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Derating Strategies for Electric Sports Cars

Tobias Engelhardt[1], Stefan Oechslen[1], Axel Heitmann[1], Hans-Christian Reuss[2]

[1] *Dr. h.c. F. Porsche AG, Porschestraße 911 71287 Weissach, tobias.engelhardt@porsche.de*

[2] *Forschungsinstitut für Kraftfahrwesen und Fahrzeugmotoren Stuttgart (FKFS)*

Summary

Electric motors for sports cars achieve high power densities. In high load cycles, e.g. on race tracks, the components of the powertrain heat quickly. To avoid overheating, the output power of the electric motor must be reduced. This reduction is called “derating” and decreases performance and drivability. This paper proposes a method to optimize race track performance and drivability simultaneously. The method uses validated lumped-parameter thermal networks to predict the endurable power losses in critical components of the powertrain and adapts the allowed output power accordingly.

Keywords: optimisation, powertrain, prediction, simulation, vehicle performance

1 Introduction

Electric sports cars require high output power to reach the intended performance. To at least partially compensate for the high weight of the batteries, the power density of the powertrain should be high. This high power density leads to a rapid increase in temperatures of the powertrain components, such as windings or magnets of the electric motor or semiconductors of the power electronics. If critical temperatures are reached, the output power of the powertrain must be reduced to avoid damaging the components. This reduction of output power is called “derating”. The temperature of the critical components can be controlled dynamically by changing the allowed output power. The temperatures then remain close to the critical temperatures and the thermal potential is exploited fully. However, this approach leads to fluctuations of the available acceleration, negatively affecting drivability. In this sense, performance and drivability are in a conflict of interest. In this paper, a derating strategy is proposed which optimizes performance and drivability simultaneously. [1]

2 Simulation Models

To investigate derating strategies, a vehicle simulation model and detailed thermal models of the electric powertrain are required. The power electronics of the investigated powertrain is non-critical. Thus, only the thermal model of the electric motor is described in this paper. The simulation models are similar to those described in [2].

2.1 Experimental Vehicle

The vehicle used for this investigation only exists virtually. It weighs 1250 kg, has rear-wheel-drive and a maximum velocity of 200 km/h. The electric powertrain however has a real-life equivalent. The electric motor is a permanent magnet excited synchronous machine with 206 kW at 710 V(dc), 250 Nm and a maximum speed of 15,000 rpm. The gearbox has a single speed.

2.2 Vehicle Model

The vehicle is modelled in Matlab and implemented as combined forward-backward simulation, similar to the approach of Wipke [3]. This results in short and constant calculation times and is robust since driver controllers are not necessary. The calculation model starts as backward simulation in every time step (Figure 1). From a velocity profile (Figure 2), the desired velocity, acceleration and the gradient of the road is derived. The traction force to achieve the desired acceleration is calculated. Through the wheels, the propshaft and the gearbox the required motor torque is calculated. This required motor torque (T_{em}) is compared to the currently available torque (T_{max}), which depends on speed, temperatures, battery conditions and the derating strategy. If the required torque is lower than the available torque, the required torque and the desired values are used in the thermal models.

If the required torque exceeds the available torque, the forward simulation is activated. The calculations now start with the available motor torque. From here, through the gearbox, the propshaft and the wheels the traction force is derived. With this traction force, the actual acceleration and velocity are calculated. The available torque ($T_{em} = T_{max}$) and the actual values are used in the thermal models.

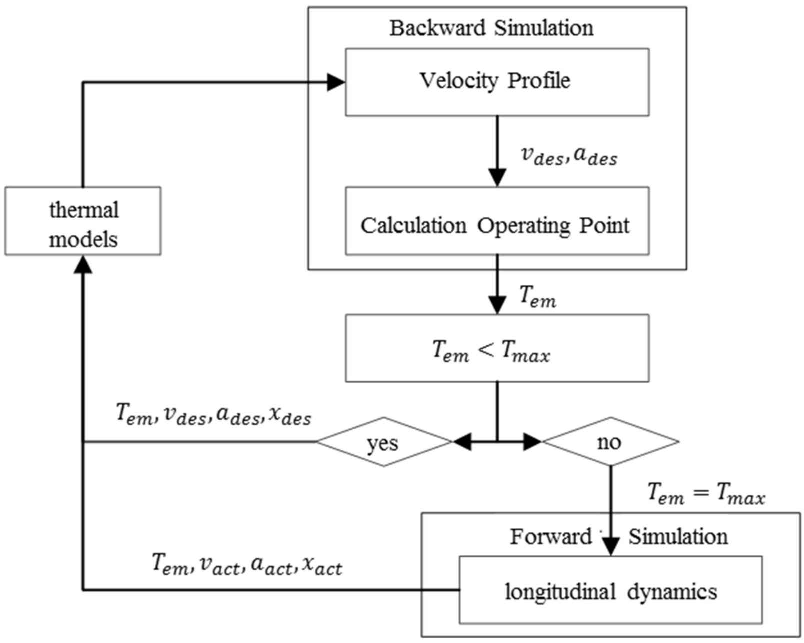

Figure 1: Flow chart of the forward-backward simulation

The velocity profile (desired velocity) is produced by a vehicle simulation including lateral dynamics. The used vehicle model for making the velocity profile must have much higher output power than the vehicle for the derating investigations [4]. On straights, the vehicle for the derating investigations cannot follow the desired velocity and forward simulation becomes active. Backward simulation however is active during braking and cornering. Figure 2 shows the desired and the actual velocity of the vehicle simulation.

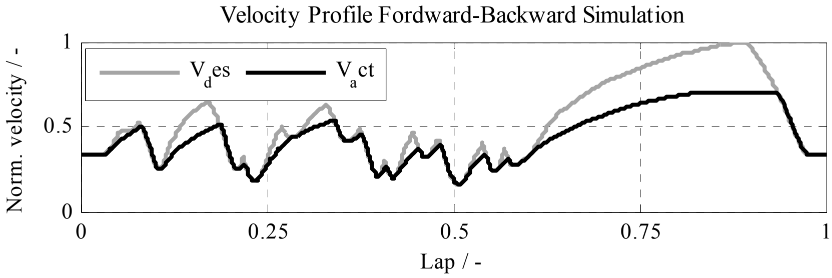

Figure 2: Desired and actual velocity of the vehicle

2.3 Thermal Model

The temperatures within the electric motor must be calculated quickly to minimize simulation times. Hence, a lumped-parameter thermal network is used.

2.3.1 Thermal Network

Thermal networks consist of lumped masses with thermal capacities connected by thermal resistances, which represent heat conduction and convection. Thermal networks yield a system of linear differential equations and allow fast calculations of relevant temperatures within the electric motor, e.g. [5], [6].

Figure 3 shows the thermal network of the electric motor with four heat capacities and four thermal resistances. It consists of heat capacities for the coolant (C1), both end windings combined (C2), the stator iron including the copper windings in the slots (C3) and the rotor iron including magnets (C4). The only heat sink is the coolant, which is modelled with infinite heat capacity to keep its temperature constant. There are three heat sources: Copper losses in the end windings, copper and iron losses in the stator, iron and magnet losses in the rotor [7]. The losses are derived from measurements on the test rig. Copper losses are calculated by measuring currents and the winding resistances. Iron and magnet losses are calculated by subtracting the copper losses and the calculated drag losses from the total losses. The distribution of copper losses between end windings and stator correlates to the copper masses. The distribution of iron losses between stator and rotor is difficult and described in the following section. The linear equation system of the thermal network is solved as matrix operation similar to [8].

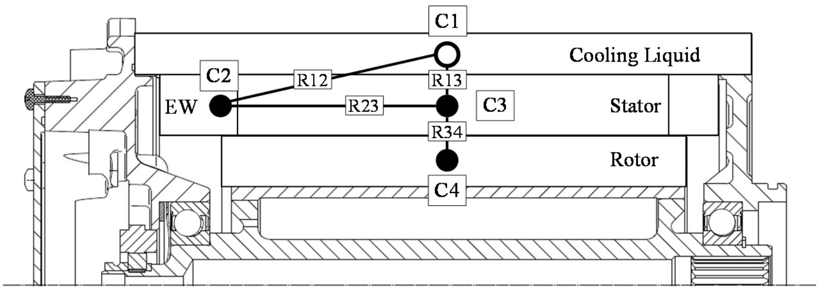

Figure 3: Thermal network of the electric motor

2.3.2 Parameter-Fitting

Predicting the values of the heat capacities and thermal resistances by analytical or numerical calculations is challenging. Also, as Dajaku [6] points out, considering the stator and the rotor as one heat capacity due to their heterogeneous heat distribution is inaccurate. Another source of error is the distribution of iron losses between stator and rotor iron. In order to avoid those difficulties, most parameters of the thermal model, including an iron loss distribution factor, are found by fitting the simulated temperatures to measurements with a genetic algorithm (NSGAII, [9]). Errors in physical modelling are compensated by this process.

The end winding temperature and the rotor temperature are crucial for simulating derating behaviour, so these are command variables. The highest measured end winding and rotor temperature signals from the test bench are used. A load cycle of the Nürburgring is used for optimisation, which is long and diversified. The parameters of the thermal network are varied by the genetic algorithm until the measured and simulated temperature curves converge.

Equations (1) – (3) define the optimisation problem. There are nine optimisation parameters, two target values and no additional conditions. The thermal resistance of the air gap is split in two optimisation parameters $R_{34,l}$ (at 0 rpm) and $R_{34,h}$ (at max. rpm), which yields a linear speed dependent thermal resistance. The iron loss distribution factor is labelled as f_{fe}. The two target values, F_{ew} and F_{rt}, are squared deviations of end winding and rotor temperature.

$$\underline{y}^* = \min_{\underline{p}} \left\{ y = f\left(\underline{p}\right) \right\} \tag{1}$$

$$\underline{p} = \left(R_{12}, R_{13}, R_{23}, R_{34,l}, R_{34,h}, C_2, C_3, C_4, f_{fe}\right) \tag{2}$$

$$\underline{y} = \left(F_{ew}, F_{rt}\right) \tag{3}$$

2.4 Validation

The vehicle model is not validated because it only exists virtually. However, it has been verified by comparing lap time and fuel consumption with an existing vehicle of similar power-to-weight ratio.

The thermal model of the electric motor has to be validated properly, since its behaviour is key to this investigation. Thus, the simulated temperature curves are compared to measured temperature signals from the test bench. The load cycle used for validation may not be the same as used for the parameter fitting, so the load cycle of the test track in Weissach is used.

Figure 4 displays the measured and simulated temperature curves of the validation load cycle over time. The graphical examination shows high congruency. Table 1 contains the temperature deviations at maximum temperature and the mean temperature deviation over time. All values are well below 5 K, which is the tolerated deviation, so the thermal model is considered to be valid.

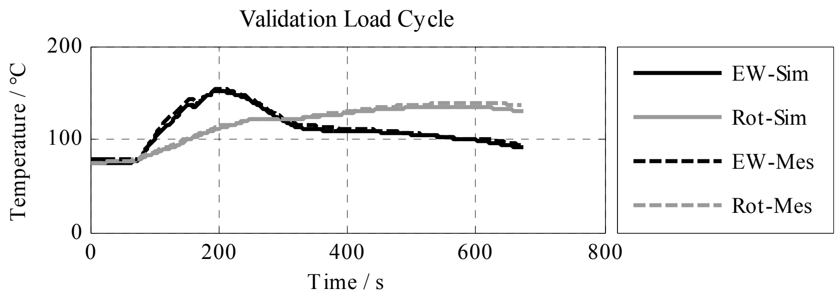

Figure 4: Validation of the thermal model on the test track Weissach load cycle

Table 1: Validation values thermal model on test track Weissach load cycle

deviation max. temp. end windings	deviation max. temp. rotor	mean deviation end windings	mean deviation rotor
1.6 K	3.8 K	2.6 K	2.0 K

3 Derating strategy

The task of the derating strategy is to reduce the output power of the electric motor if necessary to avoid overheating of powertrain components. Derating occurs mostly either if the end windings or the rotor/magnets approach their critical temperatures. In this paper, only derating caused by the end windings is investigated.

3.1 Basic Derating Strategy

Figure 5 shows the derating curve of a basic derating strategy, which is used for benchmarking the new derating strategy. The normalised torque is a function of the temperature signal that is provided by the sensor in the end windings. In this investigation, the temperature signal is replaced by the calculated temperature of the end windings. The normalised torque decreases linearly after exceeding the derating temperature. The normalised torque multiplied by the current maximum torque yields the limited allowed torque. In this case, there is no distinction between positive or negative torque.

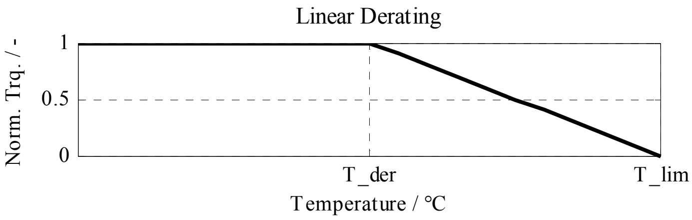

Figure 5: Linear temperature dependent derating curve

3.2 Target Values

As said before, performance and drivability are in conflict and are optimised simultaneously in this paper. Thus, measurable numbers must be used to represent them.

Performance can be measured in lap times, but measuring drivability is more complex. The dominant heat source in the end windings are copper losses. At maximum electric motor load, copper losses of this motor decrease with increasing speed. The temperature dependent derating will thus allow higher normalised torque at higher speeds than at lower speeds. This leads to fluctuations of the normalised torque. If these fluctuations are repeatable and thus the normalised torque is a function of the motor speed, they will not bother the driver. Only fluctuations occurring at the same motor speed degrade drivability. In order to measure speed dependent fluctuations, the fluctuation number is introduced. Every time step of the simulation the normalised torque is provided by the derating strategy and referred to the actual motor speed.

As can be seen in equation (4), the actual normalised torque m_f is subtracted from the normalised torque when the actual motor speed n_{em} has been reached before. The differences in normalised torque are accumulated for all time steps i.

$$f_s = \sum_{i=1}^{z} \left| m_f(n_{em}, i-1) - m_f(n_{em}, i) \right| \qquad f_s = [0, \infty) \tag{4}$$

Since the fluctuation number is a phenomenological unit which makes evaluation difficult, they are used only relatively for comparison.

3.3 Power-Loss-Prediction Derating strategy

The idea behind the power-loss-prediction derating strategy (PLP) is to use information given by the thermal model of the electric motor to predict the amount of power losses within the motor that can be endured without overheating.

3.3.1 Derating Lookup Tables

Derating lookup tables are generated in advance using the validated thermal model. The lookup tables contain the endurable power losses within the critical components (end windings, rotor/magnets) with respect to the motor speed and the inlet temperature of the cooling fluid.

To generate the lookup table, motor speed, inlet temperature and motor torque are varied and for each of these operating points, the steady state temperature is calculated. If the steady state temperature equals the critical temperature of the critical component (in this example the end windings), the power losses corresponding to the operating point is saved in the derating lookup table.

Figure 6 shows the derating lookup table for the end windings. As can be seen, the endurable power losses within the end windings decrease with the motor speed and the inlet temperature of the cooling liquid. Since the influence of the cooling liquid is trivial, the decreasing endurable power losses due to the motor speed can be explained by increasing iron losses within the stator iron. The temperature of the stator iron increases and thus less heat transfer occurs from the end windings to the stator iron. With speed, the end windings reach higher temperatures even if the power losses generated by themselves stay constant.

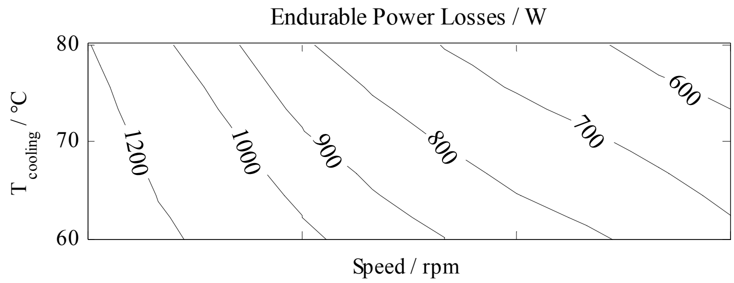

Figure 6: Derating lookup tables

3.3.2 Floating Window

While the vehicle is moving, the power losses in the end windings are recorded (Figure 7, grey line). They can either be measured or read from lookup tables. Within a floating window (Δt_{gl}), the floating average is calculated ($P_{V,fl}$, chain line). Also, within a smaller floating window ($\Delta t_{gl,s}$), the floating maximum value is calculated (black line). From this maximum value, the floating average ($\hat{P}_{V,fl}$, dashed line) is calculated within the bigger floating window.

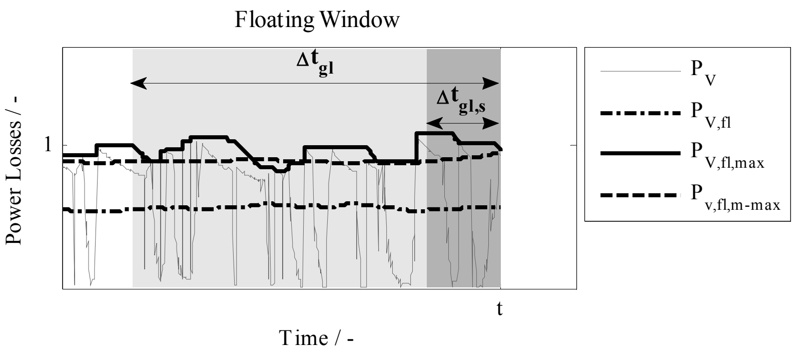

Figure 7: Floating window of power losses

In this process, a filtered load ratio (τ) can be calculated by equation (5). The load ratio quantifies the ratio between the mean power losses and the amplitude of the power losses. A high load ratio occurs if mean power is high compared to the amplitudes with also high amplitudes. This is characteristic for race track operation and yields a high thermal load on the powertrain.

$$\tau = \frac{P_{V,fl}}{\hat{P}_{V,fl}} \tag{5}$$

3.3.3 Derating Process

The PLP has discrete derating states. With a cool powertrain derating is inactive. If a certain threshold temperature is reached, derating becomes active. In this case, there is only one derating mode – derating due to the end windings.

Figure 8 shows the flow chart of the active derating strategy (PLP). The power losses of the end windings are recorded in the floating windows and the load ratio (τ) is calculated. At the same time, the endurable power losses ($P_{v,en}$) are read from the derating lookup table. The endurable power losses are mean power losses, so they are divided by the load ratio, resulting in the endurable power loss amplitudes ($\hat{P}_{v,en}$). The allowed torque (T_{em}) is read from another lookup table (e.g. power losses and torque over motor speed). Since, especially at the windings, the power losses depend on the copper temperature, at active derating the worst case for power losses is always assumed (critical temperature).

There can be a distinction between the motor and generator operation. An additional factor reduces the allowed negative power loss amplitude and thus the negative torque (regenerative braking). This factor is called "negative power factor".

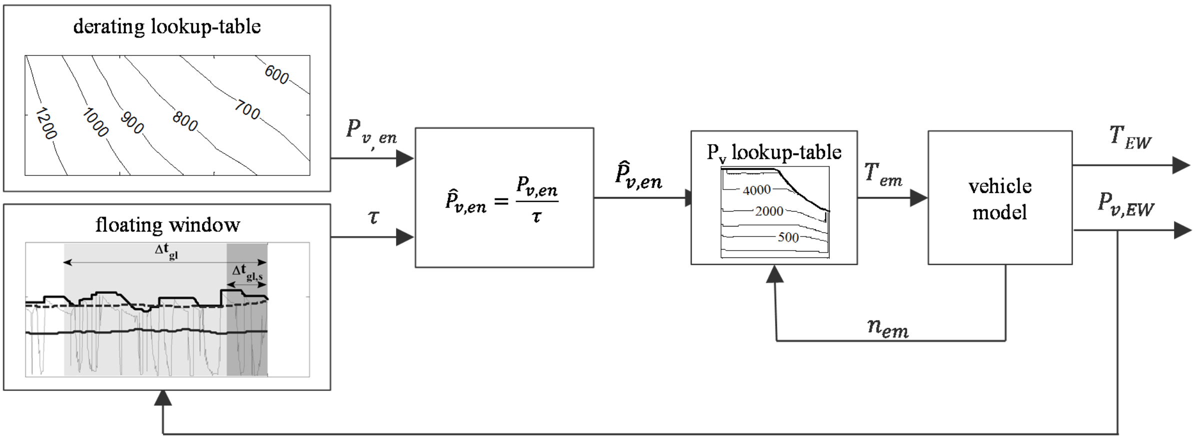

Figure 8: Flow chart of PLP

3.3.4 Optimisation

The optimisation parameters of PLP are the duration of the long (Δt_{fl}) and the short ($\Delta t_{fl,s}$) floating windows and the negative power factor ($f_{pv,gen}$). The values are optimised using an evolutionary algorithm (NSGAII) similar to Chapter 2.3.2 [9]. The target values for the multi-objective optimisation are performance (t_{lap}) and drivability (f_s) as explained in Chapter 3.2. Equations (6) – (8) show the optimisation settings.

$$\underline{y}^* = \min_{\underline{p}} \left\{ y = f\left(\underline{p}\right) \right\} \tag{6}$$

$$\underline{p} = \left(\Delta t_{fl}, \Delta t_{fl,s}, f_{pv,gen}\right) \tag{7}$$

$$\underline{y} = (t_{lap}, f_s) \tag{8}$$

3.3.5 Adaptions

Unlike the basic derating strategy, PLP has no closed-loop feedback from the actual temperature of the end windings, and is as such an open-loop controller. To avoid damaging components in case of inaccuracies in the PLP, a closed-loop controller like the basic derating strategy must be able to overrule PLP as a last resort. Inaccuracies can occur due to manufacturing tolerances or aging effects of the power train components. In order to counterbalance this, a learning factor should be added to PLP, which compares the predicted temperature at active derating with the measured temperature. If there is an offset for a longer period, the learning factor should alter the output values of the derating lookup tables slightly.

4 Results

PLP with optimised parameters is compared to the basic derating strategy. Both derating-strategies are implemented in the vehicle model and five laps of the test track Weissach are simulated.

Figure 9 shows the results of five laps on the test track in Weissach with the basic derating strategy. The temperature of the end windings approaches the critical temperatures of 180° C after about two laps. Close to reaching the critical temperature, derating becomes active and controls the normalised torque accordingly. Due to the fluctuations in the normalised torque without relation to the motor speed, the fluctuation number increases at a constant rate. Drivability is decreased significantly.

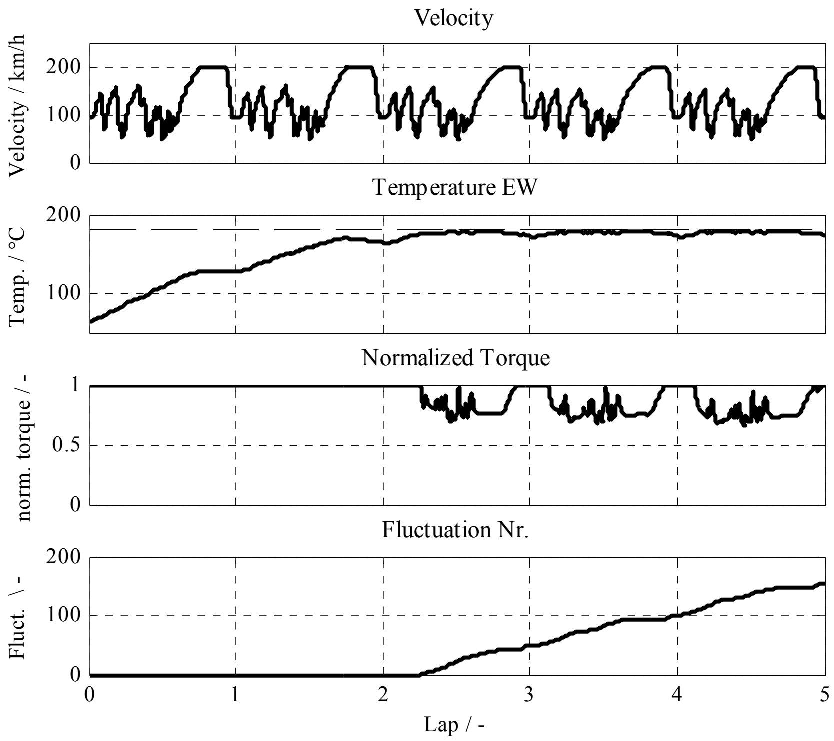

Figure 9: Results 5 laps test track Weissach with basic derating strategy

Figure 10 shows the results of five laps test track Weissach with PLP. Also, the critical temperature is approached in the beginning of the third lap and derating becomes active. The normalised torque is now different in motor and generator mode due to the negative power factor. The shape of the curves also indicates a relation to the velocity of the vehicle, and hence to the motor speed. After an initial adaption phase, the fluctuation number barely increases, so drivability is much better compared to the basic derating.

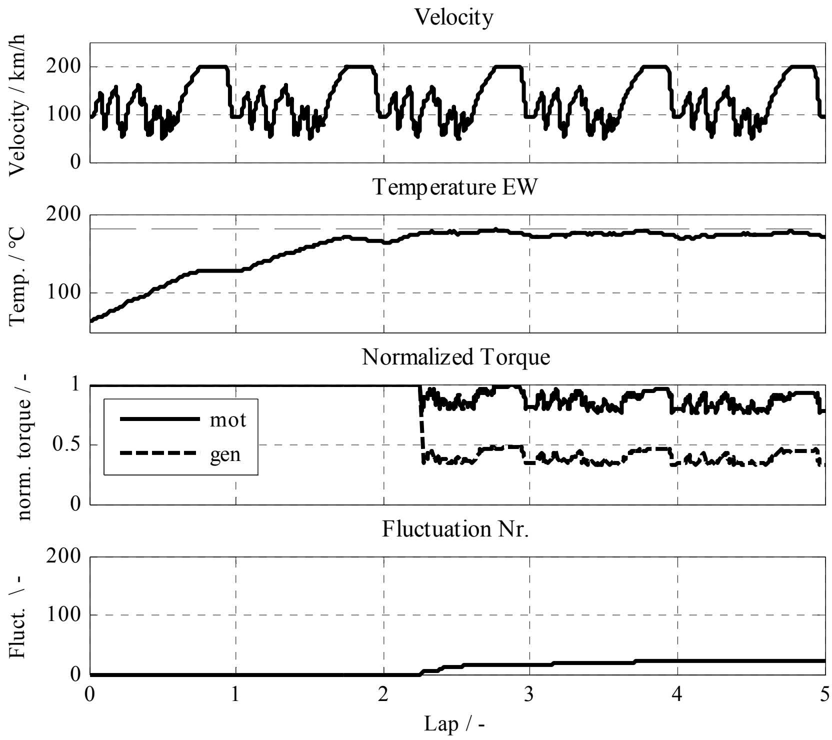

Figure 10: Results 5 laps test track Weissach with PLP

Figure 11 illustrates operating points of the electric motor during the five laps on the test track in Weissach. Many operating points are located along the maximum torque curve. Those operating points occur during the first two laps where the electric motor has not yet reached threshold temperatures. In the third lap, derating is activated by both methods to avoid overheating. With basic derating (left figure), no sharp line is visible neither in motor nor in generator operation. This indicates the fluctuations of the available torque and thus acceleration of the vehicle. Hence, the driver can no longer rely on the reaction of the vehicle to his demands. PLP (right figure) shows sharp lines in motor and generator operation with active derating. Those sharp lines yield modified maximum torque curves at active derating which are adapted to the actual driving profile by the floating windows.

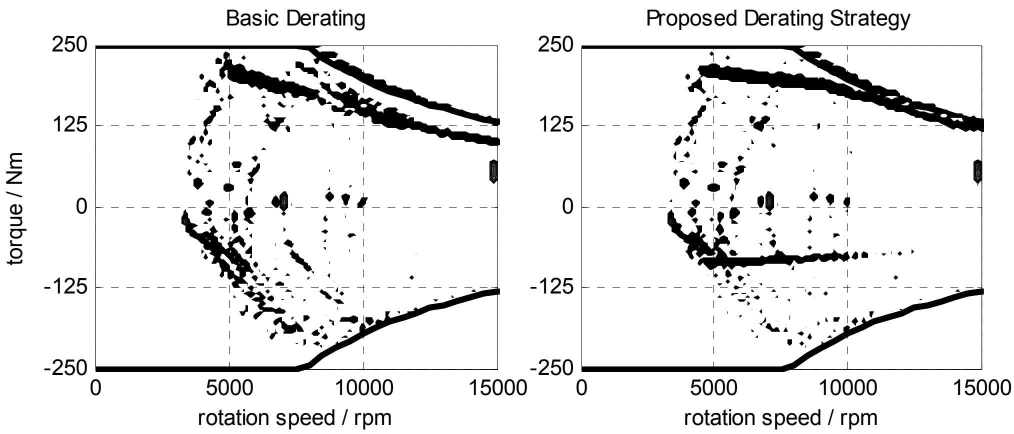

Figure 11: Basic derating (left) and proposed derating strategy (right), 5 laps test track Weissach

Table 2 summarizes the target values and the energy consumption of the vehicle over five laps on the test track in Weissach. Compared to the basic derating, PLP is able to improve both the performance (lap time) and the drivability (fluctuation number). The optimisation of the two target values was successful. However, the energy consumption is higher with PLP. The trade-off between lap time and energy consumption can be adjusted during the optimisation process. In this case, lap time was a target value and energy consumption an additional condition (85 kWh/100 km was not to be exceeded).

Table 2: Results of basic and PLP derating

	Lap time / s	Fluctuation nr. / -	Energy consumption / kWh/100 km
Basic derating	89,2	154,0	76,1
PLP derating	88,8	20,6	84,9

5 Summary

To investigate derating strategies, a vehicle model and thermal models of the powertrain have been developed. The fluctuation number is introduced to quantify drivability. A derating strategy (power-loss-prediction - PLP) is proposed, which uses specific knowledge of the powertrain and an analysis of the actual driving profile to predict the endurable power losses in critical components. The PLP derating is compared to a basic derating strategy, which is based on a closed-loop circuit using temperature sensors for feedback. Results for five laps on the test track Weissach are shown. PLP shows significant improvements for the two target values – performance and drivability. Opposed to the basic derating, PLP shows a modified maximum torque curve at active derating. This new curve is adapted to the actual driving profile by the floating windows and stays constant for the following laps. Thus, the driver can rely on the reaction of the powertrain to his demands without compromising performance within the thermal limits of the electric powertrain.

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Authors

Tobias Engelhardt was born in 1986 in Kitzingen (Germany). From 2006 to 2012, he studied automotive engineering at the University of Stuttgart (Dipl.-Ing.). From 2013 to 2015 he worked for the Research Institute of Automotive Engineering and Vehicle Engines Stuttgart (FKFS). In this time, he participated in a cooperation with the Dr. Ing. h.c. F. Porsche AG which had the aim to develop derating strategies for electric sports cars. Simultaneously, he wrote a dissertation with the title “Derating-Strategies for Electric Sports Cars” which is currently about to be published. Since January 2016, Tobias Engelhardt has been working for the Dr. Ing. h.c. F. Porsche AG in the department of advanced engineering for electric powertrains. His main task is the development of powertrain-concepts and electric motors.

Stefan Oechslen was born in 1985 in Ostfildern, Germany. He received the B.Eng. and the M.Sc. degrees in mechanical engineering from the University of Applied Sciences Esslingen, Germany, and from the University of Stuttgart, Germany, in 2012 and 2014, respectively. Since January 2015 he is with the Dr. Ing. h.c. F. Porsche AG, Weissach, Germany, in the department advanced engineering drivetrain and electric drives. His main task is the development of cooling concepts of electric motors. Simultaneously he is researching in this field and working towards the Ph.D. degree in cooperation with the University of Stuttgart.

Axel Heitmann was born in 1968 in Erlangen, Germany. He received the diploma and Ph.D. degrees in mechanical engineering from the Technical University of Munich in 1993 and 1998, respectively. In 1999, he joined ZF Friedrichshafen AG, Friedrichshafen, Germany, as advanced engineering specialist. From 2004 to 2012, he was with Audi AG, Ingolstadt, Germany, as advanced engineering specialist and project manager. Since 2013, he has been with Dr. Ing. h.c. F. Porsche AG, Weissach, Germany, as manager advanced engineering drivetrain and electric drives.

Hans-Christian Reuss was born in 1959 in Düsseldorf, Germany. He received the Dipl.-Ing. and the Ph.D. degrees in electrical engineering from the Technical University of Berlin, Germany, in 1984 and 1989, respectively. From 1989 to 1993, he was with PHILIPS Semiconductors Application Laboratory in Hamburg, Germany. In 1993 Dr. Reuss became professor at Dresden University of Technology, Dresden, Germany. In 2004 Prof. Reuss moved to Stuttgart to take over the chair of Automotive Mechatronics at the Institute of Internal Combustion Engines and Automotive Engineering (IVK) and to become a member of the management board of the Research Institute of Automotive Engineering and Vehicle Engines Stuttgart (FKFS).