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Definition And Optimization Of The Drive Train Topology For Electric Vehicles

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Abstract

Due to the limited range of battery electric vehicles, a low energy consumption is more desirable, than it is in conventional vehicles. To accomplish this objective the paper focuses on an increased efficiency of the drive train, its topologies and its components, as this is one of the most promising approaches. With a set of basic characteristics of the desired vehicle (such as maximum speed, acceleration, climbing ability, class and range) an optimal fitted drive train according to the energy consumption should be found. This includes number, type and power of electric machines, transmission ratios, dynamic running radius, axle load distribution and battery capacity. The general approach uses a method consisting of a developed optimization routine and a specific simulation model.

The developed optimization algorithm reduces the value ranges or even the design parameters to minimize the number of iterations. This intelligent algorithm is compared to conventional optimizers like pattern search or genetic algorithms. For the vehicle model valid results are important. To ensure validity for all possible topologies, vehicle and power classes an appropriate method is presented. Each relevant component model and its respective scaling concept are validated. After validation of a vehicle model with these component models, the scalability is transferable to the entire vehicle model. Some exemplary results of the model are shown, such as the influence of axle load distribution, choice of high-energy or high-power cells and potential of longitudinal torque-vectoring for multi-motor topologies.

Keywords: BEV (battery electric vehicle), powertrain, optimization, modeling, simulation

1 Introduction

One of the biggest challenges of battery electric vehicles (BEV) is the compensation of the limited range, due to the small energy density of state of the art accumulators. Although people mostly use their cars for short distances up to around 40 km, they simply would not accept paying more for less than they would get out of a conventional car.

One way to increase the range is to install a bigger battery, which leads to increased costs and weight and thus energy consumption. As the benefit of this approach is not promising, the way to go is to reduce the energy consumption of the vehicle. The result is an increased range or a smaller battery capacity with the opposite effect compared to before, less costs and weight.

To achieve this goal there are two possible methods:

- Reduce all vehicle resistances
- Increase the overall vehicle efficiency

The first option means a reduction of all vehicle characteristics such as mass, cross-sectional area, drag coefficient and rolling resistance coefficient. All values are changeable in certain ranges, but inevitably the vehicle will get smaller (seats, payload), less safe (less crash zone, higher accelerations) and/or less comfortable (suspension, less auxiliary units). Some of these disadvantages are compensated with the use of new and better materials, but this raises the costs significantly. If the value range is kept small such that none of the mentioned disadvantages appear the possible benefit in energy consumption is negligible [1].
The second option takes the overall vehicle efficiency into account. This comprises the components of the drive train, as they are directly involved in consuming energy and the combination of this drive train with the car around it. To get the lowest energy consumption for a desired vehicle, the task is to find the appropriate combination and dimensions of these components. Considering all possibilities and value ranges the solution space is very high. However, to reach the goal adequate methods like simulations and optimizations have to be utilized.
One approach is presented in the following.

2 General approach

The challenge of the wanted method is to calculate the result in an acceptable period of time with an acceptable accuracy. To know for what kind of basic vehicle the best drive train has to be found a certain set of parameters is needed. These are:

- Vehicle class (for mass *m*, cross-sectional area *A*, drag coefficient c_w)
- Payload m_p
- Maximum velocity v_{max}
- Acceleration 0-100km/h $a_{0\text{-}100}$
- Gradeability (curb ramp, % at km/h) *s*
- Range *R*

To define the most suitable drive train for this set, first the design parameters, which have relevance on the energy consumption (*EC*), have to be assigned. These are:

- Axle Load distribution *alv*
- Type of electric motors *mt*
- Number of electric motors *mn*
- Position of electric motors *mp*
- Transmission ratio(s) *i*
- Dynamic running radius *r*
- Battery cell type *ct*

With now knowing all input data and parameters a method has to be found, which is able to manage the large number of combinations as well as the dependencies of the design parameters.
As the energy consumption is the target value it is necessary to calculate it for a certain vehicle. Simulations have been an adequate choice to do so [2] and will also be the basis for the calculation here. The modeling concept will be shown in detail in chapter 3.
The size of the solution space requires a method to avoid seeking the best topology manually. Therefore different optimization algorithms exist and have been used to find an optimal solution automatically [3].
Summing all this up the whole method can be described as shown in Figure 1.

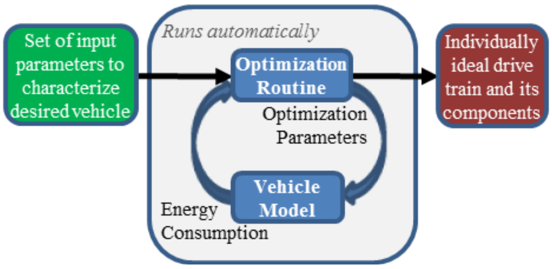

Figure 1: General approach

The set of input parameters is used to calculate a basic characteristic curve (see chapter 2.1). Together with the basic vehicle data it serves as the starting point for the optimization routine (see chapter 2.2). This routine decides about the current set of design parameters for the vehicle model. After the simulation process the model returns the associated energy consumption. Having found the lowest energy consumption, the routine shows the final result. In addition to the actual energy consumption the result consists of the final values of the afore-mentioned design parameters as well as the mass and volume of the drive train components (battery, power electronics, motor, transmission).

2.1 Derivation of basic characteristic curve

To get a proper design of the electric motor the typical constant torque/constant power characteristic has to fit the vehicle's needs. For that curve values like nominal torque/speed, continuous power and maximum speed is needed. To calculate these values, all necessary data are given by the input parameters.

The continuous power is derived either from the maximum velocity or the gradeability depending on which requirement is higher. Therefore the vehicle resistance equations are used with the relevant values of the input parameters. The maximum motor speed derives from the maximum velocity. For all mentioned calculations the dynamic running radius r is set to 0.3m.

To obtain the nominal speed, additionally the desired acceleration is used. The basic idea is that the amount of power needed for the acceleration sequence P_{acc} has to be provided by the motor P_{con}. This means mathematically spoken, that the area/integral of both curves has to be identical (see Figure 2).

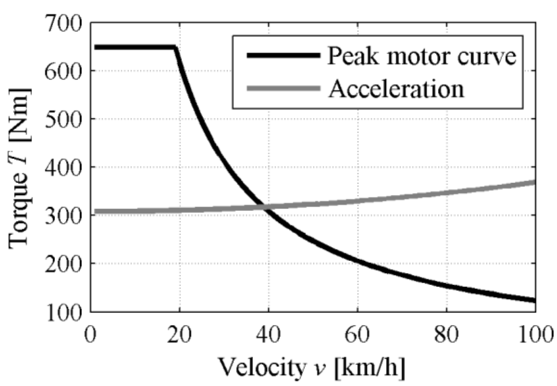

Figure 2: Acceleration and peak motor curve

Setting up the equations and solving them for the nominal speed v_{np}, the solution is:

$$v_{np} = e^{C} * r \tag{1}$$

$$C = 1 + \ln\left(\frac{100}{3.6*r}\right) - \frac{P_{acc}}{P_{con}} \tag{2}$$

$$P_{acc} = \frac{100}{3.6*r} \cdot \left(m \cdot a_m + m \cdot g \cdot f_r + \frac{1}{6} \cdot \varrho_{air} \cdot c_w \cdot A \cdot \left(\frac{100}{3.6 \cdot r}\right)^2 \cdot r^2\right) \tag{3}$$

For the continuous power P_{con} the value from the calculation above is used and a_m is the medium acceleration from 0-100km/h.

The calculated nominal speed is now defined as the nominal speed at peak torque. The nominal torque is set to the half of the peak torque, assuming that the peak torque is only used for some seconds during high accelerations, such as 0-100km/h. A ratio of two for peak torque to nominal torque is a common value for three-phase motors used in vehicle applications. With nominal torque and continuous power, the nominal speed is derived. The last check ensures that the ratio of maximum speed to nominal speed does not exceed a value of three [4]. If this is the case, the continuous power is increased until the mentioned ratio is reached. To get closer to the real-world performance, drive train losses have to be considered. The power and torque values respectively are divided by 0.9, which is a rough estimation at full load.

As a result the derived basic characteristic curve can be seen as the characteristic of a single-motor propulsion system with the transmission ratio 1, which is able to guarantee the desired driving performance.

2.2 Optimization routine

The optimization routine has the task to control the whole process from choosing the design parameters for the vehicle model to processing the result of the simulation for the next iteration. Although some well-known optimization algorithms like genetic algorithms or pattern search algorithms have been successfully used for comparable vehicle optimization problems [5], they all suffer from not being able to find the global optimum of non-smooth and discontinuous functions like in this case. To get better results, especially with a higher chance of finding the global optimum, a new routine has been developed solving the described problem [6].

The approach uses the property of the target function of not being chaotic and is divided in three major steps (see Figure 3).

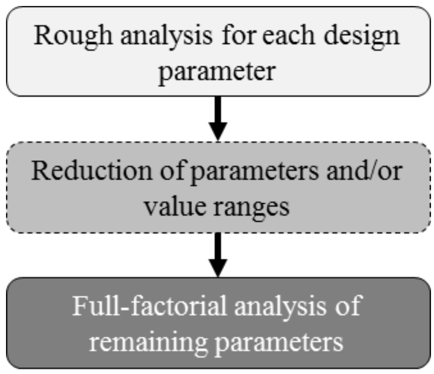

Figure 3: Approach of the optimization routine

In the first phase every design parameter is analyzed separately with a rough value step size. This results in a trend of the energy consumption, like monotony or concentration of good values in a certain value range. Because of being not chaotic all parameters will keep its characteristic even in combination. This information is used in the second step to either eliminate irrelevant parameters in case of a monotone behavior or to reduce the value range to the areas with good consumption values. In the last step a full-factorial analysis of the remaining parameters with reduced value ranges is done.
As shown in [6] the presented method always finds a better optimum in less time than a pattern search or genetic algorithm.

3 Concept of vehicle model

The target value energy consumption is calculated with a simulated vehicle model. Different boundary conditions lead to some requirements the model has to fulfill.

- Communication with optimization routine
- Stable and flexible handling of all possible design parameter combinations
- Objective basis for comparison
- Relatively fast calculation
- Validated models of all drive train topologies

The communication requirement is obvious as model and optimization are exchanging data. The model uses the design parameters to calculate the energy consumption and the optimization needs that value to determine the next set of parameters.
The model has to be very robust towards changing parameters of large scales. As the input parameters theoretically have no boundaries the model has to manage a large scope of vehicle characteristics. For example there should be no problem with a very small and light-weight car with huge power or vice versa. Flexibility is needed as topologies like front-, rear-, all-wheel drives with and without transmission and more are possible solutions. Because the whole process is running automatically it is not possible to change something in the model. Everything has to be done once beforehand.
The optimization analyses and compares the energy consumption of each set of design parameters returned by the simulation. To get comparable data the simulation has to calculate the consumption on an objective basis. Hence driving-cycles are used in the simulation. For one whole optimization process the same driving-cycle is used for every iteration step. The cycle may be changed in a following optimization run with equal input parameters to measure the influence of different cycles on the topology. Of course the simulation will return more realistic consumption values by using customer driving-cycles than synthetic cycles.
The simulation model is called in every iteration step of the optimization. Having detailed models for accurate results the simulation needs a certain amount of time for the calculation. To keep the duration for a whole optimization process in moderate bounds, like some hours on common personal computers, the number of iteration steps as well as the simulation time should be as small as possible. The absolute number of iteration steps is dependent on the performance of the optimization method, which is at a good level as described in chapter 2.2. So additionally the design of the simulation model should regard the calculation time.
To be able to make conclusions on the real world with the help of simulations it is essential to validate the model. For this purpose it would literally imply to build up more or less all possible drive train topologies for different vehicle and power classes to compare their measured energy consumption with the calculations of the model. As this is simply not possible another approach has to be found. The concept of getting a validated scalable vehicle model is shown in Figure 4.

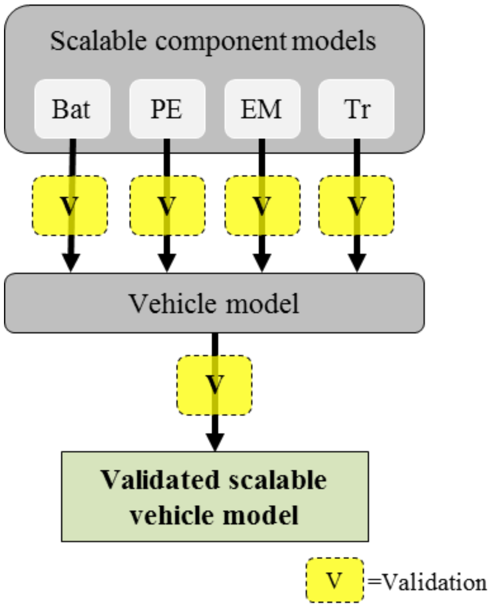

Figure 4: Concept of deriving the scalable vehicle model

This method uses validated scalable component models for the battery (Bat), power electronics (PE), electric motor (EM) and transmission (Tr). The single models build up the general vehicle model. With the validation of the vehicle model itself, conclusions on scaled vehicles are valid. The component and the vehicle models are now described in detail in the following chapters together with the validation results.

3.1 Component models

For each relevant component the modeling concept, the scalable values with its concept and validation results will be presented.

3.1.1 Battery

The literature shows that battery models differ in complexity and field of application. According to [7] the different models can be classified as follows:

- Physical-chemical models
- Equivalent circuit
- Black-Box-Models

The complexity, effort for parameterization and the needed data decrease from top to the bottom. For the goal of this model the concept according to the equivalent circuit seems to be an acceptable trade-off between accuracy and modeling effort.

Losses in batteries appear because of resistances due to electrical effects, namely ohmic losses, and electro-chemical effects, namely polarization losses because of the passage and concentration differences of the charge carriers. Considering theses effects the equivalent circuit is shown in Figure 5.

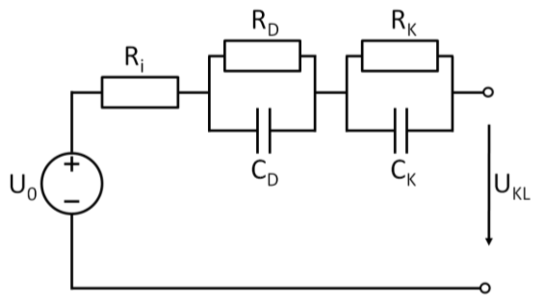

Figure 5: Equivalent circuit of battery model

The equation for the power losses compose of the single loss-parts and that is:

$$P_{loss,bat} = R_i \cdot I_{Kl}^2 + \frac{U_D^2}{R_D} + \frac{U_K^2}{R_K} \qquad (4)$$

Hence the current I_{Kl} affects the losses, which is dependent on the operating point.

If all parameterization data are available the result will have the best accuracy. As the electro-chemical effects have a big relevance on mid- and long-term analysis, the inner/ohmic resistance R_i influences the short-term behaviour. In this case at least R_i has to be known to make conclusions on battery losses in a driving cycle. For the presented model data out of cell measurements are at hand for a cylindrical high-energy and a pouch high-power lithium-ion cell. Besides these parameterization data the following values are necessary to be able to specify the whole battery pack.

Table 1: Parameters of battery model

Parameter	Formula symbol	Unit
Nominal capacity	C_{nom}	Ah
Nominal voltage	U_{nom}	V
Max. discharge current	I_{max}	A
Cell mass	m_{cell}	kg
Cell volume	V_{cell}	l

To calculate the number of cells (nc_{bat}) of the battery system together with cell mass (m_{bat}) and volume (V_{bat}) respectively the following equation is used:

$$nc_{bat} = \frac{U_{sys}}{U_{nom}} \cdot \frac{C_{sys}}{C_{nom}}; \text{with } C_{sys} = R \cdot EC \qquad (5)$$

The battery has to be checked, whether it is capable to manage the current of the maximum vehicle power. If this is not the case the parallel cell number has to be increased until the current of each cell is smaller than the maximum discharge current I_{max}. In either way the choice of high-energy or high-power cells depends on the smaller total number of cells nc_{bat}.

Mass and volume of the battery pack is derived by a multiplication with the given cell mass and volume. Besides the actual cells a battery pack consists of more components on system level. These can be grouped in electric components, battery management system (BMS), housing, structural elements and parts for cooling. [8] states values for the ratio of pack to cell mass and pack to cell volume. Considering BEV the ratio for the mass is 1.5 and for the volume 3.5.

The scalability of the battery model is described by the combination of serial and parallel cells to adapt the battery to different voltage, power and current requirements. As the losses are calculated by using an equivalent circuit for a single cell and the pack consists of these cells, the scaled loss calculation is also valid for the whole battery pack. The validation of a single cell is ensured by using real-world measurement data to parameterize the model.

3.1.2 Power electronics

From an electric point of view the power electronics has the function to conduct voltage and current between battery and motor and to transform direct current (DC) to alternating current (AC) in driving mode and the other way in recuperation mode. These functions cause the occurring main losses in power electronics, switching and conduction losses.
Common power electronics use a six-pulse bridge inverter to transform DC to AC and a six-pulse rectifier for the other way. The inverter uses insulated gate bipolar transistors (IGBT) and diodes as basic components and the rectifier only needs diodes. To calculate the switching (sw) and conduction (cond) losses of these elements the derivation of [9] is used. Hence the equations for the power electronics model are:

$$P_{cond,IGBT} = \left(\frac{1}{2\cdot\pi} + \frac{M\cdot\cos(\varphi)}{8}\right)\cdot U_{CE}\cdot i + \left(\frac{1}{8} + \frac{M\cdot\cos(\varphi)}{3\cdot\pi}\right)\cdot r_{CE}\cdot i^2 \quad (5)$$

$$P_{cond,Diode} = \left(\frac{1}{2\cdot\pi} - \frac{M\cdot\cos(\varphi)}{8}\right)\cdot U_{D}\cdot i + \left(\frac{1}{8} - \frac{M\cdot\cos(\varphi)}{3\cdot\pi}\right)\cdot r_{D}\cdot i^2 \quad (6)$$

Where *cos(φ)* is the power factor and *M* the modulation ratio between the battery voltage and half of the intermediate circuit voltage.
The switching losses are described as:

$$P_{sw,IGBT} = \left(E_{on} + E_{off}\right)\cdot f_s \quad (7)$$

$$P_{sw,Diode} = f_s \cdot E_{rr} \quad (8)$$

Here E is the energy loss, which is dependent on voltage and current. For a scalable model this is approximately linearized as follows:

$$E = E_0 \cdot \frac{U}{U_{ref}} \cdot \frac{I}{I_{ref}} \quad (9)$$

The remaining parameters of the equations can be extracted of data sheets. In sum Table 2 lists all relevant parameters necessary for the used power electronics model.
The overall power loss of an IGBT or diode is the sum of conduction and switching losses. As mentioned before the inverter has six IGBTs and six diodes and the rectifier six diodes. Hence the power loss in driving mode is the sum of IGBT and diode losses multiplied by six, whereas in recuperation mode only the diode losses have to be multiplied by six.

Table 2: Parameters of power electronics model

Parameter	Formula symbol	Unit
Collector-emittor voltage	U_{CE}	V
Collector-emittor resistance	r_{CE}	mΩ
Switch-on energy loss	E_{on}	mJ
Switch-off energy loss	E_{off}	mJ
Current reference	I_{ref}	A
Voltage reference	U_{ref}	V
Voltage diode	U_D	V
Resistance diode	r_D	mΩ
Reverse recovery energy	E_{rr}	mJ
Switching frequency	f_s	kHz

For the scaling of losses, mass and volume a set of available data sheets of power electronic modules are provided in a table. Dependent on the vehicle's power an appropriate module is chosen to get the parameters for the model. To specify mass and volume, empirical values for the whole power electronics system like housing, assembly parts, connectors and cooling are added to the data sheet values.
To validate the power electronics model simulated values are compared to manufacturer's data. Figure 6 shows the results exemplarily for the inverter with a certain module.

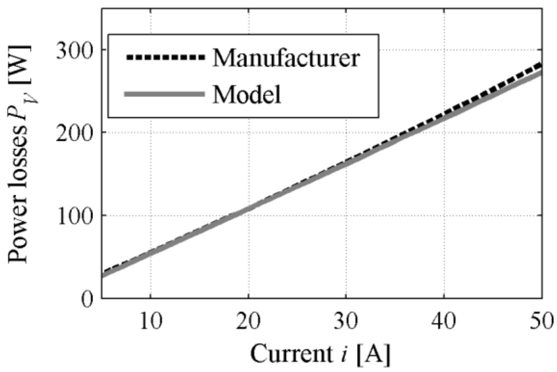

Figure 6: Comparison of model and manufacturer values

An average deviation of 3.2W or 2.2% was reached. For the rectifier the deviation is even less than 1W or 0.5%.

3.1.3 Electric motor

The model of the electric motor has to give information about its losses and its efficiency respectively. It is possible to compile models for the occurring losses, which are copper, iron and friction losses as well as additional empirical losses. For example an advanced equivalent circuit model of an electric motor would produce such information [10]. Therefore a set of parameters is needed like nominal speed, pole count, resistances, inductivities, field flux linkage or reactance. These values are sometimes available in data sheets. For a continuous scalability it is not sufficient to have efficiency maps only for discrete motors of which these parameters are available. The possibility of directly scaling these parameters is not leading to the preferred results. It is undetermined which parameters have to be scaled correctly to cause the desired effect and to keep a certain accuracy and applicability to the real world. Trying to derive these parameters by a rough dimensioning process suffers from the same constraints. A more detailed dimensioning to increase the accuracy of the needed electro-magnetic parameters is linked with a tremendous effort, which would be an own topic [11]. Another well-known scaling method are the laws of growth [12]. They scale a motor geometrically and make conclusions amongst others on torque and power respectively, losses and efficiency respectively and also mass and volume. But the method is limited to smaller scaling ratios (<2), if a certain accuracy is needed.

Here a scaling concept is presented, which offers a sufficient accuracy and only requires efficiency maps. Figure 7 shows the general approach of this concept.

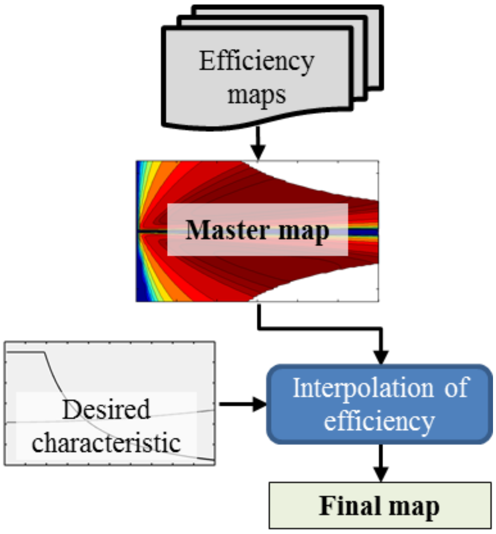

Figure 7: Motor scaling concept

With the set of efficiency maps a master map is generated. Hence the natural upper bounds of torque, speed and power in the master map are prescribed by the single maps with the highest value of these parameters. In consequence the more maps are available the more universally valid the master map gets. This conclusion is reinforced by using efficiency maps of motors developed for automotive applications.

With the desired characteristic (see chapter 2.1) the efficiency values of the final map are a result of an interpolation within the master map.

By using efficiency maps of actual motors this scaling method validates itself. Every possible map generated is in the mechanical, electro-magnetic and thermal real-world bounds. This means a generated map represents a motor, which would possibly be developable.

An interpolation is also used to derive mass and volume of the desired motor with the specifications of the data sheets.

3.1.4 Transmission

To calculate the efficiency of a transmission, very complex calculations are necessary and would exceed the scope of this work. It is sufficient to approximate the efficiency of a commonly used helical geared gear-wheel for spur gears (SG) and planetary gears (PG). The efficiency of a spur gear is more or less constant and a common value is 97% [13]. In case of the planetary gear the efficiency is dependent on the ratio, which is described by the following equation:

$$\eta_P = \frac{(i-1)\cdot 0.97-1}{i} \tag{10}$$

As a spur gear can handle a gear ratio up to six in a single step, higher ratios require a second step. The ratio of the two steps i_{s1} and i_{s2} is given in [13] as:

$$i_{s1} = 0.8 \cdot i^{2/3} \tag{11}$$

$$i_{s2} = \frac{i}{i_{s1}} \tag{12}$$

The efficiency of the two-step spur gear is the square of the single-step version.

The mass of these three transmission types (one- and two-step spur gear, planetary gear) is calculated with the volume of all involved gear-wheels and an appropriate housing multiplied with the corresponding density of the used materials. A common material for gear-wheels is steel (ϱ_{St}). The small parts of other materials in alloys are negligible. For the housing gray iron (ϱ_{GG}) is used. The volume of the gear-wheels V_{gw} is calculated according to DIN 3990, which uses the flank bearing and root bearing to derive its dimensions. The maximum torque T_{max} and the desired transmission ratio i is needed as input data. All the other necessary values in theses equations can be

extracted from the well-known literature for transmissions, like [14].
The following equation shows the calculation for the gear wheel mass m_{gw} and is generally valid for all three types:

$$m_{gw} = \varrho_{St} \cdot V_{gw}(T_{max}, i) \quad (13)$$

For the housing simplified volume models are used for scaling. Figure 8 shows the basic shapes.

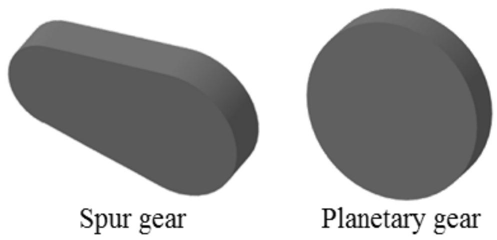

Figure 8: Housing shapes for transmissions

The volume of the housing V_{hous} depends on the size of the inner gear-wheels. Hence the mass of the housing m_{hous} is calculated as:

$$m_{hous} = \varrho_{GG} \cdot V_{hous}(V_{gw}) \quad (14)$$

The choice of the correct transmission type is dependent on the target value. If the goal is finding the smallest or lightest drive train the decision for the best suited transmission type is obvious. Mass and volume is calculated for all three types and the smallest one is chosen. But if the goal is getting the drive train with the lowest energy consumption, lowest mass or best efficiency might lead to an optimum.
Figure 9 shows the dependency of transmission mass and efficiency on the energy consumption for an exemplary vehicle in the New European Driving Cycle (NEDC).

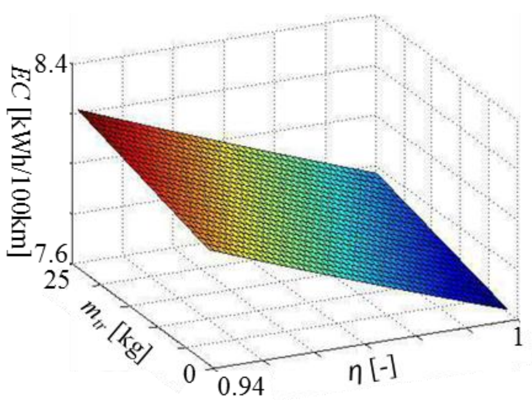

Figure 9: Influence of transmission mass and efficiency on energy consumption

Additionally the slopes of the plane change for different driving cycles. As a consequence once at the beginning of the whole optimization process this kind of diagram has to be calculated with the rough vehicle characteristics and the chosen driving cycle. The schema in Figure 10 shows the whole resulting process of the transmission model.

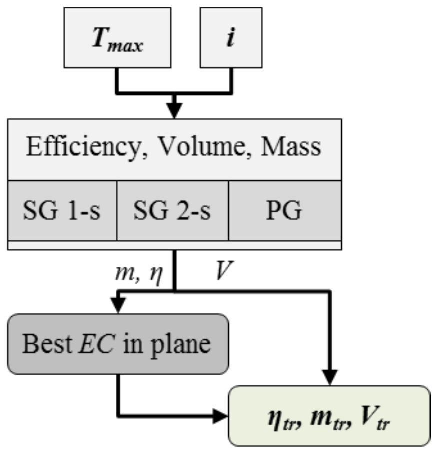

Figure 10: Transmission model concept

3.2 Vehicle model

As mentioned in chapter 3 the vehicle model has to be flexible and modular to manage all possible drive train topologies, vehicle and power classes. For that reason the model is split in two main modules, one for the front and one for the rear axle. Each group consists of the propulsion components, which are electric motor, transmission, brakes and wheels. Battery and power electronics are not directly integrated in the vehicle model. Their efficiencies are merged with the efficiency map of the electric motor, which is used in this model. The vehicle itself with resistance equations, dynamic axle load distribution etc. is modeled in another main module. The energy consumption is calculated on the basis of a driving cycle. A controller uses actual and desired speed of the cycle to force the actuating variables. To meet the model requirements of guaranteeing a stable simulation for each desired vehicle the controller parameters have to be adapted. Empirical tests have shown that the most important stability factor is the ratio of vehicle mass and power. The maximum traction force (adjusted by the transmission ratio) may not exceed the transmittable force when slip is considered. This is intercepted within the model structure. For a traction to transmittable force ratio smaller than 1 the amplification factor of the controller is increased with the same ratio. Figure 11 shows the chart of the vehicle model.

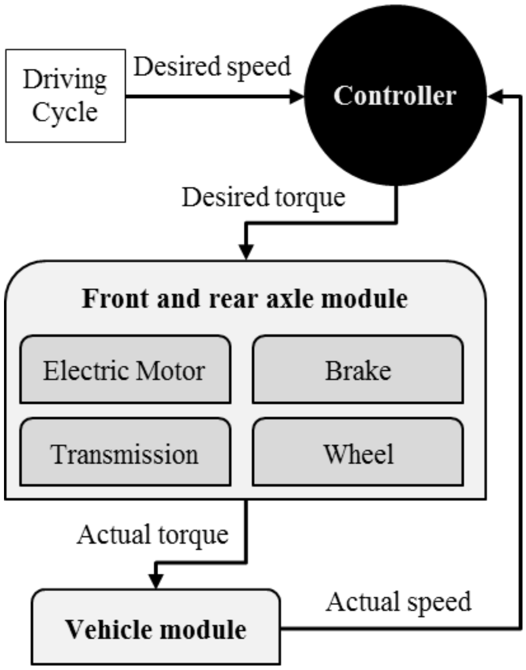

Figure 11: Chart of the vehicle model

For the validation of the model a front-driven electric vehicle with one electric machine and a two-step transmission was available. The vehicle parameters are listed in Table 3.

Table 3: Vehicle parameters

Parameter	Formula symbol	Unit	Value
Mass	m	kg	1540
Drag resistance	c_w	-	0.33
Wheel radius	r	m	0.305
Rolling resistance	f_r	-	0.01
Cross-sectional area	A	m^2	2.04
Wheelbase	l	m	2.47
Distance centre of mass to front axle	l_v	m	1.13
Height centre of mass	h	m	0.4
Gear ratio	i	-	5.35
Nominal/peak power	$P_{n/p}$	kW	45/75
Nominal/peak torque	$T_{n/p}$	Nm	150/240
Battery capacity	C_{sys}	kWh	12

As it was not possible to modify the vehicle with the relevant measurement sensors to capture the energy consumption, another method was used to get the necessary value. A test drive with a fully charged battery was done. The vehicle was equipped with a GPS-logger to get the speed and time correlation of the driven route (see Figure 12), which is needed for the basic data of the reference driving cycle. After the test drive the vehicle was recharged. The charged energy was measured with a clamp meter. To consider only the energy amount used for this drive, the losses of the charger were eliminated by using the mean efficiency of the manufacturer's data.

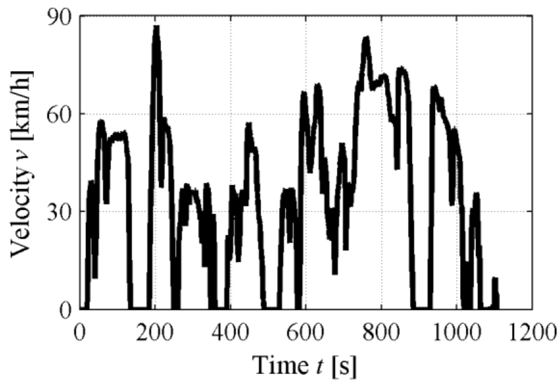

Figure 12: Speed and time characteristic of driving cycle

Hence the energy consumption for this cycle was 20.9kWh/100km. To eliminate influences of the recuperation strategy, the test drive was done without recuperation, which was also applied to the simulation.
The simulation calculates an energy consumption of 19.6kWh/100km for the vehicle model. Considering an unavoidable inaccuracy of the involved component models as well as of the measurement method a discrepancy of less than 7% is an acceptable result.

4 Longitudinal torque-vectoring

If the topology has one motor at each axle the torque is distributed according to their power ratio in driving mode. For example if both motors have the same power, both get the same amount of torque, which is half of the whole desired torque. In recuperation mode the torque is not actually distributed, because the braking torque for each axle is calculated according to the ideal brake proportioning. This braking torque is covered by the electric motor, if the torque is lower than the motor's peak torque. The exceeding torque is supplied by the friction brake.
In the case of having a motor at both axles the possibility appears to distribute the desired torque between these two motors freely. In the model this option can be activated for driving and recuperation mode separately. The general set up of the model is upgraded by an additional torque distribution module, which uses the desired torque

of the controller (see Figure 13). The implemented algorithm distributes the torque according to the lowest energy consumption for driving and highest energy recovery for recuperation respectively. Both cases consider available peak torque and transmittable force, when calculating the distribution.

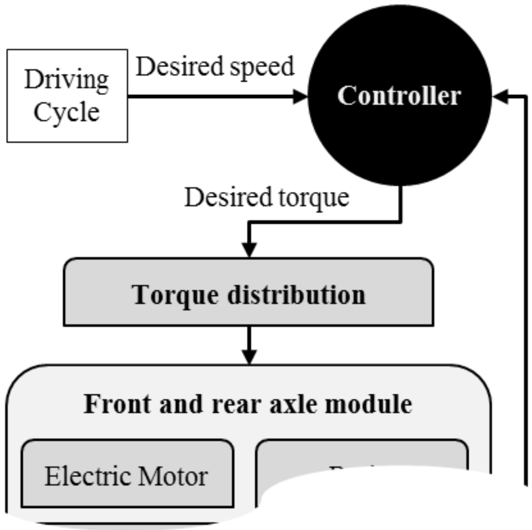

Figure 13: Vehicle model with torque distribution

The gain and influence of the longitudinal torque-vectoring is presented together with some other results in the next chapter.

5 Results

An interesting question to answer on the component level is when to use high-energy or high-power cells to get the smallest battery and the fewest cells respectively. The determining parameters are vehicle power and battery capacity, which is dependent on the desired range and vehicle.

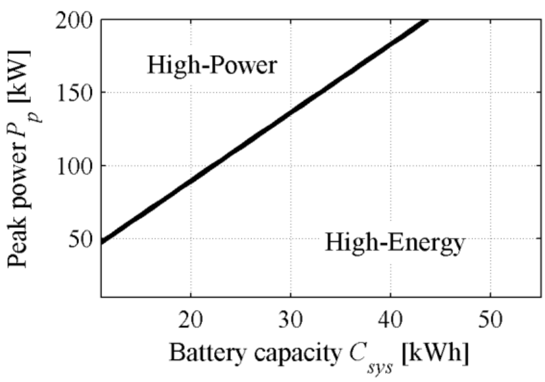

Figure 14: High-energy vs. high-power cells

Figure 14 shows that there is one line separating the upper area, where high-power cells would be the choice, from the lower area, where less high-energy cells would be needed.

Another exemplary result is the influence of the often unvalued parameter axle load distribution, which is shown in Figure 15.

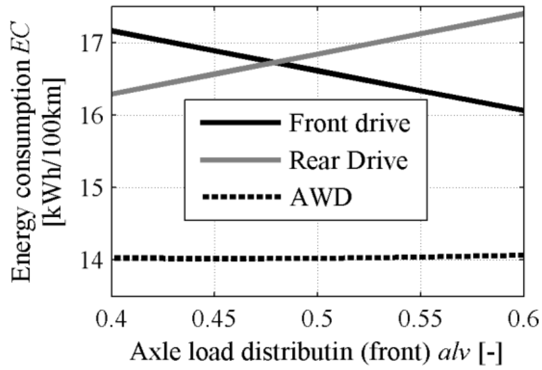

Figure 15: Influence of axle load distribution

The diagram shows the energy consumption of the vehicle presented in chapter 3.2 for the driving cycle of Figure 12 in dependency of the axle load distribution for the original front drive and additionally for the same vehicle and cycle but with rear drive. The results show that the choice of the axle load distribution can make a difference of more than 1kwh/100km. If the topology with a motor at each axle (each half of original motor power) is added to this comparison and the ideal brake proportioning is kept, the energy recovery is of course higher and the influence of the axle load distribution is almost gone.

Now the impact of the longitudinal torque-vectoring is analysed. Again the vehicle and driving cycle of chapter 3.2 is used with the motor topology of the AWD configuration from above. The diagram in Figure 16 shows a step by step comparison between the energy consumption without torque distribution and with distribution in driving and recuperation mode.

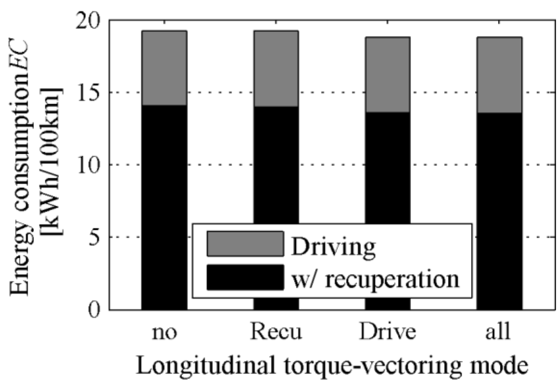

Figure 16: Influence of torque distribution

Each mode only has a slightly benefit in energy consumption up to a maximum of 0.5kwh/100km. A probable assumption of the result for this vehicle, topology and driving cycle combination is that the operation points of both motors are already in good efficiency areas, because of only having half of the power compared to the single-motor configuration. On the other hand this feature does not need additional hardware and contributes to a smaller energy consumption.

6 Conclusion

The presented paper shows a method consisting of an optimization routine and a vehicle model to find the drive train with the lowest energy consumption topology for a desired vehicle. The optimization routine is used to automatically scan the huge solution space to find an optimum. In comparison to well-known conventional optimizers, like pattern search and genetic algorithms, the developed routine finds better results in less time.

To get results that have relevance on the real world it is essential to have a validated vehicle model. Here the validation process includes even the component models, as they have to be scalable to be able to represent all possible topologies, vehicle and power classes. Together with the validation of a general vehicle model, the validity of a scalable vehicle model is ensured.

One exemplarily presented result is the influence of the axle load distribution on the energy consumption. Especially for front or rear drive vehicles the influence of this parameter is responsible for differences up to 1kWh/100km.

With an all-wheel drive topology having an electric motor at each axle the energy consumption decreases and the influence of the axle load distribution is almost gone. This kind of topology also has the possibility of a longitudinal torque-vectoring, which is able to reduce the energy consumption even more. For the analyzed vehicle and topology the benefit of torque distribution is present and hence reduces the consumption a bit more.

The preliminary results promise a right approach to the goal of finding the best drive train topology of an electric vehicle when optimization and simulation are fully integrated.

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