...,4 \tag{3.8b}$$

By incorporating these torque limit constraints into the nonlinear programming (NLP) problem as constraints, we ensure that the optimized results only contain feasible torque values that the ICE and EM can produce at each operating point.

3.5 Power Split Strategy

In recent research on hybrid long combination vehicles, all information is normally freely transferred between the electric trailer and the tractor, which means that there is a central controller to meet the various control needs of the truck and to ensure efficient operation of the system [3, 5, 6, 13]. However, when the vehicle is in a harsh environment, information transfer may be limited or interrupted, resulting in the central controller not functioning properly [4]. This situation presents a significant challenge to the energy management and control of the vehicle.

In order to deal with this problem, a power split strategy needs to be developed to specify how much energy should be provided by each of the combustion engine and the electric motor scenarios where information is incomplete. Such a strategy needs to take into account a number of factors including, but not limited to, the current vehicle state, the driving environment, energy reserves, and load demand. The goal is to ensure that the vehicle maintains a high level of energy efficiency in harsh environments by appropriately distributing the energy output of the combustion engine and the electric motor.

By introducing this power distribution strategy, it is possible to ensure the effective operation of the hybrid powertrain even when the central controller's functions are limited. This not only helps to improve the vehicle's adaptability in complex environments, but also improves the overall system's energy efficiency and reliability to a certain extent.

The aim of this thesis is to model a hybrid truck based on a conventional truck model and to find a reliable and efficient power split strategy under scenarios incomplete information. To achieve this goal, this paper focuses on the effect of two key factors affecting total fuel consumption: regenerative braking and the proportion of energy supplied by the electric motor throughout the entire trip. The energy stored in the battery is analyzed by converting it into the corresponding fuel consumption.

Specifically, this thesis first analyzes the effect of regenerative braking, where part of the kinetic energy is recovered and stored as electrical energy in the battery, thus reducing fuel consumption. Secondly, this paper investigates the effect of energy

allocation between the electric motor and the internal combustion engine on fuel consumption under varying driving conditions. Through this study of energy conversion and distribution strategies, we are able to better understand how to optimize the energy use of hybrid trucks to achieve the lowest fuel consumption.

3.5.1 Grid Search

To find the optimal combination of both regenerative braking and motor energy delivery ratio, we have chosen to adopt the Grid Search method. Grid search is a systematic and comprehensive optimization method that traverses each parameter combination through a predefined parameter grid to find the optimal solution [22]. In this study, we constructed a parameter space covering all possible combinations of regenerative braking effect and motor energy delivery ratio.

Algorithm 3 Optimization of Power Split Strategy in Hybrid Truck Model

```
Select a road profile roadflat
Initialize min_fuel_consumption ← ∞
for each regen_braking_coeff in RegenBrakingCoeffs do
    for each elec_motor_ratio in ElecMotorRatios do
        Input roadflat, regen_braking_coeff, and elec_motor_ratio into the hybrid truck model
        Compute fuel_consumption for the current combination
        if fuel_consumption < min_fuel_consumption then
            min_fuel_consumption ← fuel_consumption
            optimal_combination ← (regen_braking_coeff, elec_motor_ratio)
        end if
    end for
end for
return optimal_combination, min_fuel_consumption
```

We first set the range and step size for the variation of the regenerative braking coefficient. Specifically, the regenerative braking coefficient starts from 1/11 and increases by 1/11 each time until it reaches 1. The range is set to cover the regenerative braking effect from inefficient to efficient, aiming to comprehensively evaluate the effect of regenerative braking on total fuel consumption.

Secondly, we determined the range and step size for the variation of the motor energy provision ratio. Specifically, the electric motor energy supply ratio starts from 0 and increases by 0.05 each time until it reaches 1. This range includes scenarios from complete dependence on the internal combustion engine to complete dependence on the electric motor to ensure that the effect of the electric motor energy supply ratio on the total fuel consumption can be comprehensively assessed.

By combining the above levels of regenerative braking coefficients and electric motor energy delivery ratios, we formed a grid containing multiple parameter combinations.

For each parameter combination, we performed detailed simulations and evaluations to calculate the corresponding total fuel consumption. The simulation process includes different road conditions, load conditions and driving modes to ensure the comprehensiveness and accuracy of the evaluation results.

In the simulation process, we fix the regenerative braking coefficient for each regenerative braking coefficient, and then vary the motor energy supply ratio one by one to record the fuel consumption results under each combination. Next, the regenerative braking coefficient is varied and the process is repeated until all combinations have been evaluated.

Through this systematic and comprehensive grid search method, we were able to identify the optimal combination of regenerative braking effect and motor energy delivery ratio. This optimal combination not only significantly reduces the total fuel consumption under different operating conditions, but also improves the overall energy efficiency and environmental friendliness of the hybrid truck. In particular, this approach is able to select a strategy that minimises fuel consumption even under incomplete information conditions, which ensures that the hybrid truck can still operate efficiently even when information transfer is limited.

3.5.2 Nonlinear Optimal Control Problem Formulation

In this study, we aim to determine the optimal energy allocation strategy for a hybrid truck model under varying conditions of information availability on e-dolly's interface. While the grid search method can provide a feasible strategy in situations with incomplete information, our primary focus is on developing a real-time optimization algorithm based on a Nonlinear Optimal Control Problem (NOCP) formulation. This approach allows us to handle both fully communicated scenarios and situations with incomplete information in a predictive way, thus achieving lower fuel consumption than grid search method.
Specifically, the NOCP generates optimal control trajectories for a dynamic system over a spatial interval based on the system's initial state. The solution of the problem involves accurately modeling the system states and control inputs and determining the control strategy that minimizes fuel consumption while satisfying all physical and operational constraints.

In practice, the solution of the NOCP needs to consider various constraints, including state constraints (e.g., battery State of Charge (SOC) limits), control constraints (e.g., torque and power limits), and environmental constraints (e.g., speed limits and road grade). The introduction of these constraints ensures that the generated control strategy is not only theoretically optimal but also practically feasible. While this makes the problem closer to the actual working conditions, it also increases the complexity of the problem-solving. To cope with the complexity and non-linear nature of vehicle models, we employ efficient numerical optimisation methods.

Based on the defined Nonlinear Optimal Control Problem (NOCP) and the pow-

ertrain energy flow models, the energy management for a vehicle traveling in a deterministic operating cycle, while ignoring the lateral dynamics, can be defined as follows. The state vector is $\mathbf{x} = [v_x(s), \mathrm{soc}(s), t(s)]$ and the input vector are $\mathbf{u} = [F_e(s), F_{mw}(s), F_{br}(s), \gamma_e(s), \gamma_m(s)]$. Where s denotes the spatial position along the route [5].

Find $F_e(s), F_{mw}(s), F_{br}(s), \gamma_c(s), \gamma_m(s),$

to minimize

$$J^{nl} = \int_{s=s_0}^{s=s_f} \left(F_f(s) + F_{br}(s) - F_{mw}(s) + F_{mc}(s) + \frac{R_{w,x}(s)}{V_b^2}\left(F_{mc}(s) + F_a(s)\right)^2\right) ds \tag{3.9}$$

subject to

fuel equivalent force:

$$F_f(F_e(s), v_x(s), \gamma_e(s), s) = \frac{1}{v_x(s)} \sum_{i=0}^{5}\sum_{j=0}^{5} a_{ij} \left(\frac{r_e(\gamma_e(s))}{R_w} v_x(s)\right)^i \left(\frac{R_w}{r_e(\gamma_e(s))} F_e(s)\right)^j \tag{3.10}$$

vehicle longitudinal dynamic:

$$\frac{dv_x(s)}{ds} = \frac{1}{m v_x(s)}\Big(- F_{br}(s) + \eta_{te} F_e(s) + F_{mw}(s) + mg\sin\alpha(s) - mgf_r\cos\alpha(s) - 0.5\rho_a A f_{cd} v_x(s)^2\Big) \tag{3.11}$$

battery SOC dynamic:

$$\frac{dsoc(s)}{ds} = -\frac{1}{E_{bmax}}\left(F_{mc}(s) + \frac{R_{v_x}(s)}{V_b^2}\left(F_{mc}(s) + F_a(s)\right)^2 + F_a(s)\right) \tag{3.12}$$

time dynamic:

$$\frac{dt(s)}{ds} = \frac{1}{v_x(s)} \tag{3.13}$$

initial and terminal states:

$$\begin{aligned} &v(s_0) = v_0, \\ &soc(s_0) = soc_0, \\ &t(s_0) = t_0, \\ &soc(s_f) = soc_f \end{aligned} \tag{3.14}$$

ICE torque upper limit:

$$\frac{R_w}{r_e(\gamma_e(s))} F_e(s) - \min\left\{\sum_{j=0}^{3} b_{ij}^e \left(\frac{r_e(\gamma_e(s))}{R_w} v_x(s)\right)^j,\ i = 1, \ldots, 4\right\} \leq 0, \tag{3.15}$$

EM torque limits:

$$\begin{aligned}\frac{R_w F_{mw}(s)}{r_m(\gamma_m(s))\eta_{tm}} - \min\left\{\sum_{j=0}^{3} b_{ij}^m \left(\frac{r_m(\gamma_m(s))}{R_w} v_x(s)\right)^j,\ i=1,2\right\} \leq 0 \\ -\frac{R_w F_{mw}(s)\eta_{tm}}{r_m(\gamma_m(s))} + \max\left\{\sum_{j=0}^{3} b_{ij}^m \left(\frac{r_m(\gamma_m(s))}{R_w} v_x(s)\right)^j,\ i=3,4\right\} \leq 0,\end{aligned} \tag{3.16}$$

arrival time:

$$t(s_f) - t_{tref}(s_f) \leq 0 \tag{3.17}$$

battery SOC limits:

$$\begin{aligned}soc_{min} - soc(s) \leq 0 \\ soc(s) - soc_{max} \leq 0\end{aligned} \tag{3.18}$$

battery power limits:

$$\begin{aligned}p_{b_{\min}} - v_x(s)\left(F_{mc}(s) + \frac{R_{v_x}(s)}{V_b^2}\left(F_{mc}(s)+F_a(s)\right)^2 + F_a(s)\right) \leq 0, \\ v_x(s)\left(F_{mc}(s) + \frac{R_{v_x}(s)}{V_b^2}\left(F_{mc}(s)+F_a(s)\right)^2 + F_a(s)\right) - p_{b_{\max}} \leq 0\end{aligned} \tag{3.19}$$

speed limits:

$$\begin{aligned}v_{min}(s) - v_x(s) \leq 0 \\ v_x(s) - v_{max}(s) \leq 0\end{aligned} \tag{3.20}$$

ICE torque (force) lower limit:

$$-F_e(s) \leq 0 \tag{3.21}$$

friction brake lower limit:

$$-F_{br}(s) \leq 0 \tag{3.22}$$

In the cost function, F_{mc} denotes the equivalence between the battery and the motor. F_{mc} is given according to:

$$F_{mc}(s) = \begin{cases} \frac{1}{v_x(s)} \sum_{i=0}^{5}\sum_{j=0}^{5}\left(h_{ij}^{+}\left(\frac{r_m(\gamma_m(s))}{R_w}\right) v_x(s)^i \left(\frac{R_w}{r_m(\gamma_m(s))} F_m(s)\right)^j\right), & F_{mw}(s) > 0 \\ \frac{1}{v_x(s)} \sum_{i=0}^{5}\sum_{j=0}^{5}\left(h_{ij}\left(\frac{r_m(\gamma_m(s))}{R_w}\right) v_x(s)^i \left(\frac{R_w}{r_m(\gamma_m(s))} F_m(s)\right)^j\right), & F_{mw}(s) \leq 0 \end{cases} \tag{3.23}$$

In the NOCP constructed above, the cost function contains the fuel-equivalent force F_f, the braking force F_{br}, and the total equivalent electric dissipation force F_{del}. These forces are represented by the last three terms of the cost function.

$$F_{del} = -F_{mw}(s) + F_{mc}(s) + \frac{R v_x(s)}{V_b^2}\left(F_{mc}(s)+F_a(s)\right)^2 \tag{3.24}$$

From the cost function, we see that the main objective is to minimize fuel consumption while considering the energy usage of both the internal combustion engine (ICE) and the electric motor (EM). By including the electric power consumption

and dissipation in the cost function, we ensure that the optimization considers the total energy expenditure of the hybrid powertrain. This is important for finding an optimal energy management strategy.

Including braking force in the cost function helps penalize excessive use of the friction brakes. This encourages the optimization algorithm to prefer regenerative braking over mechanical braking when possible. Regenerative braking allows the vehicle to recover energy during deceleration, which improves overall energy efficiency. In addition, we need to take the electric dissipation into account because of the subsequent need to linearize the problem.

In the foregoing, constraint 3.11 is used to describe the longitudinal dynamics of the vehicle. Note that the effect of side-slip is not considered here. Constraint 3.12 represents the dynamics of the battery State of Charge (SOC) and is used to describe how the battery's energy level changes though charging and discharging. Constraint 3.13 represents the dynamic equation of time, relating the distance traveled to the elapsed time. By formulating the problem in terms of distance (space domain) instead of time, we can more accurately model driving cycle characteristics such as speed limits, road gradients, and other road conditions that depend on the vehicle's position. This approach allows us to handle these factors more effectively in the optimization process.

Constraints 3.14 limit the initial and final states of the vehicle, ensuring that the vehicle operates at the specified start and end states. Constraint 3.15 sets an upper limit on the torque of the internal combustion engine (ICE) to prevent it from exceeding its maximum capacity. Constraints 3.16 limits the torque of the EM in both motoring and generating modes, ensuring that the EM operates within a its allowable range. Constraint 3.17 specifies the maximum allowed travel time, making sure the travel time does not exceed a predetermined reference time.

In addition, constraints 3.18 set limits on the maximum state of the battery (SOC) and the minimum state, respectively. These limits are particularly important for the battery health and for preventing overcharging and excessive discharging. Constraints 3.19, on the other hand, limit the power input and output of the battery to ensure that the battery operates within a safe power range.

Finally, constraints 3.20, 3.21, and 3.22 limit the vehicle's speed, ensure that the force provided by the internal combustion engine (ICE) is non-negative, and ensure that the braking force is non-negative, respectively. Constraints 3.21 and 3.22 enforce the physical laws that the engine cannot produce negative force, and the friction brakes cannot apply negative force. These constraints ensure that the forces from the engine and brakes comply with physical reality.

Together, these constraints create a complete control system designed to optimize the vehicle's performance while ensuring safety and reliability under different operating conditions.

3.6 Real-Time Iteration in NMPC

In Section 2.6, we introduced the theoretical foundations of the real-time iteration method. Here, we demonstrate the application of this method to a nonlinear model predictive control (NMPC) system for hybrid long combination trucks. In this section, the embedding initial value method introduced in Section 2.61 and the construction strategy of guess trajectories are used to solve the NOCP represented by Eqs 3.9-3.22 to obtain the optimized states and output trajectories of the vehicle.

As shown in Fig 3.4, our NMPC real-time iterative process includes the following main steps:

1. Initialization and initial guess trajectories: conventional truck model generates the initial state and the initial guess trajectories of the optimal variables from the road information;
2. Solving optimization problem: the real-time iteration-sequential linear programming method is used to solve the optimization problem, and the iterative process is optimized by adjusting the step size and checking the convergence of the solution;
3. Output and feedback: Apply the values of the optimized state variables $\mathbf{x} = [v_x, \text{soc}, t]$ and the inputs $\mathbf{u} = [F_e, F_{mw}, F_{br}, \gamma_e, \gamma_m]$ corresponding to the sampling intervals to the hybrid truck model. The hybrid truck model outputs the corresponding vehicle state measurements. These output measurements are fed back to the RTI-SLP system.

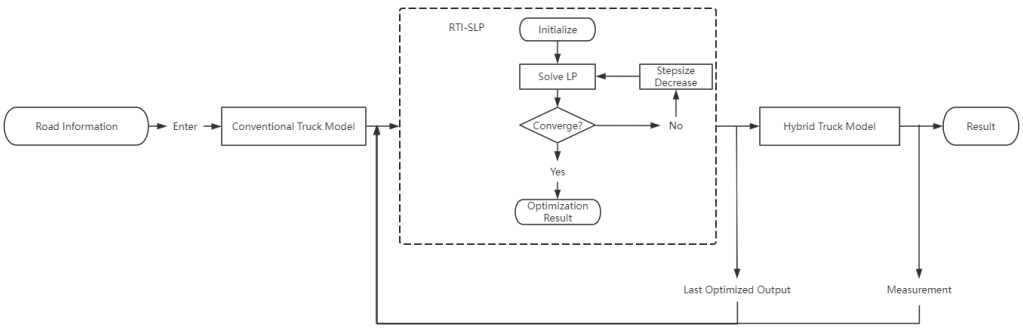


Figure 3.4: Real-time iteration nonlinear MPC workflow diagram

where the sampling interval (ds) is set to 15 meters and the control and prediction range extends to 5 kilometers. The algorithm for NMPC using real-time iteration is shown in Algorithm 4:

Algorithm 4 NMPC using real-time iteration

Input: Initial state $\hat{x}^0$, Initial guess ($x^{guess,0}$,$u^{guess,0}$), tolerance ϵ
Output: Actual inputs using in hybrid model $\mathbf{u}$ and states measurements $\hat{\mathbf{x}}$
Initialization: $i \leftarrow 0$, $x^0 \leftarrow x^{guess,0}$, $u^0 \leftarrow u^{guess,0}$
while $i \leq EndofRoad$ **do**
  Initialization: $j \leftarrow 0$, $\hat{x} \leftarrow \hat{x}^i$, $x^j \leftarrow x^{guess,i}$, $u^j \leftarrow u^{guess,i}$
  while $|x^{j+1}(s) - x^j(s)| > \epsilon$ **do**
    Linearize the objective function and constraints around guess trajectories:
      Gradient of the cost function: $\nabla_{[x;u]}(L(x^j(s), u^j(s), s) + C_t(x^j(s_f), s_f))$
      Gradient of the dynamic constraints: $\nabla_{[x;u]}g$
      Gradient of the inequality constraints: $\nabla_{[x;u]}h$
    Solve the LP 2.29 to obtain ($x(s)$,$u(s)$)
    Update the guess trajectories:
      $(x^{j+1}(s), u^{j+1}(s)) \leftarrow (x^j(s), u^j(s)) + \alpha[(x^j(s), u^j(s)) - (x(s), u(s))]$
    Stepsize α decrease
    $j \leftarrow j + 1$
  end while
  Refine guess trajectories: $x^{guess,i} \leftarrow x^j$, $u^{guess,i} \leftarrow u^j$
  Apply the first optimized value to plant model, outputting $\hat{x}^i$
end while
Return: $\hat{\mathbf{x}}, \mathbf{u}$

In our investigation, we use the real-time iteration method to implement real-time control of the truck. When information on the e-dolly interface is lost, the strategy adopted in this thesis is that the vehicle will use the control signal corresponding to the current position from the optimization result of the previous sampling interval. This approach ensures that the vehicle maintains relatively good performance even in the case of information loss between units.

3.7 Analysis of the Overall Project Implementation Process

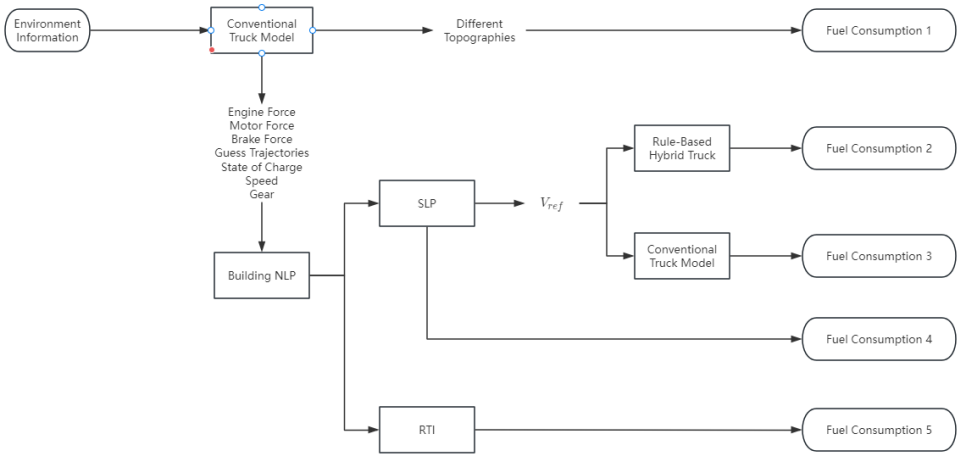


Figure 3.5: Project Flowchart

Based on the methodology described above, the overall flow of the thesis is shown in figure 3.5. First, four different driving cycles with different levels of hilliness were designed and a specific speed limit was set on each driving cycle. To provide the reference data needed for nonlinear programming (NLP), a conventional truck model was used to simulate driving as close as possible to the speed limit on these four different driving cycles. Parameters such as internal combustion engine torque, electric motor torque, braking force, and gear ratio were recorded.

Next, the Sequential Linear Programming (SLP) was used with the collected data to solve the optimisation problem and obtain the theoretical minimum fuel consumption (referred to as fuel consumption 4). The SLP not only provides the optimal fuel consumption values, but also generates a reference speed (Vref) of the vehicle over the entire route. This reference speed is then used in both the conventional truck model and the rule-based hybrid truck model to obtain the fuel consumption of both models running at the optimal speed on the four different driving cycles, denoted as fuel consumption 3 and fuel consumption 2, respectively.

In the process, the performance of the rule-based hybrid truck model is further analysed when different energy delivery modes are selected. Specifically, in this model, the electric motor (EM) provides a portion of the torque while the internal combustion engine (ICE) provides the remaining vehicle-demanded torque, and the two always maintain a certain ratio to meet the vehicle's power demand. In addition, the rule-based hybrid truck model always maintains a certain regenerative braking energy recovery factor. These two coefficients are combined using a grid search method to find the optimal energy management strategy for different road sections.

Under incomplete information conditions, the rule-based hybrid truck model will choose the optimal combination from the grid search method as the second choice to ensure that the whole journey can be completed efficiently under different operating conditions.

Furthermore, in this thesis, we implemented a real-time control method, real-time iteration (RTI), to optimize power distribution with both full communication and incomplete information conditions. The fuel consumption resulting from RTI is referred to as fuel consumption 5. This approach not only improves fuel efficiency, but also enhances the adaptability and robustness of the vehicle under complex road conditions. Through this systematic process, it is possible to optimise vehicle fuel consumption and validate the performance of different control strategies under various road conditions.

4

Results and Analysis

This chapter details the Sequential Linear Programming (SLP), conventional truck model, rule-based hybrid truck model and Real Time Iterative (RTI) results obtained from simulations in MATLAB.

Firstly, a conventional truck model was constructed in MATLAB and a rule-based hybrid truck model was introduced on this basis. Subsequently, it was verified whether the SLP was always able to achieve the lowest fuel consumption under different initial conditions. Then, the fuel consumption of the conventional truck model was compared with that of the rule-based hybrid truck model under different energy allocation strategies and regenerative braking energy recovery coefficients to determine the optimal combination by means of the reference speed (V_{ref}) obtained from the SLP. Finally, the results of RTI are used to verify its superiority over the grid search method and the effectiveness of its real-time strategy. Through these steps, the performance of different models and methods in fuel consumption optimisation and their application potential are clarified.

4.1 MATLAB Simulator

In this thesis, the result obtained by the Sequential Linear Programming (SLP) method employed the optimization problem is considered to be the theoretically optimal solution. In order to verify the validity of this result, it is first necessary to compare the fuel consumption in the truck model without the electric drive and the rule-based hybrid truck model. Specifically, the effectiveness of the grid search approach to reduce fuel consumption in the rule-based hybrid truck model is evaluated by comparing the fuel consumption of these two models under different energy allocation strategies and regenerative braking energy recovery factors.

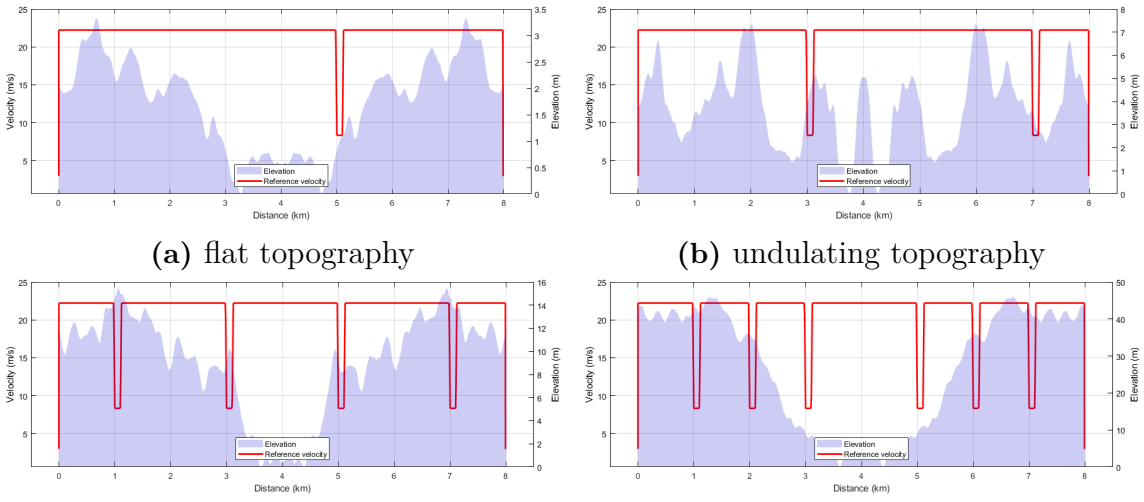
In this process, fuel consumption data will be recorded and analyzed for both the conventional truck model and the rule-based hybrid truck model under different driving conditions and parameter settings. By comparing these results, we can determine which propulsion system configuration and control strategy achieves better fuel efficiency. Ultimately, the strategy with relatively low fuel consumption is compared with the theoretical optimal solution obtained by the SLP method. Through this systematic comparative analysis, it is possible to verify that the SLP method is indeed capable of achieving better fuel efficiency than rule-based control strategies, thus demonstrating its effectiveness and reliability in vehicle energy management

and optimization.

4.1.1 Experimental Setup in MATLAB

In this project, simulation settings for different topographies were carried out using MATLAB to adapt the truck to a variety of topography conditions. These settings mainly include elevation changes and different speed limit zones to relatively realistically simulate the actual driving environment. By carefully regulating these parameters, the aim is to evaluate and optimize the performance of the truck under various complex topography and speed limit conditions, so as to improve the real-world reference value and applicability of the simulation results.

In this project, four different topography types are set up, namely flat topography (flat), slightly undulating topography (predominantly flat), hilly topography (hilly) and highly hilly topography (very hilly). These topographies and the corresponding speed limit zones are shown in the figure. It can be observed that as the topography becomes progressively rougher, more speed limit zones are set in the experiment to accurately simulate real-world driving conditions. These settings are intended to evaluate the performance of the trucks under various complex topography and speed limit conditions to ensure that the simulation results have a high degree of realism and reference value.



(a) flat topography **(b)** undulating topography

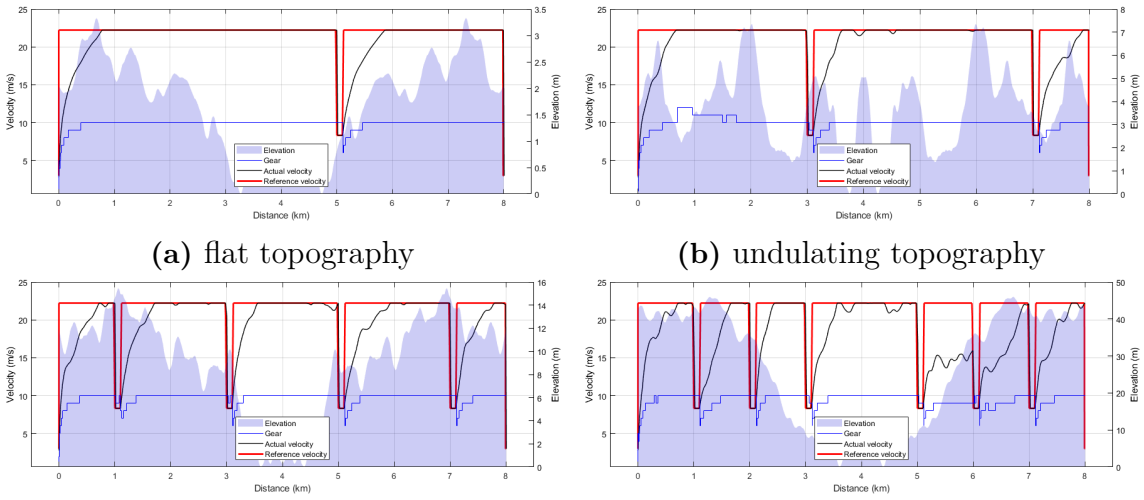
(c) hilly topography **(d)** highly hilly topography

Figure 4.1: Different road conditions

4.1.2 First Application of the Conventional Truck Model

After constructing the conventional truck model, it needs to be made to complete the entire trip at a specified speed limit. The conventional truck model will calculate

and generate a reference speed V_{ref} under these conditions. In addition, the model will provide the key data required for nonlinear programming (NLP), including parameters such as the drive force, braking force, and gear ratios required for the truck to travel. This information will be used as input to NLP to further optimise the performance of the vehicle. The figure below shows the V_{ref} calculated by the conventional truck model under different road conditions based on the respective speed limit zones.



(a) flat topography **(b)** undulating topography

(c) hilly topography **(d)** highly hilly topography

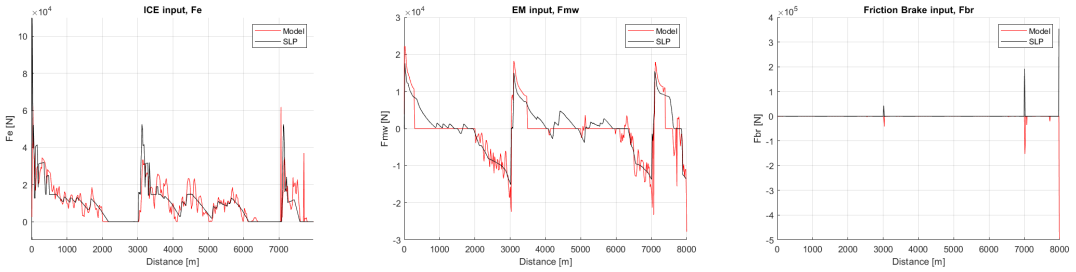
Figure 4.2: Conventional truck model runs in Different road conditions

In this case, the conventional truck model is designed to get to the destination as quickly as possible. As shown in the figure above, when a speed limit is encountered or lifted, the conventional truck model will quickly adjust to the maximum speed limit of the road. In the figure, the blue curve shows how the conventional truck model varies on the road with different gear ratios.

4.2 Analysis of Hybrid Truck Model in Following Predefined Speed Profiles

We implemented a hybrid truck model that is designed to receive a speed profile from offline sequential linear programming (SLP) that serves as a baseline for dynamic tuning during the simulation. The model follows the speed trajectory throughout the simulation, adjusting its internal combustion engine (ICE) force, electric motor (EM) force, and braking force accordingly. The model's control system uses a rule-based approach to adjust the ICE and EM contributions, as well as the necessary braking forces, to match this speed profile. The resulting force outputs are illustrated in three different graphical analyses. As shown in figure 4.3a, 4.3b, 4.3c, the figures depict the forces (shown in red) applied by the hybrid model to the optimal inputs

for the SLP calculations (shown in black) , providing a visual comparison of the model's performance with the optimal inputs from the SLP.



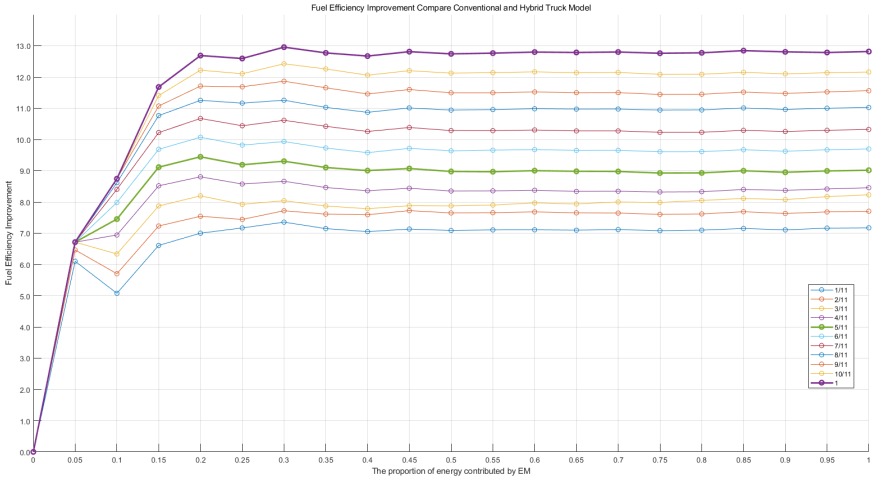
(a) ICE Force **(b)** Electric Motor Force **(c)** Friction Brake Force

Figure 4.3: Comparison of Simulated and SLP-Calculated Forces

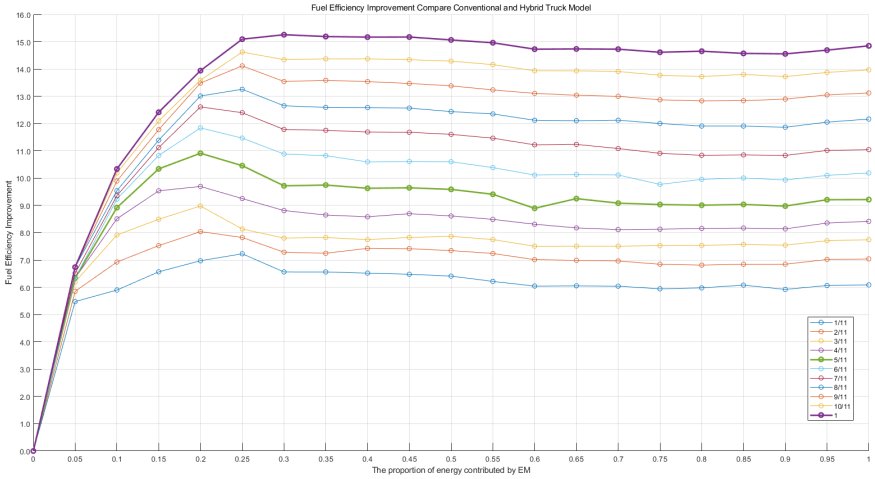
The actual use of ICE, EM and braking inputs for the hybrid model and the optimal inputs calculated by SLP shows a general consistency of trends, validating the accuracy of the hybrid model in tracking the optimal speed. Although the variation suggests that the model's control method requires further improvement.

4.3 Comparison of Conventional and Rule-based Hybrid Truck Models Using SLP-Derived Reference Speeds

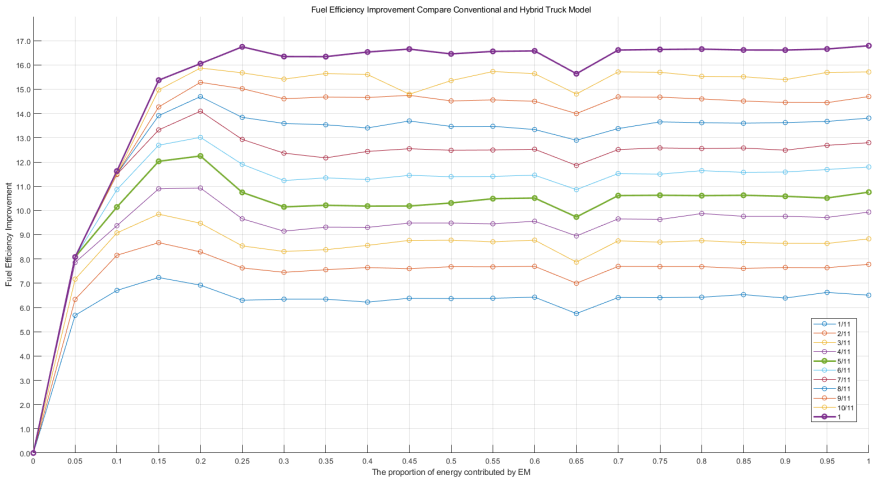
In order to compare with the theoretical optimal results from the SLP, the reference speed V_{ref} obtained through the SLP needs to be used as an input to the conventional truck model and the rule-based hybrid truck model, respectively. In the rule-based hybrid truck model, a grid search method is used to find the optimal combination of different regenerative braking recovery coefficients and electric motor energy distribution ratios. By comparing the performance of these two models, the aim is to verify whether the grid search method is effective in reducing energy consumption and thus optimising the overall efficiency of the vehicle. The following figure illustrates the details of the results of this comparison.



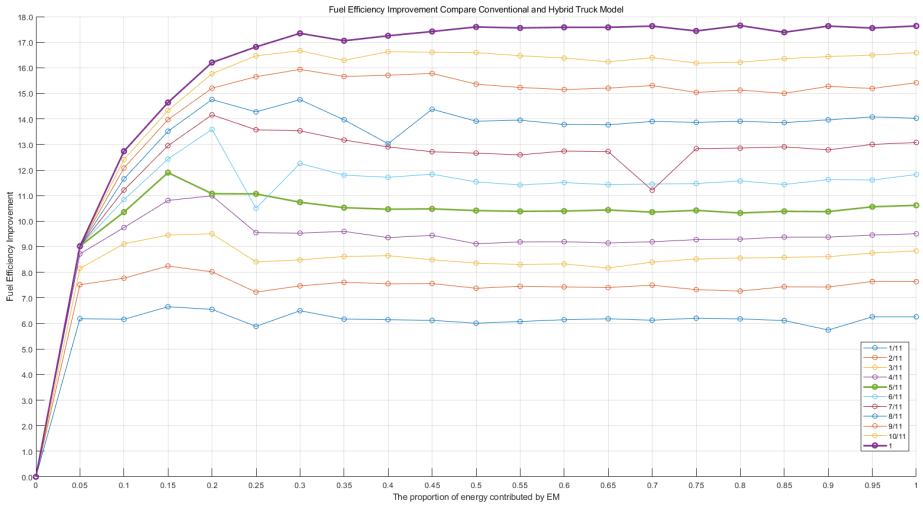
(a) Compare conventional and rule-based hybrid model in flat topography



(b) Compare conventional and rule-based hybrid model in undulating topography



(c) Compare conventional and rule-based hybrid model in hilly topography



(d) Compare conventional and rule-based hybrid model in highly hilly topography

Figure 4.4: Compare conventional and rule-based hybrid model running in Different road conditions

As shown in the figure above, the corresponding numbers in the labels indicate the regenerative braking coefficients, where the bold purple solid line indicates the performance improvement of the rule-based hybrid truck model over the conventional truck model when the regenerative braking coefficient is 1. The regenerative braking coefficients are sequentially decreased in steps of 1/11 through the grid search method. The horizontal coordinates in the graph indicate the proportion of energy supplied by the electric motor during the driving of the truck. Throughout the driving process, the electric motor will endeavour to provide energy at the given ratio until its stored energy reaches a preset minimum of 0.2. If the stored energy of the electric motor drops to 0.2, the system switches to a mode in which the energy is provided by the internal combustion engine alone.

The green line in the figure indicates the optimal upper limit of the regenerative braking factor for a given speed limit. In this project, the regenerative braking system is located on the axles of the electrically propelled dolly of an A-double truck. The e-dolly is positioned between the semi-trailers. If the e-dolly provides too much braking force, it might decelerate faster than the rest of the vehicle. This could lead to a scenario where the second semi-trailer tends to "push" the e-dolly, increasing the risk of jackknifing and causing instability. According to Erdinc, U. et al., the regenerative braking coefficient should not exceed 5/11 under the specific conditions of this project [25]. This limit is intended to ensure the safety and effectiveness of the regenerative braking system, while avoiding the instability and potential hazards caused by a too high regenerative braking coefficient.

It can be observed from the figure that there is a significant difference in the performance of the vehicle's energy consumption for different combinations of regenerative braking coefficients and motor energy ratios. Especially when the regenerative

braking coefficient is close to 1, the hybrid truck model demonstrates higher energy efficiency.

4.4 Comparison of Rule-based Hybrid Truck Models and SLP

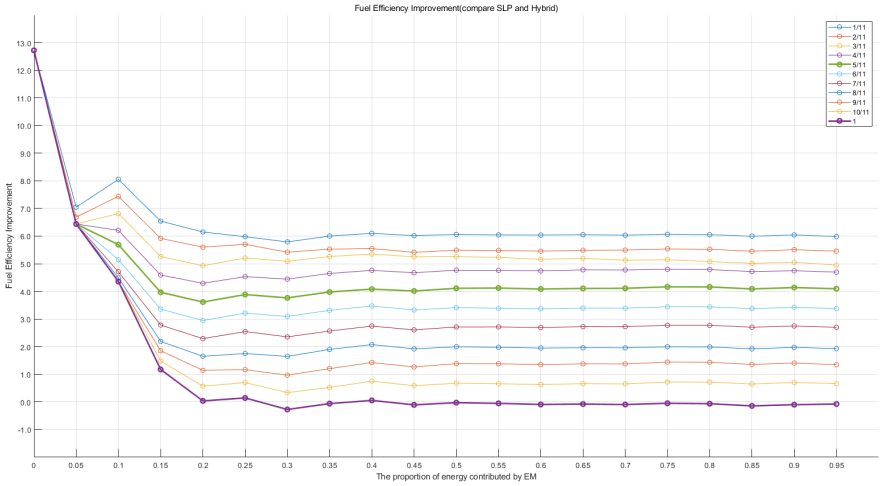
In the previous section, it has been verified that the rule-based hybrid truck model has lower fuel consumption than the conventional truck model when using the grid search method. Therefore, this section will focus on comparing the fuel consumption of the rule-based hybrid model with that obtained through the Sequential Linear Programming (SLP) method to determine which method has less fuel consumption. If the SLP approach consistently requires lower fuel consumption than the rule-based hybrid model, this will go some way to demonstrating the superiority of the SLP approach for fuel optimization. The comparison results are shown in Fig. 4.5 To ensure that the model can adapt to different topographies, the results are still based on four different topography conditions for comparison.

As shown in figure 4.5, the fuel consumption of the SLP method and the rule-based hybrid model are compared under flat topography , slightly undulating topography , hilly topography and very hilly topography , respectively. Fuel consumption data for both models are presented in detail for each topography condition in order to clearly assess their performance. This systematic comparison provides a more comprehensive understanding of the fuel consumption characteristics of the two models under different topography conditions and provides a basis for further optimization studies.

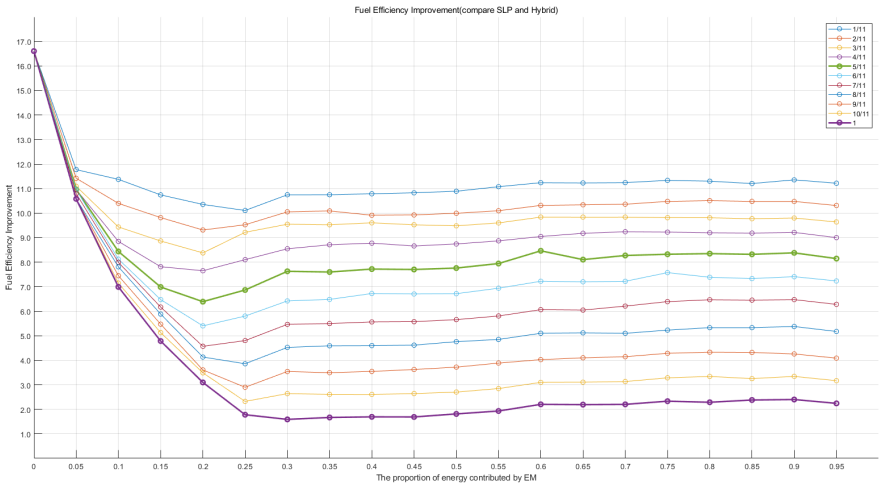
In figure 4.5, the solid line represents the same representation as in the previous comparison between the conventional truck model and the rule-based hybrid truck model. The bold purple solid line corresponds to the case when the regenerative braking coefficient is 1, showing the performance of the hybrid truck model under this condition. The green solid line represents the maximum regenerative braking factor that can be allowed under the current speed limit to ensure safety.

Specifically, the thickened purple solid line is used to show the best performance that can be achieved by the rule-based hybrid truck model when the regenerative braking coefficient reaches its maximum value of one. This curve shows that, in extreme cases, the regenerative braking system can fully recover braking energy to maximise fuel economy and energy efficiency.

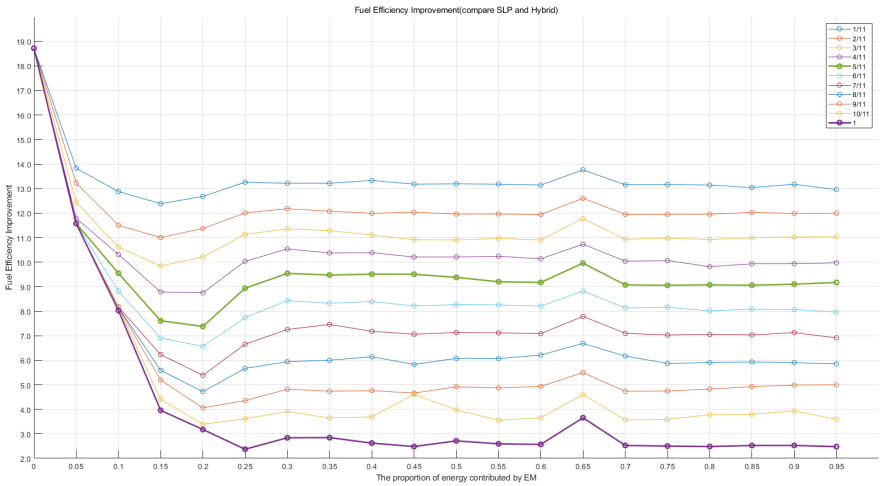
Meanwhile, the solid green bold line identifies the maximum regenerative braking coefficient allowed to ensure the safety and stability of the vehicle under specific road conditions and speed limit requirements. Based on the specific conditions of this project and references, this factor is set at 5/11, which aims to balance the energy recovery efficiency with the dynamic stability of the vehicle. This limit not only ensures the safety of the regenerative braking system in practice, but also prevents



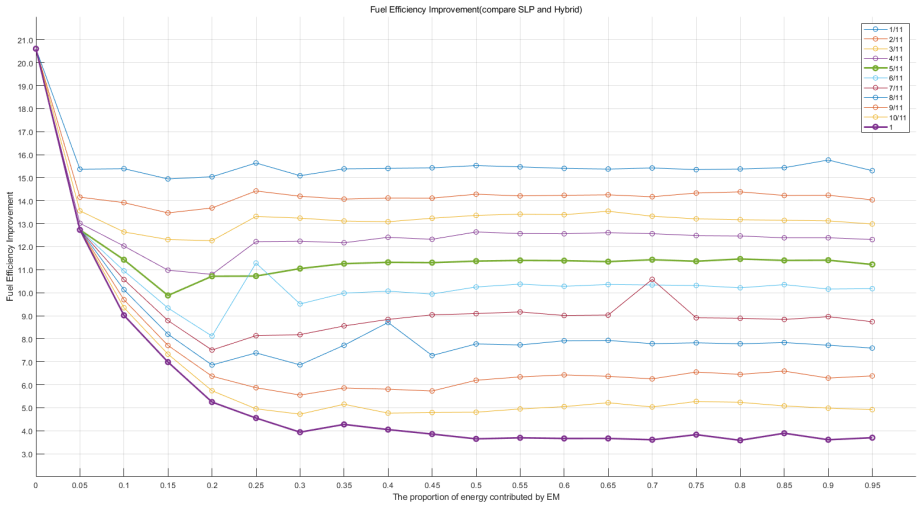
(a) Compare rule-based hybrid model with SLP in flat topography



(b) Compare rule-based hybrid model with SLP in undulating topography



(c) Compare rule-based hybrid model with SLP in hilly topography



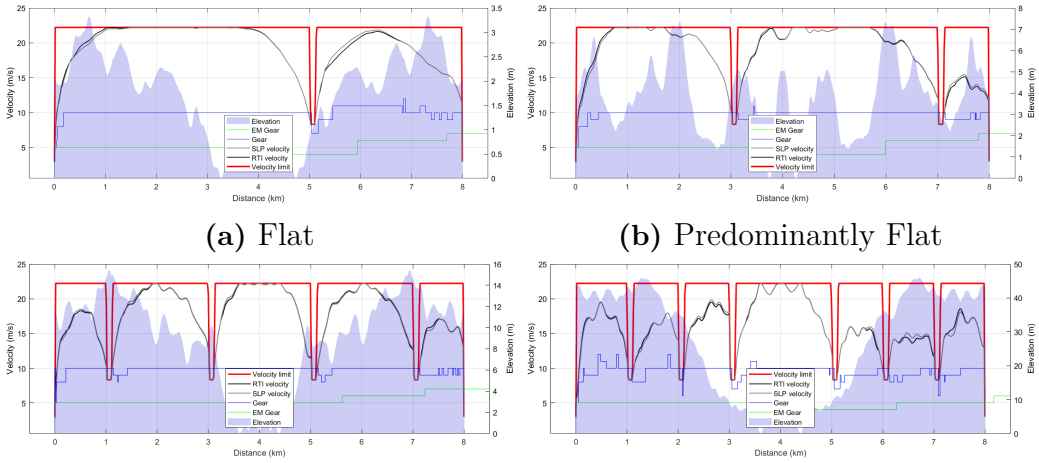
(d) Compare rule-based hybrid model with SLP in highly hilly topography

Figure 4.5: Compare rule-based hybrid model with SLP running in Different road conditions

vehicle control problems and potential risks that may be associated with excessive regenerative braking coefficients.

4.5 Comparison of Off-line SLP and Real-time Iteration

In previous sections, we compared the conventional A-double with the rule-based hybrid truck and the rule-based truck with offline SLP planning. In this section, we use the best brake-to-regenerate ratio and power distribution strategy derived in previous sections as settings, applying the SLP control signal to this rule-based truck model, use the fuel consumption obtained as the basis. We compare the optimal trajectories and speeds obtained through offline SLP and those derived from Real-Time Iteration (RTI), thus verifying RTI's optimization performance, specifically in terms of fuel savings compared to the rule-based truck. Additionally, we present the velocity trajectories under four different topographies, as shown in Figure 4.6. We focus on how each method handles vehicles over a standard 8 km stretch, and analyzing how these strategies correlate with energy savings.



(a) Flat **(b)** Predominantly Flat

(c) Hilly **(d)** Very Hilly

Figure 4.6: Gear Shift and Velocity Profiles Analysis for Real-Time Iteration vs. Sequential Linear Programming

As shown in figure 4.6, the speed profiles of RTI appear to align closely with those of SLP under all topography conditions. This indicates that the RTI has comparable performance to SLP. The RTI controller, as a closed-loop MPC, inherently faces a model-plant mismatch, where differences between the control-oriented model and the actual model can induce deviations in control outputs. In contrast, offline SLP operates without these real-time feedback discrepancies. Despite this, RTI is still able to perform similar to SLP.

In Table 4.1, RTI even slightly outperforms the offline SLP in some specific scenarios. This might be because the RTI's real-time adaptability enables it to effectively manage the impacts of model uncertainties, potentially yielding better performance than the optimal solution provided by offline SLP.

Table 4.1: Energy-saving Compared to Rule-based hybrid truck

Method	Flat	Predominantly flat	Hilly	Very Hilly
Off-line SLP	0.74%	1.41%	2.12%	4.05%
RTI	0.73%	1.46%	2.31%	3.96%

Specifically focusing on the problem we want to solve in this thesis, in the case of information loss on the e-dolly interface, we can take the approach of using the value of the optimal trajectory corresponding to the current position generated by the previous sampling interval of RTI to solve the problem of information loss. And after the information on interface is reloaded the RTI controller keep optimaizing. It can be seen in Table 4.1 that the energy savings of the vehicle using the RTI approach are higher than those of the rule-based trucks, especially when the operating cycle is mountainous, RTI can save up to 4% of fuel compared to the rule-based hybrid trucks models.

5
Conclusion

In this study, we constructed a rule-based hybrid truck model based on a conventional truck model and implemented an online nonlinear model predictive control algorithm using real-time iteration (RTI). We also compared the performance of the Sequential Linear Programming (SLP) method with the rule-based method and real-time iteration method. The main objective of this study is to obtain the best brake-to-regeneration ratio and power distribution combination, as well as to find the optimal energy allocation strategy with all the information available, so that the truck can drive according to the best control strategy, thus minimising fuel consumption. At the same time, this study also provides a sub-optimal solution to cope with various transport environments under information-reduced conditions. This study combines the vehicle energy modelling, the nonlinear optimal control problem, and the use of an online optimization solver.

The main research questions of this project are as follows:

1. How is the energy-saving performance influenced by reduced signal exchange between the vehicles of the combination?
2. How can the signal interface investigation be made independent on the power-split control strategy?
3. How can the signal interface investigation be made agnostic to the mission characteristics, such as topography, speeds etc.?

In this study, we used Casadi to construct a Nonlinear Programming (NLP) model and obtained optimal results through the Sequential Linear Programming (SLP) method as well as the Real-Time Iteration (RTI) method. Simulation results show that using SLP to solve the NLP problem is a highly effective strategy, while the SLP-based RTI method proved to be a near-optimal and computationally efficient optimization algorithm. It was verified that when using SLP-optimized inputs as references, fuel consumption for both the rule-based hybrid truck and the conventional truck models is significantly reduced. Additionally, the real-time control system using RTI results in lower fuel consumption compared to the rule-based hybrid truck.

To address the problem of information reduction between truck units, we propose two strategies. One involves using the best brake-to-regeneration and power distribution settings found based on the environment and truck model throughout the operating cycle. A more effective approach is the RTI method. RTI uses the optimal trajectory obtained by the previous sampling interval under information reduced

conditions; once communication on the interface is restored, the RTI controller continues to optimize the control inputs.

To ensure the independence of performance from road characteristics, four road profiles with different topographies and speed limits sections were chosen. The results obtained through MATLAB simulations demonstrate significant improvements compared to the conventional A-double truck model. The new model, combined with real-time control strategies, shows better performance even with limited regenerative braking recovery coefficients.

In conclusion, this thesis presents two methods to reduce fuel consumption in hybrid A-double combination optimization under reduced information scenarios. By designing robust control strategies that adapt to reduced signal exchange on the e-dolly interface, this study provides a pathway for achieving near-optimal fuel savings. These findings offer valuable insights for enhancing the fuel efficiency of A-double combinations operating in complex environments.

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