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Power for traction characterized by normal distributions

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Abstract

Most studies on power train design rely on deterministic driving cycles to define the vehicles longitudinal speed. Especially simulations on hybrid propulsion systems use driving cycles to define the speed sequence of the vehicle and backwards calculate the power for traction. Disadvantages of this deterministic approach are the limited value of one driving cycle to represent real-life conditions and the possibility of 'cycle beating' in optimizations.
Observations suggest that the distribution of the power for traction is more easily characterized than the distribution of the speed, as it tends to a bell-shaped curve. This study proposes to approximate the bell-shaped distribution with a normal (Gaussian) distribution when considering sizing hybrid electric propulsion system with a fixed gear ratio. This proposal is motivated from simulations, chassis dynamometer experiments and real-world data. In addition, mean and variance of the normal distribution are linked to the parameters of the vehicle and the properties of the driving cycle under consideration.
The resulting characterization of the power for traction with a normal distribution provides a more generic specification for the vehicles power demand than deterministic driving cycles. This simplifies decisions on the sizing power train components and the engineering of the energy management system, as results not only hold for one driving cycle but for all driving conditions that match the same statistical distribution of the power for traction.

Driving cycle, Characterization, Power distribution, Power train design, Component sizing

1 Introduction

1.1 Background

As hybrid power trains comprise a storage, it is not sufficient to size the power train components on specifications as acceleration time and top speed only. Therefore, many design studies on hybrid power trains use driving cycles -time sequences of speed samples (m/s)- as input to simulations that define the required power for traction (W) [1, 2]. Such simulations are used for component sizing [2, 3, 4, 5, 6] and the design of energy management strategies [7, 8, 9, 10, 11, 12].
For different vehicle classes and purposes, general accepted driving cycles are available. Examples are the NEDC for passenger cars, the FTP75 and JE05 for light and heavy duty vehicles in an urban environment and the Braunschweig, NYbus and Beijing Bus cycle for buses [13, 14]. As most of these cycles were initially developed for emission tests, initiatives as the LA92/UCDS as successor of the FTP75 [13], the ARTEMIS project [15, 16] and others [17] intend to provide cycles more suitable to modern requirements as a minimum fuel consumption, including hybridized propulsion systems. These driving cycles provide useful deterministic requirement definitions for several applications. Still, the cycle chosen will never be driven in real life [18]. They fall short when designing actual power trains. Then sizing the system components and engineering the vehicles energy management system need a better and richer cycle definition for specific vehicle and traffic circum-

stances, less depending on a deterministic series of speed points [19, 20].

For energy management systems, one approach to reduce this cycle dependency is to include an online cycle prediction. Such a prediction can be based on statistics and historic data [21], on GPS and navigation data [21, 22] or on dynamic traffic routing information [23, 24]. Prediction can help to increase the performance and robustness of the energy management system, but it does not support the sizing of the components in the design phase. For sizing, a characterization less depending on a predefined speed sequence is needed.

Considering characterization for design, techniques are proposed as fuzzy logic and neural networks [18, 25, 30], time series analysis [26] or statistics based methods as principle component analysis (PCA) [27]. In [28], a method is presented that generates random driving cycles with statistical and stochastic properties similar to a driving cycle provided as 'seed' to the generator. This reduces the risk of 'cycle beating' in design optimization. In a broader context, characterizations for other purposes are presented, such as the characterization of driving styles [29, 30].

The methods and approaches discussed consider a driving cycle as a sequence of *speed* samples over time (m/s). Still, propulsion systems have to provide the *power* for traction (W). Therefore, this study explores if a characterization of driving cycles in terms of power for traction is an attractive alternative.

1.2 Objective and outline

Objective of this paper is to motivate that the statistical distribution of the *power* for traction for an electric propelled vehicle, driven by a human, tends to one bell-shaped distribution. Such power distribution can cover a complete class of driving cycles.

In addition, the paper proposes to approximate this distribution with a normal distribution. The parameters of such distribution are easily linked to vehicle parameters and some key characteristics of a driving cycle representing the traffic environment. The paper provides this relation using a general vehicle model and explores the possibilities for component sizing in fuel cell hybrid electric power trains.

2 Observations

2.1 First observations

Experiments with different vehicles, different driving cycles and different conditions resulted in substantial data of speed and power for traction. This data is obtained from a delivery van (Fiat Doblo), a mid-size distribution truck (Hytruck) [6] and an articulated trolley bus. Although different, these vehicles have an electric propulsion system with one fixed gear in common.

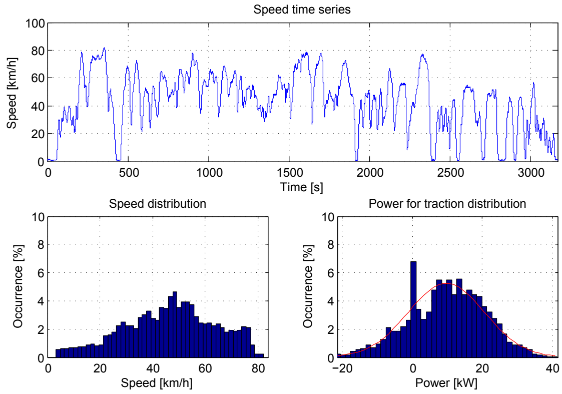

Figure 1: Example measured speed and power distribution delivery van.

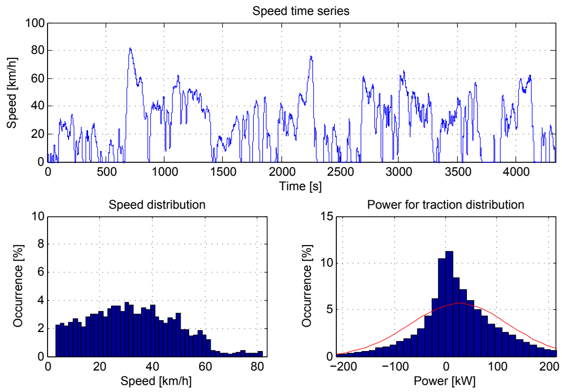

Figure 2: Example measured speed and simulated power distribution trolley bus.

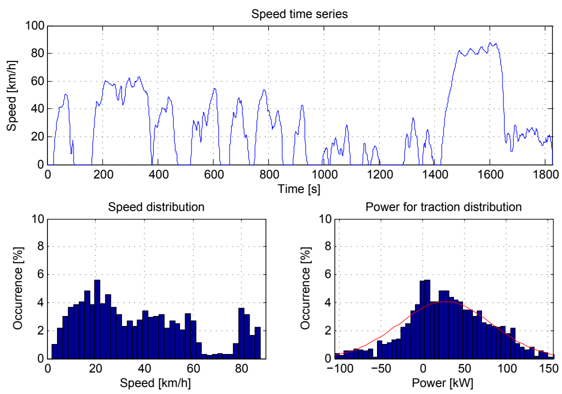

Figure 3: Example predefined speed and simulated power distribution mid-size truck.

From these experiments, three examples are presented:

- Figure 1 shows a trip of the delivery van through a suburban traffic environment, where both speed and power for traction are measured through the logging system on the vehicle.

- Figure 2 shows a driving cycle of the trolley bus in a rural area, where the speed is measured and the power for traction is derived through a vehicle model.

- Figure 3 presents simulation results where the JE05 standard is used as driving cycle, representing a mix of urban and suburban traffic conditions as traffic environment [13]. The power distribution is derived through a vehicle model of the midsize distribution truck, validated on component level [6].

Despite the differences in vehicle class and the significant differences in speed distributions, the distributions of the power for traction show some resemblance. All experiments provide bell-shaped distributions for the power for traction. Still the experiments cover a relative short time, resulting in an average number of samples per bin less than 70, making it difficult to draw statistical sound conclusions.

2.2 Long-term measurements

To cover the short observation time in the previous examples, an additional experiment was conducted, where measurements of both speed and power for the delivery van were logged over several days of operation. The resulting distributions are presented in figure 4 with the standstill/idling times skipped from the data.

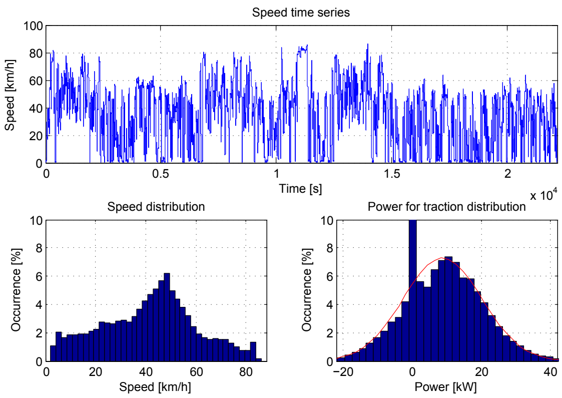

Figure 4: Speed and power distribution mid-size truck.

The experiment includes rides in the city, the suburbs and the countryside. Where the distributions presented in the previous examples refer to flat terrain, the distributions of figure 4 also include trips in some more rugged terrain.
This experiment, including over six hours of driving, supports the suggestion that, over a longer horizon, the distribution of the power for traction is bell-shaped with as exception a spike at zero power.

2.3 Chassis dynamometer results

To verify if such a bell-shape distribution also holds for predefined styled cycles as the NEDC, a comparison is made between the NEDC as simulated driving cycle and the NEDC tested on a roller test bench using the delivery van [31]. The NEDC Low Power version is used to reflect the capabilities of the considered vehicle. Figure 5 presents the results for simulation and figure 6 presents the results derived from the roller test bench.

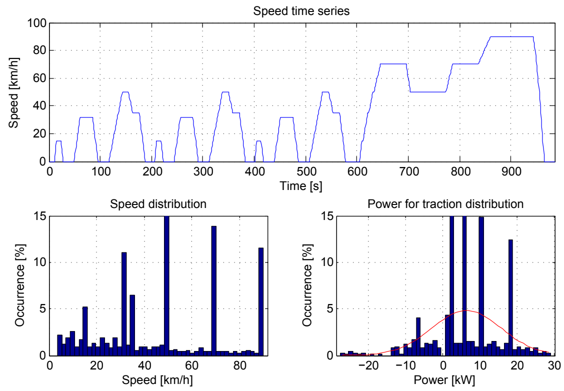

Figure 5: Simulation results for NEDC Low Power.

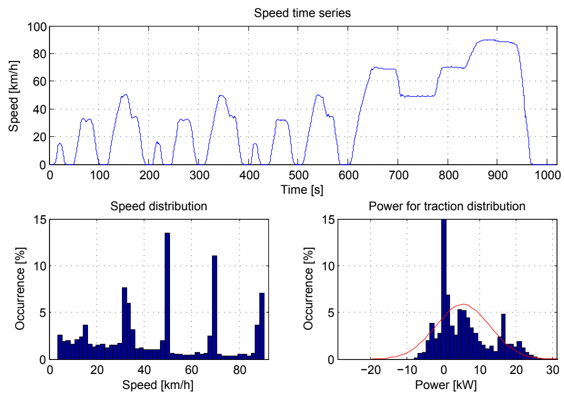

Figure 6: Chassis dynamometer results for NEDC Low Power.

Clearly, the simulated case does not result in a bell-shaped distribution, as the number of samples is limited and as the NEDC Low Power driving cycle is superficially constructed. The measured speed distribution resembles the original NEDC Low Power cycle: the dominant velocities are still clearly visible. The power distribution however is much more blurred.
To evaluate the difference between a real-world driving cycle and an experiment on the roller test bench, the measured driving cycle of figure 1 is replayed on the chassis dynamometer. The results are presented in figure 7. Except for a spike around 8 kW, both speed and power distribution resemble the results of figure 1. This indicates

the roller test bench is useful to represent real-life conditions with respect to speed and power distributions.

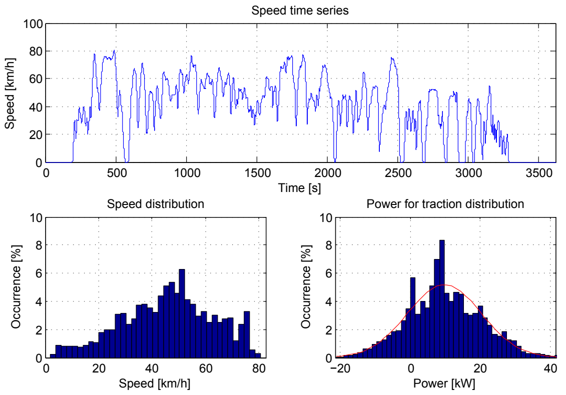

Figure 7: Chassis dynamometer results for real world data.

3 Motivation for a normal distribution

3.1 Hypothesis

Both in measurements, roller test bench experiments and simulations and for different vehicles, the distributions of the power for traction show bell-shaped curves, especially when driving cycles with a significant duration are evaluated. With respect to sizing, a much longer time is considered: the lifetime of the vehicle. Extending the horizon of observation to the lifetime of the vehicle, it is stated that the distribution of the power for traction is bell-shaped, with a peak around zero due to idling. Steady power consumption by auxiliaries or electric heating would shift this peak to non-zero values. With respect to the shape of the distribution, it is postulated that *over the lifetime of the vehicle, the distribution of the power for traction is reasonably approximated with a normal distribution*. A peak at zero to represent idling might be included when convenient, coasting will not introduce a peak as will be explained later.

3.2 Motivation

The motivation for this hypothesis is based on the combination of driver behavior and vehicle properties, as indicated in figure 8.
The figure presents a model of the driver and vehicle interaction with respect to the vehicle speed, based on [32]. Using the information of the surrounding traffic environment, the driver continuously generates a setpoint v_{ref} for the desired speed of the own vehicle. Using the observed speed v of the own vehicle, the driver acts as controller by changing the power for traction

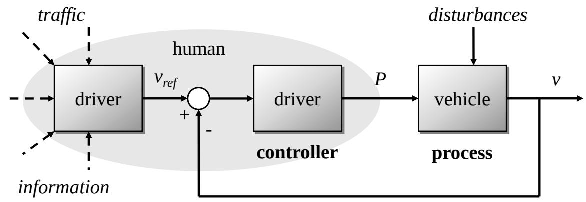

Figure 8: Power for traction as the result of a control loop.

P with the throttle pedal to reduce the difference between actual speed v and desired speed v_{ref}. The relation between the power for traction P and the vehicle speed v is generally represented with the next anti-causal relation or backwards vehicle model [33].

$$P = \frac{1}{2}\rho A c_x v^3 + M g f_r v + (M + m_j)\, v\dot{v} \quad (1)$$

Here, ρ presents the density of air (kg/m^3), A the frontal surface area of the vehicle (m^2), c_x the air drag coefficient (-), M the vehicle mass (kg), g the gravity constant of 9.8 (m/s^2), f_r the rolling resistance coefficient (-) and m_j the equivalent mass of the rotating inertias (kg).
Relation (1) shows the input-output relation from power for traction P to speed v has a low pass behavior. Therefore, the driver as controller acts as a differential action to speed up the response of the vehicle. But as capabilities of the driver with respect to response times are limited, the overall transfer function from desired speed v_{ref} to power for traction P is low pass. More precisely, literature proposes to approximate human control loops with a first order transfer function with delay [32, 34, 35].
For (linear) low pass transfer functions it can be proven that regardless the amplitude distribution of a random input signal, the output signal is normal (Gaussian) distributed. At least part of the traffic information that results in the desired speed v_{ref} will be uncorrelated or random. As the transition from the desired speed v_{ref} to the power for traction P is considered low pass, the distribution of the power for traction will evolve towards a normal distribution [36, 37].
Variables as wind speed and the inclination of the road are considered disturbances in the control loop. Over the lifetime of the vehicle, also the number of passengers and amount of payload can be considered disturbances. As several of these disturbances are uncorrelated, over time, based on the Central Limit Theorem [36, 37], these disturbances further support a normal distribution.

3.3 Coasting and gear shifting

When the control loop of figure 8 is interrupted, the motivation for a normal distribution partly fails. This is the case during coasting (the driver

releases the throttle pedal and just accepts the resulting speed change) and during gear shifting (again the throttle pedal is released and for a short moment the power for traction is reduced to zero or a constant low level). Therefore, the throttle pedal in the vehicle used in the experiments is programmed such that releasing the throttle results in a maximum regenerative braking and thus a significant deceleration. Although this behavior of the throttle pedal is uncommon in ordinary gasoline vehicles, it is implemented as such in different electric vehicles from forklifts to busses as it does maximize regenerative braking. As a consequence, coasting is not possible with such vehicles.
To examine the impact of interrupting the control loop by coasting and gear shifting, an additional experiment is done with the delivery van. During this experiment, the throttle pedal is reprogrammed such that it imitates the throttle behavior of an ordinary gasoline vehicle. When the throttle is released, a limited amount of power is regenerated from the kinetic energy of the vehicle. In addition, a 5-shift manual gearbox is used.

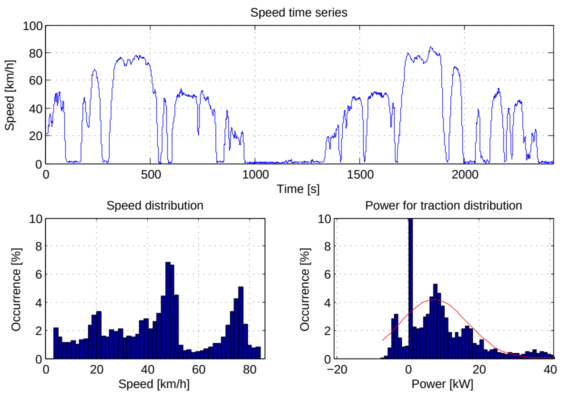

Figure 9: Distributions under gasoline vehicle imitating conditions.

As the resulting distributions of speed and power presented in figure 9 show, an additional power peak on the 'throttle released' power is visible, and the resemblance with a normal distribution is diminished. Apparently, the driver's behavior is affected by the programmed behavior of the throttle pedal. These results support the control loop as model for the interaction between driver and vehicle, provided the driver continuously controls the power for traction. This is also in line with the NEDC Low Power simulations of figure 5, where the power for traction is not the result of a control system, but from a single backwards relation (1).

3.4 Remarks

Still, the motivation for a normal distribution is an observation supported with arguments, but not considered a proof. The vehicle the driver controls is a non-linear process. This hinders a mathematical proof. Unlike linear input-output relations, non-linear properties result in higher order harmonics at the output. Therefore, ultimate low pass behavior can not be guaranteed.
Another property of a (static) nonlinearity is that it can deform the shape of the distribution. This is observed in examined distributions as some asymmetry around the average power. With respect to sizing, this does not disqualify the normal distribution as approximation, but demonstrates the normal distribution is an approximation indeed.

4 From vehicle parameters to a normal distribution

The mean μ_P and variance σ_P^2 of the normal distribution approximating the power for traction are linked analytically to vehicle parameters and key properties of the driving cycle considered, through the vehicle model (1).

$$\begin{aligned}\mu_P &= \langle P \rangle \\ &= \left\langle \tfrac{1}{2}\rho A c_x v^3 + M g f_r v + \tfrac{1}{2} v\dot{v} \right\rangle \\ &= \tfrac{1}{2}\rho A c_x \left\langle v^3 \right\rangle + M g f_r \langle v \rangle + \tfrac{1}{2}\langle v\dot{v} \rangle\end{aligned} \tag{2}$$

Here, $\langle . \rangle$ indicates the expectation value. In (2), the expectation value for $v\dot{v}$ is zero under the condition that both initial and final velocity are zero. This is true over the lifespan of the vehicle and for all standard driving cycles. Therefore the mean of the normal distribution, representing the average power for traction, is given as:

$$\mu_P = \tfrac{1}{2}\rho A c_x \left\langle v^3 \right\rangle + M g f_r \langle v \rangle \tag{3}$$

Also based on vehicle model (1), variance σ_P^2 is derived.

$${\sigma_P}^2 = \left\langle P^2 \right\rangle - \langle P \rangle^2 \tag{4}$$

with

$$\begin{aligned}&\left\langle P^2 \right\rangle \\ &= \left\langle \left[\tfrac{1}{2}\rho A c_x v^3 + M g f_r v + (M + m_j)\, v\dot{v} \right]^2 \right\rangle\end{aligned} \tag{5}$$

All expectations $\langle v^n \dot{v} \rangle$ for the driving cycle v are zero under the easy condition that both initial and final speed are zero. This reduces the number of cross terms. Hence, expectation $\left\langle P^2 \right\rangle$ relates to vehicle parameters and driving cycle properties as:

$$\begin{aligned}&\left\langle P^2\right\rangle \\ &= \tfrac{1}{4}\rho^2 A^2 c_x^2 \left\langle v^6\right\rangle + M^2 g^2 {f_r}^2 \left\langle v^2\right\rangle + \\ &\quad + (M+m_j)^2 \left\langle (v\dot{v})^2\right\rangle + \rho A c_x M g f_r \left\langle v^4\right\rangle \end{aligned} \tag{6}$$

Equations (3), (4) and (6) together provide an analytic relation between a driving cycle as design requirement for the vehicle and its statistical power distribution. Given the power distribution from the long-term experiment with the delivery van presented in figure 4, the normal distribution derived using equations (3), (4) and (5) is compared with the normal distribution based on the measured power for traction, as presented figure 10. Here, vehicle parameters c_x $(= 0.45)$, A $(= 3m^2)$, M $(= 1675 + 2 \times 75kg)$ and m_j $(= 100kg)$ are derived from the vehicle, f_r $(= 0.028)$ is used for tuning. The resulting power distribution covers not only the driving cycle considered, but all cycles representing a comparable traffic environment [28].

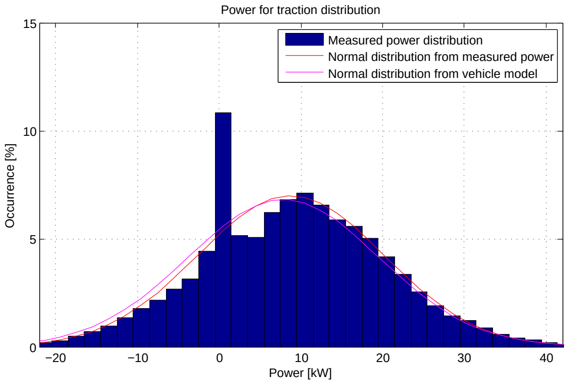

Figure 10: Normal distributions from measured power and vehicle model.

5 Application

5.1 Component sizing for fuel cell hybrid propulsion systems

As an example of component sizing using normal distributions to characterize the power for traction, a fuel cell hybrid electric propulsion system is considered. Based on the expected distribution of the power for traction and a description of the energy management strategy considered, the power distributions for both battery and fuel cell stack can be derived. For example, the fuel minimizing energy management strategy presented in [6] splits the power over fuel cell system and battery according the ratio over their internal losses.

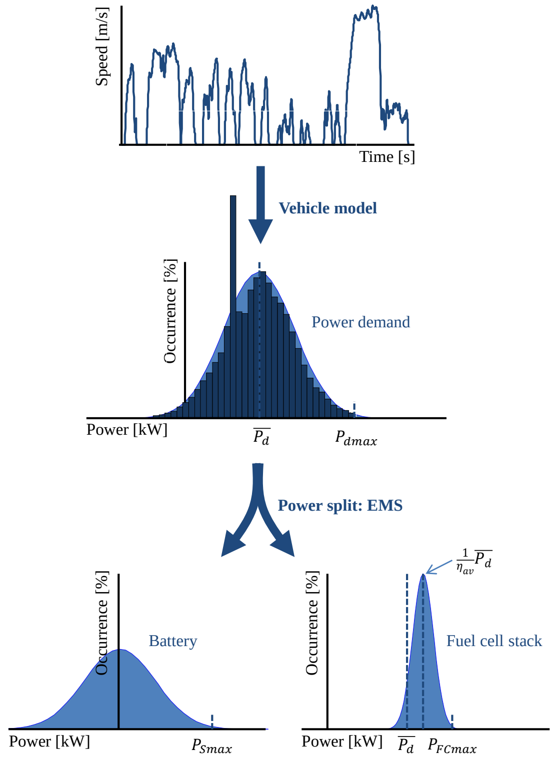

Figure 11: From driving cycle to power distributions per component.

This is summarized with relations (7) and (8), considering a constant power split ratio.

$$P_{FC} = \frac{1}{\eta_{av}}\overline{P_d} + \frac{1}{\eta_{dev}}\phi\left(P_d - \overline{P_d}\right) \tag{7}$$

$$P_S = \frac{1}{\eta_{dev}}(1-\phi)\left(P_d - \overline{P_d}\right) \tag{8}$$

Here, P_d refers to the total power demand, dominated by the power for traction P but also including the power to on board peripherals as heating or the audio system. $\overline{P_d}$ represents the average over P_d. P_{FC} refers to the power the fuel cell system has to provide and P_S to the battery power. The average efficiency of the propulsion system is represented by η_{av} and η_{dev} refers to the propulsion system efficiency with respect to deviations from the average power demand. The power split of these deviations over fuel cell stack and battery is represented by ϕ. Ratio ϕ is defined by the ratio of internal losses in fuel cell stack and battery [38].
With this definition of the EMS, the power distributions for battery and fuel cell stack are derived, as indicated in figure 11. Based on the measured power for traction or a driving cycle in combination with a vehicle model (1), the distribution of the power for traction is derived. When relevant, power consumption of on board peripherals are

included. Next, based on the power split defined by the EMS, the power distributions per component are derived.
The resulting distributions per component support the decisions on their sizing. For example, as the energy management strategy distributes deviations in the power demand over fuel cell system and battery, the deviations in battery power are less than the original deviations in the power demand. Therefore, the rated nominal power of the battery can be less than the maximum deviation in the power demand from the average power.
For the example of the discussed EMS, given the average power demand $\overline{P_d}$ and maximum power demand P_{dmax} fixed by the peak power of the electric motor, the best sizes for fuel cell stack P_{FCmax} and battery P_{Smax} are given as:

$$P_{FCmax} = \frac{1}{\eta_{av}}\overline{P_d} + \frac{1}{\eta_{dev}}\phi\left(P_{dmax} - \overline{P_d}\right) \quad (9)$$

$$P_{Smax} = \frac{1}{\eta_{dev}}\left(1-\phi\right)\left(P_{dmax} - \overline{P_d}\right) \quad (10)$$

These relations show the best sizes of battery and fuel cell stack are balanced through the power split ratio ϕ.

5.2 Classifying hybrid electric vehicles

The problem to characterize unknown distributions is also observed when classifying wind speed and turbulence for wind turbine locations. As the design of a wind turbine suitable for all locations is far from cost-effective, a norm is defined classifying locations into three classes based on average wind speed and standard deviation, *as if* wind is normal distributed [39]. Analogous to this approach, electric propulsion systems could be classified, based on their average power demand and standard deviation, into a limited number of classes. Combined with an optimal EMS, this would limit the number of relevant component sizes for fuel cell hybrid vehicles, making manufacturing fuel cell systems and batteries more cost effective. In addition, every class eventually would obtain its own 'look and feel', for example the urban class, the long distance class, etc. This would level customers' expectations to realistic and cost-effective solutions.

6 Conclusions

Objective of this study was to evaluate if characterizing driving cycles by the *power* for traction is acceptable and beneficial. Experiments with different electric vehicles on the road, on a roller test bench and in simulations, show that the distributions of the power for traction tend to be bell-shaped. Next it is motivated that a normal distribution is an acceptable approximation of this bell-shaped distribution.
Mean and variance of the normal distribution are linked to the vehicle parameters and key properties of the considered driving cycle. The resulting power distribution covers not only the considered driving cycle, but represents a traffic environment from which the considered driving cycle is only one observation. Therefore representing the requirements for a vehicle in terms of a power distribution is more convenient than using one or a limited set of deterministic driving cycles.
As example of the application of normal distributions to characterize the power for traction, sizing the components of a fuel cell hybrid vehicle for a given energy management strategy is evaluated. Finally the possibility to classify electric vehicles according their distribution of the power for traction, comparable to the classification of wind turbines, is discussed.

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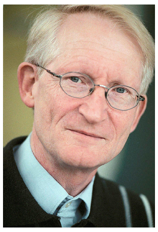

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