Energy Consumption Assessment of Fuel Cell Heavy-Duty Vehicles for Long-Haul Applications

A Comparative Study Using VECTO and GSP & AI-Assisted Regulatory Modelling

Zhiyong Cui

Mechanics and Maritime Sciences
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2026
www.chalmers.se

Master's Thesis 2026

Energy Consumption Assessment of Fuel Cell Heavy-Duty Vehicles for Long-Haul Applications

A Comparative Study Using VECTO and GSP & AI-Assisted Regulatory Modelling

Mechanics and Maritime Sciences
Chalmers University of Technology
Gothenburg, Sweden 2026

Energy Consumption Assessment of Fuel Cell Heavy-Duty Vehicles for Long-Haul Applications
A Comparative Study Using VECTO and GSP & AI-Assisted Regulatory Modelling
ZHIYONG CUI

Supervisor: Fredrik Bruzelius, Chalmers & Zikun Wang, Volvo Group & Gustavo Hindi
Examiner: Fredrik Bruzelius, Mechanics and Maritime Sciences

Master's Thesis 2026
Department of Mechanics and Maritime
Chalmers University of Technology
SE-412 96 Gothenburg
Telephone +46 31 772 1000

Cover: A Volvo Group fuel cell tractor in operation.

Typeset in LaTeX
Printed by Chalmers Reproservice
Gothenburg, Sweden 2026

Energy Consumption Assessment of Fuel Cell Heavy-Duty Vehicles for Long-Haul Applications
A Comparative Study Using VECTO and GSP
Division of Vehicle Engineering and Autonomous System.
Chalmers University of Technology

Abstract

The decarbonisation of long-haul freight transport has increased interest in fuel-cell heavy-duty vehicles, while simultaneously placing greater emphasis on reliable and comparable energy consumption assessment methods. Within the European regulatory framework, the VECTO simulation tool is used to evaluate energy consumption and emissions of heavy-duty vehicles. However, its level of abstraction and regulatory focus differ from those of engineering-oriented simulation environments commonly used during vehicle development.

This thesis presents a vehicle-level energy consumption assessment of a fuel-cell heavy-duty vehicle for long-haul applications using VECTO and compares the results with simulations performed in the Global Simulation Platform (GSP), an internal MATLAB-based simulation platform. A VECTO-compliant fuel-cell heavy-duty vehicle model was developed based on an internal prototype and evaluated under a representative long-haul mission profile. The results demonstrate that the VECTO declaration-mode model can reproduce the prescribed mission with stable longitudinal dynamics and physically reasonable energy flows. While VECTO and GSP exhibit similar mission-level trends in battery power and state-of-charge behaviour, systematic differences are observed in transient response and absolute operating levels. These differences are shown to be consistent with the backward regulatory simulation approach employed by VECTO and the forward, engineering-oriented simulation philosophy of GSP.

In addition to the simulation study, this thesis investigates the use of an AI-assisted Agentic Retrieval-Augmented Generation (RAG) framework to support the VECTO modelling workflow. The framework facilitates interpretation of regulatory documentation, parameter constraints, and XML schema definitions, reducing ambiguity during model setup while preserving engineering judgement. The results indicate that AI-assisted methods can effectively support complex regulatory modelling tasks and improve efficiency and robustness in simulation-based energy assessment workflows.

Keywords: Fuel cell heavy-duty vehicles (FC-HDVs); Long-haul freight transport; Energy consumption assessment; VECTO; Global Simulation Platform (GSP); Battery throughput; Hybrid energy management; Agentic retrieval-augmented generation (Agentic RAG)

Preface

This thesis work was carried out in collaboration with Zhenguo Wang. The work was conducted as a joint project, where both parties contributed to the development, analysis, and discussion of the study.
Zhenguo Wang was enrolled as a student at Lund University during the project. Therefore, according to the Chalmers administrative system and report requirements, he is not listed as an author on the front page of this Chalmers thesis report. Nevertheless, his contribution to the work is acknowledged here.

Acknowledgements

These past months have been a completely new experience for me, and also my first time working in a truly international environment. I learned a lot not only technically, but also about collaboration, communication, and working across different perspectives.
I'd like to sincerely thank my team for the continuous support, encouragement, and trust.
I would like to extend my sincere thanks to my thesis partner, Zhenguo Wang. Although we came from different universities and academic backgrounds, we were able to complete this project through close collaboration, shared commitment, and continuous technical discussions. Our teamwork played an important role in making this thesis possible.
I would also like to thank my supervisor at Volvo Group, Zikun Wang, and my academic supervisor, Fredrik Bruzelius, for their guidance throughout the thesis work and for consistently helping me move in the right direction. I am also grateful to Behrooz Razaznejad for his support and encouragement during the project.
Zhiyong Cui, Gothenburg, February 2026

zhiyong cui, Gothenburg, 02/2026

List of Acronyms

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

AC	Alternating current
AFC	Alkaline fuel cell
AFIR	Alternative Fuels Infrastructure Regulation
ASM	Asynchronous machine (induction machine)
BES	Battery energy storage
BEV	Battery electric vehicle
BoP	Balance of plant
CNG	Compressed natural gas
CO_2	Carbon dioxide
DC	Direct current
DC/DC	DC-to-DC converter
DER	Distributed energy resource
ECMS	Equivalent consumption minimization strategy
EMS	Energy management system
ESS	Energy storage system
EU	European Union
EV	Electric vehicle
FC	Fuel cell
FC-HDV	Fuel cell heavy-duty vehicle
FCEV	Fuel cell electric vehicle
FCS	Fuel cell system
GDL	Gas diffusion layer
GPS	Global Positioning System
GSP	Global Simulation Platform
GUI	Graphical user interface
HDV	Heavy-duty vehicle
HVAC	Heating, ventilation, and air conditioning
ICE	Internal combustion engine
LFP	Lithium iron phosphate
LNG	Liquefied natural gas
MCFC	Molten carbonate fuel cell
MEA	Membrane electrode assembly
MG	Microgrid

MILP	Mixed-integer linear programming
NCA	Nickel cobalt aluminum oxide
NMC	Nickel manganese cobalt oxide
OEM	Original equipment manufacturer
PAFC	Phosphoric acid fuel cell
PEM	Proton exchange membrane
PEMFC	Proton exchange membrane fuel cell
PFSA	Perfluorosulfonic acid
PM-SM	Permanent magnet synchronous machine
PV	Photovoltaic
REESS	Rechargeable electric energy storage system
RES	Renewable-based energy sources
RPM	Revolutions per minute
SAE	SAE International (Society of Automotive Engineers)
SOC	State of charge
SOFC	Solid oxide fuel cell
VCU	Vehicle control unit
VECTO	Vehicle Energy Consumption Calculation Tool
XML	Extensible Markup Language

Contents

Preface **vii**

Acknowledgements **ix**

List of Acronyms **x**

Nomenclature **xii**

1 Introduction **1**
1.1 Thesis outline 2
1.2 Europe carbon emission 2
1.3 Policy support 3
1.4 Simulation tools 3
1.5 Intelligent Support for Complex Simulation 4
1.6 Research Aim and Questions 4

2 Fuel Cell System **7**
2.1 Fundamental Principles 8
2.2 Fuel Cell Types and Selection for Automotive Use 8
2.3 Hydrogen fuel cell and working principles 8
2.3.1 Fuel cell unit architecture 9
2.3.2 Electrochemical reactions and operating principle 10
2.3.3 Reversible voltage and Nernst equation 10
2.3.4 Voltage losses and polarization behaviour 11
2.4 Stack and Balance of Plant 12
2.5 Hydrogen Storage Technologies 14
2.6 System Efficiency and Control Considerations 14

3 Fuel Cell Powertrain in Heavy-Duty Vehicles **15**
3.1 Alternative Powertrains for HDVs 15
3.2 Fuel Cell Technology Strengths and Deployment Challenges 16
3.3 Integration in Vehicle Powertrain and Hybrid Topology 19
3.4 Power Sources 20
3.5 Electric Motor and Transmission 21
3.6 DC-Link and Converters 23
3.7 Energy Management System 24
3.8 real-time control features for EMS systerm 26

4 VECTO Software Overview **27**
4.1 Driving Cycles and Profiles 28
4.2 Input Parameters and Modes 29
4.3 Software Implementation and Updates 30

5 Theory **33**
5.1 Backward Simulation Approach VECTO Example 33
5.2 Forward Simulation Approach – GSP 35
5.3 Theoretical Framework of the AI-Assisted Modeling Support System . 40
5.3.1 Data Preparation and Hierarchical Indexing 41
5.3.2 Agentic Query Execution and Grounded Synthesis 41

6 Battery Throughput in VECTO vs GSP Fuel Cell Truck Simulations **43**
6.1 VECTO: Battery as a Transient Power Buffer 44
6.2 GSP: Detailed Battery Modeling with Thermal and Life Considerations 45

7 Methods and experiment **47**
7.1 Vehicle model definition for long-haul applications 47
7.2 Gradient-to-altitude conversion for forward simulation 48
7.3 Data sources, confidentiality, and modelling philosophy 49
7.4 Implementation of the AI-Assisted Modeling Framework 50
7.4.1 Vehicle Case Study and Modeling Scope 50
7.4.2 Knowledge Engineering and Indexing Strategy 50
7.4.3 Agentic Workflow and Intent Orchestration 50
7.4.4 Retrieval Optimization Pipeline 51
7.4.4.1 LLM-Based Pointwise Reranking 52
7.4.4.2 Heuristic Fallback Mechanism 52
7.4.4.3 Context Windowing 52
7.4.5 Closed-Loop Verification and Recursive Retrieval 52
7.4.5.1 Domain-Aware Post-Answer Verification 52
7.4.5.2 Feedback-Driven Query Refinement 52
7.4.6 Conversation Memory and Context Management 53
7.4.7 Prompt Engineering and Output Constraints 53
7.5 Experimental Evaluation 54
7.5.1 Evaluation Design 54
7.5.1.1 Test Dataset Construction 54
7.5.1.2 Evaluation Protocol 54
7.5.2 Limitations and Future Directions 55
7.5.2.0.1 Dependence on Ground Truth Formulation . 55
7.5.2.0.2 Diagram and Figure Accessibility 55
7.5.2.0.3 Implicit Workflow Reconstruction 55
7.5.2.0.4 Regulatory Version Management 55
7.5.2.0.5 Uncertainty Representation 55
7.5.2.0.6 Multilingual Extension 55

8 Results **57**

8.1 Limitations of declaration-mode-based modelling 57
8.2 Vehicle dynamics and drive cycle tracking 58
8.3 Energy flow and battery utilisation behaviour 59
8.3.1 Cumulative Hydrogen Consumption Rate: GSP vs VECTO . 62
8.3.2 Energy Flow and Battery Utilisation 63
8.4 RAG-System Quantitative Results and Analysis 66
8.4.1 Qualitative Analysis and Practical Deployment 67

9 Conclusion **69**

Bibliography **71**

1 Introduction

This thesis, conducted within Volvo's Powertrain Strategic Development, explores the critical role of advanced simulation and artificial intelligence in the deployment of heavy-duty fuel cell electric vehicles (FCEVs). As the European Union pursues its ambitious goal of climate neutrality by 2050 under the European Green Deal [38], the decarbonization of the heavy-duty transport sector has become a primary industrial imperative. This transition necessitates not only hardware innovation but also the development of standardized, high-precision methodologies for energy consumption estimation to ensure both regulatory compliance and engineering excellence [28].

FCEV performance is currently shaped by two distinct yet complementary simulation paradigms. First, a backward-facing approach underpins the EU certification workflow, where the Vehicle Energy Consumption Calculation Tool VECTO[35] estimates energy use and CO_2 emissions for heavy-duty vehicles from standardized missions and certified component characteristics.[6] Second, engineering development typically relies on forward-facing, time-domain simulation[27], exemplified by Volvo Group's Global Simulation Platform (GSP)[36], in which driver and control actions are propagated through dynamic vehicle and powertrain models to resolve transient behavior and subsystem interactions. For fuel cell electric vehicles, the propulsion system tightly couples stack electrochemistry with balance-of-plant dynamics and integrated thermal management[37], increasing the sensitivity of results to transient modeling assumptions and control representations. Consequently, predictions from certification-oriented backward models and high-fidelity forward simulations may diverge, and a consistent interpretation framework is required to translate regulatory outcomes into robust design decisions and powertrain strategic planning[27].

Furthermore, the practical implementation of these simulation tools is increasingly bottlenecked by the "knowledge density" required to navigate their respective environments. VECTO, in its transition to accommodate zero-emission powertrains, involves a vast array of technical specifications and legislative manuals that can be difficult to interpret accurately . In this landscape, Generative Artificial Intelligence (GenAI), particularly Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG)[20][18], has emerged as a transformative tool for "Knowledge Engineering". By automating the synthesis of complex technical documentation, AI frameworks can significantly enhance the efficiency of the development cycle, allowing engineers to maintain focus on core analytical tasks rather than manual data retrieval.

To address these challenges, this research develops a dual-layered methodology. First, it conducts a comparative analysis between VECTO and GSP to quantify energy consumption variances in a 6x2 fuel cell tractor. Second, it implements an agentic RAG-based framework—referred to as the "Vecto Assistant"—to provide intelligent, context-aware support for the simulation process. This integration of traditional vehicle simulation with modern AI-driven assistance establishes a robust workflow for the future of clean, autonomous logistics.

1.1 Thesis outline

This thesis is structured as follows. Chapter 2 introduces the fundamental principles of hydrogen fuel cell systems, including electrochemical mechanisms and system-level architecture. Chapter 3 focuses on the integration of fuel cell technology into heavy-duty vehicle powertrains, covering component roles and hybrid configurations. Chapter 4 presents an overview of the VECTO simulation tool and its function within regulatory energy assessment. Chapter 5 describes the theoretical modeling approaches used by VECTO and the Global Simulation Platform, highlighting backward and forward simulation paradigms. Chapter 6 provides a comparative analysis of battery throughput behavior between the two simulation environments. Chapter 7 outlines the methodology, including vehicle modeling procedures and the implementation of an artificial intelligence-assisted modeling framework. Chapter 8 presents the simulation results, and Chapter 9 concludes the thesis with key findings and future outlooks.

1.2 Europe carbon emission

Global concern over climate change has brought a sharp focus to reducing carbon emissions, especially from the transportation sector. As noted in a recent study, a significant portion of the world's primary energy use—approximately 33%—is attributed to oil, with roughly 65% of that amount fueling the transportation industry. This reliance on fossil fuels has positioned the automotive sector as a key contributor to CO_2 emissions.[38]Consequently, there is an urgent need to develop and evaluate alternative powertrain technologies that can meet these environmental goals without compromising on performance or efficiency.[33]
In response, major industrial and research actors have redirected their efforts toward zero-emission vehicle technologies, including battery electric and hydrogen fuel cell powertrains. Hydrogen-based propulsion, in particular, has gained attention for its capability to deliver long operating ranges, rapid refuelling, and reliable energy conversion without direct carbon emissions. To combat this, Fuel Cell Electric Vehicles (FCEVs) offer a compelling solution. Unlike traditional internal combustion engines that release greenhouse gases from burning fossil fuels, FCEVs generate electricity through an electrochemical reaction between hydrogen and oxygen. The only byproducts of this process are electricity, water, and heat, resulting in zero tailpipe emissions.[28]
This has positioned Fuel Cell Electric Vehicles (FCEVs) as a key technology for reducing carbon emissions in the heavy-duty sector. To ensure FCEVs are a viable and effective solution, it is essential to understand and optimize their performance before real-world deployment. As a result, using simulations has become a critical

and indispensable part of the development [40], allowing engineers to accurately predict, analyze, and improve the operational performance of fuel cell vehicles.

1.3 Policy support

Governments worldwide are increasingly adopting policies to accelerate the transition to zero-carbon mobility, creating a more favorable environment for technologies like fuel cells. A prime example is the European Union's Alternative Fuels Infrastructure Regulation (AFIR), which sets a legally binding mandate for the deployment of hydrogen refueling stations. This regulation requires member states to ensure a station is available at least every 200 km along the EU's main transport corridors by the end of 2030[5].

This policy[5], along with significant public funding for hydrogen infrastructure projects, directly addresses the previous major obstacle for FCEV adoption: the lack of a convenient refueling network. As this infrastructure rapidly expands under government encouragement, it will become far more practical for both commercial fleets and individual consumers to choose hydrogen-powered vehicles[31], making their key benefits—such as rapid refueling and long range—increasingly accessible and desirable.

1.4 Simulation tools

To support this transition, simulation tools have become fundamental for assessing the performance and efficiency of advanced powertrains under standardized and controlled conditions. Within the European Union, the Vehicle Energy Consumption Calculation Tool (VECTO) was developed as the official platform for regulatory certification of heavy-duty vehicle energy consumption[9]. VECTO operates as a reverse simulation tool: it reconstructs the power and energy demand backward from a predefined driving cycle, evaluating the fuel or energy consumption associated with each powertrain configuration.[27] By enabling manufacturers to estimate energy efficiency under harmonised conditions, VECTO ensures comparability and compliance with EU environmental legislation.[8]

While VECTO provides an essential regulatory framework, it remains a quasi-static and mission-based model. For detailed research on component-level dynamics and control strategy evaluation, forward simulation platforms are required.[27] Volvo's Global Simulation Platform (GSP), developed on MATLAB/Simulink, represents such an environment. Unlike VECTO, GSP calculates the vehicle response from driver inputs forward in time, capturing transient interactions among subsystems such as the fuel cell stack, battery, traction motor, gearbox, and thermal management units. Through parameterization of component models, it can replicate realistic operational behavior and evaluate system-level efficiency under varying control strategies.

The combination of these two modeling paradigms establishes a powerful analytical framework. VECTO provides a standardized reference for energy certification, while GSP enables dynamic reproduction of subsystem interactions and control op-

timization. Synthesizing their results allows for both regulatory comparability and engineering precision, bridging the gap between certification-based evaluation and system-level development.
The present work investigates this integration in the context of a hydrogen fuel cell vehicle. Based on a Volvo Fuel Cell 6x2 tractor. Specifically, the study aims to synthesize VECTO-based energy consumption assessments with high-fidelity GSP simulations to analyze and optimize control strategies focused on efficiency. Since fuel cell vehicles produce no carbon dioxide during operation, the research shifts its focus from emission reduction to the improvement of overall energy utilization and power distribution. By combining the static accuracy of VECTO with the dynamic modeling capability of GSP, the thesis provides a coherent methodology to evaluate the performance of zero-emission heavy-duty vehicles under both regulatory and operational perspectives.

1.5 Intelligent Support for Complex Simulation

Despite the robustness of tools like VECTO and GSP, their implementation in the development of hydrogen fuel cell vehicles presents significant challenges. VECTO, in particular, requires meticulous parameterization of XML input files and a deep understanding of extensive EU regulatory documentation. [4]For engineers, navigating thousands of pages of technical reports and ensuring consistency between different simulation environments is both time-consuming and prone to human error.
To address these operational bottlenecks, this thesis introduces an AI-driven Knowledge Agent (Vecto Assistant) designed to streamline the simulation workflow[28]. Built upon Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) technology, the agent acts as an intelligent interface between the researcher and the complex technical specifications of VECTO[20]. By vectorizing official VECTO user manuals and Volvo-internal documentation, the agent provides real-time, context-aware support for parameter configuration and simulation logic interpretation.
The integration of such an AI Agent represents a shift towards "Intelligent Engineering".[32] It does not only serve as a query tool but also ensures that the high-fidelity dynamics from GSP and the regulatory requirements of VECTO are harmonized through a unified, AI-supported knowledge base. This dual approach—combining traditional physical simulation with modern artificial intelligence—enhances the precision of energy consumption estimation while significantly reducing the cognitive load on the system developer.

1.6 Research Aim and Questions

To address these challenges, this thesis develops an integrated workflow for the energy consumption assessment of a fuel-cell heavy-duty vehicle in long-haul operation. The work combines a regulatory VECTO model with an engineering-oriented GSP model and further investigates whether an AI-assisted Retrieval-Augmented Generation framework can support the interpretation of VECTO documentation and the

vehicle model setup process. The aim is not to replace engineering judgement, but to improve the consistency, traceability, and efficiency of regulatory modelling for fuel-cell heavy-duty vehicles.
The study is guided by the following research questions:

1. How can a fuel-cell heavy-duty vehicle for long-haul applications be represented in VECTO under declaration-mode constraints while preserving a physically meaningful description of vehicle-level energy flows?
2. How do VECTO and GSP differ in speed tracking, battery utilisation, fuel-cell system operation, and hydrogen consumption when applied to the same long-haul mission?
3. To what extent can an AI-assisted RAG framework support VECTO model setup, regulatory interpretation, and parameter-related decision-making during the simulation workflow?

By answering these questions, the thesis aims to clarify the role and limitations of VECTO as a regulatory energy assessment tool for fuel-cell heavy-duty vehicles, while also showing how forward simulation in GSP can provide complementary engineering insight into transient behaviour and powertrain control. The AI-assisted part of the work is treated as a supporting methodology for handling documentation complexity, rather than as a substitute for physical modelling or simulation expertise.

2

Fuel Cell System

This chapter establishes the theoretical foundation of hydrogen fuel cell technology, detailing the electrochemical principles, architectural components, and system-level dynamics essential for heavy-duty vehicle applications. As the transportation industry pivots toward zero-emission solutions, the Proton Exchange Membrane Fuel Cell (PEMFC) has emerged as the leading technology for long-haul logistics due to its high power density and rapid refueling capabilities. However, unlike traditional internal combustion engines, a fuel cell system is a highly coupled multi-physics environment where electrochemical reactions, fluid dynamics, and thermal management must be harmonized to achieve optimal efficiency. Understanding these fundamental mechanisms is a prerequisite for accurate energy consumption estimation and for the successful integration of vehicles into regulatory frameworks like VECTO.

The complexity of fuel cell systems extends beyond the individual cell to the Balance of Plant (BoP) and integrated storage solutions, creating a vast multidimensional parameter space. For researchers and engineers, this complexity often translates into a significant documentation burden. Navigating the intricate relationships between current density, voltage degradation, and auxiliary power consumption requires constant reference to specialized technical manuals and scientific literature. In this context, the role of intelligent digital assistants becomes paramount. By utilizing the AI-driven "Vecto Assistant" described in this thesis, the process of extracting specific fuel cell parameters—such as Nernst potentials or polarization loss coefficients—is streamlined, bridging the gap between abstract electrochemical theory and practical simulation input.

The following sections provide a detailed technical breakdown of the fuel cell ecosystem. The discussion begins with the fundamental electrochemical principles and the selection criteria for automotive fuel cells, followed by an in-depth analysis of the PEMFC architecture and its operating mechanisms. It further explores the polarization behavior that governs voltage losses and the auxiliary subsystems that comprise the Balance of Plant. Finally, the chapter addresses hydrogen storage technologies and the control strategies necessary for maximizing system efficiency. Together, these sections form the knowledge base required to interpret the simulation results produced by VECTO and GSP in the subsequent chapters of this study.

2.1 Fundamental Principles

A fuel cell is an electrochemical device that converts the chemical energy of hydrogen and oxygen directly into electrical energy, heat, and water. The process takes place continuously as long as fuel and oxidant are supplied. [24]In a proton exchange membrane fuel cell (PEMFC), hydrogen at the anode is split into protons and electrons. The protons migrate through the polymer membrane to the cathode, while the electrons flow through an external circuit, providing useful electrical work. At the cathode, oxygen combines with the incoming protons and electrons to form water vapor. The reaction is exothermic, with a theoretical open-circuit voltage of about 1.23 V at standard conditions, though practical cells operate at slightly lower voltages due to internal losses.

Unlike combustion engines, fuel cells do not rely on intermediate mechanical conversion, resulting in high efficiency and near-zero pollutant emissions. When powered by pure hydrogen, the only by-product is water. These characteristics make PEM fuel cells particularly suitable for clean transport applications and for integration into electric vehicle powertrains.

2.2 Fuel Cell Types and Selection for Automotive Use

Several types of fuel cells have been developed, differentiated by their electrolyte material and operating temperature. Alkaline fuel cells (AFC) and phosphoric acid fuel cells (PAFC) operate at moderate temperatures and have found limited stationary applications. [24]Molten carbonate (MCFC) and solid oxide (SOFC) fuel cells achieve high electrical efficiencies but require elevated temperatures above 600 °C, resulting in long start-up times and complex thermal management.[24]

For vehicle applications, the PEMFC has emerged as the most viable option. [11]It operates at 60–90 °C, delivers high power density, and can be rapidly started and stopped. Its compact design allows easy integration within vehicular platforms, and it responds quickly to power demand variations. These advantages, combined with the global maturity of hydrogen refueling infrastructure and stack manufacturing, have positioned PEMFC technology as the reference solution for heavy-duty and long-haul zero-emission vehicles.

2.3 Hydrogen fuel cell and working principles

This section focuses on hydrogen fuel cells employing an acidic electrolyte, which are currently the most prominent in automotive applications. In particular, the proton exchange membrane fuel cell (PEMFC) uses a solid polymer electrolyte membrane made of perfluorosulfonic acid (PFSA), commonly known by the trade name *Nafion*.

2.3.1 Fuel cell unit architecture

A PEMFC can be regarded as an open electrochemical energy-conversion device, requiring a continuous supply of hydrogen and oxygen (air) under controlled pressure, temperature, and humidity to achieve efficient and stable operation. A single cell unit typically consists of: (i) the electrolyte membrane, (ii) anodic and cathodic catalyst layers, (iii) gas diffusion layers (GDLs), (iv) bipolar plates (including reactant flow channels), and (v) end plates and sealing elements that provide mechanical compression and gas tightness. Electrical connectors at the cell ends provide the interface to the external load[28].

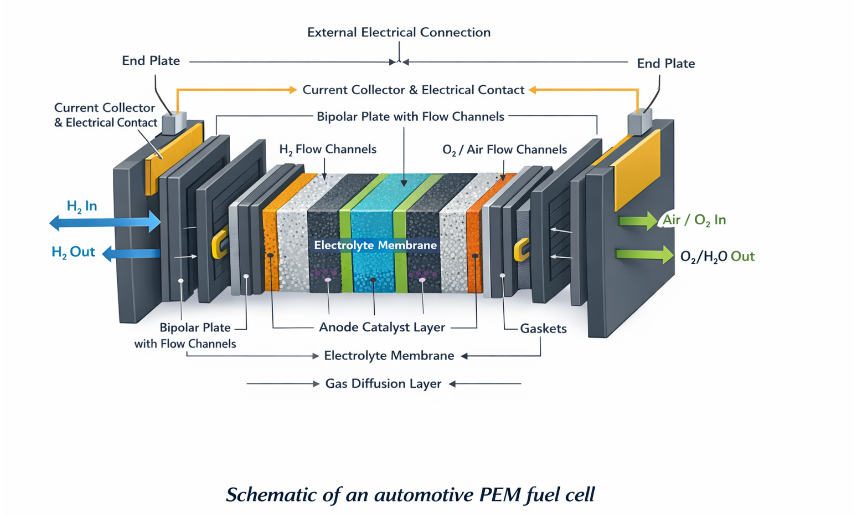

Figure 2.1: Schematic of a fuel cell unit (electrolyte, catalyst layers, gas diffusion layers, bipolar plates, and end plates).

The membrane electrode assembly (MEA) is the core component where the electrochemical reactions occur. It comprises the membrane and the adjacent porous electrodes, typically supported by GDLs. The GDL is commonly made of porous carbon material and facilitates uniform reactant distribution towards the catalyst layers while supporting water transport. Adjacent to the GDL lies the catalyst layer, usually a thin porous film on the order of 5–50 μm, containing platinum-based catalyst particles supported on carbon. The catalyst accelerates the reaction kinetics and thus improves the attainable current density and efficiency. Platinum is widely used due to its high activity and stability; however, its high cost, scarcity, and sensitivity to carbon monoxide poisoning motivate ongoing research into alternative catalyst concepts (e.g., based on ruthenium or palladium). The membrane must function as an electronic insulator while simultaneously providing high proton conductivity; therefore, hydration state and operating temperature must be carefully managed for proper PEMFC operation.

2.3.2 Electrochemical reactions and operating principle

A schematic of the PEMFC working principle is illustrated in Fig. 2.2. During operation, hydrogen is supplied to the anode-side channels, diffuses through the GDL, and reaches the anode catalyst layer where the hydrogen oxidation reaction occurs:

$$\mathrm{H_2} \rightarrow 2\mathrm{H}^+ + 2\mathrm{e}^-. \tag{2.1}$$

The generated electrons travel through the external circuit, thereby providing electrical power to the load, while protons migrate through the polymer electrolyte membrane towards the cathode. On the cathode side, oxygen is reduced and combines with the transported protons and the incoming electrons to form water:

$$\frac{1}{2}\mathrm{O_2} + 2\mathrm{H}^+ + 2\mathrm{e}^- \rightarrow \mathrm{H_2O}. \tag{2.2}$$

The overall cell reaction is:

$$\mathrm{H_2} + \frac{1}{2}\mathrm{O_2} \rightarrow \mathrm{H_2O} + \text{heat}. \tag{2.3}$$

Thus, the products are water and heat, both of which must be removed to maintain suitable membrane hydration and temperature. It should be noted that Eqs. (2.1)–(2.3) represent global reactions; in practice, several intermediate steps may occur in the catalyst layers.

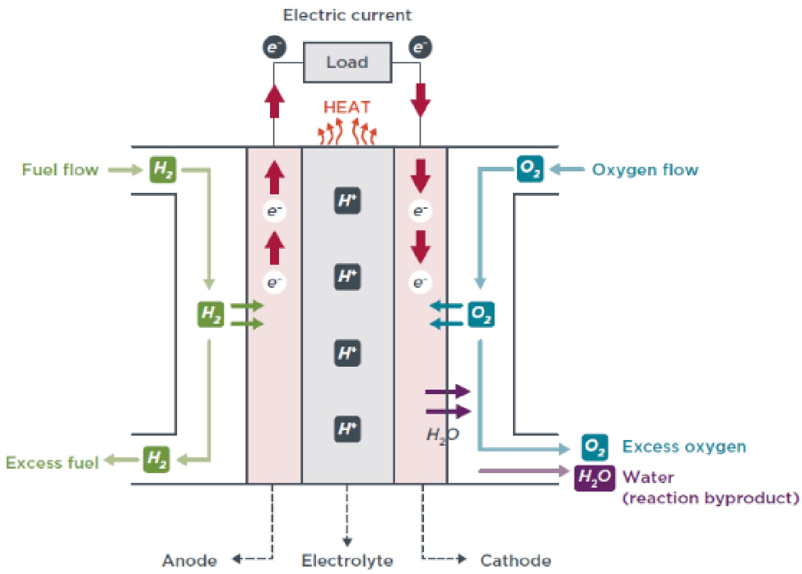

Figure 2.2: Fuel cell working principle: proton transport through the membrane and electron flow through the external circuit.[11]

2.3.3 Reversible voltage and Nernst equation

The maximum obtainable electrical work from the hydrogen–oxygen reaction is governed by the change in Gibbs free energy. For a thermodynamically reversible cell,

$$W_{\mathrm{el,max}} = -\Delta G, \tag{2.4}$$

and the corresponding reversible (open-circuit) voltage is

$$E_{\mathrm{rev}} = -\frac{\Delta G}{nF}, \tag{2.5}$$

where n is the number of electrons transferred per mole of reaction and F is Faraday's constant. For the PEMFC hydrogen oxidation / oxygen reduction reactions, $n = 2$. Under standard ambient conditions ($T = 298.15\,\mathrm{K}$, $p = 1\,\mathrm{bar}$), the ideal open-circuit voltage is approximately $1.23\,\mathrm{V}$ [11].
For non-standard operating conditions, the reversible voltage is described by the Nernst equation. Using a pressure-based form for the hydrogen-fuel cell,

$$E_{\mathrm{Nernst}} = E^0 + \frac{RT}{2F}\ln\left(\frac{p_{\mathrm{H_2}}\, p_{\mathrm{O_2}}^{1/2}}{a_{\mathrm{H_2O}}}\right), \tag{2.6}$$

where E^0 is the standard reversible potential, R is the universal gas constant, T is the temperature, $p_{\mathrm{H_2}}$ and $p_{\mathrm{O_2}}$ are the partial pressures of hydrogen and oxygen, and $a_{\mathrm{H_2O}}$ is the activity of water. If liquid water is assumed, $a_{\mathrm{H_2O}} \approx 1$, leading to the commonly used simplified expression:

$$E_{\mathrm{Nernst}} \approx E^0 + \frac{RT}{2F}\ln\left(p_{\mathrm{H_2}}\, p_{\mathrm{O_2}}^{1/2}\right). \tag{2.7}$$

2.3.4 Voltage losses and polarization behaviour

Practical fuel cells deviate from reversible behaviour due to kinetic and transport phenomena, resulting in a reduction of the terminal voltage compared with E_{Nernst}. The main voltage losses (polarizations) are typically attributed to:

- **Activation losses** (η_{act}): associated with overcoming the activation energy barrier of the electrode reactions, often dominant at low current density.
- **Ohmic losses** (η_{ohm}): caused by resistance to electron transport in electrodes/interconnects and proton transport through the membrane.
- **Concentration (mass-transport) losses** (η_{conc}): due to reactant depletion and transport limitations at high current density.
- **Fuel crossover losses** (η_{xover}): parasitic losses associated with reactant crossover through the membrane; typically smaller than the other contributions under normal conditions.

Accordingly, the cell terminal voltage can be expressed as

$$V_{\mathrm{cell}} = E_{\mathrm{Nernst}} - \eta_{\mathrm{act}} - \eta_{\mathrm{ohm}} - \eta_{\mathrm{conc}} - \eta_{\mathrm{xover}}. \tag{2.8}$$

The resulting relationship between V_{cell} and the current density is commonly illustrated by the polarization curve (Fig. 2.4), which typically shows a rapid voltage drop at low current density (activation-dominated region), a quasi-linear region (ohmic-dominated), and a steep decline at high current density due to mass-transport limitations.

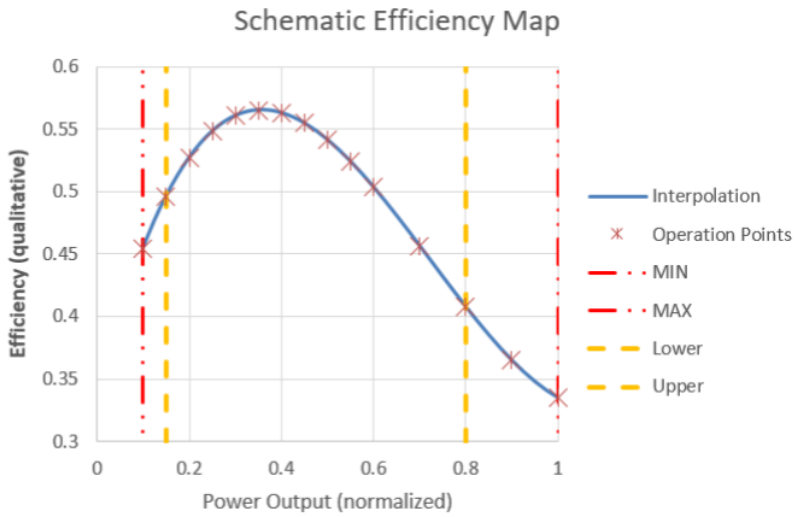

Figure 2.3: Typical PEMFC polarization curve and qualitative voltage loss contributions.

2.4 Stack and Balance of Plant

A single PEM fuel cell produces less than one volt; therefore, cells are connected in series to form a stack that provides the desired voltage and power output. The stack contains hundreds of membrane–electrode assemblies, separated by bipolar plates that ensure electrical conduction, gas distribution, and heat removal. Efficient operation requires precise control of temperature, humidity, and reactant flows.

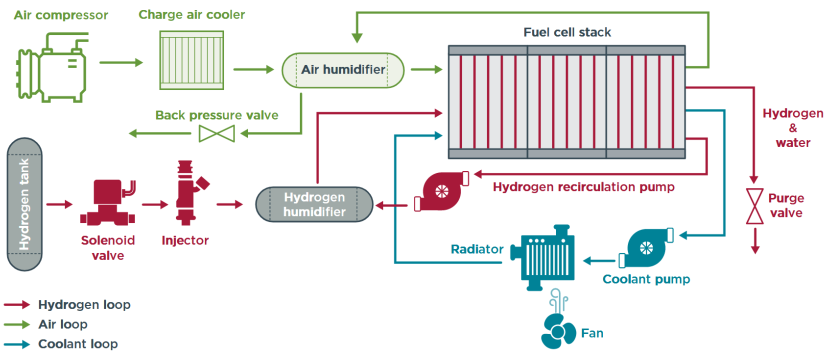

Figure 2.4: Schematic of a fuel cell stack balance of plant[2]

Surrounding the stack, a series of auxiliary subsystems collectively known as the Balance of Plant (BoP) ensures stable operation. The air supply system delivers compressed and humidified air to the cathode. The hydrogen supply system regulates fuel pressure, recirculates unused hydrogen, and periodically purges inert gases. Thermal management circuits remove excess heat, maintaining the stack within its optimal temperature range. Additional subsystems include cooling pumps, humidi-

fiers, and electronic controllers. These auxiliary components consume a fraction of the generated electrical power, meaning that the overall system efficiency is lower than the stack's electrochemical efficiency. For heavy-duty vehicles, net system efficiencies typically reach 45–55 percent depending on load and ambient conditions.
Although the reversible potential of the H_2/O_2 reaction is about 1.23 V at 25°C, a practical PEM fuel cell typically operates at a substantially lower single-cell voltage (often ∼0.6–0.9 V under load) due to activation, ohmic, and mass-transport losses; therefore, many cells are connected in series to reach the DC bus voltage required by vehicle traction drives. [7] A stack is assembled by repeating unit cells consisting of a membrane–electrode assembly (MEA) and adjacent porous transport layers, compressed between bipolar plates. Bipolar plates provide the electrical conduction path between cells, physically separate the anode and cathode reactant streams, distribute gases through flow fields, and offer a primary pathway for heat and liquid-water removal; consequently, bipolar-plate design strongly influences power density, pressure losses, and water/thermal management constraints. [19]
Beyond the electrochemical stack, the Balance of Plant (BoP) integrates air, hydrogen, thermal, water, and control subsystems required to maintain target operating conditions for example temperature, humidity, and pressure over highly transient vehicle duty cycles. [24] In automotive and heavy-duty designs, the cathode air path commonly includes filtration, a compressor, charge-air cooling, humidification (e.g., membrane humidifiers), and valves for stoichiometry and back-pressure control. [39, 16] Pressurization can improve stack power density and oxygen transport, but it increases auxiliary power demand; in system-level analyses, the air loop constitutes the most energy-intensive auxiliary subsystem, potentially consuming more than 15% of the fuel cell stack power.[2]
On the anode side, the hydrogen supply system regulates inlet pressure, meters fuel flow, recirculates unused hydrogen (via ejector or recirculation blower), and periodically purges the anode loop to mitigate nitrogen accumulation and liquid-water/inert build-up that would otherwise reduce effective reactant concentration and cause instability. [39, 16] Thermal management typically employs one or more coolant loops (often deionized water/glycol mixtures) with pumps, thermostatic valves/bypass, and radiators/fans sized for worst-case ambient and sustained-load conditions; recent heavy-duty system studies commonly assume stack coolant outlet temperatures around 90°C and cathode stoichiometries around 1.5 at rated power. [12]
The net electrical output of the fuel cell power system is reduced by BoP auxiliaries, so it is useful to distinguish gross stack power from net system power:

$$P_{\text{net}} = P_{\text{stack,gross}} - P_{\text{aux}}. \tag{2.9}$$

Accordingly, net system efficiency (often defined on an LHV basis as DC net power out divided by hydrogen LHV input) is lower than the stack electrochemical efficiency. [24] Reported net conversion efficiencies for automotive fuel cell systems span operating-point-dependent ranges, with DOE-reported values of about 42–53% at full power and 53–59% at typical operating levels, while heavy-duty Class 8 long-haul system assessments report rated-power efficiencies on the order of ∼50–56% at beginning of life and lower values at end of life due to degradation/oversizing

assumptions.
For context, DOE transportation targets specify peak (part-load) system energy efficiency targets of 65% (2020) and 70% (ultimate), with peak efficiency occurring at below 25% rated power.

2.5 Hydrogen Storage Technologies

Hydrogen's low volumetric energy density necessitates advanced storage solutions. The most widespread approach in mobile applications is compressed hydrogen gas. Tanks rated at 700 bar are standard for heavy-duty trucks, offering an energy density of roughly 32 grams per litre and typical ranges around 400 kilometres.
Liquid hydrogen storage, maintained at cryogenic temperatures near –253 °C, further increases volumetric density but introduces boil-off losses and additional insulation requirements. A hybrid cryo-compressed configuration combines moderate pressure with sub-cooled hydrogen, enabling energy densities up to 70 grams per litre, though at higher system complexity.
Research efforts are also exploring metal hydride storage systems, where hydrogen is chemically absorbed in solid alloys. While offering excellent safety and compactness, these systems remain too heavy for commercial transport but present promising potential for utility and industrial vehicles. Ongoing European projects have demonstrated integrated storage modules using metal hydrides that recover heat from the fuel cell to assist hydrogen desorption, improving total system efficiency.

2.6 System Efficiency and Control Considerations

The efficiency of a fuel cell system is governed by multiple interacting subsystems. The stack efficiency depends on current density and voltage losses, while the BoP components influence the net efficiency through their own power consumption. Maintaining optimal stack temperature, humidification, and gas stoichiometry is essential to avoid degradation and ensure consistent performance.
Hybridisation further enhances efficiency by allowing the fuel cell to operate within a narrow power band. During low-load conditions, the battery supports auxiliary loads and absorbs surplus energy; during high demand, it provides additional power to meet acceleration requirements. The control algorithm therefore aims to minimise total hydrogen consumption by maintaining the fuel cell within its most efficient region and by recovering braking energy whenever possible.
In simulation environments, these mechanisms are represented through efficiency maps and control logic blocks. VECTO uses predefined component characteristics and mission profiles to calculate overall energy use, while GSP resolves detailed subsystem equations over time. Together, they enable quantitative evaluation of how energy management strategies translate into real fuel economy and thermal behaviour

3

Fuel Cell Powertrain in Heavy-Duty Vehicles

This chapter provides the technical background required to interpret the simulation results presented later in the thesis. It first reviews the main propulsion pathways currently considered for decarbonising heavy-duty transport, highlighting why different long-haul use cases motivate different technology choices.
The chapter then focuses on hydrogen fuel cell electric powertrains, summarising their key strengths and the remaining deployment challenges from a vehicle-integration perspective. Finally, the fuel cell hybrid architecture is introduced in terms of component roles and energy management principles, including the power split between the fuel cell system and the battery, the relevance of auxiliary and thermal loads, and the implications of control strategy formulation.
These concepts form the basis for understanding how fuel cell HDVs are represented in regulatory simulation tools such as VECTO and how their behaviour can be compared against engineering simulation environments such as GSP in subsequent chapters.

3.1 Alternative Powertrains for HDVs

The current landscape for heavy-duty vehicle (HDV) propulsion is diverse, spanning from improved diesel engines to various zero-emission alternatives. Battery-electric trucks, hydrogen fuel cell trucks, catenary electric trucks (powered by overhead lines), and engines running on low-carbon synthetic fuels (e-fuels) are all being explored in parallel as routes to eliminate or reduce emissions. It is widely recognized that no single technology will serve all freight applications; instead, a mix of solutions will likely be adopted to address different use-cases and regions. Battery-electric vehicles (BEVs), fuel cell electric vehicles (FCEVs), and catenary electric trucks all qualify as zero-emission at the vehicle level, and each offers unique advantages and challenges in long-haul service. Given their advanced maturity (partly thanks to the passenger EV market) and relatively developed charging infrastructure, battery-electric drivelines are viewed as a leading zero-emission option for many trucking operations. However, batteries alone face practical constraints in the heaviest, longest-range trucking segments, so other technologies like fuel cells are being pursued in parallel.
Battery-electric trucks achieve very high tank-to-wheel efficiency and use simpler drivetrains than diesel trucks. They also produce no tailpipe emissions (only wear

particles from brakes and tires), and can recapture braking energy through regenerative braking. These attributes make BEVs attractive for decarbonization, but their limitations become pronounced in long-haul service[30]. Long charging times and limited vehicle range under heavy payloads can impact delivery schedules and fleet utilization. Moreover, the large battery packs required for long-distance trucks significantly increase vehicle weight, reducing payload capacity and economic viability. Indeed, studies suggest that battery-electric drivetrains are most feasible for lighter-duty and short-range applications, whereas fuel cell systems offer more practicality for heavier trucks and longer routes. For instance, Forrest et al. (2020) found that while BEVs could technically replace about 62–76 percent of light-duty commercial trucks, fuel cell vehicles were far better suited for the energy demands of heavy-duty trucks in California.[14] Similarly, a Canadian analysis by Ribberink et al. (2021) concluded that fuel cell powertrains are a more viable alternative for replacing medium and heavy-duty trucks and buses when compared to purely battery-based designs.[29]
Alternative strategies that retain internal combustion engines but use low-carbon fuels are also under evaluation for trucking. Engines running on liquefied or compressed natural gas (LNG/CNG) can modestly cut CO_2 and pollutant emissions (e.g. on the order of 3–14 percent less CO_2 than diesel), and such gas-fueled trucks have already seen some adoption in Europe. However, they still burn fossil fuel (or biogas) in an engine, so efficiency and emissions benefits are limited. Synthetic e-fuels (such as renewable "e-diesel" or e-DME) offer another drop-in replacement for diesel. These fuels can be used in existing engine and fuel infrastructure, potentially providing a carbon-neutral energy cycle if produced with renewable electricity. The practicality of e-fuels, though, depends strongly on the source of energy for their production – only if made with zero-carbon electricity can they approach net-zero emissions. Technically, demonstrations of e-fuels are underway and show readiness, but high production cost and concerns like NOX emissions remain hurdles for commercial use. Similarly, catenary electric trucks (which draw power from overhead electric lines on highways) can achieve zero tailpipe emissions and avoid the weight of large batteries. In fact, a catenary truck driving on electrified roads can reach efficiency and CO_2 savings comparable to a BEV, since it receives electricity directly and may only need a small onboard battery for off-wire travel. The drawback is the enormous infrastructure required – a network of overhead lines along freight corridors – which limits route flexibility and will take significant time and investment to build. Consequently, catenary systems are viewed as a longer-term option, still in experimental stages in Europe, whereas fuel cell and battery trucks are nearer-term solutions for long-haul freight.

3.2 Fuel Cell Technology Strengths and Deployment Challenges

Hydrogen fuel cell powertrain offer several compelling advantages for long-haul trucks, largely stemming from the properties of hydrogen and the design of fuel cell systems. Unlike batteries, a fuel cell system (FCS) separates the vehicle's power generation from energy storage – the stack generates electric power through electrochemical conversion of hydrogen, while the hydrogen is stored separately in tanks. This decoupling yields greater flexibility in balancing power and energy requirements. In particular, hydrogen has an extremely high specific energy (energy per unit mass) compared to electrochemical batteries. Even when stored as compressed gas, hydrogen's gravimetric energy density on the order of 33 kWh/kg forH_2's [12]lower heating value far exceeds that of current lithium-ion batteries which deliver a few hundred Wh/kg at best[22] As a result, fuel cell trucks can carry enough energy on board (in hydrogen form) for long ranges without the prohibitively heavy battery packs that a BEV would need. The storage tanks and ancillary fuel cell components, while bulky, are much lighter than a multi-megawatt-hour battery. This leads to higher payload capacity for fuel cell trucks, mitigating a key issue faced by battery trucks. For example, one analysis estimates that a fully-loaded 40-tonne truck would lose only about 230 kg of payload capacity by using a hydrogen fuel cell system,[11] versus roughly 1800 kg lost if it carried a battery large enough for similar range. In practice, this means a fuel cell truck can haul close to the same cargo weight as a diesel truck, whereas a battery-electric truck may have to sacrifice a significant portion of its payload to accommodate batteries. Fuel cell trucks also achieve longer driving range than most current battery trucks. Manufacturers have reported that anH_2-powered heavy truck can reach on the order of 350–400 km range using compressed hydrogen at 350 bar storage. This already exceeds the typical 150–400 km range of today's battery-electric freight trucks on a single charge, and further improvements (e.g. higher-pressure tanks or liquid hydrogen) can increase FCEV range substantially. Another major advantage is refueling speed. Hydrogen refueling for HDVs can be accomplished in a matter of minutes – current high-flow dispensers for trucks can achieve about 120 g/s hydrogen dispensing rate [23], enabling rapid fills even for large onboard tanks. This is roughly 10–15 times faster than charging an equivalently sized battery with today's high-power chargers.[35] Short refueling means minimal downtime: a fuel cell truck can be back on the road quickly, much like a diesel truck, whereas a BEV truck might require hours at a charging station for a full recharge. In the freight industry where time is money, the faster turnaround of hydrogen refueling is a significant operational advantage. Taken together – greater range, higher payload, and faster "fueling" – these factors make fuel cell propulsion particularly attractive for long-haul routes where battery-electric trucks would struggle to meet operational requirements without massive batteries or impractical charging schedules.Furthermore, fuel cell drivetrains share many of the benefits common to electric vehicles: simpler mechanical design than diesel engines, regenerative braking capability, quiet operation, and zero tailpipe emissions during operation. This eliminates local air pollutants and carbon emissions at the vehicle level, contributing to better air quality and climate change mitigation, provided the hydrogen is produced sustainably.

Despite these strengths, several challenges continue to impede the full commercialization of fuel cell trucks. Cost remains a primary concern.[3] Fuel cell powertrain including the stack, hydrogen storage, and power electronic are currently considerably more expensive than mature diesel engine systems, partly due to expensive materials example platinum catalysts[28], carbon fiber tanks and lower production volumes. The fuel itself – especially "green" hydrogen produced from renewable energy – is also costly today[29], and its future price trajectory is uncertain. Without incentives or subsidies, the total cost of ownership for early fuel cell trucks is high, which may deter fleet operators. Substantial investments in hydrogen refueling infrastructure are needed as well. While battery charging stations leverage the existing electric grid, hydrogen stations require new fuel production, transport, and dispensing networks. A coordinated rollout of hydrogen infrastructure is necessary to support long-haul operations, ideally with standardized refueling protocols to ensure interoperability. There are also technical hurdles in adapting fuel cell systems to the rigors of heavy-duty usage. Integrating the fuel cell, battery, and hydrogen storage into a truck chassis without compromising weight distribution or space is a complex design task. The fuel cell stack must deliver high power and withstand long operating hours; improving stack durability and lifetime under cyclical loads is an active area of research, as premature stack degradation could undermine the economic and environmental benefits. Onboard hydrogen storage capacity is limited by volume and weight constraints, even with high pressure (700 bar) tanks or cryogenic hydrogen, the energy density per liter is much lower than diesel fuel[2], meaning trucks may need multiple large tanks for long ranges. This adds complexity and requires careful attention to safety and regulations. Finally, achieving reliable, efficient operation across all components .in diverse conditions requires advanced system integration. Thermal management (for the fuel cell cooling), air and water management in the stack, and power electronics all must be optimized for heavy-duty cycles. None of these challenges are insurmountable, but they demand continued R&D and supportive policies. The trajectory of technology improvement and economies of scale is expected to bring down costs – for instance, governments and industry are investing in research to improve fuel cell longevity and reduce platinum loading, develop cheaper hydrogen production, and standardize refueling infrastructure. In the near-term, bridging strategies (suchas hybrid configurations with batteries, discussed below) and pilot projects are helping to refine fuel cell truck designs. With appropriate incentives (e.g. purchase subsidies, fuel credits) and coordination on infrastructure, fuel cell HDVs could reach competitive viability and see accelerated deployment in the coming years. In summary, hydrogen fuel cell propulsion holds great promise for decarbonizing long-haul trucking by combining the efficiency of electric drive with energy storage better suited to heavy, long-range operation. The technology's strengths in range, quick refueling, and payload capacity address key limitations of battery-only trucks. The remaining challenges – principally cost, durability, and fueling network are the focus of ongoing development efforts by both industry and government as labeled in the policy part, with the expectation that solutions will emerge to enable large-scale adoption of fuel cell trucks in the freight sector.

3.3 Integration in Vehicle Powertrain and Hybrid Topology

In modern fuel cell electric vehicles, the fuel cell system operates as a pure energy generator within a hybrid electric architecture. It supplies steady electrical power that maintains the vehicle's average energy demand, while a rechargeable high-voltage battery covers transient peaks, regenerative braking, and auxiliary loads. This configuration allows the fuel cell to remain close to its optimal efficiency region, reducing hydrogen consumption and extending component life.
Two main hybrid configurations exist, series and parallel architecture. In a series architecture, the fuel cell and battery are connected to a common DC link through dedicated DC/DC converters. The traction motor receives energy exclusively from the electrical bus, while the power management system determines how much power is drawn from each source. In a parallel configuration, both the fuel cell and the battery can feed the inverter directly. Heavy-duty applications predominantly employ a series hybrid topology because it simplifies control and maximises steady-state efficiency.

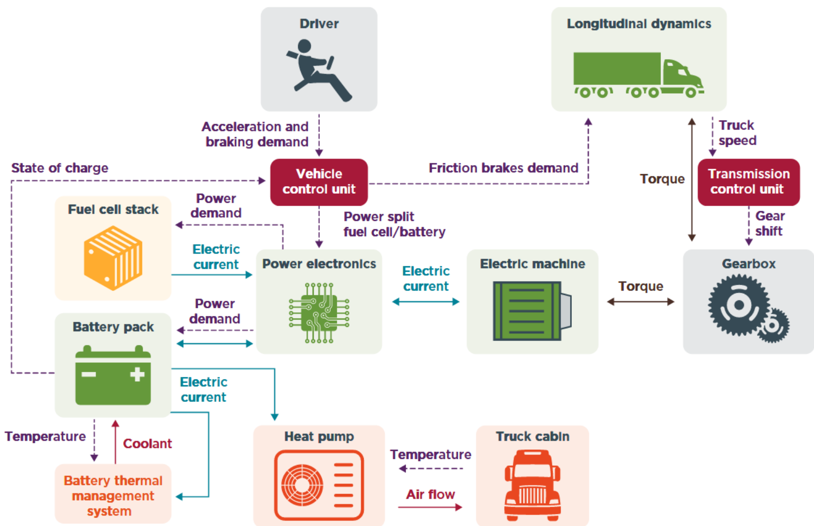

Figure 3.1: Schematic of the truck energy consumption model[2]

The powertrain architecture also includes an inverter, electric traction motor, gearbox, and auxiliary circuits. Electrical energy from the fuel cell passes through a DC/DC converter to stabilise voltage levels before reaching the high-voltage bus. The inverter converts DC power to AC for the traction motor, driving the wheels through a single-speed or multi-speed transmission. During braking or low-power operation, the motor acts as a generator, recovering kinetic energy into the battery. At the control level, an energy management system supervises the distribution of power between the fuel cell and the battery. In regulatory simulations such as those performed in VECTO, the algorithm averages fuel cell output power over a predefined distance window to emulate smooth operation and consistent efficiency. In contrast, forward simulation platforms such as GSP model the system dynamically,

incorporating subsystem inertia, compressor response, and thermal behaviour. The hybrid control strategy can therefore be validated both in steady-state and transient domains, ensuring the most efficient use of hydrogen energy under real operating conditions.
For long-haul heavy-duty vehicles, this hybrid configuration offers clear advantages. The fuel cell provides the continuous high-power output required for highway operation, while the battery enables regenerative braking in urban or hilly segments. The result is a vehicle capable of matching diesel-like ranges with significantly higher tank-to-wheel efficiency.

3.4 Power Sources

In an FC-hybrid truck, propulsion and auxiliary power are supplied by a combination of the fuel cell system and one or more onboard energy storage systems (ESS), typically rechargeable batteries. This hybrid arrangement is designed to leverage the complementary strengths of the two power sources: the fuel cell provides sustained power and energy (as long as hydrogen fuel is available), and the battery can supply additional power during transient peaks, recover braking energy, and improve overall efficiency. The battery also enables the vehicle to meet power demand dynamically without requiring the fuel cell to constantly operate at peak output, which aids in responsiveness and cold-start conditions. By coordinating the fuel cell and battery, the powertrain can deliver the necessary performance for acceleration or hill climbing while keeping the fuel cell in an efficient operating regime. The sizing of the fuel cell system in such hybrids varies with the intended duty cycle. Traditionally, designers sized the fuel cell to handle the average power demand plus a margin, with the battery covering bursts above that level. However, recent trends show a move toward oversizing the fuel cell in some designs. In other words, the fuel cell's maximum power can be significantly higher than the truck's average power requirement. Operating an oversized fuel cell mostly at partial load allows it to run in a regime where its efficiency is near the peak, thus improving overall energy efficiency of the powertrain. The trade-off is increased cost and weight of a larger fuel cell, so this approach must be balanced against economic factors. In practice, the optimal fuel cell power is chosen in conjunction with the battery capacity to meet both continuous and peak power needs efficiently.
The secondary energy storage element is a crucial component in fuel cell hybrid vehicles. The ESS smooths out power demand on the fuel cell, captures regenerative braking energy, and can power the vehicle independently for short periods if needed (for example, to handle sudden load spikes or to allow the fuel cell to start up gradually). While other high-power storage technologies like supercapacitors (can also be found in vecto) exist and offer very high specific power, lithium-ion batteries remain the preferred solution in heavy-duty fuel cell trucks. This is because batteries provide a good balance of power and energy capacity suitable for HDV needs, and they have a well-established track record for robustness and reliability in automotive applications. Supercapacitors could supplement a battery to handle sharp power spikes due to their high power density, but on their own they lack sufficient energy density for sustained operation. Most fuel cell trucks today use lithium-

ion battery packs, often somewhat larger (in capacity and current capability) than those in comparable diesel hybrid vehicles. A larger battery in the hybrid allows for greater energy recovery (regenerative braking on long downhills, for instance) and provides a buffer to maintain performance if the fuel cell cannot ramp power instantaneously. Importantly, battery energy density (Wh/kg) is a key parameter in truck design because any increase in battery weight directly subtracts from payload capacity. Thus, choosing advanced cell chemistries with high energy density is vital to minimize weight penalty. At the same time, batteries must be durable to withstand heavy-duty cycles (potentially charging and discharging multiple times per day). The most common Li-ion chemistries used are Nickel Manganese Cobalt oxide (NMC), Nickel Cobalt Aluminum oxide (NCA), and Lithium Iron Phosphate (LFP), each with different performance trade-offs. NMC batteries, for example, are widely used in electric vehicles including heavy trucks; with current technology (NMC-111 cathodes and graphite anodes) they can achieve energy densities around 300–350 Wh/kg, and future improvements (like silicon-augmented anodes) promise up to 400 Wh/kg. NMC and NCA cells typically offer high energy and power with decent cycle life (2000 cycles before significant degradation). LFP cells have lower energy density (hence heavier for the same energy), but they provide longer cycle life (>2500 cycles) and improved thermal stability, which can be advantageous for the longevity and safety in a commercial truck fleet. Ultimately, the battery in a fuel cell truck is chosen to reliably meet power assist needs and to last for many years of operation, all while minimizing weight impact on the vehicle's freight-carrying capacity.

3.5 Electric Motor and Transmission

In a fuel cell heavy-duty truck, traction power is delivered by one or more electric drive units (e-drives) consisting of an electric motor coupled with power electronics (inverter/converter) and a control system. The electric motors convert electrical energy from the fuel cell/battery into mechanical torque to drive the wheels, and they also function in reverse as generators during regenerative braking. This ability to recuperate kinetic energy on deceleration or downhills is a significant benefit of electrified powertrains, improving overall efficiency and reducing brake wear. Modern electric drivetrains for HDVs often employ AC motors, either asynchronous (induction) motors or permanent-magnet synchronous motors, due to their robustness and high power densities. Both types require an inverter to create alternating current from the DC bus. In an asynchronous induction motor (ASM), a rotating magnetic field in the stator induces current in the rotor, causing the rotor to spin. The rotor's magnetic field lags slightly behind the stator field – a phenomenon known as slip – which is necessary to generate torque. ASMs have the advantage of a simple, rugged rotor construction (no permanent magnets or windings on the rotor in many designs), which can translate to lower cost and ease of maintenance. However, induction motors typically have a bit lower peak efficiency than comparable synchronous motors and require sophisticated control of the input frequency to manage the slip and torque. In contrast, a permanent magnet synchronous motor (PM-SM) uses a rotor embedded with strong permanent magnets. The rotor's field is fixed by the magnets, and it locks in step (synchronously) with the rotating stator field, eliminating slip losses. PM-SMs tend to offer higher efficiency and power density than induction machines, and they can deliver high torque from a compact package. The downsides are reliance on expensive rare-earth magnet materials and generally higher manufacturing cost. In practice, both ASM and PM-SM technologies are used in commercial electric buses and trucks, with PM-SMs being common in newer designs where efficiency and compactness are top priorities. Regardless of type, the electric motor (or motors) in a fuel cell truck is sized to provide adequate traction under all load and grade conditions, often with a focus on high torque at low speeds for gradability.

One innovative e-drive configuration gaining attention is the use of hub motors, also known as in-wheel motors, where individual wheel hubs each integrate a motor. By placing motors directly at the wheels, drivetrain mechanical complexity (such as central drivelines or differentials) can be reduced or eliminated. Research has shown that multi-axle heavy vehicles with independent hub motors can achieve excellent dynamic performance and efficient control of power distribution, which is promising for fuel cell trucks as well. The ability to control torque at each wheel allows advanced traction control and stability management, potentially improving safety and handling. Hub motors also free up space since there's no need for a large transmission or driveshaft, which could ease packaging of fuel cell and hydrogen tanks. However, challenges remain: putting motors in the wheels increases the unsprung weight (affecting ride and suspension), and each wheel motor's power is limited by the space available. Hub motors for heavy trucks may also face cooling and durability issues due to their exposure. Notably, regenerative braking capability per wheel is limited by the motor size – smaller hub motors can't absorb as much braking energy, which might reduce regen efficiency unless supplemented by friction brakes. Additionally, cost is a factor, as four or more high-power motors (one per wheel) with robust construction can be expensive. Thus, while hub-drive concepts are intriguing and have been demonstrated in prototypes, most current fuel cell truck designs use one or two central electric motors to drive the axles via a simpler reduction gearbox.

Between the electric motor(s) and the wheels, a transmission is typically used to ensure the vehicle can achieve both high torque at low speed (for starting and climbing) and efficient operation at higher speeds. Unlike passenger EVs which often use a single-speed gearbox, heavy-duty trucks benefit from multi-speed transmissions to cover their broad range of operating conditions. Multi-speed gearboxes allow the electric motor to run closer to its optimal speed more often, improving efficiency and allowing a smaller motor to do the job. For instance, climbing a steep grade with a full load might use a low gear to multiply torque, whereas cruising on a highway can use a higher gear to reduce motor speed and losses. Studies indicate that using multiple gear ratios in electric trucks can improve acceleration and gradability while also enabling motor downsizing (reducing weight and cost of the e-drive). In practice, heavy electric trucks use far fewer gears than their diesel counterparts – perhaps 2–6 forward gears, compared to 12+ gears in a conventional diesel semi-truck. This is because electric motors have a much wider efficient speed range and can deliver peak torque from zero speed, obviating the need for the many gears required to keep a diesel engine in its narrow power band. Some fuel cell truck manufacturers have adopted 2-speed or 3-speed automated transmissions to balance performance and efficiency. Others use dual-motor setups geared for different speed ranges (one motor geared for low-end torque and another for high-speed efficiency)Volvo e-axle is designed for that, instead of a shifting gearbox. The trend toward simpler transmissions in EVs helps reduce maintenance and drivetrain losses, The IEPC component in the VECTO perfectly meet this requirement but the use of at least one or two speeds in heavy trucks appears advantageous to meet all performance targets.

3.6 DC-Link and Converters

All the power sources and loads in a fuel cell truck's propulsion system – including the fuel cell stack, battery, electric motor drive, and auxiliary devices – are interconnected through a high-voltage DC bus (also called a DC-link). This DC bus typically operates at a system voltage in the range of roughly 350–800 V in heavy-duty vehicles. Higher voltages in that range are favored for high-power vehicles as they allow lower currents for the same power, which in turn enables the use of lighter cables and reduces resistive losses. The DC bus voltage is actively regulated by a controller to maintain stable operation across different conditions. Multiple power electronic converters interface the various components to this common DC-link, providing the ability to control power flow and voltage levels. For example, the inverter that drives the AC traction motor is connected to the DC bus and draws power as needed to produce AC waveforms for the motor. If the motor goes into regeneration mode, the inverter channels power back into the DC bus (charging the battery or reducing fuel cell load).

Crucially, the fuel cell stack cannot usually be connected directly to the high-voltage bus without a converter, because a fuel cell's output voltage varies with load and it typically produces a lower voltage than the bus requires (a single fuel cell stack might generate on the order of 250–400 V at no load and less at full load, depending on design). Therefore, a DC/DC boost converter is used between the fuel cell and the main DC-link. This unidirectional converter steps up the fuel cell's variable DC voltage to the stable high voltage of the bus and allows the control system to actively manage the fuel cell operating point (by adjusting the current drawn). On the other hand, the battery (or ESS) is connected through a bi-directional DC/DC converter. This device can boost or buck the voltage and permits power flow in both directions: it can charge the battery from the DC bus or discharge the battery to support the bus. The bi-directional converter typically also provides isolation and ensures the battery can be utilized over its normal range of state-of-charge without letting the bus voltage sag below optimal levels. If no DC/DC converter were present for the battery, the bus voltage would directly follow the battery state and load, which could lead to suboptimal motor performance under heavy load or low battery charge. Thus, DC/DC converters are key for maintaining consistent performance and efficiency in the powertrain by decoupling the operating voltages of the fuel cell, battery, and motor drive.

Another critical role of power electronics in the fuel cell truck is managing the auxiliary power systems. Heavy-duty vehicles have numerous auxiliary loads: air compressors for brakes, power steering pumps, cooling pumps and radiator fans for thermal management, HVAC (heating, ventilation, air conditioning) for driver comfort, onboard electronics, lighting, and possibly trailer refrigeration units or other equipment. Traditionally, many of these ran off engine accessory drives or 12/24 V alternators in diesel trucks. In an electric/fuel cell truck, most auxiliaries are electrified and powered from the main battery/fuel cell system. HDVs commonly use a 24 V or 48 V low-voltage (LV) system for auxiliaries and control units, higher than the 12 V standard in passenger cars, to better handle the power needs of larger components. To supply this, a DC/DC converter steps down the high-voltage bus (hundreds of volts) to the auxiliary voltage (24 or 48 V). Often a 28 V nominal system (for 24 V batteries) is used for things like cabin devices, lights, and control circuits, whereas 48 V might be used for higher-power auxiliaries like steering or air compressors to reduce currents. In some designs, two DC/DC converters are used – one providing a regulated 28 V for legacy systems and a second providing 48 V for more power-intensive accessories. These converters ensure that even as the main bus voltage fluctuates or the fuel cell turns on/off, the auxiliary systems see stable voltage. The electrification of auxiliaries in fuel cell trucks not only enables the replacement of the diesel engine but also provides opportunities to optimize energy use (e.g. only running pumps or compressors when needed, and at variable speeds) which can further improve overall efficiency.

3.7 Energy Management System

Managing the flow of energy in a fuel cell hybrid truck is a complex task that is handled by the vehicle's Energy Management System (EMS). The EMS is a supervisory control system that oversees the multiple power sources (fuel cell and battery) and power sinks (traction motor and auxiliaries) to ensure safe, efficient operation. The primary goal of the EMS is to minimize hydrogen consumption (and thereby maximize efficiency) while meeting the driver's power demands and maintaining system constraints. It does so by dynamically deciding how much power should come from the fuel cell versus the battery at any given moment, and by controlling charging or discharging of the battery. For example, during a highway cruise, the EMS might command the fuel cell to provide the bulk of the power, running at an efficient load point, while keeping the battery at a sustain charge level. During a sudden acceleration or climb, the EMS can temporarily draw additional power from the battery to supplement the fuel cell, preventing the need to oversize the fuel cell for infrequent peaks. Conversely, during braking or downhill coasting, the EMS will route the regenerated power into charging the battery (or in some cases, reducing fuel cell output) to capture energy that would otherwise be wasted. In effect, the EMS orchestrates an optimal distribution of energy between the fuel cell and the battery at all times. This also extends to managing power to auxiliary systems: modern strategies might reduce or shift non-essential loads (like air conditioning) during high power demand moments to prioritize traction, or do load leveling to smooth out spikes in auxiliary consumption.

A critical function of the EMS in fuel cell hybrids is to maintain the battery state-of-charge (SOC) within prescribed limits and ensure longevity of both the fuel cell and battery. Fuel cell trucks used for long-haul are typically designed as charge-sustaining hybrids (also termed “Not Off-Vehicle Charging” hybrids), meaning the battery is not intended to be externally recharged from the grid; all energy comes from hydrogen fuel. In such NOVC-HEV operation, the EMS must keep the battery’s net energy change over a drive cycle approximately zero – essentially using the battery only as an intermediary storage but not as a primary energy source. To do this, the control strategy maintains SOC within a target band by adjusting the fuel cell output: if the battery tends to discharge, the fuel cell is ramped up to recharge it, and if the battery is full, the EMS may reduce fuel cell output or bleed off excess energy. Typically, the EMS will keep SOC between an upper and lower bound (a charge sustaining window) and avoid deep discharges or overcharging, which not only ensures that the battery is ready to accept regenerative braking energy but also prolongs battery life. Managing the thermal and health constraints of the fuel cell is another aspect – the EMS may avoid requesting rapid load changes from the fuel cell that could stress it, instead using the battery to buffer fast transients. By smoothing the fuel cell load profile, the EMS can help extend the fuel cell stack lifetime (for instance, avoiding too many rapid start-stop cycles or operation in low-efficiency regions). Ensuring component longevity is crucial in heavy-duty use, as trucks accumulate very high mileage; thus the EMS may include algorithms to limit fuel cell power if it approaches certain temperature or degradation limits, or to prevent the battery from cycling at extremes of SOC which accelerate aging. In summary, the EMS seeks a balance between efficiency and component protection: it meets driving needs with minimalH_2 usage while respecting all physical constraints (voltage, current, temperatures) and keeping the battery and fuel cell within healthy operating ranges.

The control of a hybrid fuel cell powertrain is often organized in a hierarchical structure. A top-level supervisory controller monitors the overall vehicle state, driver inputs, and possibly navigation data, and makes high-level decisions such as selecting the vehicle’s operating mode (e.g. normal, eco-mode, or perhaps an automatic shutdown at idle). This supervisory layer might also decide when to start or stop the fuel cell (for systems that can idle off), when to initiate a battery charge-sustain strategy, or whether to curtail certain loads under critical conditions. Beneath this, an energy management controller handles the continuous optimization of power split between the fuel cell and battery according to the strategy dictated by the supervisory level. This middle layer takes inputs like current battery SOC, fuel cell efficiency maps, and power demands, and computes the instantaneous power commands: for example, it may output a target fuel cell power and a target battery power for the present time step. Finally, low-level controllers interface with each component – the fuel cell system controller ensures the stack and its Balance-of-Plant (air compressor, hydrogen regulator, etc.) deliver the requested power safely, the battery management system manages battery currents, and motor controllers regulate torque from the e-motor accordingly. This hierarchical scheme allows complex decision algorithms at the high level (which may incorporate predictive elements or mode logic) and fast, stable control loops at the low level to track the commands.

3.8 real-time control features for EMS systerm

Various energy management strategies can be implemented in the EMS. Broadly, they can be categorized as online strategies – those that operate in real-time on the vehicle using available information – and offline strategies, which are computed with full knowledge of the vehicle's route or using heavy computation that cannot be done onboard.[33]Online strategies include rule-based heuristics maintain SOC within a band, turn fuel cell on above a certain power demand, and more advanced real-time optimization like ECMS – Equivalent Consumption Minimization Strategy – which minimizes a cost function at each instant.[21] These must be causal and computationally light enough for the truck's onboard computer. Offline strategies, on the other hand, involve computing the theoretically optimal energy usage over a known drive cycle (for instance via dynamic programming or linear programming approaches). They are useful as a benchmark to gauge how close the online strategy is to optimal, or to generate insights and control policies, but they are not directly used in driving since they require future knowledge. The development of EMS for fuel cell trucks has benefited from decades of experience with hybrid transit buses and passenger car hybrids. In fact, many control techniques originally developed for diesel hybrid buses or plug-in hybrids can be adapted to fuel cell hybrids, because the control problem (managing a primary engine and a secondary battery) is analogous. The main difference is the characteristics of the fuel cell versus an internal combustion engine – for example, a fuel cell might have a slower transient response and different efficiency curve, but it doesn't suffer from efficiency penalties at low load the way an engine does. [7]Thus, while specifics differ, the underlying control architecture and strategy (charge-sustaining operation, regenerative braking capture, etc.) are shared between ICE hybrids and FC hybrids. With continuous improvements in algorithms and computing power, fuel cell truck EMS can incorporate predictive elements (like route topography from GPS) to further optimize fuel usage, though such approaches blur the line between online and offline strategies. Ultimately, a well-designed EMS is pivotal for unlocking the full benefits of fuel cell propulsion – it maximizes efficiency and fuel economy, preserves the health of costly components, and ensures the vehicle delivers the required performance seamlessly. Through careful energy management and system integration, hydrogen fuel cell hybrids can meet the rigorous demands of long-haul freight transport, providing a viable zero-emission solution without compromising on operational effectiveness.[7]

4

VECTO Software Overview

VECTO (Vehicle Energy Consumption Calculation Tool) is the official simulation software developed under the European Commission for determining the fuel/energy consumption and CO_2 emissions of heavy-duty vehicles [6] Jointly created by the European Commission and the Graz University of Technology, VECTO has been continually expanded and updated to serve as the mandatory tool for EU HDV CO_2 certification since 2019 [17]. It covers a wide range of vehicle categories (various lorry configurations, buses, coaches, etc.), each with dedicated driving cycles ("mission profiles") in the software to represent typical real-world operation.[11] Manufacturers must use VECTO to simulate and report their vehicles' standardized CO_2 emission and energy consumption values, and this information is also made public as per EU regulations[6] Simulation Approach: VECTO performs a longitudinal dynamic sim-

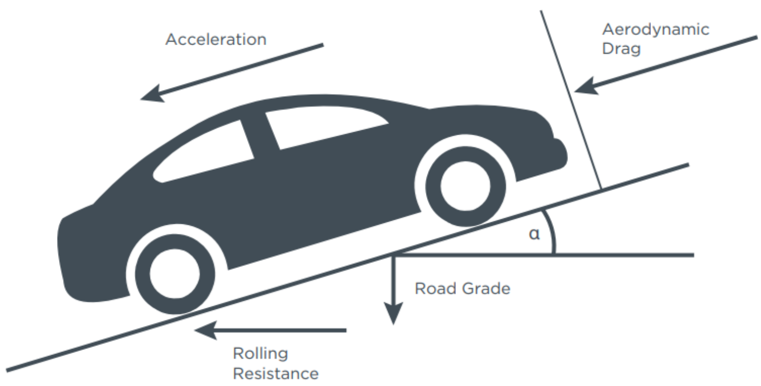

Figure 4.1: Vehicle driving resistances

ulation of the vehicle over a specified driving cycle using a predominantly backward-looking modeling approach.[6] This means the vehicle's target speed profile (with road grade over distance) is the primary input, and the tool calculates backwards to infer the required engine power and energy usage at each time step. The simulation operates at a temporal resolution of about 0.5 seconds[6], capturing transient behavior. While the core logic is backward-facing (starting from the demanded wheel motion), VECTO incorporates certain forward-looking control elements to realistically mimic driver behavior and predictive driving strategies.[11] For example, it includes a generic driver model that can handle acceleration/deceleration, gear shifting, and look-ahead features – such as allowing brief overspeed, Eco-Roll coasting on downhills, or anticipative deceleration before a lower speed limit – which would

be difficult to model with a purely backward method. [17]These added modules ensure that VECTO can simulate real-world driver assist functionalities (e.g. cruise control with look-ahead) and adhere to the target-speed nature of the cycles.
Energy Flow and Vehicle Dynamics: At each time step of the cycle, given the instantaneous vehicle speed and acceleration, VECTO computes the total resistive forces the vehicle must overcome – including aerodynamic drag, rolling resistance, gravitational force, and inertial forces (both translational and the rotational inertia of drivetrain components).Total force:

$$F_{\text{Total}} = F_{\text{AD}} + F_{\text{RR}} + F_{\text{Acc}} + F_{\text{RG}} \tag{4.1}$$

[13] Using these resistances, the tool calculates the traction force and power required at the wheels to follow the cycle. It then works upstream through the powertrain: accounting for drivetrain losses (in the transmission, axle, etc.) and any auxiliary power consumption, to determine the instantaneous engine power demand that would produce the required wheel power. The corresponding engine speed is obtained based on the current gear selection, the gear ratio set, and the dynamic tire radius, so that an engine operating point (torque and RPM) is defined for that moment.
For a conventional diesel or gasoline vehicle, VECTO uses the engine operating points to look up the fuel rate and CO_2 emission rate from the engine's certified fuel map. In other words, each operating point is mapped to a specific fuel consumption (and CO_2) value, and by integrating these over the drive cycle, the total fuel usage and CO_2 emissions are calculated.[11] This allows VECTO to output standard metrics like liters per 100 km and CO_2/km for the test cycle, as well as payload-specific or ton-km specific emissions if needed. In the case of hybrid-electric or full electric vehicles, the simulation includes additional steps to handle powertrain split and electrical energy flow. VECTO will calculate the electrical power drawn by the traction motor to meet the wheel power demand and then trace that demand back through the DC link to the battery or other onboard energy sources. A vehicle supervisory controller model (energy management strategy) is applied to decide how power is sourced from the engine versus the battery in hybrid architectures. This strategy which can involve rules for battery state-of-charge usage, charging, and blending of engine power influences the final fuel and energy consumption result. In summary, VECTO's simulation architecture is flexible to accommodate different powertrain types, but the fundamental calculation – resolving the longitudinal dynamics from speed demand and summing the energy required remains consistent across conventional and hybrid vehicles.

4.1 Driving Cycles and Profiles

VECTO comes with a set of predefined mission profiles (standard driving cycles) tailored to various vehicle applications, ensuring a common basis for comparison. Each cycle is defined by a target speed vs. distance curve (including road gradient) that the simulated vehicle must follow.[11]For example, the "Long Haul" cycle represents primarily highway operation (high average speed 80 km/h, very few stops),

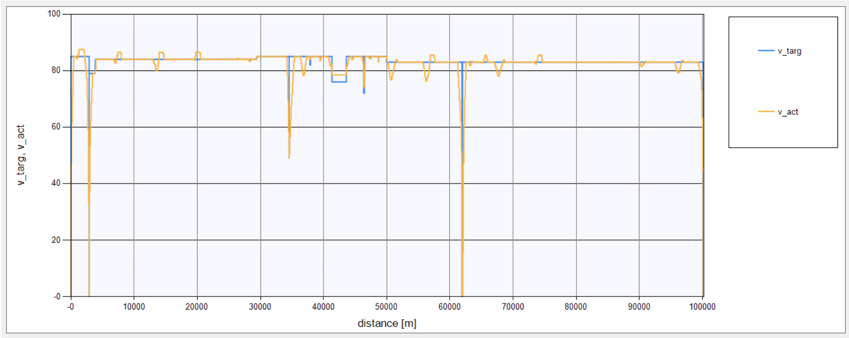

Figure 4.2: VECTO driving cycles.

"Regional Delivery" includes a mix of urban and inter-city driving with moderate speeds (60 km/h average and more stop-and-go), and "Urban Delivery" is a low-speed city driving cycle with frequent stop events. Additional cycles exist for other use cases (municipal utility, construction, coach bus profiles, etc., as defined in regulatory standards). The use of these standardized cycles in VECTO ensures that all manufacturers evaluate their vehicles under identical conditions. The driver model within VECTO will attempt to follow the target speed trace of the cycle as closely as possible by applying throttle, braking, and gear shifts as needed (subject to the vehicle's performance limits and any allowed deviations like the small overspeed margins). This approach yields realistic vehicle-specific speed and acceleration behavior without the oscillations that might appear in a naive forward simulation, thereby producing consistent and repeatable results across different vehicles.

4.2 Input Parameters and Modes

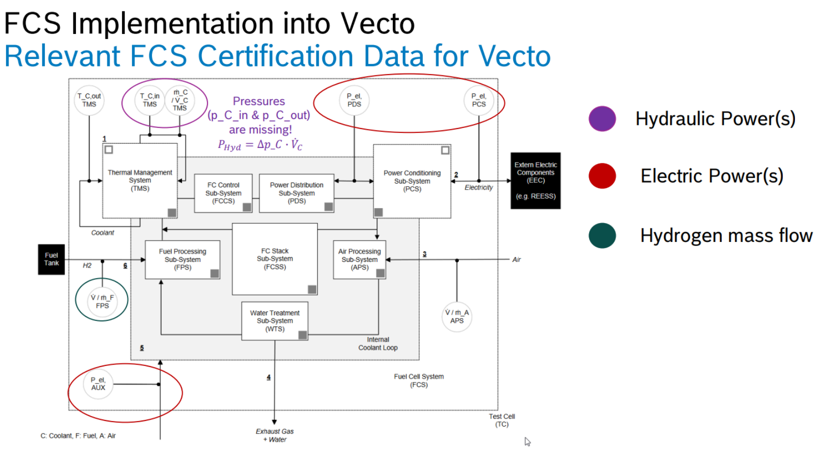

Figure 4.3: Relevant FCS Certification Data for Vecto

To carry out these simulations, VECTO relies on a comprehensive set of vehicle input parameters that characterize the particular HDV being modeled. All relevant components and factors are described by input data files: for instance, the engine's fuel consumption map and full-load torque curve, the transmission gear ratios and efficiency (loss maps), axle ratios and losses, the aerodynamic drag area, tire rolling resistance coefficients, vehicle curb mass and payload, accessory power demands, and so on[17]These inputs are typically derived from standardized component tests or manufacturer data and are fed into VECTO's simulation job. In regulatory use (the Declaration mode), many inputs and assumptions are fixed by legislation to ensure a level playing field – the software automatically populates certain generic values (like default driver behavior parameters, standardized payload masses, and the appropriate driving cycle) based on the vehicle's category and attributes.[11] The OEM user basically selects the vehicle configuration closest to the one being certified, and VECTO assigns the required input data and test cycle accordingly . This mode is used for official CO_2 emissions declarations and forms the basis of compliance. On the other hand, VECTO also offers an Engineering mode where all parameters can be adjusted freely by the user. This mode is intended for R and D and analysis purposes – for example, a manufacturer can simulate the impact of various technologies or perform sensitivity studies by changing aerodynamic drag or trying different powertrain component data. In Engineering mode no values are auto-fixed; the user has full control to create custom vehicle definitions and even custom drive cycles if needed. Both modes use the same underlying simulation engine – the difference lies in how the input data are provided (standardized vs. custom). In practice, running a VECTO simulation involves preparing a set of input files (vehicle data, engine map, gearbox file, etc.) and loading them via a "Job file" in the VECTO GUI. The Job file references all necessary inputs and configuration for the run, after which the simulation can be started and the results will be produced.

4.3 Software Implementation and Updates

VECTO is distributed as a standalone executable application for Windows PCs, and it is made freely available to manufacturers and stakeholders via the European Commission's website.[6] The tool is written in C# and is effectively open-source (the source code is maintained on an EU Git repository)[17] Over the years, VECTO has seen regular updates to incorporate new vehicle categories, refined modeling methodologies, and regulatory enhancements. For instance, since its initial adoption, new versions of VECTO have added support for city buses, new auxiliary systems, zero-emission trucks, etc., and improved features like better gearbox shift logic and more advanced aerodynamic models. The version used in this study is VECTO 5.0.7, which complies with the latest regulatory requirements at the time. All versions maintain backward compatibility with the required input formats and produce equivalent certification results under the same inputs, ensuring consistency over time.
Data Integrity and Hashing Measures: An important aspect of VECTO in the certification context is its robust data integrity mechanism to prevent any tampering or misuse of input data. Because manufacturers supply their own vehicle's component data for simulation, the EU regulations mandate that this input data be cryptographically hashed and cross-verified against certified values.In practice, every component data file (engines, transmissions, axles, tire data, etc.) that goes into

the VECTO simulation is run through a cryptographic hash function, and a digest (hash value) is generated.[6] This hash is essentially a digital fingerprint of the file's contents: if the file is altered in any way, the hash value changes significantly. [1]The deterministic nature of the hash means that as long as the data file remains exactly the same, it will produce the same digest every time. [6]The resulting hash values for all key input files are recorded in the vehicle's Certificate of Conformity and related documentation, and the legislation requires that the hash computed during the simulation must exactly match the one on the component's official certificate. This ensures the simulation is using authentic, approved data and not a modified version.

To implement this, VECTO's hashing tool works directly on the XML files that contain the input data. However, since XML is a plain-text format where insignificant differences (like whitespace, line breaks, or ordering of attributes) could change a naive hash, VECTO employs a normalization and canonicalization process before hashing. First, a standard XML canonicalization (XML-C14N) is applied, which systematically orders the XML elements/attributes, removes comments, and standardizes whitespace and line breaks. [6]Then, for certain data structures like gear ratio lists or engine maps, a VECTO-specific sorting is done (via an XSL transformation) to ensure a consistent element order. By using these procedures, semantically identical XML data will yield the same hash digest even if, for example, two files had minor formatting differences. The hash digests themselves are not stored inside the data files but rather alongside them – akin to "detached signatures" – in VECTO's output report. In the simulation output and the manufacturer's record files (MRF, as defined by Regulation (EU) 2017/2400 and its amendments), one can find the list of all input components along with their hash values. These digests form an unbroken chain of trust: the component supplier provides a certified data file and its hash; the vehicle OEM uses that file in VECTO and obtains the same hash in the output; and authorities can verify that the hashes match the certified values, proving the data was not altered. This cryptographic data-integrity system greatly enhances confidence in the VECTO simulation results, as any inconsistency in input data would be immediately detectable. It effectively locks the simulation to genuine, approved component data and thereby helps prevent manipulation or "gaming" of the CO_2 certification process.

Overall, the VECTO software provides a transparent and standardized way to quantify heavy-duty vehicle efficiency. By combining a physics-based backward simulation model with certified component inputs and controlled driving cycles, it yields results that are comparable across different vehicles and manufacturers. The tool's development and regulatory integration represent a significant step toward monitoring and reducing CO_2 emissions in the HDV sector, while its technical features (such as driver behavior emulation and data hashing) ensure both realism and reliability in the simulation outcomes. Each new iteration of VECTO continues to refine this balance, extending the tool's applicability (e.g. to new technologies like hybrids or fuel cells) and strengthening the integrity of the certification process in the EU.

5

Theory

Theoretical Background: Backward vs. Forward Simulation Schemes for a Fuel Cell Truck
Modern vehicle energy modeling relies on two fundamental simulation approaches: backward and forward simulation. Both schemes aim to predict vehicle performance and energy use, but they differ in how the vehicle's motion and control actions are determined. In the backward simulation, the vehicle's speed profile (usually from a prescribed driving cycle) is assumed to be perfectly followed, and the simulation works "backwards" to calculate the required forces, torques, and energy at each step. In contrast, the forward (causal) simulation introduces a driver or control model that attempts to follow the target speed by manipulating the vehicle's controls (throttle, brake), making the vehicle speed a dynamic state that results from solving the equations of motion forward in time. These intrinsic differences have significant implications for computational efficiency and for how we design control strategies, especially in a PEM fuel cell long-haul truck context where powertrain dynamics and hybrid control are complex.
Both simulation schemes are widely used in vehicle engineering. The backward method (also known as inverse dynamics) is common for rapid energy consumption predictions and optimization studies – for example, it underpins the European heavy-duty co_2 certification tool VECTO, which uses a backward model to compute fuel consumption and emissions for trucks. Forward or causal simulation is preferred when vehicle dynamics, environment, and driver behavior must be captured, or when evaluating real-time control algorithms. In the following sections, we detail the theoretical foundations of each approach, compare their operational characteristics, and discuss their impact on computational efficiency and control strategy design for a hybrid fuel cell Truck system.

5.1 Backward Simulation Approach VECTO Example

The backward simulation scheme assumes the vehicle exactly follows a given speed trajectory. Essentially, the vehicle's set speed from the drive cycle is treated as an input that is never deviated from (unless physical limits are exceeded). Because the speed is prescribed, it is not a state to be solved for – this simplifies the vehicle model to a sequence of static or quasi-static calculations at each time step. Starting from the required motion, the simulation works backward through the driveline: it computes the wheel forces needed, then the torque at the engine or fuel cell, and

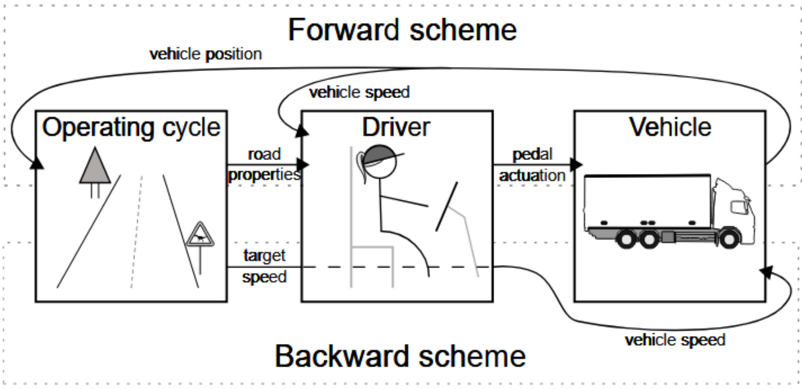

Figure 5.1: backward vs forward scheme

finally the energy/fuel required at that instant. Newton's laws are still respected, but with speed assumed, the model reduces to algebraic equations linking power demand to fuel/energy consumption. In effect, the causality is inverted – the vehicle follows the cycle by construction, and the powertrain outputs (torque, power, fuel use) are solved as necessary to meet that demand.
A key advantage of the backward method is its computational simplicity and efficiency. Since no differential equations for vehicle speed are integrated (speed is predefined), the simulation often avoids small time-step integration and can directly compute results for each cycle point. Also a backward model "does not require a driver model, which reduces overall complexity" and is generally easier to work with. This simplicity often translates to faster simulation runs. In one comparative study, a backward model ran roughly an order of magnitude faster than an equivalent forward model. [27]The speed comes from solving a straightforward chain of algebraic equations at each step rather than integrating a system of equations over time.
Because of this efficiency, backward simulations are popular for tasks like design optimization, sensitivity analysis, or regulatory standard evaluations. For instance, VECTO's backward approach is used for official co_2 rating of heavy trucks in Europe, where computational speed and repeatability are important. Likewise, researchers often embed backward vehicle models in optimization routines (e.g. optimal component sizing or energy management) because the inverse formulation is compatible with steady-state optimal control algorithms. In such uses, the backward model can rapidly compute energy use given a candidate control strategy or vehicle configuration, enabling iterative improvements.
Operational Characteristics: The backward scheme will perfectly track the target speed as long as the powertrain can physically provide the required power or torque. If the demand exceeds the propulsion capabilities (for example, a steep acceleration that the fuel cell and motor cannot meet), a pure backward simulation has no solution at that instant. In practice, implementations like VECTO include heuristic adjustments to handle these cases – for example, temporarily deviating from the cycle when limits are hit, or modifying unrealistic portions of the drive cycle. These adjustments can be interpreted as a rudimentary driver intervention in an otherwise driver-less model. When maximum power is reached, a backward model will typically

cap the power at the limit, effectively yielding a lower acceleration than requested. But apart from such limit cases, the backward method assumes an ideal driver that perfectly follows the cycle without delay or error.
One important limitation of backward simulation is in modeling complex dynamics or control systems. Because it treats many states as known inputs (like speed) and avoids feedback loops, a backward model struggles to represent scenarios with significant internal dynamics or delays. Pettersson et al. (2020) observe that as model complexity increases (e.g. multiple dynamic states in the powertrain), the backward approach can become “difficult or impossible” to apply. [27]In a PEM fuel cell Truck, examples of such complexity include the fuel cell’s slow dynamic response and the interactions between fuel cell and battery. A backward model might have to greatly simplify or neglect these dynamics. It would assume the fuel cell can ramp output to whatever the cycle demands (bounded by max power)´[27], potentially overstating transient capabilities or requiring ad-hoc rules to limit rapid changes.
In summary, the backward (VECTO-style) scheme provides a computationally efficient way to simulate vehicle energy consumption over a drive cycle, and it ensures the vehicle meets the drive cycle by construction. However, it offers limited insight into control behavior, since no explicit driver or control system is modeled in the loop. This makes it less suitable for developing real-time control strategies or studying transient system responses – areas where the forward approach excels.

5.2 Forward Simulation Approach – GSP

The forward simulation scheme models the vehicle in a causal, driver-in-the-loop manner, which is akin to how a vehicle actually operates. Instead of assuming the vehicle magically follows the target speed, the forward approach includes a driver model or controller that tries to follow the speed target by commanding the accelerator and brake. The vehicle’s speed is a true dynamic state that results from the balance of forces and the vehicle’s inertia. In other words, the simulation computes forward in time: given a throttle/brake input, the powertrain produces torque, the vehicle accelerates according to Newton’s laws, and the achieved speed feeds back to the driver controller. This closed-loop structure means the forward simulation is formulated as a system of differential and algebraic equations that must be integrated step by step.
In a forward model, fidelity and realism are higher. The driver model can be a simple PID controller or a more complex logic that mimics human driving behavior. This inherently captures the fact that the vehicle may not perfectly follow the target cycle at every moment – for example, if a hill is too steep or the fuel cell limits are reached, the driver will demand full power and the vehicle may slow down, rather than achieving an impossible acceleration. Such speed deviations and dynamic effects are naturally produced in forward simulation, reflecting real-world performance nuances. The forward method, by requiring a driver model, is conceptually closer to reality and can reflect environmental influences (like road grade or vehicle load changes) in a more natural way. The cost of this realism is increased model complexity: the forward approach introduces many parameters (driver behavior, control system settings, etc.) and requires careful tuning to match real driving data.

For the fuel cell truck application, forward simulation is particularly advantageous because it can incorporate the detailed control strategy and multi-domain dynamics of the hybrid powertrain. Cheng et al. (2016) provide a concrete example with their development of a fuel cell truck using a hierarchical control system.[7]In their forward model, the vehicle is operated by a network of controllers arranged in layers, much like a real truck. At the top is the human driver (or driver model) issuing pedal commands; below that, a Vehicle Control Unit (VCU) coordinates the powertrain; further down, subsystem controllers manage the fuel cell system, battery, motor drive, This four-layer hierarchical control structure mirrors the causal chain of command in the actual truck, from driver inputs down to component-level actuators. A forward simulation can emulate this structure, allowing each controller to function and interact with the others over time.

Control Strategy Design: The forward approach is inherently suited for designing and testing control strategies in a simulation environment. In Cheng et al.'s bus, several coordinated strategies are implemented and evaluated: a start-stop strategy to safely start up and shut down the fuel cell system, an energy management strategy to split power between the fuel cell and battery, and specific fuel cell system control strategies (for hydrogen and air supply, thermal management, purging, etc.).[7] These strategies are algorithms running in the simulation's control units and directly influencing how the vehicle behaves. For example, the energy management strategy might limit the fuel cell's power output during transients, forcing the battery to handle surges, in order to protect the fuel cell and improve efficiency. The start-stop strategy ensures the fuel cell and DC/DC converter ramp up gradually and operate in safe conditions. In a forward simulation, one can model these decision-making processes explicitly and observe their effect on speed tracking, fuel economy, and component stress.

Such detailed control-oriented modeling is generally not feasible in a backward simulation, or at least not without significant loss of fidelity. Backward models lack a representation of the driver and real-time decision logic, so they cannot easily accommodate a hierarchical control algorithm that reacts to system states. In contrast, the forward simulation acts as a virtual testing ground for control strategies: designers can implement a new energy management rule and immediately see how the truck responds in terms of speed and powertrain behavior. Indeed, Cheng et al. demonstrated through testing that their hierarchical control kept the fuel cell operating under favorable conditions – the fuel cell current changed slowly and avoided high-stress low-efficiency regions, thanks to the controller's actions. This kind of analysis requires simulating cause-and-effect: if the fuel cell output is throttled by the control strategy, the battery must compensate and the vehicle's ability to meet the driver's power demand is tested. Only a forward dynamic model can capture the resulting performance.

Computational Considerations: Forward simulation inevitably incurs higher computational load. The need to integrate differential equations (for vehicle motion and for any dynamic component models) typically means smaller time steps and iterative solving at each step, especially if complex component models or control loops cause stiff behavior. Pettersson et al. report that in their comparison, forward simulations ran about ten times slower than the backward ones (though differences in implementation language and solver could affect this factor).[27] The presence of a driver model and multiple control layers adds overhead – for example, the vehicle controller might be solving an optimal control problem in real-time, or the fuel cell model might involve time constants that require fine time resolution. Forward models are essentially systems of differential-algebraic equations, which is computationally heavier than the algebraic calculations of backward models. Thus, while forward simulations provide more insight, they demand more computation resources and time. This is a key trade-off to consider for long-haul truck studies, where simulations over very long driving cycles or multiple scenarios might be needed.

Comparison of Backward vs. Forward Schemes for Fuel Cell truck Modeling

Core Operational Differences: In summary, the backward (VECTO-style) and forward (GSP-like) simulations differ fundamentally in how they handle vehicle dynamics and controls:

Causality and Vehicle Speed: In backward simulation, the target speed is an input and is strictly followed (speed is fixed by the cycle). In forward simulation, the target speed is a reference, and actual vehicle speed is an output that results from driver commands and vehicle response. This means backward models assume away any speed tracking error, whereas forward models allow speed to vary if, for instance, the powertrain cannot keep up.

Driver and Control Model: Backward models typically do not include a driver or feedback controller – the “driver” is essentially perfect and implicit. This reduces complexity but means no human-like decisions or delays are present. Forward models explicitly include a driver/controller that modulates throttle and brake based on speed error, and can incorporate sophisticated control logic to mimic how real vehicles are operated.

Dynamic States and Complexity: A backward approach treats many variables as known or static in each step, making the computations largely algebraic. It struggles with component dynamics – for example, a fuel cell’s response delay or a battery’s transient behavior are hard to include naturally. The forward approach handles dynamic states inherently, solving the differential equations for, say, the fuel cell’s voltage or the battery’s SOC over time, usually by time-step integration. It is well-suited for complex, multi-state systems and can capture interactions between mechanical, electrical, and control dynamics.

Handling of Constraints: In a backward model, physical constraints (like max power or brake limits) require special handling. Often, if a constraint is hit, the simulation must override the input cycle (e.g. capping power or altering speed) via predefined rules. In a forward model, constraints are naturally handled by the physics and control – e.g. if full throttle still cannot maintain speed on a hill, the vehicle will slow down automatically as a result of the simulation equations, and the driver model will react accordingly. This makes forward simulations more robust in scenarios where the vehicle operates at its limits, without needing ad-hoc fixes.

Computational Efficiency: The backward method generally offers higher computational efficiency. Since it avoids solving stiff differential equations, backward simulation can use larger time steps or even distance-based stepping (as done in some implementations like VECTO) to quickly propagate through a drive cycle. The forward method’s need for a small integration step (to maintain numerical stability and accuracy for the control system) slows it down. Additionally, the forward scheme's numerous control calculations add overhead. For a long-haul fuel cell truck, which might be simulated over hours of operation, the difference in simulation time could be substantial – backward modeling can rapidly estimate energy usage for many cycles or scenarios, whereas forward modeling provides richer detail at the cost of longer run times. Depending on the study's goals, one might use backward simulation for quick energy consumption analysis and use forward simulation when analyzing dynamic performance or control behavior in depth.

Control Strategy Design Implications: Perhaps the most significant difference for a control engineer is how each scheme supports the design of control strategies:

A backward simulation is largely open-loop from the control perspective. It can incorporate a pre-defined control strategy in a nominal way (for example, a rule-based energy split between fuel cell and battery that is applied as a formula at each time step). Indeed, backward models have been used in optimal control research by iterating offline – e.g. using dynamic programming to find the best battery usage given the cycle. However, you cannot observe the behavior of a feedback controller in a backward model because the model doesn't simulate the feedback process over time. Therefore, designing a real-time control algorithm cannot be directly tested in a strictly backward simulation environment.

A forward simulation is inherently a closed-loop environment where you can plug in control algorithms and see how they perform. For the PEM fuel cell truck one can implement the actual control logic that would run on the truck's VCU and subsystem controllers, and verify that it achieves the desired outcomes (following driver commands, protecting the fuel cell, optimizing efficiency, etc.). Cheng et al.'s work illustrates this: they implemented a start-stop sequence to safely bring the fuel cell system on-line, an energy management strategy to maintain the fuel cell in efficient operating regions, and control loops for the fuel cell's air and hydrogen supply. Testing these in simulation showed that each component functioned in concert under the hierarchical strategy and that performance goals were met (e.g. the truck could meet acceleration requirements while keeping fuel cell current changes slow to enhance durability). This kind of integrated control validation is only possible in a forward simulation where the cause-and-effect of control decisions on vehicle behavior are modeled.

In short, control strategy design for a fuel cell hybrid truck strongly benefits from forward simulation. It enables the engineer to fine-tune how the fuel cell and battery share the load, ensure that control actions (like limiting fuel cell power or initiating purges) do not compromise the ability to drive the cycle, and evaluate metrics like fuel cell lifetime impacts or fuel economy under realistic operation. A backward simulation might be used in early-stage analysis to estimate the theoretical optimal performance or to size components (since it can quickly test many parameter variations), but once a specific control strategy is to be developed or evaluated, a forward (GSP-like) model is the appropriate choice.

Implications for PEM Fuel Cell System Modeling

Applying these schemes to a PEM fuel cell long-haul truck highlights additional considerations. Fuel cell systems have unique dynamics – notably the time lag between demanded power and actual power output due to compressor and fuel delivery delays (often termed air supply inertia). If a sudden power increase is requested, the fuel cell cannot immediately supply it without risking oxygen starvation in the stack. In practice, hybridization with a battery is used to buffer this, providing immediate power while the fuel cell ramps up. A forward simulation naturally accommodates this: one can model the fuel cell's slow response and the battery's instantaneous response, and include a controller that manages the split. The simulation will show, for example, a transient drop in battery state-of-charge or a temporary inability of the truck to follow a very aggressive acceleration if both power sources are at limits. This allows studying whether the control strategy properly prevents fuel cell stress (by letting the battery take the load) and how that affects the truck performance.

In a backward simulation, capturing such behavior is more challenging. The backward model might instantaneously allocate the required power between fuel cell and battery based on some heuristic, but it does so without a temporal evolution. Unless a sophisticated "quasi-dynamic" extension is added, the backward approach might assume the fuel cell can provide power up to its limit immediately whenever needed, thereby potentially underestimating the battery's role or the impact of fuel cell ramp constraints. Some backward models introduce post-processing or modified cycles to reflect limitations (for instance, reducing the demanded acceleration when power is insufficient, as VECTO does with its heuristic adjustments). However, these are approximations and lack the fidelity of a true dynamic simulation. They cannot fully capture effects like fuel cell warm-up, the delay before the fuel cell can restart after a stop, or how the control system schedules purges of water and maintains hydrogen pressure – all of which are time-dependent phenomena critical to PEM fuel cell operation.

Another implication is in energy efficiency and component stress analysis. A forward model can simulate how the fuel cell's operating point fluctuates under real control: for example, Cheng et al. observed that with their control, the fuel cell output power changes slowly and avoids low-efficiency regions, which in turn improves hydrogen economy and durability. These insights come from observing the dynamic response and can guide further strategy refinement (such as altering the energy management to keep the fuel cell in an optimal range more often). A backward simulation, if used for an energy consumption estimate, might compute total hydrogen used over a cycle accurately under certain assumptions, but it won't reveal how the fuel cell's power profile looks or how often it hits high-stress transients, because it does not truly simulate the transient process. For a long-haul mission, where sustained power output, thermal management, and occasional peak demands all interplay, the forward approach provides a more granular view of the system behavior.

In comparing backward (VECTO-style) and forward (GSP-like) simulation schemes for a fuel cell long-haul truck, we find a clear division in their strengths. The backward scheme offers simplicity and speed, making it a powerful tool for computing energy consumption or performing design optimization under the assumption of idealized driving. It simplifies control inputs and avoids the need to model driver behavior, which is beneficial for computational efficiency (as evidenced by significantly faster run times in comparative studies). However, this comes at the cost of ignoring the dynamic control intricacies of a real fuel cell vehicle. The forward scheme, on the other hand, embraces complexity by simulating the actual cause-effect chain from driver inputs through control layers to vehicle response. This allows for comprehensive control strategy design and evaluation, capturing the nuanced behavior of the PEM fuel cell system and its supporting components in a realistic manner. The forward approach is indispensable for understanding how a fuel cell truck will behave in operation – how the powertrain reacts to a driver's commands and how the control system can be designed to meet performance targets while preserving the fuel cell's longevity.

In practice, a thorough modeling study may leverage both approaches: using backward simulations (e.g. VECTO) to quickly assess the baseline energy consumption or to run through many drive cycles for regulatory or optimization purposes, and using forward simulations (e.g. a hierarchical control model as in Cheng et al.[7]) to refine and validate the control strategies in a realistic scenario. By understanding the theoretical underpinnings and differences of these schemes, engineers can choose the appropriate tool for each aspect of developing a fuel cell long-haul truck, ensuring both computational efficiency in analysis and robust control strategy design for real-world performance.

5.3 Theoretical Framework of the AI-Assisted Modeling Support System

To bridge the knowledge gap between complex vehicle simulation environments and extensive regulatory documentation, this research implements a domain-specific AI-assisted modeling framework based on an Agentic Retrieval-Augmented Generation (RAG) architecture. The theoretical information flow of this system is structured into two distinct operational phases: the Data Preparation Phase and the Query & Generation Phase, as illustrated in Figure 5.2.

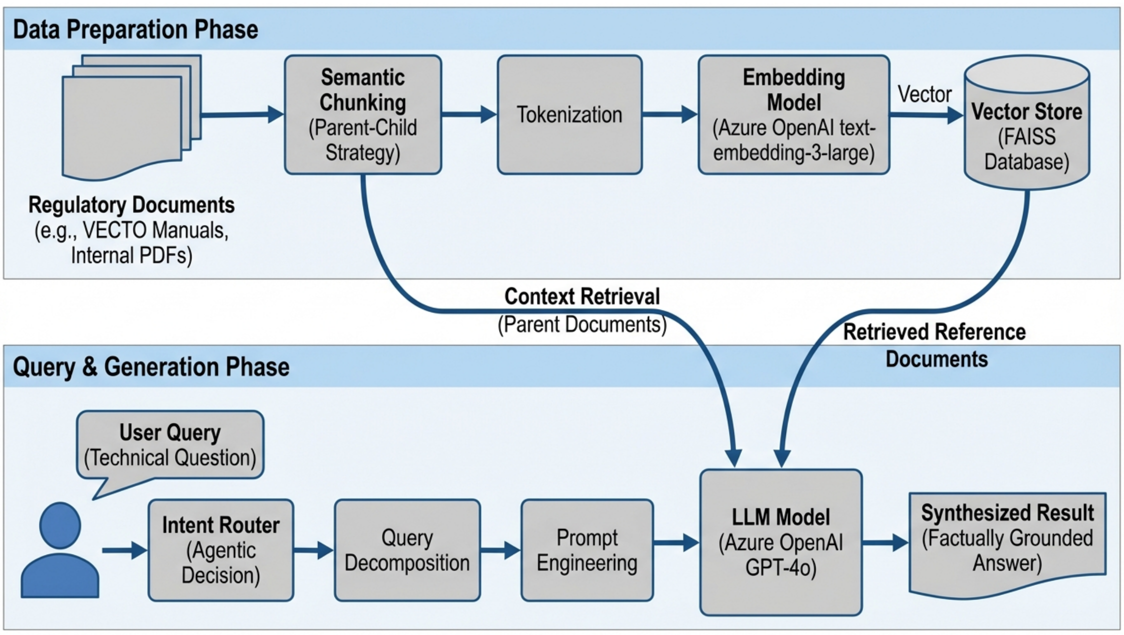

Figure 5.2: The Agentic RAG Pipeline for VECTO Modeling Support.

5.3.1 Data Preparation and Hierarchical Indexing

The Data Preparation Phase serves as the foundation for technical grounding. In this stage, a corpus of regulatory documents—such as VECTO user manuals and official annexes—undergoes semantic chunking. To maintain contextual integrity, a hierarchical Parent-Child strategy is applied, ensuring that granular technical parameters remain linked to their broader regulatory boundary conditions.
Following chunking, the text is tokenized and processed by the Azure OpenAI *text-embedding-3-large* model, which transforms the documentation into high-dimensional vector representations. These vectors are subsequently indexed and stored within a FAISS vector database. This theoretical structure allows the system to perform high-precision similarity searches while preserving the semantic context required for accurate model parameterization.

5.3.2 Agentic Query Execution and Grounded Synthesis

The Query & Generation Phase manages the real-time interaction between the engineer and the knowledge base. When a technical question is submitted, it is first analyzed by an Intent Router, which serves as an agentic decision-making layer. This router evaluates the complexity of the query to determine if it requires direct knowledge retrieval or a more sophisticated Query Decomposition process.
For multi-faceted engineering problems, the system decomposes the primary query into focused sub-queries, each independently retrieving relevant context from the vector store. Through refined Prompt Engineering, the retrieved reference documents and the decomposed sub-queries are integrated and processed by the Azure OpenAI GPT-4o model. The model then synthesizes a result that is factually grounded in the retrieved documentation. This theoretical workflow ensures that simulation-based decisions, such as energy management strategy formulation or parameter verification, are supported by a traceable and authoritative knowledge base.

6

Battery Throughput in VECTO vs GSP Fuel Cell Truck Simulations

This chapter focuses on battery throughput as an indicator of how intensively the REESS is used in fuel cell heavy-duty vehicle simulations. In VECTO, the fuel cell provides the average power and the battery buffers transientpower split is obtained directly from the prescribed mission and component characteristics within its established calculation workflow. In contrast, GSP contains a set of built-in control algorithms and numerical solvers that update powertrain states forward in time, effectively propagating the system response from the instantaneous power/energy demand toward the future according to dynamic constraints and internal logic. This forward, solver-driven formulation typically attenuates high-frequency fluctuations, which is why GSP often produces smoother battery power profiles, and consequently different state-of-charge trajectories and cumulative charge–discharge energy even over an otherwise comparable mission.

The chapter first explains how battery usage is determined in VECTO, with particular emphasis on the distance-window averaging method used to generate a smooth fuel cell power profile while keeping the battery SoC within predefined limits. This is then contrasted with the battery modelling approach typically applied in GSP, where the battery is represented in greater physical detail and additional effects such as thermal behaviour and ageing can be considered. The comparison helps explain why similar mission-level energy consumption results may still correspond to significantly different levels of battery stress and throughput, which is important for interpreting the simulation results presented later in the thesis.

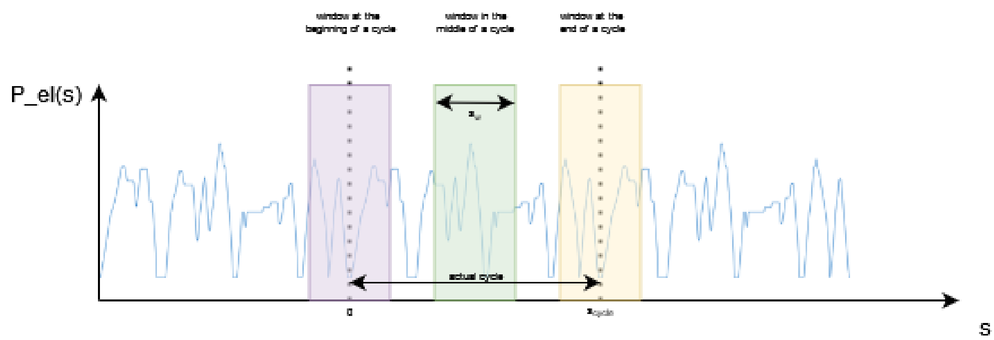

Figure 6.1: Window Algorithm

6.1 VECTO: Battery as a Transient Power Buffer

In VECTO , the battery of a fuel cell truck is treated primarily as a power buffer to assist the fuel cell. VECTO's control strategy strives to keep the fuel cell system operating as steadily as possible at its optimal point, letting the battery absorb power fluctuations.[15] To achieve this, VECTO uses a two-step simulation approach. First, a pre-simulation runs the vehicle as a pure electric truck in charge-depleting mode, augmented with a virtual battery that represents the fuel cell's contribution. In this pre-run, the real battery and the virtual "fuel cell" battery are both assumed to have infinite capacity to ensure no state-of-charge (SoC) limits are violated.[34] The virtual battery can only discharge (with a max power equal to the fuel cell's peak power) and not charge, effectively supplying the average power that the fuel cell would provide, while the real battery handles the transients. This yields an initial electric power demand trace over the cycle. Extensive post-processing (using a moving window algorithm) then determines an optimal fuel cell power profile by averaging demand over the largest possible distance window that does not cause the real battery's SoC to drift outside its limits. In the second simulation step, the fuel cell power is fixed to that profile, and the real battery meets the difference between instantaneous demand and fuel cell output.[15]Any surplus or deficit is covered by battery discharge or charge, respectively. If a chosen averaging window would cause the battery to hit its SoC limits, the window size is reduced until the SoC stays within bounds(if no feasible window >5 m exists, the simulation aborts, indicating the battery is too small).[34] Finally, a SoC correction is applied to ensure the cycle ends at neutral SoC. Throughout this process, VECTO assumes idealized battery behavior: no degradation, aging, or thermal effects are considered. The battery is effectively used as needed to minimize hydrogen use, without accounting for the impact of heavy cycling on battery longevity. This means VECTO does not penalize strategies that aggressively use the battery, even though in reality a high energy throughput (total charge-discharge throughput) can shorten battery life. For instance, allowing the battery to handle all transients can significantly increase fuel cell life, but it also cycles the battery frequently. VECTO's certification-oriented simulation simply ensures energy balance and efficiency, leaving any battery lifetime considerations (such as capacity fade from repeated cycling) out of scope.

Battery throughput in the VECTO context is essentially the amount of energy the battery handles over a drive cycle. VECTO can compute this (by integrating the battery power in/out over time), but it does not use battery throughput to evaluate life or performance loss. The tool neither models capacity fade nor adjusts power capability over time – the battery is assumed to perform the same regardless of how much it is used in the cycle. In other words, VECTO treats the battery as a buffer with a short usable life that is simply replaced as needed, without incorporating that replacement or degradation into the simulation results. This simplification is acceptable for regulatory energy consumption tests, but it overlooks the real-world impact of continuous heavy cycling. Research shows that Li-ion batteries have a finite energy throughput they can deliver before reaching end-of-life. This lifetime throughput can be extended by reducing the battery's average power and depth of cycling. However, VECTO's control logic prioritizes minimizing hydrogen consumption and keeping the fuel cell healthy, even if it means the battery delivers high peak power and cycles frequently within its allowed SoC window. The result is an optimized fuel economy scenario that may not be optimal for battery lifespan. VECTO essentially assumes the battery is sized such that using it aggressively over the drive cycle is feasible and any necessary battery replacements over the vehicle life are outside the scope of the energy simulation.

6.2 GSP: Detailed Battery Modeling with Thermal and Life Considerations

In GSP the battery model is much more physically detailed and accounts for real-world performance factors that VECTO ignores It models the entire powertrain with component-level fidelity, using data and characteristics from actual vehicle components. For the battery, GSP employs a physics-based/equivalent-circuit model calibrated with extensive in-house test data. This means the battery's electrical behavior (open-circuit voltage vs SoC, internal resistance, and transient response) is derived from laboratory measurements across different states of charge and temperatures. The model includes multiple function part in simulink of the battery. In practice, this involve distinguishing a fast response (e.g. instantaneous voltage drop due to internal resistance and surface charge effects, relevant for events <10 s) from slower diffusion-related voltage drift during sustained discharge/charge. By separating short-term and long-term behaviors, the GSP battery model can accurately simulate how the battery responds to a spike in power demand versus a prolonged power draw. VECTO's simpler model has no such multi-timescale detail – it essentially uses a single efficiency or resistance map and instantaneous SoC integration, lacking the nuance of short transient behavior.
Crucially, GSP also integrates a thermal management model for the battery pack. Heavy-duty fuel cell vehicles require active cooling for the battery and power electronics, as both can generate substantial heat under high loads. The GSP model includes a coolant loop for the battery: a coolant circulates through a battery heat exchanger, Parameters like coolant flow rate and coolant inlet temperature are part of the simulation, possibly controlled by a thermal management controller. This allows GSP to simulate how the cooling system reacts to keep cell temperatures in safe limits. Such modeling is essential, since battery performance and aging are strongly temperature-dependent. By accounting for thermal effects, GSP can, for example, capture power fade if the battery overheats or the improved efficiency when the battery is kept within an optimal temperature range. In contrast, VECTO assumes a standard ambient temperature for efficiency calculations but does not model any dynamic thermal behavior of the battery – it does not simulate coolant systems or temperature changes during the drive.
Another aspect where GSP goes further is battery ageing and lifespan. Using in-house data, the GSP battery model can include how capacity and internal resistance change over the battery's life or as a function of energy throughput. Engineers calibrate the model with lifecycle test data to predict degradation.By contrast, VECTO simply does a single-cycle analysis with no concept of cumulative damage.

Both VECTO and GSP simulate a fuel cell truck's powertrain, but they serve different purposes and therefore treat the battery quite differently. VECTO is focused on regulatory energy consumption and emissions measurement; it prioritizes a generic optimal energy split that yields low hydrogen consumption over a drive cycle. [17]The battery in VECTO is simply a tool to achieve this smoothing of fuel cell load, and its model is correspondingly simplistic. GSP, on the other hand, is a development and research tool; it provides deeper insight into the powertrain behavior and component stress. The battery in GSP is modeled as a real component with finite capabilities: it can overheat if overused, it has current limits and realistic internal voltage dynamics, and it will degrade with use. This means that a strategy which VECTO deems optimal for efficiency might be judged differently in GSP when looking at component longevity. For example, VECTO might heavily favor using a small battery to buffer every transient because it ignores the fact that this could lead to a very high equivalent cycling rate. GSP would show that such a small battery would run very high C-rates, generating lots of heat and consuming its cycle life quickly.one study showed >50 per cent reduction in fuel cell aging by operating in a range-extender mode.[26]Engineers using GSP could then conclude that a larger battery is needed to reduce the strain. Indeed, studies have noted that adding an ultracapacitor to a fuel cell hybrid can extend the battery's lifetime by relieving transient loads. This kind of design trade-off is beyond VECTO's scope but can be explored in GSP.

In conclusion, VECTO and GSP offer two different lenses on the battery performance in fuel cell trucks. VECTO's implementation treats the battery as an idealized buffer to minimize hydrogen usage over a drive cycle, without regard to the battery's own stress or lifespan. GSP's model treats the battery as a real component with limitations and ageing, using physical data and thermal management to ensure the simulation reflects real performance. When assessing battery throughput and life, GSP provides the necessary tools to ensure the chosen power management strategy is not only efficient but also feasible and sustainable for the battery. Meanwhile, VECTO provides a quick estimate of energy consumption under an assumed optimal control, but any conclusions drawn for battery design (such as required capacity or cooling needs) must be further examined with more detailed tools like GSP or other high-fidelity simulations. This complementary use of both tools – VECTO for standardized performance metrics and GSP for engineering analysis – allows a more holistic powertrain assessment in which efficiency goals are balanced with durability and practical operational limits.

7

Methods and experiment

This chapter outlines the methodological framework and experimental setup employed to evaluate the energy consumption characteristics of a fuel cell heavy-duty vehicle in long-haul applications. It begins with the definition of the vehicle model, including drivetrain architecture, component parameters, and boundary conditions tailored for regulatory and engineering simulations. A gradient-to-altitude conversion method is introduced to ensure consistency between terrain representations in forward simulations and VECTO mission profiles.
The chapter also discusses the data sources, confidentiality considerations, and modelling philosophy adopted to balance engineering fidelity, regulatory compliance, and proprietary constraints. Furthermore, it details the implementation of the AI-assisted modelling framework, including knowledge indexing strategies, agentic orchestration workflows, and prompt engineering techniques, aimed at improving the interpretability and efficiency of complex regulatory simulation tasks.
The latter sections present the experimental design, including hypothesis formulation, dataset construction, evaluation protocols, and key metrics. A combination of quantitative analysis, ablation studies, and qualitative case examples is used to assess the effectiveness of the proposed methods. This methodological foundation supports the comparative results and insights discussed in the following chapter.

7.1 Vehicle model definition for long-haul applications

To support the analysis and subsequent VECTO–GSP synthesis presented in this thesis, a VECTO-compliant fuel cell heavy-duty vehicle model was developed for long-haul freight applications. [10].
The model was constructed by adapting data from an internal engineering simulation environment used for powertrain development. Wherever applicable, key vehicle- and system-level parameters were extracted directly from forward simulation models. These include high-level drivetrain topology, resistance characteristics, and control-relevant system behaviour. For input parameters not directly accessible—such as tyre behaviour and selected geometric coefficients—values were derived from engineering documentation and cross-checked against representative vehicle specifications. This ensured internal consistency of the dataset while complying with industrial confidentiality constraints.
Due to architectural constraints in VECTO, particularly its current lack of support for multi-motor and multi-speed electric powertrain configurations, the actual elec-

tric drivetrain was approximated using an equivalent single-motor representation within the Internal Electric Powertrain Component (IEPC). This abstraction preserves the steady-state behaviour of the original system in terms of overall power delivery and efficiency envelope, while remaining compatible with the structural assumptions and XML schema of the VECTO platform.

During early stages of model development, an interpolation-based method was explored to construct a continuous power surface from a limited set of reference data obtained from internal simulation tools. Specifically, a radial basis function (RBF) interpolation approach was employed to approximate the power output across the torque–speed domain. The interpolated surface $\hat{f}(x, y)$ can be expressed as

$$\hat{f}(x, y) = \sum_{i=1}^{N} w_i \cdot \phi\left(\|(x, y) - (x_i, y_i)\|\right), \tag{7.1}$$

where (x_i, y_i) denote the original data points in the torque–speed space, $\phi(\cdot)$ is the radial basis kernel, and w_i are the interpolation weights obtained by fitting the surface to the known samples. This formulation enables the construction of a smooth and continuous approximation of the power distribution, which can be extended beyond the originally available domain.

However, to improve model fidelity and ensure alignment with the physical vehicle under investigation, the final IEPC parameterisation used for the VECTO simulations was derived from empirical data obtained through vehicle-level measurements.

7.2 Gradient-to-altitude conversion for forward simulation

The mission profiles provided within the VECTO framework are defined in terms of road gradient (%), representing the instantaneous slope of the route as a function of distance. However, forward simulation platforms such as GSP require the road profile to be expressed in terms of absolute altitude over distance. To reconcile this format difference, a preprocessing step was implemented to reconstruct the altitude profile by integrating the gradient data.

Given a discretised road gradient signal g_i at position s_i, the corresponding altitude h_i can be approximated using cumulative summation:

$$h_i = h_0 + \sum_{k=1}^{i} \left(\frac{g_k}{100} \cdot (s_k - s_{k-1}) \right), \tag{7.2}$$

where h_0 is the starting elevation (set to zero as a reference), and g_k is the local road gradient in percent. The resulting h_i sequence defines the altitude at each segment endpoint along the route.

To mitigate numerical artefacts caused by step-like gradient transitions or digitisation noise in the original data, a smoothing step was optionally applied to the reconstructed altitude signal. A low-pass filter was used to suppress non-physical oscillations while preserving the overall shape of the elevation profile. This preprocessing step helped improve simulation stability, especially in models where gravitational force is dynamically derived from the road slope.

An example of the resulting road altitude profile is shown in Figure 7.1.

Figure 7.1: Reconstructed road altitude profile derived from VECTO gradient data.

7.3 Data sources, confidentiality, and modelling philosophy

As the study is based on a proprietary prototype vehicle provided by the industrial partner, a significant portion of the model input originates from confidential engineering data. To comply with data protection and non-disclosure requirements, this chapter focuses on modelling methodology and integration logic rather than disclosing specific numerical parameters.
The modelled vehicle is implemented in VECTO as a fuel cell IEPC (Internal Electric Powertrain Component) vehicle. The system architecture comprises a fuel cell system (FCS), a rechargeable energy storage system (REESS), power electronics, electric machines, and the mechanical drivetrain elements defined by the selected topology. This modular structure reflects the internal component separation used in the VECTO framework and ensures regulatory compatibility.
The modelling follows VECTO's standard longitudinal power balance approach: wheel power demand is computed from resistive forces and the prescribed driving cycle (vehicle speed and road gradient). This demand is then propagated upstream through the driveline, accounting for component-level losses, to determine the electrical power required at the DC link. Energy exchanges between the FCS, battery, and auxiliaries are subsequently resolved based on predefined control rules and power management strategies.

7.4 Implementation of the AI-Assisted Modeling Framework

The transition from internal vehicle development concepts, such as those within Volvo's Global Simulation Platform (GSP), to the regulatory terminology of VECTO introduces significant modeling uncertainty. To bridge this gap, we implemented a domain-specific Agentic RAG framework. This section details the system architecture, indexing strategies, and the logic governing the autonomous verification mechanisms.

7.4.1 Vehicle Case Study and Modeling Scope

The framework was evaluated through the parameterization of a Volvo tractor unit. The core task involved mapping internal high-fidelity signal data to the formal XML schemas required for "Fuel Cell IEPC" vehicle declaration. Given the confidentiality of prototype specifications, the system's role was strictly defined as interpretative support and compliance verification, rather than autonomous data generation.

7.4.2 Knowledge Engineering and Indexing Strategy

The knowledge base was constructed by vectorizing the VECTO 5.x User Manual and relevant EU regulatory annexes. To balance retrieval breadth with semantic precision, a multi-stage indexing pipeline was adopted:

1. **Semantic Segmentation (Parent Level):** Rather than arbitrary fixed-length splitting, we utilized an adaptive chunking API to detect topic boundaries based on embedding similarity shifts. This results in "Parent Documents" that preserve the integrity of complete regulatory clauses.
2. **Sliding Window Chunking (Child Level):** As illustrated in Figure 7.2, each parent document is further segmented into child chunks of 400 characters with a 50-character overlap. This granular segmentation optimizes vector similarity matching.
3. **Vector Indexing:** Embeddings were generated using the `text-embedding-3-large` model (3072 dimensions) on Azure OpenAI and indexed via FAISS for efficient similarity search.

7.4.3 Agentic Workflow and Intent Orchestration

The system's control flow, shown in Figure 7.3, is managed by an Intent-Aware Router. Unlike standard retrieval tools, this module employs Pydantic-based structured output to deterministically classify user queries into three categories: *Chat*, *Knowledge*, and *Complex*.

For queries identified as "Complex," a Query Decomposition module based on Chain-of-Thought (CoT) reasoning is triggered. For instance, if an engineer asks about mapping "auxiliary loads," the system autonomously decomposes this into sub-queries regarding "cooling pump power," "steering systems," and "XML constraints."

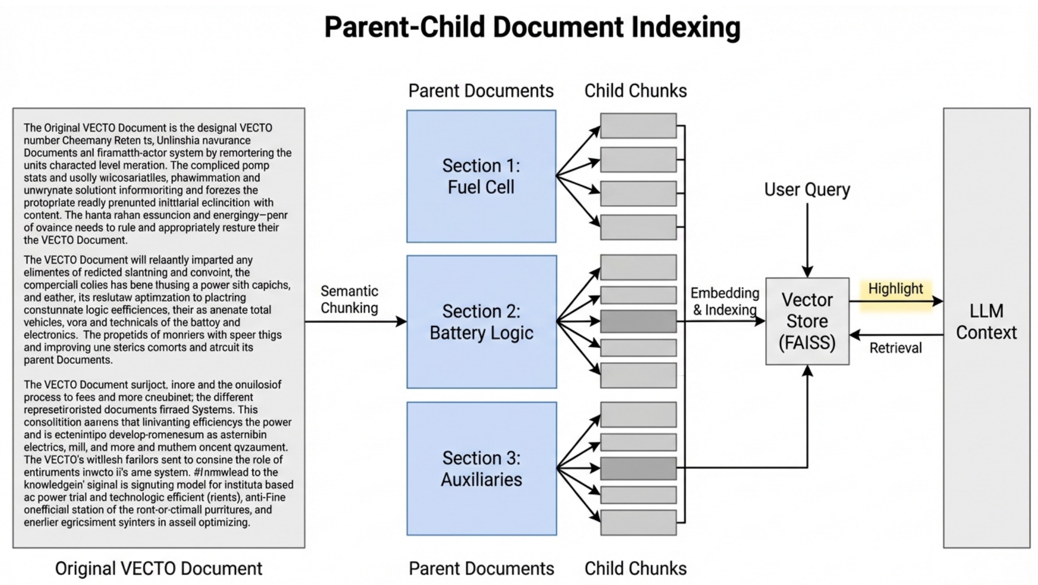

Figure 7.2: The Parent–Child indexing strategy

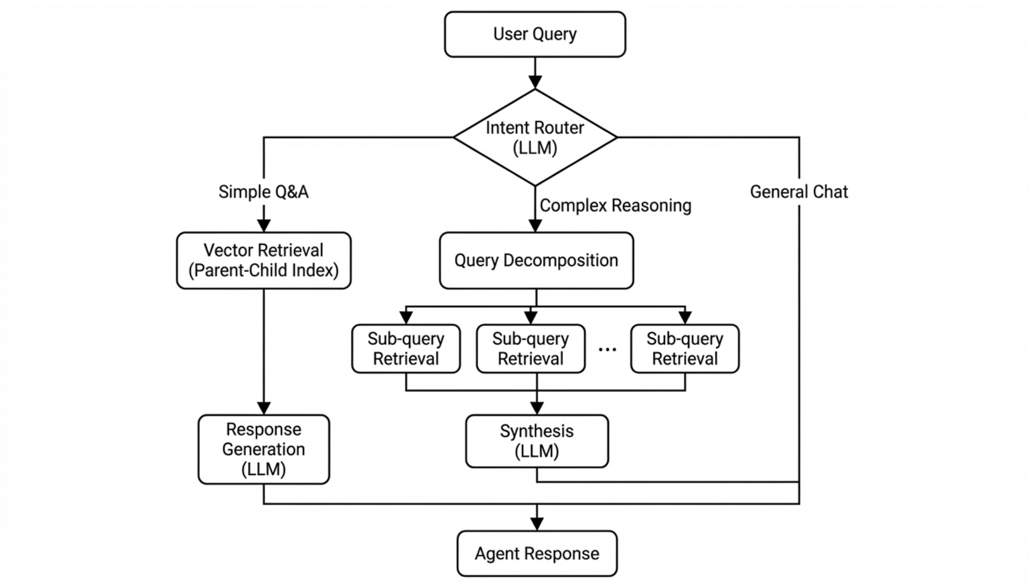

Figure 7.3: Architecture of the Agentic RAG system.

This ensures that the final synthesis incorporates information distributed across disjoint documentation sections.

7.4.4 Retrieval Optimization Pipeline

To mitigate the "lost-in-the-middle" phenomenon common in long-context retrieval, a hybrid two-stage refinement strategy was implemented:

7.4.4.1 LLM-Based Pointwise Reranking

The initial vector search retrieves the top $2k$ candidate parent documents (default $k = 5$). To filter out noise from approximate nearest neighbor search, a Pointwise Reranking mechanism is applied. Each candidate is evaluated by an LLM (GPT-5.1) which assigns a relevance score $s \in [0, 1]$. This step effectively removes documents that share lexical overlap but lack contextual relevance to the specific engineering query.

7.4.4.2 Heuristic Fallback Mechanism

To ensure system robustness, a heuristic ranking function serves as a fallback mechanism in cases of API latency. This function aggregates keyword overlap, exact phrase matching, and positional weighting (prioritizing introductory definitions), ensuring reliable operation even under degraded network conditions.

7.4.4.3 Context Windowing

For regulatory sections exceeding 2,000 characters, a relevance-focused windowing strategy is applied. The system extracts the first N characters of the document, truncating at the nearest sentence boundary to preserve semantic coherence. This reduces context window usage while maintaining the integrity of key definitions.

7.4.5 Closed-Loop Verification and Recursive Retrieval

A critical limitation of generative models in engineering contexts is the risk of hallucination. To address this, the framework incorporates a Self-Correcting Feedback Loop, shifting the architecture from a linear "Retrieve-Then-Generate" pipeline to a recursive "Generate-Verify-Refine" cycle.

7.4.5.1 Domain-Aware Post-Answer Verification

Upon generating an initial response, a Post-Answer Verifier module evaluates the content against VECTO domain constraints. Acting as a quality assurance auditor, the model checks:

1. Relevance: Whether the answer addresses the specific sub-domain (e.g., "Driving Cycles") identified by the Domain Router.
2. Completeness: Whether the answer includes specific enumerated lists (e.g., "Long Haul", "Urban") required by the query.
3. Validity: Whether the answer avoids fabricating unsupported regulatory claims.

7.4.5.2 Feedback-Driven Query Refinement

If the verifier rejects the response (validity score $< \theta_{verify}$), a Recursive Retrieval process is triggered. The system constructs a refined query vector using a hybrid expansion strategy:

$$Q_{refined} = Q_{original} \oplus K_{domain} \oplus S_{feedback} \tag{7.3}$$

where K_{domain} represents injected domain-specific nomenclature (e.g., "specific names list") and $S_{feedback}$ represents the missing information identified by the verifier. The refined query is re-submitted with relaxed retrieval parameters ($k' = k+2$) to expand the search space, effectively correcting incomplete answers.

7.4.6 Conversation Memory and Context Management

To support iterative workflows, a hierarchical memory structure maintains session context:

- **Recent Context:** The last 5 turns are retained verbatim to resolve anaphoric references (e.g., "What is its default value?").
- **Key Facts Store:** Technical entities such as XML parameters and numerical constraints are extracted via structured output and persisted globally.
- **Semantic Compression:** Older turns are summarization to manage token usage without losing technical continuity.

7.4.7 Prompt Engineering and Output Constraints

Prompt engineering was focused on enforcing factual grounding. For knowledge-based responses, the model is explicitly constrained to cite specific numerical values and procedural steps found solely within the retrieved text. Furthermore, structured tasks (intent classification, decomposition) utilize Pydantic schemas enforced via the `with_structured_output` method, ensuring downstream reliability without heuristic parsing.

7.5 Experimental Evaluation

To quantitatively assess the reliability of the proposed framework and its applicability to VECTO modelling tasks, a systematic evaluation was conducted using the RAGAS (Retrieval-Augmented Generation Assessment) framework. Rather than focusing on isolated architectural components, this evaluation aims to characterize overall system behaviour across different query types and to analyse how retrieval limitations and answer abstraction influence metric outcomes. This section describes the experimental setup, dataset construction, evaluation protocol, and identified limitations.

7.5.1 Evaluation Design

The evaluation adopts an observational design based on a fixed system configuration. Queries are stratified by complexity to reflect typical interactions encountered during VECTO parameterization. The objective is not to perform component-wise ablation, but to examine how system performance varies between simple factual queries and complex synthesis queries that require integration of information across multiple documentation sections.

7.5.1.1 Test Dataset Construction

The evaluation dataset consists of eighteen queries covering a representative range of modelling tasks:

- *Simple factual queries*: Direct lookup questions such as hardware requirements or supported file formats.
- *Procedural queries*: Questions requiring stepwise explanation, for example configuration workflows or declaration procedures.
- *Complex synthesis queries*: Questions requiring integration of definitions, correction factors, and modelling logic, such as fuel consumption calculation or hybrid powertrain handling.

These categories were introduced to distinguish extractive retrieval behaviour from multi-step reasoning behaviour.

Ground truth reference answers were manually authored based on the official VECTO 4.x User Manual and related regulatory documentation. Reference answers were intentionally formulated at a compact, engine-level abstraction consistent with regulatory writing style. This choice reflects practical engineering documentation, but also introduces abstraction differences relative to physics-expanded generated explanations.

7.5.1.2 Evaluation Protocol

All queries were processed using a single, fixed system configuration. Generated answers were evaluated using RAGAS v0.1.x with `deepseek-chat` as the judging model. The temperature was fixed at $T = 0.1$ to ensure deterministic generation. A retrieval parameter of $k = 5$ was used throughout, and the maximum context length was limited to 8,192 tokens.

The reported metrics include Faithfulness, Answer Relevancy, Context Precision, Context Recall, and Answer Similarity. These metrics are interpreted primarily as indicators of retrieval coverage and answer grounding rather than as absolute measures of language model quality.

7.5.2 Limitations and Future Directions

Several limitations of the current evaluation and system implementation should be acknowledged.

7.5.2.0.1 Dependence on Ground Truth Formulation RAGAS metrics exhibit sensitivity to reference answer abstraction. Compact ground truth formulations penalize technically correct but more explanatory system outputs. This effect is particularly pronounced for complex synthesis queries and contributes to reduced Answer Similarity and Context Precision scores.

7.5.2.0.2 Diagram and Figure Accessibility A substantial portion of VECTO system knowledge is conveyed through figures and flow diagrams. As the current pipeline operates on text-only documents, this information is not retrievable, directly impacting Context Recall and indirectly affecting Faithfulness. This represents a multimodal retrieval limitation rather than a modelling error.

7.5.2.0.3 Implicit Workflow Reconstruction Complex questions often require reconstruction of modelling workflows that are distributed across multiple documentation sections. In such cases, the system relies on general engineering reasoning to bridge missing links, which improves practical usability but is penalized by context-based evaluation metrics.

7.5.2.0.4 Regulatory Version Management The current implementation does not automatically track documentation updates across VECTO releases. Future work should incorporate version-aware indexing and change detection to ensure continued regulatory alignment.

7.5.2.0.5 Uncertainty Representation At present, the system always produces a single consolidated answer, even when documentation is ambiguous. Future extensions should include confidence estimation or uncertainty signalling to reduce the risk of over-trust in borderline cases.

7.5.2.0.6 Multilingual Extension The framework currently targets English-language documentation. Extending retrieval and generation to additional European languages would improve applicability in international engineering environments.

8

Results

This chapter presents the simulation results obtained from the VECTO declaration-mode model of the fuel-cell heavy-duty vehicle. The analysis focuses on vehicle-level dynamic behaviour, energy flow characteristics within the electric drivetrain, and the utilisation of the rechargeable electrical energy storage system (REESS) under a representative long-haul mission profile. In addition, practical modelling limitations encountered during the attempted transition towards engineering-mode simulations are discussed.

8.1 Limitations of declaration-mode-based modelling

During the course of this study, attempts were made to extend the analysis by transitioning from declaration mode to engineering mode within VECTO, with the intention of enabling greater flexibility in parameter modification and control strategy representation. In practice, this transition revealed several toolchain limitations.

It was observed that XML-based vehicle definitions created for declaration mode could not be directly reused in engineering mode without triggering software errors. In particular, the inclusion of the Fuel Cell IEPC configuration resulted in a *NullReferenceException*, indicating that certain component attributes were not fully supported or instantiated within the engineering-mode framework. Despite communication with the VECTO development team, these issues could not be fully resolved within the timeframe of this thesis.

Consequently, the results presented in this chapter are based exclusively on declaration-mode simulations. While this choice limits the flexibility of parameter manipulation and control strategy modelling, it is fully aligned with the regulatory scope for which VECTO is designed. Within this framework, the results obtained in this thesis provide a consistent and representative assessment of vehicle-level energy behaviour for long-haul fuel-cell heavy-duty applications. At the same time, the observed modelling constraints clearly delineate the boundary between regulatory energy assessment and detailed engineering optimisation, emphasising the complementary role of forward simulation environments such as GSP.

8.2 Vehicle dynamics and drive cycle tracking

As a first step, the longitudinal speed response of the vehicle was analysed to assess the consistency between the regulatory simulation environment and the forward engineering simulation.

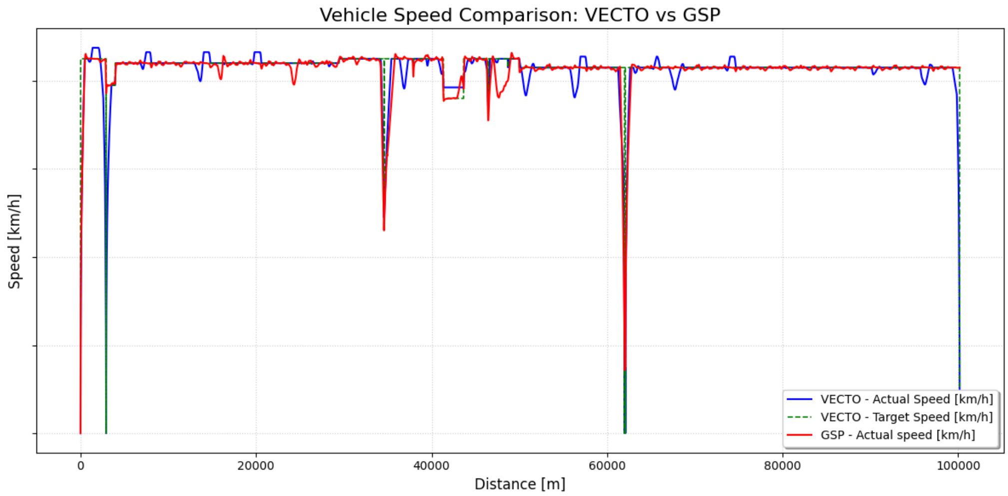

Figure 8.1: Comparison between target vehicle speed and simulated actual vehicle speed for the long-haul mission profile.

Figure 8.1 compares the prescribed target speed of the long-haul mission profile with the simulated vehicle speed obtained from both GSP and VECTO.
Overall, the two simulation environments produce very similar speed trajectories over the full driving cycle, indicating a consistent representation of vehicle longitudinal dynamics at the mission level. This agreement confirms that, under comparable boundary conditions, both tools are capable of reproducing the intended long-haul operating profile with similar steady-state behaviour.
However, differences can be observed during phases where the target speed exhibits rapid changes. In these regions, the vehicle speed predicted by VECTO follows the target speed with abrupt transitions, whereas the GSP simulation shows a smoother speed response. This behaviour is consistent with the modelling philosophy discussed in the earlier chapters: Although both tools reproduce comparable mission-level speed trends, their formulations differ: VECTO is treated as a backward regulatory assessment tool, whereas GSP resolves forward time-domain vehicle and powertrain dynamics.VECTO relies on a simplified driver and control representation tailored to regulatory assessment, whereas GSP resolves vehicle and powertrain dynamics with higher temporal fidelity. As a result, VECTO exhibits less damping of transient speed changes, which is acceptable within its intended regulatory scope.
Minor deviations between target and actual speed are primarily observed during transient events such as acceleration phases and changes in road load. These deviations are consistent with the simplified driver and control logic implemented in declaration mode and do not indicate numerical instability or infeasible operating points.

The corresponding vehicle acceleration profile is shown in Figure 8.2. The acceleration levels remain within physically reasonable limits throughout the mission, further supporting the validity of the vehicle dynamics representation.

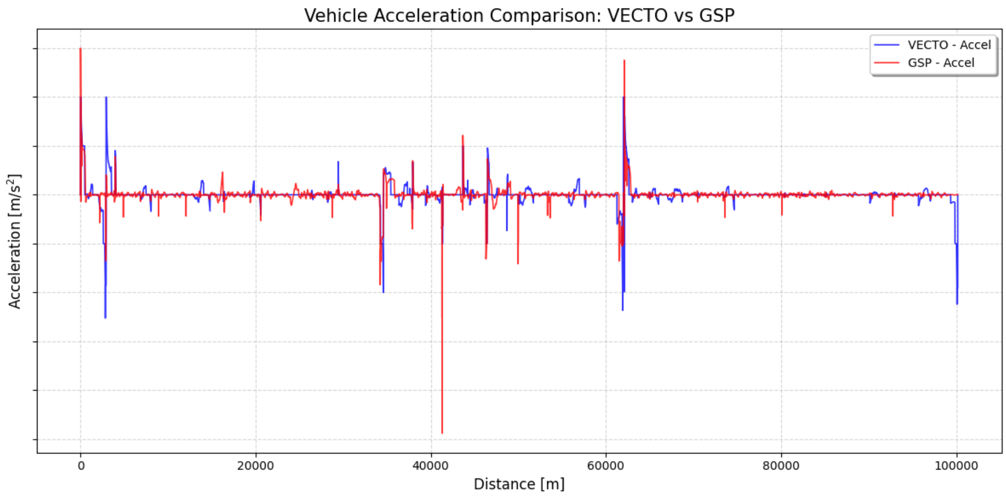

Figure 8.2: Simulated vehicle acceleration profile over the long-haul mission.

Overall, the close agreement between target and actual speed demonstrates that the VECTO model provides a stable and consistent basis for subsequent analysis of energy consumption and component-level behaviour.

8.3 Energy flow and battery utilisation behaviour

The energy flow within the electric drivetrain was analysed with particular focus on the rechargeable electrical energy storage system (REESS), as the interaction between the fuel cell system and the battery plays a central role in fuel-cell long-haul applications. Figure 8.3 illustrates the REESS power profile over the mission, highlighting alternating charging and discharging phases associated with traction demand, regenerative braking, and power balancing between the fuel cell system and the battery.

Overall, the battery power profiles obtained from the GSP and VECTO simulations exhibit similar temporal trends over the long-haul mission. This indicates that, at a mission-aggregated level, both simulation environments impose a comparable energy buffering role on the REESS, despite differences in modelling detail and control implementation. Deviations between the two profiles can be observed during transient operating phases, which is consistent with the different simulation philosophies: GSP resolves drivetrain and control dynamics using a forward engineering simulation framework, whereas VECTO just use the battery power to fill the gap between current required energy and fuelcell throughput.

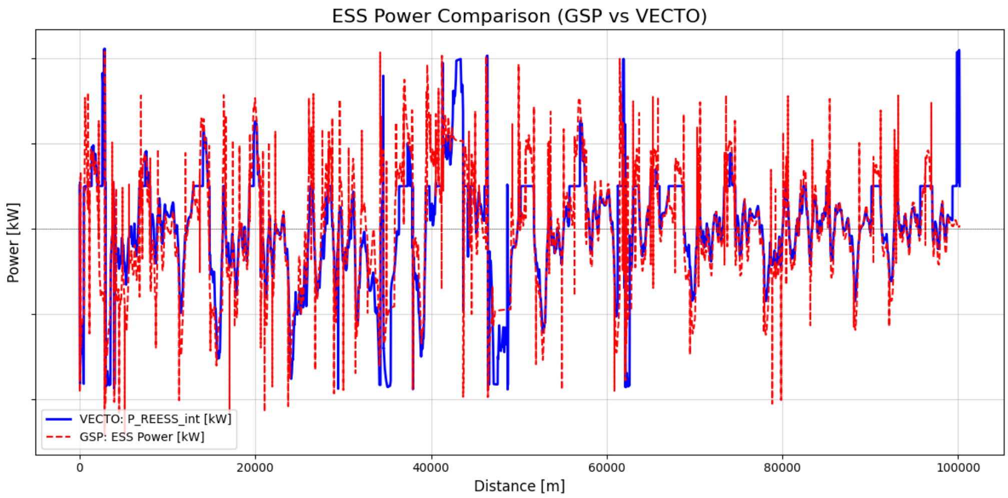

Figure 8.3: Battery power profile over the long-haul mission, showing charge and discharge events of the REESS.

Figure 8.4 compares the REESS state-of-charge (SoC) evolution obtained from the VECTO and GSP simulations over the long-haul mission. Both simulations exhibit comparable SoC trends at the mission scale, indicating that the REESS fulfils a similar energy-buffering role under long-haul operation. However, a consistent offset in the absolute SoC level is observed, and the GSP simulation does not return exactly to its initial SoC by the end of the mission.

This behaviour is consistent with the different modelling objectives and system boundaries of the two simulation environments. VECTO is primarily designed for regulatory energy assessment and employs a simplified representation of powertrain control and auxiliary loads. Its charge-sustaining behaviour is therefore enforced at an aggregated level, focusing on mission-level energy balance rather than detailed component dynamics. In contrast, GSP is an engineering forward simulation environment in which additional subsystems and internal control interactions can be represented explicitly. In particular, the inclusion of thermal management and cooling-related modules introduces additional electrical loads and transient energy exchanges that are not resolved with the same level of detail in the regulatory model. Consequently, the REESS in GSP can be utilised more actively as an energy buffer to accommodate transient power demands and auxiliary loads, leading to a lower average operating SoC and a non-zero terminal SoC offset for a single mission without an explicit terminal constraint.

Importantly, the terminal SoC offset in GSP does not necessarily indicate an inconsistency in the overall energy balance, but rather reflects the absence of a requirement to exactly restore the initial SoC at the end of one driving mission. Over longer horizons or repeated mission cycles, the SoC behaviour is expected to converge towards a statistically charge-sustaining operating range, whereas the regulatory tool emphasises comparability and repeatability of mission-level results.

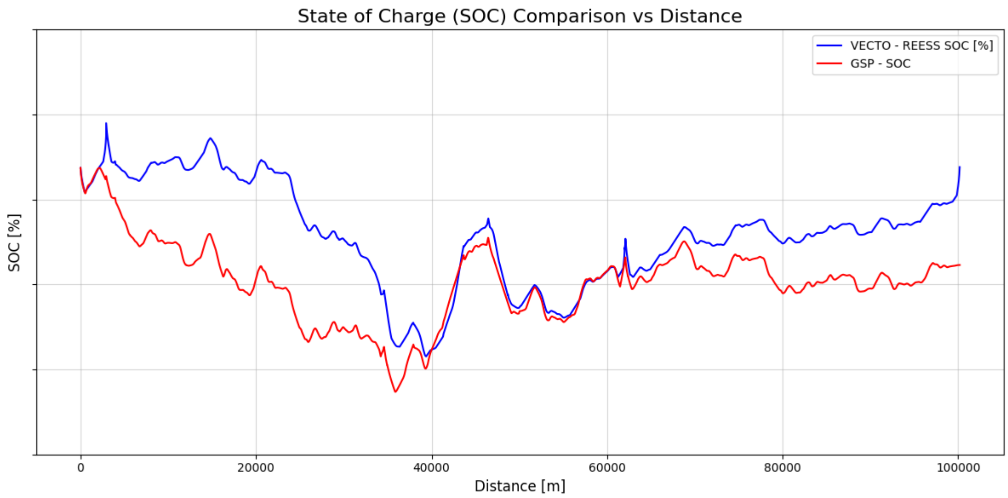

Figure 8.4: State-of-charge (SoC) evolution of the REESS during the long-haul mission.

To further assess battery utilisation, the REESS current profile is presented in Figure 8.5. The current magnitude and frequency reflect the repeated charge–discharge cycles induced by traction demand and energy buffering. Periods of higher current correspond to acceleration phases and load transients.

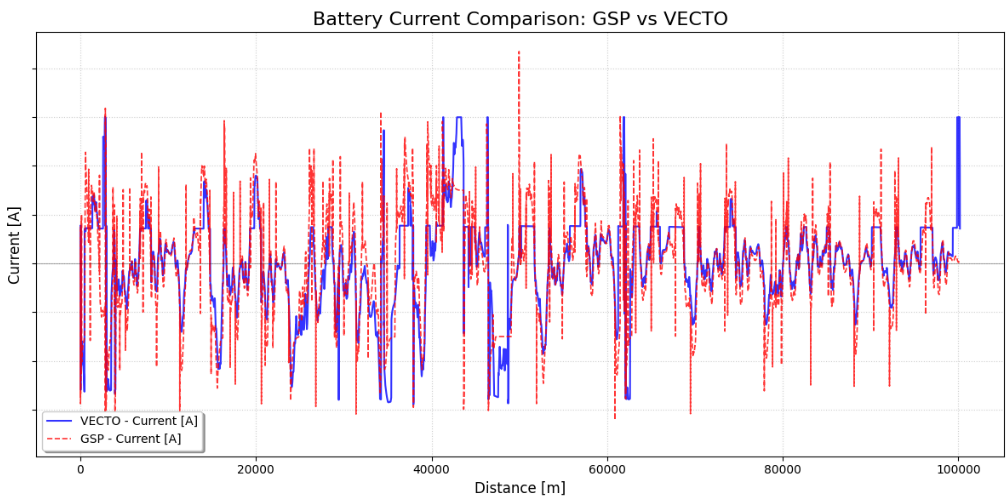

Figure 8.5: REESS current profile over the long-haul mission.

The internal power losses associated with battery operation are shown in Figure 8.6. Losses are predominantly concentrated during periods of elevated current, indicating that resistive effects dominate under high-load conditions. Although the battery model employed in VECTO is simplified compared to forward simulation tools, the loss trends remain physically consistent.

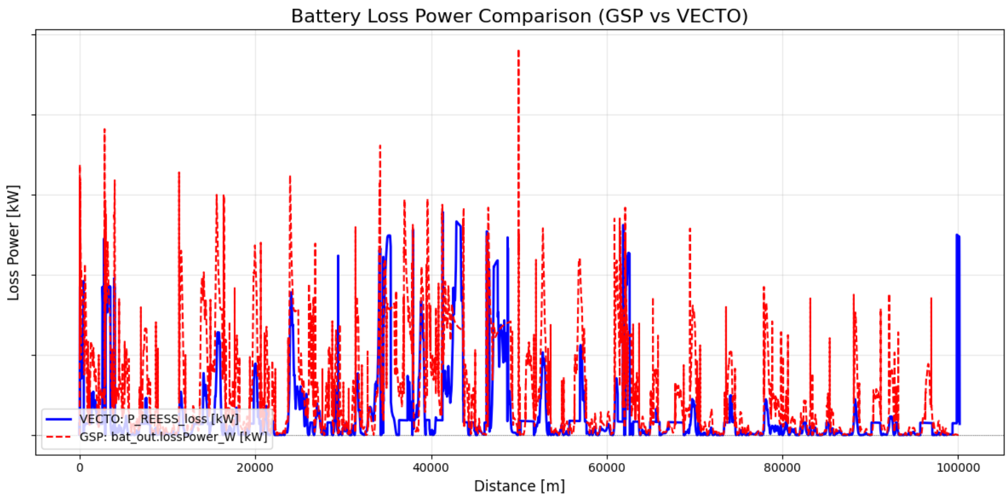

Figure 8.6: Estimated power losses within the REESS during the long-haul mission.

8.3.1 Cumulative Hydrogen Consumption Rate: GSP vs VECTO

To complement the analysis of energy flow and battery utilisation, Figure 8.7 illustrates the cumulative average hydrogen consumption rate for the studied fuel cell heavy-duty truck under both VECTO and GSP simulations. The metric, expressed in kg/100 km, enables a direct comparison of fuel efficiency trends along the mission distance.

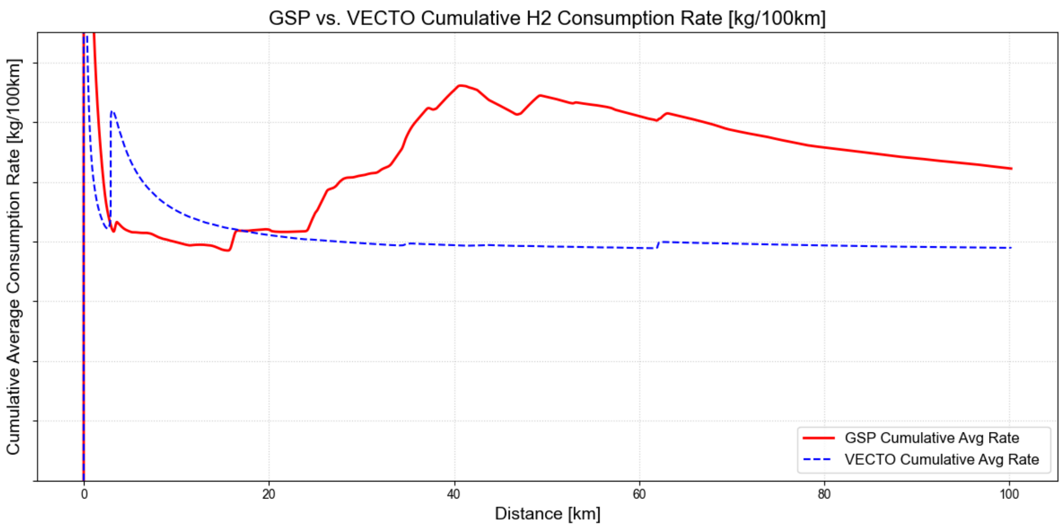

Figure 8.7: Cumulative average hydrogen consumption rate comparison between GSP and VECTO simulations.

The results reveal a systematic deviation between the two simulation environments: the GSP simulation converges to a cumulative average rate approximately 33% higher than the stabilized value observed in VECTO. This discrepancy is attributed

to the fundamental difference in simulation paradigms: VECTO employs a backward-facing, quasi-static energy accounting method optimised for regulatory compliance, whereas GSP resolves the powertrain dynamics in a forward, time-domain fashion. In particular, the transient nature of fuel cell power delivery and auxiliary loads—such as those from the compressor and thermal management systems—are more explicitly captured in GSP. As a result, GSP may report higher instantaneous demands, especially during phases of steep gradients or rapid accelerations, which accumulate to a higher total fuel consumption over the mission.
This divergence underscores the importance of context when interpreting simulation results. While VECTO provides a consistent and regulation-aligned baseline, it may under-represent transient inefficiencies and overshoot events that are critical from a design and control perspective. Conversely, GSP reflects a more realistic dynamic picture of the energy flow, albeit at the cost of simulation complexity and parameter sensitivity.
The next section investigates how these modeling philosophies influence the estimated battery throughput, providing further insight into hybridisation behaviour and energy management effectiveness under both regulatory and engineering-oriented simulations.

8.3.2 Energy Flow and Battery Utilisation

The evolution of the state of charge (SoC) of the Rechargeable Electrical Energy Storage System (REESS) provides key insight into the energy management behaviour of the hybrid powertrain. In parallel, the fuel cell system power output reflects how transient power demands are distributed between the available energy sources.

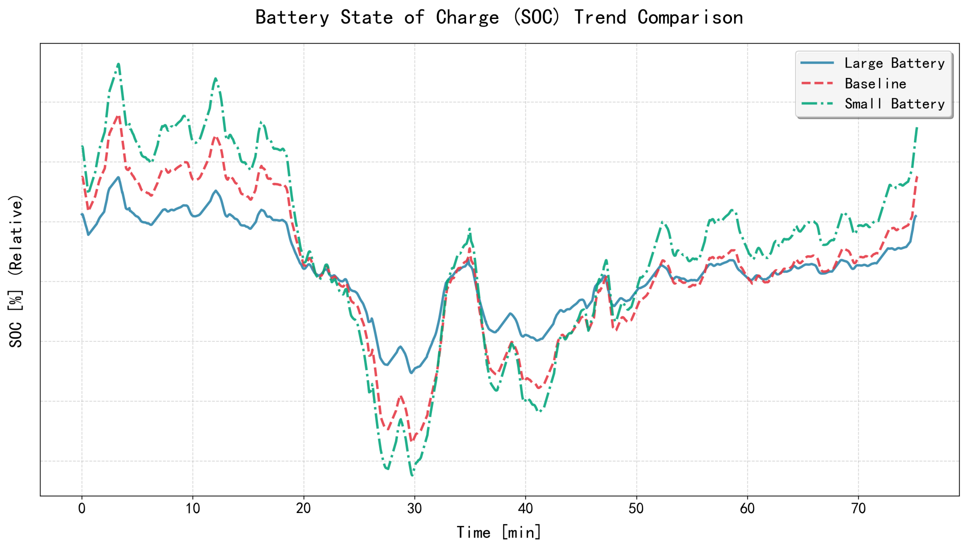

Figure 8.8: State-of-charge (SoC) evolution of the REESS for three battery capacity configurations

Figure 8.8 shows the SoC trajectories of the REESS for the three investigated battery capacity configurations. Clear differences can be observed in both the amplitude of

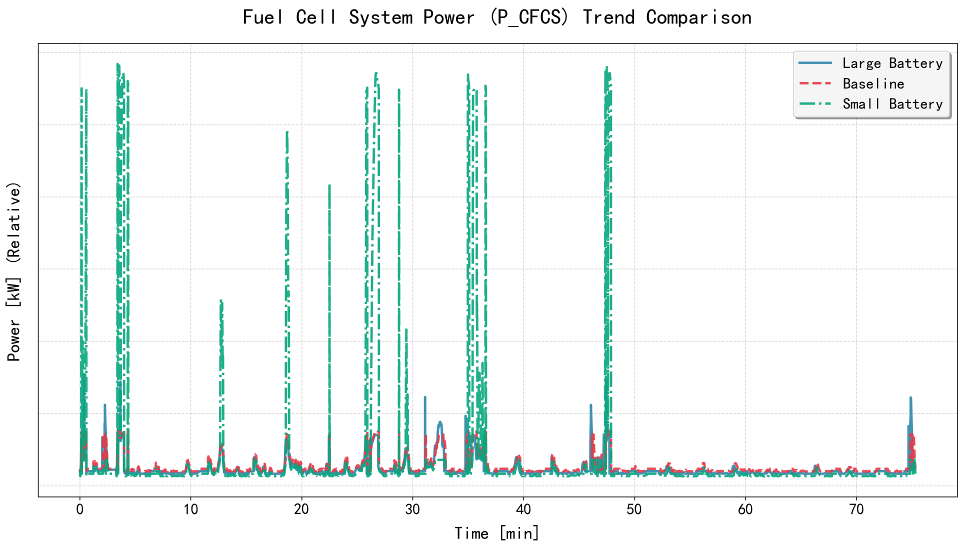

Figure 8.9: Fuel cell system power output (P_{CFCS}) for three battery capacity configurations

the SoC fluctuations and the absolute SoC level.

The Small battery configuration exhibits the largest relative SoC variations, whereas the Big battery configuration shows the smoothest trajectory over the mission. This behaviour is physically intuitive, as the relative SoC change is inversely proportional to the available energy capacity. For a given amount of exchanged energy, a smaller battery undergoes a larger relative change in stored energy, while a larger battery provides greater buffering capability and therefore attenuates short-term fluctuations.

In addition to the fluctuation amplitude, a systematic shift in the average SoC level can be identified. The Small battery configuration maintains a consistently higher SoC compared to the Baseline and Big battery cases. This indicates that the underlying energy management strategy in VECTO adapts to the available battery capacity by limiting deep charge–discharge excursions for smaller energy storage systems. Such behaviour is consistent with common hybrid control philosophies, where smaller batteries are protected from excessive cycling to preserve robustness and maintain sufficient reserve for transient events.

The corresponding fuel cell system power outputs are shown in Figure 8.9. A clear capacity-dependent trend can be identified: as the battery capacity decreases, the fuel cell power becomes increasingly dynamic, exhibiting more frequent and more pronounced transient peaks.

In the Small battery configuration, the fuel cell responds more directly to rapid variations in traction power demand, leading to larger short-term power excursions. In contrast, the Big battery configuration results in a significantly smoother fuel cell power profile, indicating that the battery effectively acts as a transient power buffer.

Taken together, Figures 8.8 and 8.9 highlight the fundamental role of battery capacity in shaping the energy flow dynamics of the hybrid fuel cell powertrain. A larger battery enables stronger decoupling between the instantaneous vehicle power

demand and the fuel cell operating point, allowing the fuel cell to operate in a narrower and more stable region. Conversely, a smaller battery reduces the available buffering capability, forcing the fuel cell to compensate for a larger share of short-term power variations.
It should be noted that the internal energy management logic of VECTO is not explicitly accessible to the user. Therefore, the present analysis does not attempt to infer the exact control laws governing the power split between the fuel cell system and the battery. Instead, the interpretation is based on the physically observable system-level behaviour. The consistent trends observed in both the SoC dynamics and the fuel cell power output indicate that VECTO adapts the power distribution as a function of battery capacity, resulting in qualitatively reasonable and physically consistent energy flow patterns.

8.4 RAG-System Quantitative Results and Analysis

Table 8.1 summarizes the quantitative evaluation results of the proposed AI-assisted documentation support system. The reported metrics are interpreted from an engineering and regulatory modelling perspective rather than as generic indicators of language model performance. For VECTO-based vehicle modelling, the primary objectives are to avoid omission of regulatory constraints, ensure consistency with official documentation, and support engineering decision-making.
To better characterize system behaviour, the evaluation queries were grouped into simple factual questions and complex synthesis questions. Simple queries typically correspond to clearly defined documentation sections (e.g., parameter definitions or supported modes), whereas complex queries require integration of information distributed across multiple sections and, in some cases, implicit reconstruction of modelling workflows.

Table 8.1: RAGAS evaluation results for simple and complex query categories.

Metric	Simple	Complex
Faithfulness	91.1%	56.8%
Answer Relevancy	90.2%	78.0%
Context Precision	96.2%	33.9%
Context Recall	76.7%	32.0%
Answer Similarity	85.5%	73.4%

For simple queries, high scores were obtained across all metrics. These questions generally map directly to specific documentation passages, allowing precise retrieval and largely extractive answers. The resulting high context precision and faithfulness indicate that the generated responses closely follow the retrieved regulatory text.
For complex synthesis queries, substantially lower Context Precision and Context Recall values were observed. This behaviour is primarily related to the structure of the VECTO documentation and to limitations of text-only retrieval. Key elements of the modelling workflow, such as power-flow relationships and system architecture, are frequently presented in figures and diagrams, which are not accessible to the current retrieval pipeline. Consequently, parts of the information required to answer complex questions are unavailable to the system, leading to reduced recall.
In these cases, the model tends to compensate by producing physics-based explanatory answers that explicitly describe intermediate steps (e.g., wheel power demand, drivetrain losses, and engine operating point derivation). While these explanations are technically consistent with VECTO's modelling principles, they extend beyond the textually retrievable content. As a result, RAGAS penalizes such answers in terms of context precision and faithfulness, even when the final conclusions are correct.
A further contributing factor is the difference in abstraction level between reference answers and generated responses. The reference answers are intentionally compact and focused on engine-level calculations, whereas the system often provides

expanded end-to-end explanations. This abstraction mismatch also affects Answer Similarity scores for complex queries.
Answer Relevancy remains comparatively high in both categories, indicating that the system generally addresses the intended engineering questions. Lower faithfulness values for complex queries are mainly associated with multi-step reasoning that is logically valid but not explicitly documented in a single retrievable text segment.
From an engineering perspective, the observed trade-off is acceptable: missing regulatory constraints would be more critical than including additional explanatory detail. In practical use, engineers can disregard surplus information, whereas absent constraints may lead to invalid vehicle configurations.

8.4.1 Qualitative Analysis and Practical Deployment

Qualitative inspection confirms these quantitative findings. For well-scoped queries, the system reliably aggregates definitions and constraints while preserving regulatory terminology. For workflow-oriented questions, the system produces coherent explanations that reconstruct modelling steps from partial documentation.
During the Volvo tractor case study, the system was used primarily as a documentation navigation and clarification tool. It facilitated faster identification of parameter definitions, improved consistency between internal simulation terminology and VECTO XML schemas, and reduced iteration cycles caused by misinterpretation of regulatory defaults.
All generated outputs remained traceable to official documentation wherever explicit references were available, ensuring that final modelling decisions remained under full engineer control.

9
Conclusion

This work compared the energy consumption results of a long-haul fuel cell heavy-duty vehicle obtained from VECTO and the Global Simulation Platform (GSP). Although the two tools are based on fundamentally different modelling philosophies, the results show that VECTO is able to reproduce the main vehicle-level performance characteristics in a consistent and stable manner. Key indicators such as speed tracking, mission execution, and overall power demand trends were found to be largely comparable to those from GSP. This suggests that, despite its simplified and regulation-oriented structure, VECTO provides a sufficiently solid basis for calibration and standardized energy assessment at the vehicle level.

Nevertheless, noticeable differences in absolute energy consumption were observed. These deviations are mainly related to the backward simulation approach used in VECTO and its limited representation of auxiliary subsystems, such as cooling and detailed thermal management. In contrast, GSP explicitly models these effects and resolves transient behaviour in a forward time-domain framework. As a consequence, VECTO tends to predict lower energy consumption. This indicates that VECTO results should be interpreted primarily as regulatory reference values rather than as direct estimates of real-world operational performance. For engineering design and system optimisation, forward simulation tools remain indispensable.

Beyond the simulation comparison, this thesis also demonstrated the successful deployment of an AI-assisted VECTO chatbot based on an Agentic RAG framework. The system enables users to retrieve relevant information from manuals and regulatory documentation using natural language queries. In practice, this significantly reduces the time required for model setup and parameter interpretation, while also lowering the risk of misinterpretation. The results show that such tools can provide meaningful support in complex regulatory modelling tasks without replacing engineering judgement.

In summary, this work confirms that VECTO can serve as a reliable regulatory baseline for fuel cell heavy-duty vehicle assessment, while GSP offers the level of detail required for engineering-oriented analysis. The integration of AI-based assistance further improves the usability and robustness of this workflow. Together, these elements form a practical framework for future studies on zero-emission heavy-duty vehicles.[25]

Bibliography

[1] Muhammad Anwar, Desy Apriani, and Irsa Adianita. *Hash Algorithm in Verification of Certificate Data Integrity and Security*. 2021.

[2] Hussein Basma and Felipe Rodríguez. *Fuel Cell Electric Tractor-Trailers: Technology Overview and Fuel Economy*.

[3] Hussein Basma and Felipe Rodríguez. *The European Heavy-Duty Vehicle Market until 2040: Analysis of Decarbonization Pathways*.

[4] Sofia Berglund. *IEPC CO2 Data Influence on VECTO Simulation*. 2025.

[5] Marie Rajon Bernard. *European Union Alternative Fuel Infrastructure Regulation (AFIR)*.

[6] Evangelos Bitsanis et al. "Experimental Evaluation of VECTO Hybrid Electric Truck Simulations". In: *SAE Technical Papers* (2023). ISSN: 0148-7191. DOI: 10.4271/2023-01-0485.

[7] Siliang Cheng et al. "Development of a PEM Fuel Cell City Bus with a Hierarchical Control System". In: *Energies* 9.6 (June 2016), p. 417. ISSN: 1996-1073. DOI: 10.3390/en9060417.

[8] Dg Clima. *Framework Contract CLIMA.C.2/FRA/2013/0007*.

[9] *Commission Implementing Regulation (EU) 2022/1362*. 2022.

[10] *Commission Regulation (EU) 2017/2400 of 12 December 2017 Implementing Regulation (EC) No 595/2009 of the European Parliament and of the Council as Regards the Determination of the CO2 Emissions and Fuel Consumption of Heavy-Duty Vehicles and Amending Directive 2007/46/EC of the European Parliament and of the Council and Commission Regulation (EU) No 582/2011 (Text with EEA Relevance)Text with EEA Relevance*. Jan. 2023.

[11] Simone De Vivo. "Energy performance evaluation of Fuel Cell Heavy-Duty Vehicles for long haul applications: A study of the European fleet through VECTO simulations". laurea. Politecnico di Torino, Apr. 2024.

[12] *DOE Hydrogen and Fuel Cells Program Record*.

[13] *DRIVING RESISTANCES OF LIGHTDUTY VEHICLES IN EUROPE: PRESENT SITUATION, TRENDS, AND SCENARIOS FOR 2025*.

[14] *Estimating the Technical Feasibility of Fuel Cell and Battery Electric Vehicles for the Medium and Heavy Duty Sectors in California*.

[15] *Expansion of VECTO to Include Methods for Fuel Cell Vehicles*.

[16] *Fuel Cell System Cost for Transportation – 2008 Cost Estimate (Revised)*.

[17] *FUEL CONSUMPTION SIMULATION OF HDVS IN THE EU: COMPARISONS AND LIMITATIONS*.

[18] Yunfan Gao et al. "Retrieval-Augmented Generation for Large Language Models: A Survey". In: *arXiv preprint* arXiv:2312.10997 (Mar. 2024). DOI: 10.48550/arXiv.2312.10997. arXiv: 2312.10997 [cs].

[19] Hafiz Muzammil Irshad and Samaneh Shahgaldi. "Comprehensive Review of Bipolar Plates for Proton Exchange Membrane Fuel Cells with a Focus on Materials, Processing Methods and Characteristics". In: *International Journal of Hydrogen Energy* 111 (Mar. 2025), pp. 462–487. ISSN: 03603199. DOI: 10.1016/j.ijhydene.2025.02.300.

[20] Patrick Lewis et al. "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks". In: *Advances in Neural Information Processing Systems*. Vol. 33. Curran Associates, Inc., 2020, pp. 9459–9474.

[21] Huan Li et al. "Equivalent Consumption Minimization Strategy for Fuel Cell Hybrid Electric Vehicle Considering Fuel Cell Degradation". In: *2017 IEEE Transportation Electrification Conference and Expo (ITEC)*. June 2017, pp. 540–544. DOI: 10.1109/ITEC.2017.7993328.

[22] Marek BIELEWSKI. *BATTERIES FOR ENERGY STORAGE IN THE EUROPEAN UNION*.

[23] Michele Martorelli, Matteo Genovese, and Petronilla Fragiacomo. "Enhancing Heavy Duty Vehicle Hydrogen Refueling by Alternative Approach to SAE J2601/2 Protocol and Flow Dynamics". In: *International Journal of Hydrogen Energy* 101 (Feb. 2025), pp. 234–249. ISSN: 03603199. DOI: 10.1016/j.ijhydene.2024.12.378.

[24] O'Hayre. *Fuel Cell Fundamentals*.

[25] Agada Joseph Oche et al. "A Systematic Review of Key Retrieval-Augmented Generation (RAG) Systems: Progress, Gaps, and Future Directions". In: *arXiv preprint* arXiv:2507.18910 (July 2025). DOI: 10.48550/arXiv.2507.18910. arXiv: 2507.18910 [cs].

[26] Nicolò Parola et al. "Impact of Control Strategies on the Degradation of Hybrid Hydrogen-Battery Powertrains in Railway Applications". In: *International Journal of Hydrogen Energy* 177 (Oct. 2025), p. 151529. ISSN: 03603199. DOI: 10.1016/j.ijhydene.2025.151529.

[27] P. Pettersson et al. "Intrinsic Differences between Backward and Forward Vehicle Simulation Models". In: *IFAC-PapersOnLine* 53.2 (2020), pp. 14292–14299. ISSN: 24058963. DOI: 10.1016/j.ifacol.2020.12.1368.

[28] Peeyush Phogat et al. "Hydrogen and Methanol Fuel Cells: A Comprehensive Analysis of Challenges, Advances, and Future Prospects in Clean Energy". In: *International Journal of Hydrogen Energy* 109 (Mar. 2025), pp. 465–485. ISSN: 0360-3199. DOI: 10.1016/j.ijhydene.2025.02.133.

[29] Hajo Ribberink et al. "Electrification Opportunities in the Medium- and Heavy-Duty Vehicle Segment in Canada". In: *World Electric Vehicle Journal* 12.2 (June 2021), p. 86. ISSN: 2032-6653. DOI: 10.3390/wevj12020086.

[30] Shemin Sagaria et al. "From Microcars to Heavy-Duty Vehicles: Vehicle Performance Comparison of Battery and Fuel Cell Electric Vehicles". In: *Vehicles* 3.4 (Dec. 2021), pp. 691–720. ISSN: 2624-8921. DOI: 10.3390/vehicles3040041.

[31] Robb Shawe. "The Impact of Alternative Fuels on New York State: Environmental, Economic, and Infrastructural Implications". In: *Journal of Sustain-*

able Bioenergy Systems 15.03 (2025), pp. 105–119. ISSN: 2165-400X, 2165-4018. DOI: 10.4236/jsbs.2025.153006.

[32] Aditi Singh et al. “Agentic Retrieval-Augmented Generation: A Survey on Agentic RAG”. In: *arXiv preprint* arXiv:2501.09136 (Feb. 2025). DOI: 10.48550/arXiv.2501.09136. arXiv: 2501.09136 [cs].

[33] N. Sulaiman et al. “A Review on Energy Management System for Fuel Cell Hybrid Electric Vehicle: Issues and Challenges”. In: *Renewable and Sustainable Energy Reviews* 52 (Dec. 2015), pp. 802–814. ISSN: 1364-0321. DOI: 10.1016/j.rser.2015.07.132.

[34] *Vecto User Manual.*

[35] *Vehicle Energy Consumption Calculation TOol - VECTO.*

[36] Stefan Venbrant. “Towards a Simulation Environment for Operating Cycle Analysis of Road Transports”. In: ().

[37] Yujie Wang et al. “A Systematic Review of System Modeling and Control Strategy of Proton Exchange Membrane Fuel Cell”. In: *Energy Reviews* 3.1 (Mar. 2024), p. 100054. ISSN: 27729702. DOI: 10.1016/j.enrev.2023.100054.

[38] Volodymyr A. Yartys et al. “HYDRIDE4MOBILITY: An EU HORIZON 2020 Project on Hydrogen Powered Fuel Cell Utility Vehicles Using Metal Hydrides in Hydrogen Storage and Refuelling Systems”. In: *International Journal of Hydrogen Energy*. Special Issue on HYPOTHESIS XV 46.72 (Oct. 2021), pp. 35896–35909. ISSN: 0360-3199. DOI: 10.1016/j.ijhydene.2021.01.190.

[39] Zhao, Y. et al. *Air and Hydrogen Supply Systems and Equipment for PEM Fuel Cells: A Review10.1080/15435075.2021.1946812.*

[40] Chrysovalantou Ziogou et al. “Modeling, Simulation and Experimental Validation of a PEM Fuel Cell systemPEM ”. In: *Computers & Chemical Engineering*. Energy Systems Engineering 35.9 (Sept. 2011), pp. 1886–1900. ISSN: 0098-1354. DOI: 10.1016/j.compchemeng.2011.03.013.

DEPARTMENT OF Mechanics and Maritime Sciences
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden
www.chalmers.se

AVANCEZ
1829
CHALMERS
UNIVERSITY OF TECHNOLOGY