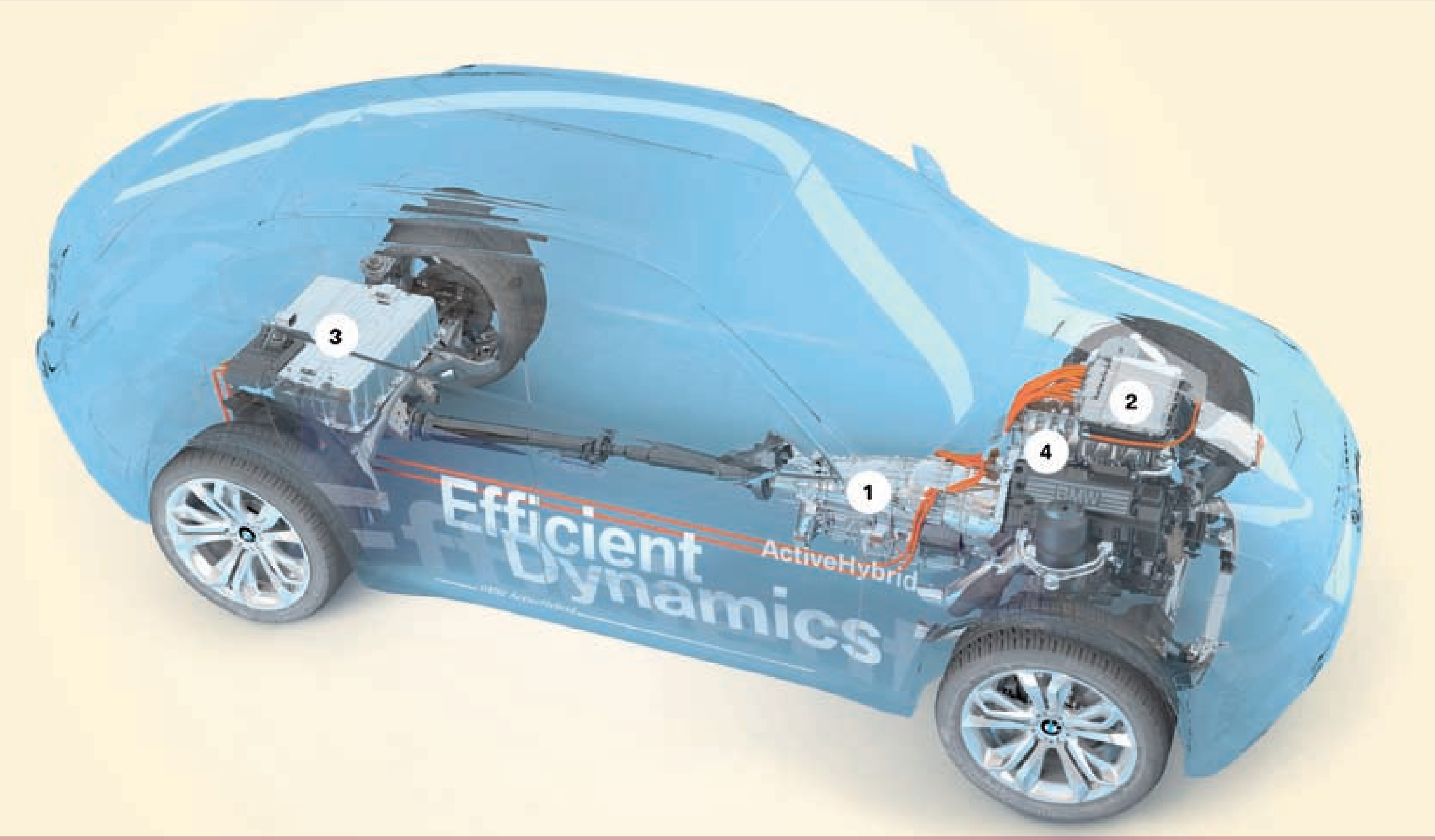

1 Full hybrid two-mode active transmission, 2 Power and control electronics,
3 High performance battery, 4 Highly efficient combustion engine

Driving Situation and Driving Style Dependent Charging Strategy in Hybrid Electric Vehicles

Adaptive and situation-dependent charging strategies of batteries in hybrid electric vehicles aim to resolve the conflict between high efficiency and optimal driving performance. By using inputs from devices such as navigation system, radar and camera, as well as from standard sensors, driving situations challenging the electrical energy storage device are identified and predicted in real time, onboard the vehicle. BMW provides an overview of energy potentials of such adaptive energy functions and presents a method for driving situation classification using fuzzy probabilistic networks.

1 Introduction

Due to the relatively low energy density of electrical energy storage devices, the control strategy of hybrid electric vehicles has to fulfil a variety of requirements in order to provide both, the availability of hybrid functions, and their efficient execution. Energy consuming functions such as electric drive or electric boost need a very high amount of energy stored in the battery. On the other hand, for the optimal use of the energy regeneration a lower state of charge is preferable in order to enable storage of the kinetic energy of the vehicle in all situations, including upon deceleration from high speeds or downhill driving. These diverging requirements yield a conflict of objectives for the charging strategy of hybrid electric vehicles. **Figure 1** shows driving performance measurements of a mild hybrid vehicle marketed today. Depending on the state of charge of the traction battery the time needed for acceleration from 0 to 100 km/h varies dramatically.

BMW proposes a way to overcome the restrictions on driving performance in hybrid electric vehicles without deteriorating overall efficiency. By setting a higher average state of charge only when it is needed – for example during overtaking manoeuvres, dynamic driving style, etc. – the availability of the boost function can be increased significantly. On the other hand adaptive charging strategies allow lower states of charge whenever wide open throttle acceleration manoeuvres are not likely to happen, leading to better use of stored energy for electric drive and higher efficiency.

2 State of the Art

2.1 Charging Control Strategies

Up to now a large variety of methods for controlling the state of charge of traction batteries in hybrid electric vehicles has been published. Online optimization algorithms are a main field of research, most of them not including information about forthcoming driving situations. Their real time capability has been proven at least once [1, 4]. But from the point of view of the automotive industry their compatibility with the established development processes seems to be noticeably lacking. Until the production stage, all functions controlling the drive chain of a vehicle have to go through several stages of development in various departments. The suitability of new energy functions for a hybrid drive chain to a complex and long development process including

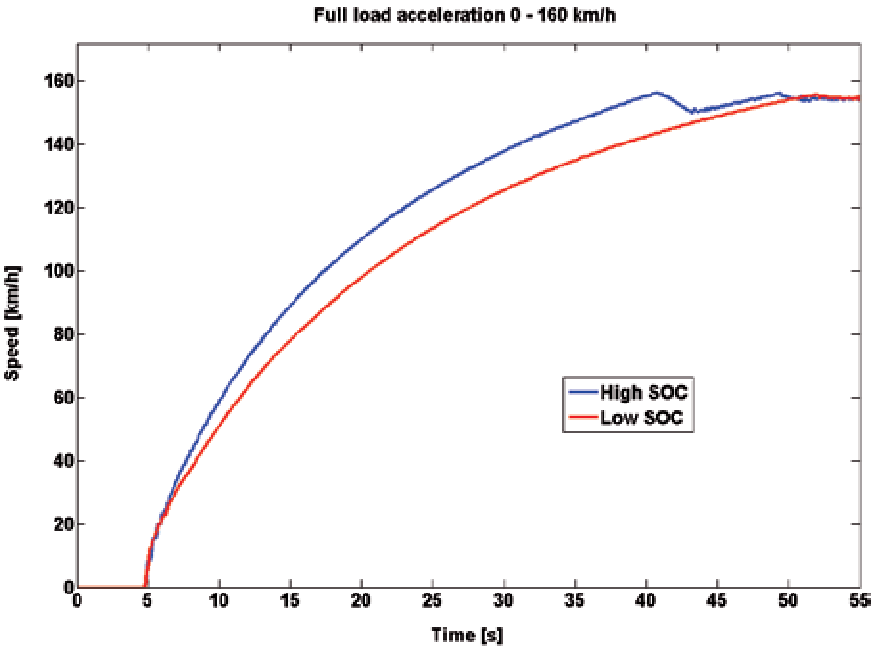

Figure 1: State of charge dependent performance of a mild hybrid

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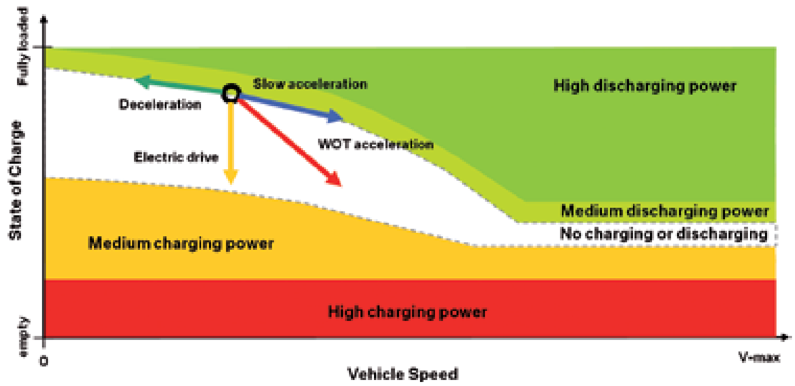

Figure 2: Conventional speed dependent charging strategy

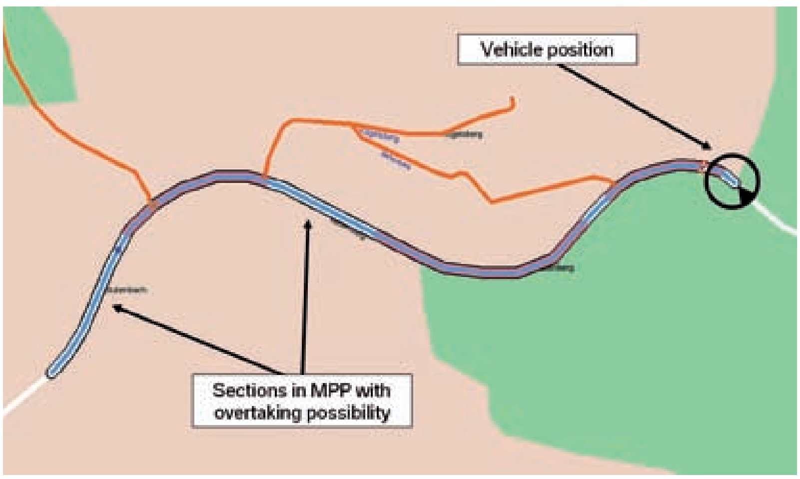

Figure 3: Route estimation with ADAS-Protocol (Advanced Driver Assistance System-Protocol)

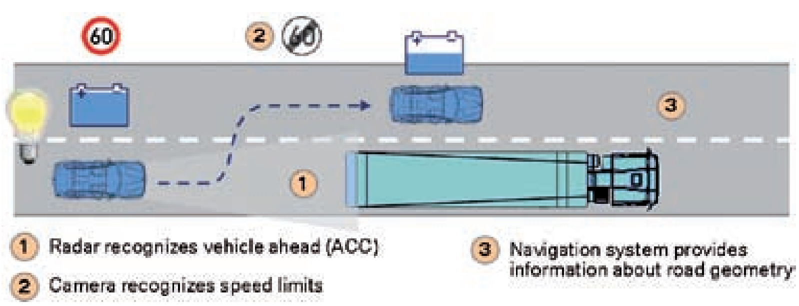

Figure 4: Detection of forthcoming overtaking manoeuvres

vast numbers of developers over many years is a constricting requirement.

The following analysis is based upon a conventional charging strategy for parallel hybrid electric vehicles that seems to be compatible with the development processes due to its comprehensible parameterization. **Figure 2** shows the basic characteristics: Whenever the vehicle is not in one of the states "energy regeneration", "electric drive", or "boost" the charging strategy controls the electric battery power and with it a delta of the torque of the combustion engine and electric motor respectively.

The charging strategy defines the battery power depending on the current vehicle speed and SOC (State of Charge) . By doing so, it ensures both a minimum SOC for boost and electric drive availability and a maximum SOC for the regeneration of kinetic energy especially at high speeds. Whenever the system state is in the remaining white area, there is no need for charging or discharging the battery and the SOC solely depends on the characteristics of the driving profile. In case of an SOC at the upper boundary of the white area with a soft acceleration phase following, the charging strategy will lower the SOC along the dotted line by assisting the combustion engine with electric power. The remaining states of operation and their consequences for the SOC are indicated by black arrows in Figure 2. Whenever extensive electric drive reduces the SOC to a certain low limit, the combustion engine is started and the control strategy requests medium charging power until the lower boundary of the white area is reached and new energy for electric drive is available again.

Due to a lack of information about current and future driving situations this charging strategy is a compromise between the availability of boost and electric drive on one side and energy regeneration capability on the other side. After repetitive WOT (Wide open throttle) acceleration manoeuvres or through extensive electric drive the SOC can reach a level where no further driving assistance by the electric motor is possible. This may lead to severe restrictions on driving performance, customer acceptance and driving safety. General prioritization of driving performance with a higher average SOC is not an option since this would result in low overall efficiency.

2.2 Modern Driver Assistance Systems and Sensors

The reliable detection of different driving situations, where priority to either performance or efficiency should be given, is a prerequisite for allowing the control strategy to diverge from the described compromise. Modern driver assistance systems together with standard sensors provide a variety of information about the environment of the vehicle in order to detect such driving situations predictively [1, 7, 8]. The new generation of navigation systems is already capable of sending bus signals with information regarding the current and coming situation on the road. The ADAS protocol (Advanced Driver Assist System) for navigation control units contains information about the category, geometry and speed limits of road segments that the driver is likely to follow. Figure 2 shows a map illustrating the ADAS-based route estimation. Depending on the road category and the angle of direction compared to the preceding road segment, every segment is ascribed an individual probability that the vehicle will drive on it. The sequential combination of the most probable segments yields the MPP (Most Probable Path) whose length varies depending on the number of crossings along the route. Recent message catalogues for CAN-bus systems already contain signals describing the MPP with all its attributes allowing a sufficiently accurate road prediction in a range between 1 km and 10 km. The MPP in **Figure 3** also shows bright and dark sections which correlate with road segments with or without the possibility for an overtaking manoeuvre.

Further information about the vehicle's surrounding situation can be taken from radar and camera systems. Coupled with light or rain sensors a grid of information can be set up that enables an assessment of probable driving situations in the immediate future. According to **Figure 4** a high probability for a forthcoming overtaking manoeuvre can be computed if the MPP shows no curve, the radar sensor a low distance to the vehicle ahead, and if the current driving speed is significantly lower than the prevailing speed limit [2].

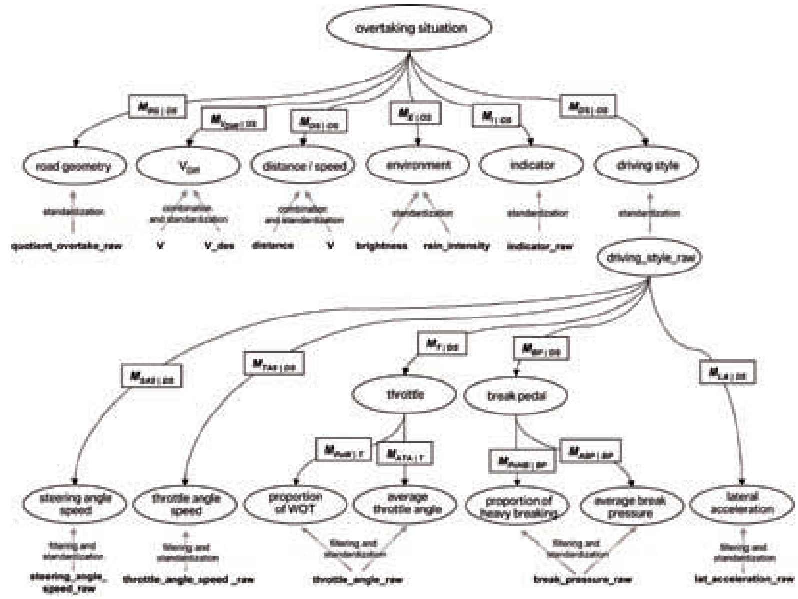

Figure 5: Cascaded network structure for probabilistic detection of driving style and overtaking situations

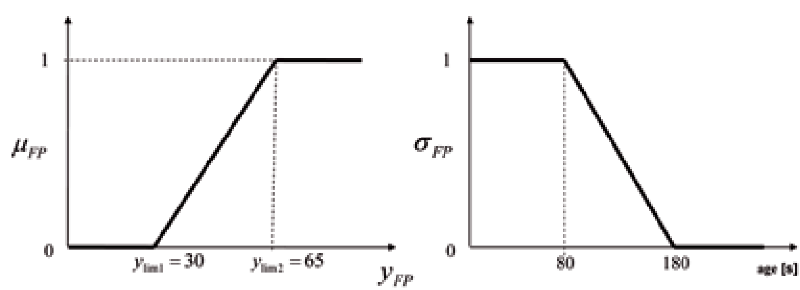

Figure 6: Membership and time weight function for processed throttle angle signal

3 Bayes Networks for the Classification of Driving Situations

To obtain quantitative statements about the probability of future driving situations one needs a method for sensor data fusion. Since a car driver already has expert knowledge about the attributes of different driving situations, it would appear reasonable to use this knowledge within a mathematical network. Other than in neural networks [3, 6] the expert knowledge can also be directly represented by Bayes networks [5], whose inner structure is known. In this paper these networks are combined with correlation functions obtained from fuzzy logic methods. The signals x_i are fed into the network and have been previously filtered and merged in order to gain the relevant situation attributes y_i.

These attributes are then matched with predefined perceptions of situations or manoeuvres over a continuous degree of membership $\mu_{y_i} = f(y_i)$ analogous to the membership functions known from fuzzy logic. Figuratively, an evidence measure regarding a certain situation is associated to the attribute value y_i. The degrees of membership can be interpreted as virtual evidence and serve as inputs to a tree-like Bayes network that computes the probability for a driving situation.

The detection of complex driving situations often requires cascaded networks. Situations with their probability can act as attributes of superior networks resulting in a multi-level structure. **Figure 5** shows a Bayes network structure consisting of two cascaded sub-networks classifying the driving style and the probability for an overtaking manoeuvre. The original bus signals are marked with "_raw" in the end and are then filtered and processed in order to serve as proper network inputs.

3.1 Driving Style Identification

The current driving style is computed from moving averages of signals like throttle angle and speed, lateral acceleration, break pressure and steering angle speed, while each signal x_i is subject to a specific pre-processing method that only interprets signals as relevant under conditions (for example throttle angle only during accelerations, break pressure only during deceleration, etc.). Further signals appropriate for driving style identification are mentioned in [3], but in the case of a vehicle with automatic transmission, the throttle angle itself contains information about engine speed and acceleration since they are roughly proportional.

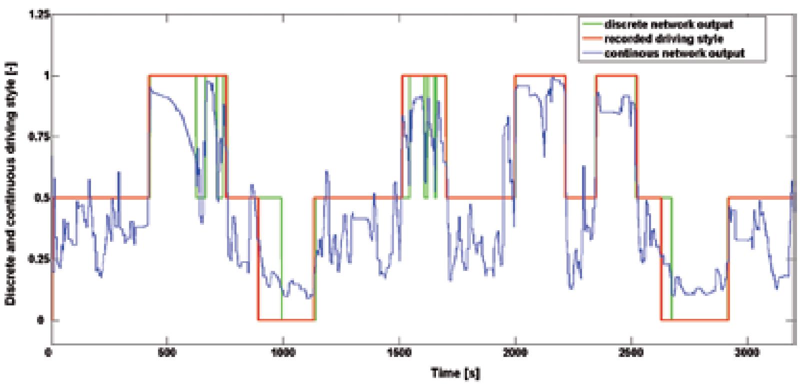

Figure 7: Recorded and detected driving style

Whenever a driver previously characterized as dynamic starts to follow a car ahead and begins to show attributes of calm driving, parameters in the network are duly changed in a way that his driving style will nevertheless continue to be interpreted as dynamic. Additionally, input-signals are weighted according to their age using a weight function σ_i(age). **Figure 6** shows the membership and weight functions of the filtered moving average of the throttle angle: During acceleration phases and with an average throttle angle of up to 30 % the attribute does not plead for dynamic driving style. The function output then increases linearly and reaches its maximum at a value of 65 % of average throttle angle. According to the time weight function on the right, the signals begin to lose their relevance after 80s linearly.

The specified Bayes network for driving style identification achieves satisfactory results. **Figure 7** shows a section of measurements during which the driver had to evaluate his driving style by pressing buttons corresponding to the three main groups "dynamic", "normal" and "relaxed". The y-axis corresponds to the probability for dynamic driving (1 = 100 % dynamic). The discrete network output corresponding to the same three groups is showing only slight errors and correctly detects the driving style in more than 90 % of the measurements. The priority has been given to a quick detection of dynamic driving while the detection of calm driving styles is accepted to be slower.

3.2 Detection of Overtaking Manoeuvres

The network structure for the predictive detection of possible overtaking situations consists of six independent input variables (compare with Figure 4).

The variable representing the surrounding environmental conditions is composed of data from light and rain sensors and is standardized with a two-dimensional membership function: The probability for an overtaking manoeuvre is only significantly lower when heavy rain and darkness occur at the same time.

The road geometry is represented by the quotient of the length of stretches on the estimated route where overtaking is possible and the total length of this route. During first tests in an experimental vehicle, the overtaking detection function shows very high detection rates. Only in dense or queued traffic there is the risk of false alarms: In these driving situations the network can compute high probabilities for an overtaking manoeuvre even though there is not a chance that it will happen in the near future. But the consequences of such errors are not severe as there will only be a request for a certain minimal SOC for the duration of the driving situation. Restrictions on efficiency coming along with this request are very limited in the hands of a customer.

3.3 Other Driving Situations with High Power Demand

Other driving situations demanding a high SOC for optimal power availability (entering a highway, exiting urban areas or driving uphill) are all detectible or predictable only through the use of the navigation system data along the MPP and do therefore not require a probabilistic sensor data fusion. But again, the most important prerequisite is a sufficiently high probability for the occurrence of a specific situation. If the number of crossings between the vehicle and the beginning of the predicted driving situation is low, the assumption that the vehicle will actually follow the estimated route is valid in most cases, as measurements in an experimental vehicle have demonstrated.

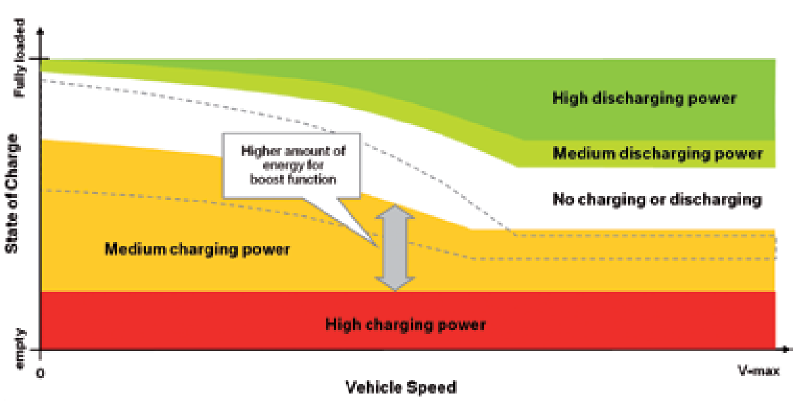

Figure 8: Charging control strategy for optimal performance

4 Adaptive Charging Strategies

If one of the probabilistic networks or data along the MPP suggests a driving situation with high energy demand, the available energy in the storage device has to be compared to the amount of needed energy. In case of a lack of energy the proposed charging strategy of Figure 3 has to be adjusted in order to provide the needed amount of energy for the predicted full acceleration manoeuvre.

For the duration of a detected dynamic driving style the control strategy is adapted as shown in **Figure 8**. Compared to the previous figure the white area of "no charging power" has been moved upwards at all speeds, resulting in less energy regeneration potential but greater boosting capability due to the higher average SOC. Once the driver shows a normal or calm driving style again, the charging strategy is set back to its original operating status – the conflict of objectives between efficiency and performance is solved depending on the behaviour of the driver.

When driving situations are detected where the target speed can be estimated (overtaking, entering of a highway, etc.), the amount of stored energy required for full boost availability is computed based on a vehicle model. This amount of energy mainly depends on the vehicle speed at the start of the manoeuvre V_{Start} and the speed difference V_{Delta} the driver wants to obtain by accelerating. It can either be computed in offline simulations or in real-time onboard the vehicle. During the operation of the vehicle the energy possibly needed according to the predicted situation and the available energy are continuously compared. If this comparison yields a lack of energy as in the SOC will be raised by the value and will not drop below afterwards. **Figure 9** shows the simulated amount of energy needed for various acceleration manoeuvres in a full hybrid vehicle. Additionally, areas with sufficient stored energy are marked brightly.

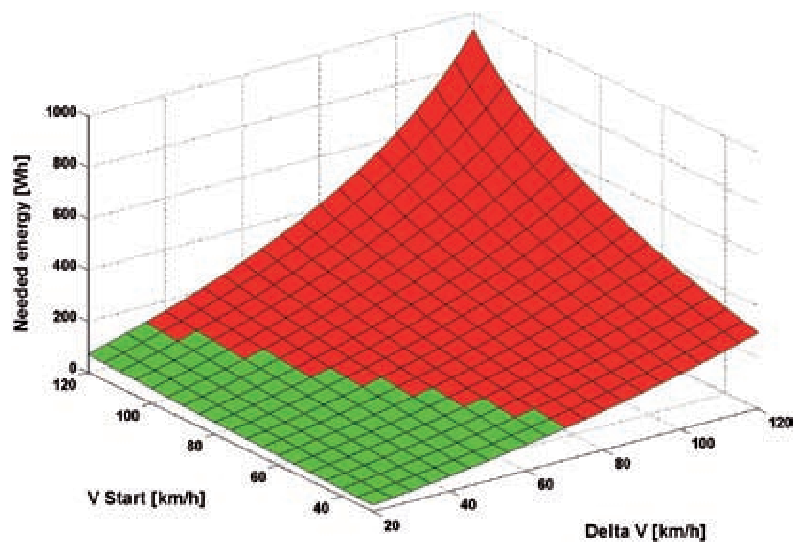

Figure 9: Needed electric energy for various WOT (Wide open throttle) accelerations

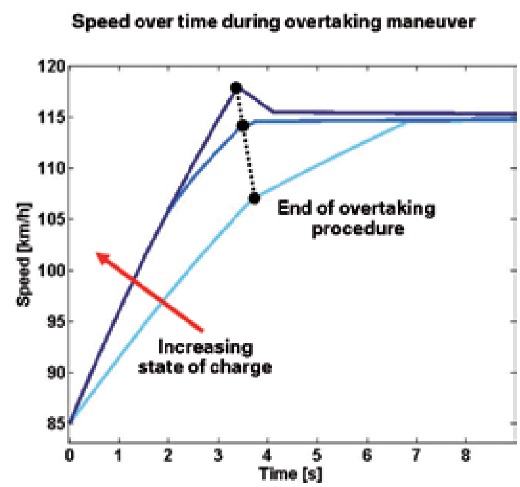

Figure 10: Improvements in driving performance with adaptive charging strategy

5 Simulation Results

For the evaluation of driving performance benefits, real driving cycles taken from measurements have been used with special focus on dynamic driving on the German autobahn. The resulting trajectories of the SOC were generated with a Matlab/Simulink vehicle model that had been validated for driving performance issues. Using the static, conventional charging strategy an average boost availability of 84 % was computed for an upper-class mild hybrid vehicle, that means during 16 % of the time, when the driver wished to get full power, the boosting function was not fully available.

With the specific charging strategy for dynamic driving the availability can be improved up to 100 % in most hybrid electric vehicles. **Figure 11** shows plots of a driving cycle that was simulated, including detailed views of the SOC and vehicle speed in a situation where a lack of stored energy occurs.

Moreover, the driving style classification algorithm can be used to improve efficiency of full hybrid vehicles. Under the assumption that a calm driver needs less boosting potential, the charging strategy can allow electric drive down to lower states of charge. The widening of the electric drive potential results in a fuel saving potential of up to 4 % depending on the drive cycle.

The benefits of a predictive detection of likely overtaking manoeuvres are displayed in **Figure 10**. The vehicle shows a much more reliable behaviour with increasing SOC due to the constant acceleration process.

6 Conclusions

In order to cope with the conflict of objectives of energy management in hybrid electric vehicles, an adaptive charging strategy was proposed that seems to be compatible with the established de-

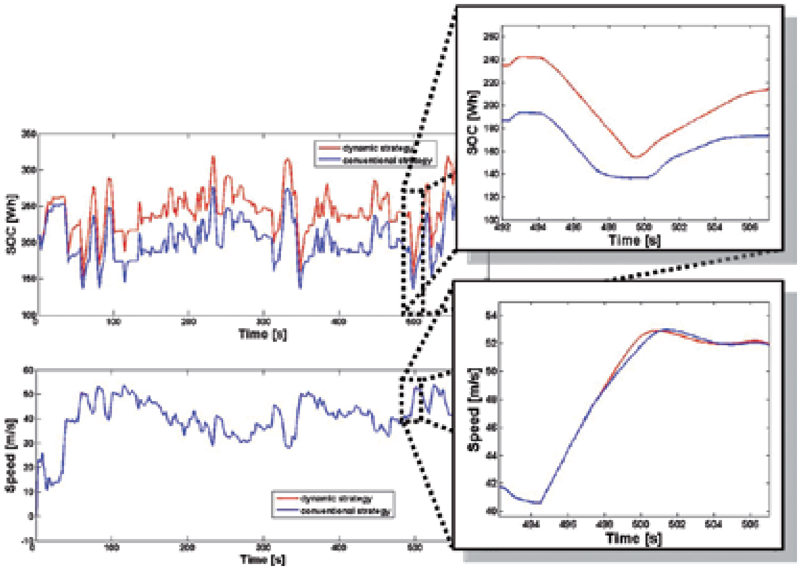

Figure 11: Driving performance during overtaking manoeuvres with varying SOC

velopment processes in the automotive industry.

The strategy raises the state of charge of the electric energy storage device only when there is a significant probability for the need of high amounts of energy – for example during phases of dynamic driving style or according to special predicted driving situations. In all other cases a conventional control strategy ensures high efficiency.

BMW proposed a method based on probabilistic networks for driving situation detection. Using predictive driver assistance systems as well as standard sensors, Bayes networks coupled with fuzzy membership functions were shown to be capable of providing quantitative information about the probability of driving situations in the immediate future.

Simulation results show significant improvements in driving performance without deteriorating the overall efficiency of hybrid electric vehicles. Adapting the charging strategy to calm drivers can even result in less fuel consumption. For optimization of energy regeneration and availability of the electric drive function, BMW is also analyzing specific charging strategies for slow driving areas, downhill driving and other driving situations.

References

[1] Back, M.: Prädiktive Antriebsregelung zum energieoptimalen Betrieb von Hybridfahrzeugen. Dissertation, Universitätsverlag Karlsruhe, 2005

[2] Heckel, J.; Lehner, P.: Verfahren zur Erkennung eines bevorstehenden Überholvorgangs. Patent DE 10 2005 007 800 A1

[3] Langari, R.; Won, J.-S.: Intelligent Energy Management Agent for a Parallel Hybrid-Vehicle. Part I: System Architecture and Design of the Driving Situation Identification Process, in: IEEE Transactions on Vehicular Technology, Vol. 54, No. 3, 2005

[4] Musardo, C.; Rizzoni, G.; Staccia, B.: A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management. In: Proceedings of the 44th IEEE Conference on Decision and Control, and the European Control Conference, 2005

[5] Pearl, J.: Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference. Morgan Kaufmann Publishers, San Mateo, 1989

[6] Richter, R.; Goßlau, D.; Binnenbruck, R.; Steinberg, P.: Reduzierung des Kraftstoffverbrauchs durch vorausschauendes Wärmemanagement. In: Wärmemanagement des Kraftfahrzeugs V, Expert-Verlag, Renningen, 2006

[7] Schüssler, M.: Entwicklung, Optimierung und Bewertung vorausschauender Hybridfahrzeuge. In: Tag des Hybrids, 2007

[8] Schuricht, P.; Cassebaum, O.; Wagner, S.; Bäker, B.: Multi-Sensor Network for Full Surround Perception for Advanced Driver Assistance. In: 7. Internationales Stuttgarter Symposium Automobil- und Motorentechnik, Stuttgart, 2007

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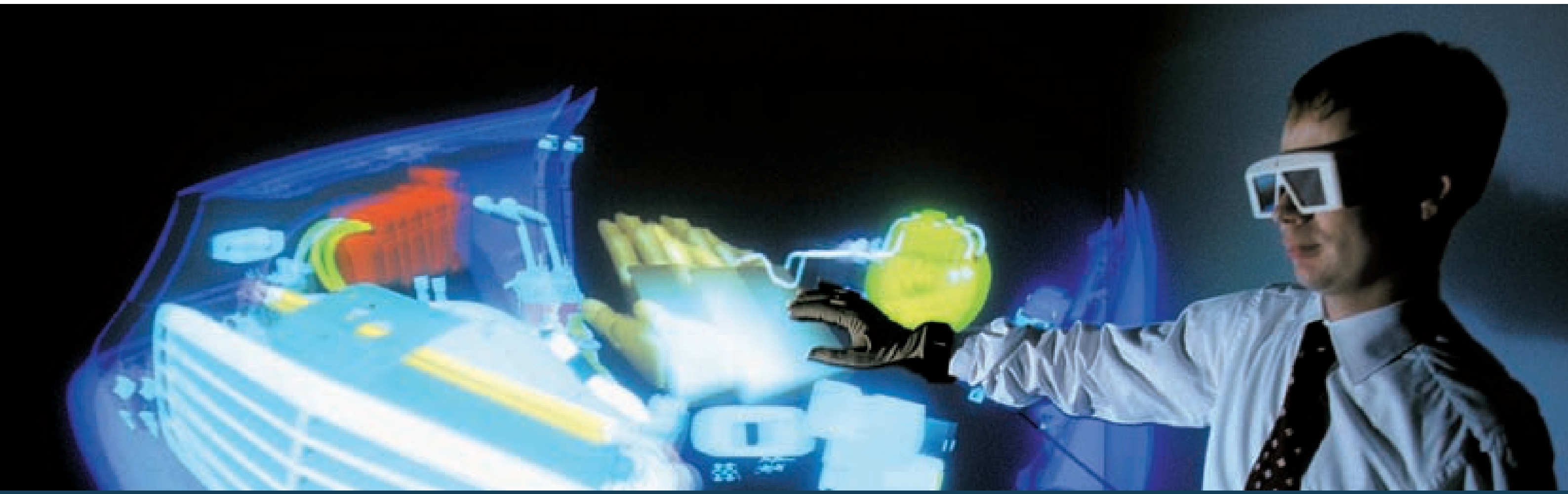

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