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Development of a modular and scalable electric powertrain platform: Powertrain analysis and constituent features definition

A thesis presented by

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Dedication

I want to thank my family for all the support during this process, especially my parents Sergio and Ana, for their unconditional love and support in each of my decisions. Infinite thanks to Karina for her love, patience, and encouragement in each of the stages of this process and for always push me forward. The journey has been long and despite being far away, they were always on my mind, and became my biggest inspiration from afar to get here.

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Development of a modular and scalable electric powertrain platform: Powertrain analysis and constituent features definition

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Abstract

The new business practices are moving towards a more sustainable future and mobility is one of the most crucial areas to achieve it. Electrification is regarded as the most promising technology to achieve sustainable mobility, but the question is how to offer different solutions to meet different customer requirements with the highest performance, in the shortest development time, and in the most cost-effective way possible. Modularity can drive electrification and provide modular solutions with the necessary foundation to adapt to market trends and customer needs and reduce costs. Therefore, modularity can be the key to achieve the wide-spread adoption of electric vehicles thus more research is necessary. One of the main questions about modularity today is if a modular system can compete with the current conventional systems concerning capacity, efficiency, and performance.

This work is focused on the development of a modular and scalable electric powertrain platform for a heavy-duty truck and it is made up of two main parts. The first part, from a technical point of view, is the powertrain modeling and optimization for a 40 tons capacity truck using various driving cycles and various powertrain topologies to find the one with the highest efficiency and lowest energy consumption and that will be the basis for the platform. The second part, from a more analytical aspect, deals with the analysis of the variance characteristics from the product structure of the electric powertrain to identify critical characteristics and define the main constituent features through a variance sensitivity analysis. With this it is possible to generate the first approximation of the potential feature structure of the modular electric powertrain kit.

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1 Introduction

1.1 Background

The global trend towards urbanization demands sustainable development in all fields. Cities, and transport, energy, water, and waste infrastructures that sustain urban life, are crucial sites for creating more sustainable futures. [1] Transport is one of the fundamental aspects of modern society, thus, a power indicator of future prosperity. Transport systems are complex and cannot be isolated from the city's infrastructure, energy systems, and urbanization. [2] Therefore, transportation had become one of the critical infrastructure sectors since market integration, economic growth, and transport activity are strongly related.

Last decades, congestion in urban road systems has grown exponentially, approaching near capacity in many cities around the world. Traffic increases travel times, fuel consumption, the number of accidents per year, all aspects that affect the health and incomes of households related to noise pollution, air pollution, and the emission of greenhouse gas (GHG) [3]. Moreover, transport is the least diversified energy end-use sector, with about 93% of the sector fueled by petroleum products in 2015. [4] Hence, this sector generates the largest share of greenhouse gas emissions among the industries positioning it as the major contributor to greenhouse gas emissions. The transport sector currently accounts for 8.2 Gt of the global CO_2 emissions and about 24% of direct CO_2 emissions from fuel combustion. Road vehicles, as cars, trucks, buses, and two- and three-wheelers – account for nearly three-quarters of transport CO_2 emissions, remaining stable in 2019 since the turn of the century. [5] This number is projected to remain the largest contributor to global GHG emissions by 2050. [6] Therefore, the transport sector represents the key to climate change and requires an urgent transformational change to meet its full emissions reduction potential. [4]

1.2 Motivation

Since 2000, heavy-duty vehicle (HDV) energy consumption and tailpipe CO2 emissions have increased by 2.6% per year, with trucks responsible for more than 80% of this growth. Despite some improvements in fuel efficiency in recent years, rising emissions and energy on HDVs are driven primarily by greater economic activity and demand for goods, increasing road freight traffic. [7] The global transition towards a low-carbon economy has started, supported by the Paris Climate Agreement in 2015 and the 2030 Agenda of Sustainable Development, mainly influencing the light and commercial vehicle industry. The first-ever EU-wide CO2 emission standard for heavy-duty vehicles was adopted in 2019 and set targets for reducing the average emissions from new HDV for 2025 and 2030.

While the scope of energy efficiency and emissions regulations are being expanded, especially in heavy-duty vehicles, it will be very important to accelerate the development and commercialization of low-carbon technologies, especially for the heavy-duty vehicle sector that lags behind light-duty vehicles. It has been found that comparing the specific CO2 emissions in the different size classes, the impact is much greater in heavy vehicles compared to that of commercial vehicles. The light-vehicle industry has started to move from oil in the last few years, and its recent success in electrifying light commercial vehicles will be able to provide a foundation for the development and deployment of technology and infrastructure, and the necessary support for the introduction of new policies and regulations that encourage the adoption of zero-emission vehicles in heavy-duty sectors and long-distance trips.

1.3 Structure of the thesis

This thesis is part of the project "LiVe: Life cycle cost reduction in electrical distribution transport" from the RWTH Aachen University in conjunction with the “Renewable Mobile” funding program. The main goal of the entire project is to develop a modular drivetrain for electrified trucks that can be scalable, to adapt to different customer requirements and vehicle classes.

This thesis plans to contribute to the definition of the powertrain modules, and the analysis and optimization of the most relevant components of the drivetrain. Some expected results are the analysis of different drivetrain topologies, the identification of the most relevant components of the powertrain, and an analysis of the sensitivity of the powertrain in different perspectives to define the constituent features that can lead the modular design most optimally and cost-effectively.

This work is subsequently organized as follows:

- Chapter 2 covers the introduction to the main concepts used in this work, such as: electromobility, modularity, modeling, and powertrain optimization. Furthermore, a first discussion of the connection between these concepts for this thesis is presented.
- Chapter 3 addresses the concepts in more depth by specifying the methods selected and the reason why they were selected. This chapter gives to the reader all the necessary information to comprehend the subsequent chapters.
- Chapter 4 contains the implementation of the methods and the preliminary results of necessary data for the full method execution. This chapter complements the previous chapter, but this includes tasks and results.
- Chapter 5 is the core of the thesis. It covers in-depth all the analyzes carried out and their respective results divided into two main deliverables: a variance sensitivity analysis for the definition of the constituent features and the analysis of different topologies of the electric powertrain. Furthermore, the two deliverables are integrated as an interdisciplinary final deliverable and its contribution to the development of the modular powertrain is discussed.
- Chapter 6 concludes this work, points out our main findings, discusses our limits and ways to improve the current work, and finally, a proposal for future work for this line of research is presented.

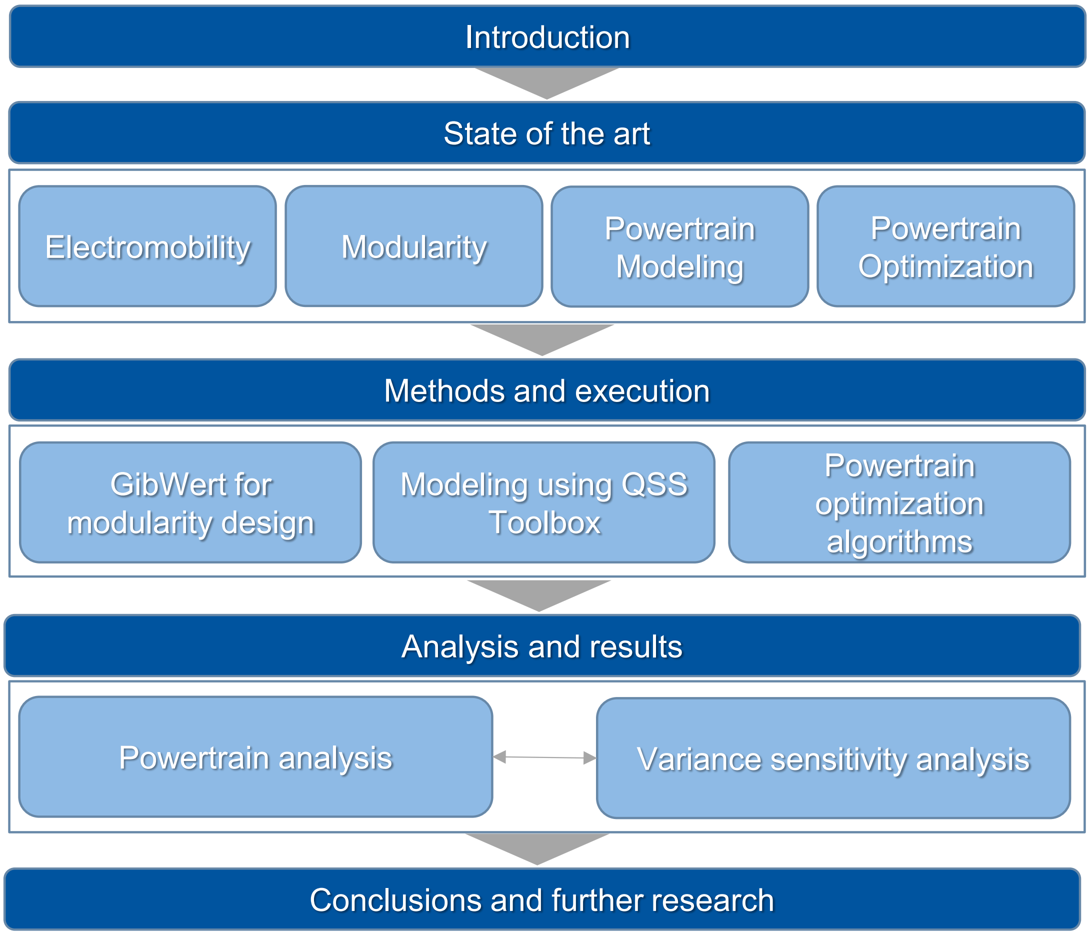


Figure 1.1 Proposed structure of the thesis.

2 State of the art

2.1 Electromobility

2.1.1 Strategic Goals of the European Union

2.1.1.1 Paris Climate Agreement

The global transition towards a low-carbon economy has started, supported by the Paris Climate Agreement in 2015 and the 2030 Agenda of Sustainable Development. During the 21st Conference, 195 countries agreed to reduce carbon and GHG emissions to contribute to limit global warming to “well below 2 °C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5 °C”. The Paris Agreement is the first international climate agreement that refers to the need for net-zero emissions by achieving a balance between GHG emissions by sources and removals by sinks. [7] In order to achieve those established goals by the agreement, mitigation of GHG emissions from power generation and end-use sectors (i.e. transportation, industry, commerce) is necessary. An irreversible shift to low-emission transport, as the greatest producer of carbon and air pollutants, is indeed the solution.

2.1.1.2 White Paper on Transport

According to a 2011 White Paper, by 2050 GHG emissions from transport should be at least 60% lower than in 1990 and move steadily towards zero. This strategy also reunites measures and proposes legislative and non-legislative initiatives meant to accelerate the pace of the shift towards low-emission mobility, accentuating the opportunities arising for the industry, services, energy companies, and investors to contribute to sustainable growth and provide new jobs. The strategy addresses three key levers because of the development of the transport sector towards low-emission mobility: increasing efficiency of the transport system, speeding up the deployment of low-emission alternative energy for transport and moving towards zero-emission vehicles. The targets outlined can be achieved through electric mobility solutions.

2.1.1.3 European Strategy for Low Emission Mobility

The 2016 European Strategy for Low Emission Mobility supported the transition towards low and zero-emission vehicles, building on the aim of the 2011 Transport White Paper. [8] This strategy provides a framework for targeted measures that will speed up the deployment of low-emission alternative energy for transport and remove obstacles to electrification transport. [9] Through this framework, the EU will create enabling conditions and provide strong incentives for low-emission mobility. The action plan requires a long-term engagement of all stakeholders, including Member States of the EU.

2.1.1.4 Regulation (EU) 2019/1242

Despite some improvements in fuel efficiency in recent years, rising emissions and energy on heavy-duty vehicles are driven primarily by greater economic activity and demand for goods. [7] The first emission standard for heavy-duty vehicles was adopted in 2019 and set targets for reducing the average emissions from new lorries for 2025 and 2030. From 2025, manufacturers will have to meet the targets set for the fleet-wide average CO2 emissions of their new lorries registered in a given calendar year. The targets are expressed as a percentage reduction of emissions compared to the EU average in the reference period, a baseline determined from 2019 and 2020 data: by 15% in 2025 and by 30% in 2030. The 2025 target can be achieved using technologies that are already available on the market. The 2030 target will be assessed in 2022 as part of the review of the regulation. The regulation also includes incentives for zero- and low-emission vehicles in the form of super-credits from 2019 until 2024 and a benchmark-based crediting system from 2025 on-wards. [10]

2.1.2 Germany position regarding electric mobility

The Federal Government aims to make Germany a lead market and top provider in the field of electric mobility. Since 2009, the Federal Ministry for the Environment, Nature Conservation, and Nuclear Safety has been supporting companies and research institutes with sophisticated R&D projects related to electric mobility to develop Germany into a lead market for electric mobility. Since 2012, these activities have been funded through the "Renewable Mobile" program, which was launched within the framework of the second economic stimulus program. More than 100 companies and institutes will implement challenging R&D projects by the end of this year with funds of around 280 million euros. [11]

In 2010, the German Federal Government created the National Platform for Electric Mobility (NPE). It covers the whole value chain: representatives of industry, science, and government observe and analyze the development of electric mobility and electric vehicles within the context of the Platform. The thematic focal points are being discussed in working groups regarding Research and Development, Standardization, Education and Qualification, Development of a publicly accessible Charging Infrastructure, and Legal Requirements. [12]

Furthermore, the Federal Ministry for Economic Affairs and Energy is providing one billion euros in funding from the Energy and Climate Fund up until 2022 to establish Germany as a global leader in battery cell production under the European Battery Alliance. The European Battery Alliance is the central platform for dialogue on the future of battery cell production in Europe between the European Member States, the European Commission and European industrial companies. Moreover, the Federal Government is taking the necessary steps to create a regulatory environment in which electric mobility can thrive, and is also providing incentives to boost the demand for electric vehicles: the measures include the purchase grant, uniform charging standards, and privileges for electric car owners, e.g. special parking arrangements. [13]

2.1.3 E-mobility ecosystem

The call for clean energy, have made the transport industry (i.e. governments, manufacturers, suppliers) start moving fast towards comprehensive solutions for the next generation of cost-effective and efficient vehicles. Electromobility (also known as electric mobility or e-mobility) is the most promising key technology to develop a clean and effective transportation system based on vehicles propelled by electricity, to meet the reduction targets for 2025 and 2030.

Electromobility represents the concept of using electric powertrain technologies, clean energy supply as well as charging infrastructure to enable the electric propulsion of vehicles and fleets. Electric vehicles can be classified by their level of electrification, energy storage used, and if they can connect or not to the grid. Most relevant electric vehicles for the industry include full electric vehicles (BEV) and plug-in hybrids (PHEV), as well as fuel cell vehicles (FCV).

On a higher level, electromobility is a complex phenomenon that involves technological development, policymaking, innovation, new business models, new driving behavior, and new linkages between industries. [14] The main actors of this ecosystem are industry, academy, government, investors, entrepreneurs, and end-users. The so-called transition to electric mobility brings various new players into the market, and it will be necessary to establish transfer networks and communication links between stakeholders. Given the number of actors and components involved, different fields of research and development not only technological, but also political, economic, and social aspects are key enablers for the deployment of electric vehicles.

Within the electromobility ecosystem, basic components such as charging infrastructure, electric vehicles, and consumers can be identified. Furthermore, more complex components are required for the deployment of electric vehicles compared to the current automotive industry. As can be seen in Figure 2.1, research and development are made up of different agents which helps policymakers/regulators from any levels of government to define the regulations, incentives, and subsidies for the deployment of the ecosystem. Policies continue to have a major influence on the development of electric mobility. Then, regulators directly influence technology development (for battery, drivetrain, electric components, chargers, etc.), infrastructure deployment, and sales. In the value chain, a new agent can be identified, which are integrators, who oversee technical challenges and are usually existing players, new players, or a combination of both. Finally, the charging stations are directly influenced by the energy producers and the power grid. Most of the links are bilateral between the components, both for data and technology transfer.

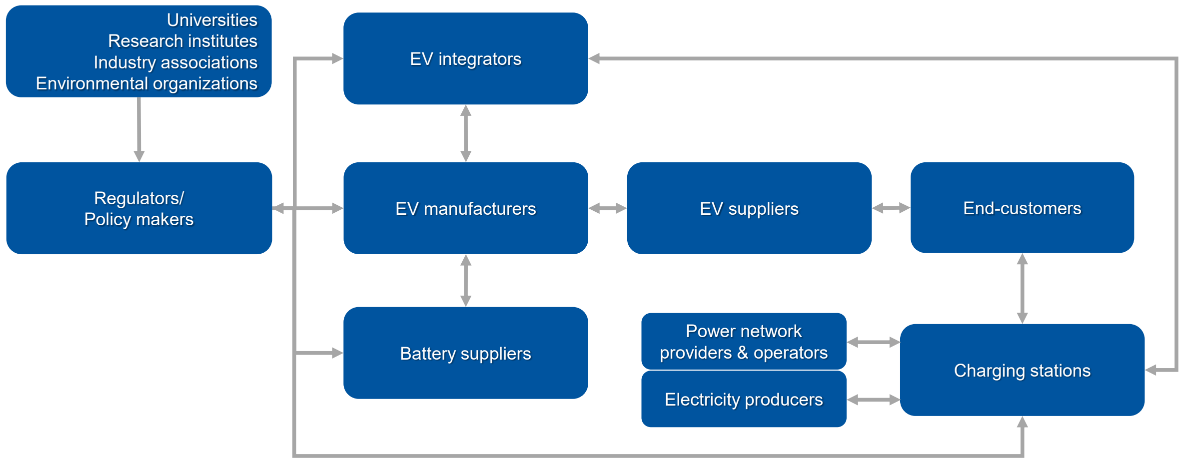


Figure 2.1 E-mobility ecosystem components

The overall ecosystem will work properly if all the components are connected, and if all the actors work together to develop integrated solutions (see Figure 2.1). In fact, for the players in the current automotive industry, it will be essential to make strategic alliances to achieve a gradual transformation of technology and portfolio and transformation of the supply chain.

The most important issues or challenges regarding the transition towards electromobility solutions are related to infrastructure questions, the maturity of technologies, and consumer aspirations (mainly price, until today). [15] Electric vehicles must be able to compete, especially in range and price, with other powertrain concepts as conventional ICE powertrains, to achieve market penetration.

2.1.4 Automotive Technology

Achieving the new strategic objectives for the decarbonization of the transportation industry in a cost-effective way requires the evaluation of current technologies, as well as the development, adoption, and penetration of new ones. Therefore, innovation and new intelligent technologies have a major role to play in shaping future mobility. One of the main focuses is on developing alternative powertrains concepts and, developing and enhancing critical components, such as combustion engines, electric engines, batteries, fuel cells, electronics, etc.

Since electrified powertrains are a fundamental part of the future mobility system, three electromobility drivetrain configurations are presented in this section (shown in Figure 2.2). Electrified vehicles include powertrain architectures such as battery electric (EV), hybrid (HEV), and fuel cell electric (FCV). Greater market success for vehicle electrification came with the combination of ICEs and electric motors in hybrid vehicles[16] with a smoother transition and later with the introduction of the plug-in hybrid electric vehicles and full-electric vehicles.

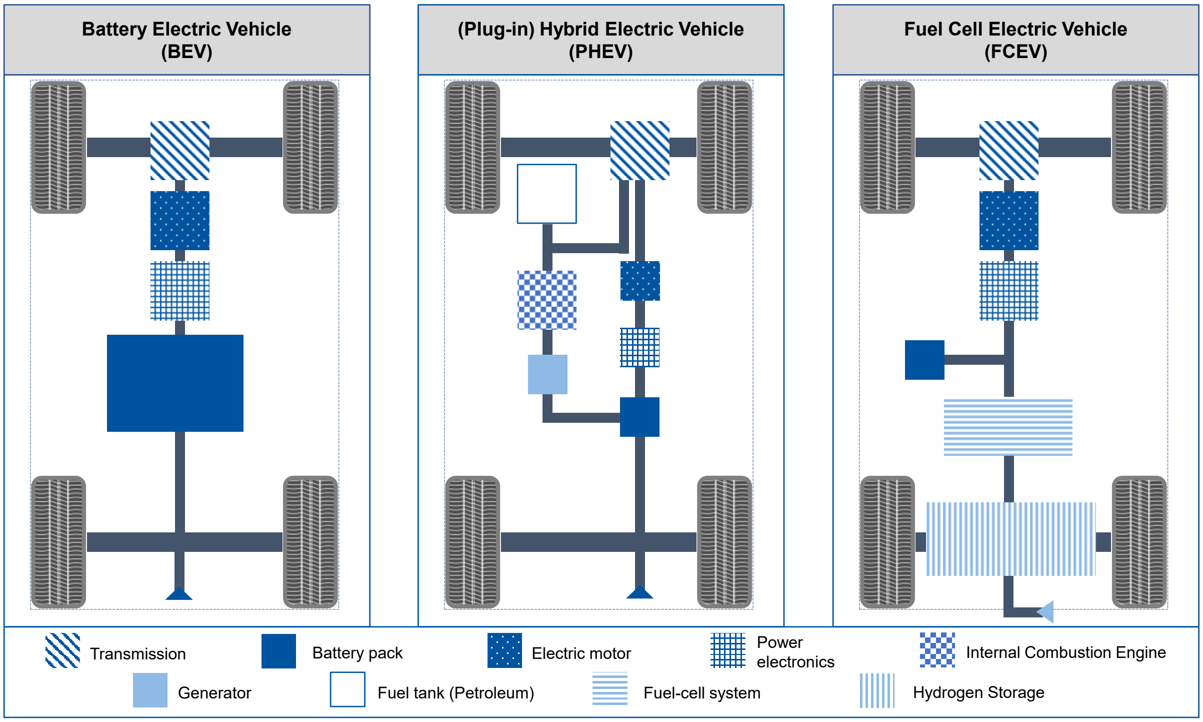


Figure 2.2 Overview of different types of electric vehicles

A BEV transforms the chemical energy of a battery pack into mechanical energy using an electric drive. The electric drive features an electric motor and power electronics. EVs are charged by plugging the vehicle into an electric power grid. While the BEV is very efficient in on-board energy conversion, the battery range may be limited due to the low battery energy density compared to a conventional ICE vehicle.

A conventional HEV uses a battery pack to power an electric drive (using the same principle as BEV) and another propulsion source, usually an internal combustion engine. A PHEV is an HEV with a battery pack that can be recharged from the grid, but the ICE is still the main propulsion system. Using electricity from the grid reduces operating costs and fuel use, relative to conventional vehicles. PHEVs have larger battery packs than HEV. This makes it possible to drive moderate distances using only electricity, commonly referred to as electric range (about 10-50 miles). Beyond battery storage and motor power, there are various ways to combine the power from the electric motor and the engine. The two main configurations are parallel and series. Some PHEVs use transmissions that allow them to operate in either parallel or series configurations (as shown in Figure 2.2), switching between the two based on the drive profile: Parallel hybrid operation connects the engine and the electric motor to the wheels through a mechanical coupling. Both the electric motor and the engine can drive the wheels directly. Series plug-in hybrids use only the electric motor to drive the wheels. The internal combustion engine is used to generate electricity for the motor. Vehicles of this type are often referred to as extended-range electric vehicles. [17]

An FCV uses a propulsion system similar to that of the BEV, where energy stored as hydrogen is converted to electricity by a fuel cell. The most common fuel cell is based on polymer electrolyte membrane technology. The hydrogen storage can be fueled in less than 4 minutes and to have a driving range of over 300 miles. During its conversion process produce no tailpipe emissions, they only emit water vapor and air. Therefore, FCV offers high efficiency, petroleum-free transportation like BEV but without the driving range limitations of the battery. The only limitation for the deployment of the FCVs is the extensive infrastructure required. [18]

The BEV and the FCV have the highest overall well-to-wheel efficiency at 27% and are followed by the parallel HEV at 24% (without considering renewable or nuclear power adoption). A conventional gasoline vehicle has an efficiency of 14%. Thus, electrification can significantly improve overall well-to-wheel efficiency. [19]

Even though electrified powertrains are more expensive than conventional vehicles until today, technology advances are delivering substantial cost cuts. Key enablers are developments in batteries and expansion of production capacity in manufacturing plants for EVs. Other solution implemented includes the redesign of vehicle manufacturing platforms using innovative design architecture, such as modularity, and the application of industry 4.0 to batteries and components production. [20]

2.1.5 Global EV Outlook

The transition to electromobility has grown exponentially in recent years. Even though the level of development of the technology among countries is dissimilar, adoption levels are still incipient in most of the world compared to conventional vehicles. The global EV fleet exceeded 7.2 million in 2019, with sales of electric cars of 2.1 million globally this past year, surpassing the record of 2018. EVs accounted for 2.6% of global car sales and about 1% of global car stock in 2019, registering a 40% year-on-year increase. [20] At the global level, China is leading in terms of market development and adoption. China was the largest electric car market with nearly 1.06 million electric cars sold in 2019, and with 3.3 million units, it accounted for almost half of the global electric car stock (as shown in Figure 2.3). Europe and the United States continue to be positioned as the second and third-largest market in electric vehicles respectively. Pure electric vehicles (BEVs) currently make up 67 percent of the global EV stock. BEV sales are growing faster than those of plug-in hybrid vehicles (PHEV). However, specific markets have very different powertrain preferences, which are influenced by regulatory actions, customer choice, and the availability of specific models.

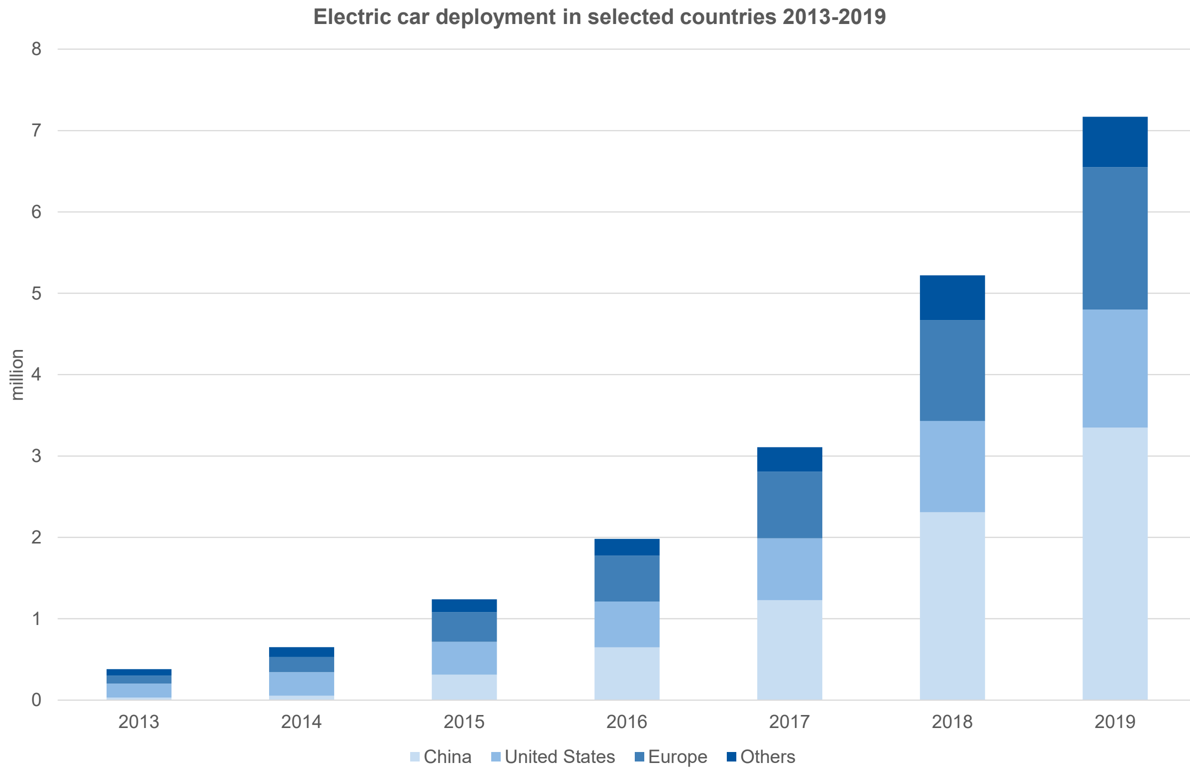


Figure 2.3 Global electric vehicle stock, Global EV Outlook 2020

In terms of market share, Europe hosts the countries with the largest penetration of electric car sales. Norway continues to have the highest market share for sales (56% in 2019), followed by Iceland (23%) and the Netherlands (15%).

While 2019 was marked by continuous technology announcements in EV model diversification and battery performance progress, policy changes in key markets led to electric car sales stagnating in China (-2%, following a purchase subsidy reduction in June 2019 after which sales decreased); declining 10% in the United States, and accelerating in Europe (+50%) relative to 2018. Unlike other key EV markets, Europe has seen significant EV growth. EV sales in Germany and the Netherlands contributed nearly half—44 percent—of overall EV-market growth in Europe; in both countries, units sold increased by about 40,000 units. Those numbers translate into a 2018 growth rate of 55 percent for Germany and 144 percent for the Netherlands. [21]

The EV market has grown quickly, but the dynamics vary by region. In key markets, the transition from ICEs to electric powertrains reached a tipping point in 2019, fueled by more stringent emissions regulations, access restrictions in cities, advancing EV technologies that lengthen driving ranges, and cut prices, and the expansion of the charging network. The same forces will further expand uptake over the coming years, but their evolution will vary by market.

2.2 Modularity

New business practices focus on the customer as the main player in the economy. Further, different customer requirements lead to demand for different solutions with the highest performance and shortest development times. Therefore, organizations must be able to offer products that adapt to market trends and customer needs, to gain greater competitiveness. The modularity concept can provide the necessary foundation for organizations to design products that can respond quickly to customer needs in the best cost-effective way.

Modularity arises from the way a product is physically divided into components. [22] However, it is important to understand that a modular system is different from an integral system (see Figure 2.4). Product architecture is integral when functionals elements are implemented using more than one subsystem but interaction among the subsystem is not well defined. In an integral architecture, the change of a single component may require a new product design. [23]

For a modular architecture, the principal characteristics are structural independence, functional independence, minimization of interfaces, and interactions with other modules and of external influences. Modularity facilitates upgrades, adaptations, modifications, and product assembly and disassembly, it also increases product variety, enables economies of scale, and reduces production time. [24] Moreover, reduces risk and improves efficiency by decomposing a complex system into more manageable modules and interfaces. [25] Once the system or problem has been divided, one can hide the complexity of each part behind abstraction and an interface. [26]

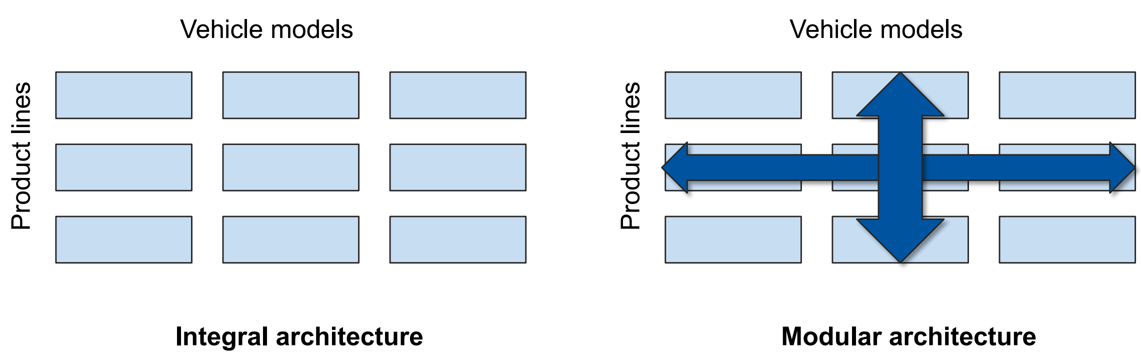


Figure 2.4 Synergies in integral and modular architectures. [27]

Product architectures can show any degree of modularity between these two theoretical extremes of full modularity and full integrality. The increased functional independence and standardization of interfaces in modular product architectures create multiple benefits for the manufacturer. These include reduced complexity and increased interchangeability in engineering, a lower rate of production errors, and reduced component variety in manufacturing. Despite these multifaceted advantages, potential risks, such as high implementation costs and product-specific-technical restrictions, should be analyzed. The risks also provide good reason to pursue an optimal rather than maximal degree of modularity, depending on the individual characteristics of the focal company. [28]

Since the early 20th-century modularity has been applied in many fields such as biology, art, medicine, industrial design, construction, computer science, product design, manufacturing, etc. Industry 4.0, includes modularity as one of its six design principles in order to achieve a successful digital transformation. [29] Within the framework of sustainable development, sustainable design has gained special attention to meet customer requirements and integrate environmental concerns, and the concept of modularity is a fundamental strategy to achieve this. [30]

Nevertheless, there are three general fields where modularity can be applied: modularity in product design, modularity in production, and modularity in-use. The net benefit of modularity is different depending on whether the focus is on the value of modular design, production, or in-use. [31]

2.2.1 Modularity in product design

Modular products are products that fulfill various overall functions through the combination of distinct building modules, in the sense that the overall function performed by the product can be divided into subfunctions that can be implemented by different modules or components. [32] Modules can be rearranged to create different configurations and variants, and even complete product families can be formed based on the same limited number of modules and without increasing the internal complexity of the product. Decisions about how to divide the product are tightly linked to several issues to the entire enterprise as product change, product variety, component standardization, product performance, manufacturability, suppliers, investment, customer requirements, and product development management. [33]

The product architecture maps the functional elements of the product (functional structure) to the physical components of the product (product structure) and then specifies the decoupled interfaces between components. [31] Modularity focuses on decomposing the overall problem into functionally independent sub-problems, in which interaction or interdependence between sub-problems is minimized. Thus, a change in one problem may not affect other sub-problems. [32]

Modular product architectures can show gradual properties of modularity. The relations between modules and the number of functions define the rate of modularity adoption in a product. In Figure 2.5, the most relevant properties for modularity are presented.

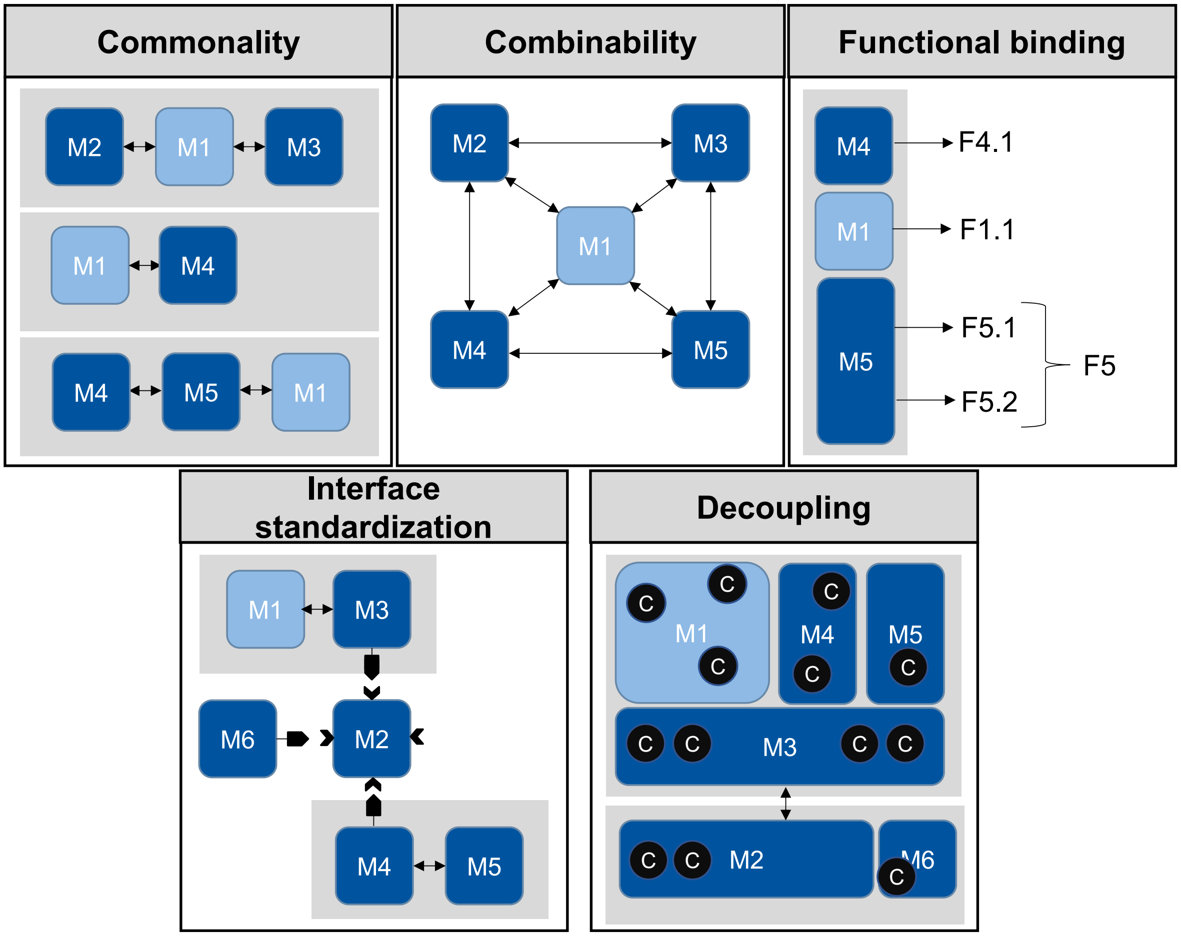


Figure 2.5 Properties of product modularity [34], [35], [23].

Commonality refers to the existence of modules that allows the variety of the product and its use in different product lines or families. The second property of combinability refers to the ability to maximize the combinatorial variety of the assembly from several components or modules, based on a set of options. Furthermore, this property increases the range of options in a product line. Then, functional binding property describes the product in terms of functions and how those functions are related. This property is an essential step in the development of product modular architectures. Further, interface standardizations allow modules to be compatible with each other. The interfaces must be shared and standardized connections between modules and components to achieve multi-level compatibility. The last property refers to the ability of a system to be broken into smaller elements, or modules with a high level of independence.

2.2.2 Modularity applied to the automotive industry

The use of “modules” in the automotive industry is not a new concept. However, for many years vehicles were considered an integral system due to the high dependence between the so-called “modules”. The adoption of the modularity concept was first introduced in the production line, especially in assembly operations involving complex and ergonomically difficult tasks. [36]

The automotive industry has increased its competitiveness over the past 10 years thanks to globalization. This has led OEMs to add new versions to their model range and adapt their designs to specific customer requirements. Modularization has gained attention due to the ability to achieve a wide variety of customer requirements, in the shortest development times and cost-effectively. Therefore, automakers have introduced modular platforms, which have a new and scalable design that allows them to variate some characteristics of the vehicle. Some implemented modular platforms in the current automotive industry are explained next [37]:

MQB (Modularer Querbaukasten) by Volkswagen: started in 2012 in the plant in Ingolstadt (Germany) manufacturing the Audi A3, and continued with the production of the new Volkswagen Golf in 2013 and 2014. The MQB is being used for four of the Volkswagen brands (VW, Audi, Seat, and Skoda) and replaces the standard PQ25, PQ35, and PQ46 platforms, on which the models in segments B, C, and D are assembled. The European manufacturing network will comprise 14 plants for the assembly, initially, of 24 different models of these four brands with an annual production capacity of 3.91 million units.

EMP2 (Efficient Modular Platform) by PSA Peugeot-Citroën: began in the plants of Vigo (Spain), with the new Citroën C4 Picasso, and Sochaux (France) with the new Peugeot 308 in 2013. It will support the assembly of 13 different models in segments C and D of the group’s two brands, which were previously assembled on the PF2 and PF3 platforms. Once it has been fully adopted, 6 of the group’s plants in Europe will assemble on this modular platform, which has a production capacity of 1.87 million units/year.

CMF (Common Module Family) by Renault-Nissan: adopted at the end of 2013 with the production of the new Qashqai in the plant in Sunderland (United Kingdom), and towards the end of 2014 in Renault, beginning with the Espace in the Douai plant (France). The end of the adaptation of the manufacturing network is planned for 2020. Initially, 10 models will be assembled on this new platform in Europe by 2016 —two Nissan and eight Renault, rising to 14 models worldwide when adaptation reaches 100%. The implementation of this platform will involve 7 plants with an assembly capacity of 1.48 million vehicles per year.

UKL (Unter Klasse) by BMW: there are two versions of this platform —UKL1 for front-wheel-drive models and UKL2 for rear-wheel-drive models. 12 Mini and BMW models can be assembled on it. The first model to use this platform was the Mini Hatchback in the plant in Oxford (United Kingdom) in 2014, and other models will gradually be included until the process is complete in the two German plants that are currently producing the BMW series 1 models. The aim is to produce 900,000 vehicles a year on this platform.

MRA (Mercedes Rear-wheel drive Architecture) by Daimler: While the first platform named MFA (Mercedes Front-wheel-drive Architecture) developed for this new vehicle architecture allows only one wheelbase so it cannot be considered a modular platform, the new MRA is a modular platform because it allows for different wheelbases and different vehicle widths. Daimler completes this vehicle architecture with what it calls its Modular Strategy, with common modules for the most important components shared by all its models. This strategy brings added benefits to the production process, especially shorter production time and lower production costs. This MRA modular platform will allow the assembly of 8 models in segments D, E, and F. The plant in Bremen (Germany) started producing the CClass model with this platform in 2014, and the European manufacturing network using this platform will have an annual capacity of 900,000 vehicles.

D2XX (Delta 2 XX) by General Motors: the D2XX will replace the standard Delta II and Theta II platforms, so on a worldwide level it will be possible to assemble 12 models of different brands (Opel, Chevrolet, Buick, GMC, and Cadillac), allowing for the production of 2.5 million vehicles a year by 2018. Production on this platform began in late 2014 with the Chevrolet Cruze at the plant in Lordstown (USA), but it only started to be used in Europe in 2015 at the plant in St. Petersburg (Russia). Only 6 models using this platform will be manufactured in Europe because the others are sold on non-European markets. The estimated annual capacity is about 1 million vehicles.

SPA (Scalable Platform Architecture) by Volvo: the new Volvo XC70 started manufacturing in Europe using the SPA platform in 2015 at the plant in Torslanda (Sweden). With its high modularity, this platform aims to serve as the base for 7 models in the D and E segments and to achieve a production capacity for the network in Europe of 500,000 vehicles a year. Volvo has been investing $11 billion in its new Scalable Platform Architecture over the period 2013 to 2016. This includes the development and implementation of a new engine named Volvo Engine Architecture (VEA).

2.2.2.1 Modularity in Electric mobility

Modularity has been essential for the development of electric mobility. Although the transition from mobility to electrification is undoubted, there are still barriers that avoid its penetration in the market compared to conventional vehicles, among which are the high overall costs and the driving range. Batteries are the main reason for the high prices of electric vehicles, and although their prices are decreasing rapidly, it is going to take a few years to reach a profitable price for manufacturers. OEMs have found in modularity, at component and vehicle level, a strategy to compensate for these losses, which for now are absorbed by themselves.

The power system of an electric vehicle includes a battery pack, a driving system, and a transmission. The modularization of core technologies in electric vehicles allows easy switching between EV models with low transfer and material costs. Designing EV modular and scalable platforms are the key to reducing significant costs, and meeting various customer requirements, without losing performance, acceleration, and interior space.

OEMs are developing their own platforms to be able to use the same platform to build a range of different models for decades. Each platform offers a slightly different approach, depending on the OEM and its objectives. Below are some of the EV platforms that are in development: [38]

MEB (Modular Electrification Toolkit) is a modular system for manufacturing electric vehicles and is currently being developed by Volkswagen. It has been undergoing development since 2015. So far, Volkswagen has presented three e-concept vehicles that are based on the MEB: the e-Bus BUDD-e, which made its debut in 2016, the I.D., which caused a stir at the Paris Motor Show in 2016, and the I.D. BUZZ, showcased at the Detroit Auto Show in January 2017. Some example models presented until today are the Volkswagen ID3 and ID4, Seat El Born, Audi Q4 e-tron, and Skoda Enyaq. The plan is to start series production of ID3 based on the MEB in 2020. Ford signed with Volkswagen Group to use the same platform for a European-market SUV, for 2023.

Global EV Platform was released for GM on March 4, 2020 in Michigan. This platform features high levels of configurability built-in, thanks to the LG Chem-sourced pouch cell Ultium batteries used that allow more flexibility of formats. This platform will use GM-developed motors, feature DC fast charging capability, and Super Cruise ADAS as standard. To date there are no vehicles built on this platform, however, the first vehicle will be the Cadillac Lyriq SUV. Honda will design and built two EV's using GMs EV platform.

e-TNGA (Toyota Electric New Generation Architecture) is the EV platform designed by Toyota in collaboration with Subaru. The key for this platform was the successful implementation of the TNGA architecture rolled out under the latest Prius, and then fully electrified for the first time in the Toyota C-HR shown in 2019 at Shangai Motor Show. The platform can offer three different wheelbase lengths, three different battery sizes, and three power outputs. Toyota aims to offer an initial 10 models globally by 2025.

CMF-EV (Common Module Family-Electric Vehicle) is the modular platform designed by Renault, Nissan, and Mitsubishi. Although the ICE version of this platform is already in use, the EV version is planned to launch in 2020. In 2019 an EV-platform concept was introduced on the Nissan Ariya with a twin-engine powertrain. Renault officially debuted the platform as a CMF-EV architecture early in 2020 with the Morphoz concept, a shape-shifting showcase designed to highlight the flexibility of the platform. In the next two years, it is planned to build 12 models based on the platform.

2.3 Powertrain modeling

2.3.1 Model-based approach

Model-based is an approach widely adopted by the automotive industry today. Although its main application is focused on control development, in practice it has many applications. The complexity of current and future powertrains has placed model-based development as the key to gaining a deeper understanding of the overall system.

Model-based can formulate advanced functional characteristics by using continuous-time and discrete-time computational building blocks, instead of using complex structures and extensive software code. [39] This approach is based on a system-theoretical model understanding, in which a technical product can be regarded as a system, which on the one hand is a component of a superior system and on the other hand can be divided into subsystems. [40]

In general terms, model-based design is a process that enables fast and cost-effective development of dynamic and complex systems, including control systems, signal processing, communications systems on the one hand and mechanical systems on the other hand. In this approach, a system model is at the center of the development process, from development requirements through design, implementation, and testing. At each stage of design, the model reflects the state of knowledge about the designed system. The model is an executable specification that you continually refine throughout the development process. This is especially important for complex systems whose operation is difficult to predict. Then, through simulations performed on the model, we can therefore determine whether the development of the system is going well. The simulation shows whether the model works correctly. [41] These models and associated simulation support tools can provide rapid prototyping, virtual functional verification, and software testing and hardware/software validation. A model-based approach is especially beneficial if its core idea is pervasively persecuted over the whole development process to provide traceability and consistency of information. [42]

In general, model-based applied to vehicle and powertrain modeling allows you to simulate different powertrains configurations and determine if design goals are met. Further, these simulations are fast and cost-effective. Finally, performance and energy balance can be analyzed.

2.3.2 Backward-facing model

The ability of the vehicle model to meet the demands of the drive cycle is the principle assumption of a backward-facing model (see Figure 2.6). The force required to accelerate the vehicle through the time step is calculated directly from the required speed trace. The required force is then translated into a torque (often by assuming some efficiency) that must be provided by the component directly upstream, and the vehicle's linear speed is likewise translated into a required rotational speed. Component by component, this calculation approach carries backward through the drivetrain, against the tractive power flow direction, until the fuel use or electrical energy use that would be necessary to meet the trace is computed. No model of driver behavior is required in such models. [43]

During the optimization routine, the powertrain component sizing is determined by the ability of the component to address both the speed and torque imposed on the component (i.e. power requirements). Backward-facing models rely on efficiency maps that were created based on torque and speed data and usually produced during steady-state real-world testing. This results in the calculation being relatively simpler than forward-facing models (essentially lookup tables instead of state equations) and can therefore be run over relatively larger time steps. [44]

Weaknesses of the backward-facing approach come from its assumption that the trace is met and from the use of efficiency or loss maps. Because the backward-facing approach assumes that the trace is met, this approach is not well suited to computing best-effort performance, such as occurs when the accelerations of the speed trace exceed the capabilities of the drivetrain. Also, because efficiency maps are generally produced by steady-state testing, dynamic effects are not included in the maps and therefore also not in the backward-facing model energy use estimate. [43]

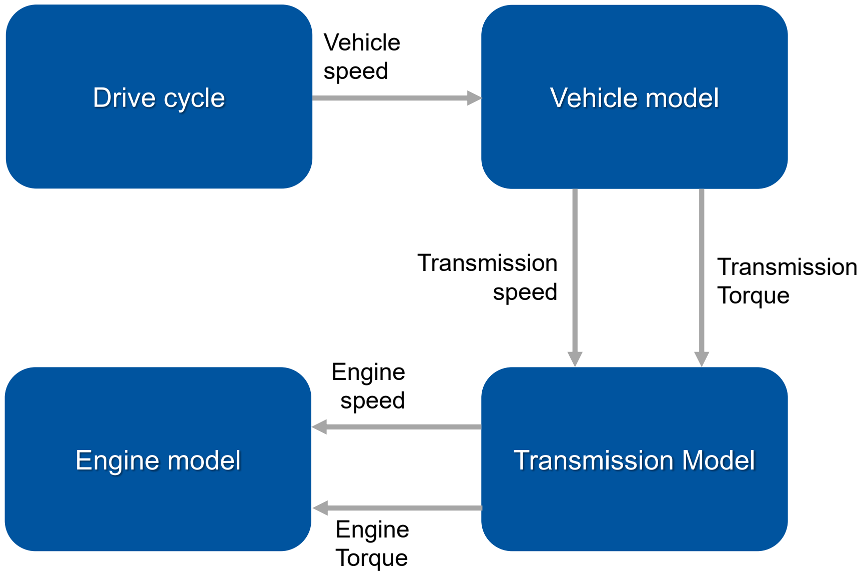


Figure 2.6 Backward-facing vehicle model.

2.3.3 Forward-facing model

A forward-facing vehicle model features a driver model that provides torque demand in the form of desired engine torque and brake torque, to meet the speed trace from a drive cycle (see Figure 2.7). A basic driver model typically uses one or more Proportional-Integral (PI) controllers to achieve the torque demand, regarding the desired speed trace. The torque produced by the engine propagates through the transmission and final drive ratios, before ending up as torque applied at the wheels. This is then exerted to the vehicle mass via force on the tire contact patch. The vehicle speed that results from the applied force is propagated back through the drivetrain and returns to the engine as angular velocity at the crankshaft. Brake torque is applied directly at the wheels. In forward-facing, the speed trace is not imposed into the model, so there will be an error margin between the actual speed and the speed trace. In this kind of model, the aim is minimizing this error through the driver. [44]

The forward-facing approach is particularly desirable for hardware development and detailed control simulation. Because forward-facing models deal in quantities measurable in a physical drivetrain such as control signals and true torques (not torque “requirements”), vehicle controllers can be developed and tested effectively in simulations. Also, dynamic models can be included naturally in a forward-facing vehicle model. Finally, the forward-facing approach is well suited to the calculation of maximum effort accelerations, as they are essentially wide-open throttle events. [43]

The major weakness of the forward-facing approach is its simulation speed. Drivetrain power calculations rely on the vehicle states, including drivetrain component speeds that are computed by integration. Therefore, higher-order integration schemes using relatively small-time steps are necessary to provide stable and accurate simulation results. [44]

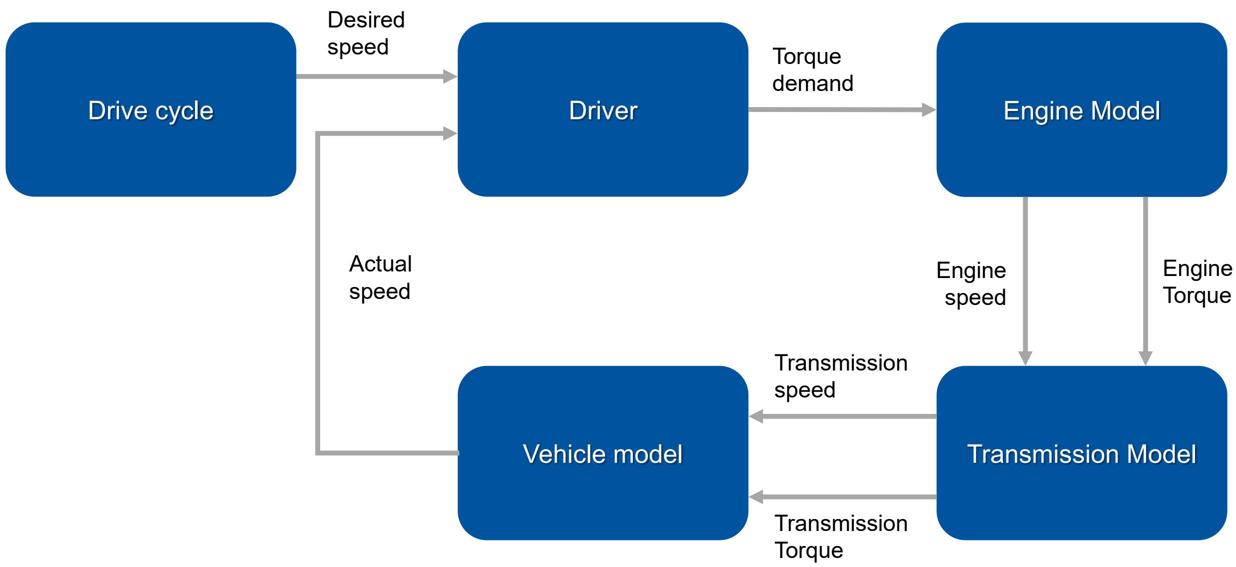


Figure 2.7 Forward-facing vehicle model.

2.4 Powertrain optimization

Electric powertrains can be seen as a complex system. It involves interaction between subsystems. When optimizing a powertrain, multiple design objectives are considered. There are general methodologies on how to model powertrain interactions breaking the overall system into manageable subsystems to later be optimized individually. The complex system design optimization can be solved for the synergized optimum solution that meets the system level targets while complying with the subsystem level constraints. Although there are defined methodologies for modeling the powertrain, there are no defined optimization strategies. The following sections introduce the design method and the optimization approach applied in this thesis.

2.4.1 System-level design framework

When optimizing a system, it is critical to achieving optimal system performance rather than optimal components, because assembling optimized components cannot ensure optimal performance for the overall system. [45] A system-level model should be a complete specification in the sense that it should contain all system properties that can be modeled by the chosen formalism. [46] System-level design is a method where the optimum considers all the components of a system when solving. A good system-level design offers different levels of abstraction and integration between hardware and software. This method has been widely used in electronic and embedded systems and recently applied to the optimization of hybrid and electric vehicles.

The design of a vehicle powertrain can be subdivided into four different layers: topology, component technology, sizing of components, and powertrain controls (see Figure 2.8).

[47] Since electric vehicles have great flexibility in design and control, the system-level design seems to be the right application for this approach.

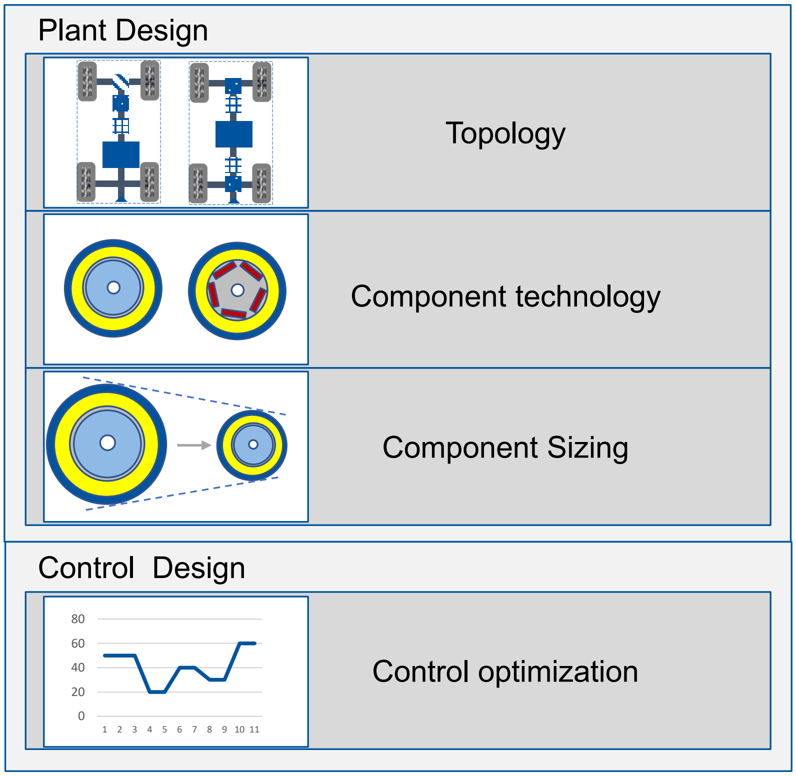


Figure 2.8 Powertrain system-level design problem and sub-levels.

Considering all four design levels leads to a multi-level problem, which requires a large number of function evaluations, which quickly increases depending on the number of parameters added. [48] This methodology gives you the flexibility to design the powertrain for 1, 2, or more levels depending on computational capacity. This thesis aims to cover a two-level design.

2.4.2 Single-level optimization

A complex system involves multi-physics subsystems that interact together to perform a task. In order to optimize the overall system-level performances, it has to be formulated as a multi-disciplinary optimization problem. In this approach, the problem is centralized in a single level where all the subsystems are evaluated together (at the same time, see Figure 2.9). This kind of problem can produce high efficiency when the system model is simple and differentiable concerning continuous design variables. [49]

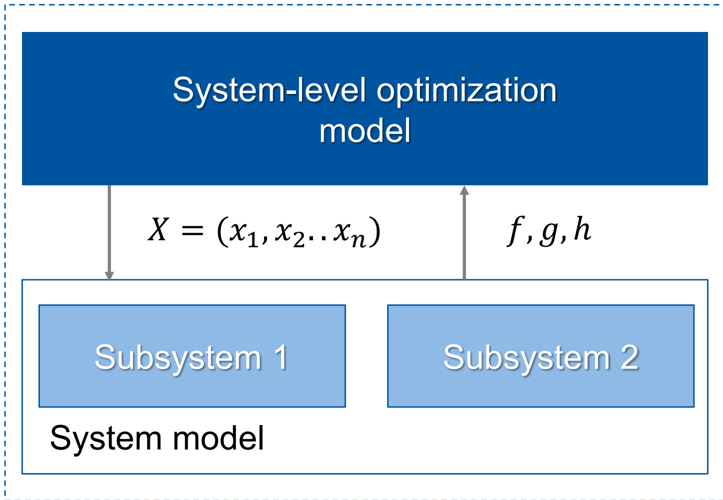


Figure 2.9 Single-level representation

This method is easy to implement but may result in huge computing costs, as powertrain design problems are generally high-dimensional and nonlinear with strongly coupled multidomain design and analysis. Different domains have different analysis techniques and software, and the computation cost of the whole system is very expensive. [50], [51] When there is more than one objective function in the system model, the multi-objective optimization techniques can be adapted to handle them simultaneously, but it becomes difficult when there are more than three objectives. [49]

2.4.3 Multi-level optimization

In the case of single-level optimization, all the design decisions are made by a single optimizer. Instead, in multi-level optimization, the complex problem can be broken into multiple manageable subsystems based on their functionalities. These subsystems can be solved by exploiting different expertise depending on the subsystem domain and using different modeling tools and different optimizers (shown in Figure 2.10). As appropriate algorithms are used for each subsystem, the solutions are obtained with reduced computational effort. The system-level coordinates the subsystems to achieve a synergistic solution that meets the overall targets. [49]

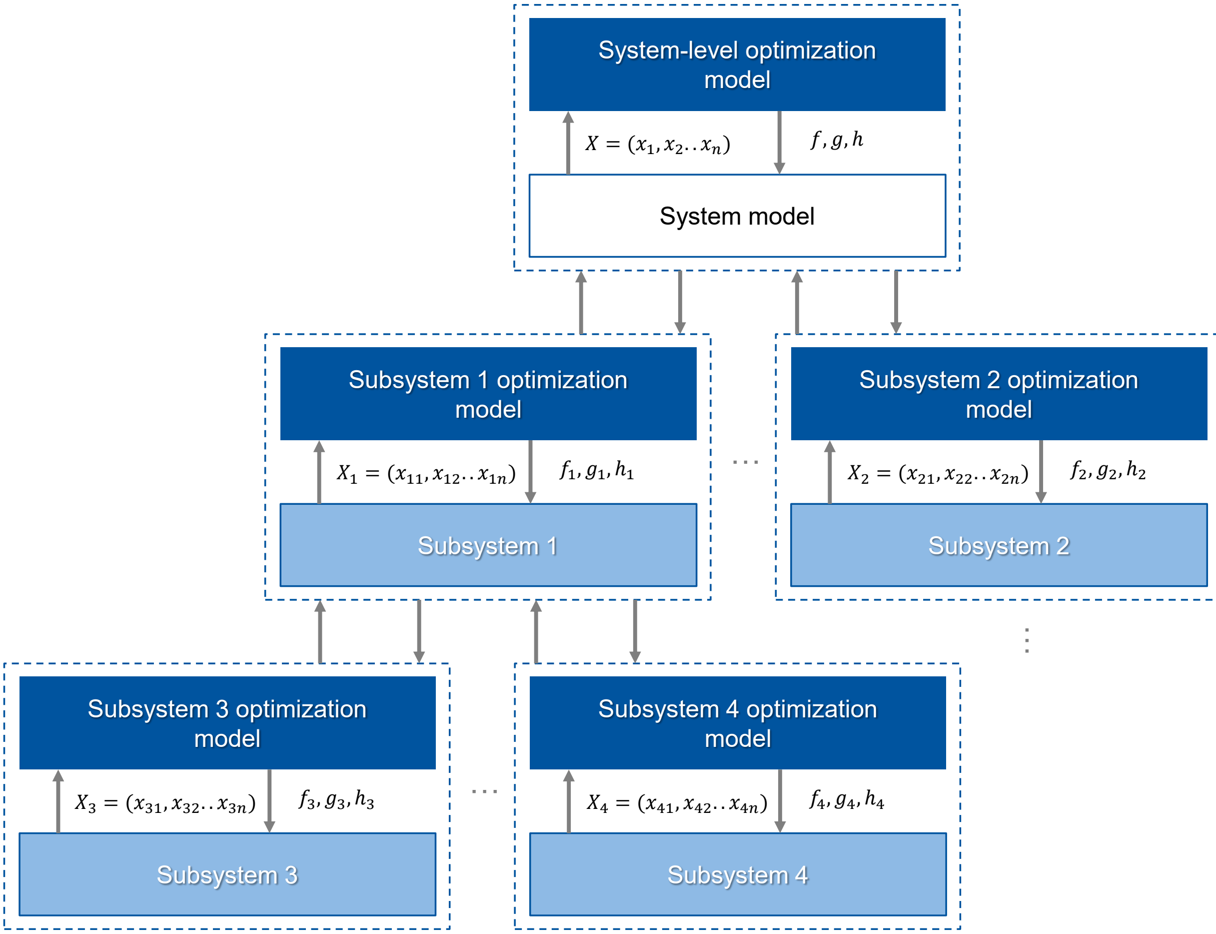


Figure 2.10 Multi-level representation

Multi-level optimization addresses problems where an upper level depends on the result of a lower level, and conversely the context of the lower level is defined by the variables of the upper level. [52]

3 Methods

3.1 Modularity

For the development of modular products, several methods already exist, but those design approaches lack an integrated view of product and process elements. In general, the specific modularization approaches lack the holistic view of a development process, from customer needs, the setting of standards by taking into account the effects of the production system and the decision for specific modules and variants. The important areas of product architecture, production system, and the market requirements must be considered in every case. [53] Most of these approaches focus on specific parts of the development process or some specific modularization problems. Therefore, for the development of an electric powertrain modular kit, a method for the development of modular product architectures that take into account the different perspectives of the market, product, and production, and was selected and it is presented below. [54]

3.1.1 Designing Innovative Modules and Added Value Structures

The aim of the methodology of Designing Innovative Modules and Added Value Structures (known as GiBWert, by its acronym in German of Gestaltung innovativer Baukasten- und Wertschöpfungssysteme) is to provide a systematic approach to modular design, which enables companies to systematically introduce a modular system. This allows a shorter introduction time for new products, high flexibility for customer requirements, and lower costs through the development of economies of scale.

The process model is divided into four phases, which are run through one after the other (see Figure 3.1). In the first stage, the potentials of the modular product platform are identified. This includes the external framework, where the market is analyzed and future sales volumes and customer requirements are determined, and the internal framework, where existing products and value chain are analyzed. From there, the requirements and goals for the modular system can be derived, which are summarized into a requirements specification. Subsequently, in the second stage, based on the requirements specification obtained in the first stage, the individual component variants are evaluated about their standardization potential and the constituent features derived from it. Constituent features are characteristics that are critical in terms of internal product interdependencies and production processes and are not influenced by customer requirements or can be decoupled from them and hence can be standardized. Thus, these are the product characteristics that can remain constant for all products and thus define the scope for the individual variants. Based on this, the platform structure can now be defined in the third stage. The modular structure is adapted according to the constituent features and the module variants, as well as the configuration and the interfaces, are defined. The result is the specification of the modular product architecture including the needed standards as well as flexible elements of the platform. To support the implementation of the modular design, the organizational structure and the processes must be adapted to the requirements of modular product architectures. Based on these modular product architectures the different products can be developed within a normal product development process. The overall process model can be visualized in the following figure.

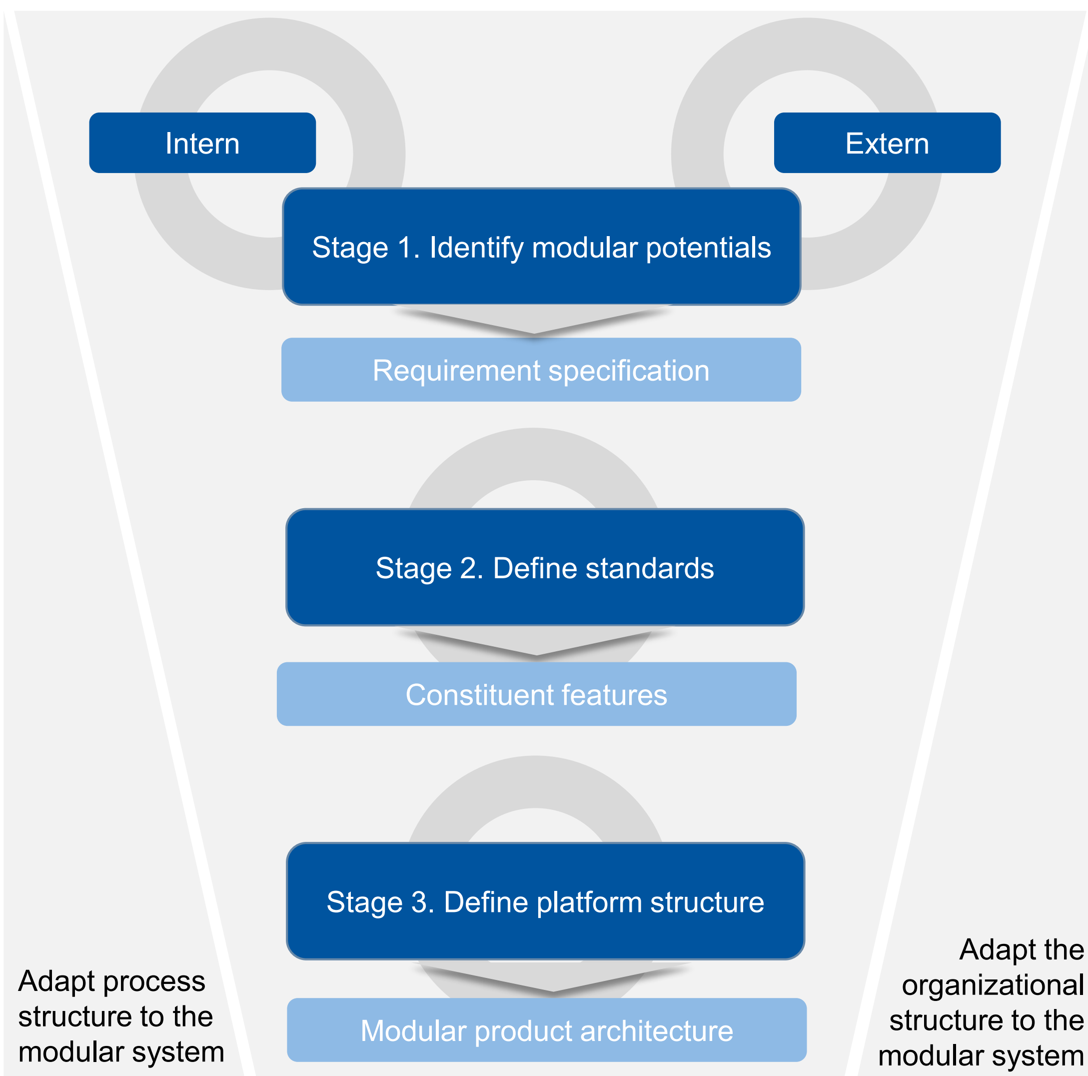


Figure 3.1 Modular product architecture development process (GibWert).

During this work, the focus was on the development of the second stage, which is where the emphasis will be made in the next section, considering that the external and internal framework had already been previously analyzed and the specification requirements were defined. Besides, the second stage is one of the most critical because here it is defined how optimal the platform can be.

3.1.1.1 Definition of the constituent features

The second stage aims to systematically analyze the effort in the product production system depending on the features that define the modular standards. The stage is divided into four steps, and the target output is the constituent features of the kit. The process can be visualized in Figure 3.2, and each step is described in detail next.

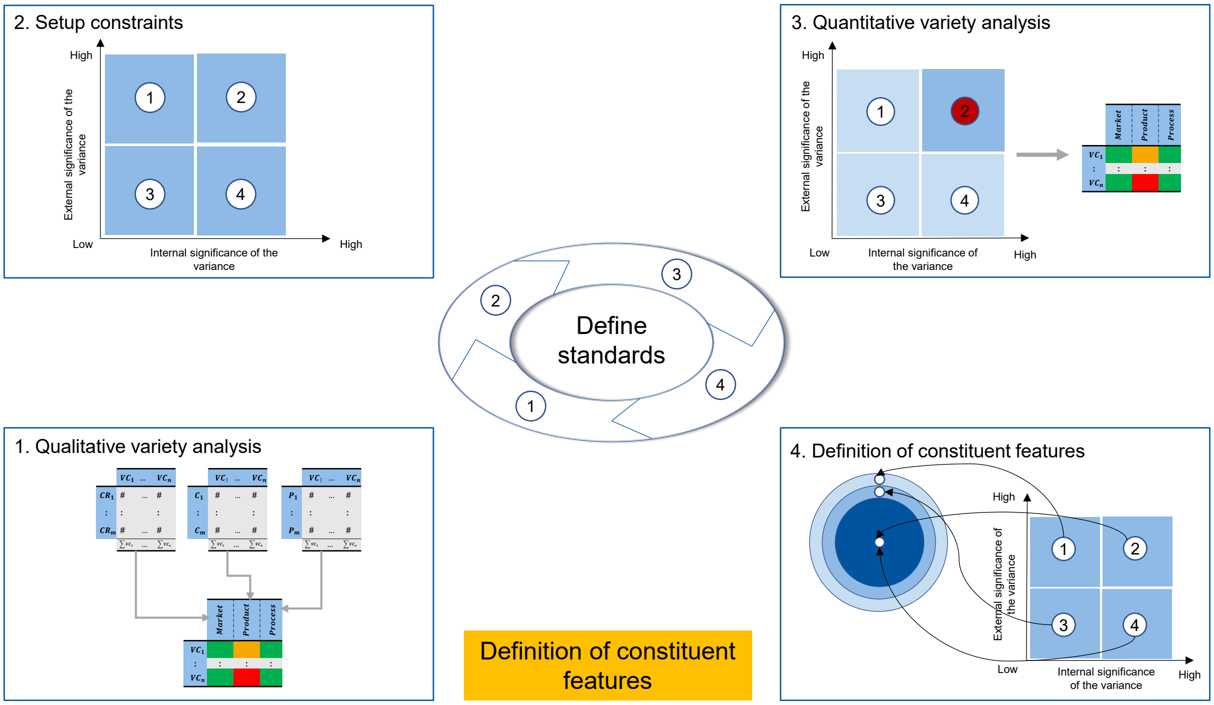


Figure 3.2 Overview of stage two, definition of constituent features.

1. Qualitative variety analysis: This step is needed to identify critical attributes of the product in terms of market requirements (external) and complexity costs (internal). Therefore, three perspectives: market, product, and production are taken into account, where the most relevant attributes of the product are evaluated in each perspective. The influence of each requirement on the attributes is determined on a qualitative scale. Additional weighting coefficients are added based on particular factors depending on the perspective and the importance of each requirement. This evaluation is done for the influence of the attributes on the customer requirements, components, and production processes. The results from the evaluations are combined in an overall assessment, and the results are aggregated into an internal value. Finally, a portfolio for the attributes can be set up.
2. Setup of constraints for the modular product architecture: In the portfolio representation, the x-coordinate represents the criticality level from the internal perspective, and the y-coordinate the criticality of the external perspective. The attributes in the lower right field are candidates for constituent features since they are critical in terms of internal complexity and not critical from a market point of view. However, there might be some smaller market segments that require a different characteristic of the chosen attribute. There are different strategic reasons why a market segment could be interesting or needed for a company, e.g. because it is demanded by a big customer. Therefore, a strategic decision is needed to either realize the additional variant and address the market segment or not to offer in this segment due to the effort needed and the low benefit. Attributes that are not mandatory for one of the market segments can be standardized.

3. Quantitative variety analysis: The attributes resulted as critical are analyzed. These are critical from the market perspective which means a high variety is demanded by the market as well as from an internal perspective which means that these attributes are very expensive in terms of variety. To solve this target conflict the first step is to find ways to reduce the internal complexity. Therefore, the construction of the relevant parts can be adapted, or the production process can be optimized in terms of variety.
   For the attributes which cannot be optimized in this way the number of offered variants will be defined based on the benefit and the costs of a variant. Since the customer requirements which should be fulfilled are clearly defined in stage one the only way to reduce variants is by engineering. Therefore, the complexity costs of each characteristic of the attribute are determined and will be compared to the costs of engineering (especially the additional material costs). Based on this cost analysis the optimal number of variants can be defined based on the economic evaluation.
4. Defining constituent features: The interdependencies between the defined attributes are analyzed. Clusters of attributes that are independent can be evaluated in terms of their internal and external criticality defined in step one. Based on this evaluation a hierarchy of the different clusters can be set up and constituent features can be defined based on this analysis. The result of stage two is the constituent features which are defined by the critical attributes in terms of internal complexity and their optimal number of characteristics based on the economical evaluation.

As this work is being carried out at a very early stage of product development, some considerations and assumptions must be taken into account, since for example there is no information on production costs, only prototypes. Therefore, this stage was adapted and is focused on step one of stage two, which we will explain in detail below.

3.1.1.1.1 Qualitative variety analysis

The variance sensitivity analysis in this phase provides information about in which areas of the modular system the expected yield due to an increased product variance exceeds the necessary effort and where high additional costs are to be expected through the creation of variants that are not appropriately rewarded by the customers.

The analysis can be assessed in three dimensions market requirements, product interdependencies, and production processes. For this, so-called variance characteristics must be identified. These are the functional and technical product properties that are responsible for the variance in the product. Variance characteristics, as a technical and functional characteristic of a modular system, enable a statement to be made about the influences of diversity in the product and production. Individual customer requirements have a significant impact on variance characteristics.

Based on their market, product, and process perspective, the variance characteristics are individually examined for variance sensitivity. In this partial analysis, the variance characteristics are compared, so-called market, product, and process properties in a matrix. The results of the three perspectives can then be compared in an overall assessment. By further evaluating this comparison, among other things, statements regarding the modular boundaries and constituent variance characteristics are made. The modular limits determine the number and design of the individual modular variants by taking into account the external and internal complexity.

In the case of more complex products, an iterative procedure is expedient for determining the essential variance characteristics, in which the product is broken down into its individual assemblies and components until the relevant characteristics can be determined. The variance characteristics are defined at the component level within the modules. For this purpose, systematically variable characteristics for all components are identified based on the determined product structure. To limit the effort, it is advisable to start with the most cost-intensive component per module based on the cost structure within the module and, if necessary, to make restrictions on the consideration of the parts. This can be, for example, geometric dimensions and design forms, surface qualities, or tolerance information.

Table 3.1. Summary of the analysis of sensitivity per each perspective

Perspective		Market	Product	Production
Object of evaluation		Customer requirements	Components	Production process steps
Purpose		Customer benefit resulting from product variants is assessed	Structural change effort on all components when a characteristic is varied	Influence that the creation of variants has on the production processes
Valuation logic result	High	Greater customer benefit	High change effort and strong influence in other components	Increase in manufacturing costs
	Low	Low customer benefit	Easy and inexpensive to implement	Decrease manufacturing costs and increase economies of scale

A sensible level of detail should be selected when determining the variance characteristics. For example, it is important to choose which dimensions, properties, and tolerances appearing in the design drawing should represent a variance characteristic. A too-small listing of all characteristics of the components leads to quickly increasing expenses due to the subsequent evaluation from the three perspectives of the market, product, and production. Therefore, when defining the variance characteristics, those that do not influence customer requirements are excluded.

The actual qualitative analysis of the variance takes place through a respective evaluation of the defined variance characteristics in the perspectives market, product, and production (see summary in Table 3.1). The market is the driver of the diversity of variants. A strong market orientation creates added value for the customer and is therefore essential for the successful implementation of a modular system. When evaluating variants on the market, the customer benefit resulting from product variants is assessed. This assessment is made by evaluating the relationship between the variance characteristics defined at the component level and the customer requirements. The market perspective is weighted by forecast sales figures.

When characterizing the variance characteristics from the product perspective, it is determined how strongly they influence components. The evaluation is carried out in the same way as for the market-side assessment. An assessment of the resulting structural change effort on all components when the characteristic is varied is made based on a predefined scale. The proportional manufacturing cost contribution of the component to the overall product is used as the weighting factor. The reason for this is that, on the one hand, modifying expensive product components is usually more complex and, on the other hand, economies of scale should be achieved through the modular system, particularly in the case of more expensive components. Furthermore, a variant-rich design of an expensive product component usually means a higher capital commitment through an appropriate provision in the warehouse. Finally, the weighted evaluation sum for each variance characteristic is determined and shown concerning the total sum over all variance characteristics. Analogous to the procedure for the analysis of variance at the market level, a table is filled in and the sensitivity of the variance characteristic is determined from the product perspective.

The valuation logic in the product perspective is to be interpreted in reverse to that from the market perspective. High numbers here mean that a change results in a high change effort and a strong influence on other product components. Low values mean that a variance characteristic is easy and inexpensive to implement from a product perspective.

The production perspective analyzes the influence that the creation of variants has on the production processes. It is determined whether and to what extent the change in a variance characteristic has an impact on the production processes. This value is multiplied by the process variance sensitivity factor. Finally, a sum standardized for all variance characteristics is determined for each variance characteristic.

Analogous to the product perspective, a reversal in the valuation logic compared to the market perspective must also be considered when considering the influence of variants on added value. High values of a variance characteristic in the analysis from the value creation perspective mean that there is a strong connection to variance-sensitive process steps. In this case, creating variance means increasing costs in the manufacture of the product. This is due to increasing complexity costs and decreasing economies of scale.

To identify the differentiation and standardization potential of the modular system, the results of the variance sensitivity analysis from the three perspectives of market, product, and production are first combined to form an overall assessment. For this purpose, a tabular representation is chosen, which compares the results of the analysis of the three perspectives on the respective variance characteristic Figure 3.3. To achieve comparability, the numbers are scaled to an equal maximum in the three columns. Besides, for better visualization, a conditional coloring of the results from "red" for low to "green" for high values is chosen from the market perspective. In the product and production perspective, the color scheme is inverted.

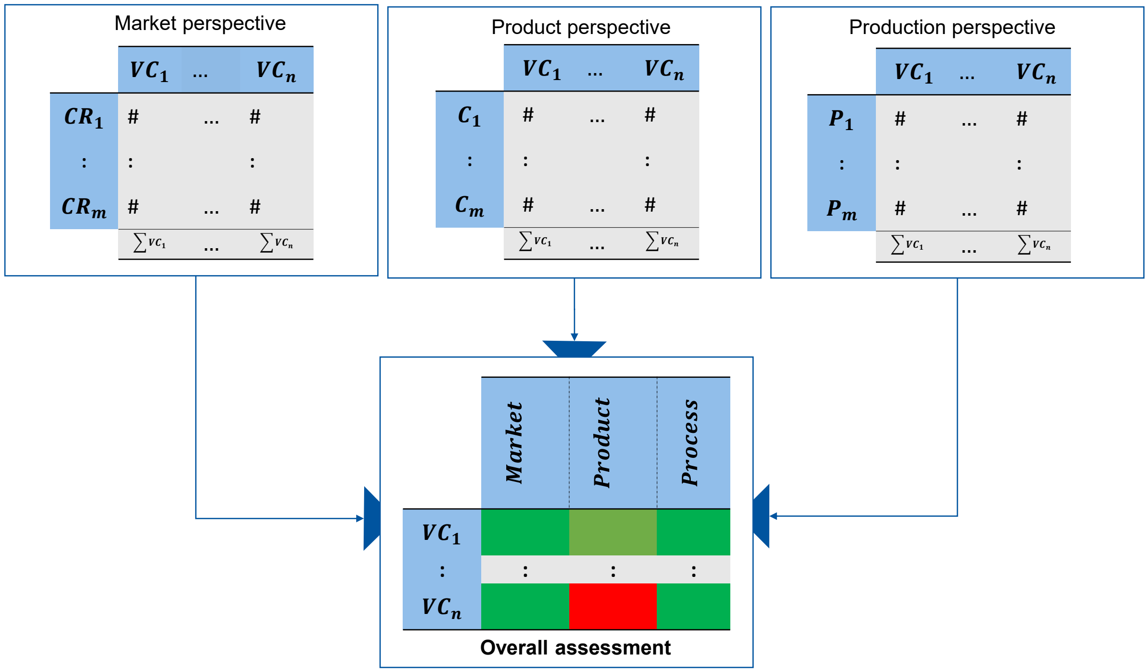


Figure 3.3 Visual representation of the variance sensitivity analysis

The following section presents the applied case of the modular electric powertrain kit and how it was developed at this stage for this thesis.

3.2 Electric powertrain modeling

An appropriate modeling approach for the purpose of optimization needs to combine the good adaptability of the system parameters and a low computational effort. This is obtained by the so-called backward approach. Therefore, QSS Toolbox, an open-source lightweight vehicle simulation platform developed in MATLAB Simulink from the ETH Zürich is chosen to modeling the electric powertrain. This toolbox makes possible designs quickly and in a flexible manner different powertrain systems and calculate easily fuel and energy consumption. To optimize the electrified powertrain for the most optimal topology and size given a drive cycle, the QSS toolbox seems to be perfect.

3.2.1 Modeling using QSS Toolbox

This section is based on the manual of the toolbox[55], and the book "Vehicle Propulsion Systems" by the same author. [56] The following references are also two works used as the basis for this section, as they also use the toolbox for related applications. [57], [58]

3.2.1.1 QSS approach

In quasistatic simulations, the input variables are the speed v and the acceleration a of the vehicle as well as the grade angle of the road. These three variables are assumed to be constant for each time step h. The traction force F_t that must be acting on the wheels to drive the chosen profile for a vehicle described by its main parameters $\{A_f, C_d, C_r, m_v\}$ is computed. This calculation can be done by a discretization in time of the speed and the acceleration profile. These variables are defined for the given time instants $v(t_i) = v_i, t_i = i \cdot h, i = 0, \ldots\ldots, n$; $a(t_i) = a_i, t_i = i \cdot h, i = 0, \ldots\ldots, n$. Accordingly, the traction force is computed for the average speed and acceleration as follows:

$$v(t) = \bar{v}_i = \frac{v_i + v_{i-1}}{2}, \forall t \in [t_{i-1}, t_i]. \tag{1}$$

$$a(t) = \bar{a}_i = \frac{v_i - v_{i-1}}{h}, \forall t \in [t_{i-1}, t_i]. \tag{2}$$

The basic equation used to evaluate the force required to drive the chosen profile is derived from Newton's second law and resulting in the following equation:

$$F_{t,i} = m_v \cdot \overline{a_i} + F_{d,i} + F_{r,i} + F_{g,i} + F_{a,i}. \tag{3}$$

$F_{d,i}$ = aerodynamic drag resistance

$F_{r,i}$ = rolling resistance

$F_{g,i}$= gradeability

$F_{a,i}$= acceleration force

m_v= vehicle mass

$\overline{a_i}$= average acceleration

Using the expressions of each force calculation, the traction force at time instant i is given by the next equation:

$$F_{t,i} = m_v \cdot \overline{a_i} + \frac{1}{2} \cdot \rho_a \cdot A_f \cdot C_d \cdot \bar{v}_i^2 + c_r \cdot m_v \cdot g \cos \alpha_i + m_v \cdot g \sin \alpha_i. \tag{4}$$

ρ_a = density of the ambient air

A_f = frontal area

C_d= aerodynamic drag coefficient

$\overline{v_i}$= average speed

c_r= rolling friction coefficient

α_i= grade angle

g= gravity

The quasistatic method is well suited for the optimization of energy consumption of complex powertrain structures. It is possible to design supervisory control system that optimizes power flow and the numerical effort still being relatively low. The accuracy of experiments on engine dynamometers is very high.

Due to the purely backward modeling technique, this approach is not suitable for performance simulation.

3.2.1.2 Driving cycle

A driving cycle is a representation of vehicle behavior as a function of time under different driving conditions. Drive cycles were introduced to compare pollutant emissions of different vehicles, and then for comparison of fuel economy. These are standardized data acquired during a normalized test drive. In practice, these cycles are often used on chassis dynamometers where the force at the wheels is chosen to emulate the vehicle energy losses while driving that specific cycle. In general, a driving cycle is composed of at least two vectors:

1. Time vector (with equal time steps h)
2. Vehicle speed vector $v(h)$, where h represents the position in the speed vector

Thus, the acceleration can be derived from vehicle speed as follows:

$$a_f(k \cdot h) = \frac{v_f(k \cdot h + h) - v_f(k \cdot h)}{h}, \qquad k = 1, \ldots k_{max} - 1, \qquad a_f(k_{max}) = 0 \tag{5}$$

The QSS toolbox lets the user choose the desired driving cycle or the possibility to define its own cycles.

3.2.1.3 Electric motor

The electric motor can be represented as a block with two inputs: torque T_{EM} and rotational speed ω_{EM}. The output is the required electric power P_{EM}. A positive value of P_{EM} is absorbed by the machine operating as a motor, a negative value is delivered by the machine working as a generator. Thus, two operating modes are considered for the electric motor and they are respectively represented on two quadrants. The first quadrant represents the machine operating as a motor when both torque and rotational velocity are positive. The electric power required by the motor, in this case, can thus be expressed as follows:

$$P_{EM} = \omega_{EM} \cdot T_{EM} \cdot \frac{1}{\eta_{EM}(\omega_{EM}, T_{EM})}, \qquad (\omega_{EM} > 0 \; and \; T_{EM} > 0) \tag{6}$$

The second quadrant represents the machine operating as a generator when the rotational velocity is positive, and torque is negative. The electric power delivered is expressed as follows:

$$P_{EM} = \omega_{EM} \cdot T_{EM} \cdot \eta_{EM}(\omega_{EM}, T_{EM}) \,, \qquad (\omega_{EM} > 0 \; and \; T_{EM} < 0) \tag{7}$$

The third and fourth quadrants, for which the rotational speed is negative, are not considered since reverse movement is not relevant for the energy consumption determination.

By combining Eq. 7 and 6, a single efficiency map is generated (as shown in Figure 3.4), to avoid distinguishing between these two cases.

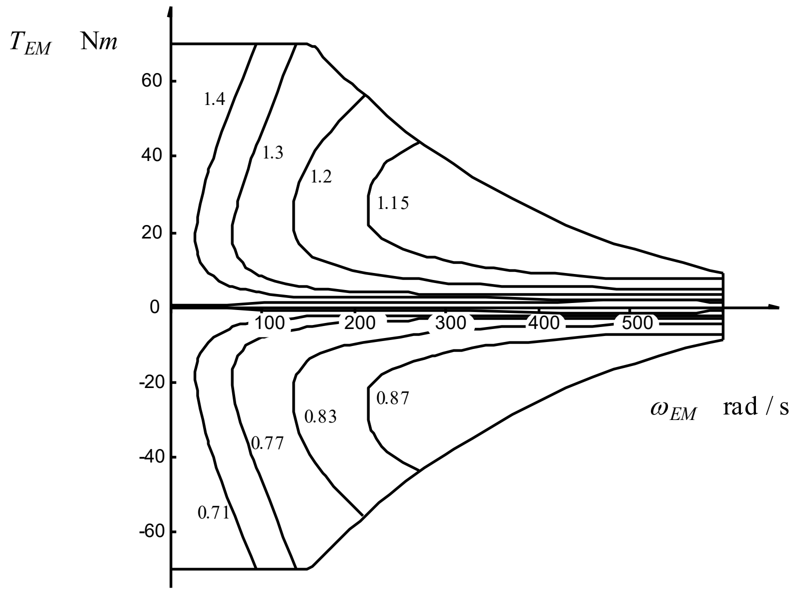


Figure 3.4 Efficiency map of QSS toolbox electric motor.

QSS toolbox allows the electric motor model to be scaled by simply scaling the support vectors and assuming the motor efficiencies to remain unaffected.

3.2.1.4 Transmission

The gear system, differential, or drive shafts can be simulated by a transmission block which provides the transmission of mechanical work between the vehicle and the electric motor. Three models of gear systems can be used in the QSS toolbox: simple transmission (i.e., fixed relationships between torque levels or rotational speed levels), manual gearbox (i.e., a finite number of relationships between torque levels or rotational speed levels), and CVT (i.e., continuously variable relationships between torque or rotational speed levels, respectively).

For this work, a simple transmission is used, where the kinematical relationships are assumed to be ideal, i.e., there are no inertia effects by backlashes. The losses are described by the next relationship:

$$P_{out} = \eta_{gear} \cdot P_{in} - P_0 \tag{8}$$

where P_{out} and P_{in} represent the power leaving and entering the system, respectively; and P_0 the idle speed losses. Since the flow may be reversed, the transmission model interprets the flow case by case (wheel-to-engine, engine-to-wheel).

3.2.1.5 Battery

The battery is simulated by a single block of a basic physical model of a battery (as shown in Figure 3.5) with two inputs and two outputs. The first input corresponds to the electric power flowing into the battery. Depending on the motors operating mode, the power can be positive, when discharging the battery, or negative, when charging. A zero-power will keep the battery at idle mode. The second input corresponds to the distance traveled by the drive cycle. This value is used to compute the first output related to energy consumption per kilometer. The second output corresponds to the current battery charge.

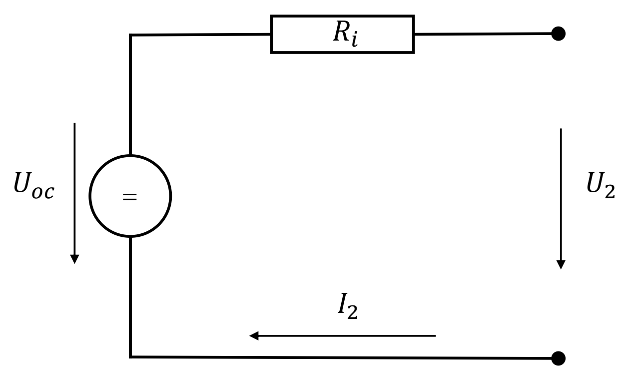


Figure 3.5 Basic equivalent circuit of the battery system

The battery is modeled integrating the power flowing, obtained from the known power and actual voltage of the battery, to calculate the current battery charge. The voltage depends at any moment on the battery charge and the current charging or discharging the battery.

The model eliminates the current flow in the battery and presents the voltage as a function of power only for charging and discharging as follows. For further information about the quasistatic approach of the battery, see reference [56].

$$U_2(t) = \frac{k_1 + k_2 \cdot q(t)}{2} \pm \sqrt{\frac{(k_1 + k_2 \cdot q(t))^2}{4} - P_2(t) \cdot (k_4 \cdot q(t) + k_3} \quad (9)$$

where k_n are coefficients that depend only on the battery construction, and $q(t)$ is the charge rate. The ambiguity in the solution of the quadratic equation obtained can be resolved using physical arguments. When charging, the amount of power entering the battery is limited by the maximum storage capacity. When the battery is discharging, the current is limited by the internal resistance of the battery.

The model described above is valid only for the normal operating range of the battery, i.e. between approximately 10% and 90% of its nominal capacity. Outside of this range, rather strong nonlinear effects may be observed. The electronic power system controls the amounts of the current running between the battery and other electrical components as well as among those components themselves. The details of these losses are not being considered or modeled separately; rather they can be ascribed to the losses of the motors or generators.

3.3 Optimization approach

Powertrain optimization in both electric and conventional vehicles has become critical for any car manufacturer due to the global environmental situation and new emissions regulations. Powertrain optimization is key to meeting new emissions and energy consumption targets. Therefore, our case study is formulated as an optimization problem, with an objective function on energy consumption. Two algorithms for the optimization of the powertrain are proposed in this section and compared later.

3.3.1 Problem formulation

The formulation of an optimum design problem involves translating a descriptive statement of it into a well-defined mathematical statement. [59] The system under investigation is that of an electric powertrain with different topologies. The optimization problem is to find the topology that minimizes the energy consumption by the system given a drive cycle. The system is described using a time-discrete quasistatic model.

The design levels for the optimization problem are the powertrain topology and the sizing of the components, that depends directly on the topology. Thus, it can be divided into upper and lower optimization respectively. The lower optimization is taking into account the electric motor size and the fixed transmission gearbox ratio. A topology is required to define the number of electric motors, as well as the gearboxes that can vary from 1 to 2. This problem can be mathematically described as follows:

$$
\begin{aligned}
\min_{P_m, r_g} \quad & J_1\left(P_m, r_g \mid \psi(\mathrm{t})\right), \qquad (10)\\
\textit{subject to} \quad & g_{1,1} = P_{m,min} \leq P_m \leq P_{m,max} \\
& g_{1,2} = r_{g,min} \leq r_g \leq r_{g,max}
\end{aligned}
$$

where P_m represents the electric motor power size, r_g the ratio of the fixed transmission and the ψ represents the drive cycle, which consists of speed $v(t)$ and a slope $\alpha(t)$. Further, J_1 is the objective function for the sizing problem and $g_{1,n}$ are the inequality constraints for the problem. Equality constraints $h_{1,n}$ can also be defined, but for this case study, they do not exist. The lower optimization is solved for each evaluation of the upper level. Therefore, it is important to define the upper optimization that can be described as follows:

$$\min_{x_t} \quad J_2(x_t \mid \psi(t)), \tag{11}$$

$$subject\ to \quad g_{2,1} = 0 \leq x_t \leq x_{t,max}$$

where x_t refers to the powertrain topology and is represented by a vector $x_t = \{1,2,3,4\}$ where each number is a topology. J_2 represents the objective function for the topology problem and $g_{1,n}$ are the inequality constraints. As mentioned above, equality constraints also can be included when applies.

The objective function for the overall system is the energy consumption of the vehicle model over the drive cycle and can be described as follows:

$$J = \frac{1}{\psi} \cdot \int_{t_0}^{t_1} P_{battery}(t) \cdot dt \tag{12}$$

where ψ is the total distance covered by the drive cycle, and $P_{battery}$ is the power drawn by the battery to complete the drive cycle.

Although in this optimization problem there are two optimization levels and therefore two objective functions, in this case of study they have the same objective, so they can be equated.

$$J = J_1 = J_2 \tag{13}$$

This type of optimization is a simplification of a multi-objective function to a single objective and has been widely used in the literature.

3.3.2 Optimization algorithms proposal

Different heuristic optimization approaches have been developed for optimization problems due to problem size or complexity. Heuristic methods are based on finding the best possible solution by using knowledge of the search space, information gained in the optimization process, and sound judgment. [60]

In the literature about hybrid electric vehicles, which is a very frequent application in optimization problems, a wide variety of algorithms has been selected to achieve optimum design (See Table 1 from [61]). One may distinguish between derivative-free and gradient-based algorithms. Derivative free algorithms include simulated annealing, dividing rectangles, genetic algorithms, and particle swarm optimization. [61] Genetic algorithms are among the most widely adopted heuristics due to its early introduction, but the most recent particle swarm optimization has rapidly grown its application showing very good results.

As these two algorithms have been widely applied in related applications, they are chosen as the best options. Since they are both population-based methods, they have a very similar structure and a similar algorithm. Therefore, the next section plans to explain the main differences and compare them for our specific application.

3.3.2.1 Genetic algorithms

Genetic algorithms (GA) are stochastic global search techniques, which mimic the process of genetics and natural selection. The basic elements of natural genetics are reproduction, crossover, and mutation. GA has been shown to be an effective strategy to solve complex engineering optimization problems characterized by non-linear, multimodal, non-convex objective functions.

The GA can be obtained by the following iterative procedure[62], [63], [64]:

1. Population initiation: Creating an initial population taking into account the lower and upper bounds of the variables. The number of individuals in the initial population is input from the user. After the number of individuals is defined, the initialization of the chromosomes is found in the population.

2. Individual evaluation: Evaluation of the performance of each individual of the population, through a fitness function.

3. Parental chromosome selection: Selection of individuals through a certain method, which selects the chromosomes with better fitness performance to do a crossover for the next generation.

4. Crossover and mutation: Crossover is the process that forms a new chromosome from two-parent chromosomes by combining information of each chromosome. Crossover makes high-performance individuals evolve into even better offspring through mutual gene exchanging. Mutation is the process to change one or more genes from a chromosome. This allows the reappearance of genes that do not appear in the initial population to further search in a broader solution space.

5. Iteration and termination: The steps above are repeated iteratively until the termination criteria are fulfilled.

3.3.2.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary computation technique based on a natural system. More specifically, in the movement and intelligence of the swarms. PSO is a population-based stochastic optimization technique developed by Kennedy and Eberhart. [65] PSO algorithm is an optimization algorithm that is easy to understand, quite simple, and has work that has proven to be reliable. [64] Most of the problems that can be solved using GA could be solved by PSO, [63] and that is due to it shares many characteristics with GA. For example, the system also starts with a random population and looks for the optimal one by updating their generations.

In the process during PSO, particles, referred to as solutions, are moving around the search space guided by their own best-known position as well as the entire swarm best position until a satisfactory solution is finally found. [62] Unlike GA, PSO has no evolution operators such as crossover and mutation, therefore, PSO updates the particles through velocity and position.

The first position and particle velocity are generated from a collection of particles generated randomly using the upper and lower limit.

Then, the velocity of each agent can be updated by the following equation:

$$v^{k+1} = w \cdot v_i^k + c_1 r_1 \cdot (p_{best} - s_i^k) + c_2 r_2 \cdot (g_{best} - s_i^k). \quad (14)$$

where

v^k = current velocity of agent i at iteration

v^{k+1} = updated velocity of agent i

r_1, r_2= random number distributed [0,1]

s_i^k= current position of agent i

p_{best}= best value of the particle found so far

g_{best}= best-known position of any particle so far

w= weight function for the velocity of agent i

c_1, c_2= self-confidence and swarm confidence, positive constants

And the position, that is the searching point in the solution space, needs to be updated by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (15)$$

Also, this iterative procedure stops when the criteria are fulfilled.

4 Method execution

This thesis work is composed of two different deliverables in a single project. In the previous chapters, two main concepts or themes can be identified: modularity and powertrain analysis. Although this work has a twofold objective, these are linked and can be carried out in parallel.

The first deliverable is focused on powertrain analysis, that is, the formulation of a representative model of our modular powertrain with all its characteristics, which allows us to simulate its performance given specific requirements. Then, an optimization framework allows us to identify which configurations of our powertrain are the most optimal. This deliverable provides a greater understanding of our product structure as well as allows us to filter and refine it.

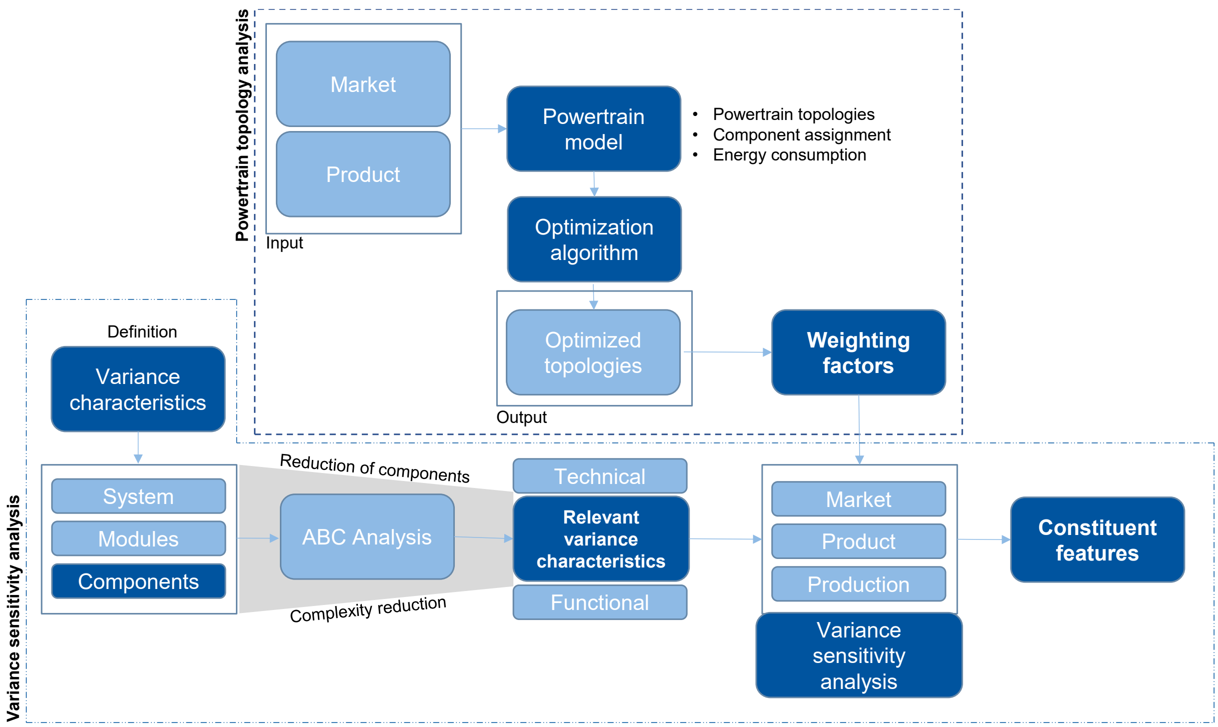


Figure 4.1 Two-fold deliverable work representation

The second deliverable focused on modularity is based on a sensitivity analysis based on the most relevant variance characteristics of the product. The sensitivity analysis is carried out in three perspectives: market, product, and production. The link between the two projects is in this task. Although having results of the first deliverable during the execution of the second gives us a broader and more precise field of vision in decision making throughout the stage, the greatest advantage of a defined and optimized structure is found at the time of our analysis of sensitivity, since it gives us a more robust result than when you have a more ambiguous structure and with more variance.

Figure 4.1 shows us in a more structured way the components of each main deliverable, as well as their main tasks. It also shows what the outputs of each deliverable are and how they are related to each other.

Once the structure and interaction of the two deliverables of this work have been defined, this chapter presents the beginning of the execution of the methods presented in the previous chapter. The following sections contain the description of the execution for the two deliverables, as well as the preliminary results of the decision making for the implementation of the methods. The results of this chapter are the basis for generating the final results presented in the next chapter.

4.1.1 Variance sensitivity analysis

The electric modular powertrain platform must be considered as a complex system due to the interaction of different multi-domain systems. Thus, the general structure at the vehicle level is broken into a lower level, and thus components, processes, requirements, and variance characteristics are defined.

4.1.1.1 Identification of the most relevant components

To limit the effort of the analysis, and thus the quality of the analysis, a prioritization of the components is required. Constituent features can be defined by the most cost-intensive components since these would be the ones whose modularization would have the most impact. For the electric powertrain platform, it should be considered that the current costs are not production costs, but prototype costs. Even so, if we normalize the costs, the analysis can give us a reference of which components are more relevant. In this case, no more restrictions are necessary.

The analysis is carried out in detailed product parts, so-called, bill of materials (BOM). This BOM includes all components that keep the integrity of the product at different levels. Thus, the product is not divided into modules yet but rather grouped depending on their functions and their location. The general structure is divided into 11 main groups (shown in Table 4.1) and then subdivided into 40 subgroups, composed of about 100 components in total. Not all product costs are available, but we have the cost of about 70 components, which is a reasonable number to do the analysis. The total cost of the powertrain components at this stage of the development process is about €128.499, considering some assumptions.

Table 4.1 Leader groups of the current product structure of the electric powertrain

Group
1. Full Vehicle
2. Drivetrain
3. Body
4. Chassis
5. Interior
6. Battery System
7. Thermal Management
8. E/E
9. HV BN
10. Fuel Cell
11. Pantograph

This prioritization is done through an ABC analysis. This principle suggests that 80% of the total output is generated only by 20% of the valuable efforts. ABC analysis typically segregates inventory into three categories based on its revenue and control measures required where “A” represents the most valuable products, “B” means interclass items, and “C” the items with the lowest values. [66] This case of study is based on acquisition costs.

Rules for the analysis:

A: 20% of your products, making up 80% of the cumulative annual cost

B: 30% of your products, making up 15% of the cumulative annual cost

C: 50% of your products, making up 5% of the cumulative annual cost

Since the level of analysis was not defined at this point. Three studies were carried out with the same rules at group, subgroup, and component level. The analysis was carried out in Minitab using the Pareto Chart Tool.

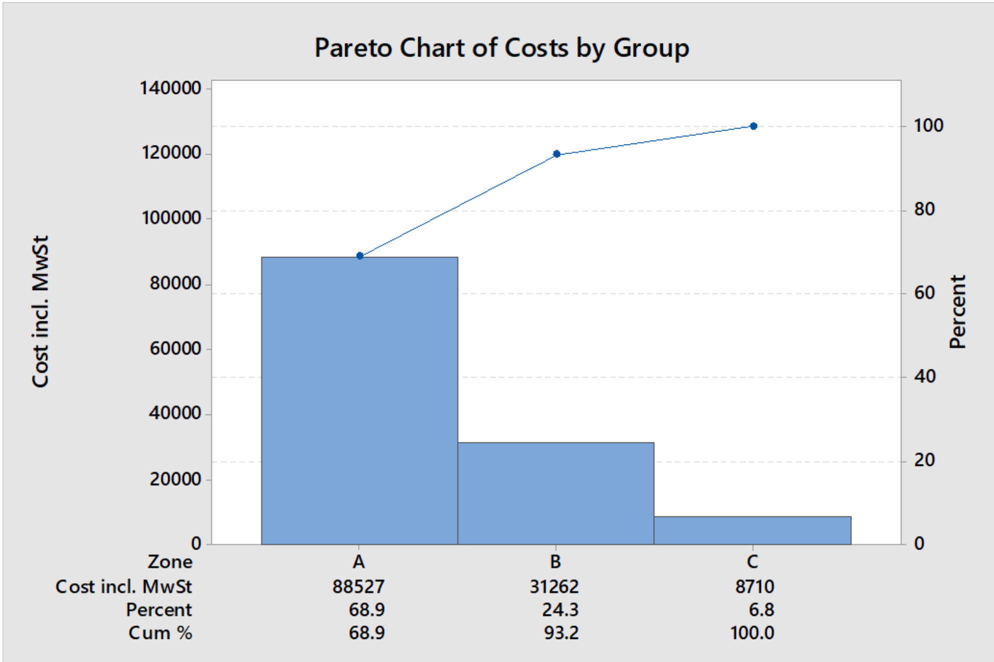


Figure 4.2 ABC analysis at Group level

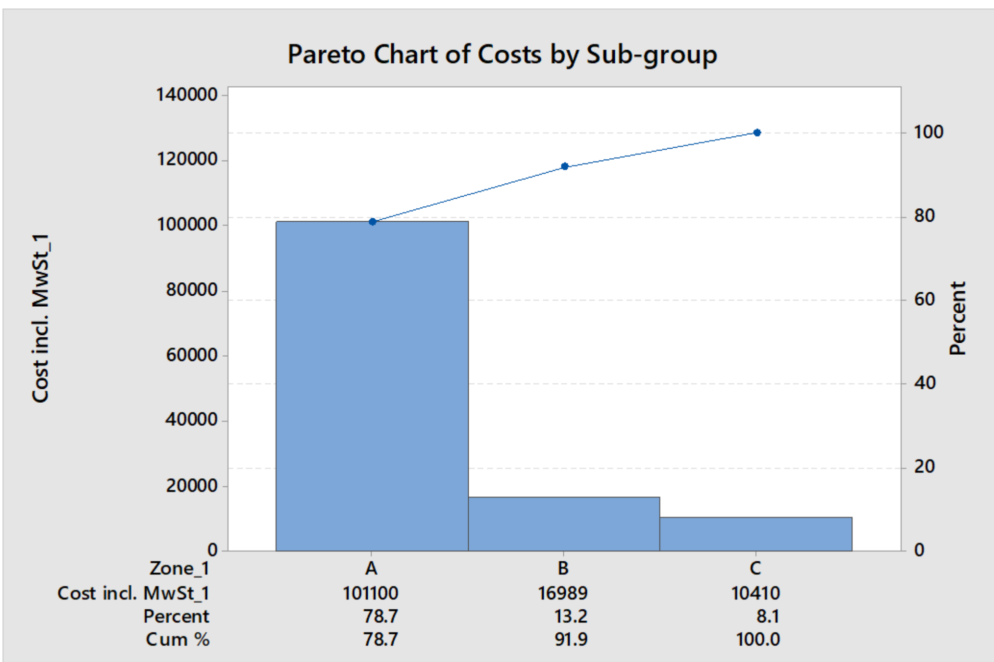


Figure 4.3 ABC Analysis at Subgroup level

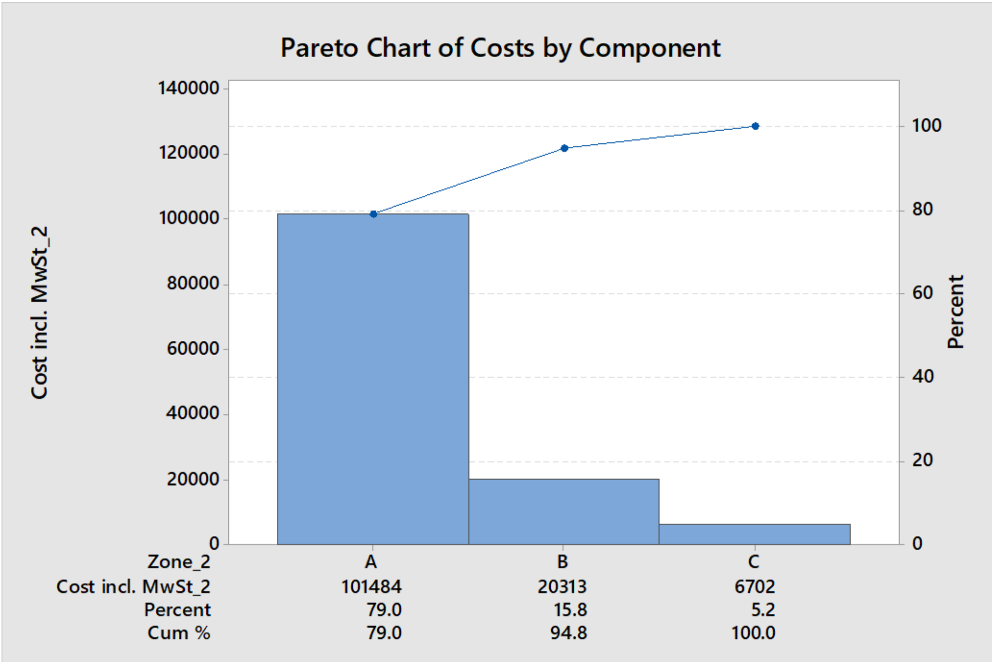


Figure 4.4 ABC Analysis at Component level

In Figure 4.2, the resulting percent at group level is so far from the rule 80-20%, so, this level was excluded. Next in Figure 4.3 and Figure 4.4, the behavior is very similar, but definitely, at component level accuracy is better. Hence, component level was selected as the reference for the analysis. The most relevant components are listed in Table 4.2.

Table 4.2 Relevant components of the product

ID	Components
C1	Power steering pump
C2	Range extender interface (FC, PG)
C3	DC/DC converter REX
C4	Recuperation energy storage
C5	Power distribution unit
C6	Battery pack (including BMS)
C7	OBC
C8	LV DC/DC converter
C9	LV cabling
C10	HV cabling
C11	HV DC/DC converter
C12	Coolant pump
C13	Radiator

C14	Cooling medium
C15	Cooling storage
C16	Motor
C17	Inverter
C18	Mechanical transmission (Gearbox)
C19	Cardan shaft
C20	Parking brake

4.1.1.2 Identification of the most relevant processes

Due to the early point in the product development process, the electrified modular powertrain platform does not have a production system yet. Thus, the process part was based on a production concept developed by the Laboratory for Machine Tools and Production Engineering of the RWTH Aachen University (WZL by its acronym in German of Werkzeugmaschinenlabor). The full concept includes not only production but also logistics as well as indirect areas, but the only production processes will be considered for the analysis. The aim of the industrialization concept is a series production of electrified commercial vehicles with variable drivetrain topology using low-investment means of production. In this work, it is not intended to go into detail about the production system, but the main characteristics are detailed in Table 4.3.

Table 4.3 Industrialization concept by WZL, RWTH Aachen.

LiVe Production System	
Assembly of electrified trucks to the base vehicles:	OEM series 1 (3.1 to 9.5 tons)
	OEM series 2 (10 to 32 tons)
Energy supply concepts:	High voltage storage
	Pantograph
	Fuel Cell Stack
Powertrain variants:	Central motor
	Wheel hub motor
	Motor close to the wheel
Production System:	Mixed Model Line
Logistics concept:	Semi-knocked down (SKD)
Production volume:	10,000 vehicles per year
Floor space:	12,200 m2
Employees:	152
Number of layers:	2
Cycle time:	15 minutes

As a summary of the process, the production of the product range considered (3.2 – 32 tons heavy-duty trucks) is concentrated in one production system. The process is planned as a pure final assembly plant, where the base vehicles are fed to the final assembly plan partly broken down into individual assembly kits.

The final assembly is distributed to 13 assembly stations. 23 assembly process steps have been identified in the production concept. Some processes were excluded as they were not relevant to the case study or were excluded by discarding components from the previous section. The resulting process steps are in Table 4.4.

Table 4.4 Relevant process steps for production

ID	Process steps
PS1	Cable harness
PS2	Brake lines
PS3	Front axle
PS4	Rear axle
PS5	Pneumatic brake system
PS6	Powertrain variant assembly
PS7	PDU, HV-storage brackets
PS8	Brake resistor
PS9	Cooling system braking resistor
PS10	Cooling system vehicle
PS11	Cooling system high voltage storage
PS12	Cooling system powertrain
PS13	High voltage storage (1-4 BP)
PS14	Fuse box
PS15	Control Unit
PS16	24V battery
PS17	Range extender (none, PG, FC)
PS18	Wheels
PS19	Media filling

4.1.1.3 Identification of the customer requirements

As mentioned in the methodology, customer requirements are derived from external and internal requirements. This is done in the first stage of the method and defined in a requirements specification. Then, said specification is translated into customer requirements. Opposite to product and production, the effort in terms of customer requirements should not be limited, since these elements directly influence customer satisfaction, and the objective of the modular kit is trying to fulfill it as much as possible. The resulting customer requirements are presented in Table 4.5.

Table 4.5 Defined customer requirements

ID	Customer requirements
CR1	Cost must be affordable
CR2	Meet the required driving range (km)
CR3	Low energy consumption as possible
CR4	Daily operation time (12-14 h)
CR5	Annual distance expectation (130000 km)
CR6	High charging efficiency (reduce charging time, save energy and costs)
CR7	High battery efficiency (energy, power)
CR8	Service/maintance must not exceed those of the base vehicle (frequency, costs)
CR9	Materials must be suitable for automotive applications
CR10	Operational temperatures (-11-48°C)
CR11	Must meet a climbing ability of 10%
CR12	Must meet a maximum speed of 87 km/h
CR13	Modular battery concept depending on the application (region, variant)
CR14	Must be able to be charged either AC or DC
CR15	Charging socket must be lockable
CR16	Batteries and most components must be recyclable
CR17	Kit cover weight classes from 7,5t and up to 40t
CR18	Kit must match safety of the base vehicle
CR19	Kit must match durability of the base vehicle
CR20	Kit must be easy to install
CR21	Kit must use most parts of the base vehicle
CR22	Kit must not reduce the load capacity
CR23	Kit offers more than one energy source
CR24	Kit must have a recuperation mode

4.1.1.4 Definition of the variance characteristics

Due to the complexity of the product, determining the variance characteristics is one of the most complicated tasks. It is important at this point to have previously defined requirements, components, and processes since the better structured you have the approach, the easier it will be to derive the relevant characteristics. To determine the variance characteristics, an iterative process of listing all the possible characteristics of the whole product structure at the lower possible level is necessary independently of the prioritization of the components. The objective of reviewing the entire product structure is not to lose any essential variance characteristic in a non-relevant component. Then, essential characteristics can be chosen with a group of experts. For the electric modular powertrain platform, 15 relevant variance characteristics are defined and presented in Table 4.6.

Table 4.6 Relevant variance characteristics

ID	**Variance characteristics**
VC1	High Voltage
VC2	Low Voltage
VC3	Vehicle Weight Class
VC4	Topology (EM-GB-DF, EM-GB; 2EM-2GB, 2EM)
VC5	Motor power
VC6	Motor torque
VC7	Motor speed
VC8	Energy converter/inverter capacity
VC9	Electrification concept (battery, battery+fuel tank, battery+panto)
VC10	Battery technology (energy/power density)
VC11	Battery type (cylinder, pouch, prismatic)
VC12	Battery pack energy
VC13	Charger type (plug and AC/ACDC)
VC14	Thermal management
VC15	Gearbox (ratio, single/double shift, CVT)

4.1.1.5 Variance sensitivity analysis

Some methods used for this analysis of variance in successful implementations on German companies are feature and variant trees, evaluation of the technology databases, and expert workshops. The last was selected for this work due to the early stage in the product development process. Table 4.7 presents the details of the workshop that was carried out for the sensitivity analysis and its participants. The results of this workshop are shown in the following chapter.

Table 4.7 Experts Workshop

[LiVe] Baukasten Workshop: Varianzmerkmale		
Place	Aachen, DE	
Date	13/08/2020	
Hour	13:30	
Organizer	Rivas Torres, Jonathan	
Experts	Dorantes Gomez, Guillermo	Electric Drive Production
	Dünnwald, Simon	E-mobility Production Engineering
	Pandey, Rahul	E-mobility Production Engineering
	Vienenkötter, Janis	Battery Components & Recycling

Considering the expertise of the workshop members, and due to the limited information on the product, an analytical hierarchical process (AHP) is proposed to determine tradeoff weights for the evaluating objects (e.g. customer requirements, components, process steps) based on pairwise comparisons for each level. [67] AHP is a multi-criteria decision-making tool that has been used in weighing customer requirements[68], and this work plans to replicate it also for components and processes, but considering the weighting factors suggested by the methodology but in a more subjective way. Therefore, three AHPs are built (as shown in Figure 4.5) and designed to evaluate customer requirements, components, and processes. The output of this analysis is a scaled weight that represents the level of importance of each object and is used in the next matrix.

Pairwise comparison matrix

INSTRUCTIONS: Fill only the **white cells** with the following criteria.

Criteria:
1 Equally important
3 Weakly important
5 Important
7 Strongly important
9 Absolutely important
and their reciprocals

Customer requirements/Components/Processes

Customer requirements/Components/Processes	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Criteria weights	Rank	Scaled weight
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1/3	1	1	1	1	1	0.04	24	1.00
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.05	1	5.00
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
12	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
14	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
19	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	2	3.64
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
21	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
23	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
24	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	3	2.28
	30.0	23.2	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	23.3	24.0	24.0	24.0	24.0	24.0			

Figure 4.5 Analytical hierarchical process proposed.

The evaluation criteria in this matrix are from 1 to 9, where the lowest value represents equally importance, and the highest value represents that one of them is absolutely more important than the other one.

QFD:

INSTRUCTIONS: Fill only the white cells with the following criteria.

Criteria:
1 Very low
3 Low
5 Medium
7 High
9 Very high

Variance characteristics

Customer requirements/Components/Processes	Importance	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1.00	5					3						1			
2	5.00	1			5											
3	2.28	3										7				
4	2.28	5			3											
5	2.28															
6	2.28	7														
7	2.28	1										3				
8	2.28															
9	2.28															
10	2.28															
11	2.28			1								1				
12	2.28															
13	2.28	5										3				
14	2.28															
15	2.28			1												
16	2.28						1									
17	2.28															
18	2.28	3														
19	3.64			1												
20	2.28	5														
21	2.28															
22	2.28															
23	2.28	5														
24	2.28															
	Absolute	87.67	0	8.211	31.85	0	5.284	0	0	0	0	31.98	1	0	0	0
	Relative	53%	0%	5%	19%	0%	3%	0%	0%	0%	0%	19%	1%	0%	0%	0%
	Rank	15	1	12	13	1	11	1	1	1	1	14	10	1	1	1
		5.00	1.00	1.37	2.45	1.00	1.24	1.00	1.00	1.00	1.00	2.46	1.05	1.00	1.00	1.00

Figure 4.6 Quality-function deployment proposal.

Consequently, three matrices are built for each perspective: market, product, and processes, which simulate a quality-function deployment (QFD) approach where the variance characteristics are evaluated in each perspective (as shown in Figure 4.6). The weight obtained in the previous step is used for each element. These matrices are filled with the same logic as a QFD. The evaluation criteria in the matrix are also from 1 to 9, where the lowest value represents a very low relationship, and the highest value represents a very high relationship.

In general terms, the sequence for the variance sensitivity analysis is filling the AHP matrix to compute the relative importance of the evaluating objects, and then filling the QFD matrix to compute the relative importance of the variance characteristics in each perspective. A zero-step is to define a scale since it will define the scale of the weighting factors and in the end, it defines the range of qualitative benefit criteria in the overall assessment that declares when a value is high or low in each perspective. The scaled numbers are calculated by using Eq. 16.

$$m \to \frac{m - r_{min}}{r_{max} - r_{min}} \times (t_{max} - t_{min}) + t_{min}. \quad (16)$$

r_{min} = denote the minimum of the range of your measurement

r_{max} = denote the maximum of the range of your measurement

t_{min}= denote the minimum of the range of your desired target scaling

t_{max}= denote the minimum of the range of your desired target scaling

$m \in [r_{min}, r_{max}]$ denote your measurement to be scaled

Finally, the three QFD matrices are concentrated in an overall assessment matrix (shown in Figure 4.7) where the results of each perspective are computed from the already filled matrices and are shown more qualitatively with a three-color scale. Each color is calculated depending on the previously chosen numerical scale because each one represents a range on the numerical scale. Not necessarily the ranges of each color are divided into equal parts. This is part of the decision-making. The overall assessment represents the output of the variance sensitivity analysis and from this, concrete conclusions can be drawn, and a classification of components can be built depending on their complexity in the external and internal framework. The results are presented in the next chapter.

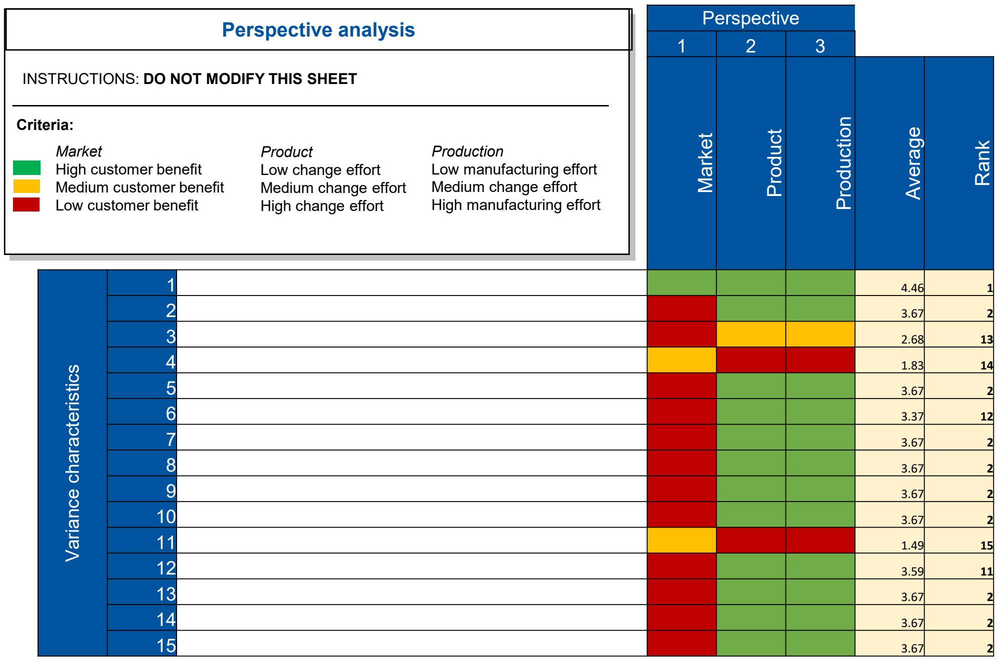


Figure 4.7 Overall assessment proposed.

4.1.2 Powertrain analysis

4.1.2.1 Modeling of the powertrain

4.1.2.1.1 Vehicle model

The electrified powertrain is modeled using the QSS toolbox in MATLAB Simulink. The model is composed of those elements described in the previous sections. All parameters defined for each block are specified in the next sections. The goal of the model is to simulate the behavior of an electrified electric truck with a given drive cycle and estimate its energy consumption. The model has two main features: the drive cycle estimation for heavy-duty trucks and the topology selection. Both features will be discussed later.

As the model is using the backward-facing approach, the first block is the driving cycle. This interface provides the user with a selection of pre-defined driving cycles. Next to the driving cycle is the vehicle block. This block requires all the vehicle parameters to be able to compute the vehicle dynamics that then will be translated to the wheel model in the next block. The simple wheel model only requires basic characteristics of the wheel as the radius of the wheel. Then, the next block is the topology model. This block allows the user to select an architecture variation for the powertrain that can be composed of a different number of electric motor(s), gearbox(s), and differential. This block will require different parameters depending on the topology selected. The last block is the battery model, where the user will define the battery pack size (number of batteries in parallel and number of batteries in series) and the initial state of charge, to compute the energy consumption and final state of charge considering the battery losses. Inside the model, most of the block's output variables are sent to the workspace and then used in the analysis block to perform different calculations, and display data of interest, for example, efficiencies, energy consumed, range, etc.

To run the model, you only have to set all the parameters inside each mask (all the parameters are defined in the masks at the top level) and run the model. You must ensure that all calculations are carried out correctly.

The duration of each simulation may vary depending on the duration of the drive cycle but using a Dell XPS 9350 with Intel Core i5-6200 @ 2.30 GHz, 2 cores, 4 logical processors, the maximum duration for a drive cycle of 3100 seconds it is 10-20 seconds for the first calculation. It should be considered that when the model is run for the first time the simulation takes longer since the driving cycle is calculated. For optimization purposes, only the first simulation takes the mentioned time, and then each iteration takes about 1 second just to update parameters.

Modeling in this library is relatively simple and very visual thanks to the modular structure. The advantage of using QSS is that the model can be updated to add more features, such as a greater variety of topologies as well as different types of transmissions.

The full vehicle view can be seen in Figure 4.8. Lower level views of main components can be found in Appendix A.

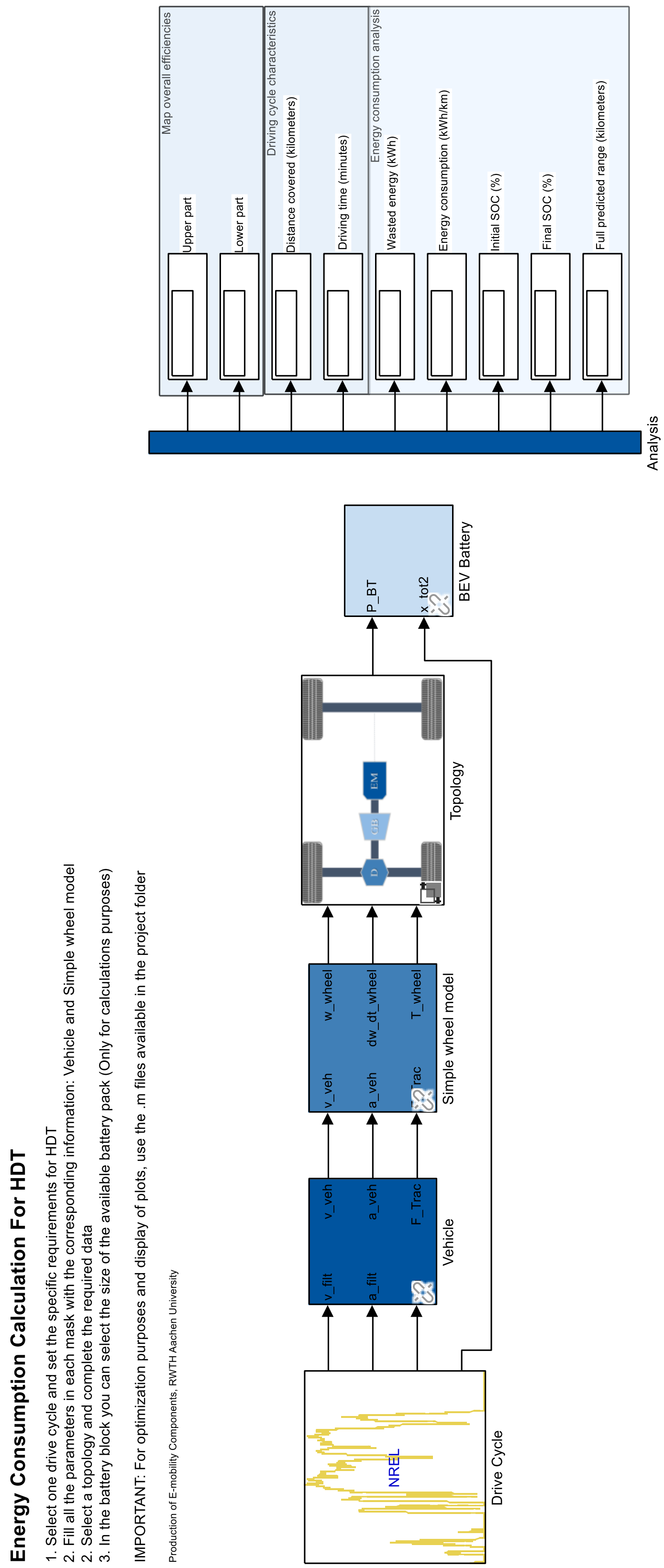


Figure 4.8 Electric powertrain model using QSS toolbox.

4.1.2.1.2 Vehicle parameters

The electric powertrain modular kit is expected to cover the heavy-duty vehicle ranges from 7.5 to 40 tons. As the aim of this work is to estimate fuel consumption with different topologies, the parameters of the heaviest truck are considered to simulate the most critical conditions.

The data is based on combustion engine trucks, and the scope of the kit is to be able to replace the powertrain with an electric one without altering the current characteristics of the truck, thus, a benchmark of heavy-duty trucks for long distances and heavy loads is carried out to determine the vehicle parameters. Reference data is based on OEMs trucks with similar load characteristics (see Table 4.8).

Table 4.8 Vehicle parameters for the simulation

Vehicle parameters	
Total mass [kg]	40,000 (GVW)
Vehicle cross-section [m^2]	10
Drag coefficient [-]	0.6
Rolling resistance [-]	0.01
Differential ratio [-]	3.364
Differential efficiency [-]	0.98
Gearbox efficiency [-]	0.9
Max. Speed [km/h]	90
Max. Acceleration [m/s^2]	0.57

The total mass of the vehicle is divided into 7400 kg of the curb weight of the truck, that is also a restriction for the design of the modular kit (electrified powertrain must weigh same or less than that weight), and 32600 kg of payload for a total of 40000 kg of gross vehicle weight.

The other parameters as cross-section, coefficients, differential characteristics and efficiencies are derived from the ICE truck and manufacturer data. The maximum speed is defined by law and depends on the country or state. In this case, is assumed a 90 km/h as the maximum speed for the truck. The last parameter related to maximum acceleration is a difficult piece of data to extract from a commercial benchmark because it is information that is not found in the sales specification sheet. Therefore, this data is obtained based on a study of experimental accelerations with 40 trucks in three cases of study: lightly, moderately, and heavily loaded. The data is examined and evaluated. For this case-specific, the data of the trucks heavily loaded is considered due to the payloads are close to the payload defined in the vehicle parameters. The acceleration ranges obtained in the experiments vary from 0.12 to 0.57 m/s. Due to the aim of having the best possible performance in the electric powertrain, the maximum possible acceleration of the study was taken as a reference. For more in-depth information on the experiment check the reference. [69]

4.1.2.1.3 Driving cycles

In order to evaluate the performance of our model of the electric powertrain, it is necessary to define the driving cycles to estimate energy consumption. Although the model allows the user to choose between several drive cycles, two drive cycles are selected for this analysis: National Renewable Energy Laboratory (NREL) driving cycle and Worldwide harmonized Light vehicles Test Cycle (WLTC). The first cycle is a series of data extracted by the National Renewable Energy Laboratory of the U.S. Department of Energy that is focused on comparing the variation of the driving cycle in the entire spectrum of medium-duty and heavy-duty trucks. This data is representative of a cycle on the highway. [70] The second cycle was designed by the European Union and presents a more homogenous acceleration with higher average speed and speed standard deviation making the cycle more realistic. WLTC covers a wider range of engine conditions and is more representative of real driving. Due to the high load points, the WLTC also has high fuel consumption results. There are different categories of power-to-mass (PMR) ratio where the Class 3 cycle is the most representative of vehicles driven in Europe and Japan. [71]

Despite the two drive cycles are highly representative samples of realistic driving conditions, which have become relevant for estimating fuel consumption and emissions, they cannot be directly extrapolated to our case study. Most of the driving cycles are focused on the light and commercial vehicle market, so the speed curves are made according to the restrictions of a light-duty vehicle. In order to use these drive cycles in our application of a heavy-duty truck with maximum payload, the drive cycle block in the model filters the data based on two restrictions: maximum speed and maximum acceleration. The first restriction establishes a limit for the amplitude of the speed and the second restriction establishes a limit for the acceleration slopes. These two parameters were defined as quantitatively in the previous section. The result of the cycle is a new drive cycle representative of an NREL(shown in Figure 4.9) and a WLTC3 (shown in Figure 4.10) for heavy-duty applications.

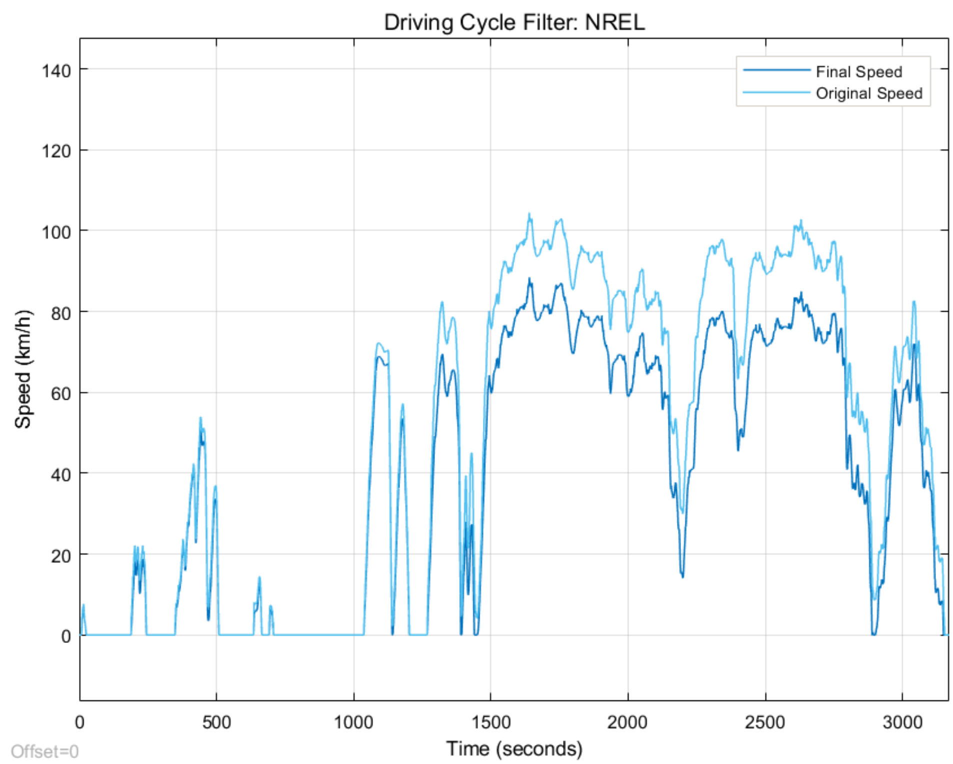


Figure 4.9 National Renewable Energy Laboratory (NREL) driving cycle

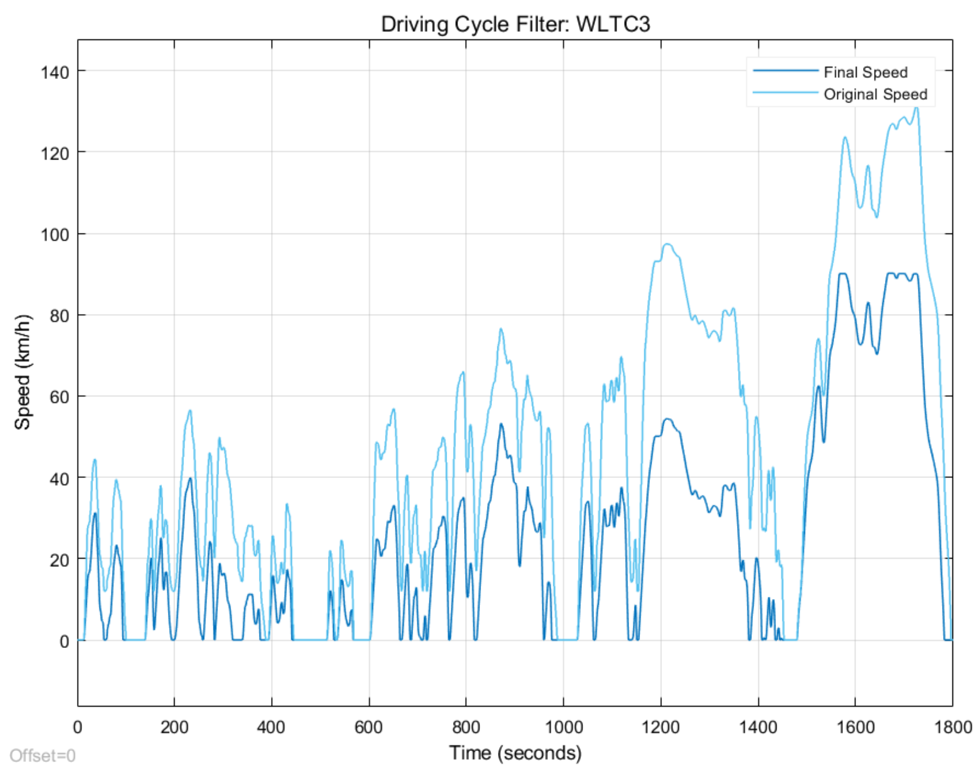


Figure 4.10 Worldwide harmonized Light vehicles Test Cycles (WLTC) Class 3 Cycle

4.1.2.1.4 Powertrain topologies

In the model, four different electric powertrain topologies are studied. It can be noted that the upper part of the figure includes two topologies with a centralized single motor and the lower part shows two topologies with a decentralized double motor, each one close to each wheel.

This feature of the model aims to study the performance of different topologies given a driving cycle, but more specifically: the variation between a central electric motor or two motors near the wheel/in-wheel; the influence of the central gearbox with fixed transmission, or two gearboxes (for each motor); and finally the influence of the differential since as a modular concept when converting a conventional vehicle to electric, it is not known whether to remove or maintain the OEM differential. Next, each of the topologies will be analyzed in depth.

Topology A represents a central drive and is the most conventional configuration that can be found in commercial electric vehicles. This topology is based on a single electric motor for traction and allows a smooth conversion from conventional to electrical, as most components can be re-used.

Topology B represents the same central drive as topology A, but this eliminates the high cost of the gearbox transmission with a motor that can meet the same operating conditions.

Topology C represents a close-to-wheel drive topology. In this drive, an electric motor and a gearbox with a fixed ratio are integrated into an assembly and connected to the wheel through a drive shaft. Depending on where the assembly is mounted (under or above the suspension), it can compromise handling and ride comfort of the vehicle. Few commercial vehicles have adopted this topology, but it is already in the current market.

Topology D represents the simplest electric powertrain topology with an electric motor directly in the wheel hub and without any other mechanical element (such as gearbox, differential, or driveshaft). This configuration eliminates all losses due to mechanical components, as well as allows a better layout of the electrical components. Further, different control strategies could allow active control of the motors, which would improve handling. Despite the advantages, this topology is not fully developed due to its influence on the driving behavior when mounted on the unsprung mass, and complications with cooling and the slight design space.

Each of the topologies seeks to demonstrate different concepts. Although these concepts are already found in commercial electric vehicles or prototypes (in the case of the in-wheel concept), there is very little research related to heavy-duty vehicles and topologies. This work aims to analyze the behavior of these different concepts in heavy trucks to validate whether these topologies are feasible or not. Besides, as mentioned before, the flexibility of this model allows more topologies to be added within the same mask, but for now, the topologies studied are those defined in Figure 4.11.

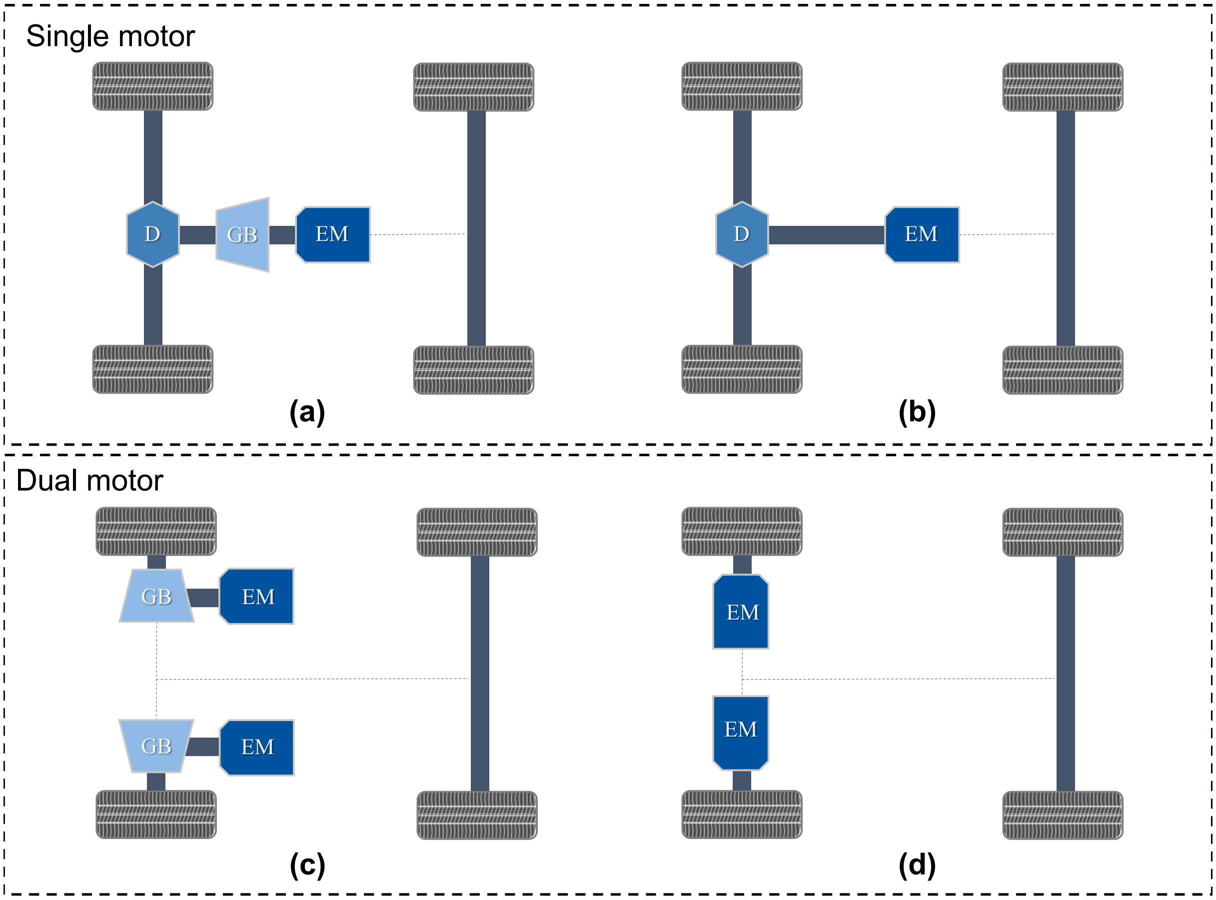


Figure 4.11 Topologies available in the model of the electric powertrain. D=Differential, GB= Gearbox, EM=Electric Motor.

4.1.2.2 Powertrain optimization

4.1.2.2.1 Solver comparison in MATLAB

As GA and PSO are two of the most used algorithms in the optimization area, and there is no methodology to select the best algorithm for your problem, a direct comparison was made in MATLAB between these two algorithms. Although in the MATLAB documentation you can find a comparison between several solution methods, including GA and PSO, the objective of this section is to determine which algorithm has better performance for our specific case study.

For the comparison, a MATLAB script is written in which the genetic algorithm function 'ga' and the particle swarm optimization function 'pso' is called. Both algorithms are not run at the same time, but alternately. The comparison is focused on comparing the performance with the same initial population for each of the algorithms(5, 10, and 20), which means, compare the accuracy of evolution operators by the GA versus the velocity and position by the PSO. Figure 4.12 shows the result of the comparison.

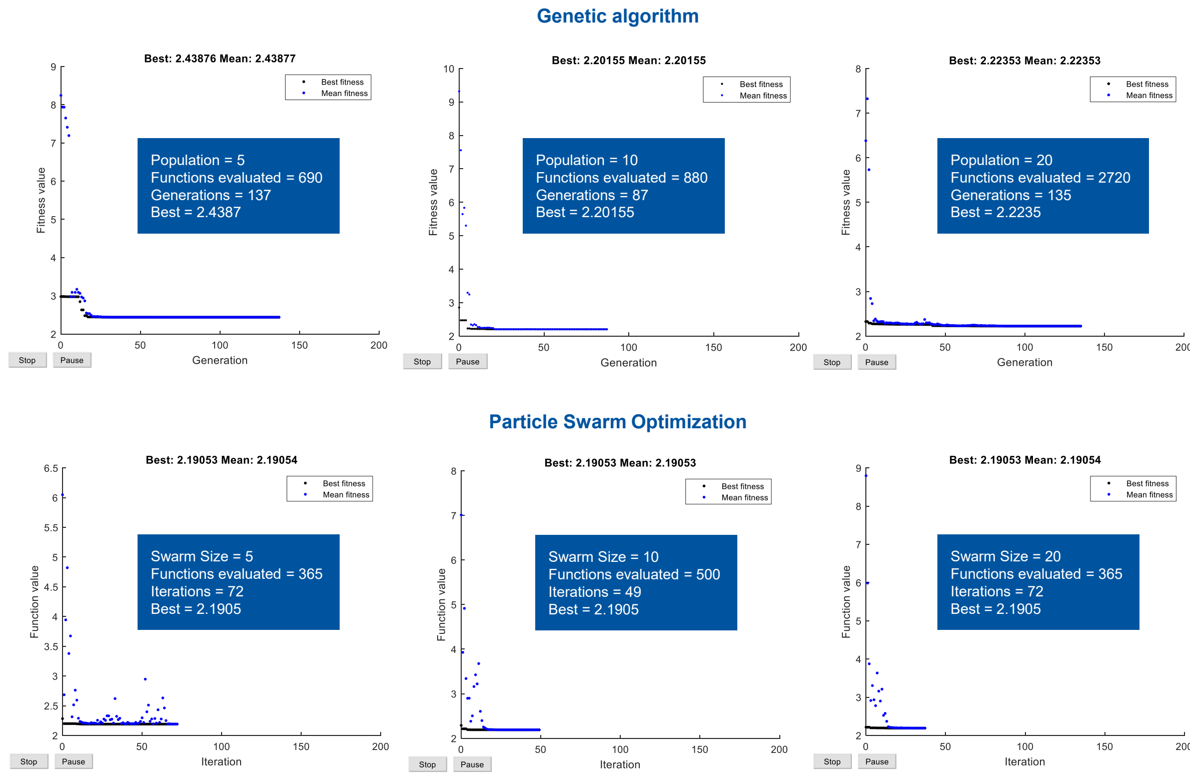


Figure 4.12 GA vs PSO comparison

As can be seen in the figure, in the case of GA, many more functions need to be evaluated than in PSO. Also, the number of generations by the GA always doubled the number of iterations of the PSO. Finally, the 'best' for the GA varies with the population, and in the case of the PSO, it always reaches the answer even with the swarm size varying.

After comparing the results, both algorithms find similar optimal solutions, but the PSO always reaches the same solution, whereas the GA has variation. Further, PSO has a slightly better performance in terms of average and standard deviation from multiple runs of the algorithm. Moreover, in terms of computational efficiency, which is a key requirement for the algorithms in the design problem, PSO shows better performance than GA significantly.

In all population cases, PSO converges faster with higher robustness of the algorithm coefficients, which indicates that fewer evaluations are necessary. By analyzing and comparing the results, it is shown that PSO is more efficient than GA to achieve the optimal performance for an electric powertrain model in MATLAB Simulink.

Therefore, PSO is selected as our main plant design optimization algorithm. The swarm size chosen for our optimization problem is 10 since although in the comparison the population of 5 also converges to the global optimum, this is for a particular case. A population of 10 presents a good performance, with an acceptable number of evaluated functions and iterations to cover the largest possible design space with a computational time of approximately 2 hours.

4.1.2.2.2 Optimization framework

After comparing several solvers, and thanks to its good results and its frequent application for problems related to hybrid and electric vehicles, a PSO was selected as the optimization algorithm for the design problem. Its main advantage is that the algorithm allows searching the entire design space and can find the global minimum. Next, the algorithm optimization framework for topology selection and sizing is presented.

The procedure starts by defining all the input parameters required to run the model, as well as its requirements and restrictions that the powertrain must meet. These include driving cycle, vehicle parameters, motor and gearbox size ranges, efficiencies, and more. Once all the parameters have been established within the model, a MATLAB script can be run to perform the optimization. This script will call the model and run the framework presented in Figure 4.13.

First, the script systematically selects a topology in order to enter the optimization inner loop. Inside the loop, a population is generated based on a pre-defined initial population that will move throughout the design space. Every time the particles change position, the objective functions are evaluated, and the algorithm stops until all the particles converge to a point or the maximum number of iterations is reached. Each position represents different sizing of electric motor and transmission ratio, and the evaluated functions represent the energy consumption for that sizing iteration. The exit criterion for the inner loop is met when a global minimum is reached for the topology in turn. When this criterion is met, the algorithm returns to the outer loop, where the results of the inner loop are compared to the global best. If the result is better than the current global one, it is replaced by the new one, and the algorithm returns to the systematic selection of the topology and the loop is repeated. The stop criterion for the outer loop is to have found the global minimum among all the topologies studied.

Once the optimal topology for the management cycle is obtained, the algorithm displays the results of the optimization in the model and generates an efficiency map with the operating points of the management cycle. This optimization approach allows us to evaluate different electric powertrain topologies in a relatively short time, as well as find their optimal sizing given a specific drive cycle, thus giving us a holistic view of powertrain behavior, which can certainly help in decision making in the future of the project.

The main MATLAB scripts for the optimization can be found in Appendix B.

The next chapter presents the results obtained using this optimization framework.

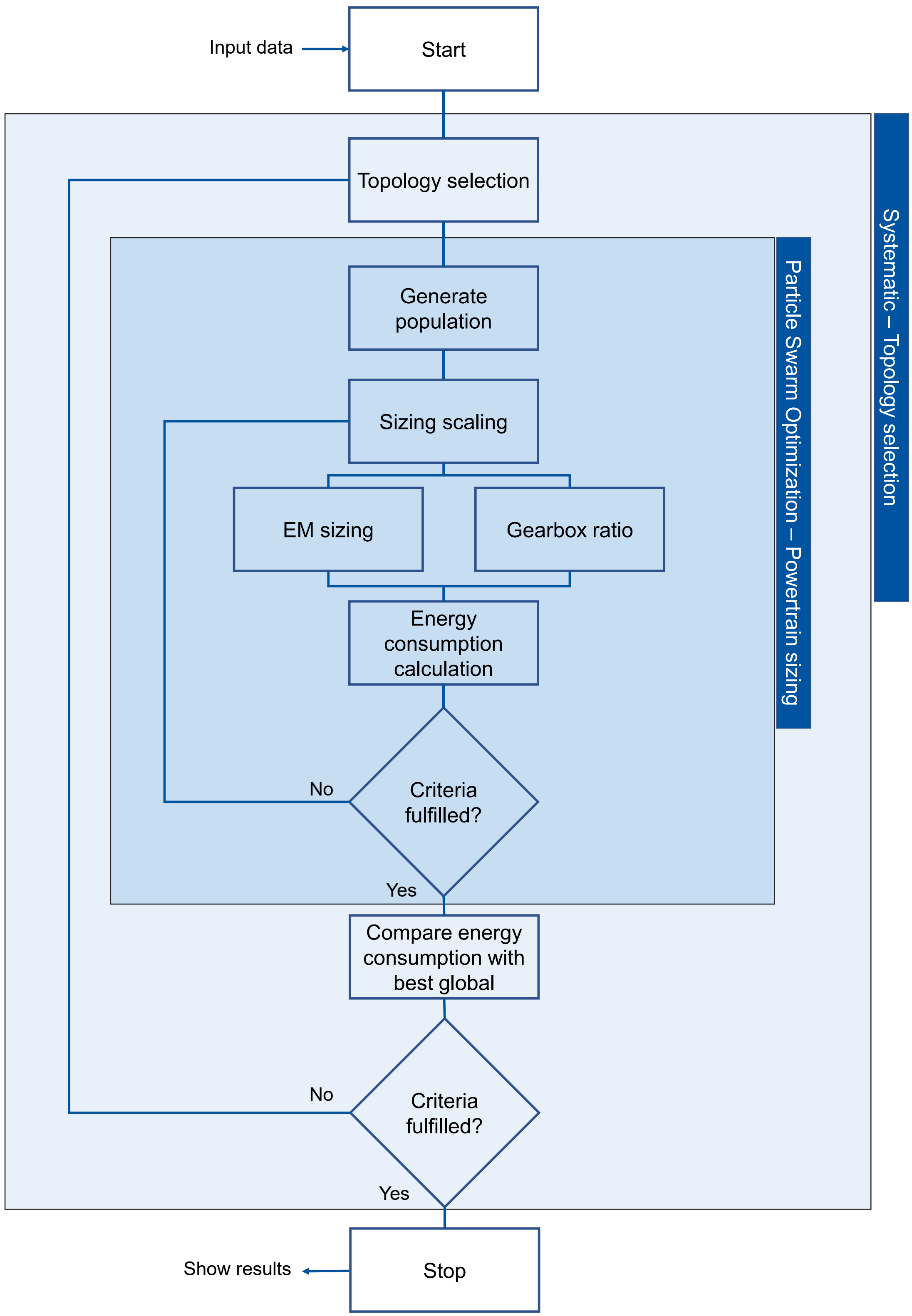


Figure 4.13 Optimization framework proposed

5 Analysis and results

The preliminary results of the execution of the method are now used to obtain the final results. This chapter presents the results of each deliverable. For the variance sensitivity analysis, the results obtained in the workshop are shown with their respective analysis in the three perspectives. For the powertrain analysis, the simulation results and the optimization strategy are shown for the driving cycles specified in the previous chapter.

5.1 Variance sensitivity analysis

Due to the early stage of product development, the analysis of variance was carried out through a workshop with experts as specified in chapter three. Experts evaluated the influence of each variance characteristic regarding the market, product, and process perspective. The reliability of the results is strongly dependent on the expertise of the workshop participants. The analysis was performed individually for each of the perspectives (see Appendix C) and documented in an overall assessment. Figure 5.1 shows us a summary of the qualitative evaluation for each variance characteristic.

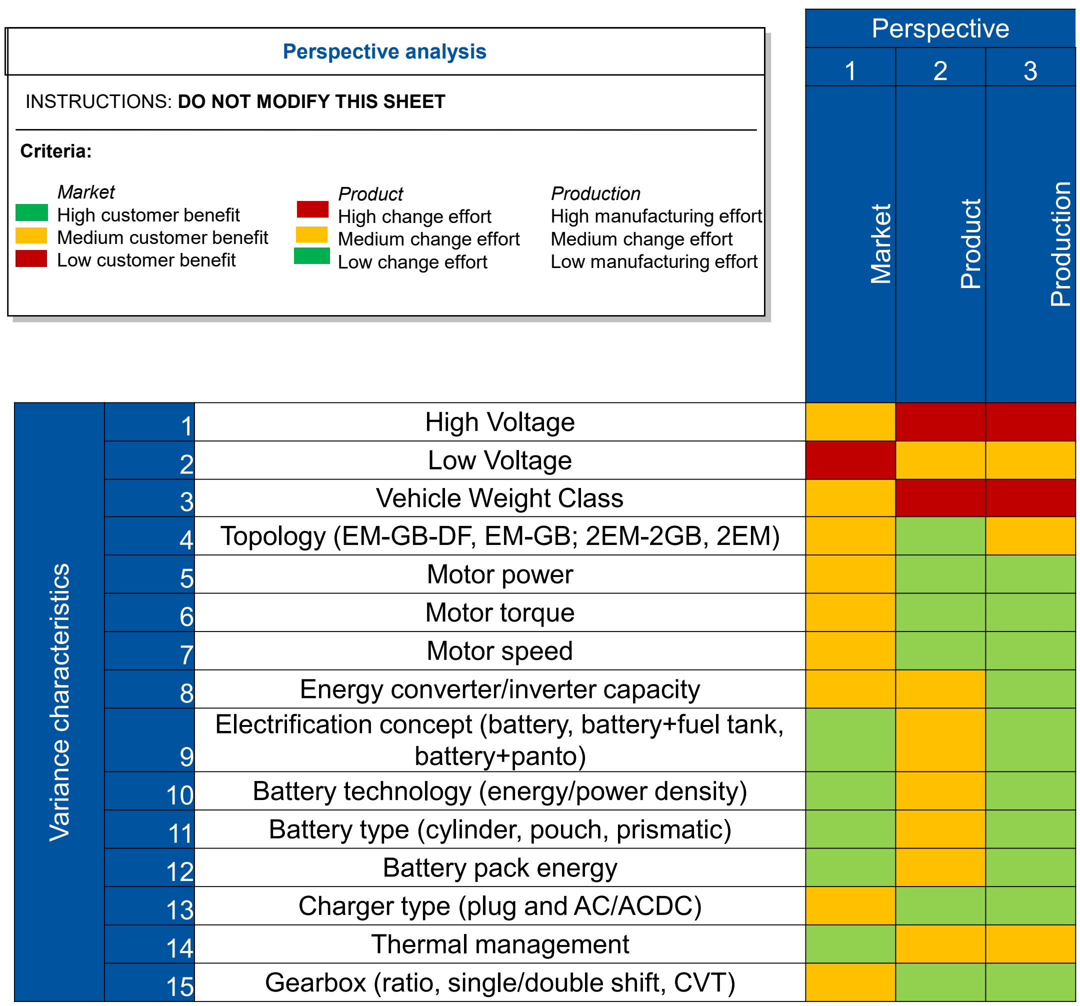


Figure 5.1 Overall assessment results

From the market perspective, most of the characteristics are medium and high customer benefit. In the product case, most of the variance characteristics appear to be from low to medium change effort. From a production perspective, most characteristics are from low to medium manufacturing effort. The two most critical resulting characteristics are high voltage and weight class, where both presented medium customer benefit and high change effort for product and production respectively.

Product and production perspectives are evaluated similarly. These two perspectives can be integrated into the internal framework to be able to show the results in a two-dimensional grid system, giving an overview of the variance characteristics concerning their external and internal significance as follows (see Figure 5.2).

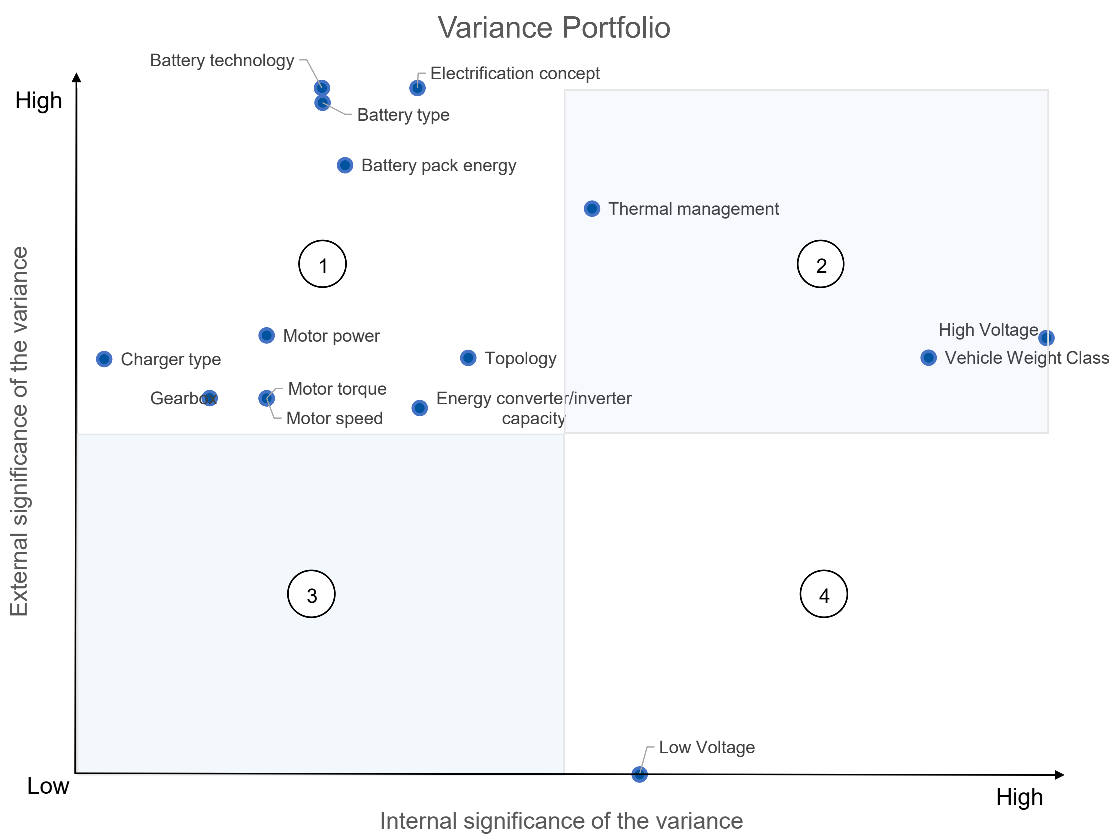


Figure 5.2 Variance portfolio results

Table 5.1 Classification in the variance portfolio

Zone	Description
1	Candidates for the design of variance (active product differentiation)
2	Critical Variance Characteristics (Potential Candidates for Constituent Characteristics)
3	Non-critical variance characteristics (high standardization potential)
4	Variance characteristics to be standardized (Potential Candidates for Constituent Characteristics)

The variance portfolio aims to derive scenarios and clusters of the individual characteristics regarding their importance for the internal and external variance. The portfolio can be divided into four zones, which result from the gradation low and high on the two axes.

Table 5.1 shows the description of each zone.

The results show us that most of the variance characteristics identified are suitable candidates for the variance design (Zone 1). These characteristics do not lead to high-cost increases in product design or production in the value chain. Also, a variant design rich in these features can result in additional increments of profit for customers. This area includes the characteristics of the battery, motor, inverter, charger, among others.

The characteristics in Zone 3 are characterized by low internal and low external significance of the variance. That means that these characteristics offer a high standardization potential. In our results, no characteristics appear in that zone.

The variance characteristics classified in Zone 4 have a high standardization potential due to their low external importance and at the same time high internal importance of the variance. In this case, the low voltage must be standardized. Also, can be represented as a potential candidate for a constituent feature.

Finally, the most critical variance characteristics are in Zone 2, characterized by the importance of variance in both external and internal valuation. These critical characteristics are high voltage, weight class, and thermal management. Also, due to the proximity to zone two, we include topology as a critical feature. For this type of characteristic, it is necessary to investigate thoroughly the sensitivity to variance to later define it as a constituent feature or not. Further, constituent features can be derived through product-specific knowledge and engineering thinking.

Vehicle weight class: although the variance concerning this characteristic is very complex for both, external and internal framework, one of the main objectives of the modular kit is that it should be scalable, so this characteristic cannot be converted into a constituent feature, but it should be taken into account when defining the variant specifications of this characteristics.

Thermal management: this is the characteristic that represents the most benefit to the client according to the results in the variance portfolio. Due to its complexity and the impact it has, it could become a constituent feature related to technology (e.g. define the optimum technology for the battery, motor, braking, etc.), but due to its relationship with the weight class of the vehicle, the sizing would be optimal only for one class of vehicles.

High voltage: it is one of the variance characteristics that have the most impact since a change in it directly influences the main and most expensive components of the electric powertrain (e.g. motor, inverter, battery). This is the main candidate to become a constituent feature.

Topology: Due to its proximity to zone 2, the topology of the electric powertrain is considered a critical characteristic. Because the customer's benefit is medium, and its significance of internal variance is also medium, it is a characteristic that we can standardize, as long as the topology that is defined as the standard is the optimal one for all classes and driving conditions. From here, the second deliverable of this work is derived.

Finally, other characteristics that were broken down for the sensitivity analysis can be integrated back into one and standardized, such as battery technology and type, to only handle different pack sizes. In addition, directly co-dependent components such as the motor and the inverter can also be integrated into a single package since they will depend directly on the size of each one. Likewise, in order to standardize part of the thermal management, we decoupled it in technology and sizing. The following table (Table 5.2) presents a matrix with the proposed features of the product for the modular electrical kit.

Table 5.2 Powertrain product feature matrix proposal

No.	Features	Spec. 1	Spec. 2	Spec. 3	Spec. 4
1	High Voltage	Constituent feature			
2	Thermal management technology	Constituent feature			
3	Battery technology (energy/power density)	Constituent feature			
4	Battery type (cylinder, pouch, prismatic)	Constituent feature			
5	Topology	Constituent feature			
6	Low Voltage	Constituent feature			
7	Electrification concept (Range extender)	None	Type 1	Type 2	
8	Vehicle Weight Class	Size 1	Size 2	Size 3	Size 4
9	Thermal management sizing	Size 1	Size 2		
10	Battery pack energy	Size 1	Size 2	Size 3	
11	Motor/Inverter	Size 1	Size 2	Size 3	
12	Gearbox ratio	Size 1	Size 2		
13	Gearbox type	Type 1	Type 2		
14	Charger type (plug and AC/ACDC)	Type 1	Type 2		

The proposed feature matrix can be visualized using the shell model (see Figure 5.3) where features are assigned to a core, middle, or outside area (see

Table 5.3). In the core, the variance characteristics that remain constant are classified (due to internal significance or low relevance). The middle shows features that cause an average change effort. By cleverly defining the variants to be implemented, market-side requirements can be met in this area with limited additional costs (e.g. scalable weight classes from 7.5t to 40t can be covered by just 4 vehicle sizes). The outer area is characterized by easily changeable variance characteristics. These characteristics offer a high differentiation potential for modular products. A high market-side diversity can be created through low-cost expenditure. The simplest example is the driving range offered by the variance of a battery pack.

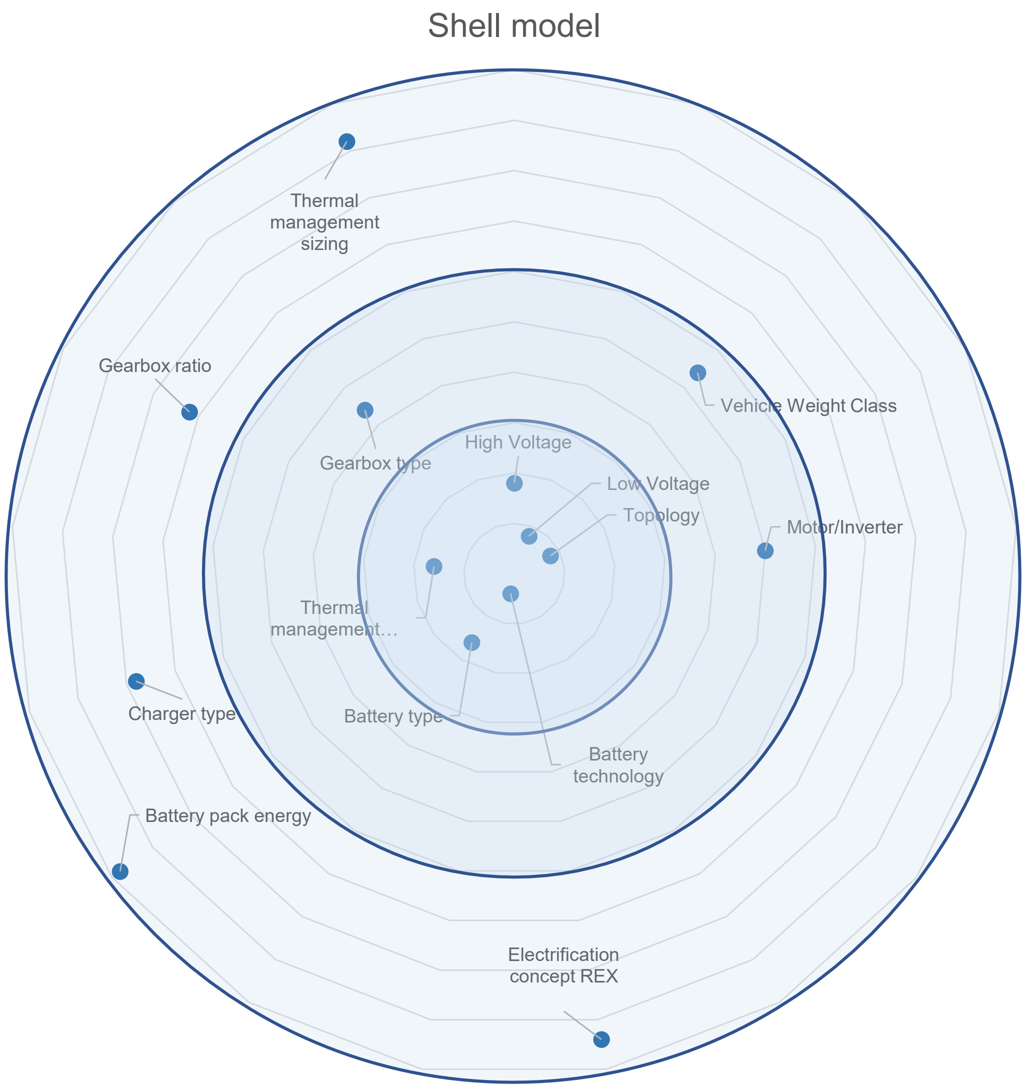


Figure 5.3 Shell model results

Table 5.3 Shell model classification

Zone	Description
Outside	Easily changeable variance characteristics with little change effort
Middle	Modifiable variance characteristics with average change effort
Core	Constant variance characteristics with high change costs

5.2 Powertrain analysis

Regarding powertrain analysis, this deliverable is focused on topology analysis and sizing to help define the specification of product features. To achieve this, four topologies are studied given two different driving cycles previously specified in chapter three. The results are divided by the driving cycle, and are composed of three main components: the operating points of each topology with the optimal sizing, the surfaces generated for each topology varying the sizing of the engine and transmission, and finally the comparison of the optimization routine for each topology. It is expected to provide an optimized powertrain concept that can serve as a reference for product development and highlight the tradeoffs between the main components studied (e.g. motor and gearbox). All simulations were implemented in MATLAB.

5.2.1 NREL Results

The results for this test cycle are shown below. The efficiency maps are the result of a systematic optimization for each topology with the same restrictions to compare the performance and optimal sizing of each topology.

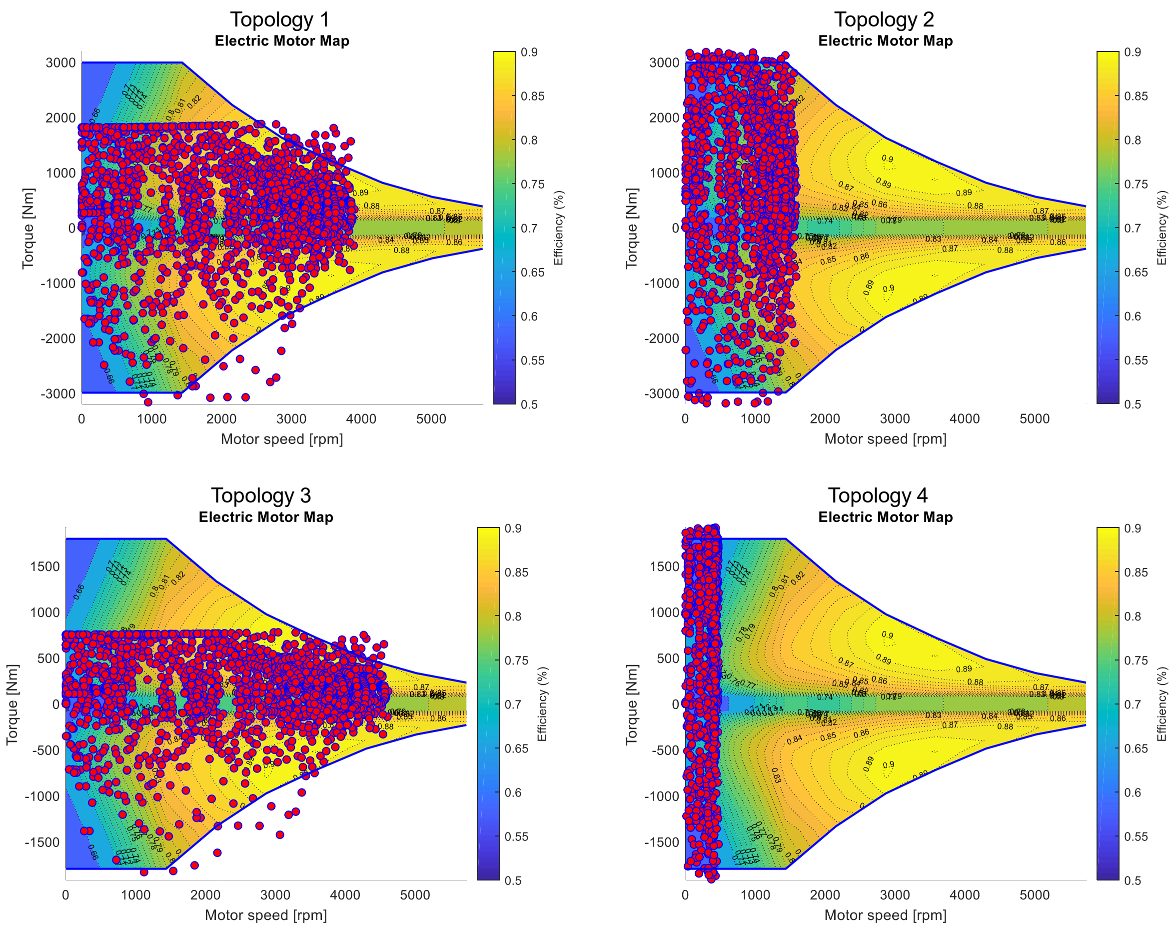


Figure 5.4 Electric motor operating points for the NREL using the proposed vehicle model.

For the operating points of the optimized electric motor of this cycle (see Figure 5.4), different graphical trends can be seen for each topology. For the first topology, most of the operating points are concentrated in the lower part of the efficiency map. In this case, the gearbox allows them to be distributed horizontally, that is, higher rpm at lower engine torque. In the second topology, where the gearbox is eliminated, it can be seen how the points are concentrated in a vertical rectangle with higher torque but at lower rpm. For the third and fourth topologies, a phenomenon similar to that of the first and second topologies respectively can be noted. The third topology is the one with the best efficiency since the torque requirement of the motor is divided between the two motors, and with the help of the gearbox, the points are located in the most efficient area on the map. Otherwise, for the fourth topology, it can be noted that removing the gearbox would require too much torque. In the case shown, the points are concentrated on the torque axis, in the area of lowest efficiency.

As the efficiency maps shown in Figure 5.4 were optimized using a PSO, it is difficult to describe the behavior of the powertrain by analyzing only the optimal one. To visualize the behavior of each topology, a script was designed where it systematically evaluates functions to analyze the tradeoff between design variables, energy consumption, and efficiency of the motor.

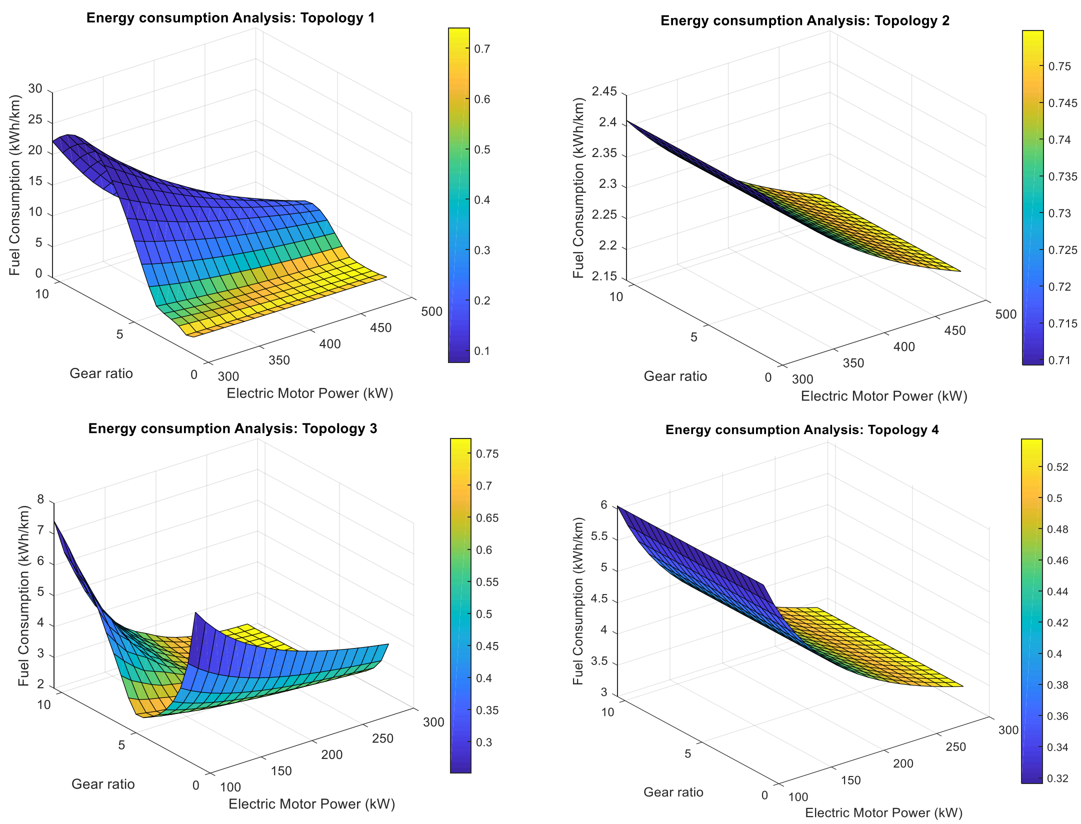


Figure 5.5 Surface plot representation of each topology. NREL test cycle.

The surface plots shown in Figure 5.5, are a very visual reference to our powertrain and can help us in our decision making of the project. It can be seen that each topology has different non-linear behavior. Only for the case of topology 2 and 4, which do not have a gearbox, the power consumption is constant. The highest efficiencies in all cases are found in the local optimum zones. The global optimum varies for each topology.

Topology 1 has its optimal zone at low gear ratios and high motor power. What is most surprising is how the higher gear ratio increases the energy consumption exponentially and it is because in this topology there is a differential involved that also adds to the overall transmission ratio. An oversized ratio displaces the operating points from the most efficient area.

Topology 2 does not have a gearbox, which shows us the behavior of the electric motor directly coupled to the differential. You can see that it is a slightly exponential behavior. The most optimal area is at higher electric motor power.

Topology 3 is the one that shows the most notable non-linear behavior. In this case, there are no external components that influence the behavior, e.g. a differential, so energy consumption is directly dependent on this tradeoff. More than one optimal zone can be identified (local minimums), but the global minimum is found at a high gear ratio and high motor power. Any deficiency in one of these increases fuel consumption dramatically.

Topology 4 behaves similarly to Topology 2, but eliminating the differential shows a dramatic increase in power consumption. This topology requires a motor with higher power and torque.

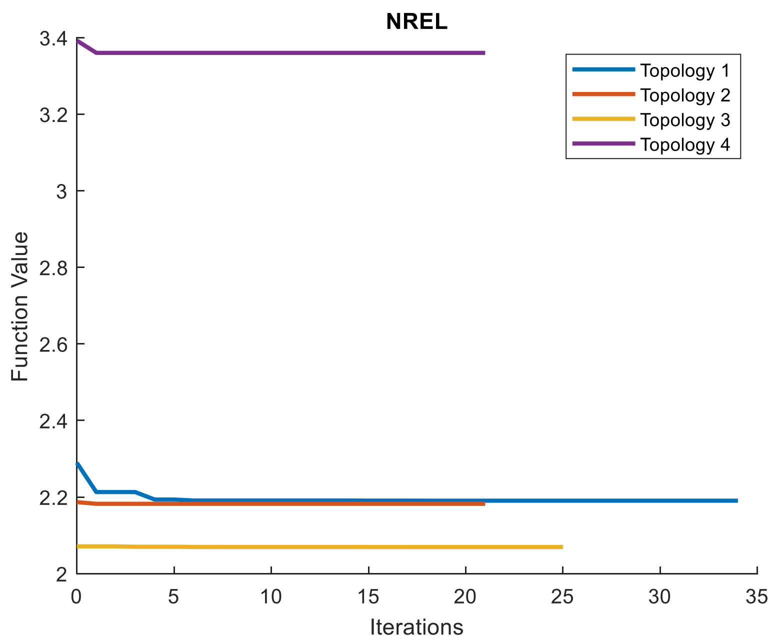


Figure 5.6 PSO comparison for different topologies.

Finally, the results of the optimization for a swarm size of 10 are shown in Figure 5.6. You can compare the convergence of each topology and the number of iterations required for each optimization. Furthermore, it can be noted that with the given restrictions, topology 3 is the one with the lowest energy consumption compared to the other topologies. Topology 1 and 2 show very similar behavior, and this means that even eliminating the gearbox, the differential can cover part of the gearbox's work. Topology 4 notably is the one with the highest fuel consumption because engine size restrictions cannot be met with this configuration, a larger engine size is required than the current maximum.

5.2.2 WLTC Results

The results of this cycle are shown below. In general, the results are analogous to the NREL cycle but as the WLTC cycle is more aggressive, as expected, the results show a notable increase in energy consumption for this cycle.

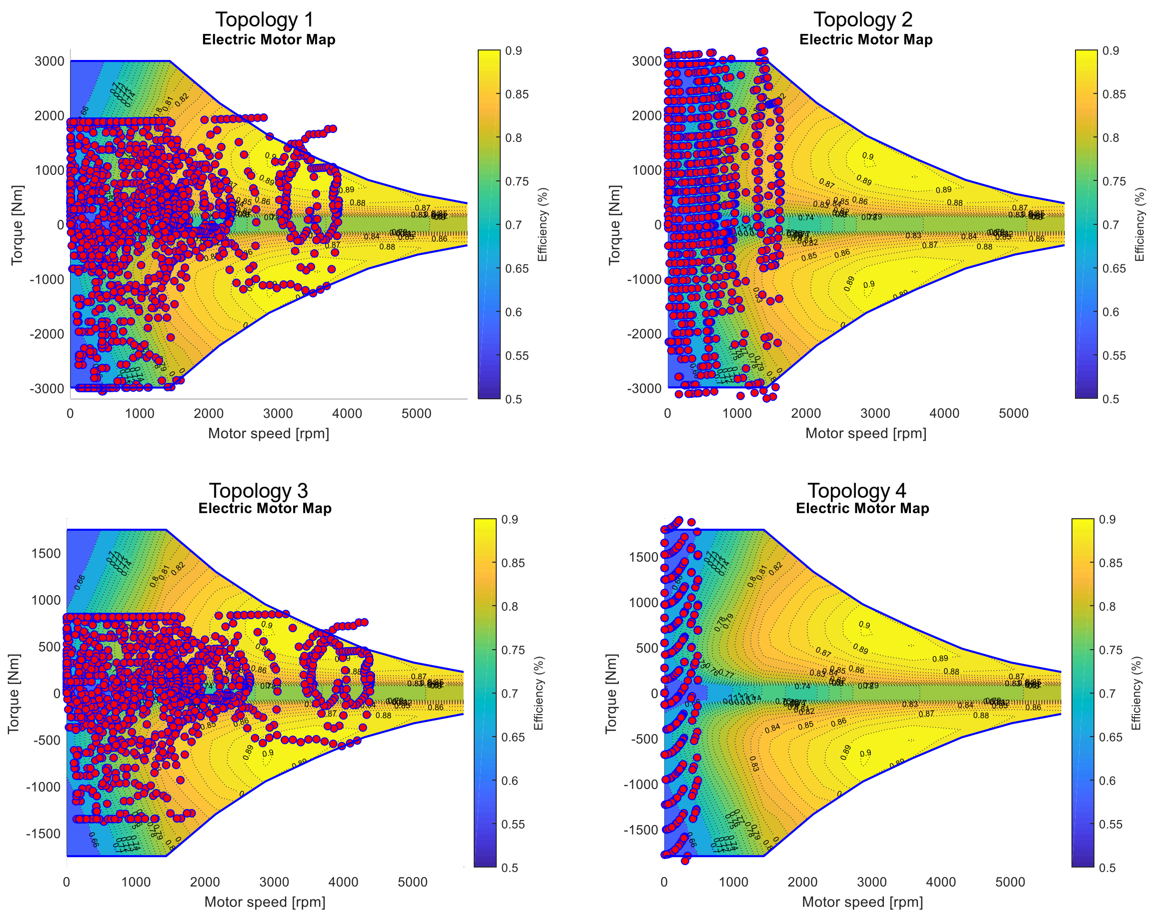


Figure 5.7 Electric motor operating points for the WLTC using the proposed vehicle model.

Since the WLTC cycle has a shorter duration than the NREL cycle, the operating points are displayed with less density (see Figure 5.7). In general, the behavior for each topology is the same as that presented for the NREL, but there is an increase in the required torque in all cases, which also represents an increase in the energy consumption of all topologies. In the case of topology 4, the results tell us that it is impossible to conduct this cycle with this configuration and these restrictions, since a large part of the motor operating points is outside the efficiency map, even using the greatest possible sizing.

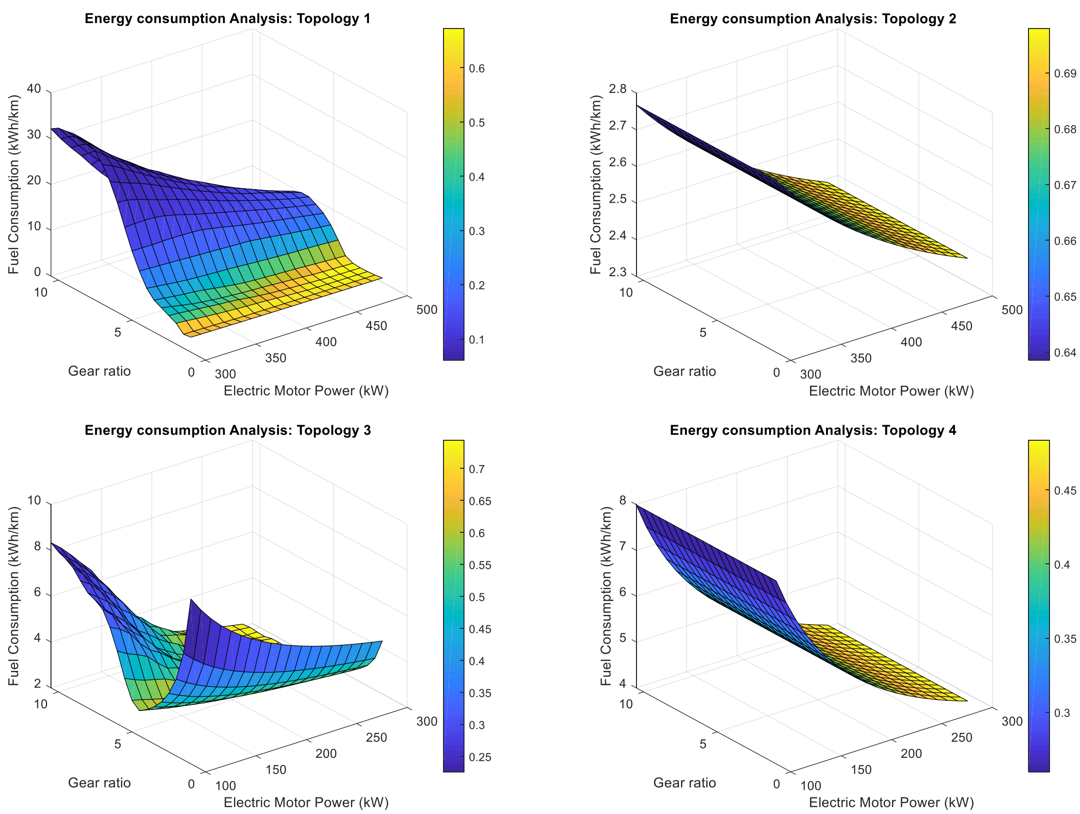


Figure 5.8 Surface plot representation of each topology. WLTC test cycle.

Similarly, the surface plots show (see Figure 5.8) a behavior similar to that of the NREL cycle, which can help us to assume that this surface can represent the behavior of our topologies for these design variables. In all cases, the efficiency was significantly reduced and the scale of the axis of the function value increased.

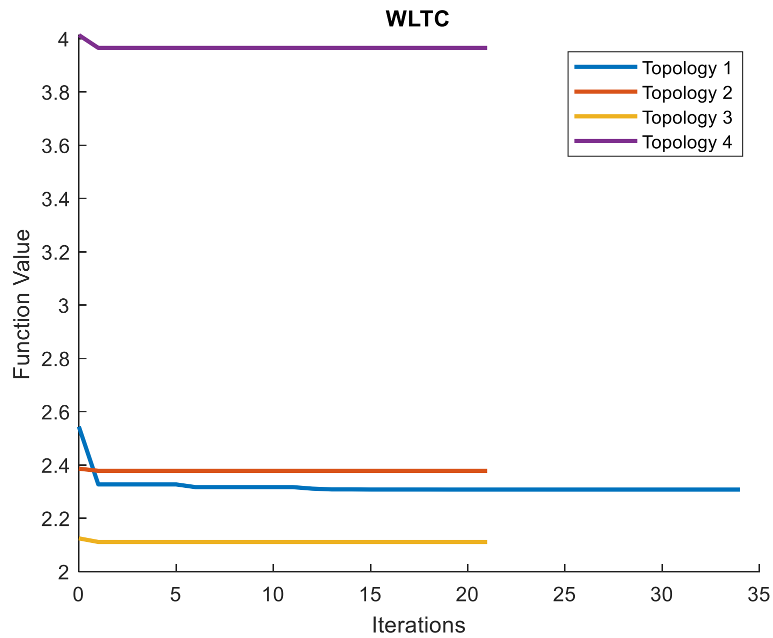


Figure 5.9 PSO comparison for different topologies.

Finally, the optimization results are also compared for this cycle for the same swarm size of 10 and shown in Figure 5.9. Topology 1 and 2 are again the topologies with similar power consumption, but with greater discrepancy than for the NREL cycle. Topology 1 is the one that takes the longest to converge. Topology 2 and 3 are the most stable and with the fastest convergence. Topology 4 presents the highest power consumption and also presents early convergence.

5.2.3 Summary

After analyzing the visual aids, a comparison can be made with the results obtained from the optimization (shown below in Table 5.4). In general, the four topologies present stability concerning the two cycles studied. In all cases, there was always a tendency in the sizing of the motor towards the upper limit. For the two topologies with gearbox, there is no trend in the selection of the gear ratio, and it depends directly on the configuration. Energy consumption for the NREL cycle is less than for the WLTC. Topology 3 is the one with the greatest stability since the energy consumption is equivalent in both cycles, which gives us a greater working range for this topology, with less variation.

Due to the early stage in the development of this product, we do not have a validation method for our model, but the results presented seem robust since numerically the energy consumption obtained is comparable within a benchmark with vehicles of the same characteristics.

The results obtained for the four proposed topologies and the two management cycles chosen for the analysis are a reference for the design of our modular topology.

Table 5.4 Optimization summary for each topology.

Topology	1		2		3		4	
Driving cycle	NREL	WLTC	NREL	WLTC	NREL	WLTC	NREL	WLTC
Energy consumption (kWh/km)	2.1905	2.3076	2.1800	2.3779	2.0696	2.0763	3.3601	3.9650
EM Power (kW)	500	500	500	500	300(2)	291(2)	300(2)	300(2)
Gear ratio (-)	2.4582	2.3801	-	-	9.7863	9.0817	-	-

6 Conclusion and Outlook

The development of modular platforms is a job that involves a deep understanding of the product and decision-making. This work contributes to the development of a modular electric powertrain kit through a variance sensitivity analysis to identify the constituent features of the powertrain, and a vehicle model in MATLAB Simulink for validation of some technical concepts, such as the selection of the most optimal topology to decide if the topology should be a constituent feature or not.

6.1 General conclusion

This work presents a two-fold deliverable. The results of the first study are based on a proposed model and an optimization framework of an electric powertrain that accurately describes the behavior of different topologies and the tradeoff between the design variables. The precision of the results looks good mathematically and is compared with the energy consumption in a benchmark of vehicles with similar characteristics to validate the results. Simulation results indicate how powertrain efficiency can be improved and what design space to work on for each topology. The use of PSO as an optimization algorithm is also critical in finding optimum parameter setups for each topology, in the most efficient way for our application. The topology with the best results is the third one, but 1 and 2 also present good stability and low energy consumption. During the early stages of the powertrain design, the topology, the characteristics of the motor and the gear ratios are usually unknown, so this proposed model is a valid reference for the decision making. This study helps decision-makers better understand the behavior of our powertrain and the individual and integrated effect of each of the components at the system and vehicle level which reduces development times and improves the quality of results in the early stages of development. Furthermore, offers a quantitative basis of the characteristics of the product concerning individual requirements and priorities. In this case, the study was focused on topology analysis and sizing, but further research can be derived from the same proposed model. The present results are considered in the variance sensitivity analysis that is part of the second deliverable.

The second part is the implementation of a holistic methodology for the development of modular platforms applied to an electric powertrain, where the potential constituent features are defined for this case study. Constituent features describe standards in product design as well as in production processes and enable cost potentials to increase cost-effectiveness. Various design and product approaches are used to derive these features. Within this approach, customer requirements, components, production processes, and variance characteristics of the current product structure are analyzed to identify critical product constituent features that cause instability or high costs in the product structure. This deliverable proposes a variance portfolio, a product features matrix, and a shell model to represent the resulting variance sensitivity through a workshop with experts. To replicate this method, it is necessary to consider that results depend directly on the expertise of the participants. From the analysis of the results, 3 potential constituent features are identified in the variance sensitivity analysis, and a total of 6 are proposed in the structure. This can lead to the next steps of the methodology that are outside the scope of this work. The definition of the constituent features is the basis for specifying the modules and their variants, as well as to define the interfaces of the modular product architecture in the following stages. The methodology used can be applied to almost any product, and this work validates its flexibility with a modular kit of an electric powertrain.

In general conclusion, these two parts in an integral way are part of a proposed framework to evaluate variance sensitivity and validate technical aspects (e.g. topology, sizing, components, etc.). The main framework consists of the exchange of information between each of the parties to improve and strengthen the individual results.

6.2 Further research

Based on the two studies presented in this work, more research can be derived.

Regarding the next steps for the development of the modular electric powertrain kit, and with their respective constituent features already defined, would be the definition of each of the modules and their product variants. This definition provides an overview of the generic structure of the powertrain composed of the constituent features, with their potential product variants in the form of a feature tree.

For the technical part of the model and optimization, different research proposals can be derived from this present work:

1) replicate the study carried out but extending the model to consider more non-technical variables such as the weight and cost of the components, which help us balance the results from the optimization to a more robust result integrating feasibility.

2) replicate the approach but now considering the vehicle weight class as a variable to study the behavior of the topologies concerning the weight class of the vehicle and identify an optimal topology for the full range of study of the project (7.5 – 40 t).

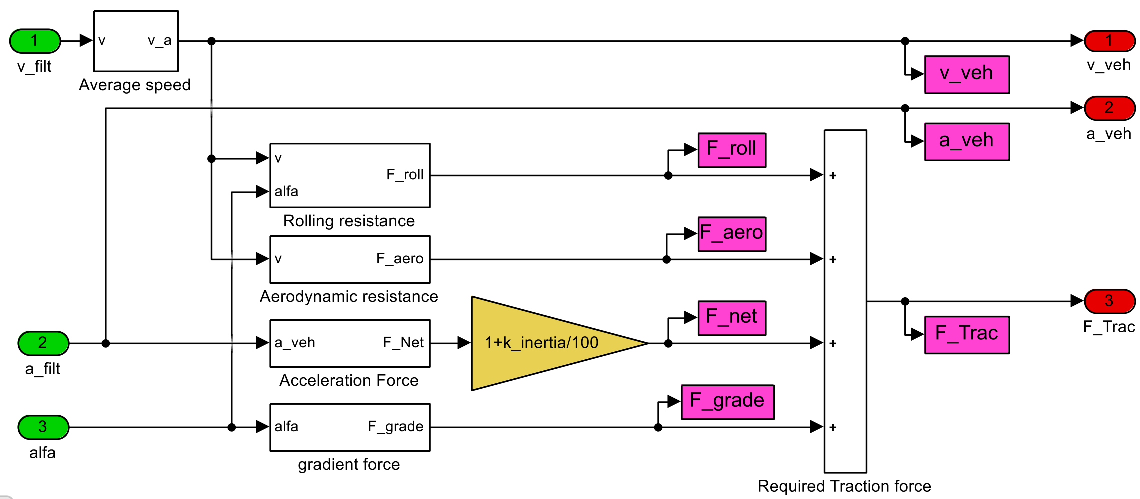
3) use the proposed model to study the impact of different technologies of specific components (e.g. compare the performance between a single gearbox and a double shift gearbox, or a permanent magnet motor and an induction motor)

4) extend the proposed model to add new fully electric powertrain topologies (e.g. four electric motors), or topologies that hybridize the powertrain with alternative technologies (e.g. ICE, fuel cell)

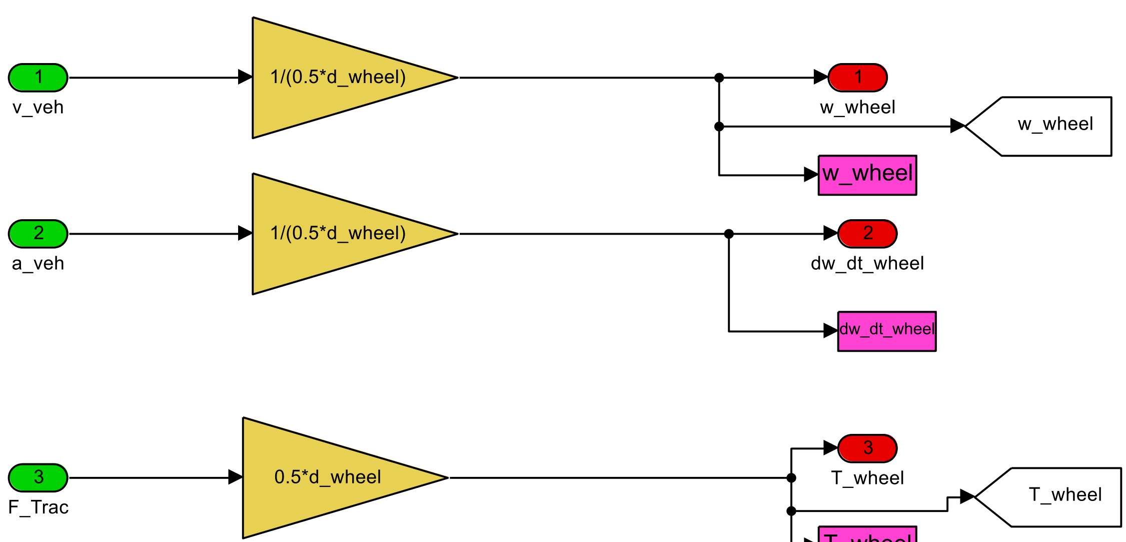
Appendix A

Electric vehicle model in Simulink

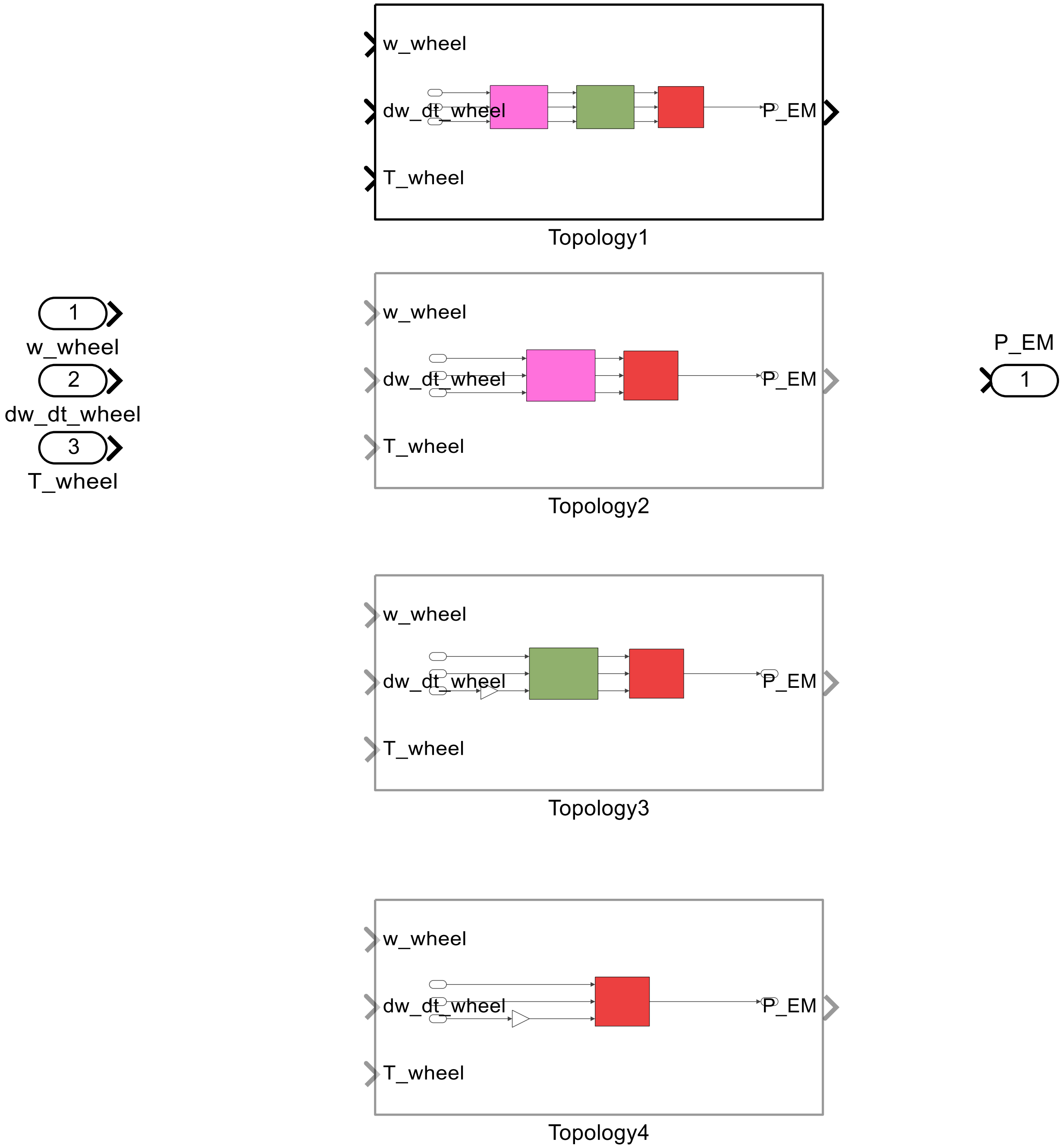
A1. Vehicle dynamics block model based in Newton's second law



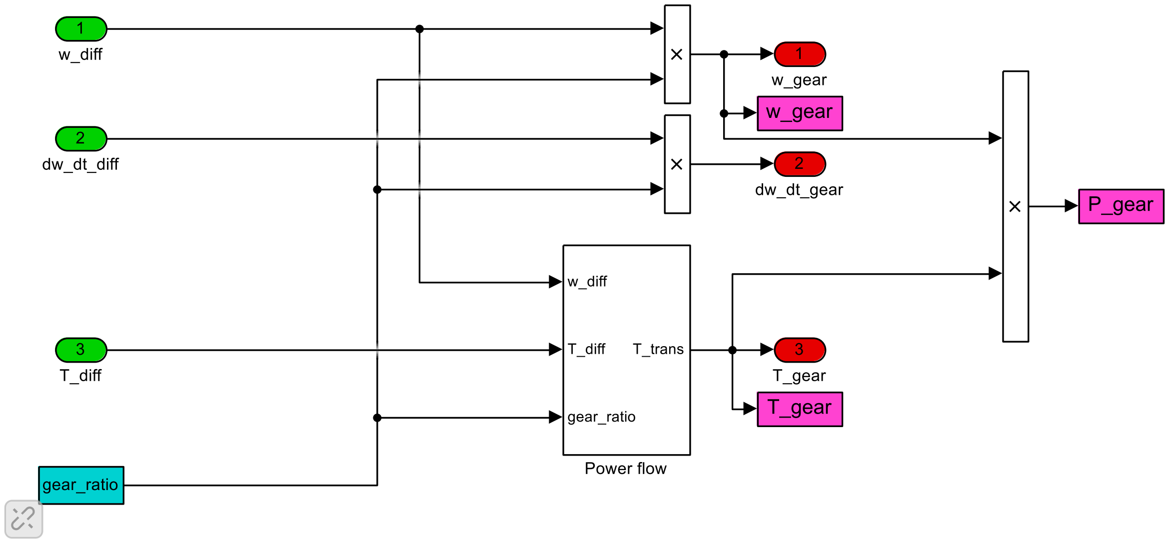
A2. Top level of the simple wheel model block for the transmission of the kinematics to the wheel



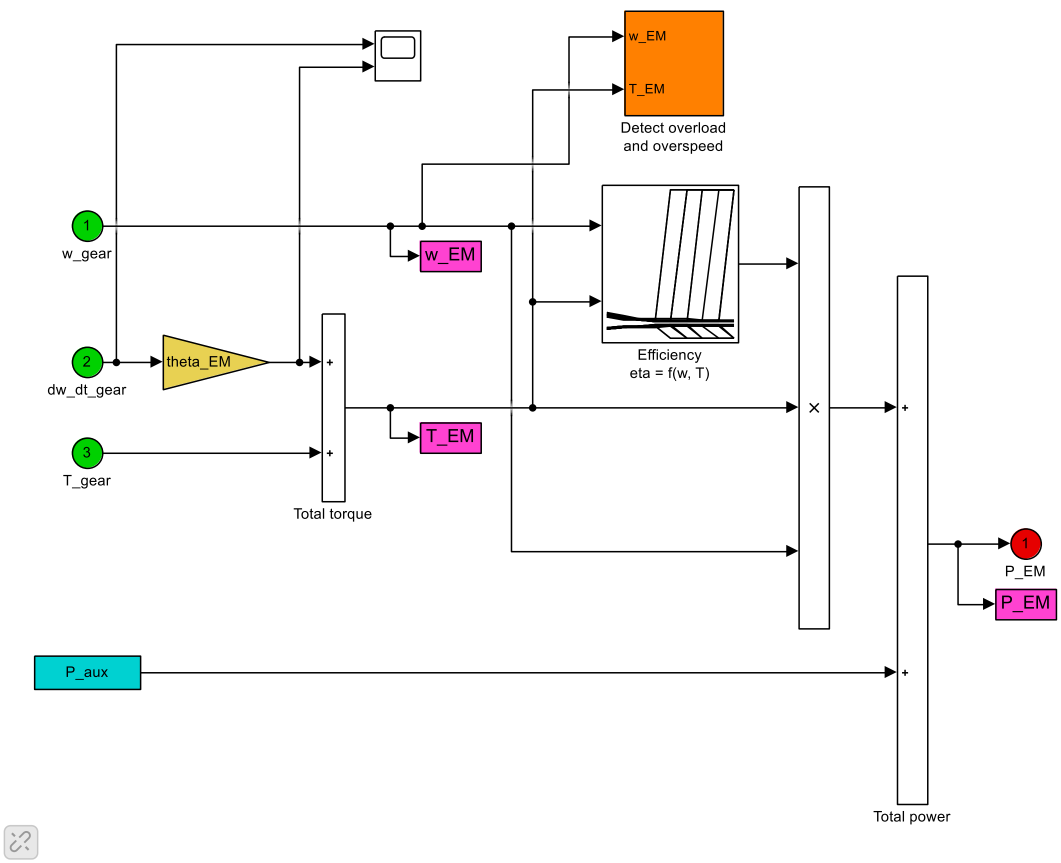
A3. Topology block model at first level using variant component blocks



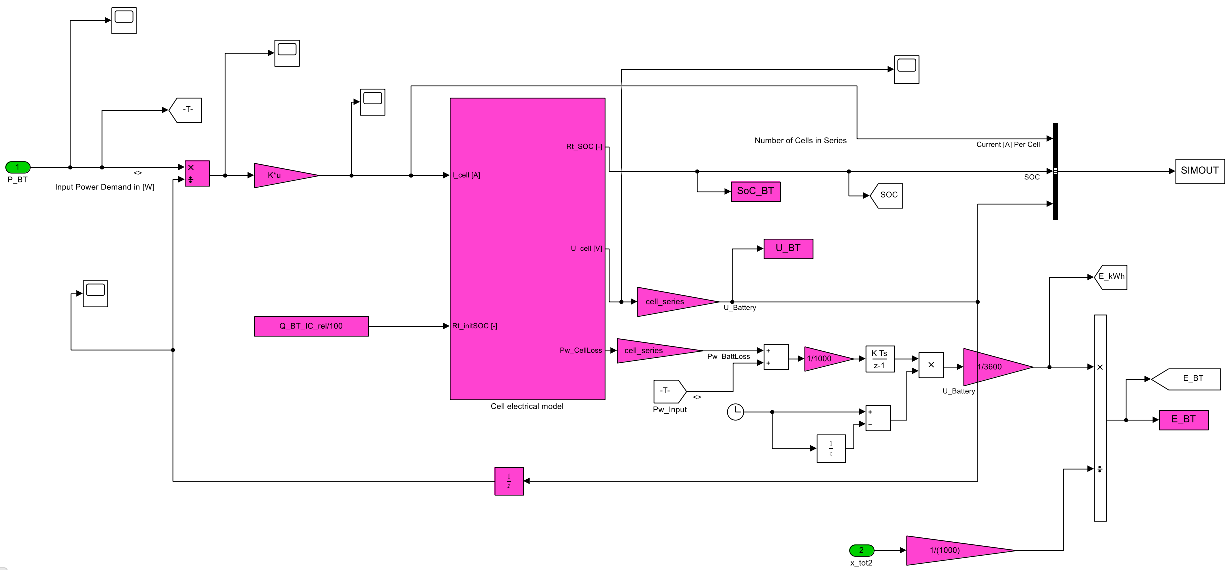
A4. Top level of the simple transmission model block



A5. Block model of the electric motor using a 2D lookup table with an efficiency map of a Permanent Magnet Synchronous Motor (PMSM)



A6. Top level of the battery block model with a cell electrical model



Appendix B

MATLAB scripts

B1. Script to generate the efficiency map of the electric motor with the operating points from the driving cycle

```
function plotEM(EMpow, T, w)
%-------------
%   This script is a function that shows the work points for an EM given
by the EM Assignment using the QSS Toolbox. You can call this function
after run the Simulink model, or add this function as a callback Stopfcn*
in model properties of your model.
% ------------
%   Input:
% =====
%   EMpow = Power of motor [kW]
%   T = Motor torque vector [Nm]
%   w = rotational speed of motor [rad/s]
%
%   Example: plotEM(50,T_EM,w_EM) [Plot of a 50 kW motor]
%-------------
% Created by Daniel Härensten 201?-??-??
% Modified by Daniel Härensten 2016-05-26, updated script due to changes
% in EM model.
% Modified by Jonathan Rivas-Torres at PEM, RWTH Aachen 2020-07-01
% ------------
%   Version: Matlab2018a
% ------------

    load Ass2EMmap
    T_EM_col = EMpow / 11.7 * T_EM_col;
    T_EM_max = EMpow / 11.7 * T_EM_max;
    clf
    hold on
    xlabel('Motor speed [rpm]')
    ylabel('Torque [Nm]')
    %Filtering of motor and generator
    [m,n] = size(eta_EM_map);
    eta_EM_map2 = zeros(m,n);
    for c = 1:n
        for r = 1:m
            if eta_EM_map(r,c) >= 1 && eta_EM_map(r,c) <= 10
                eta_EM_map2(r,c) = 1./(eta_EM_map(r,c));
            else
                eta_EM_map2(r,c) = eta_EM_map(r,c);
            end
        end
    end
    %Meshing and plotting of the efficiency map
    [X,Y] = meshgrid(w_EM_row.*30/pi,T_EM_col);
    [C,h] = contourf(X,Y,eta_EM_map2',[0.5:0.08:0.7 0.7:0.01:1 1:0.01:1.2
1.2:0.08:2],':','ShowText','on');
```

```
    clabel(C,h,'FontSize',6);
    c = colorbar;
    c.Label.String = 'Efficiency (%)';
    fill([w_EM_max.*(30/pi) max(w_EM_max*(30/pi)) w_EM_max(1)*(30/pi)
w_EM_max(1)*(30/pi)] ,[T_EM_max' max(T_EM_col) max(T_EM_col)
T_EM_max(1)],'w','edgecolor','white');
    fill([w_EM_max.*(30/pi) max(w_EM_max*(30/pi)) w_EM_max(1)*(30/pi)
w_EM_max(1)*(30/pi)] ,-[T_EM_max' max(T_EM_col) max(T_EM_col)
T_EM_max(1)],'w','edgecolor','white');
    %Plotting work points
    scatter((w.*30/pi),T,30,'MarkerEdgeColor','b','MarkerFaceCol-
or','r','LineWidth',0.75);
    plot(w_EM_max.*(30/pi),T_EM_max,'b','LineWidth',1.5);
    plot(w_EM_max.*(30/pi),-T_EM_max,'b','LineWidth',1.5);
    axis([w_EM_max(1)*(30/pi) w_EM_max(end)*(30/pi) -max(T_EM_col)
max(T_EM_col)]);
    title('Electric Motor Map')
    hold off
```

B2. Main script to run the optimization of the topology. This script calls a function file. Only one solver should be uncommented

```
% ==========================================================
% Main file for the example "Optimal Powertrain Design"
% ==========================================================
% Instructions:
% 1. Select an optimization solver (Comment/Uncomment)
% 2. Initialize your parameters
% 3. Replace your @function in the optimization routine
%
##########################################################################
clear all
close all
clc
warning off
%
##########################################################################
% Global variables
% ----------------
    % Simulation
    global t
    global N_sim
    global w_EM T_EM
    global gear_result
    global V_liter
    global dratio gratio empower

    % Electric motor map
    global eta_EM_map
    global w_EM_row
    global T_EM_col
    global w_EM_max
    global T_EM_max
```

```
% % Unconstrained multivariable optimization @fminsearch
% % ====================================================
% % Initialization
% % ------------------------------------------
%     gear_result = [];
% %     x0 = [30; 5; 2];
%     options = optimset('PlotFcns',@optimplotfval);
% % Optimization routine
% % -------------------------------------------
%     disp('Optimization using derivative-free method started...')
%     disp(' ')
%     [x,fval,exitflag,output] = fminbnd('OptiDriveTrain', 100, 300, op-
tions)
%     disp(' ')
%     disp('... optimization finished!')

% % Pattern Search Optimization
% % ====================================================
% % Initialization
% % -----------------------------------------
%     lb = [300,1];
%     ub = [500,10];
%     A = [];
%     b = [];
%     Aeq = [];
%     beq = [];
%     x0 = [400; 5];
%     options = optimoptions('patternsearch','PlotFcn',@psplotbestf);
%     rng default
% % Optimization routine
% % -------------------------------------------
%     disp('Optimization  using Pattern Search started...')
%     disp(' ')
%     [x,fval,exitflag,output] = patternsearch(@Op-
tiDriveTrain,x0,A,b,Aeq,beq,lb,ub,[],options)
%     disp(' ')
%     disp('... optimization finished!')

% Genetic Algorithm Optimization
% ====================================================
% Initialization
% ------------------------------------------
    nvars = 2;
    lb = [300,1];
    ub = [500,10];
    A = [];
    b = [];
    Aeq = [];
    beq = [];
    options = optimoptions('ga','PlotFcn',@gaplotbestf);
    options.PopulationSize = 20;
    rng default
% Optimization routine
% -------------------------------------------
    disp('Optimization  using Genetic Algorithm started...')
```

```
    disp(' ')
    [x,fval,exitflag,output] = ga(@Op-
tiDriveTrain,nvars,A,b,Aeq,beq,lb,ub,[],options)
    disp(' ')
    disp('... optimization finished!')

% % Particle Swarm Optimization
% % ====================================================
% % Initialization
% % ------------------------------------------
%     nvars = 2;
%     lb = [300,1];
%     ub = [500,10];
% %     nvars = 1;
% %     lb = 100;
% %     ub = 300;
%     options = optimoptions(@particleswarm,'PlotFcn',@pswplotbestf1);
%     rng default
%     options.SwarmSize = 20;
% %     options.HybridFcn = @fmincon;
% %     rng default
% % Optimization routine
% % -------------------------------------------
%     disp('Optimization using PSO started ...')
%     disp(' ')
%     [x,fval,exitflag,output] = particleswarm(@OptiDriveTrain, nvars,
lb, ub,options)
%     disp(' ')
%     disp('... optimization finished!')

% Plot results
% ------------
%     disp(' ')
%     disp('Hit a key to plot results:')
%
%     pause
%     clc

% Results vs Iteratios
    fig = figure;
    set(fig,'NumberTitle', 'off')
    set(fig,'Name', 'Optimized variables')
    plot(gear_result)
    xlabel('Iterations')
    ylabel('Design Variables [-]')
    title('Variations of the design variables during the optimization')
%
%
#######################################################################
```

B3. Script that contains the function to call the model and run the optimization within the Simulink model

```
% ======================================================
```

```
% Function for the example "Optimal Powertrain Design"
% ======================================================
#########################################################################
function V_result = OptiDriveTrain(x)
#########################################################################

% Global variables
% ----------------
    % Simulation
    global t
    global N_sim
    global w_EM T_EM
    global gear_result
    global E_Cons
    global empower dratio gratio

    % Electric motor map
    global eta_EM_map
    global w_EM_row
    global T_EM_col
    global w_EM_max
    global T_EM_max

% Set actual variables
% ----------------------
    empower      = x(1);
%     dratio       = x(2);
    gratio       = x(2);

% Build matrix of gear ratio values
% ---------------------------------
    gear_result = [gear_result; x'];

% Do simulation
% -------------
    sim('EnergyConsumption_JRT');

% Consider last value of the computed fuel consumption vector
% -----------------------------------------------------------
    V_result = E_Cons(max(size(t)));
%     last     = t(end);
%     V_result = V_liter(last);

% Check whether cycle could be finished exactly in N_sim computational
steps;
% if cycle duration is less than N_sim, set fuel consumption to infinite
% ----------------------------------------------------------------------
%     if (max(size(t)) < N_sim)
%       V_result = Inf;
%     end

% Plausibility check of the computed gear ratios
% ----------------------------------------------
%     if (empower >= 50) && (empower <= 150) && (third_gear >
fourth_gear) && (fourth_gear > fifth_gear)
%         V_result = V_result;
```

```
%     else
%         V_result = Inf;
%     end

% Display actual fuel consumption
% -------------------------------
    disp(['Energy consumption [kWh/km] =         ',num2str(V_result)]);

%
##########################################################################
```

B4. Script that create a surface plot based in Simulink model through vectors

```
clear all close all
clc
global empower gratio E_Cons Upp_eff
 disp('Plotting started...')
% [empower,gratio] = meshgrid(20:30,1.5:0.5:6.5);
x = [];
y = [];
Z = zeros();
W = zeros();
empower = 100;

for m = 1:1:20
    gratio = 1;
    for n = 1:1:20
        sim('EnergyConsumption_JRT');
         x(m)=empower;
         y(n)=gratio;
%         z(i j)=V_liter;
        V_final = E_Cons(max(size(t)));
%         Upp_final = Upp_eff(max(size(t)));
%         V_final = E_BT(end);
        W(n,m)=Upp_eff(end);
        Z(n,m)=V_final;
        disp(['V [liter/100 km] =        ',num2str(V_final)]);
        gratio = gratio +0.5;
    end
    empower = empower +10;
end

% Plotting the surface
[X,Y] = meshgrid(x,y);

surf(X,Y,Z,W)
title('Energy consumption Analysis: Topology 1')
xlabel('Electric Motor Power (kW)')
ylabel('Gear ratio')
zlabel('Fuel Consumption (kWh/km)')
colorbar
```

Appendix C

Variance Sensitivity Analysis Results

C1. Results of the market perspective of the workshop with experts.

QFD: Market

INSTRUCTIONS: Fill only the white cells with the following criteria.

Criteria:
1 Very low
3 Low
5 Medium
7 High
9 Very high

Customer requirements / Variance characteristics

No.	Customer requirements	Importance	1 High Voltage	2 Low Voltage	3 Vehicle Weight Class	4 Topology (EM-GB-DF, EM-GB; 2EM-2GB, 2EM)	5 Motor power	6 Motor torque	7 Motor speed	8 Energy converter/inverter capacity	9 Electrification concept (battery, battery+fuel tank, battery+panto)	10 Battery technology (energy/power density)	11 Battery type (cylinder, pouch, prismatic)	12 Battery pack energy	13 Charger type (plug and AC/ACDC)	14 Thermal management	15 Gearbox (ratio, single/double shift, CVT)
1	Cost must be affordable	**1.03**	5	3	7	7	5	5	5	7	8	8	7	7	7	7	7
2	Meet the required driving range (km)	**3.52**	3	2	6	5	5	5	5	7	8	8	7	7	5	7	5
3	Low energy consumption as possible	**1.71**	5	2	8	6	5	5	5	5	7	7	7	7	5	7	5
4	Daily operation time (12-14 h)	**1.65**	4	4	7	5	7	5	5	7	7	7	7	7	5	7	5
5	Annual distance expectation (130000 km)	**1.68**	5	3	5	3	3	3	3	7	7	7	7	7	5	7	5
6	High charging efficiency (reduce charging time, save energy and costs)	**1.64**	6	4	3	3	3	3	3	1	7	7	7	7	5	7	1
7	High battery efficiency (energy, power)	**1.65**	1	1	3	5	1	3	3	1	7	7	7	7	5	3	1
8	Service/maintance must not exceed those of the base vehicle (frequency, costs)	**1.69**	3	1	6	6	1	3	3	5	7	7	7	7	5	5	5
9	Materials must be suitable for automotive applications	**2.12**	6	4	5	6	5	5	5	5	6	6	5	5	5	7	3
10	Operational temperatures (-11-48 C)	**1.84**	7	1	1	5	5	3	3	7	5	5	7	7	5	8	3
11	Must meet a climbing ability of 10%	**2.11**	1	1	1	5	8	8	8	3	7	7	5	5	3	7	7
12	Must meet a maximum speed of 87 km/h	**2.39**	5	1	4	5	8	8	8	3	7	7	5	5	3	7	7
13	Modular battery concept depending on the application (region, variant)	**1.69**	6	3	5	1	5	1	1	1	5	5	7	5	3	5	3
14	Must be able to be charged either AC or DC	**1.71**	4	3	1	1	3	1	1	1	7	7	7	5	9	5	1
15	Charging socket must be lockable	**1.76**	7	1	1	1	1	1	1	1	7	7	7	5	7	3	1
16	Batteries and most components must be recyclable	**1.68**	7	1	1	1	1	1	1	1	6	6	7	5	3	5	5
17	Kit cover weight classes from 7,5t and up to 40t	**1.68**	5	1	8	5	7	7	7	5	5	5	5	7	5	5	5
18	Kit must match safety of the base vehicle	**3.64**	5	4	5	5	5	5	5	5	7	7	5	5	5	5	5
19	Kit must match durability of the base vehicle	**2.60**	7	1	3	5	5	5	5	5	5	5	5	5	5	5	5
20	Kit must be easy to install	**1.69**	5	3	5	5	5	5	5	5	6	6	5	5	5	5	5
21	Kit must use most parts of the base vehicle	**1.69**	3	1	7	7	7	5	5	5	5	5	5	5	5	5	5
22	Kit must not reduce the load capacity	**1.70**	5	3	6	5	5	5	5	5	6	6	7	5	3	5	5
23	Kit offers more than one energy source	**1.73**	5	3	7	5	5	5	5	5	1	1	5	5	3	3	3
24	Kit must have a recuperation mode	**1.66**	5	1	8	9	7	5	5	5	5	5	7	5	1	1	7
	Technical Weights	Absolute	220.4	101.1	215	215	221.1	203.9	203.9	201.3	288.7	288.7	284.7	267.6	214.6	255.7	203.9
		Relative	7%	3%	6%	6%	7%	6%	6%	6%	9%	9%	8%	8%	6%	8%	6%
		Rank	9	1	8	7	10	3	3	2	14	14	13	12	6	11	5
		Scaled	**3.54**	**1.00**	**3.43**	**3.43**	**3.56**	**3.19**	**3.19**	**3.14**	**5.00**	**5.00**	**4.91**	**4.55**	**3.42**	**4.30**	**3.19**

C2. Results of the product perspective of the workshop with experts.

QFD: Product

INSTRUCTIONS: Fill only the white cells with the following criteria.

Criteria:
1 Very low
3 Low
5 Medium
7 High
9 Very high

Variance characteristics

Components		Importance	1 High Voltage	2 Low Voltage	3 Vehicle Weight Class	4 Topology (EM-GB-DF, EM-GB; 2EM-2GB, 2EM)	5 Motor power	6 Motor torque	7 Motor speed	8 Energy converter/inverter capacity	9 Electrification concept (battery, battery+fuel tank, battery+panto)	10 Battery technology (energy/power density)	11 Battery type (cylinder, pouch, prismatic)	12 Battery pack energy	13 Charger type (plug and AC/ACDC)	14 Thermal management	15 Gearbox (ratio, single/double shift, CVT)
1	Power steering pump	**1.00**	7	6	7	1	1	1	1	1	1	1	1	1	1	5	1
2	Range extender interface (FC, PG)	**2.05**	7	5	7	1	1	1	1	7	8	7	1	1	1	5	1
3	DC/DC converter REX	**4.45**	7	6	7	1	1	1	1	7	7	7	7	7	1	5	1
4	Recuperation energy storage	**5.00**	7	6	8	1	1	1	1	7	7	7	5	6	1	6	1
5	Power distribution unit	**2.09**	9	7	5	5	1	1	1	7	8	7	5	5	1	3	1
6	Battery pack (including BMS)	**2.09**	9	7	8	1	7	7	7	7	7	7	7	8	5	7	1
7	OBC	**1.29**	8	6	9	1	3	3	3	5	7	7	5	5	7	5	1
8	LV DC/DC converter	**1.66**	6	6	5	1	1	1	1	3	3	3	5	5	5	5	1
9	LV cabling	**2.73**	5	5	5	5	5	5	5	5	6	5	5	5	6	5	1
10	HV cabling	**2.09**	8	5	5	5	5	5	5	5	6	5	5	5	6	5	1
11	HV DC/DC converter	**4.74**	8	5	5	3	3	3	3	5	5	5	5	5	5	5	1
12	Coolant pump	**2.09**	7	6	5	5	3	3	3	5	3	3	5	5	5	8	1
13	Radiator	**2.09**	7	5	5	5	3	3	3	5	3	3	5	5	3	8	1
14	Cooling medium	**3.33**	5	3	3	3	3	3	3	5	3	3	5	5	3	8	1
15	Cooling storage	**2.09**	5	3	3	3	5	5	5	5	5	3	5	5	3	8	1
16	Motor	**2.09**	8	7	7	7	9	9	9	5	5	5	3	3	3	7	7
17	Inverter	**2.09**	8	7	5	5	9	9	9	5	5	5	3	3	3	7	5
18	Mechanical transmission (Gearbox)	**2.09**	5	1	8	8	8	8	8	1	1	1	1	1	1	1	9
19	Cardan shaft	**3.95**	5	1	6	6	7	7	7	1	1	1	1	1	1	1	9
20	Parking brake	**2.09**	5	5	8	7	7	7	7	1	1	1	1	1	1	1	9
Technical Weights		Absolute	344.3	252.8	306.9	183.6	202.7	202.7	202.7	247.1	243.6	230.5	215.6	222.7	148.7	265.2	137.1
		Relative	10%	7%	9%	5%	6%	6%	6%	7%	7%	7%	6%	7%	4%	8%	4%
		Rank	1	4	2	13	10	10	10	5	6	7	9	8	14	3	15
		Scaled	**5.00**	**3.23**	**4.28**	**1.90**	**2.27**	**2.27**	**2.27**	**3.12**	**3.06**	**2.80**	**2.52**	**2.65**	**1.22**	**3.47**	**1.00**

C3. Results of the production perspective of the workshop with experts.

QFD: Production

INSTRUCTIONS: Fill only the white cells with the following criteria.

Criteria:
1 Very low
3 Low
5 Medium
7 High
9 Very high

Variance characteristics

Processes		Importance	1 High Voltage	2 Low Voltage	3 Vehicle Weight Class	4 Topology (EM-GB-DF, EM-GB; 2EM-2GB, 2EM)	5 Motor power	6 Motor torque	7 Motor speed	8 Energy converter/inverter capacity	9 Electrification concept (battery, battery+fuel tank, battery+panto)	10 Battery technology (energy/power density)	11 Battery type (cylinder, pouch, prismatic)	12 Battery pack energy	13 Charger type (plug and AC/ACDC)	14 Thermal management	15 Gearbox (ratio, single/double shift, CVT)
1	Cable harness	**1.00**	8	7	1	3	1	1	1	1	1	5	1	1	5	1	1
2	Brake lines	**2.19**	5	3	7	3	1	1	1	1	1	1	1	1	1	1	1
3	Front axle	**3.74**	5	1	7	5	1	1	1	1	3	1	1	1	1	1	5
4	Rear axle	**4.50**	5	1	7	5	1	1	1	1	3	1	1	1	1	1	5
5	Pneumatic brake system	**1.93**	5	1	7	5	1	1	1	1	1	1	1	1	1	1	5
6	Powertrain variant assembly	**1.93**	5	1	6	7	5	5	5	1	3	1	1	1	1	6	5
7	PDU, HV-storage brackets	**1.23**	8	6	3	5	1	1	1	3	1	3	1	1	7	1	3
8	Brake resistor	**1.54**	6	5	7	3	1	1	1	3	3	1	1	1	1	4	1
9	Cooling system braking resistor	**1.93**	5	3	7	3	1	1	1	1	1	1	1	1	1	6	1
10	Cooling system vehicle	**1.93**	7	5	6	3	3	3	3	5	1	1	1	1	1	6	1
11	Cooling system high voltage storage	**5.00**	7	5	5	3	1	1	1	5	3	1	5	5	1	6	1
12	Cooling system powertrain	**1.93**	6	5	5	3	7	7	7	1	1	1	1	1	1	6	1
13	High voltage storage (1-4 BP)	**1.93**	7	5	5	5	1	1	1	1	3	6	7	8	1	3	1
14	Fuse box	**2.99**	3	5	1	1	1	1	1	3	1	1	1	1	1	1	1
15	Control Unit	**1.93**	1	5	1	3	1	1	1	1	1	1	1	1	1	1	1
16	24V battery	**1.93**	1	7	3	3	1	1	1	1	3	3	1	1	1	1	1
17	Range extender (none, PG, FC)	**1.93**	4	4	3	1	1	1	1	1	1	1	1	1	1	6	3
18	Wheels	**1.93**	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
19	Media filling	**3.52**	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Technical Weights		Absolute	214.9	151.8	205	148.7	68.2	68.2	68.2	84.28	86.18	65.01	76.62	78.55	56.41	126.8	99.78
		Relative	13%	9%	13%	9%	4%	4%	4%	5%	5%	4%	5%	5%	4%	8%	6%
		Rank	1	3	2	4	11	11	11	8	7	14	10	9	15	5	6
			5.00	**3.41**	**4.75**	**3.33**	**1.30**	**1.30**	**1.30**	**1.70**	**1.75**	**1.22**	**1.51**	**1.56**	**1.00**	**2.78**	**2.09**

Appendix D

Formula symbols and abbreviations

D1. Table of symbols and abbreviations

Formula Symbol	Unit	Description
a	m/s2	Vehicle acceleration
A_f	m2	Frontal area
C_d	-	Aerodynamic drag coefficient
c_r	-	Rolling friction coefficient
g	m/s2	Gravity
h	-	Timestep
J	-	Objective function
m	kg	Vehicle mass
P_{batt}	kW	Battery power
P_{EM}	kW	Electric motor power
$q(t)$	-	Charge rate
r_g	-	Transmission ratio
U	V	Voltage
v	m/s	Vehicle speed
α	rad	Grade angle
η	-	Efficiency
ρ	kg/m3	Air density
ψ	[]	Drive cycle vector
ω	rad/s	Rotational speed

Abbreviation	Description
BEV	Battery electric vehicle
CMF	Common Module Family
CO2	Carbon dioxide
CVT	conventional variable transmission
D2XX	Delta 2 XX
EMP2	Efficient Modular Platform
ETH Zürich	Eidgenössische Technische Hochschule Zürich
e-TNGA	Toyota Electric New Generation Architecture
EU	European Union
EV	Electric vehicle
FCV	Fuel cell vehicle

Formula Symbol	Unit	Description
GA		Genetic algorithms
GHG		Greenhouse gas
GiBWert		Gestaltung innovativer Baukasten- und Wert-schöpfungssysteme
Gt		Gigatons
GVW		Gross vehicle weight
HDV		Heavy-duty vehicle
HEV		Hybrid electric vehicle
ICE		Internal combustion engine
LiVe		Lebenszykluskostenreduktion im elektrischen Verteilerverkehr durch individuell adaptierbaren Antriebsstrang
MEB		Modular Electrification Toolkit
MQB		Modularer Querbaukasten
MRA		Mercedes Rear-wheel drive Architecture
NPE		National Platform of Electromobility
NREL		National Renewable Energy Laboratory Test Cycle
OEM		Original Equipment Manufacturer
PEM		Production Engineering of E-Mobility Components
PHEV		Plug-in hybrid electric vehicle
PI		Proportional-Integral
PMR		Power-to-mass ratio
PSO		Particle Swarm Optimization
QSS		Quasi-static simulation
RWTH		Rheinisch-Westfälische Technische Hochschule Aachen
SPA		Scalable Platform Architecture
UKL		Unter Klasse
VEA		Volvo Engine Architecture
WLTC		Worldwide harmonized Light vehicles Test Cycle

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Curriculum Vitae

Jonathan Rivas Torres was born in Monclova, Coahuila, Mexico on July 10, 1995. He graduated with honors from the degree of Automotive Design Engineer at the University of Monterrey in 2017 where he did research stays at the Polítecnico di Milano and the Università degli studi di Modena e Reggio Emilia, in Italy. Later he carried out work in the industry in product design and research positions in companies such as Navistar International and Siemens. Later, he was accepted to the Tecnológico de Monterrey in the Master of Science in Engineering with a specialty in Manufacturing Systems program with a full scholarship. During the program, he was selected for a one-year stay at RWTH Aachen University in Germany with an extended scholarship from the German Academic Exchange Service (DAAD). His research interests are electric vehicle modeling, powertrain optimization, and modularity applied to electric vehicles.