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Bachelor Thesis

A dynamic techno-economic evaluation framework for hybrid regional train architectures

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Abstract

Germany has committed itself to cut down its greenhouse gas emissions by 55 % by 2030. While most emission sectors make good progress, the transportation sector remains behind its goals. Shifting traffic from road to rail can help to bring the transportation sector closer to that goal. To get the most benefit out of the rail systems' advantages, innovative propulsion systems are needed. Particular potential for innovative drive trains lies in the sector of regional passenger transportation. As the sector experiences high cost pressure from road, it is important to find cost-effective drive trains that cut down on emissions in order to maintain and increase competitiveness of the rail sector.

As of today, there are two main propulsion options for regional railway vehicles: diesel propulsion on non-electrified tracks and electric vehicles with a catenary set up. The first option causes a lot of emissions while the second one has prohibitively high investment costs for many operational cases. Therefore, an obvious question arises: Can we find propulsion concepts for regional railway vehicles that provide better environmental performance than current diesel vehicles with investment costs lower than those for infrastructure electrification?

While a number of hybrid concepts have been studied or announced to enter service soon, few systematic approaches to vehicle architectures have been made. A previous paper in the TORPA (Toolbox for Optimized Railway Propulsion Architectures) project assessed a wide range of drive train configurations and drew first conclusions about their performance. We build upon this work and incorporate a track model and a driving dynamic model. The presented framework is capable to optimize vehicle drive trains for any railway track with respect to environmental impact and investment costs.

We choose one specific test case to demonstrate our framework, a battery diesel-electric vehicle on a typical regional route. We make sense of the results to discover patterns that enable innovative hybrid drive trains to outperform conventional ones. Finally, we assess undominated vehicle variants along conventional propulsion systems, and provide a method that supports deciding for the best specific vehicle in the metrics of investment cost and emissions.

Zusammenfassung

Deutschland hat sich verpflichtet seine Treibhausgasemissionen bis zum Jahr 2030 um 55 % zu verringern. Während in den meisten Sektoren gute Fortschritte zu verzeichnen sind, bleibt der Transportsektor hinter den Zielen zurück. Eine Verlagerung von Verkehren von der Straße auf die Schiene kann einen wesentlichen Beitrag zur Zielerreichung leisten. Um jedoch das Potenzial des Schienenverkehrs besser zu nutzen sind innovative Antriebe erforderlich. Ein besonders großes Potenzial liegt dabei im Personennahverkehr. Da dieser unter erheblichem Kostendruck durch Straßenfahrzeuge steht, ist es wichtig kosteneffiziente und emissionsarme Antriebssysteme zu finden, um die Konkurrenzfähigkeit des Schienenverkehrs zu erhalten und auszubauen.

Derzeit existieren zwei Varianten von Antrieben in Fahrzeugen des Regionalverkehrs: Dieselantrieb für nicht elektrifizierte Strecken und elektrische Antriebe in Kombination mit durchgehender Oberleitung an der Strecke. Erstere Option verursacht hohe Schadstoffemissionen während für letztere Option in vielen Betriebsszenarien die Investitionskosten oft unverhältnismäßig hoch sind. Daher kommt eine naheliegende Fragestellung auf: Ist es möglich Antriebskonzepte für Regionalverkehrsfahrzeuge zu finden, die emissionsärmeren Betrieb erlauben als konventionelle Dieselantriebe zu Investitionskosten die unter denen einer Infrastrukturelektrifizierung liegen?

Während zahlreiche hybride Antriebskonzepte untersucht wurden oder in unterschiedlichen Entwicklungsstadien bis kurz vor der Markteinführung stehen, wurde dabei nur selten ein systematischer Ansatz zur Untersuchung von Systemarchitekturen verfolgt. Eine frühere Veröffentlichung im Projekt TORPA (Toolbox for Optimized Railway Propulsion Architectures) hat eine große Bandbreite verschiedener Antriebskonzepte und deren Leistungsfähigkeit abgeschätzt. Aufbauend auf dieser Arbeit werden die Simulationswerkzeuge um ein Streckenmodell und ein Fahrdynamikmodell erweitert. Der vorgestellte Algorithmus erlaubt es, Antriebseinheiten für beliebige Strecken hinsichtlich Investitionskosten und Emissionen zu optimieren.

Die Möglichkeiten des Modells werden mit einem Beispielszenario, einem dieselelektrischen Hybridfahrzeug mit Batterie auf einer typischen Regionalverkehrslinie, veranschaulicht. Durch Analyse der Simulationsergebnisse werden Konzeptionsparameter entwickelt, die einen vorteilhaften Einsatz mit deutlichem

Mehrwert gegenüber konventionellen Antrieben erlauben. Nach der Fokussierung auf dominierende Fahrzeugvarianten, auch unter Einbezug bisheriger Antriebe, wird ein Entscheidungswerkzeug vorgestellt, das es erlaubt eine Entscheidung für ein hinsichtlich Investitionskosten und Emissionen optimales Fahrzeugkonzept zu treffen.

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Symbols

Symbol	Unit	Name
v	$\frac{m}{s}$	velocity
m	kg	mass
l	m	length
U	V	voltage

List of Acronyms

DB AG	Deutsche Bahn AG
DDM	Driving Dynamics Model
EU ETS	European Union Emission Trading System
L/D	Lift-to-drag ratio
GA	Genetic Algorithm
ICE	Inter City Express
IC	Inter City
ÖBB	Österreichische Bundesbahnen
RB	Regional Bahn
RE	Regional Express
TGV	Train à Grand Vitesse, "high speed train"
TEU	Twenty-foot container equivalent unit
TORPA	Toolbox for Optimized Railway Propulsion Architectures

1. Introduction

1.1. Motivation

Slowing down global warming is a large and worldwide challenge of the current time. A major cause of this warming effect are anthropogenic greenhouse gases. In 2015, 197 nations have negotiated common goals to reduce emission of these gases, leading to the Paris Agreement. As of July 2018, 179 countries have ratified the agreement [2]. After the predecessing agreement, the Kyoto Protocol, covered not more than 15 % of global emissions [3], now 89 % of annual global greenhouse gas emissions are covered through the ratifying nations [2]. Therefore, the Paris agreement is an unprecedented achievement in its extent. Then-US President Barack Obama called the contract "a turning point for our planet" in 2016 [4].

Part of The Paris Agreement is that all countries have to set up national plans describing in detail how they aim to contribute to the reduction of global warming. The EU and its member states have agreed to reduce emissions by 40 % by 2030 compared to 1990 [2]. Some countries also went beyond that limit on a national level. For example, Germany has targeted to decrease its emissions by 55 % in the described time. The goals of the German emission reduction plan are visualized in Tab. 1.1. The amount of emissions is described by sector and year. It is measured in million tons of Carbon dioxide equivalent. Equivalent refers to the climate warming impact a specific gas has in a 100-year period in the atmosphere compared to the impact of CO2. Frequently, the focus is simplified to only measure CO2, as it is most easy to measure and contributes about two thirds of the anthropogenic global warming effect [5].

After most sectors have seen considerable achievements in the years since 1990, the sector of transport remains problematic. Its emissions grew in the recent years, so that the amount of emissions of 1990 was even exceeded in 2016 [6]. The sector currently emits 24 % of CO2 in Germany with further increase. Therefore, the transport sector is in the focus of policy makers and finding a solution becomes more and more urgent.
One main measure that is deemed capable to deliver relevant mitigations in emissions is to shift more transport services from road to rail [7]. But even after this goal was part of multiple policies [8] [7], the fraction of goods and passengers transported on rails continuously decreased in recent years [9].
While rail transport has an indisputable environmental advantage compared to road, the real measured differences are not as big as they could be. Road vehicles have seen numerous attempts to introduce new technologies in order to cut

Tab. 1.1.: Annual emissions in Germany in Mio. tons of CO2 equivalents in 1990 and 2014 and target for 2030 set up by the Government in 2016. On the right, share of targeted emission reduction between 1990 and 2030 that was reached by 2014 [1].

Sector	1990	2014	2030 (target)	% of targeted reduction reached by 2014
Energy	466	358	183	38%
Industry	283	181	143	73%
Buildings	209	119	72	66%
Agriculture	88	72	61	59%
Transportation	163	160	98	5%

down on emissions, while rail vehicles still often rely on classical diesel engines without any hybridization. On the other hand, government and manufacturers are still grappling with the introduction of electrified cars and trucks [10] while electric vehicles have been available in rail for long time. However, full electrification of networks and hybridization of rail vehicles is often not implemented yet due to a high cost pressure in the transportation sector and reluctance of stakeholders to invest large amounts of money [11].
To gain relevant nationwide emission mitigations in transportation, it is of major importance to further improve the CO2 performance of rail vehicles and to find cost-effective propulsion architectures.

1.2. General thesis objectives

In the following, we find the general research question by evaluating the role of rail traffic in the context of transportation, investigate the challenges in the whole rail sector, decomposition of the sector in its specific domains, picking the most important of those domains for further investigations and analyze stakeholders and their specific needs.

1.2.1. Rail in context of transportation

For the evaluation of system architectures, figures of merit have to be introduced. We take the amount of emissions as a first performance factor and consider two other factors: economical performance and speed of the transport

service (Tab. 1.2).
Economical performance is measured in costs and is important for the transportation sector as transport is an integral part of trade, which is driven by economic reasoning.
The third factor we consider is performance in terms of transportation time. That transportation time is critical for transport services gets visible in some examples: food products may spoil when transported for too long, goods like consumer electronics can rapidly loose market value, and passengers are willing to pay higher prices for a faster transportation service like it was done for many years in case of the Concorde [12].

Tab. 1.2.: Factors of performance chosen to compare transportation services

1	Emission of greenhouse gases
2	Costs for market participants who are willing to pay expenses for transport services
3	Speed as reciprocal value of transportation duration

Focusing on the first two factors of Table 1.2, we find a correlation between the factors. The emission of greenhouse gases is a function of energy consumed and a factor of how much greenhouse gases are emitted per energy unit. The latter factor depends on the form of energy that is used. Factors for some specific forms of energy will later be given in Section 2.3.2. While fuels used for one type of vehicle can vary, the amount of energy that is required to propulse a vehicle type much more stays the same. Considering factor 2 of Table 1.2, the costs to operate a mean of transport, we observe that energy consumed is an important factor as well, as it directly determines fuel expenses, which make up a considerable amount of total costs. They make up more than a third of total costs in case of commercial subsonic airlines [13], about 20 % in freight rail transport [14], and 30 % for trucks in Germany [15]. After finding that both factors, emissions and costs, depend on the amount of energy consumed, we reason that this factor is still depending on energy efficiencies of vehicles that vary over time. A more basic factor the amount of energy consumed linearly depends on is the force required to move a vehicle. This factor allows to compare energy consumption of vehicle types independently from motor efficiencies, leading to the largely unchangeable key indicators of emissions and fuel costs.

In Figure 1.1 the third performance factor, the cruise speed of currently used modes of freight transportation is compared with their respective force required to attain that speed.

The Lift-to-drag ratio (L/D) on the vertical axis is a number frequently used to compare aerodynamic performance of aircrafts [16]. It divides the aerodynamic lift force generated by a certain body by its drag force, both at the same given

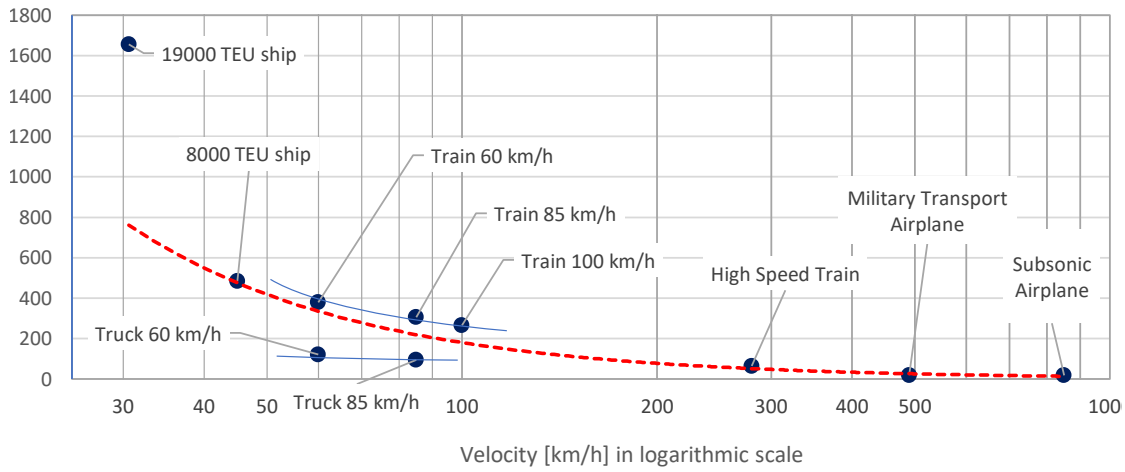


Fig. 1.1.: Lift-over-drag number plotted over cruise speed for a wide variety of transport modes.

speed. Maintaining cruise speed in horizontal flight, the lift force equals the mass of the aircraft multiplied by earth's gravitation and drag is the negative of thrust force. Aircraft designers aim to maximize the L/D, as this means that more mass can be carried per drag force. In other words, the L/D allows us to state how much drag needs to be overcome per unit mass of a vehicle, so that vehicles of different sizes can be compared.
In the following, we extend this figure to all modes of transport. Similar to the case of an airplane, we reason that lift is the weight force of a vehicle. In a similar way, all drag forces, like rolling drag, or drag due to movement in water, are summed up and treated as one.
As L/D is defined for exactly one speed, we use the horizontal axis in Fig. 1.1 to compare L/D numbers at different speeds. The axis is set to logarithmic scale to cover a large range of speeds.
Considering the general trend in the Figure, we observe that L/D decreases rapidly with higher speeds. All vehicles shown, traveling on water, land or in the air have in common that they experience drag while moving, may it be water drag or air drag. This drag is known to increase quadratically with velocity, which explains the form of the curve shown.

Considering data points for **airplanes** in Fig 1.1, points of respective best L/D are shown. The airplanes are likely to be operated at a speed where they perform best in terms of L/D, as anything else would mean to generate more drag than necessary. The data for subsonic airplane is a mean of all current commercial subsonic airplanes designs, like the Airbus A320 or Boeing 737, which tend to be operated at similar speeds and have a similar L/D [17].

Forces for **freight trains** shown in the Figure are calculated with an available online tool [18]. This online tool calculates pulling force and power requirements for different kinds of trains after inputting the train configuration of locomotives and wagons and a value for current speed. We specify a freight train to be

propelled by a locomotive type 'ÖBB Taurus 1116' and to have 30 waggons, leading to an overall weight of 1886 tons. The same tool has also been used to calculate drag forces of a high speed train. For the speed an lift values, the case of the TGV La Poste, a high speed freight train in service from 1973 to 2015 in France has been used [19].

For the case of **trucks**, semi trailers with a permissible weight of 40 tons used in Germany and all over the European Union are considered. Calculations are made with an available online tool [20] similar to [18], where we need to input the aerodynamic surface area, the rolling resistance coefficient of the tires, overall mass of the vehicle, and velocity. We used a mass of 40 tons, the maximum and common dimensions for these trucks, 4 m of height and 2.55 m of width, a c_d value, the dimensionless coefficient to determine aerodynamic drag of an object, of 0.51 and a rolling resistance coefficient, determining the rolling resistance force of a body per contact force, of 0.006.

Concerning **ships**, lift force is calculated by multiplying gravitational force with their mass. Mass is calculated from the tonnage [21] [22], given in Twenty-foot container equivalent unit (TEU), stating a measure of payload volume, multiplied with a deemed mass of 15000 kg per TEU and a factor of 1.8 for overall mass to payload mass ratio [23].
We don't find direct sources for the drag of these ships, but the drag can be estimated from other numbers. As ships mostly maintain one current speed, we reason that they have only little power reserves to go faster than the normal cruise speed and accelerate to that speed. We find sources for the power of the considered ships [22] [24] and reason that they use 80 % of that power to maintain cruise speed. Dividing the 80 % power by the cruise speed, we obtain the drag number.

Considering the results from Fig. 1.1, we conclude that the most energy efficient transport is provided by ships, while airplanes provide the fastest mode of transport. In between are the options of rail and road transport, both providing a moderate L/D value in a velocity range faster than ships but slower than airplanes. In the following, we focus on the velocity range of ground vehicles. To be able to make clear comparisons of L/D numbers of different vehicles, we focus on comparing numbers of the same speed. This means we assume isoperformance in one dimension, here in terms of speed, as introduced by de Weck et. al. [25] in order to reduce complexity.

Fig. 1.1 states a significant difference in L/D between road and rail transport at given speed. The reasons for this discrepancy are as follows: Drag for ground vehicles at their common cruise speeds has two major sources. These are aerodynamic drag and rolling drag of the wheels.
The major part of aerodynamic drag originates at front and back ends of vehicles [26]. In aerodynamics, trains and trucks are therefore classified as bluff bodies, as counterpart to slender bodies, whose main design criterion is aero-

dynamic performance, like e. g. an aircraft wing. Truck lengths are either legally limited directly or by a maximum vehicle weight to around 20 meters, where train lengths up to 740 meters rely on a common standard in the European Union [27]. Hence, on a train more freight containers can be transported with a vehicle of one front and one back end, resulting in less aerodynamic drag per freight unit.

The second aspect of drag is rolling drag. Equation 1.1 states the calculation of the rolling drag F_R.

$$F_R = F_N \cdot c_R \tag{1.1}$$

In Equation 1.1, F_N is the normal force on the ground, which is proportional to the vehicle mass and assumed to be constant per payload mass here. The differing factor for rail and road is c_R, the rolling resistance coefficient. It is known to be 0.001 for a steel wheel on a steel rail and 0.006 [28] for a truck tire on asphalt. We observe that rolling resistance per freight unit for trucks is six times higher than those of trains.

To conclude, in comparison with rail vehicles, both main drag factors for ground vehicles are significantly higher, leading to more drag per freight unit and a lower L/D number. At given vehicle mass and speed, the consequences are higher energy consumption, higher energy costs, and more emissions of Carbon Dioxide. From this perspective, there are significant advantages to transport goods on rails rather than roads.

1.2.2. Challenge to find vehicles with improved environmental performance

We observed that rail transport has a significantly better L/D than road and therefore is superior in terms of emissions and energy costs. However, not all goods are transported on rails. Less than 20 % of all ton-kilometers of cargo transport in Germany have been done on rails in 2016, and the share is further declining [6]. As stated in section 1.2.5, costs are a important decision-making factor for companies deploying transport services. Further investigating costs for rail transport, we find some disadvantageous cost factors that might lead to a worse cost performance compared to road, despite the favorable energy costs.

We have found in a previous study [29], that the way of rail operation with the lowest energy cost is driving under a catenary. This means, that the vehicle itself does not transport the energy it needs for driving. Instead, energy is provided by a copper wire hung over the railway track, called catenary, which the

vehicle is in permanent contact with. In order to provide high amounts of energy, voltage of this catenary needs to be significantly higher than on household electric grids. In Central Europe, this voltage is 15 kV.
Having an external energy supply is advantageous for the vehicle design. There is no need to carry fuels and to convert them on board, which leads to less components and therefore mass on board, among other ramifications for the vehicle, which will be stated in section 1.2.3. Another advantage of the external electrical power supply is the possibility to regenerate energy while braking or going downhill and feeding back this energy into the grid. Especially on tracks with frequent stops, a relevant amount of energy can be saved, e. g. about 40 % for suburban trains in Munich [30]. Moreover, electric traction equipment is significantly more efficient than power generation with diesel motors. In general, the net amount of energy consumed, meaning energy consumed minus recuperated energy, is the relevant parameter for energy costs and emissions. Therefore, due to better efficiency and the possibility to regenerate energy, electric vehicles under catenary perform best in terms of energy costs and emissions.
A disadvantage of the catenary is, that an infrastructure to supply energy is required. Providing the high power levels required for rail vehicles on the full track length requires setting up a costly infrastructure. This includes the catenary itself, substations to supply the catenary with energy, and adaption of other infrastructure that needs to be in a safe distance to the electrically unprotected catenary [31]. Analyzing recent projects, where existing tracks have been electrified, and complying with Baumgartner [31], we find that the electrification amounts to about 1 million € of investment cost per kilometer [32] [33].
It is obvious that this infrastructure investment only pays off with equal savings in other kinds of costs. A rule of thumb to estimate the profitability of investing in a catenary is given in [34]. According to this source, the Deutsche Bahn AG (DB AG) will invest in an electrification of a track if more than 1350 tons are transported per hour on this track. Stating the profitability as a function of transported mass seems reasonable, as the net amount of energy consumed is directly proportional to the mass when accelerated. Still, the stated number neglects the influence of the track profile, the number of trains per mass and the number of stations on a track. However, setting up an estimate for a regional railway track, which is commonly operated once per hour [35] in two directions with a two car train [36], we calculate a mass of about 250 tons per hour transported. According to the rule of thumb, an electrification is by far not profitable in this case. Profitability of electrification with the chosen two car train and the cited number would be reached, if a trainset runs every six minutes in each direction of the track. Earlier in the project, we built a model for the life cycle costs of electrification and found that the minimum required timing of trains is 6.4 minutes [29]. This value compares very well to the cited value of DB AG. Obviously, this threshold of train frequency is only reached for few tracks operated with regional passenger trains.

Another form of propulsion, working on tracks without an external electrical power supply, runs with diesel engines. In this case, energy required for driving

is stored in the vehicle, namely diesel fuel in a tank. The chemical energy in form of diesel is then converted into mechanical energy by an engine. This mechanical energy is then either directly transmitted to a gearbox and the driven axles, or again converted into a different form of energy, like hydraulic or electric energy. This vehicle design has the advantage that vehicles can operate without a catenary. Therefore, the infrastructure investment costs are low. However, as stated above, diesel vehicles require more net energy than electric vehicles under catenary. Therefore, they come with higher energy costs and more emissions.

To conclude, rail generally performs better than road in terms of emissions. Vehicles designed for operation under catenary have low energy costs and are energy efficient, but the concept only works on highly frequented tracks. The other option is driving with an on board diesel engine. This concept requires lower investment cost, but has higher energy costs and is environmentally not as beneficial. To challenge the road transport sector, it is important to provide a high environmental benefit with competitive costs. As by far not all railway tracks are electrified and would also not be profitable to electrify, a question arises:

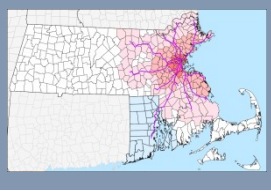
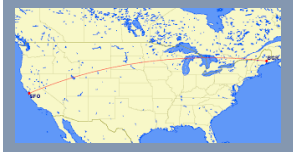
Can we find concepts with a better environmental performance than current diesel vehicles with investment costs lower than those for electrification of infrastructure?

1.2.3. Classification of vehicles in the railway industry

In order to further specify the cases where finding new vehicle concepts is the most beneficial, we investigate use cases for railway vehicles and the current vehicle deployment. Among those vehicles currently operated on railways, we observe a wide range of different forms and types. There are very large vehicles, used to transport heavy goods like iron ore. On the other side there are small vehicles like shunting locomotives or small passenger units not much larger than buses.
Also, operational environments of vehicles are different, some provide not much more than the rails themselves, others have an external power supply for the vehicle. A lot of interfaces to other infrastructure like crossings and stations, and sophisticated train protection systems manage traffic on rails and provide security.
On a lower level of system integration, these systems only give instructions to the vehicle and it's driver, like permissions to go or prompts to stop, as it is mostly realized with light signaling, matching to 'green light' and 'red light' on roads. The vehicle and its driver are then responsible to abide by these instructions. On a more higher level of system integration, infrastructure systems can track positions and velocities of vehicles and interact with them. These more complex systems would manage safe operation of many vehicles within one

network and for instance keep track of safety clearances and also automatically brake vehicles in case of dangers. However, it is necessary for a vehicle to fit its specific environment to be deployable.
The described differentiators of scaling and operational environment show only exemplary why there are a lot of different vehicles on rails. To cluster the wide variety of rail vehicles we choose two relevant dimensions for their design and subsequently define cases in this cluster (see Tab 1.3).

Tab. 1.3.: Use cases for railway vehicles set up by the dimensions of transported object and distance of one scheduled ride

	Local 	Regional 	Long distance 
PAX	A **Local passenger transport** - Underground or suburban trains - electrified	B **Regional passenger transport** - w/o electrification - usually less than 200 km per scheduled ride	C **Long distance passenger transport** - high speed trains - electrified
Cargo	D **Local cargo distribution** - mostly unelectrified	E **Regional cargo transport** - w/o electrification	F **Long distance cargo transport** - electrified

The first dimension is the transportation of either passengers or goods. Considering current vehicles, it gets visible that what is transported must be one major differentiator in vehicle design. For example, there are, with the exception of a few vehicles, no self-propulsed (operationally non-divisible unit capable of propelling itself) railcars used in freight transportation, only trains consisting of unpropulsed wagons and propulsed locomotives, while in passenger services, self-propulsed railcars are much more likely to be used. Even when considering only locomotives themselves, most locomotives of Deutsche Bahn AG are either used only for passenger transport, like classes 101, 120, 245, or only used for cargo services, like classes 152, 185, 232 [37].
The second dimension we use to distinguish cases for rail vehicles is the total distance traveled within one scheduled ride. We distinguish between long distance, regional transport, and suburban transport within the vicinity of one city. Considering [37], all passenger vehicles of Deutsche Bahn AG are designed to serve exactly one of the three named cases and there are no vehicles that

would be operated in another case than the designated.
In the following, six cases for vehicles resulting from this classification are described. We address the vehicles' operational environment as well as the consequential design characteristics with regard to the current vehicle deployment in Germany.

Case A, local passenger transportation, includes underground railways and suburban, in Germany called 'S-Bahn', transport. These networks tend to be operated in densely populated areas. A higher population density also means a higher number of riders per area.
The high density of riders leads to three different environmental factors relevant for the vehicle design:

- A higher number of trains per time
- Larger trains with more cars
- Higher frequency of stops

Taking the Munich S-Bahn as an example, the standard frequency of trains would be 20 Minutes, the trains consist of four to twelve cars, and, taking the line 'S8' as an example, the average distance between stops is 2.3 kilometers [38]. The average distance between stops is relevant, because this also means an energy-intensive acceleration process for at least every stop. All three factors together, stating a high number of large trains with frequent acceleration procedures, result in a high energy demand per track length. As mentioned in Section 1.1, one argument for setting up a catenary is the difference in energy costs, which is directly proportional to the net amount energy consumed.
The most important reason against setting up a catenary is investment costs, which are proportional to the track length. Considering this, the high amount of energy demand per track length of Case A makes a profitable installation of a catenary likely. In fact, 14 out of 16 suburban rail networks in Germany are completely electrified [39]. It should be mentioned, that vehicles on suburban lines are likely to be not propelled with diesel: in the cities, the lines often use tunnels or big station halls, where diesel exhaust gases are not tolerated [40]

Case B in Germany comprises of the train lines advertised and named "Regional Express (RE)" and "Regional Bahn (RB)".
Different to Case A, lines of these classes are often operated less frequently, often once per hour [35]. Also, these trains tend to be operated in less densely populated areas. Train lengths down to a single car are common. The greater line distance combined with smaller trains and lower frequency of operations per line lead to a low amount of energy consumed per track length, so that the break even point for installation of a catenary is often not reached. However, regional lines share one rail network with lines from all other cases that may run under catenary, so that often at least a part of a regional line has a catenary set up. A preliminary evaluation of 15 out of 103 existing RE lines in the state of Bavaria shows that these regional lines have a catenary set up for 0 . . . 75 % of their track length. The catenary is not used in these cases. We assume that the

length of a regional line is 200 kilometers or less. All trains on longer lines are considered long-distance.

Case C, long distance passenger transportation, means operation with vehicles that are capable running high speed. In terms of railway in Germany, we define high speed to be faster than 160 km/h. Above this speed many technical features are required by governmental regulations [41]. In Germany, there are the classes of Inter City Express (ICE) and Inter City (IC) trains that operate long distance lines. High speed trains like the German ICE, the French Train à Grand Vitesse, "high speed train" (TGV) and the Japanese Shinkansen are exclusively operated on electrified lines [42] [19] [43]. The operation on catenary-only tracks is due to technical reasons. As stated in Section 1.1, the high speeds come with a very high aerodynamic drag which must be overcome, which entails high energy demand at cruise speed. Producing and storing this amount of energy on board would lead to critical high mass and volume required for tanks, diesel motors and power transmission equipment. The difficulty in building diesel vehicles with a power density comparable to vehicles operating under catenary gets visible at the comparison of current locomotives, which are are all subject to similar mass and volume constraints. Locomotives having four or six axles have limited length of about 20 meters and a mass limited by the infrastructure, where the highest permissible mass per axle is 22.5 tons [44], leading to a maximum mass of 135 tons. Under this constraint, the most powerful electric locomotive of the DB AG has power output of 7780 kW [45], while the most powerful diesel locomotive only comes with an power output of 2940 kW [46].

Case D covers vehicles meant for local distribution of goods, which mostly means the connection of a single or multiple plants to the railway network. Local distribution in cities is rarely done on rails. The summed amount of energy consumed per track length is very small as there are only few trains running on those lines. Therefore, lines for Case D tend to be non-electrified.

Case E is defined by freight transport that is not only done on main routes of the rail network, so that routes are partially or completely non-electrified. Furthermore, due to less traffic than on main routes, freight trains may not necessarily reach their greatest permissible length, leading to a lower energy consumption per train. Operating on routes with and without a catenary and lower power and energy demands per vehicle make the deployment of more flexible, hybrid vehicles evident. All over the world, there have been several approaches to deploy shorter cargo trains that are not conventionally powered by a locomotive. The British Multi-purpose Vehicle, as well as the Japanese M250 and the German CargoSprinter all pursue this approach [47] [48] [49]. Being developed in the 1990s, when hybrid technologies were not as powerful as they are today, all three vehicles do not use hybrid drivetrains. However, vehicles of Case E only play a marginal role among rail vehicles. Specifically the CargoSprinter entered a test phase in Germany, which drew a negative conclusion of the concept's

performance, but many reasons outside the vehicle's design impeded the test phase, like unfortunate political and strategic management decisions [47]. No more vehicles were deployed after that test phase.

Case F covers cargo transport on main routes in Germany. Vehicles serving this Case are electrified for three specific reasons: First, as freight trains on main routes are heavier than passenger trains, they consume higher amounts of energy for their acceleration. Additionally, the main routes are operated frequently, leading to a high amount of energy consumed per track length and therefore to a profitable electrification of lines. Second, the main routes are often shared with long-distance passenger trains, which require a catenary anyways as stated in the description of Case C. Third, the high mass combined with the less powerful diesel locomotives would lead to unsatisfactorily low acceleration rates, slowing down traffic on the network that is shared with other trains, which makes the use of electric vehicles under catenary preferable.

1.2.4. Selecting a case

We aim to find a trade-off between investment costs and environmental performance for one of the described cases. As the Cases A, C, and F are defined to be fully electrified, they need no further optimization.
Vehicles designed to serve Case D serve a small market segment and are therefore not taken into considerations. Hybrid drivetrain solutions for Case E seem to be a reasonable solution. However, the case of the CargoSprinter shows that the deployment of vehicles serving case E is determined by many factors outside the vehicle design, leading to the fact that there is no or small market for such vehicles in Germany.
We will look for hybrid drivetrains that are capable of outperforming current designs in terms of costs and environmental performance using Case B. The current infrastructure for vehicles of this Case comes with a widely varying grade of electrification of lines as stated in the case description. Furthermore, regarding the 103 RE lines only in the state of Bavaria, there is a considerable market for such vehicles. Current government incentives like the "Bayerische Elektromobilitätsstrategie Schiene (Bavarian Policy for Electric Mobility on Rails)" [50] which proposes a number of hybrid test cases on specific parts of the rail network, show large public interest to find affordable solutions providing increased environmental performance for rail vehicles described by Case E.

Having defined the most impactful environment for improvements, we further specify our research question:

Can we find concepts for regional railway vehicles that provide better environmental performance than current diesel vehicles with investment costs lower than those for electrification of infrastructure?

1.2.5. Stakeholder Value Network

Before optimizing a vehicle, we need to determine motivations to buy vehicles or propulsion units on the railway market. A useful tool to improve understanding of a market and its needs is the Stakeholder Value Network, first used under that name by Cameron et. al. [51].
After setting up the Stakeholder Value Network for regional passenger rail in Germany (Fig. 1.2), we determine the most important actors in the market and select their relationships towards each other. Considering these relationships, we figure out which can be influenced by the vehicle design. This helps us to check if the set up metrics to evaluate performance of vehicles are really the factors that lead to a deployment decision. Following, we focus on the perspective of an operator, as this is the actor responsible for vehicle deployment.

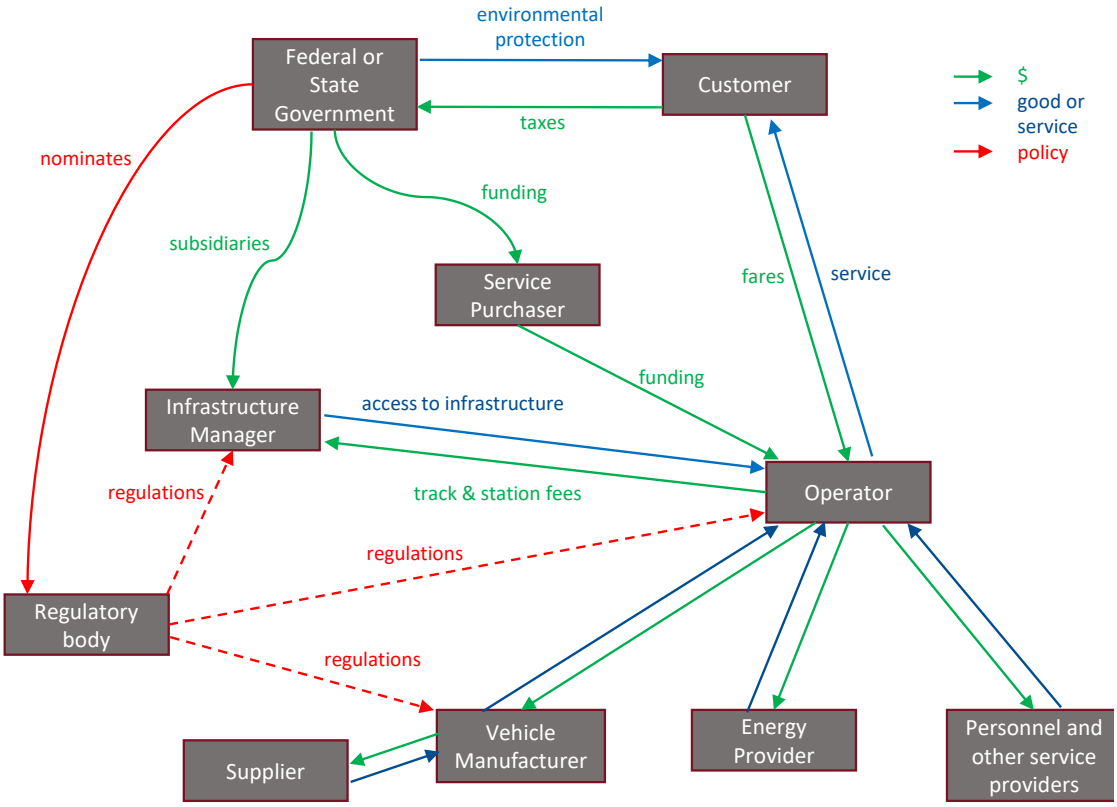


Fig. 1.2.: Stakeholder Value Network for regional railway in Germany

In Germany, the federal states are responsible for the regional railway system. Every state owns a service purchaser, e. g. Bavaria has the Bavarian Railway Company. This service purchaser works out a detailed call for tenders for a contract period, typically between 8 and 15 years [52]. Prospective railway operators then submit offers to the call for tenders. The railway operators are either regional subsidiaries of the DB AG or other private companies. The call

for tenders specifies a wide variety of operational issues for the operators, leaving few freedoms in operations. For example, every railway line is given with its minutely operating schedule. Revenues for the operator depend on the tariff, which is given in the contract, among objectives for sales and marketing systems. Service quality is covered with a bonus-malus system specified in the traffic contract and measured according to the European Standard EN 13816 "Transportation - Logistics and services - Public passenger transport - Service quality definition, targeting and measurement". Its parameters include reliability, punctuality, accessibility, vehicle design especially of amenities, capacity of vehicles, safety, facilities of stations, environmental protection including emission standards, passenger information, and cleanliness of vehicles and stations [53].

Complying to these specifications, prospective operators submit offers to the call for tenders. The awarding of contracts is subject to more complex regulations based on the European Community Regulation EC 1370/2007 and represents a proper law discipline [54]. In short, the first premise is that the contract should be awarded to the bidder which provides the demanded service at lowest price [55].

The infrastructure where vehicles operate is privately owned by the infrastructure manager, which gets subsidized by the federal government. Operators pay the managers fixed fees per track kilometer or usage of stations.
Other expenses are vehicles, their personnel and energy.
On the side of revenues through the market, the most important source of revenues are the customer's fares. They make up on average 76.3 % of all revenues, including the traffic contract [56].
It should be mentioned that the state is not only responsible for the design of the traffic contract, but also presides over a regulatory body. This regulatory body imposes regulations for infrastructure, vehicles, and operations. Regulations play an important role in the railway sector, as they may have a significant impact on costs and possible revenues [57].
All governmental activities described here need to be financed. In the end, the required money is drawn by the countries' citizens in form of taxes. The reason why governments make large efforts to subsidize contracts and infrastructure and employ a regulatory body lies in the benefits of rail traffic compared to its alternatives [58]. As Lalive reasons, governmental subsidiaries have a direct, positive effect on traffic safety and emissions [59].

As this thesis proposes a model to optimize vehicles, we look for the reasons why a specific vehicle will be bought and make sure that the optimization's metrics correspond with operators' possible needs.
Like every actor in a free market, operators will aim to minimize costs and maximize revenues in order to make the best profit. It is therefore important to analyze which factors can be influenced by operators with their vehicle deployment decision.

First, we exclude options that are not influenced by the vehicle decision. We assume that personnel and other services do not change significantly with the vehicle. The number of drivers, ticket sellers and others is assumed to stay constant. Furthermore, all vehicles and operations are object to the same regulations, these can not be changed. Track and station fees are also fixed per use. On the revenue side, the ticket fares are fixed in the traffic contract.

What remains are the factors that are indeed dependent on the vehicle deployment decision. These are investment costs for the vehicle, and, as every vehicle has a specific energy type and consumption, energy costs. As described, operators will strive to minimize these expenses. Logically, there is a certain tradeoff that needs to be found: Lower investment costs will lead to a worse performing vehicle, meaning a bad fuel efficiency. Therefore, low investment costs will be offset by high fuel expenses.
The one remaining source dependent on the vehicle decision is the funding through the traffic contract. It is the state's decision how much funding will be provided for a specific contract. Therefore, we recall the state's needs: These are safety and environmental protection. It is assumed that the level of safety stays constant for different vehicles. Therefore, the amount of state subsidiaries for the operator depends on the environmental benefit he provides. As described before, this benefit can be expressed in amount of CO2 emissions. If emissions are reduced, the state may be willing to raise grants for a traffic contract.

In conclusion, there are three cost and revenue factors that are depending on a vehicle deployment decision. These are investment costs for the vehicle, energy expenses for operations, and subsidiaries stipulated in traffic contracts depending on emissions. We set minimized investment costs as a first objective. As previous research in this project has shown, energy expenses and CO2 emissions approximately depend linearly on each other [29]. Therefore, we can set up minimal emission of CO2 as a second suitable objective. It ensures low energy expenses and high grants from the traffic contract, which is beneficial for the operator.

1.3. Literature review

Considering existing literature of how the defined research question has been approached, we find a complex variety of methods. Numerous sources investigate new vehicle concepts of all kinds. As we aim to approach the question more systematically, we need tools that allow us to explore all possible solutions. Appropriate methods are provided by System Architecture framework. We set up architectures, that are defined by a set of decisions to choose submodules as proposed by Crawley et. al. [60].

Useful inputs for an investigation of regional railway vehicles have been defined by Pagenkopf and Kaimer [61]. In their techno-economic paper, they chose the railway track between Ulm and Oberstdorf as an example. As a first step, they made estimations for energy consumptions of vehicle runs on that track. The rail track as well as the energy values provided initial values for our models and were later used to validate submodules.
Some of the possible architectures have been subject to further investigations. Again, we reference the paper of Pagenkopf and Kaimer, where they confirmed economic feasibility of battery-electric vehicles as well as fuel cell systems on the dedicated track. Furthermore Fichtl et. al. have developed a serial hybrid concept for the Erzgebirgsbahn, which operates on relatively hilly routes. As of today, the concept is announced to demonstrate its performance with operations beginning in 2018. The serial hybrid concept is claimed to save 35 % CO2 compared to a conventional vehicle [62].
The named concepts that have more or less proven their feasibility represent only a few of the possible architectures, meaning combinations of subcomponents. The project called Toolbox for Optimized Railway Propulsion Architectures (TORPA), which this Thesis is part of, has worked on further exploring the possible Design Space. It was started in 2017 by M. Guerster and C. Moser, whereas the author of this Thesis and two other students joined the project after the first paper was released. The named paper of fall 2017 conducts a more general approach on all possible combinations of submodules [29]. It confirmed the competitiveness of some concepts while other options have been excluded after that study, as they have not been expected to be competitive. Overall, this preliminary study helps us to narrow down the space of possible architectures approximately by half.
A previous paper in the project TORPA conducted a multi-objective optimization of all architectures with a subsequent comparison of their performance. We will further pursue this approach in this thesis. With the narrowed down design space, we like to increase the level of detail of the optimization models and allow to vary more input parameters. Pursuing this approach, we aim to make more detailed statements which architecture can be expected to perform well under which environmental conditions.

1.4. Specific thesis objectives

We formulate overall research goals of this thesis after reviewing literature and available methodologies, as well as past progress within the TORPA project. The thesis should address the specific research question of Section 1.2.4 in a unbiased, neutral way.

With the **To-By-Using** goal statement formalism, we phrase the specific research objective in a more structured way:

To find solutions consisting of vehicle drivetrains and infrastructure that provide the best environmental performance for the least cost
by:

1. Defining a design space for vehicle and infrastructure architectures
2. Building a framework to optimize each architecture
3. Defining suitable Metrics to compare results and make decisions
4. Visualizing and analyzing results to draw conclusions about promising and non-promising architectures as well as areas of the design space

Using the existing tradespace exploration tool within the TORPA framework.

1.5. Thesis overview

In the following Chapter 2, a design space is defined building on past findings of the TORPA project. After applying logical constraints, we find a number of architectures to further investigate and create a naming scheme for them.
Subsequently, the built framework to optimize each architecture is described, including interfaces between optimization model and input parameter models.
In the end of Chapter 2, we define performance metrics and a tool to support making a decision for one vehicle.

Chapter 3 describes the exemplary optimization and results of one of the defined architectures. We specify one problem setup with vehicle architecture, track environment and input data.
We analyze overall optimization results before focusing only on the best performing vehicle variants. We show how the decision supporting tool can be applied to propose deployment of one specific vehicle.
Finally, we compare the new vehicle variants with conventional vehicles and reason if a deployment can be recommended.

Chapter 4 summarizes the Thesis with its main findings and describes applicability and limitations of the created framework and the exemplary results. Lastly, an outlook for planned and possible future work on the research topic is given.

2. Model

In this chapter, we will further describe our approach to the defined research question. First, in Section 2.1, we will describe **what** we investigate by setting up a scheme to define a vehicle. **How** we investigate each of those vehicles with a simulation Model is described in Section 2.2. After that, in Section 2.3, we define how the performance of the simulated vehicles is evaluated.

2.1. Design space definition

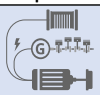
An architecture is the composition of the drivetrain of a simulated vehicle. It defines which modules the drivetrain consists of, such as different motor types, or options for energy storage. A variant then defines one specific prorated scaling of the included components, e. g. how much power a motor has compared to total power. Variants within an architecture are distinguished by one or more design variables. These variables range from 0 to 1 and define a balance of a physical variable between two components. For example, we look at energy consumption as physical variable and like to know its distribution between the components battery and engine. Then, the design variable is used to define how much of total energy is drawn form the battery and how much is drawn from the engine, e. g. 0.3 of total energy comes from battery and 0.7 of it is drawn from an engine. The sum of all component values of one design variable add up to 1. A more practical example of how these design variables are applied is given in Chapter 3.
The possible design space of an architecture then comprises all its possible variants with unique sets of design variables ranging from 0 to 1.
Subsequently, we develop a method to define architectures that will be optimized later.

2.1.1. Decision Matrix

In order to define which vehicles and infrastructure environment will be assessed, a Morphological Decision Matrix is set up (see Tab. 2.1). The method introduced by Zwicky and developed by Hall in the 1960s aims to explore all possible solutions of multi-dimensional problems [63]. The decision matrix' rows contain important architectural decisions, while columns contain possible op-

tions. An architecture is then defined by choosing one option in each row.

Tab. 2.1.: Decision Matrix defining architectures. An architecture is set up choosing one option per row. The first three rows contain vehicle options, the last one infrastructure options.

	ID	Option 1	Option 2	Option 3	Option 4	Option 5	Option 6	Option 7	Σ
Driving / Producing configuration	**EDrivProd**	 Diesel-Mechanic (D_M)	 Diesel-Hydraulic (D_H)	 Diesel-Electric-Serial (D_E)	 Diesel-Electric Parallel (DEM)	 Fuel Cell-Electric (F_E)	 Fuel Cell+Diesel, Electric Serial (FDE)	 Electric (__E)	7
Storing of electric energy on board	**EStoring**	 Battery (b_)	 Supercap (_s)	 Flywheel (_f)	 Battery + Supercap (bs)	 Battery + Flywheel (bf)	None (__)		6
Pantograph + Trafo	**Pant**	 0 (_)	 1 (P)						2
build external energy supply in section i	**extE**	recharger at initial stop	catenary	NaN					3
									252

The first row of this matrix describes the method of energy production on the vehicle, the kind of energy transmission and which form of energy is used for generating propulsion. There are vehicles that use more than one kind of energy production as well as vehicles with no energy production on board. In more detail, the suboptions of the energy production are listed in Table 2.2.

Tab. 2.2.: Suboptions for the first choice of the Decision Matrix. The three letter code consists of two options for modes of energy production onboard and one for transmission.

Letter	Suboption	Options	Symbols
1	First mode of energy production	Diesel Engine, Fuel Cell, None	D, F, _
2	Second mode of energy production	Diesel Engine, Fuel Cell, None	D, F, _
3	Mode of energy transmission	mechanic, hydraulic, electric	M, H, E

The second row describes the method of storing energy within the vehicle with the options batteries, flywheels or supercapacitors and combinations of them.
Row three includes the decision if a vehicle has a pantograph to draw electric energy from an overhead wire. As current from the overhead wire can not be used directly to drive electric motors, transformers or, in case of the more rare direct current systems, chokes are used.
Multiplying the numbers of all three vehicle options, the number of theoretically

possible vehicle architectures is 84.
While the first three decisions in 2.1 define the vehicle, the last decision is an issue of infrastructure. Generally, the decision matrix can be set up for every section of track, but it is assumed that the vehicle architecture does not change within one track and only infrastructure may vary from section to section. Multiplying all vehicle options with the infrastructure options, 252 different combined architectures result.

2.1.2. Vehicle Architecture Matrix

In order to narrow down the architectural space, we use common sense to reduce the number of architectures examined. All theoretical combinations of vehicle decisions are shown and named in the Vehicle Architecture Matrix (Fig. 2.3).

Tab. 2.3.: Vehicle Architecture Matrix

		Energy producing, transmission and driving							
	name	Diesel-Mechanic	Diesel-Hydraulic	Diesel-Electric Serial	Diesel-Electric Parallel	Fuel Cell-Electric	Fuel Cell + Diesel-Electric Serial	Electric	
	transmission shortcut	mechanic D_M	hydraulic D_H	electric D_E	mechanic DEM	electric F_E	electric FDE	electric __E	
	storage option 1/2								
Energy storage	Battery (b_)	_[b]	_[b]	D_E-b_-_	DEM-b_-_	F_E-b_-_	FDE-b_-_	__E-b_-_	
		_[b]	_[b]	D_E-b_-P	DEM-b_-P	F_E-b_-P	FDE-b_-P	__E-b_-P	
	Supercap (_s)	_[b]	_[b]	D_E-_s-_	DEM-_s-_	F_E-_s-_	FDE-_s-_	__E-_s-_	_
		_[b]	_[b]	D_E-_s-P	DEM-_s-P	F_E-_s-P	FDE-_s-P	__E-_s-P	P
	Flywheel (_f)	_[b]	_[b]	D_E-_f-_	DEM-_f-_	F_E-_f-_	FDE-_f-_	__E-_f-_	_
		_[b]	_[b]	D_E-_f-P	DEM-_f-P	F_E-_f-P	FDE-_f-P	__E-_f-P	P
	Battery+Supercap (bs)	_[b]	_[b]	D_E-bs-_	DEM-bs-_	F_E-bs-_	FDE-bs-_	__E-bs-_	_
		_[b]	_[b]	D_E-bs-P	DEM-bs-P	F_E-bs-P	FDE-bs-P	__E-bs-P	P
	Battery+Flywheel (bf)	_[b]	_[b]	D_E-bf-_	DEM-bf-_	F_E-bf-_	FDE-bf-_	__E-bf-_	_
		_[b]	_[b]	D_E-bf-P	DEM-bf-P	F_E-bf-P	FDE-bf-P	__E-bf-P	P
	None (__)	D_M-__-_	D_H-__-_	D_E-__-_	_[b]	_[c]	FDE-__-_	_[a]	_
		_[b]	_[b]	D_E-__-P	DEM-__-P	_[c]	FDE-__-P	__E-__-P	P

In the Vehicle Architecture Matrix, the energy production options from Tab. 2.1 are stringed horizontally. Storage options are stringed vertically on the left and

the pantograph option is listed vertically on the right.

By using logical and technological constraints, which are shown in 2.4, the number of possible architectures is reduced. Non-feasible architectures are marked with a dash and a small lowercase letter in the Vehicle Architecture Matrix, where the letter indicates due to which specific constraint a set of decisions is not considered a feasible architecture. Constraint A is obvious, as a vehicle will not generate propulsion without any source of energy. Constraint B refers to the fact that a electric motor only operates with electric energy, not with mechanic. The other way round, it makes no sense to have electric energy stored in a battery, when the drivetrain is full mechanical without an electric interface to use that source. Constraint C is due to characteristics of fuel cells. They achieve their best efficiency only in a narrow range of output power. As the power demand for a typical driving cycle is fluctuating, the fuel cell would operate at bad efficiency rates for part of the cycle [64]. Therefore, their deployment is done along with a battery to compensate for the fluctuations and operate the fuel cell at a more constant power output level.
After applying the named constraints, all remaining and feasible architectures are named in the Vehicle Architecture Matrix with their acronyms.

Tab. 2.4.: Architectural constraints to limit the number of feasible options in the Vehicle Architecture Matrix.

A	A vehicle without any power supply from internal generation or a pantograph can not generate propulsion
B	An electric mode of driving requires an electric mode of storing or drawing from catenary and vice versa
C	A fuel cell can not cover the fluctuating power requirement of driving without an intermediate storage option.

The architecture acronym comprises the energy decision, the storing decision and the decision if the vehicle has a pantograph or not.

The energy decision is represented by three letters, standing for first energy production option, second energy production option, and transmission. To give an example, (FDE) stands for energy production with a fuel cell (F) and a diesel motor (D), combined with an electric transmission (E). As another example, the vehicle with the code (__E) has no energy production and the driving energy is transferred electrically, originating directly from outside the vehicle.
The storing option is abbreviated with two lowercase letters, followed by the pantograph decision with either the letter P or an underline for the "None"-option.

Using the constraints in Tab. 2.4, the 84 possible vehicle architectures resulting from the first three architectural decisions in Tab. 2.1 are downselected to 59 feasible architectures which are named in Tab. 2.3. These 59 architectures are subject to the investigations conducted subsequently.

2.2. Software Architecture

The architectures defined in section 2.1.2 are optimized separately within the software loop described in the following.

We use a Genetic Algorithm (GA) to optimize each architecture with its specific set of design variables. The more specific function of GA is discussed later. First, an overview of the algorithm's function is given.

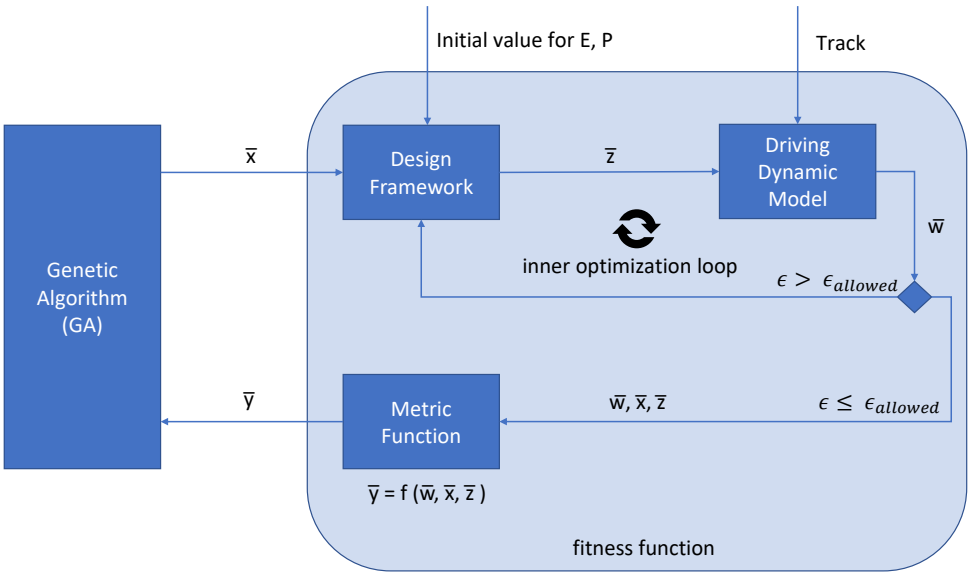


Fig. 2.1.: Overview of the software tool architecture consisting of a Genetic Algorithm multi-objective optimizer, an inner optimization loop for the design framework and the driving dynamic model, as well as a metric function.

Fig. 2.1 shows the GA and the fitness function which itself decomposes into the inner optimization loop and the metric function.

In brief, the software loop for works as follows: GA outputs a specific set of design variables that define one variant. They are written into vector x. With these design variables, the design framework calculates the physical values required for the DDM simulation, which are masses, power, and energy components (z). With this train design and a given track, the DDM simulates a run on the track

and obtains new power and energy results based on the mass of the train (w). A decision point evaluates the convergences of the loop by comparing the initial guess of the required total energy (in z) with the newly calculated total energy of the DDM (in w). If this value is below a threshold of 1 %, the inner optimization loop has converged for the given set of design variables (x) and a metric function transforms all the available variables into an objective of interest (y). Later, the objectives of investment cost and CO2 emission will be used. The metric function is described later in Section 2.3. After values for objectives of interest are calculated, they are returned to the GA.

How the described procedures are implemented in Matlab is shown in Figure 2.2. The algorithm starts in the function "main". After that, variables are passed to the "Main optimization function". There, functions that define architectures and read input data are run. After that, the optimization in form of the GA is started. As shown in Fig. 2.1, the fitness function and the subordinate Whileloop are started. Within Whileloop, the Design framework, mass model, and DDM are run. After functions have finished, their resulting variables are returned to their superordinate functions.

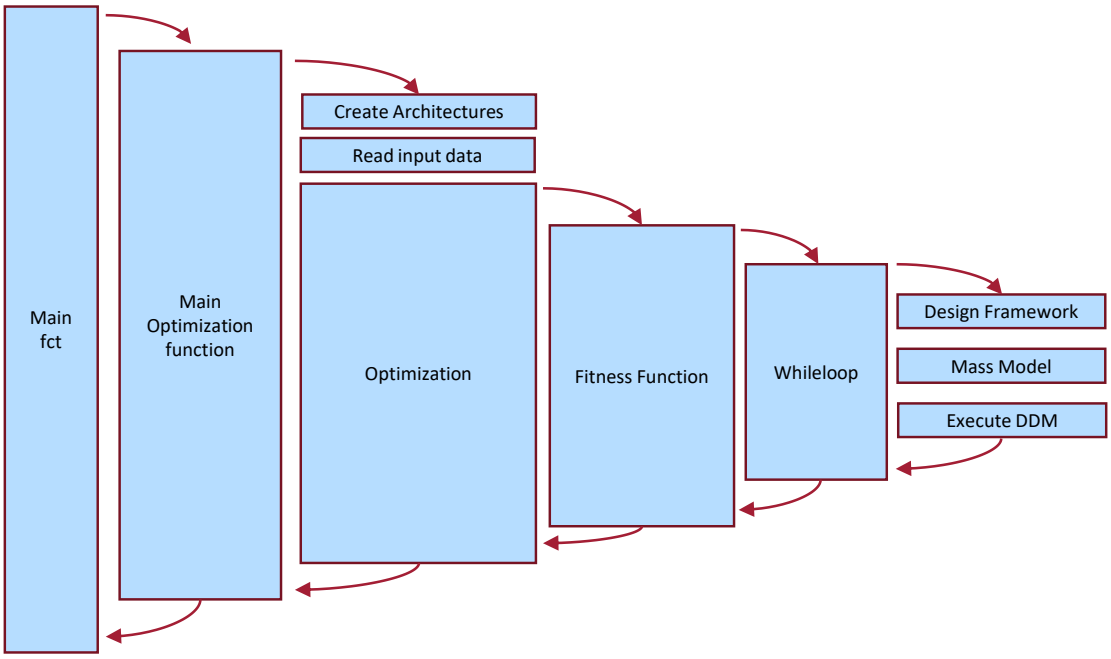


Fig. 2.2.: Overview of the code setup in Matlab. The software is started from the main function on the left. Variables are then passed to the next function on the right. After a function has run, it returns its variables to its superordinate function.

2.2.1. Multi-objective optimization

To solve the given multi-objective optimization problem, a GA is used. This kind of algorithm has already been applied previously in the project. It is implemented in an toolbox in Matlab which we use [65].
As a first step of the optimization, the GA outputs a number of individuals, where each **individual** represents one vehicle variant with a unique set of design variables. These variants created within one step are called a **population**. Each population represents one **generation**. Generations are numbered continuously. For individuals of the first generation, design variables of the variants are distributed randomly. Each of the generated variants is then evaluated within the previously described software loop. The evaluation is done with multiple objectives. Performance values for each variant are then pared back to the GA. Therefore, GA determines which set of design variables leads to a well performing vehicle and which does not. With that information, the individuals of the next generation are created. As in natural selection processes, the GA crosses and mutates design variables of previous individuals. Well performing individuals are preferred in this process [66]. This way, the generations' performance converges towards an optimum. Convergence is reached when a new generation's performance does not improve significantly compared to the previous ones. In the tested case described in Chapter 3, we checked how convergence is approached. A corresponding figure showing performance over generations is included in the Appendix.

Evaluating performances of individuals, we use not one but multiple objectives. Matlab's GA function is well capable of taking this into account. However, it is favorable to chose not more than two objectives at once in order to keep complexity in result analysis at an acceptable level. Having two objectives, every performance of an individual consists of two values. Therefore, results are shown in a plane instead of a straight. As two different objectives can not be directly compared, a single optimal point can not be determined. Instead, the optimum is a straight in the performance plane. A point is part of that straight, if no other point can be found that performs better in one metric without worsening the second one. The point then is called **Pareto optimal**. By connecting all neighboring points that fulfill this criterion, a curve of connected straights is derived as optimal curve. This curve is called **Pareto frontier**. Eventually, it is our goal to find vehicle variants with Pareto optimal performance.

2.2.2. Design Framework

After the GA has generated a set of design variables, the design framework uses them to derive physical properties of the vehicle variant. Together with values for energy and power, either from an estimate or from a previous run of DDM, the physical parameters for energy and power requirement are generated. As

an example, if the design variable for power from the battery as proportion of total power is 0.6 and estimated total total power is 100 kW, then the battery power output would be 60 kW.
In a second step, all other physical parameters of the vehicle are determined with the generated values. This can be done because all vehicle drivetrain components scale with either energy or power in some way. In general, storage options like tanks scale with energy. This means that physical parameters like mass and volume of a tank are a functions of its energy capacity. Similarly, most other components scale with their maximum power, e. g. axle diameters of transmission gears are a function of their maximum torque [28]. The torque again is function of power. The mass of the gearing is a function of the axle diameter. We determine mass of a component as a function of its maximum transmitted power. We used available component data to create a regression model for the scaling of components. We assume linear functions as we only focus on parts for regional trains. Their range of energy and power does not exceed one order of magnitude and the desired output functions show linear scaling relationships to energy and power.
An input data sheet comprises data for all metrics each component has an impact on. The output metrics of the Design Framework that we obtain for every component are: mass of CO2 emitted, component mass, volume, investment cost, and energy cost.

The design framework also determines values important for the DDM that is run afterwards and some values that are not functions of energy and power. Examples for this would be the number of driven axles important for the DDM and vehicle structure mass. How the total vehicle mass is calculated is described in the next section.

2.2.2.1. Mass Model

Our previously proposed software tool [29] optimized a propulsion unit with a fixed-value mass and a given vehicle mass. To extend this model towards a generic vehicle with variable mass of the chassis and the propulsion unit, a mass model is required.
The Mass Model is part of the block Design Framework in Fig. 2.1.

Input for the DDM is the overall vehicle mass. The mass of the vehicle drivetrain is now an objective of our optimization. To obtain the overall vehicle mass we need to add the non-optimized part of mass to the optimized drivetrain mass. The calculation of this mass is described as a mass model in the following. We define this model for a regional train with two or more cars. It consists of the following components: passenger cabin structure mass, bogie mass, mass of driver's cab and crash structure, payload mass, and mass of the propulsion

system including motors, drivetrain, fuel, and energy storage (as seen in Figure 2.3).

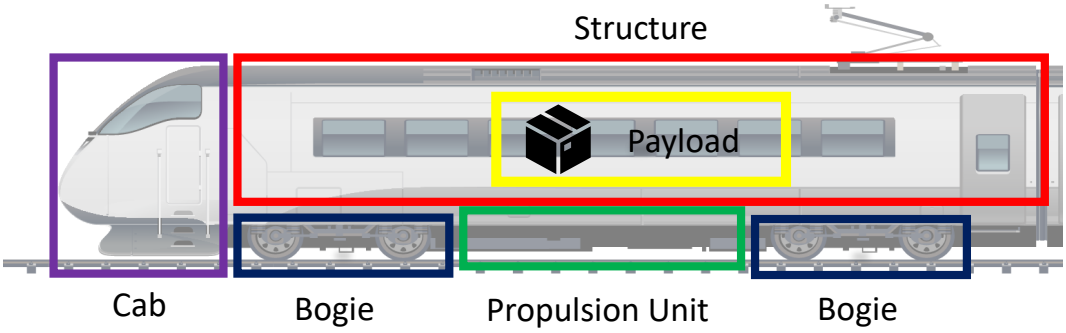


Fig. 2.3.: Overview of our structural decomposition of a regional railway vehicle. It consists of driver's cabs, bogies, the optimized propulsion unit, and from the passenger numbers depending components, the payload, and the structure.

The payload mass per seat is assumed to be 75 kg as defined by common industry standards [67].
Based on manufacturer data [68], we assume that a bogie for a regional train traveling slower than 160 km/h has a mass of 6 tons, under addition of 1 ton if the train is a tilting train. For most vehicles, the motor is integrated into the bogie. However, we consider motor mass as part of the (optimized) drivetrain mass and not the bogies' mass.

The structure mass is calculated with data published by Stadler Rail AG of all available full-electric Stadler Flirt railcars with their passenger capacities, their mass and their output power [69]. Comparable values are also found on Wikipedia [70].
All trains given by Stadler composed of three to six cars have the same power output. Therefore we know that motor and transformer mass are constant for these vehicles. The two-car train has less power. The additional mass difference is calculated with an estimate value taken from a transformer used in the Siemens ICE 3 [71]. Its mass and transformer power together with the motor output power lead to values for transformer power per motor power and transformer mass per motor output power. Therefore, we can now calculate motor and transformer masses for all vehicles. Subtracting these masses and the cited masses for payload and bogies, we obtain a structure mass for all vehicles, which is again divided in mass of the drivers' cab including crash structure and the passenger carrying structure.
Taking the empty mass of the 2-car Flirt and subtracting all above mentioned masses, a mass of 22 tons for each driver's cab remains. This value seems very high, but, as an example, the New York MTA M7 cars complying with FRA (Federal Railroad Authority) standards have a 29 ton higher mass than similar cars not matching these standards just because of crash structure [57]. Furthermore, a change of this parameter does not lead to better consistency of the

mass model with real trains within the validation.
The remaining structure mass is considered a function of the number of passenger seats. Subtracting all other calculated masses from the given total masses and dividing by number of seats, we obtain a passenger carrying structure mass of 268 kg per seat.

Tab. 2.5.: Validation of the developed mass model of regional train architectures

Manufacturer	Model	DB AG Class	# of cars	Calculated mass [t]	Source mass [t]	Relative Difference
Bombardier/ Adtranz	Regio-swinger [36]	612	2	111.63	116	-3.91%
Bombardier	Talent 4-car [72]	4024 (ÖBB)	4	125.73	116	7.74%
Siemens	Desiro [73]	642	2	72.25	69	4.49%
Alstom	Coradia Cont. [74]	440-4	4	111.41	119	-6.81%
Alstom	Lint 54 [75]	622	3	108.21	98	9.43%
Alstom	Lint 81 [76]	620	4	154.35	138	10.59%

We validated this model with six other state-of-the-art regional trains deployed in Germany and neighboring countries. Validation data is shown in Table 2.5. It shows manufacturer and model name of the referenced vehicles with their class number of DB AG or Österreichische Bundesbahnen (ÖBB), respectively. Additionally, the number of cars in the validated trainset is shown. After that, we compare the mass of the vehicle calculated with the proposed model with the real mass of the vehicle found in the referenced sources. The relative difference of our model masses to the real vehicle masses ranges between -6.8 % and +10.6 %. With equal weighting of all reference cases, the average discrepancy between calculated and real vehicle masses is 3.6 %. Overall, this mass model provides sufficient accuracy for further calculations.

2.2.3. Track Model

The Track Model is set up by other members of the TORPA project, but we give a brief overview of its function here, as it is important to explain the context of our models.
Main input to the Track Model are two arbitrary railway stations in Germany. Using data from OpenStreetMap, the Track Model then produces a detailed data file of the track connecting the two selected stations. The generated file includes an elevation profile, positions of intermediate stops and segmental permitted top speeds as well as availability of external power supplies like a catenary.

Utilization of the Track Model instead of a generic track allows us to optimize vehicles specifically for every chosen track. This approach has not been conducted before and allows us to obtain much more detailed results than any of the cited sources in Chapter 1.3.
Compared to an approach with a generic track, we can take the following properties of different tracks into considerations:

- Amount of energy consumed between stops and in total
- Number and quality of acceleration procedures
- Possibility to recuperate energy
- Possibility to use an existing catenary

The relevant data from the Track Model for our optimization model are those affecting power and energy used during a ride on the track, as those define the scaling parameters as described in Section 2.2.2.
Overall, the track file is an input to Driving Dynamics Model (DDM), as seen in Fig. 2.1.

2.2.4. Driving Dynamic Model (DDM)

As the Track Model, the DDM was part of TORPA, but specifically developed in this Thesis. Nonetheless, it is important to understand the overall function of this model and its interfaces. The DDM simulates a run of a virtual vehicle on the selected track, using the previously generated track file. The properties of that vehicle are defined by vector z generated by the Design Framework. The modularized DDM is implemented in Matlab and Simulink. All physical components mentioned in the Vehicle Architecture Matrix (section 2.1.2) are modeled and connected in DDM. To simulate the different architectures, the modules are enabled or disabled.
Following, it is described how the simulation procedure of the DDM is done in every discrete time step: With a given driving strategy and the track file, a desired speed is calculated. Comparing this speed with the current speed, we derive the required acceleration of the vehicle. Using physical values of vector z, we calculate all current resistance forces due to acceleration, inclination, aerodynamic drag, and rolling drag. Multiplying the required force with the current speed, we get the power demand. An intelligent power manager decides which subcomponent of the drivetrain provides which share of this power demand. The more specific function of the DDM and the power manager are subject to works that are to be published soon. Integrating the power of components over time, we derive values for energy.
After running the simulation, vector w is generated. It includes values for energy and power for every time step of the simulation and for all vehicle components separately. They will subsequently be used in the Design Framework to calculate a new set of physical values for the vehicle.

2.3. Metrics

2.3.1. Metric 1: Investment cost per drivetrain

The first performance factor evaluated is the investment cost per vehicle drive train. As described in Section 2.2.2, investment costs of all subcomponents are output of the Design Framework. Figure 2.4 visualizes how the investment cost model within that function is set up.

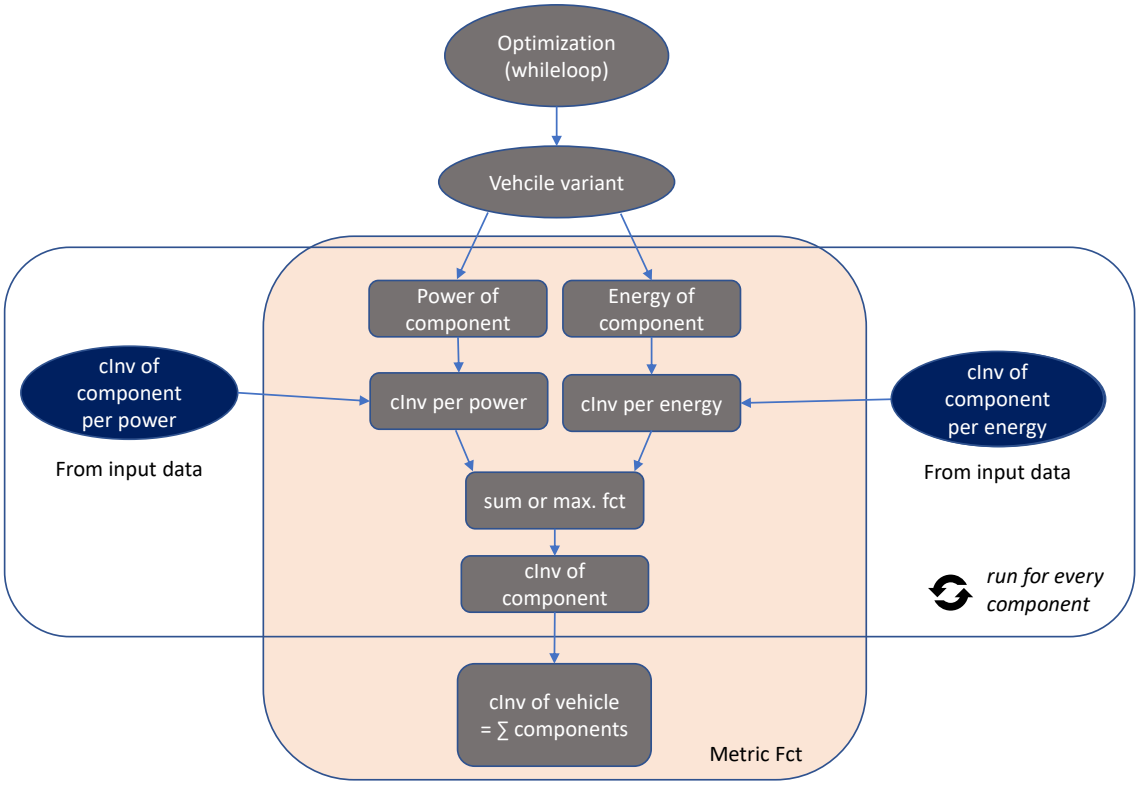


Fig. 2.4.: Setup of the investment cost (cInv) model. The cost of every component is a specific factor times energy or power. In some cases, when costs depend on both energy and both power, the greater value is taken. Overall costs are then the sum of component costs.

In detail, the optimization loop outputs a vehicle variant including all its energy and power flows between subcomponents. Investment costs are calculated for every component separately. For every component, its specific energy and maximum power are multiplied with the respective scaling factor, taken from input data outside Matlab. With this operation, two values for investment costs are derived. The cost due to energy consumption and the cost due to power output. The two costs are then cumulated. For most components, one cost factor is dominant. For example, if the energy of a diesel tank is increased, the mass of diesel and therefore the volume of the tank needs to be increased. This needs

more material and adds costs. The power output of the tank is defined by the flow of diesel per time. It can be easily increased with a larger outlet, but this does not draw significant additional costs. On the other hand, there a components where costs depend on both energy and power. For example, capacity, meaning amount of storable energy, and power of a battery are a function of each other. Therefore, the larger of both cost values is taken. After all component costs are calculated, they are added up to create the drivetrain costs.
A similar model to the vehicle investment costs is set up for infrastructure costs. Similarly, physical parameters and component specific factors are multiplied to output the components' costs. For example, investment costs for recharge stations depend mostly on their transformer's output power [77] or, as mentioned in Section 1.2.1, catenary costs, which are a function of track length. As the evaluated architecture in Chapter 3 does not use the infrastructure cost model, it is not discussed in depth here.

2.3.2. Metric 2: Mass of Carbon dioxide per run

As a second metric, the mass of emitted CO2 per vehicle run and track is evaluated. More specifically, we evaluate the mass for every form of energy separately and sum them up in the end. Every form of energy has its specific CO2 emission per energy unit. The amount of energy consumed is the difference of stored energy of the beginning of the drive cycle and its end, meaning e. g. the state of charge of batteries or amount of diesel in the tank.
One kg of diesel causes emissions of 3.14 kg CO2 or roughly 2.65 kg CO2 per liter, depending on its exact density [78].
A kWh of electric energy from the German electrical grid drew emissions of 489 grams of CO2 [79] in 2017. This factor is taken into account for charging batteries at initial stops.
While still not used in the following simulations, it should be mentioned that the factor for CO2 per kWh of electricity varies widely. CO2 per kWh from the German household grid is declining by about 3 % per year. Emissions for diesel fuel, of course, always stay the same. If a rail vehicle operates under catenary, it draws electricity from the railway electrification system, which has its own power plants. Therefore, the CO2 factor is different. In 2015, the factor was 19 % lower than for conventional electricity [80]. Also, other countries have much different emission factors. For example, in Switzerland, 24 g/kWh are emitted on average, about 95 % less than for conventional German energy production [81].
As a comparison, diesel fuel emits 269 g CO2 per kWh of primary energy [78]. The reason diesel engines perform worse than electric motors with energy from the grid lies in different energy efficiencies of motors.

2.4. Trade-off between CO2 and investment cost

After having two metrics to measure performance of vehicles, it is not possible to find one optimal vehicle variant. Therefore, it is necessary to take into account further considerations. Only relying on these two metrics, it is possible to compare them using some assumptions. One reason why emission of CO2 should be avoided is that it causes environmental costs through global warming [82] While it is very difficult to determine these costs, the European Union, among other countries, has set up a system to directly price emissions. It is called European Union Emission Trading System (EU ETS) [83]. Within this system, a limited number of permissions to emit CO2 is put to the European market. While trading those permissions, a certain price is established. The price is around 24 € per ton of CO2 emission as of September 2018 [84]. If a company can avoid to emit CO2 at a price less than the price of a permission, it will do so and sell or buy less permissions to make a profit. If a company can not avoid emitting CO2 at a price lower than those of a permission, it will buy a permission. The goal of this trading system is to establish a limit of CO2 emission with lowest-possible costs. While diesel fuel for transportation is yet not included in the relatively young trading system, it might be included in the future [85]. However, this price allows to transform the metric of CO2 into a metric of cost, making it possible to directly compare it with the metric of investment costs. To do so, it is necessary to first calculate the mass of emitted CO2 per vehicle during the depreciation time, the same amount of time that applies to investment costs. After that, that amount of CO2 is multiplied with the price per mass of CO2. Eventually, overall costs for investment in the drivetrain and CO2 emission over depreciation time can be added up to one value. The best performing vehicle is the one with lowest overall costs.
A concrete graphical example of how CO2 and investment costs can be compared is given within the simulation results in Section 3.2

3. Results and discussion

3.1. Problem setup

3.1.1. Architecture

This Chapter discusses optimization results for the architecture introduced as 'D_E-b_-_' in Section 2.1.2. As shown in Fig. 3.1, it consists of a diesel motor, whose power is transferred to the driving axles electrically after being transformed by a generator. Additionally, energy can be stored in a battery. This includes an initial charge as well as recharging during driving, which can be done during braking or by charging with a part of the motor output power. As indicated by the last character of the architecture code, an underscore, the vehicle has no pantograph to contact to an existing catenary.

Within this vehicle configuration, there are two possible sources of energy and two possible sources of power that can be used: the battery and the diesel motor.
Therefore, two design variables are defined:

- **FractEStor:** Fraction of the energy stored in the battery compared to total energy.

- **FractPStor:** Fraction of the maximum output power of the battery compared to the total maximum output power on wheel level. The remaining power is covered by the diesel engine.

As mentioned in Section 2.2.1, these design variables are varied by the Genetic Algorithm and used to define a variant of an architecture. By varying them, we cover the whole possible design space of variants within this architecture.
We vary the Design Variables within boundaries as shown in Table 3.1:

The boundaries of Design Variables are set up to allow a clear distinction between architectures when interpreting results. For example, if the Design Variable FractPProd for the chosen Architecture 'D_E-b_-_' is close to zero, the vehicle is not really what is commonly known as "Diesel-electric battery vehicle", as the battery is small and can not cover a relevant part of the vehicle's

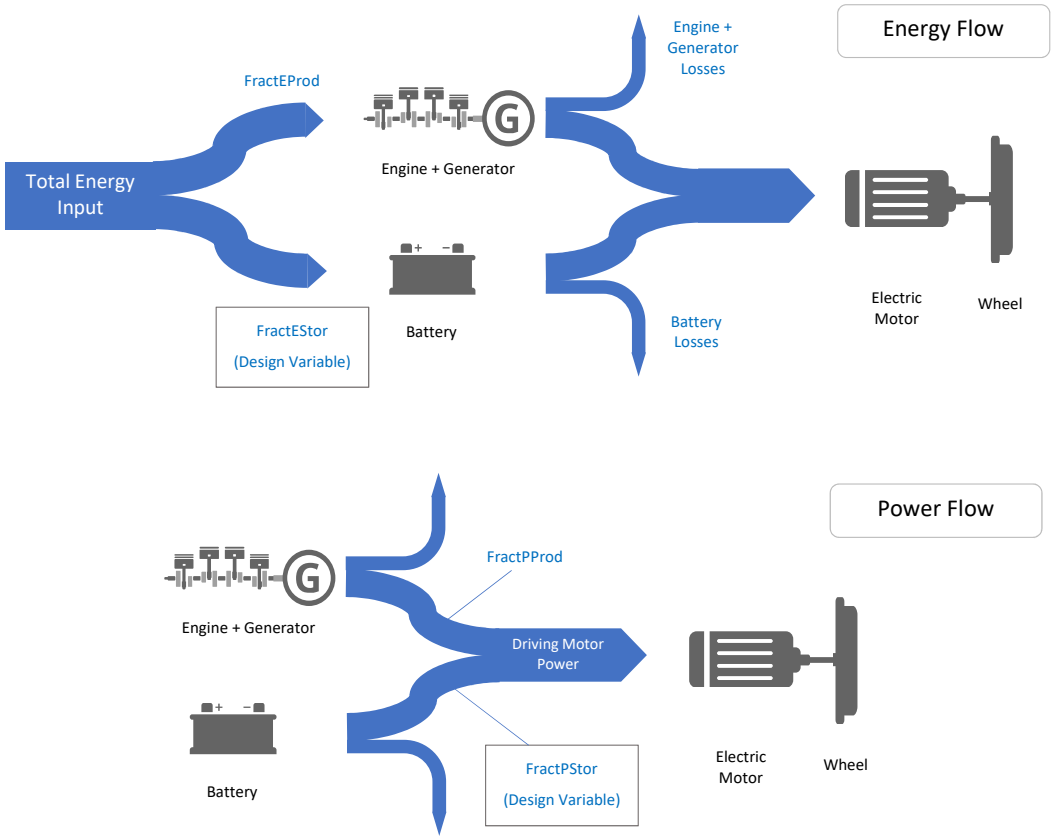


Fig. 3.1.: Function of the architecture D_E-b_-_ and definition of design variables: Both power and energy are drawn from a diesel engine and a battery. As design variables, energy at the system input level and power at driving motor level are used.

power demand. On the other end of the scale, if the Design Variable FractP-Prod for this architecture is close to 1, we would have a small diesel motor. The linear motor input data functions that define investment cost, mass, volume, and efficiency of the motor do not apply to such small engines.

Tab. 3.1.: Boundaries for variation of the Design Variables used for the Architecture D_E-b_-_

Design Variable	lower boundary	upper boundary
FractEStor	0.1	0.9
FractPProd	0.1	0.9

3.1.2. Track

In the shown case, the railway track between Ulm and Oberstdorf situated in southern Germany is used. A map view of the track is shown in Figure 3.2. The track has a length of 130 km and 13 intermediate stops. Its elevation profile is shown in Figure 3.3. Until kilometer 70, the profile is slightly inclining. After that, the profile is more hilly, and more inclining overall.
To simulate a ride on the track, the same fixed driving strategy was used for all variants of the architecture. In short, the driving strategy is to accelerate with 1 m/s until maximum permitted speed is reached, keep that speed and starting to recuperate and brake with a previously user determined constant deceleration of -1 m/s. The acceleration and deceleration parameters like the given ones are often fixed requirements towards manufacturers when operators buy vehicles. Only rides in the named direction are considered, not the return trip.

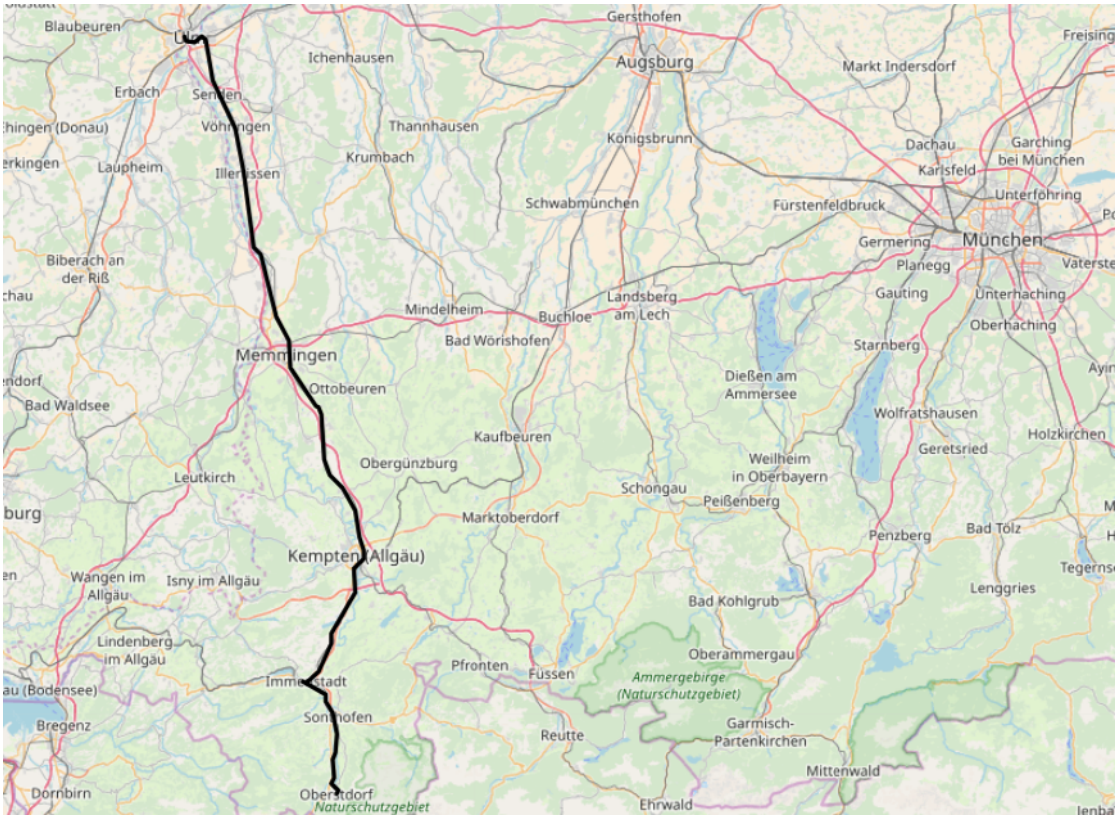


Fig. 3.2.: Map view ot the simulated track ride from Ulm (top left corner) to Oberstdorf (at the bottom of the map). To provide orientation, the next bigger city, Munich, is shown on the right of the map.

3.1.3. Assumptions

Rounded values of the most influential parameters of the input dataset are provided in Table 3.2.

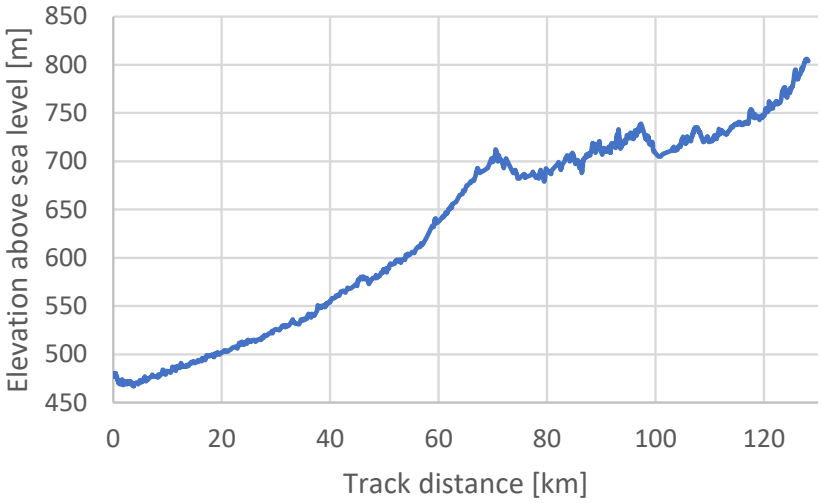


Fig. 3.3.: Elevation profile of the track Ulm - Oberstdorf plotted over track distance, starting in Ulm

Tab. 3.2.: Rounded values for some key input parameters of the simulated architecture

Component	Variable	Value	Unit	Source
Diesel engine	mass	4e-3	kg/W	[86]
Diesel engine	investment cost	0.5	€/W	[61]
Battery cells	mass	2e-6	kg/J	[87]
Battery cells	investment cost	2e-4	€/J	[88]
Battery cells	short-time C-Rate	10	kW/kWh	[89]

These values represent only a few out of a large and complex database. Their values represent the state of the art technology of 2018. They can easily be varied and applied to future models. As most of them are constantly changing and also vary for different use cases, it is sufficient to provide rounded values. The vastness of the input dataset makes it unreasonable to optimize the accuracy of single input data values.

3.1.4. Optimization setup

For the optimization, we used a workstation with 192 logical cores. The optimizations of variants within one generation are done independently, which allows us to parallelize calculation of variants with the built-in functions of the GA in Matlab. The population size is set to 192, one variant per logical core. Convergence for this architecture is set to 1e-4 and is reached after 107 Generations.

In the end, 20 544 variants are created and evaluated during the optimization. The runtime on the chosen workstation is about two days. It is possible, that a set of Design Variables does not lead to a vehicle variant that can drive on the given track, e.g. because the desired acceleration of the vehicle's mass can not be covered by the subcomponents. For this reason, the performance figures contain less than 20 544 variants, and the data points do not necessarily cover the full range of the design variables. For example, no feasible vehicle configuration is found for a FractEStor of 0.9, therefore the range of data points only reaches up to 0.87, the highest FractEStor where a feasible configuration could be found.

In the following, the results of Architecture 'D_E-b_-_' are discussed. First, we consider the performance of all variants that have been created in the Design Space (Fig. 3.4 and 3.5), then, we focus on the variants that represent the Pareto frontier (Fig. 3.6). The latter ones represent those vehicles that are likely to be built.

3.2. Result plots

In this section, vehicle variants are compared in their performances in terms of CO2 emissions per ride on the chosen track and investment cost per vehicle drivetrain. Each variant in the following plots represents one variant.

Figure 3.4 shows all design points of the Architecture D_E-b_-_ that are generated by the GA and found to be feasible during simulations. The coloring indicates the FractEStor for every variant. On the vertical axis, investment costs per vehicle drivetrain are shown, ranging from 700 000 € to 1.7 million €. The horizontal axis describes CO2 emissions per ride on the chosen track, ranging from 200 to 550 kg per ride. A high FractEStor means that a large proportion of overall energy required to ride the track is drawn from the battery instead of the diesel tank. Every one of the 7 colored groups in the picture contains the same number of variants.

On the vertical axis with investment costs per vehicle drivetrain, we see a weak correlation with FractEStor. Variants with a high FractEStor tend to be more expensive than variants with a low FractEStor. This is plausible, as energy storage in diesel tanks draws less investment than in a battery. However, the groups of data points with similar FractEStor all have a similar range of investment costs. On the horizontal axis, we see that FractEStor is strongly correlated with emission of CO2 per ride on the chosen track. The general trend states that CO2 emissions increase with decreasing fraction of energy stored in the battery. Good environmental performances with a CO2 emission of less than 300 kg

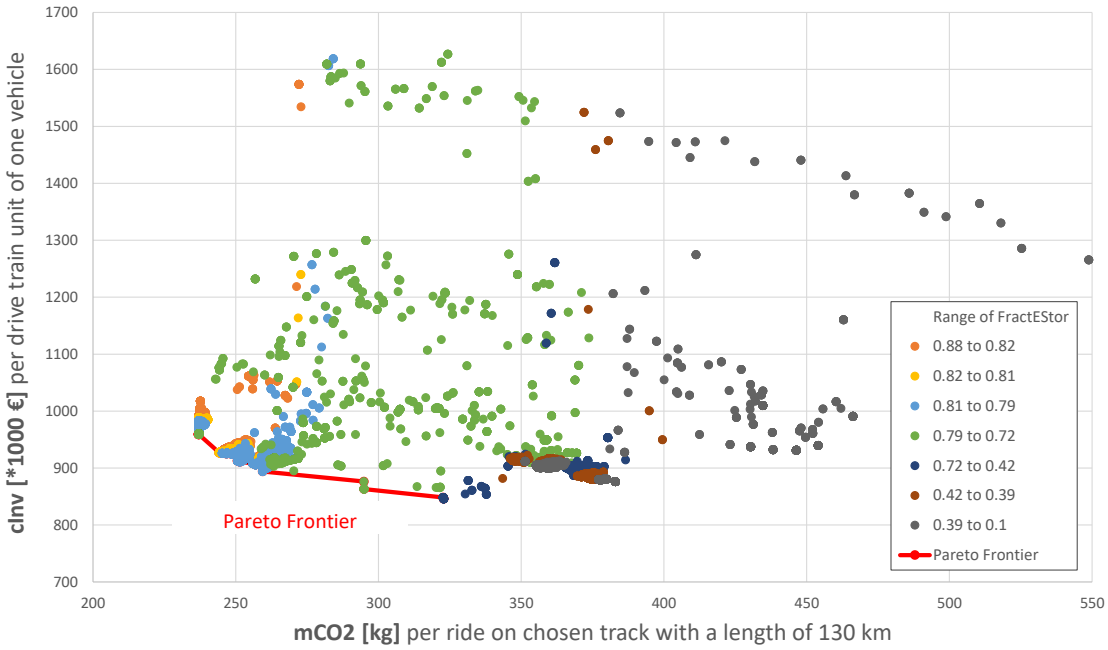


Fig. 3.4.: Performance in terms of investment cost per vehicle and mass of emitted CO2 for all variants in the Design Space of a diesel-electric vehicle with a battery, colored by fraction of energy drawn from the battery compared to overall drawn energy.

per ride can be achieved with vehicle architectures that draw more than 72 % of their energy from the battery.
Considering which architectures of Fig. 3.4 could dominate others, we focus on architectures that perform well in both metrics. It gets visible that variants that draw less than 42 % of their required energy from a battery are dominated. The Pareto frontier itself is further investigated in Fig. 3.6 subsequently.

After investigation of how architectures perform depending on their energy distribution, it is also of interest how they perform depending on power distribution, as energy and power are scaling different components of the vehicle. Fig. 3.5 shows all feasible variants of architecture D_E-b_-_ grouped by colors depending on the fraction of maximum output power of the battery.

We observe that investment cost clearly increases with decreasing fraction of power from the battery, and therefore higher fraction of power from the diesel engine.
Variants which draw less than 20 % of power from their battery have investment costs of more than 1.25 million euros per vehicle, more than 50 % more than the best performing variants.
The colored groups in Fig. 3.5 do not have an equal range of FractPStor. Few

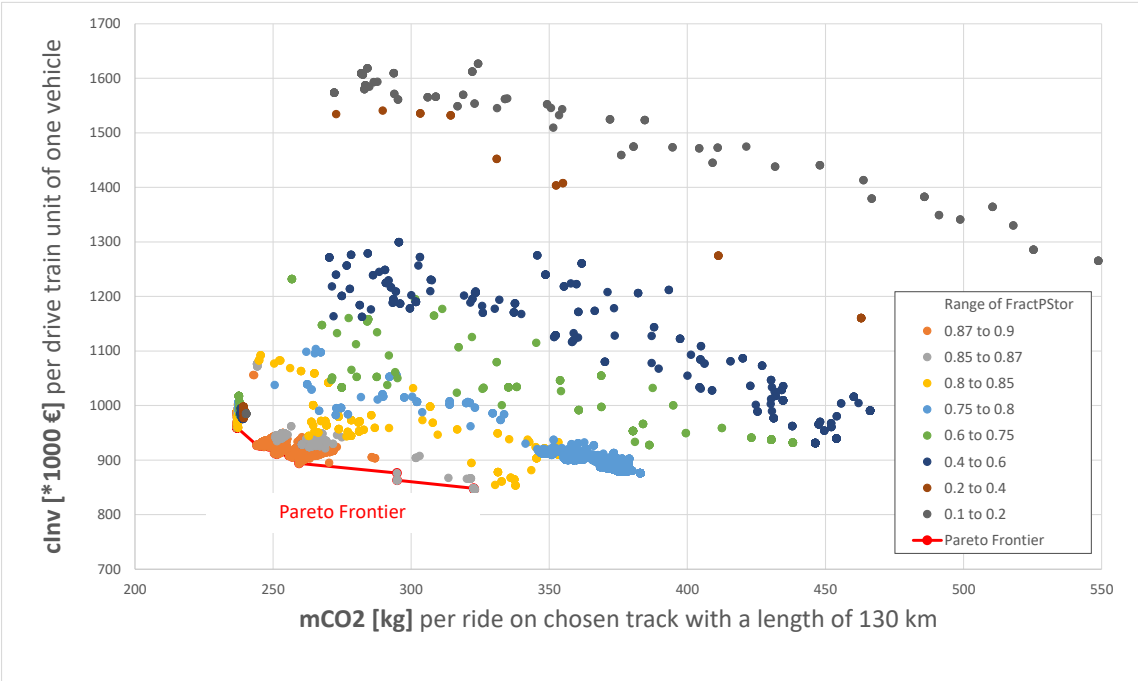


Fig. 3.5.: Performance in terms of investment cost per vehicle and mass of emitted CO2 for all variants in the design space of a diesel-electric vehicle with a battery, colored by fraction of maximum power output of battery compared to overall maximum power.

dots are shown e. g. for a range of FractPStor from 0.2 to 0.4, because not many feasible vehicle configurations can be found in this range. Most feasible configurations have been found for a FractPStor greater than 0.75.
On the very left of the figure, we observe an almost vertical line of dots with variants that all have CO2 emissions of around 240 kg and varying investment costs. Further investigation of these variants shows that they have a similar high FractEStor of around 0.8, what determines the low emissions. Within this group, the least costly variants have a FractPStor close to 0.9. With increasing FractPStor, the investment costs increase as well. Very few variants have a low FractPStor values down to 0.25. Apart from the general trend for increasing cost with decreasing FractPStor, which is discussed in detail in the following, the reason for the variation of FractPStor within this small group can not be fully explained. To analyze larger groups of data points efficiently, a special data output interface in the code would be required.

However, the Figure shows that all vehicle variants that draw less than 85 % of their maximum power from their battery are dominated.
This general trend can be explained as follows: Investment costs for diesel motors are directly correlated with their maximum output power. The amount of energy they draw, also meaning how much time they operate per ride, is not an important scaling parameter. Energy consumption only affects consumed fuel

and therefore energy costs.
Batteries are primarily sized by their energy capacity. Their output power is a linear function of capacity, also known as C-Rate [90]. Therefore, the amount of time power is drawn from the battery matters more than the peak power we consider in the design variable FractPStor.
In conclusion, investment costs increase with maximum power fraction covered by the diesel engine, because costs for engines are a function of their maximum power, whereas this does not apply to batteries. A typical driving cycle includes high, short power demands during acceleration and long phases of lower power demand. It makes sense to cover the short and high power demand with a battery and scale the motor only in a way so that it can cover the power demand required for cruising. This way, the vehicle has an engine that runs close to its maximum output power for a high fraction of driving time. Otherwise, the engine would be designed for an output power that remains unused during most of the driving cycle, leading to increased mass and investment costs. Furthermore, a diesel engine reaches its best fuel efficiency when outputting around 50 to 60 % of its maximum design power [91]. If the cruise power demand, which is dominant over most of the driving cycle, is significantly lower than those 50 to 60 %, efficiency worsens.
However, battery scaling is not completely independent from the output power. It is possible that the battery needs to be larger than required for the energy needed during the drive cycle, just to cover power requirements. To give an example: If a battery requires 100 kWh of energy for a ride and has a C-Rate of 6 kW/kWh, then its maximum output power is 600 kW. If more than 600 kW output power is desired in this case, the battery needs to be scaled up, without using the energy capacity but leading to higher investment costs and mass. For this specific reason, a vehicle design with highest FractPStor is not necessarily the one with lowest investment cost or best environmental performance. More precise data for the best performing vehicle variants is given in the following.

Combining interpretations for both design variables for energy and power, we observe that CO2 emissions mainly decrease with a larger fraction of energy stored in the battery while the fraction of maximum power output mostly affects investment costs. Subsequently, we focus on the variants that perform best in the two chosen metrics, regarding their design variables.

As an result of our optimization, we find a set of vehicle variants, that are not dominated and therefore likely to be deployed. The performance of these vehicle variants is shown in 3.6.
After excluding dominated variants and reducing such with very similar input and output values, namely with a deviation of less than 0.01 %, to single variants, we found 23 variants to be part of a Pareto frontier.

Figure 3.6 shows the Pareto frontier of the investigated architecture. The vehicle variants shown here dominate all other options. Both axes show a relatively narrow range of performance compared to the overall results. Investment costs

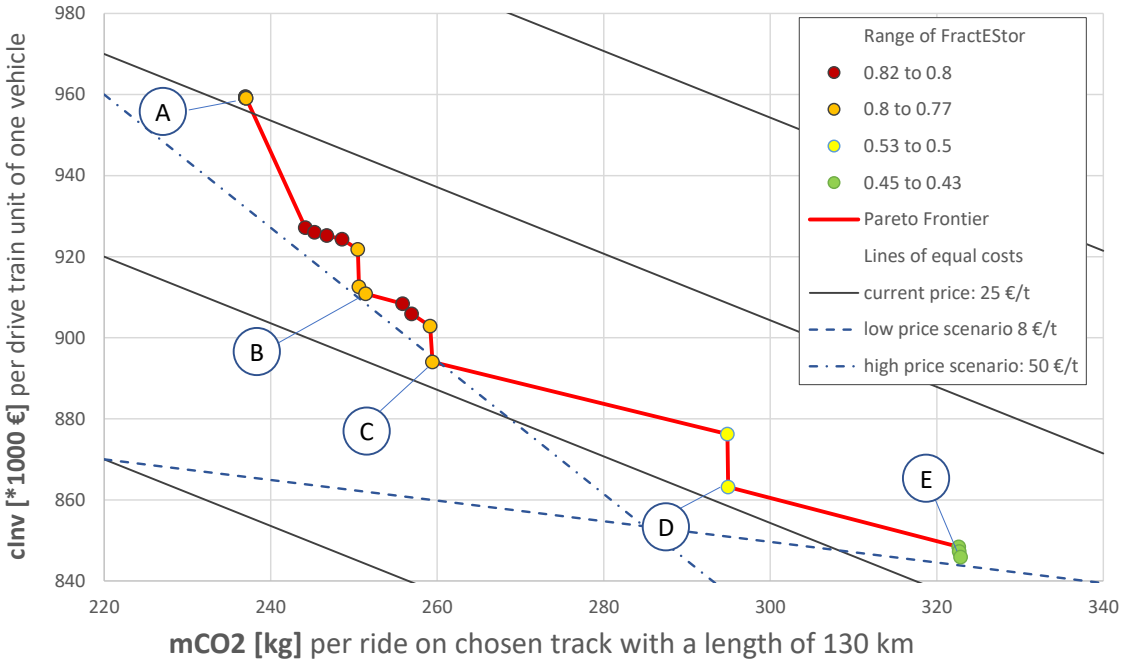


Fig. 3.6.: Performance of non-dominated variants (Pareto frontier) of a diesel-electric vehicle with a battery, colored by fraction of energy drawn from the battery compared to overall consumed driving energy. Included are the diagonal lines of equal costs. Costs decrease towards the lower left corner of the shown graph.

per vehicle range from 846 000 € to 959 000 €, while CO2 emission per ride on the simulated track is between 237 and 323 kg. As described in Section 2.4, Figure 3.6 includes tilted lines, which represent equal costs for investment and CO2 combined and will be discussed later. A line closer to the lower-left corner means lower costs and therefore a higher likelihood of the vehicle to be deployed. As described before, the angle of lines in the Figure may change. Market prices of CO2 have varied largely recently. Two exemplary other inclinations of lines are shown in the Figure: one as a low price scenario as it prevailed in 2017 and the years before with prices around 8 € per ton [92] and a high price scenario with 50 €/ton as predicted for the year 2030 [93]. Independently from the actual determined price, variants more in the lower left corner tend to be more important. The most important ones are named with letters A to E and discussed later.

For the fraction of energy stored in the battery, the Pareto frontier shows the general trend described in the previous section: a lower fraction of energy stored leads to more CO2 emissions. The trend does not apply to the points in the left corner with less than 260 kg of CO2 emission. The variant with lowest overall CO2 emission of 237 kg has a fraction of 77.9% of its energy required for driving

stored in the battery. Data for this Variant is also shown in Table 3.3 as Point A. Referring to the general trend, we would expect lower CO2 with a larger fraction of energy stored in the battery. Indeed, 77.9 % means a relatively high fraction. The reason why we do not find better architectures may lie in our Design Variable Limits (shown in Tab. 3.1) and the driving cycle: Using the minimum FractPStor of 0.1 for the engine, meaning the engine provides 10 % of the maximum power, it makes sense to use the motor for a certain amount of time in order to keep the vehicle mass low. In general, outputting more energy with an existing motor increases the overall vehicle mass only irrelevantly, specifically only the amount of diesel fuel carried rises. The engine mass itself does not depend on the outputted amount of energy. This fuel mass is much lower compared to the surplus mass it would require to store the same amount of energy in a battery. For this reason, we conclude that it makes sense to use a motor that is already on board.

Tab. 3.3.: Performance and Design Variables of outstanding points in the Pareto frontier

Marker	mCO2 [kg]	cInv [1000 €]	FractEStor	FractPStor
A	237	959	0.779	0.893
B	251	911	0.794	0.890
C	259	894	0.787	0.892
D	295	863	0.502	0.865
E	323	846	0.437	0.859

Unlike the fraction of energy, the second Design Variable for power does not differ a lot among the variants of the Pareto frontier. As already visible in Fig. 3.5, FractPStor only ranges from 0.85 to 0.89 within those variants.
More specific values of FractPStor are shown in Fig. 3.3, along the Design Variable for energy and exact performances of important vehicles of the frontier.
As stated in the previous section, we observe the general trend that investment costs increase with increasing fraction of maximum power provided by the battery. Lowest investment cost is achieved by variants with a FractPStor of around 0.86, represented by points D and E in Fig. 3.3. On the other end of the Pareto frontier, variants with a FractPStor between 0.8 and 0.85 provide best environmental performance.

After finding a Pareto frontier with 23 vehicle variants likely to be deployed, it is to investigate if a further reduction of variants to focus on is possible. This is done under utilization of lines of equal costs, as introduced in Section 2.4 and shown in Figure 3.6. Again, the price per mass of CO2 defines the inclination of the lines of equal costs in Figure 3.6. Here, a EU ETS price of 25 € per ton was used, as this is the current price of September 2018 [84]. It should

be mentioned, that this price represents a long-term high, but is also expected to grow much more in the next years and decades [94]. To give an example, Ferdinand ran several scenarios for the price development in 2030 and expects a price of around 40 €/ton by then [93].
Using the CO2 price level of September 2018 as shown in Fig. 3.6, it appears that Variant C is most likely to be deployed. This vehicle draws 78.7 % of its energy from a battery and 21.3 % from a diesel tank. Maximum output power is covered to 89.2 % by a battery. At an investment cost of 894 000 € per vehicle drivetrain, 259 kg of CO2 are emitted on a ride from Ulm to Oberstdorf. With the CO2 price of September 2018, Variant A would be the most unlikely to be deployed within the frontier, as it has the highest combined investment and emission costs.
By further variation of CO2 prices and therefore inclination of the lines in Fig. 3.6, we find that Variant E is to prefer if CO2 costs are lower than 19 €/ton. On the other end of the frontier, a CO2 price of more than 137 €/ton would be required to support Variant A. To prefer Variant B over Variant C, the CO2 price needs to be more than 64 €/ton.
In conclusion, vehicle variants C, D, and E are most favorable at medium CO2 price ranges as those prevailing today. These vehicles draw between 44 and 79 % of their energy from a battery.

3.3. Comparison

As a comparison to the optimized battery-diesel-electric architecture, a diesel-electric architecture without a battery (D_E-__-_) has an investment cost of 849 000 € at a CO2 emission of 554 kg CO2 per ride on the same simulated track and with unchanged input parameters.
This investment cost is higher than the cheapest variant found during optimization, which requires an investment of 846 000 €. This investment cost difference is insignificant given the uncertainty in the assumptions. However, the battery vehicle only emits 323 kg of CO2, compared to 554 kg for a conventional vehicle. Therefore, a CO2 reduction of 42 % is possible at a similar level of investment.

As stated in Chapter 1, the most environment friendly option is full electrification of the track. Our built model supports to include investment costs for infrastructure electrification, but the interface has not been fully implemented and is future work. To provide a reference for the shown case, we compare both investments for infrastructure electrification and the previously optimized battery diesel-electric architecture (D_E-b_-_). First, it is important to know the infrastructure investment costs. These have been found in Chapter 1 to be about 930 000 €/km. Calculating the track length that needs to be electrified, we need to consider the overall track length, if it has one track for both directions or more, and if there are sections that are already electrified. The track length from Ulm to Oberstdorf is 130 km, where 24 km of those are double track and already

electrified or to be electrified by 2020 [33]. A single track of 106 km remains to be electrified, therefore electrification costs of around 100 Mio. € are expected.

To calculate overall vehicle investment costs, it is important to know how many vehicles would be required to run the track. We assume one run per hour, as stated to be typical for this case in Chapter 1. The current run time on the track is 2 hours per direction [95], or 4 hours for both directions. With some operational time margin, we assume that a train can run again after 6 hours, therefore 6 train sets are required for service on the track. Taking Variant C of Table 3.3 as an example, the deployment of 6 new vehicle drivetrains requires an investment of 5.4 Mio. €. We assume a depreciation time for vehicles of 15 years, which is defined in the so called AfA table, a guideline of the German Ministry of Finance to support estimations of typical usage periods of goods [96]. Furthermore, 15 years are a typical traffic contract period, as described in Section 1.2.5 and may be applied by the vehicle operator for that reason. On the other hand, the depreciation time for electrification infrastructure is defined as 20 years in the AfA table. Therefore, 1.33 vehicles are depreciated within one depreciation period of the infrastructure, accounting to 7.2 Mio. € in the 20 year period for the vehicles. This value is about one magnitude lower than the 100 Mio. € for infrastructure electrification. Therefore, we can conclude that that a full electrification of the track is not reasonable; a deployment of hybrid vehicles is economically more viable.

To demonstrate the benefits of the built model, it is of interest if it leads to better or more detailed conclusions than mere intuition of experts in the field. Therefore, we set up expectations for outcomes concerning performance of different architectures before running the model. Team members of TORPA, including a long-term expert for rail vehicles, have documented their personal estimations. The estimates were dominated by the thought, that a larger battery leads to higher investment costs, as they are known to be expensive in the market and not deployed yet because of their high costs. Furthermore, we expected the CO2 emissions to decline with larger batteries, probably peaking at a certain size, as the battery may get so heavy that its surplus capacity can not outweigh its mass. In other words, we expected a Pareto frontier for conventional vehicles and variants of the diesel-electric architecture with battery. Specifically a vehicle without battery would be at the low-cost and high-CO2 end of the Pareto frontier, and investment costs increase while CO2 emission decrease when the battery is enlarged. The variants with best-CO2 and highest cost within the Pareto frontier would then have been the ones with largest battery.

Regarding those expectations, the following findings are derived from the simulation results:

- A conventional diesel-electric vehicle without a battery is not the cheapest to invest in

- Vehicles with small batteries are more expensive than those with medium-sized ones
- Lowest investment cost is achieved when about 44 % of energy is covered by a battery
- Best environmental performance is not achieved with the largest batteries. Lowest CO2 is provided by a vehicle which draws 80 % of its energy from a battery
- Therefore, even in the most environment friendly case, it makes sense to have a diesel engine on board, which then covers 20 % of required energy

Possible reasons for these findings have been explained in the previous sections. A more detailed analysis is part of future work within the project.

4. Conclusion

4.1. Summary

By comparing the L/D of different vehicles over their speed, we found a figure that puts mode of transport in context to each other. Furthermore, we found that rail transport has a systematic advantage over road, because of lower energy consumption and therefore lower energy expenses and emissions.
Researching on possible cases for the built software model, we found that there is vast potential for improving the CO2 emissions at reasonable costs. Furthermore, many operated lines already have a catenary on a part of their length set up. A considerable market for vehicles that makes use of this catenary is expected.

As part of our software architecture, we proposed a mass model that allows to make estimations for the mass of a passenger railway vehicle using only a few uncomplicated input parameters.

The TOPRA project as a whole has set up a software tool set to optimize and compare a vast range of different vehicle architectures. The tool is capable of considering existing infrastructure and possible investments in it, which has not been pursued as an approach yet. Furthermore, it is highly adaptable towards the vehicle's environment and technological development. It is possible to fit the vehicle to specific tracks. We showed before that the requirements for tracks vary widely.

By using the designed tool to optimize a battery diesel-electric drivetrain architecture, we showed which results can be generated with the tool and how they can be evaluated.
For the given architecture, we found general trends for how costs and emissions depend on energy and power distribution between the components battery and diesel unit. Specifically, we found that investment costs tend to be higher as the engine provides more of the maximum power, while CO2 emissions rise with the fraction of energy provided by the engine unit.
Additionally, not all combinations of energy and power fractions are equally favorable. We gained a small number of battery/diesel unit sizing combinations that perform best.
We introduced a model to weigh investment cost and CO2 emissions in one factor, allowing to make decisions for options with differing CO2 emission and

costs. Using this decision tool, we make recommendations for today's deployment of vehicles.
Assuming current state of technology and costs, we propose one specific vehicle configuration to be deployed. This vehicle covers 80 % of its driving energy and 90 % of its maximum power with a battery and the remaining fractions with a diesel engine unit. This vehicle emits less than half of the CO2 of a conventional vehicle at only slightly increased investment costs.

In general, we have shown that CO2 emissions of regional railway vehicles can be reduced by over 40 % with deployment of vehicles that are in the same price range as current diesel vehicles or even cheaper.

After reasoning the competitiveness of vehicles with batteries as of today, we expect them to be even more profitable in the future, if batteries get more powerful and cheaper in investment in the future.

4.2. Applicability of results and limitations

As all models, the built software model is only an approach to reflect reality and comes with limited accuracy.
There are three main sources of how the shown results may not directly lead to a vehicle deployment:

- Uncertainty in input functions
- Inaccuracies of the DDM: functions of subcomponents are simplified and the driving strategy is fixed instead of optimized
- The chosen metric functions can not reflect the whole scope of reasons that lead to a vehicle deployment decision. Especially, investment costs only reflect a share of overall costs for an operator

As described in Section 2.2.2, the software requires a large database of inputs for emissions, masses, and costs of components. These inputs are all subject to technological development and values change over time. The goal is to reflect state of the art of 2018, therefore values need to be adapted in case of future applications. Markets for rail components are relatively small. Oftentimes, there are only few suppliers for one component, which leads to non-transparent prices. It is possible that components are simply not available yet for rail vehicles in case of technologies new to the sector. In some cases, technology is adapted from other vehicles like trucks. Even if the technology transfer can be done, performances and costs of parts may differ significantly, because rail vehicles need to fulfill standards stipulated by the railway authority, other than

trucks [41].

Another consequence of the small market is a small database for research. Therefore, inputs functions have a large uncertainty. Because of the number of data points required, it was not possible to find perfectly accurate data in the given time.

A second source for uncertainties is the DDM which simulates all components shown in the Vehicle Architecture Matrix (Fig. 2.3) during a ride on a chosen track. Many of the components' functions reflect the first level of their functions, but not more. For example, maximum charging power a of battery of a certain size is implemented in the model, but not how this may vary if the battery heats up while driving.
Additionally, a fixed driving strategy was used, instead of optimizing it for all vehicle variants. For example, it is possible that not the full capacity of a battery is used and a small amount of energy is left at the end of a driving cycle. Therefore, the found costs and emissions are not necessarily as low as possible. To improve this, a separate driving strategy optimization for every vehicle variant would have been necessary. However, the potential of this optimization is of minor importance for the results for all vehicle variants and was not objective of the TORPA project.

A third reason how the optimization outcomes do not directly lead to a vehicle deployment lies in the chosen metric functions. Those metric functions do not represent a full set of factors important for vehicle deployment.
As described in Section 1.2.1 and extended later, we assume isoperformance for vehicle variants in all metrics apart from costs and emissions. Potentials for other improvements compared to current vehicles are neglected. This would be, for example, increased revenues if vehicles were able to accelerate faster and save driving time, or more comfort for customers and more acceptance among residents along tracks if vehicles are less noisy. However, these additional benefits were not subject to the projects optimization models.
The most important limitation for interpretation of the generated outcomes is the cost function: As described in Section 1.2.5, operators aim to maximize their benefits, which is the difference of costs and revenue. After already having assumed isoperformance for revenues, investment costs are only a part of total costs caused by the vehicle. A model of life cycle costs would be required to provide deeper insights here. Operational costs, maintenance costs and resale values of vehicles need to be included in that model. The large variety of vehicles and components covered would require equally as much input data and modeling to draw appropriate conclusions. For some of the components, a secondary market for used parts does not exist yet, therefore estimations for resale values and long-term maintenance costs are hard to make with a satisfying accuracy.
Considering maintenance costs, it can be assumed that improvements com-

pared to current diesel vehicles are possible, as Fassbinder states that diesel locomotives have three times higher maintenance costs than electric ones [34]. Considerable differences in costs also lie in operational costs. Previous research within the TORPA project states fuel expenses of 1.16 €/km for a diesel vehicle as used in optimizations here and 0.34 €/km for a electric vehicle [29]. To calculate the kilometers run per vehicle within the considered depreciation, we refer to assumptions made in 3.3. Starting a run on the considered track every 3 hours within 18 operational hours, a vehicle runs 780 kilometers a day. Within the assumed 15 years of deprecation, one vehicle runs 4.3 Mio. kilometers. Multiplying this value with the respective costs per kilometer, a diesel vehicle draws about 4.95 Mio. € of fuel costs, while an electric vehicle draws 1.45 Mio. €. The fuel costs for hybrid vehicle variants lie in between those two values. Considering the calculated investment costs of around 900 000 € per vehicle drivetrain for the considered architecture, it gets visible that differences in fuel costs are significantly higher than those in investment costs. As fuel costs are a function of energy consumption, similar to the considered CO2 emissions, they are already included in the current model. We chose to show only investment costs as a metric in order to provide more clarity.
Concerning the metric of CO2 emissions, it is important to point out that this is only one method to measure environmental benefit. Other greenhouse gases, or emissions during manufacturing and recycling of components are neglected. However, reflecting environmental benefit with CO2 emissions is common, as the EU ETS or current governmental goals show [1]. Therefore, we conclude that results in this metric can directly be used for decision making.

After having considered uncertainties in results of the built model, it is important to keep other economical factors, described in Section 1.2.5, in mind. Whatever outcome the optimizations show, vehicle operators may not necessarily invest in the technology with the overall lowest emissions or costs. There are factors that lead to economically distorted incentives. This can be special governmental incentives to invest in certain technologies or obscure, non-linear rewards, for saving CO2. Also, the tendering in contracts for multiple years may lead to a temporal delay of investments or economical insecurity for them. For example, an operator who has been awarded a contract will not get more governmental grants for saving CO2 after the contract has been awarded, so an investment during the contract term is unlikely. On the other hand, an operator may only invest with a time horizon not more than the duration of the transport contract, as the renewal of the contract is insecure.

In conclusion, there are some uncertainties in input functions which can be improved if desired or adapted to future technology. Emission and cost values for different vehicle architectures could still be optimized. This work shows a more holistic approach to compare architectures and variants among each other. The values in the metric for CO2 emissions can directly be used for decision making, while investment costs only represent a share of overall costs. However, the current model includes important cost factors for today's vehicle deployment decisions of operators. As vehicle operators do not operate in a completely free

market and need to apply for fixed contracts, decisions also rely on the specification of the respective contract.

4.3. Future work

During optimization of the first architecture shown in Chapter 3, computation times turned out to be critically long. Therefore, it is a primary goal to achieve improved efficiency of the optimization algorithm. The issue will be ongoing work within the TORPA project.

To provide more insights into the generated data, it is planned to include a tool to analyze vehicle variants and their component scaling systematically. With this tool, we can generate more insights into the observed performance of vehicles depending on their properties. It will be a focus of research, which vehicle properties make a variant dominate over others and which properties are less important. Furthermore, we hope to be able to reason what makes an architecture dominating over others. Especially, the overall mass and the state-of-charge curve of the battery are of interest.

With the designed framework, we are able to optimize all given architectures. Running those optimizations and drawing conclusions is the next goal within the project. As done in previous research, we will gather more insights which architectures dominate over others. Extending the number of architectures will also include investments in infrastructure. Therefore, it will be possible to propose solutions that include both investment in vehicles and in infrastructure.

Some questions to investigate in the near future are: How does the optimal variant of an architecture change when track characteristics are varied? How does the optimal architecture change with varying infrastructure electrification? How does the optimal architecture change with possible future technological performance and costs?
With the last question, we aim to estimate which technology might prevail in the future. The most obvious variations would be in energy prices, and improved battery and fuel cell performances and costs.

As the pictured investment costs and and the already calculated energy costs only represent a share of overall costs, it is our goal to build a tool to include all life cycle costs of a vehicle. This makes it possible to draw direct conclusions which vehicle variants should be deployed.

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B. Appendix

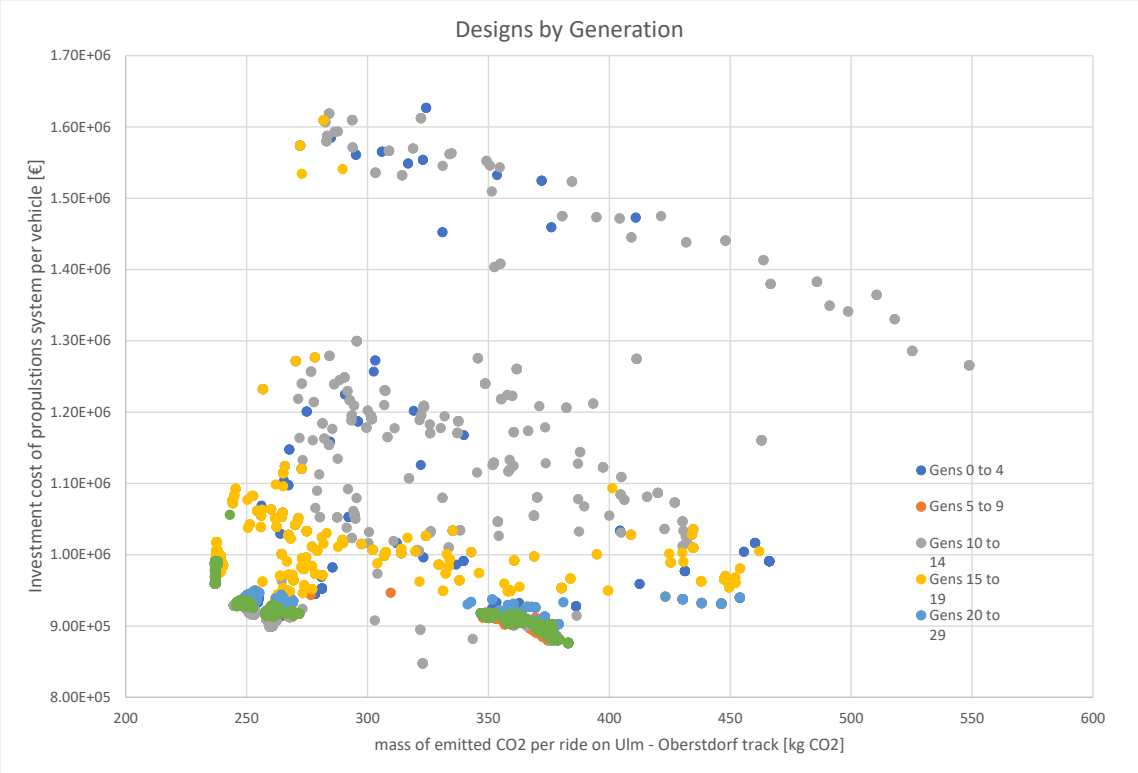

Fig. B.1.: Performance of vehicle variants colored by generation during evaluation of GA.