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# **Model-based economic analysis of electrification in railway**

**Understanding the impact of track, operations, and uncertainties**

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## Model-based economic analysis of electrification in railway

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### Abstract

This paper presents results on the impact of different tracks on the economic viability of track electrification for regional railway. Since regional railway still heavily relies on pollutive diesel propulsion systems, track electrification can be key to reduce CO<sub>2</sub> emissions. While complex methods exist to assess the economic viability track per track, little work has been done to study the impact of widely varying track parameters and uncertainties. The proposed approach utilizes a model to simulate vehicle power management for a given track. Based on these outputs, we develop and validate a cost model to compute the life cycle costs for diesel and electric track operation. A sensitivity analysis with regard to track parameters, operational parameters, and economic uncertainties reveals where track electrification is economically beneficial. Furthermore, we provide the reader with a set of criteria to support decision in future electrification projects. The main conclusion is that diesel and electrical drivetrain have a similar total cost, but a different composition.

### Keywords

Regional railway, track electrification, sensitivity analysis, economic viability, uncertainty analysis

# 1 Introduction

As we have shown in Mueller (2018), railway is the most energy efficient way of land transportation. However, regional passenger rail still often runs on unelectrified tracks with polluting diesel engines. Indeed, a number of track electrifications are included in the German Government's "Plan for Federal Traffic Routes" (Bundesverkehrswegeplan). In addition to that, a number of other stakeholders, such as federal state governments, public initiatives, or railway operators, have proposed plans to electrify additional tracks.

As of 2019, 40 % of tracks in Germany are not electrified (Allianz pro Schiene (2018)). Given this large number of unelectrified tracks, not all of them can be electrified simultaneously. While from an environmental perspective, complete track electrification is always the preferred solution, there are economical concerns that need to be considered. Therefore, tracks have to be prioritized based on their cost-benefit relationship. There is a variety of different methods that are currently used to determine which tracks should be electrified. Whereas the German Federal Government requires a thorough and lengthy cost-benefit analysis for each specific track, other stakeholders tend to argue with more general and political arguments. The Federal Ministry for Transport and Digital Infrastructure (2015) evaluates the cost-benefit relation of electrification projects based on a strict methodology. Following this methodology for every possible project would consume a significant amount of time.

Regional railway is the only or most important user of all of the 40 % unelectrified tracks. These tracks are heterogeneous in their characteristics. For example, Pagenkopf (2018) found that driving time from start to end for a subset of tracks in Germany varies between 4 and 340 minutes. Other track and operational parameters show similar variation, such as track length, stop distance, and number of trains per day. Since these large variations influence the cost-benefit analysis, making general statements about justifiability of electrification is challenging.

Therefore, the general objective of this paper is to develop an approach that is less complex than the one from the German Federal Government, but still allows to make track specific statements about the cost-benefit of electrification. Our goal is to address this broader question:

## **How do track specific characteristics influence the economics of track electrification?**

Analyzing recent projects, where existing tracks have been electrified, and complying with Baumgartner (2001), Pressemitteilung Bayerisches Innenministerium (2018), and Schwaebische Zeitung (2018), we find that electrification costs around one million Euro per kilometer. This 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 by Stefan Fassbinder (2018b). According to this source, Deutsche Bahn AG (DB AG) will invest in an electrification of a track if more than 1350 tons are transported per hour. This threshold is easily reached in case of major cargo

corridors in Germany, comparably the mass of a single cargo train in Germany typically is around 1600 tons (see Forschungsinformationssystem (2016)). Similarly, high speed passenger corridors are operated with InterCity Express (ICE) trains with a mass of 800 tons per unit and at least once per hour. There are additional technical reasons that require ICE trains to operate under overhead wire (Mueller (2018)). Therefore, all high speed trains in Germany operate on electrified tracks.

Mueller (2017) evaluated the cost performance of six drivetrains on a 102 km long real track from Dresden and Goerlitz. He studied the influence of three factors: First, varying the headway between 0.5, 1, or 2 hours (headway is the time between two trains on schedule per track direction). Second, an "electrification difficulty factor", assuming that either 70% or 85% of the track are "easy to electrify", whereas the remaining part is assumed to be more costly to electrify. Third, the assumption that 0%, 20%, 50%, 80%, or 90% of the track are already electrified, thus reducing the electrification cost. Mueller (2017) concluded that electrification is the cheapest option if:

1. Headway is less than one hour, at least 80% of the track is already electrified, and 85% for the track are easy to electrify,
2. Headway is 0.5 hours and 85% for the track are easy to electrify, or
3. Headway is 0.5 hours, at least 50% of the track is already electrified, and 70% for the track are easy to electrify.

While these results provide general suggestions which electrification projects are likely to be more beneficial than others depending on headway, existing electrification, and electrification difficulty, Mueller (2017) does not quantify the impact of other parameters.

Pagenkopf (2018) et. al. set up a database of 469 diesel operated regional railway tracks in Germany. The included parameters are track length, stop distance, driving time per ride, average speed, and share of already electrified track sections. They found that these parameters vary widely between tracks. However, Pagenkopf (2018) did not assess the impact of the different tracks on the economics of electrification. We will use their database as a basis to define our scenarios in Section 3.

The existing literature shows two gaps. First, only point designs are compared for one specific track, without identifying what the relationships are between track characteristics and costs. Second, existing approaches do not consider uncertainties for key cost parameters. This paper addresses both gaps by conducting a sensitivity analysis regarding track specifics and uncertainties. Thus, we can distinguish between important and unimportant influences on a much broader scope than previous studies. To summarize, the specific objectives of this paper are to:

1. Develop a model to estimate the life cycle costs for diesel and electrical trains,
2. Investigate the impact of tracks, operational patterns and uncertainties on total costs, and

3. Provide decision makers with insights which drivetrain type is more beneficial to deploy for which cases.

In the remainder of this paper, we will first describe the model with particular focus on the cost model and its validation (Section 2). In Section 3, we will describe our approach. The impact of different parameters on power requirement consumption are shown in Section 4.1, while Section 4.2 describes the impact on cost values. The final result in Section 4.3 is a combination of the results to lay out the space of possible cost values for different tracks, operational parameters, and uncertainties. We conclude with a set of recommendations and insights in the final Section 5.

## 2 Models

In this Section, we describe two models. First, to calculate costs, maximum power and energy consumption are necessary to be known. Power sizes the components (and determines their cost) and energy determines the required amount of fuel/electricity. We have developed a tool to determine energy and power requirements from given vehicle properties on a specific track. The tool is here called "Driving Dynamic Model" (DDM) and will be used for all calculations. We give in the following Section 2.1 an overview to support our reasoning throughout the Result Section 4. Further details are described by Guerster *et al.* (2018). Second, in Section 2.2, we develop and validate a cost model to compute Life-Cycle-Costs (LCC) from energy consumption and maximum power.

### 2.1 Driving Dynamic Model (DDM)

The DDM calculates maximum power consumption of a parametrizable vehicle given track and drivetrain specifics. Energy is calculated by integrating the consumed power over the driving time (considering efficiencies). There is a dependent relation between vehicle properties and the needed energy and power: If the mass of a vehicle changes, the power requirement changes. Changed power requirement for the drivetrain again changes the vehicle's mass, as components need to be larger and heavier. A tool to find a set of mass, energy, and power for every vehicle and its components has been developed within the Toolbox for Optimal Railway Propulsion Architectures (TORPA) project and is used here (further details in Mueller (2018)). TORPA is an overarching project with focus on economic emission reduction in regional railway.

An example is given in Table 1. We compare the diesel and electric vehicle on the same default scenario for which we define in details in Section 3. We use the following definitions for the table:

**Power requirement** is the power for which drivetrain components are scaled.

**Gross energy** is the amount of energy from diesel fuel or electricity before subtracting recovered energy.

**Recovered energy** is the amount of energy that is recovered while braking. It is zero for the diesel drivetrain.

**Net energy** is gross energy minus recovered energy.

**Energy recovery rate** is ratio of recovered energy to gross energy.

Table 1: Energy and power outputs for diesel and electric vehicle for default scenario

Parameter	Unit	Diesel vehicle	Electric vehicle
Vehicle mass without propulsion system	t	97.5	97.5
Vehicle mass including propulsion system	t	115	108
Power requirement at wheel level	kW	1385	1292
Gross energy consumption in form of diesel/electricity	kWh	1477	335
Recovered energy	kWh	-	174
Energy recovery rate	%	-	52%
Net energy consumption in form of diesel/electricity	kWh	1477	161

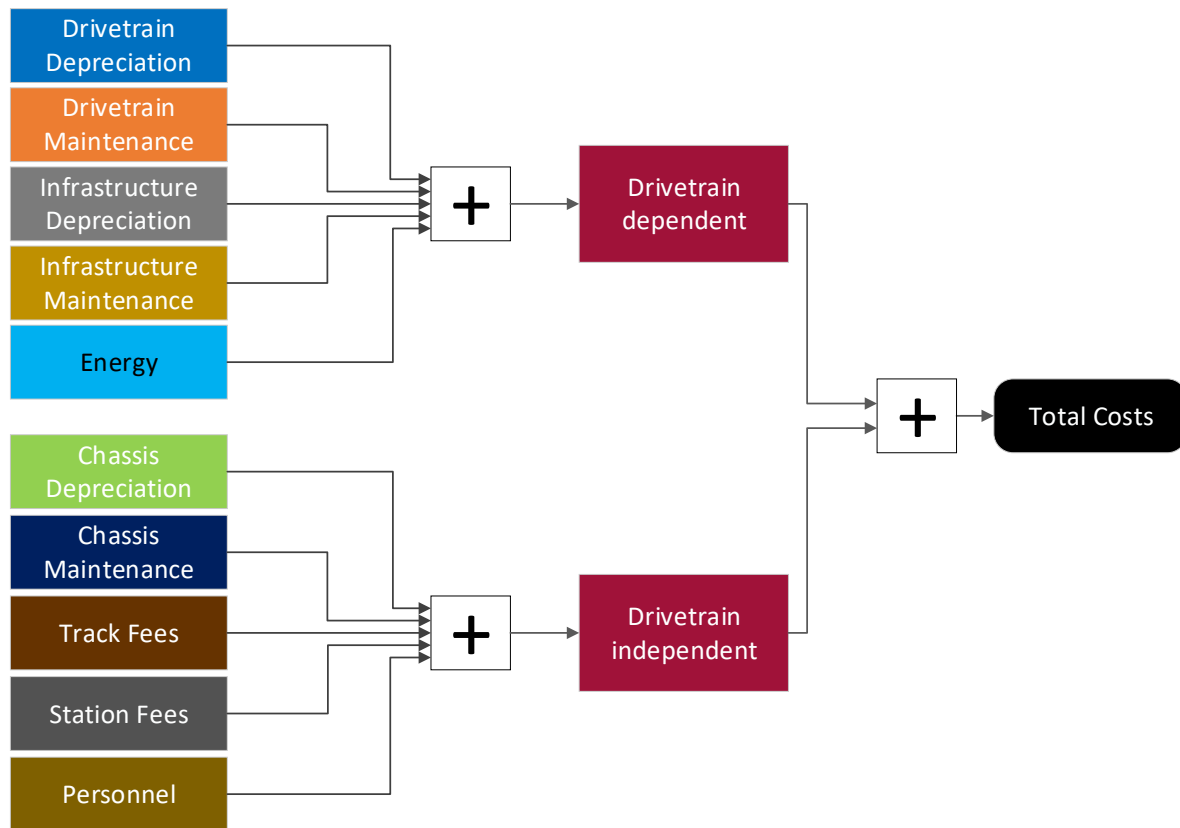
The vehicle without drivetrain has a mass of 97.5 tons. With the drivetrain, the diesel and electric vehicle have a mass of 115 and 107 tons, respectively. Due to the 7 % higher mass of the diesel vehicle, the power requirement at wheel level is also 7 % higher. The gross energy consumption is 335 kWh for the default electric scenario. In case of the diesel vehicle, gross energy requirement is 1477 kWh, which corresponds to 152 liters of diesel (Valdes and Warner (2010)). With an electric drivetrain, energy can be recovered while decelerating and fed back to the grid. The amount of energy that can be recovered is around 52 % of drawn energy in the default scenario. The higher energy consumption is due to the worse efficiency of the diesel drivetrain compared to electric.

## 2.2 Cost Model

### 2.2.1 Cost model Development

We develop a cost model that is decomposed into components that depend on the drivetrain and such that are independent (see Figure 1). The drivetrain dependent cost are further divided into drivetrain depreciation and maintenance, and infrastructure depreciation and maintenance. In addition, the cost of diesel or electricity energy are accounted towards the drivetrain dependent. The independent costs are a sum of the chassis depreciation and maintenance, track and station fees, and costs for personnel.

Figure 1: Composition of total costs for all propulsion types



The following paragraphs list and explain all components of the cost model as shown in Figure 1. Specifically, we describe the method used to build our data base and reference the considered literature. In general, we critically reviewed literature values and adapted if necessary. First, we describe the five subcategories of drivetrain dependent costs:

**Drivetrain depreciation** includes depreciation of all drivetrain components within the vehicle. For diesel vehicles, these are diesel tank, engine, generator, AC-to-DC converter, DC-DC converter, traction inverter (converting from DC to AC), electric motor, and axle transmission. For electric vehicles, these are pantograph, transformer, AC-to-DC converter, DC-DC converter, traction inverter, electric motor, and axle transmission. For all component costs (with two exceptions explained subsequently), we performed a linear regression between cost and power, i.e. every component's cost is made dependent on its designed maximum power. For example, if the linear function for diesel engines is 100 £ per kW of engine output power, and the engine output power is 1000 kW, then investment cost for the engine is 100 000 £. The two exceptions to the linear scaling with power are (1) pantograph costs, which we assume to be independent of power, and (2) diesel tank costs, which scale with energy instead of power. After determining initial investment

costs for all components, these are divided by component specific depreciation times. J Pagenkopf and S Kaimer (2014) and Toni Schirmer, Johannes Pagenkopf, Holger Dittus (2019) provide input data for our component costs.

**Drivetrain maintenance** consists of regular inspection costs depending on time and drivetrain type, and component replacement costs depending on mileage. The diesel engine is the only component which is considered for replacement. All data points are taken from Mueller (2017).

**Infrastructure depreciation** are catenary costs divided by their depreciation time. Catenary costs per kilometer are taken from Baumgartner (2001) and two recent projects in Germany (see Pressemitteilung Bayerisches Innenministerium (2018) and Schwaebische Zeitung (2018)). The costs for catenary themselves are divided in costs to "put up an electrification gauge" (Baumgartner (2001)), costs to change signaling, and costs to set up the electrification infrastructure itself (overhead wires, masts, supply stations, etc.). The latter part is subject to maintenance which we describe in the next paragraph. Depreciation times are taken from Baumgartner (2001) and Mueller (2017).

**Infrastructure maintenance** includes maintenance for catenary infrastructure and gas stations (in case of diesel drivetrain). Gas stations are assumed to cost 20 k€ per year (Mueller (2017)). Aligned with Baumgartner, we assume 200 k€ per kilometer as catenary investment cost (note that this value is given in 2001 euros, which we adjusted for inflation to 2019 (In2013dollars.com (2019))). Of this sum, a defined share (between 1% and 3% per year) needs to be paid for maintenance (Baumgartner (2001)).

**Energy** includes energy from diesel and electricity. The amount of electricity needed is taken from our Driving Dynamic Model. In case of electricity, drawn and fed back energy have a different price (fed back energy price is 3/4 of drawn energy, see Stefan Fassbinder (2018a)).

Second, we describe the five subcomponents of drivetrain independent costs:

**Chassis depreciation** includes all vehicle parts that were not already considered as drivetrain. We took chassis costs of three comparable vehicles from Mueller (2017) and subtracted the self-calculated drivetrain costs for each to derive chassis investment costs. Chassis investment costs are divided by the vehicle depreciation time given by Baumgartner (2001) to derive depreciation rates.

**Chassis maintenance** is assumed to be 0.2 €/km. The value is kept constant for all further contemplation.

**Track fees** are assumed to be 5.07 €/km. This value was taken from DB AG's tables (DB AG (2019a)) and confirmed by calculating values for several relevant tracks using the online tool "Trassenfinder" by Deutsche Bahn AG (DB AG) (DB AG (2019b)).

**Station fees** are estimated with 3.50 € per stop. Real prices for stops in Bavaria are between 2.57 € and 3.98 € for stations without long-distance services, depending on



station size (DB AG (2019a)).

**Personnel** costs are 37.5 £ per hour, with the underlying assumptions that a driver costs 60 k£ per year while working 8 hours on 200 days per year. With an average velocity of 55 km/h (J Pagenkopf and S Kaimer (2014)), we find that 0.02 driving hours are required per kilometer. Additionally, it is assumed that 1.5 working hours are required per driving hour. Therefore, personnel costs are 1.02 £ per km (constant throughout this work).

### 2.2.2 Cost model validation with diesel drivetrain

We validate our model with literature values for diesel propulsion as shown in Table 2 (Pally (2016), Gattuso and Restuccia (2014)). Here, vehicle maintenance costs consist of drivetrain and chassis maintenance costs. Similarly, vehicle depreciation consists of drivetrain depreciation and chassis depreciation.

Table 2: Validation of the cost model for diesel drivetrain with literature values

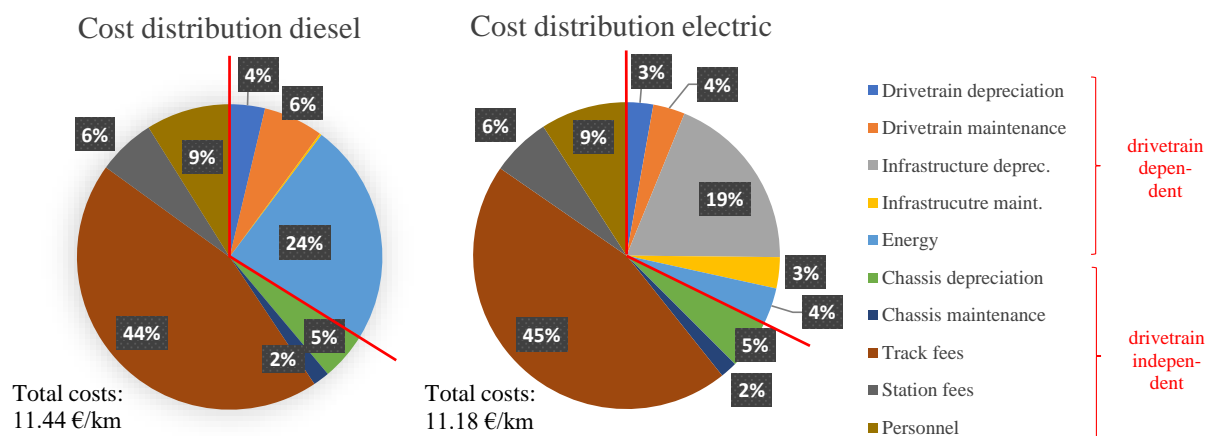
Cost shares					
	Our cost share	Cost share (Gattuso)	Cost Share (Pally)	Relative deviation from Gattuso	Relative Deviation from Pally
Vehicle maintenance	3%	33%	27%	-90%	-88%
Vehicle depreciation	7%	7%	21%	-7%	-69%
Energy	25%	7%	12%	+258%	+109%
Track and station access fees	55%	28%	0%	+97%	-
Personnel	10%	25%	40%	-60%	-75%
Disposal	0%	0%	1%	-	-
Total costs					
	Our model	Gattuso			
Total costs [€/km]	11.44	10.6	-	+8%	-

We observe that the cost shares do not comply well with literature values. However, literature values do not agree with each other either. When it comes to total costs, we found that they are well aligned with the literature. We provide additional, well matching, validation data points in the following Section 2.2.3 and in Section 4.4.

### 2.2.3 Cost model applied to diesel and electric drivetrain

Cost distributions for both drivetrain types for the default scenario are shown in Figure 2 (default scenario is a generic track with a length of 60 km, a stop distance of 5 km, and a maximum velocity of 120 km/h, further details are shown in Table 3).

Figure 2: Chosen values for default scenario and worst- and best-case for the sensitivity analysis



Diesel operation has a total cost of 11.44 €/km, whereas electric operation is slightly cheaper at 11.18 €/km. The figure shows that the total costs of drivetrain types are similar, however we describe subsequently that the composition differs.

Both cost distributions show that drivetrain related costs make up a third of total costs. The major difference between the two drivetrain types is that in case of diesel, by far the largest part is energy costs, whereas the largest part in the electric case is made up by infrastructure depreciation and maintenance.

With the computed total costs, we can add an additional validation point by comparing with Mueller (2017): He found that diesel is 1.5% cheaper if the track is not partly electrified yet. With the calculations shown here, diesel operation is 2.3% more expensive.

Subsequently, we explain the contributors to each cost share and compare the drivetrain types.

The diesel **drivetrain depreciation** is higher than in the electric case. One reason is the higher power requirement for the vehicle as seen in Table 1. Also, the diesel vehicle has higher **maintenance** costs. However these drivetrain costs only contribute about 10% and 7% to overall costs, respectively. In case of diesel operation, **energy** makes up the most important part of drivetrain dependent costs, accounting for 24% of overall cost. For electric operation, the energy cost share is as low as 4%.

Contrary, diesel has no **infrastructure depreciation** costs and almost no **infrastructure maintenance** costs with only a gas station. Electrification infrastructure depreciation accounts for 19% costs of the electric case. Maintenance of this infrastructure causes another 3% of the costs for electric operation. Overall, the sum of drivetrain related costs only differs to a minor extent between the drivetrain types, with the main contributors being diesel fuel and electrification infrastructure, respectively.

**Drivetrain independent costs** are by definition the same for both drivetrain types. Their largest share is made up by track fees with 5.07 €/km. 6% of total costs are station fees, which are calculated by stop numbers and defined "categories" of the stops. Therefore, the cost per km changes with the stop distance. Personnel costs make up roughly 9% of overall costs. Chassis costs make up a combined 7% for depreciation and maintenance. These chassis costs later change with the annual distance that is operated by one vehicle.

In sum, we found that both drivetrain types have similar total costs, but the costs are composed differently.

### 3 Approach

After describing the models, this section discusses the approach that we follow to answer the following three questions in the result Section 4: What is the sensitivity of energy and power with respect to changing scenarios (Section 4.1)? What is the impact on the costs (Section 4.2)? And how do variations in track and uncertainties (Section 4.3) impact the comparison between diesel and electric drivetrain?

We define a *scenario* as the combination of track and operational parameters. The *default scenario* is the combination of our best guesses for each parameter. Table 3 shows the three categories of parameters. The default values are our best guesses, whereas best- and worst-case determine the boundaries investigated. We rationalize the numbers in Appendix A.

Table 3: Chosen values for default case and worst- and best-case for the sensitivity analysis

Nr.	Parameter	Unit	Default value	Uncertainty Range	
				Worst case	Best case
Track parameters					
1	Track length	km	60	5	190
2	Stop distance	km	5	1.2	15
3	Elevation gain and loss	m	0	250	0
4	Share of double track sections	-	0.2	1	0
Operational parameters					
5	Max. speed	km/h	120	160	50
6	Desired acceleration	m/s <sup>2</sup>	1	1.3	0.5
7	Headway	h	1	2	0.5
8	Number of vehicles in fleet (Annual vehicle mileage)	- km	4 vehicles (197 100)	8 vehicles (98 550)	2 vehicles (394 200)
Uncertainty parameters					
9	Diesel cost	€/liter	1.00	2.65	0.75
10	Electricity cost	€/kWh	0.12	0.17	0.1
11	Electrification cost	k€/km	930	2 000	150
12	Electrification depreciation time	a	40	30	76

The first category are track parameters. They are defined by the given track. Second, there are operational parameters. They are dependent on a specific rail line, but can be influenced by the operator. For example, the speed profile can adhere to maximum speeds of tracks, but can also be lowered. Third, there are parameters that have a particular large uncertainty range. Either because their values in the literature vary widely (electrification costs, depreciation time), or their forecast is inherently uncertain (diesel costs).

Within the uncertainty analysis, we use the default scenario and vary one parameters at a time.

## 4 Results

In Section 4.1, we analyze how track and operational parameters (a scenario) affect the power and energy consumption for both drivetrains. This is followed by Section 4.2 in which the impact of different scenarios and uncertainties on the vehicles' costs is analyzed. Section 4.3 compares both drivetrain types including scenario and uncertainty considerations.

### 4.1 Power and energy sensitivities for different scenarios

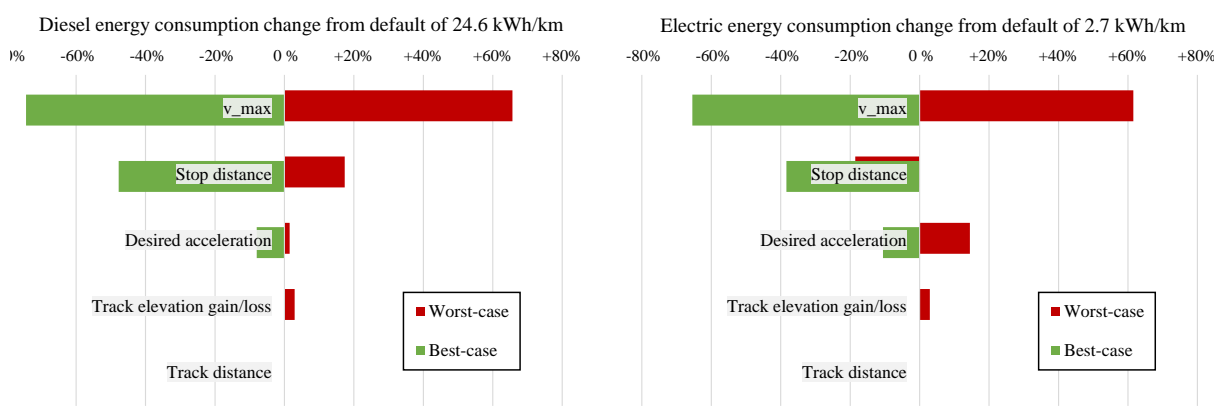
In Section 2.2, we investigated the fundamental differences of the two drivetrain types in terms of power and energy requirements. This section investigates how these requirements vary with the defined scenarios. We use Table 4 and Figure 3 to explain the encountered relationships. Table 4 shows outputs of the DDM for all tested scenarios.

Table 4: Sensitivity analysis for energy and power requirements

Calculated vehicle requirement	Unit	Default case	Track length		Stop distance		Elevation gain/loss		V_max		Acceleration	
			5 km	190 km	1.2 km	15 km	+/- 250 m	0 m	160 km/h	50 km/h	1.3 m/s <sup>2</sup>	0.5 m/s <sup>2</sup>
<b>Diesel vehicle</b>												
Power at wheel level	kW	1385	1385	1385	1385	1385	1385	1385	1385	581	1385	1385
Energy consumption	kWh/km	24.6	24.6	24.6	28.9	12.9	25.3	24.6	40.8	6.3	25.0	22.7
Change from default	-	-	0%	0%	+17%	-48%	+3%	0%	+66%	-74%	+1%	-8%
<b>Electric vehicle</b>												
Power at wheel level	kW	1292	1292	1292	1292	1292	1292	1292	1292	582	1292	1292
Gross energy per km	kWh/km	5.58	5.58	5.58	6.21	2.19	5.75	5.58	8.63	1.43	5.66	5.23
Change from default	-	-	0%	0%	+11%	-61%	+3%	0%	+55%	-74%	+1%	-6%
Recovered energy	kWh/km	2.90	2.89	2.89	4.55	0.97	2.97	2.90	4.29	0.50	2.58	2.83
Change from default	-	-	52%	52%	73%	44%	52%	52%	50%	35%	46%	54%
Net energy consumption	kWh/km	2.69	2.69	2.69	2.19	1.66	2.78	2.69	4.34	0.93	3.07	2.40
Change from default	-	-	0%	0%	-19%	-38%	+3%	0%	+62%	-66%	+15%	-11%

The most important detail in this table is the change of net energy compared to the default scenario. We outlined in Figure 2 how energy costs play a major role in case of the diesel drivetrain, but only a minor one for the electric drivetrain. The larger the total energy consumption is,

Figure 3: Sensitivity of net energy consumption for diesel and electric drivetrain



the larger is the cost difference between the two drivetrain types. We focus in the subsequent description of Table 4 only on the scenarios with the highest variation from the default.

We visualize the changes in net energy for each drivetrain type in Figure 3. Both Tornado plots display the change in energy consumption from the respective default scenario. In case of electrified operation, the listed parameters of gross energy and energy recovery rate from Table 4 serve to explain the encountered phenomenons.

In general, we observe that maximum track velocity and stop distance are the most impactful parameters. Desired acceleration plays a minor role. Track elevation gain/loss and track distance have negligible influence on energy consumption. Subsequently, we explain the seen changes, while pointing out differences between the drivetrain types.

We start with the most important parameter,  $v_{max}$ . For  $v_{max}$  best-case, there is a notable quantitative difference between the two drivetrain types. While the gross energy change of electric is -74%, exactly as for diesel, the net energy change is lower. The reason is a drop in energy recovery rate, which is caused by the inability to recover the whole amount of deceleration energy while braking at low speeds.

In case of **stop distance**, we find that electric vehicles are especially well suited for tracks with under average stop distances. The reason is that energy from acceleration can be recovered, while energy from aerodynamic drag can not. With the best-case of stop distance, which means stopping every 15 km, required energy decreases by 48% in case of diesel and 38% in case of electric operation. The decrease for electric is smaller because there is also less energy recovered. For electric operation and the worst-case stop distance, a non-intuitive observation is made: This “worst-case” actually improves the energy consumption, with a 19% reduction compared to the default scenario. The reasons for this are found in Table 4. Actually, gross energy consumption rises by 11%, which compares well to the 17% for the diesel-case. However, the amount of recovered energy rises from 52% to 73%. Thus, the increased consumption in gross energy is more than compensated. The reason is that with more stops, the amount of

recoverable acceleration energy rises, while the average velocity, and with that the amount of non-recoverable energy to overcome aerodynamic drag, falls.

The impact of **desired acceleration** affects electric energy consumption more than diesel. The reason again is the amount of recoverable energy, while gross energy change is similar (worst case) or slightly smaller (best case) than for diesel. In our DDM, we assume that the desired deceleration is equal to the desired acceleration. When deceleration should be higher with unchanged motor scalings, less of the braking energy at low speeds can be recovered. The parameter of **elevation gain and loss** only has a minor impact on energy consumption and especially reveals no relevant differences between the two drivetrain types. **Track length** only influences the number of repetitions of the track sections. It has no impact on energy consumption per kilometer.

To summarize, we have outlined the decisive parameters for energy consumption. The  $v_{\max}$  best and worst case and the desired acceleration best case have a considerable impact for both drivetrain types. Stop distance affects the two drivetrain types in a different way.

## 4.2 Cost sensitivities for different scenarios and uncertainties

With the next two subsections we discuss how changes in energy consumption translate into changes in overall costs, and which other factors come into play. We start with the diesel case.

### 4.2.1 Cost sensitivity of diesel drivetrain

The baseline of the horizontal axis ( $\pm 0$  €/km) are the costs of the default scenario with 11.44 €/km. First listed is the impact of scenario changes. Second, there are uncertainties. The most obvious observation is that high diesel costs can make operations significantly more expensive. Variations in stop distance and maximum speed also turn out to have an important positive or negative impact on total costs. In general, scenario changes in terms of costs show a strong correlation with the changes in energy (Figure 3).

Subsequently, we explain changes in costs by the respective parameters in more detail. The most important factor in terms of costs is **stop distance**, which was shown to have a large impact on energy consumption. The reason that the contribution is stronger than for  $v_{\max}$ , which changes energy by a larger extent, is that station fee variations add up to the energy cost changes.

**Maximum speed** impact goes proportionally with the changes in energy and is in sum the second most important cost variance in the diesel case.

The **number of vehicles in the fleet** directly affects depreciation costs of drivetrain and non-drivetrain components of the vehicle. Also, driving more kilometers per vehicle means a reduced

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**Figure 4: Cost sensitivities of a diesel operation**

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per kilometer share of one part of maintenance costs, namely the major inspections that occur after a defined time. As the diesel drivetrain is more expensive than the electric one, we observe a larger effect of change in the number of vehicles in use. Track distance changes the distance driven per vehicle, as there is a larger distance driven at constant waiting times. Therefore, the effect is comparable to a change in number of vehicles per fleet. We quantify this with a short calculation: For the default scenario, the 60 km track ride operated by four vehicles results in an average of 30 km driven per vehicle and hour. It is assumed that the 10 km track is operated with one vehicle, therefore this vehicle drives 20 km per hour (going there and back). For the 190 km track, 8 vehicles are assumed to be required. Therefore, a vehicle drives 47.5 km per hour. Although the assumed numbers of vehicles are made without further research, the overall trend is justified: the longer a track ride, the larger is the share of driving times compared to waiting times for the ride back at the next full hour. It is to mention that energy costs per km, and for the electric drivetrain type also infrastructure costs per km, remain constant. Therefore,

the larger share of vehicle costs in case of diesel leads to a larger impact of the track distance parameter compared to the electric drivetrain type.

Cost variations in desired acceleration and elevation gain also change energy costs proportionally to the changes in energy as seen before. Overall, the variation caused by these two factors is comparably small. Headway only changes the negligibly small amount of gas station maintenance costs per km. Double track share has no effect on the diesel drivetrain life cycle costs in the shown model. Analyzing sensitivity to uncertainty factors, diesel cost turns out to be more influential than any scenario parameter. The variation between best and worst case adds up to 4.65 km. Electricity cost and cost for catenary infrastructure have no influence on diesel costs.

Summarizing, we found that increased electricity costs pose the most important cost uncertainty for the diesel drivetrain costs. A track's stop distance and maximum speed are important parameters as well, however they also affect the electric drivetrain costs. Subsequently, we explain cost changes in case of electric operation.

#### 4.2.2 Cost sensitivity of electric drivetrain

For electric drivetrain cost, we already found that infrastructure costs make up the largest variable cost share (Figure 2). Accordingly, the parameters that affect the infrastructure costs turn out to be the most important ones. These are headway, double track share, catenary investment cost, and the depreciation time. Mostly for the reason of station fees, stop distance has a considerable impact as well.

Following, the impact of each scenario variation is analyzed and compared for the electric drivetrain case. Of scenario parameters, headway is the one with the largest sensitivity, because doubling or halving headway means doubling or halving the infrastructure costs per km.

Stop distance is the second most sensitive scenario parameter for this drivetrain type. The effect on total costs is smaller than in case of diesel because of both a smaller contribution and smaller variation of energy costs. Therefore, the worst-case for stop distance would more favour an electric drivetrain type, whereas the best-case would more favour a diesel drivetrain type. The sensitivity analysis for energy consumption revealed that the short, worst-case stop distance even lowers energy consumption compared to the default scenario. Analyzing cost sensitivity, this reverse effect can not be observed anymore. There are two reasons for this: first, as mentioned, net energy consumption does not directly correspond to energy costs. Second, increased station fees more than compensate the effect.

As headway double track share directly affects the dominating share of electrification infrastructure costs. It decreases them by 17% or increases them by 67%, respectively, and is therefore



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**Figure 5: Cost sensitivities of electric operation**

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the third most important scenario parameter.

The effects of  $v_{\max}$  worst-case correspond to the changes in energy consumption. For best-case, not only energy is reduced, but also power output, leading to less powerful and cheaper components.

Sensitivity to track distance and number of vehicles in the fleet works accordingly to the diesel case, whereas the influence is smaller for the electric drivetrain type because of cheaper vehicle drivetrains and their maintenance. Desired acceleration and track elevation gain each have a comparably small impact on overall costs.

In short, there are five parameters encompassing both scenario and uncertainty that make electric operation more expensive by more than €1/km, whereas the most important ones impact infrastructure costs.

### 4.3 Cost comparison of diesel and electric drivetrains

With the last section, we have determined sensitivities of both drivetrain types towards scenario changes and uncertainties. What the Tornado plots do not show is how variations translate into total cost differences between the two drivetrain types, which we cover in this section.

Figure 6 shows total costs per kilometer on the vertical axis. On the very left of the horizontal axis, the default case values are displayed for both drivetrain types. On the right of that, scenario parameters displayed, in decreasing order of the sum of the impact on both drivetrain types. Further on the right, uncertainty parameters are listed with decreasing sum of impact. Data points for the diesel drivetrain type are shown as squares in blue frame color. Data points for the electric drivetrain type are shown as triangles in orange frame color. The markers are filled either with green to display the best case or in red to display the worst case for each variation. Best-case points should only be compared with best-case points for each variation (and similarly for worst-case points).

With the data visualized in Figure 6 shows an overall cost range from 9.0 €/km to 15.5 €/km. We observe that this is well aligned with Toni Schirmer, Johannes Pagenkopf, Holger Dittus (2019), who state a cost range between 9.0 €/km and 15.5 €/km as empirical value. Using the visualized data, we are able to answer a range of questions:

Which are the important parameters for deciding on the drivetrain type? Which ones are negligible? Stop distance,  $v_{max}$ , headway, diesel fuel costs, and electrification costs are significant variables to decide which drivetrain type is cheaper or to determine the cost difference between the two. More precisely,  $v_{max}$  and stop distance affect diesel costs to a larger extent than they affect electric costs. Headway and double track share mostly affect electric operation. The number of vehicles per fleet and the track length have a similar impact on both drivetrain types and are therefore only of importance for absolute costs. Desired acceleration, track elevation gain and loss, and electricity costs are more negligible compared to overall variations.

How significant are uncertainties compared to variations in the scenario? Uncertainties in input parameters turn out to be in the same order of magnitude as the variation caused by different scenarios. With variations in the relevant uncertainties, it is possible that one drivetrain type is cheaper for all scenarios. A considerable increase in long-term diesel costs could put track electrification in favour in many cases.

Which scenarios are in favour of the diesel drivetrain, which are in favour of the electric drivetrain? In the default scenario, electric operation is slightly cheaper than diesel. Electric operation is also beneficial for small headways and small double track shares. It should be mentioned that these two parameters are not independent, because single tracks do not allow for very small headways. Uniting these two factors, we confirm that tracks with high utilization

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**Figure 6: Absolute costs of all investigated cases**

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favour a electrification, while such with low utilization are more suitable for diesel operation. Diesel operation is the cheaper option for tracks with a high stop distance and low velocities. Overall, tracks with few and short acceleration periods are preferably operated with diesel vehicles if costs should be minimized.

Which operational parameters can help reduce costs? With  $v_{\max}$  being the most important influence on energy consumption, reducing operational velocities is an option to reduce costs. Accelerations should only be as high as required or determined by reasonable safety. From the large share of track, station, and personnel costs, it gets visible that multi-unit operation may be an attractive option, so that more people can be transported while these cost parts remain constant.

## 5 Conclusion

In this paper, we conducted a sensitivity analysis on the economic viability of track electrification for a wide range of tracks, operational parameters, and uncertainties. A model to evaluate total costs of regional railway operation, including required infrastructure, was built and validated. We also support decision makers with a reasonable subset of parameters to decide on electrification projects in the future.

The main conclusion is that diesel and electrical drivetrains have similar total costs and it depends on the track specifics if electrification is economically viable. The decision is further complicated as the uncertainty analysis indicates that the impact of uncertainties in external parameters are at least in a similar order of magnitude than the cost differences between both drivetrains.

What was found more in detail is that for both drivetrains,  $v_{max}$  has the largest impact on energy consumption followed by the stop distance. While energy cost poses a rather small share for electric drivetrains, it makes up the largest share of drivetrain-dependent costs for diesel vehicles. Therefore, uncertainty in future diesel price has the highest impact on the total cost of diesel drivetrains. On the other side, the total cost of electric operation strongly depends on the infrastructure costs and the headway (as the fixed infrastructure costs can be spread over more vehicles). Nevertheless, we found that diesel propulsion is the cheaper option in case of stop distances larger than 5 km and maximum velocity lower than 120 km/h (given diesel prices remain at a level of 1.5 €/liter). Electric propulsion is especially economically viable for smaller stop distances, velocities above 120 km/h, headways of less than an hour, and when the share of double track sections is not much larger than necessary for operations.

While we aim with our model to approximate reality as close as possible, there are obvious limitations. In particular, the cost shares vary widely between our model and within the studied literature, while the total costs are well aligned. We approached this challenge with the sensitivity analysis by showing in which ranges the costs are likely to fall. Additionally, as we showed in one of our studies (Mueller (2018)), regional passenger railway has a complex stakeholder value network. Hence, besides cost, there are likely additional criteria that influence the electrification decision. However, with this paper we presented work that aims to illuminate the economic aspects of track electrification.

In future work, we intend to understand what role hybrid vehicles can play in reducing the emission of regional railway vehicles while remaining economically competitive. As illustrated by DB AG (2018), track electrification projects take up to 10-15 years. Therefore, it is not a near-term solution for emission reduction. Besides other effects, this motivates the use of hybrid vehicles, which can be deployed faster once on the market.

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## A Explanation of input values for the sensitivity analysis

Here, we provide more details on the values used as defaults and in the uncertainty analysis as seen in Table 3. For each parameter, we state the default value as well as a worst and a best-case. What is listed as best and what is listed as worst case is determined by the expected impact on life cycle costs. The meaning of each value is explained subsequently. Also, some parameter changes entail other changes. E. g. a variation in track length might require a variation in number of fleet vehicles in order for the case to remain realistic.

Subsequently, we refer to statistical track data as presented by Pagenkopf (2018). In his research, data is presented in box plots, which we like to shortly introduce here for a better understanding. In general, data points are grouped in outliers and non-outliers. The non-outlier range is shown between "whiskers", which represent the margin values. In between margins, there are three more distinctive values defined: "median" (meaning 50% of non-outlier values are larger, 50% are smaller), Quartile 1" (Q1) (25% smaller, 75% larger), and "Quartile 3" (Q3) (75% smaller, 25% larger). The difference between Q3 and Q1 is called Interquartile Range (IQR).

Table 5: Chosen values for default case and worst- and best-case for the sensitivity analysis

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1. Track distance: The default track distance is 60 km. This corresponds to the median length of 58 km of 469 regional rail tracks in Germany that Pagenkopf (2018) found. The minimum track length of 5 km corresponds to the Q1 track length minus 1.5 times IQR. The used maximum track length corresponds to  $Q3 + 1.5 \cdot IQR$  value and is 190 km. It is to mention that the number of vehicles per fleet is likely to change within the track distance range. Whereas by default we assume four vehicles per fleet, the scenarios assume 1 and 8 vehicles, respectively. The effect of changing the number of vehicles in a fleet is displayed with a separate parameter and described in Point 8 of this list.
  2. Distances between two stops as well closely adhere to Pagenkopf et. al.s' data. The median value of 5 km is used in the default case. Best and worst case are 1.2 km and 15 km again representing  $Q1 - 1.5 \cdot IQR$  and  $Q3 + 1.5 \cdot IQR$ .
  3. The default track is flat. An elevation gain and loss of 250 m means that the track constantly rises to 250 m over starting level on its first half and descends again by 250 m in the second half. We have found no tracks in Germany with an elevation gain of more than 500 meters. On real tracks, elevation loss would likely occur on the ride back to the starting destination. In order to represent the same inclinations in simulations within one track ride, we assume half of the elevation gain and loss, but within one track ride instead of two.
  4. Tracks can have one line of rails, or two next to each other, called double-track. By default, we assume that 20% of a track's distance is built as double track, whereas the remaining share is single-track.
  5. The default maximum speed is 120 km/h as it is e. g. the design high speed of the



commonly used Stadler RS1 vehicle (Bosch (2017)). The best case value is 50 km/h. Regional lines with high speeds lower than this are not known to the authors. The worst case value is 160 km/h, which commonly is the highest speed regional railway can run in Germany. Regulatory reasons prevent vehicles from going faster without supporting considerably more expensive train protection systems (German Federal Ministry of Justice (2018)). It was decided not to use Pagenkopf et. al.s' whisker values for average speeds, as the values appear to be unreasonably low to us. Possibly, they included stop times in their calculations. With our utilized DDM, 50 km/h max. speed lead to an average of 46 km/h, 120 km/h max. speed lead to 87 km/h on average, and 160 km/h lead to 94 km/h on average. The found average speeds correspond well to the range found by Pagenkopf et. al.: 46 km/h on average mean the found Q1 value. 94 km/h on average compares well to their  $Q3 + 1.5 \cdot IQR$  value of 95 km/h.

6. The default desired acceleration is set to  $1 m/s^2$ . The value is relatively high for diesel vehicles, but common to electric ones like the DB series 423 (Daniel Lurz (2006)). Best-case value is  $0.5 m/s^2$ . Worst-case value is  $1.3 m/s^2$ .
7. Headway refers to the time between two scheduled vehicle rides per track direction. Standard headway is assumed to be one hour, as commonly utilized for regional railway lines (Bayerische Eisenbahngesellschaft (2018)). The worst-case value of two hours represents a few lowly frequented lines. The best-case value is 0.5 hours. It should be mentioned that it is unlikely to operated half-hourly on a track with no double track sections, however we do not change this parameter when changing headway.
8. The default number of vehicles is four. With the default average speed of 87 km/h, the default track of 60 km is driven within 41 minutes plus stops times. With a likely stop time of one minute, 11 minutes are additionally added per journey. Thus, one track ride is expected to take 52 min, so that 68 minutes waiting or bu er time remain until the vehicle in the fleet of four starts the return ride. The best-case number of vehicles two, which would lead to only 8 minutes bu er time. The worst-case of 8 vehicles in the fleet allows for more bu er time.
9. Diesel costs are 99.65 cents/liter by default. We need to mention that this price only applies to DB as a bulk consumer. As a model input, we add 5.3 cents/liter that DB charges for transport of the fuel to accessible gas stations. The best-case value of 75 cents/liter represents a 6-year low (Bundesverband Güterkraftverkehr und Logistik (2019)). The worst case value can only be taken from rough predictions. We apply a reasonable prediction value that is within the lifetime of vehicles deployed in 2019 and settle for 2.65 euro/liter (Jenny Gross (2013)).
10. Similar to diesel costs, electricity costs are lower for a railway operator than for consumers. DB AG especially makes use of laws to reduce taxes on electricity. By default, we use a value of 12.2 cents/kWh. Best and worst-case values are 10 and 17 cents/kWh. In general,

diesel and electric energy prices tend to change proportionally on the market (Eicke Weber (2012)). However, the two price variations are considered separately.

11. According to Baumgartner, the major part of track electrification costs is made up by requirements to put up an "electrification gauge", e. g. requiring increased clearances under bridges and in tunnels, and requirements to change signalling infrastructure. Costs for the overhead wire itself, masts, and power supply stations are about one order of magnitude lower (Baumgartner (2001)). Therefore, we reason that electrification depreciation is largely dependant on the track environment (number of crossings and tunnels) and existing signalling, causing this parameter to vary in a large range. It is to mention that another parameter varied separately plays a role for electrification costs, which is the track speed. However, we can assume from Baumgartner (2001) that electrification costs do not vary within the considered speed range for regional railway tracks.
12. Depreciation time means the time within which the electrification investment has to be paid in constant rates. By default, we adhere to Baumgartner and use 40 years (Baumgartner (2001)). He also suggests to use at least 30 years. The best-case value is taken from Mueller's studies (Mueller (2017)), although the value seems high even for publicly financed projects.