A Novel Predictive Energy Management System

Philipp Rehlaender, Philipp Kemper, Andreas Schwung, Ulf Witkowski
Department of Automation Technology
Department Electronics and Circuit Technology
South Westphalia University of Applied Sciences
Soest, Germany
Email: {rehlaender.philipp, kemper.philipp, witkowski.ulf, schwung.andreas}@fh-swf.de

***Abstract*— Global warming, the decline of oil resources, as well as the introduction of emission regulations, has led to a research focus in new drive technologies. Whereas hybrid electric vehicles (HEV) can only be considered as a transition technology, electric vehicles (EV) and fuel cell vehicles (FCV) are zero emission technologies; HEV are only considered a bridge technology. FCV enable longer ranges and faster refills at the cost of a moderate increase in fuel cost. Challenges for an overall acceptance of fuel cell vehicles are the degradation mechanisms of the fuel cell that lead to a very limited lifetime. Current research focuses on energy management strategies to reduce the overall energy demand by predicting the vehicles coarse power consumption on the overall trip. This prediction is used to optimize the control of the drivetrain components. This paper reviews energy management strategies and points out the lack of research in the prediction of short-term speed changes. The knowledge of short-term speed changes can drastically reduce degradation mechanisms by avoiding power fluctuations in the fuel cell as well as in the battery. The proposed hierarchical model predictive control strategy is able to incorporate the knowledge of long-term energy consumption to minimize the energy demand as well as the short-term speed predictions to avoid degradation mechanisms. The suggested system will lead to longer lasting vehicles and to a better acceptance of fuel cell vehicles. To incorporate a drive data pool, this paper describes the development of onboard micro trips by evaluating the driving information and splitting them into sub-trips.**

Keywords*— *energy management systems, fuel cell vehicles, speed prediction, model predictive control, hierarchical model predictive control, degradation mechanisms

I. INTRODUCTION

A fuel cell vehicle (FCV) can be in many ways considered superior to electric vehicles (EV) due to its fast refill possibilities and longer ranges. This paper deals with the use of a proton exchange membrane fuel cell (PEMFC) as a primary electric energy source. Almost all major car manufacturers have already provided prototypes of PEMFC vehicles [1]. Limitations for the introduction are the high vehicle costs, the hydrogen storage, battery and fuel cell reliability and infrastructure deployment of refill stations [2–4]. Therefore, the selection of the best power train type and its control remains one of the challenges of FCV. Typically, a FCV consists of the fuel cell (FC) as the primary energy source and at least one additional energy storage element (ESE) (battery or supercapacitor). Due to the use of an energy management system (EMS) these FCV are also referred to as hybrid FCV. Considering the ESE, batteries have a higher energy density than supercapacitors but can only provide less power. Moreover, batteries are vulnerable to power fluctuations. In contrast, vehicles tend to have a high dynamic power demand. Deceleration and acceleration procedures lead to great power fluctuations. An example of the power demand of a vehicle is shown in figure 1. Therefore, many hybridization possibilities have been proposed over the years. A review of the powertrain types has been given in [1, 4, 5]. Source [1] shows that the ideal FCV consists of a fuel cell, a battery as well as a supercapacitor. This optimizes the fuel consumption and enhances the lifetime of the battery [5–8]. The supercapacitor works as a short-term energy buffer while the battery as a long-term energy storage.

The use of two ESEs increases the degree of freedom of the system and makes the control problem more complex. An energy management system (EMS) has to optimize the global efficiency of the vehicle as well as the component's lifetime. Obviously, the control parameters change with regard to the power demand, the state of charge (SOC) of the battery and the supercapacitors and vehicle speed. Therefore, the EMS is most critical for the FCVs operational characteristics. The operation strategy can be fundamental in order to enhance the drive train components. While supercapacitors are very robust against any way of operation, fuel cells and batteries are more complex. Fuel cells are vulnerable to high dynamic load variations as well as operations near ideal [9, 10]. Batteries degrade depending on the number of cycles in relation to its depth of discharge (DoD) as well as to high currents. Cycling at high DoD leads to an exponential degradation of the capacity [10–12]. An EMS has to minimize the overall costs of the trip. That means it should not only minimize the fuel consumption but also minimize the components degradation. Finally, the EMS can be coupled with the thermal management by adjusting the temperature set point dynamically.

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II. Related Work

A. Energy Management Strategies Overview

A review of hybridization topologies has shown that a combination of a fuel cell, a battery, and a supercapacitor improves the lifetime of the components and optimizes the fuel consumption. The addition of the supercapacitor causes the control problem to have an additional degree of freedom. This makes the control more challenging. Due to the similarities of control between FCV and hybrid electric vehicles (HEV) many control strategies of HEV can also be applied to FCVs.

Many control methods for HEVs and FCVs have been proposed. Strategies can be split into rule-based strategies and optimization strategies [13]. Rule-based strategies formulate rules and define instant power split decisions in order to ensure that the vehicle operates optimally. Rules are defined based on heuristics, intuition, human expertise as well as mathematical models [14]. [14] classifies rule-based strategies into deterministic and fuzzy rule-based methods.

Another dominant group is optimization-based energy management strategies. This group can be split into global optimization and real-time optimization. Global optimization is a non-causal approach because it requires knowledge about the whole process which is usually not the case. Typically, global optimization is achieved through dynamic programming or linear programming [14].

Present real-time optimal EM strategies focus extensively on Equivalent Consumption Minimization Strategy (ECMS) [15]. ECMS is based on the Pontryagin's Minimum Principle and correlates the use of electrical energy stored in the ESE to the fuel consumption for instant power split decisions [13]. The utilization of electrical energy stored in the ESE results in an increased fuel consumption as long as no electrical energy has been recovered during braking [16]. ECMS focuses on the charge sustaining mode, which is characterized an equal SOC at trip start and end respectively [15]. Other real-time optimal control strategies are decoupling control, robust control approach and model predictive control [14].

B. Predictive Energy Management Strategies

ECMS is in its core idea a reactive EMS that cannot take future predictions into account [17]. Nevertheless, many modifications have been presented such as [18], which shows that an optimal modification of the equivalent factor (EF), significantly improves the fuel economy in hilly terrain. [19] uses a chained neural network (NN) as well as vehicle-to-vehicle and vehicle-to-infrastructure communication to predict future velocities. This information is used for an impact on the EF and results in a significant improvement in fuel economy as well as charge sustainability. [13] proposes an adaptive ECMS (A-ECMS) strategy that uses a neural network to predict the energy demand of the vehicle and generates an SOC reference strategy. Source [20] states that adoption of ECMS can be grouped into three A-ECMS strategies: *adoption based on driving cycle prediction, adoption based on driving pattern recognition* and *adoption on the exclusive feedback of SOC.*

Another optimal EMS is model predictive control (MPC). Model predictive control is a modern control method for predictive control of multi-variable processes. It is especially promising due to its ability to control constrained multi-input-multi-output (MIMO) processes [17] as well as linear and nonlinear plants.

Many solutions have been presented in order to achieve MPC on hybrid vehicles. MPC uses numerical methods to solve the optimal control problem over a finite moving horizon. Usually, stability is ensured by the definition of terminal region constraints [21]. Model predictive control solutions for hybrid vehicles have been presented in [17, 21–23].

Dynamic programming is a global minimization strategy. It involves a recursive resolution of the optimization problem backward in time and splits the optimization problem into several sub-optimization problems. The finding of a global minimum is guaranteed. Dynamic programming is often considered to require too much processing power in order to be implemented in real time but Back showed in [24] that a real-time implementation is possible.

III. Novel Predictive EMS

In the development of an ideal energy management strategy the different energy flows have to be considered:

- **Fuel cell to motor**
- **Battery to motor**
- **Fuel cell to battery**
- **Motor to battery** (regenerative breaking)

For the optimal energy management strategy, the whole drive train has to be regarded. Charging the battery during low speeds can be useful before an acceleration process while charging the battery before driving downhill is meaningless because the vehicle might not be able to recover all energy from the deceleration process. This means that knowledge about future driving conditions and the trip will lead to an improved efficiency and a lower degradation of the drive train.

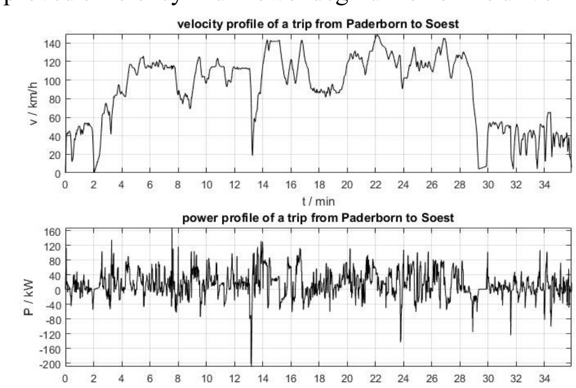

Fig. 1: Speed and power profile example of a vehicle

It is most critical for the improvement of the drive train control that conversion losses are avoided and it is further guaranteed that the energy from deceleration processes is recovered [25]. Forecasting future driving conditions will from now on be referred to as driving speed prediction (DSP). EMSs that use information about future driving conditions are referred to as predictive EMSs. Many types of research show that information about the future trip can lead to a significant improvement of the overall efficiency [16, 24].

There are a number of sensors in a vehicle that can be used for predicting the future speed and energy demand of the vehicle: A modern vehicle consists of a camera sensor, radar sensors, and a light and rain sensor as well as map data for navigational purposes. These sensors are currently used for driving assistance only. The use of these sensors can be extended to provide speed information for a better drive system control. Map information can identify incoming road types and speed limits as well as future slopes [16, 24]. This information is static because the drive control cannot adjust to dynamic acceleration and deceleration processes due to dense traffic conditions. This means that the sensor use has to be adapted to traffic condition information. This information can be provided through the camera sensor, which recognizes vehicles on the road visually, or radar sensors.

Furthermore, an integration of weather conditions can be considered [24]. Weather conditions such as rain may result in a reduced visibility and thus in a more careful and slower driving style. For this purpose, the use of vehicle sensors as well as online information can be combined. The vehicle can provide information on the intensity of the rainfall while online information can announce snow or hail. The investigated EMSs lack the ability to take short-term changes of velocity into account. Short-term changes of velocity depend on the driver's reaction to events such as a decelerating vehicle, a change in the speed limit or to environmental factors like intersections.

Short-term changes of velocity can be considered in two ways.

1. Predicting changes of velocity through a neural network that learns the driving behavior depending on the environmental factors.
2. Using time series analysis to detect certain changes of speed that are similar to changes of speed in the past.

The proposed system is shown in figure 2. It uses a hierarchical model predictive control structure. The outer model predictive control uses the trip information to define a scalable prediction horizon of up to ten minutes. The inner model predictive control uses the described methods of prediction of the speed through a neural network and the data fusion for the optimization problem. It is designed for a prediction horizon of up to 10 seconds.

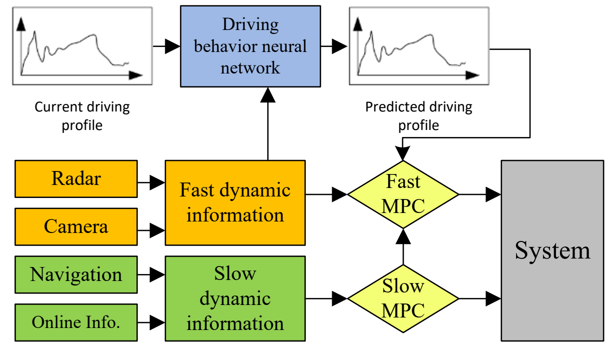

Fig. 2: Proposed System

A. Online learning of driving behavior

Driving behavior differs from trip to trip. For this purpose, it is insufficient to learn the driving behavior of one specific driver only. The driving behavior has to be learned continuously and adjusted to each trip. For this purpose, the proposed system uses an online learning neural network that starts the learning procedure as soon as the driver starts driving the vehicle. The architecture can be a deep neural network RELU activation function, whereas online stochastic gradient descent is a suitable learning algorithm. The longer the driver drives the more the system improves in performance.

The neural network predicts the vehicle speed depending on the inputs for finite time horizon. Inputs for the system are positions and speed of other vehicles gathered from the camera and the radar sensor, information gathered from navigation system such as the type of road, speed limits, and information about intersections and finally on vehicle information provided through the OBDII socket.

B. Time series analysis for velocity forecasting

Time series analysis is the process to use past data to predict future data. Several researches have focused on time series analysis to predict the future speed in a vehicle and to use this data in the control. It is clear that depending on the type of road, time series analysis can only be used to predict short to intermediate time periods. Research has shown that time series analysis can achieve very good results. Mozaffari has proposed a vehicle speed prediction using a sliding-window time series and an evolutionary least learning machine (ELLM) in [26]. The author proposed to predict the vehicle speed every 10 seconds for a period of 10 seconds and to select a control law for this prediction.

It is possible to implement time series forecasting models into state space representation that can be used by model predictive control [27]. [28] gives an extensive review about time series developments in the past. Research results prove that time series analysis is well suited for the control.

Time series analysis shall be used to predict the vehicle speed for the long-term future. Using time series analysis for the speed prediction considers not only the static road conditions but also considers dynamic traffic condition. This speed information can then be used to calculate a coarse energy consumption that is fed to the supervising model predictive control, see section C.

C. Hierarchical model predictive control

The proposed system uses two prediction horizons. Horizon 1 is very broad. It cannot clearly predict the vehicle speed. Nevertheless, horizon 1 cannot know all acceleration and deceleration processes. Main purpose of the broad Horizon 1 is to enable a long-term MPC with a long control horizon but a medium-grained resolution. Despite the large control horizon, admissible computing time is ensured through medium-grained resolution and reduced model complexity. Especially energy related process variables like the SOC of the supercap and in particular, the battery SOC can be controlled. Horizon 2, on the other hand, has clearer information about upcoming short-term changes in velocity but it has no information about the overall future. Therefore, time critical processes, like SC or battery control, are target of this MPC.

Because of these two independent and opposing prediction horizons, the use of a hierarchical structure for the model predictive control is quite obvious. A hierarchical model predictive control structure with emphasis on the stability of the overall system has been given in [29, 30]. The control structure used has been designed similar to the hierarchical control of multi-time scale systems proposed in [29]. This structure ensures that the overall system also considers the different power demands of trip phases while adapting to fast changes in driving behavior.

D. Driving behavior

The driver is most critical for the velocity behavior. While some drivers might drive more slowly and carefully, others tend to have a more aggressive driving strategy. Every driver has his own driving style. Information about the driving style provides information about acceleration and deceleration behavior as well as data about maximum speeds. For predicting reactions to certain events, the individual driving behavior has to be learned based on each trip because the driving style may differ depending on the state of mind of the driver.

There has been extensive research in the area of driver classification for hazards detection and driving assistant systems [31, 32]. Driver classification can be used for the design of an EMS to improve fuel economy [33]. Furthermore, research has focused on predicting driving behavior. [34] models driving behavior by a Markov decision process.

IV. Driving Cycle Analysis

A key feature of the proposed predictive EMS is the drive pattern archive. In order to implement such an archive and to enhance the development of the suggested predictive EMS strategy, real-world time series are required. Especial important are the velocity and road inclination, which have to be recorded while driving [35]. For validation purpose, the current vehicle position needs to be logged. In order to guarantee a significant varying number of recording drivers an easy to use sensor system should be used to record the required data. Therefore, a smartphone application including an automated data upload was developed and distributed.

A common way to process and analyze driving data based on real world driving, is the micro trip approach, where a micro trip (MT) includes the velocity and inclination profile between two consecutive stops [36, 37]. Usually these MTs are used to synthesize test-oriented driving cycles (DC) or driving scenarios to estimate energy consumption or pollution, as well as to support vehicle simulation or design tasks [38–40].

With the goal to create a drive pattern database, the recorded data was separated into MTs, which afterwards were classified related to their characteristic driving profile. Typical drive pattern can be described as urban driving, main roads or motorways [39]. Figure 3 shows exemplary a driving scenario, including three urban micro trips in the beginning and two at the end of the pattern surrounding two motorway MTs.

In order to classify the single MTs significant features describing a specific DC or MT need to be identified. [41] names a list of 30 parameter to characterize a specific DC. Since an MT-approach was used, only parameters not related to stops are chosen. Consequently, the set could be reduced and a five parameter comprising feature space was extracted. Table I lists the extracted parameters.

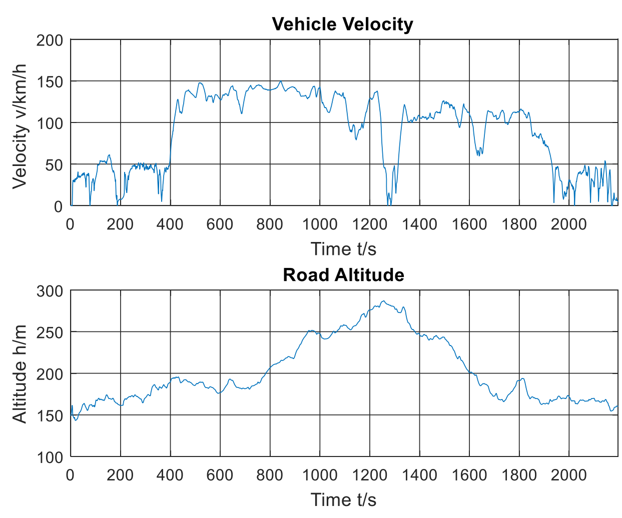

Fig. 3: Example data real world driving

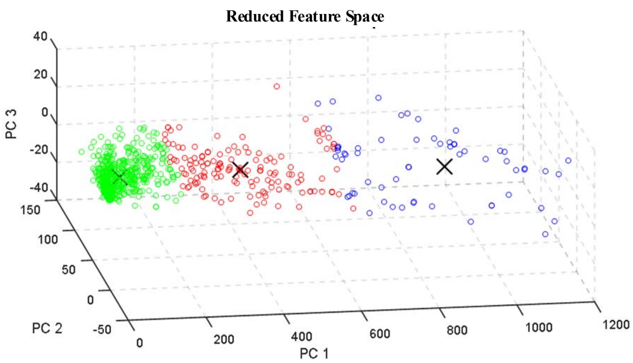

Fig. 4: Reduced feature space and cluster centers

Furthermore, a principle component analysis (PCA) was applied to reduce the feature space. In order to identify the three specified driving scenarios, fuzzy-k-means clustering was used to find characteristic clusters in the reduced feature space. Figure 4 depicts the reduced feature space as well as the specified cluster, representing the characteristic drive scenarios. For each cluster, the weighted center is highlighted.

TABLE I
FEATURE AND CLUSTER CENTER

Feature	**Motorway**	**Main Road**	**Urban**
Distance (km)	25	8	1
V_{max} (km/h)	136	106	55
V_{av} (km/h)	102	73	40
$A_{+,av}$ (m/s²)	0.33	0.45	0.8
Time (s)	883	385	68

In order to identify and specify an arbitrary MTs, a fuzzy-mamdani interference system (FIS) was implemented. The five characteristic features form the inputs. Furthermore, the cluster centers in Table 1 specify the input membership functions. The rules of the FIS were rated related to the PCAs weights. If the influence of a feature is high, also the corresponding rule is rated high. Figure 5 depicts the implemented FIS. The FISs output is a real number, representing the likelihood of an MT to be classified as a specific driving pattern. To validate the proposed MTs classification method, reference DCs including position data were used.

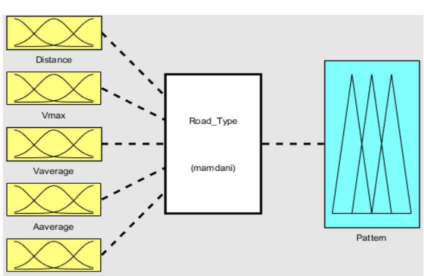

Fig. 5: Mamdani-Fuzzy Interference System

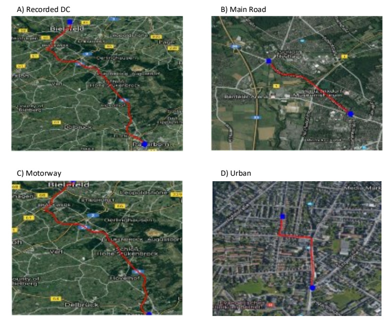

Fig. 6: Example MT identification

Therefore, a defined set of 250 MTs per driving pattern were used to evaluate the performance of the FIS. Using the FIS, an overall rate of positive identified MTs of 92% was achieved, where the identification of motorway and urban driving was more reliable than to correctly identify main roads. Figure 6 shows exemplary a recorded drive cycle as well as three exemplary corresponding characterized MTs.

V. CONCLUSION

In this paper, a novel EMS for hybrid fuel cell vehicles was proposed. For this purpose, a review of operational degradation mechanisms was given to show that an adoption into the EMS is necessary. Furthermore, the EMSs of hybrid vehicles were reviewed. Chapter IV showed the necessity of a predictive EMS in hybrid vehicles. Many implementations of optimal predictive EMS were described.

All lacked the ability to include short term changes of velocity in the EMS. For this purpose, a novel EMS was presented that can, on the one hand, react to short-term changes in velocity and, on the other hand, include long term trip information. Short-term changes of velocity were predicted by using a neural network that learns the driving behavior online and can thus adapt to different driving styles.

Naturally, this paper is a proposal for a new EMS and outlines the lack of research. Since here only initial work is described, detailed tests have not been done so far. Nevertheless, first simulations are promising and our future work is to implement the proposed EMS on a simulation test bench and prove applicability. Therefore, this paper can be seen as a preliminary document for presenting the research idea to a broader community.

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