Multiobjective Optimization of the Power Flow Control of Hybrid Electric Power Train Systems within Simulation and Experimental Emulation Applications

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Vorwort

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Kurzfassung

In dieser Arbeit wird die Leistungsflussregelung bei hybridelektrischen Antriebssystemen mit dem Schwerpunkt der Mehrkriterienoptimierung diskutiert. Hierbei werden geeignete Algorithmen, basierend auf verschiedenen Stellgrößenoptimierungsmethoden, entwickelt und in Simulationen sowie in experimentellem Umfeld angewendet. Aufbauend auf die Grundzusammenhänge hybrider Antriebssysteme wird eine weiterentwickelte experimentelle Umgebung zur Untersuchung und Bewertung vorgestellt und der entsprechende Hardware-in-the-Loop (HiL)-Versuchsstand zur Emulation entsprechender Systeme demonstriert. Diese Emulationstechnik erlaubt eine generalisierte Betrachtung von Antriebssystemstrukturen (Betrachtung der Komponenten als Quellen, Senken, Übertragungselemente, Speicher etc.) und der entsprechenden Leistungsflussregelung. Den Hauptteil dieser Arbeit bildet die Diskussion sowie die Entwicklung, Anwendung und Bewertung von Algorithmen zur Optimierung der Leistungsflussregelung hybridelektrischer Antriebssysteme. In diesem Zusammenhang erfolgt eine mehrkriterielle Betrachtung und Bewertung des Antriebssystems in Hinblick auf die Dynamik, die Kraftstoffökonomie und die Komponentenlebensdauer. Das hieraus resultierende mehrkriterielle Optimierungsproblem der Stellgrößenfolge kann hierbei als Überlagerung von Leistungs-, Energie- und Lebensdauermanagement aufgefasst werden. Basierend auf den Haupteinflüssen der Leistungsflussregelungen auf verschiedene Systemeigenschaften erfolgt die Entwicklung, Anwendung, Bewertung und Diskussion verschiedener Stellgrößenoptimierungsmethoden und -algorithmen. Diese werden am Beispiel eines Brennstoffzellen/Supercap-basierten hybridelektrischen Antriebssystems mit Bremsenergierekuperation demonstriert. Zur Optimierung der Leistungsflussregelung werden als erstes Parameteroptimierungstechniken vorgestellt, wobei eine Embedded-online-Optimierung basierend auf der Methode des Goldenen Schnitts sowie eine Offline-Optimierung unter Verwendung von globalen Optimierungsalgorithmen diskutiert und angewendet werden. Nachfolgend werden direkte Stellgrößenoptimierungstechniken vorgestellt, wobei die Verfahren der Dynamischen Programmierung und des Modelprädiktiven Reglers realisiert werden. Abschließend wird die Entwicklung und Anwendung eines Algorithmus basierend auf der momentanen Optimalität (Instantaneous Optimality) diskutiert, welcher aus einem kombinierten Geschwindigkeits-Prädiktionsalgorithmus und vordefinierten Kennfeldern für die Regelung besteht. Die verwendeten Methoden werden vergleichend gegenübergestellt und gemäß ihrer Stärken und Schwächen bewertet.

Abstract

In this thesis, the power flow control of hybrid electric power train systems is discussed using the focus of multiobjective optimization goals and related algorithms, based on different control optimization methods, are developed and applied within simulation and experimental environments. Based on the basic relations of hybrid power train systems, an improved technique for the experimental realization and evaluation of these systems is developed and the related Hardware-in-the-Loop (HiL) hybrid electric power train emulation system is demonstrated. Hereby, it is shown that this emulation system technique is suitable to be applied for a more generalized view of the power train structures (consideration of the components as power sources, sinks, transmission elements, storage elements etc.) and its power flow control. The principal applicability of the system is demonstrated using the example of a hybrid electric vehicle as well as other system technologies such as hybrid hydraulic power trains and wind energy conversion systems. The core of the thesis is the discussion, development, application, and evaluation of power flow control optimization algorithms. Hereby, the considered power flow control techniques of the power train are realized with respect to a multiobjective framework using the example of drivability, fuel economy, and component life time as system requirements to be optimized during the operation. From this requirements, a multiobjective control optimization problem results consisting of a suitable combination of the known control goals power management, energy management, and lifetime management is realized. After a discussion about the principal influences of the power flow control on the different performance properties, the application of different control optimization techniques is discussed. Hereby, the example of a fuel cell/supercapacitor-based hybrid electric power train system including braking energy recovery is used. As control optimization methods, parameter optimization techniques are applied at first. Hereby, an embedded-online optimization based on a Golden Section search and an offline optimization based on Global Optimation methods are discussed and applied. Furthermore, direct optimization techniques based on Dynamic Programming (DP) and Model Predictive Control (MPC) are realized. Subsequently, an Instantaneous Optimality (IO)-based technique, which consists of a lookup table-based Time-Invariant Feedback Controller technique, is developed. It becomes clear that all methods leads to suitable results and significant improvement of the control performance. A concluding overview of the methods and its strengths and weaknesses dependent on the application is provided.

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Nomenclature

Important abbreviations

ANN	Artificial neural network
DP	Dynamic Programming
ECE	Economic commission for Europe
ECMS	Equivalent consumption minimization strategy
EM	Energy management
EUDC	Extra urban driving cycle
GA	Genetic Algorithm
GO	Global Optimazation
HEV	Hybrid electric vehicle
HiL	Hardware-in-the-Loop
ICE	Internal cumbustion engine
IO	Instantaneous optimal control
LM	Lifetime management
MPC	Model Predictive Control
PCA	Power flow control algorithm
PM	Power management
SC	Supercapacitors
SDP	Stochastic Dynamic Programming
SOC	State of charge
WECS	Wind energy conversion system

1 Introduction

In the context of the United Nations Conference on Environment and Development (UNCED), held in Rio de Janeiro/Brazil in 1992, the United Nations Framework Convention on Climate Change (UNFCCC) was established with the objective of stabilizing the greenhouse gas concentration in the atmoshere [UN92]. Based on this framework, in December 1997, in the context of the Kyoto Protocol, a treaty for the legal binding of the limitation/reduction of greenhouse gases was signed by 192 parties (191 states and the European Union) [UN98]. In 1993, the 5th Environmental Action Program [Com93] was established, where the EU-15 states[1] established long-term objectives for the air quality in Europe, which also included greenhouse gases. In the context of the Kyoto Protocol these states agreed to reduce their greenhouse gases by 2012 to 8% below the level of 1990.
As reported in [Age13], carbon dioxide is by far the most important greenhouse gas with 82.5% of total EU-15 emmisions and 82.3 % of EU-27 emmisions in 2011. Hereby, the road transportation sector (including light-duty vehicles such as passenger cars, heavy-duty vehicles, and three-wheelers) is the second largest source with 20.4% of total greenhouse gases emissions. Between 1990 and 2011, the emissions of carbon dioxide from road transportations increased by 16% for the EU-15 states, and except of Germany (-2%) all states increased the emissions in this sector.
Another problem the automotive industry is confronted with are the rising oil prices. As shown e.g. in [Bun12], crude oil prices have continously been rising since the 1980s.
Motivated by these discussions and the related governmental regulations, the research and development efforts on energy-efficient systems have become a growing issue within industrial development and scientific research. An important aspect in this context is the reduction of fossile fuels (basically gasoline and diesel) for vehicles. For this reason, their power train systems are increasingly equipped with electric power train components, which are either integrated in a hybrid power train structure or completely replace the combustion engines within fuel cell-based hybrid or pure electric power trains.
In this context, a large number of new challenges has to be faced. The electrification and hybridization in recent years' power train development projects makes changes on systems and components necessary. One typical task is the increase of the power train system's efficiency, power availability, and reliability. Hereby, approaches based on design optimization and optimal arrangement of the system components are commonly used.
In automotive context, as main topologies for combustion engine-based hybrid vehicles are according to e.g. [Cha07, ERWL05, GS07] parallel, serial, and combined hybrid power train structures are used. Hereby, for parallel hybrid electric vehicles

[1] The EU-15 states include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom

the mechanical drive trains (prime movers) are used to operate either individually or simultaneously the same drive shaft. For the series hybrid architecture of vehicle power trains, the mechanical power of the combustion engine is converted to electric power, which, in combination with a storage element, supplies an electric motor to propulse the vehicle. Further drive train topologies are combinations of these concepts such as series-parallel HEVs or complex HEVs. The principal setup of these topologies is illustrated in Figure 1.1.

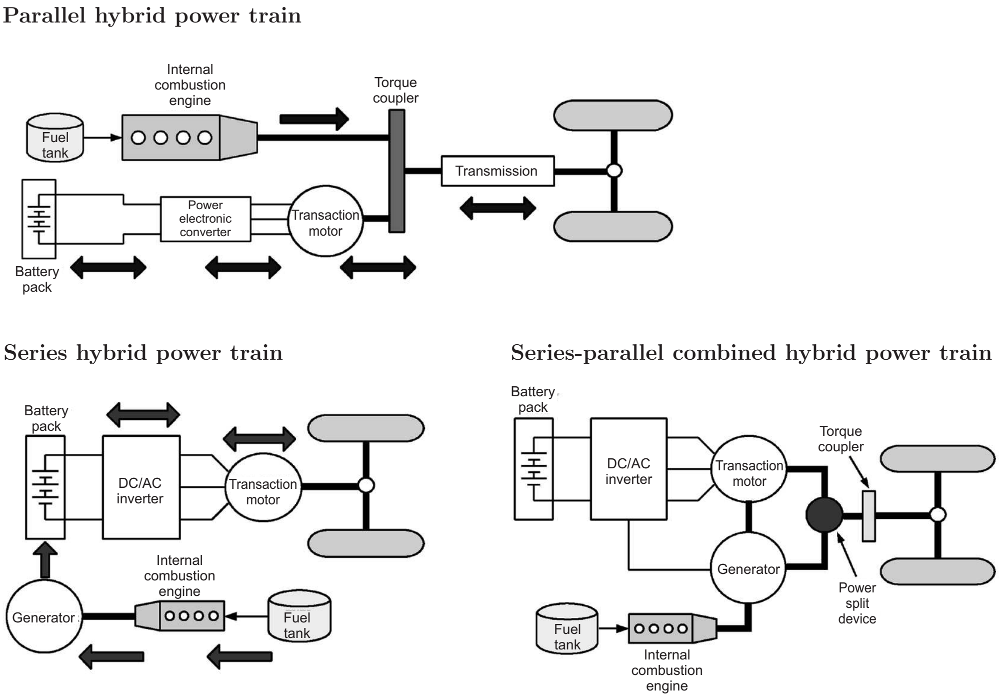


Figure 1.1: Typical topologies of hybrid vehicle power trains [ERWL05].

Additionally, there exist different types of fuel cell vehicles. As discussed in e.g. [Cha07], the principal structure of these vehicles can be considered as series-type hybrid vehicles. Hereby, the engine in combination with the generator is replace by a fuel cell system to deliver the required primary electrical energy. Details and a further classification will be given in chapter 2.

For each hybrid vehicle topology, the electric motor can be used as a generator to recover kinetic energy, e.g. during braking, which is an important point to increase the fuel efficiency of the power train system.

For the development of hybrid power train systems, one typical task is the design and dimensioning of its structure. This includes the choice of the system components and its sizing and the decision about its operation structure as discussed e.g. in [LP08]. In this context, there also exist methods for the evaluation and optimization of the power train system in literature, as described e.g. in [GS07]. Hereby, especially for

series hybrid vehicles, an important task is the design of the electric power train architecture with multi-storage and multi-sources topologies and, related to this, the interaction and operation of these components within complex structures.
Aside from design issues, another important aspect is the development of the operation strategy of hybrid power trains. For the improvement of the performance of the power train system and for a suitable combination of the different components of a typically complex system topology (power sources, loads and storage elements) with different properties, the electric power flow control between the individual power train components plays an essential role. In this context, the development of power and energy management approaches are central topics in recent year's research activities.
Typical research projects in this context aim at the minimization of fuel consumption for a given driving behavior. Others include further aspects as e.g. comfort or drivability constraints to their algorithms. But also the consideration of aging-related operation is a field of increasing research activity.

1.1 Setup of the thesis

Within this thesis, a number of optimization approaches are investigated with respect to the design and particularly the control of a hybrid electric power train system structures.
Hereby, the focus of this thesis is the discussion of several aspects of the power flow control within hybrid electric power train structures containing multiple energy sources, sinks, storage elements as well as power converters. Therefor, the main foundations of hybrid electric power trains, its components, and typical topological structures will be briefly described in section 2. This context is essential for the design and optimization of power flow control algorithms, which is a central aspect to be considered within this thesis.
Whereas most research projects focus on the optimization with respect to only one target, e.g. the maximization of the system efficiency or the minimization of the fuel consumption, the power flow control algorithms introduced within the context of this thesis are designed within a multi-objective optimization frame work. For this reason, the power flow control can be distinguished between power management, energy management, and lifetime management of the power train, since the control algorithms have different effects on the system behavior, which are typically also related to different time ranges.
The algorithms are demonstrated within offline and experimental environments. Hereby, for the offline algorithms dynamic models and their simulation during the optimization procedure are typically applied methods. For the experimental evaluation of hybrid electric power train structures, a concept of an emulation structure is introduced, which allows a modular setup and thus the realization of different system topologies. This emulation system is basically set up by electric power sources,

sinks, and converter elements and can easily be completed by further electrical components such as motors, supercapacitors, batteries etc.
The applicability of this emulation approach is demonstrated using the example of different hybrid electric power train topologies including a wind energy conversion system. The implementation of electric hydraulic analogy models even allows the emulation of hybrid hydraulic power train systems within an electric environment.
For the optimization of the algorithms with respect to given load profiles and a previously defined control structure, the implementation of heuristic search algorithms as well as Global Optimization (GO)-based approaches are applied within simulation and experimental environments to optimize the power flow control of the hybrid electric power train systems. Hereby, it can be shown that the control optimization leads to a considerable improvement with feasible results. Furthermore, also the applicability of the approaches without a detailed knowledge of the dynamic behavior of the power train or the load profile is shown.
The implemention of algorithms for the load profile prediction into the electric power flow control allows the adaptation of the control to the expected driver behavior. In addition to simulation results, this is also shown within experimental environments.
Similiarly, the optimization by Dynamic Programming (DP)-based approaches for the direct optimization of the control is applied based on given system dynamics and load profile. The implementation of a knowledge-base, based on optimal input trajectories, which are offline optimized by a Dynamic Programming appoach, into the power flow control of the power train allows the implementation of optimal control inputs into an experimental environment, e.g. by the usage of lookup tables, and may lead to a better performance than e.g. classical rule-based algorithms. To do so, a combined identification and prediction algorithm is integrated to estimate the instantaneous system states and the related load situation. For the identified measurements, the control signals are generated with the predefined knowledge-base. In the context of this thesis, this optimization approach will be called instantaneous optimality (IO)-based power flow control.
The contents of this thesis are developed with respect to the results of the predecessor research project shown in [Özb10], where the results of the predecessor research project are described. Hereby, the principle relations about the dynamical system behavior as well as the simulation of hybrid electric power train systems and the principal relations for the experimental realization are demonstrated on a fuel cell/supercapacitor-based hybrid electric power train and discussed.
In the following, the state of the art within the development of power flow control algorithms, especially power and energy management, and the related optimization approaches are stated and the related literature is provided. It will be shown that a multiobjective consideration of the control approaches may lead to improved results. Further aspects to be discussed are aging mechanisms within hybrid electric power train components and the usage of an emulation concept for the experimental investigation. In chapter 2, the description of the general relations of hybrid electric powertrain systems, its components, and typical system topologies, especially

those with respect to electric, fuel cell hybrid and series hybrid power trains, will be given. Additionally, typical problems (component sizing, control design etc.) and design conflicts (influencing drivability, fuel economy, aging etc.) in this field are described and discussed. In chapter 3 the emulation technique, which is applied for the experimental investigations, is described. The main principle relations are demonstrated using the example of a fuel cell/supercapacitor-based hybrid electric powertrain Hardware-in-the-Loop test rig, as introduced in [Özb10]. The usage of an emulation concept applying controllable electric power sources, sinks, and transmission elements allows a more generalized consideration of power train concepts consisting of e.g. sources, sinks, transmission, storage elements etc. The applicability of the emulation system is shown for the electric flows of a hybrid electric power train and a wind energy conversion system (WECS). Additionally, also the principal applicability of this emulation technique for the emulation of a hybrid hydraulic power train system is demonstrated using an electric hydraulic analogy model to calculate equivalent electric signals for a hydraulic power train.
In chapter 4 general aspects of the power flow control in the context of hybrid electric powertrain systems are described. Typical methods to be applied in this context such as rule-based methods, the equivalent consumption minimization strategy (ECMS) as well as the control using Model Predictive Control (MPC)-based approaches are described and discussed. Additionally, typical system properties for the evaluation of the control performance are introduced and related evaluation parameters are defined. Applying three simplified power flow control strategies within an experimental investigation, the influence of the power flow control on fuel economy, drivability is demonstrated. It becomes clear that there is an interdependency between the performance parameters of the typically conflicting performance properties, which depends on the chosen controller designs and parameters. This lead to the necessity of the development and integration of control optimization approaches. Since multiple performance properties are affected, the design of an optimization power flow control leads to a multiobjective optimization problem including power management, energy management, and lifetime management.
Typical optimization approaches within this context and their application are described in chapter 5. This includes methods based on an embedded optimization-based heuristic search algorithms, Global Optimization (GO) approaches such as Genetic Algorithms (GA), Model Predictive Control (MPC), and Dynamic Programming (DP). The chapter is completed by results of an instantaneous optimality (IO)-based control approach, which consists of an identification and load profile prediction algorithm in combination with an offline-optimized database with optimal input trajectories for different system states and previously defined load profile trajectories.
It will be shown that all methods lead to feasible results but also that their applicability depends on the tasks to be solved. The thesis is completed by a summary of the main results and contriutions as well as discussions about future steps.

1.2 State of the art

Due to the increasing importance of the energy efficiency consideration hybrid electric power trains are an essential part of the research and development of vehicle power train systems but also further industrial applications as e.g. the aircraft industry [ZMB$^+$10] include these concepts for the improvement of their products. For the design and the operation of electric and hybrid electric power train systems several system properties have to be considered. Hereby, system modeling approaches play a key role. There is a large amount of literature considering modeling aspects of these kind of system. A broad overview about vehicle propulsion systems considering combustion engine, fuel cell, battery and supercapacitor-based hybrid power trains is provided in [GS07]. Hereby, also topological aspects, power flow control algorithms, and optimization methods are briefly presented.
An alternative approach to the classical state space and transfer function-based methods is the Energetic Magnetic Representation (EMR), which is based on the action-reaction principle according to the physical causality [CBL08]. Other methods are based on Bond Graphs [KR75] or Causal Ordering Graphs [GDH00].
A central and often discussed property of hybrid power train systems is the energy efficient operation of the individual system components and the fuel consumption of the total system and, related to this, the task of the emissions minimization e.g. for combustion engine applications. As summarized in [MOS14], the efficiency of the powertrain system and the efficiency of its individual components should be distinguished. The efficiency of the components can be influenced by the choice of a suitable operation point (e.g. point of best efficiency) of the system. Therefor, a suitable arrangement and sizing of the components has to be chosen during the design process. An important point in this context is that, in order to operate the system at its optimal efficiency, it might be possible that some of its individual compontents operate inefficiently. In this context, the load profile applied to the system, which has the main influences on the dynamical behavior of the power train, has to be considered in particular. Apart from the choice of the components size (related to the predefined system requirements), the system efficiency also depends significantly on the energy flow control and, if applicable, on the individual component control. Here the interdependency between the energy flow and the load profile as well as the component status respectively has to be taken into consideration.
Aside from structure, sizing, and control of the system, the operation state of the powertrain system itself (including the energy storage components) combined with the present and future load situation is an important aspect for the consideration of the overall system efficiency. This becomes particularly clear by using the recovery of kinetic energy during braking as an example. In this context in [DOW00] a simulational study about the energy maximization based on a power train capable of recovering braking energy is conducted regarding the control using electric circuits. The power train is based on supercapacitors and Buck-Boost converters. In [HJ07]

algorithms controlling the wheels are presented to maximize the energy recovery during braking. The storage elements' capability of recovering electric energy is larger if the state-of-charge is lower due to the fact that the amount of electric energy to be stored is higher [AP02]. The concept of electric energy recovery is not only limited to braking energy but also to other forms of mechanical energy, such as regenerative damping within vibrating structures as described e.g. in [Scr07]. Another aspect to be considered in this context is the power availability of a power train system for the realization of a required load profile. In vehicle application this property is equivalent to the drivability of a vehicle. Considering this property of the powertrain system (including the energy storage), two further important design aspects have to be discussed. The first one is the capability of the energy source and storage elements of the system of delivering a required peak power and the other one is the maximization of the range of the system with respect to the stored energy. Typically, during the design process there are conflicts between the system's availability to realize the required power and energy on one side and to maintain the system efficiency on the other side [SBDS05].
A further design aspect is defined by the requirements regarding the lifetime of specific system components. The lifetime can typically be determined by the evaluation of time or trajectory-dependent load spectra as discussed e.g. in [Her10]. In recent research studies several power train components are considered in detail whose lifetime significantly depends on the electrical load, such as lithium-ion batteries, fuel-cell systems, etc. In this field of research two main research questions are considered:
I: What kind of performance losses occur due to aging of components? In this context in [HFNJ09, RHWP03] approaches based on pregiven aging models of Li-ion batteries are shown. Similiar considerations for the evaluation of the system drivability can be applied here. Additionally, the possibility of integrating a parametrized aging model into the power train control structure has to be proven.
II: Which influence has the system operation on the aging mechanisms of the specific components and how can a control scheme be applied to prevent or at least to minimize the aging? The task to prevent or to minimize these mechanisms by an appropriate design or operation is an important issue in research. Aging models [KPS07,Liu06,BBB+05] and methods for the identification of the current State-of-Health (SoH) [TKT06] are commonly used in this field of research.
Since the properties of fuel economy, drivability, and lifetime of a hybrid power train structure depend on completely different influences, there might be conflicts between them during the operation of the system. One common method to overcome these design conflicts is the hybridization of the power train system components. Hereby, the basic idea is to combine the strengths of the individual components by setting them a within a suitable arrangement (topology). A typical and prevalent example for this kind of hybrid power train systems is the combination of a combustion engine and an electric motor as introduced e.g. in [SBS06]. Here the strengths of the electric motor operating with high efficiency at slow speed and high torque (e.g. during the run-up or strong acceleration phases) can be combined with the

higher energy density and range of the fuel-based combustion engine. In the context of hybrid vehicle power trains, a number of topologies such as serial hybrid system, parallel hybrid system, range extender etc. are known, which are detailed e.g. in [GS07, ERWL05, Jon02].
In [GK13], a range extender topology based on an ICE and a Li-ion battery is demonstrated for the propulsion of a 4-Wheel hub motor EV. Additionally, there exist miscellaneous species of hybrid electric systems. A typical example application is provided in [Ros07], where the integration of an electric intermediate system is a central element to realize the supply of the required electric energy defined by a load profile. Systems of this kind typically consist of an electric power source and at least one electric energy storage [KPF+05] component. Typical examples of power sources are fuel cells [VBR06, GA07], generators, which are propulsed either by a combustion engine or by the kinetic energy of the vehicle (energy recovery during braking), and solar modules [PBB06, IINP06]. Typical energy storage elements are accumulators (e.g. based on lithium-ion, nickel metal hydride, lead acid etc.) and capacitors (e.g. supercapacitors [SPA07, AM07], conventional double-layer-capacitors etc.). By the application of the hybridization concept, it is possible to combine the strengths of the individual power sources and storage elements. As illustrated in the Ragone plot, shown in Figure 1.2, fuel cell systems have a comparatively high gravimetric energy density, which makes them capable of supplying the electric energy for a long-term time range with a near-stationary power flow, whereas supercapacitors are suitable for the supply of peak power and for rapid and efficient storage of recovered electric energy (high gravimetric power density). However, for long range applications, supercapacitors have only a limited applicability due to their small energy density and thus their limited capacity.

Additionally, hybrid electric power train systems contain components for the conversion of electric voltages and currents as e.g. DC/DC converters within DC circuits or inverters and rectifiers for the conversion between DC and AC current flows and vice versa. The integration of these elements allows the control of the electric power flow within the power train system structure. This aspect has an essential relevance for the realization of the power flow control algorithms of these power trains.
Using power flow control algorithms such as e.g. power and energy management, the control of the power flows within the power train system can be actively influenced. Depending on the system state, the distribution of the energy demand on the energy sources and storage elements can be controlled as well. Hereby the existence of sufficient degrees-of-freedom of the system concerning the supply and the usage of electric energy is a structural requirement, which implies that either suitable energy sources are available or that the energy requirement can be influenced by the system state itself [Wag04].
Principal relations of fuel cell-based hybrid electric power trains and, resulting from this, significant effects caused by the application of powerflow control algorithms are described e.g. in [ÖS08]. An overview about the relations between work

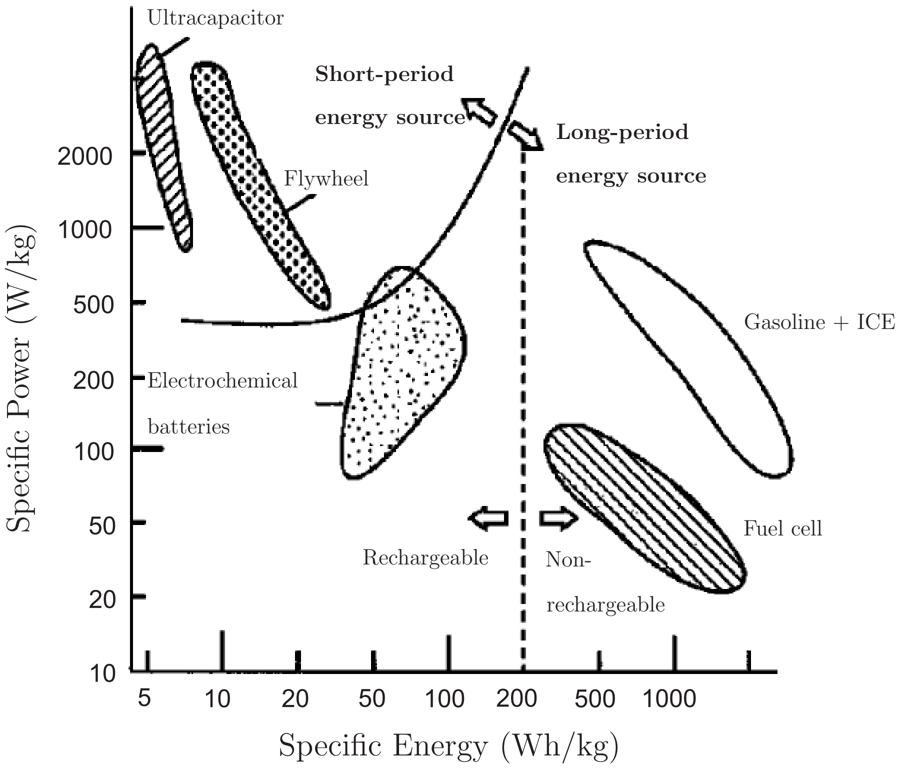


Figure 1.2: Characteristics of different energy sources and storages (Ragone diagram) [Cha07]

load, component sizing, and the choice of the relating control parameters are given in [ÖS09, Özb10].
Hereby the necessity for the usage of control optimization approaches of power trains especially considering the expected work load of the system becomes obvious. Typical optimization approaches are designed to minimize the hydrogen consumption of a fuel cell-based powertrain system [XHL+08, YKM11] or the fuel consumption [KP07] for an Internal Combustion Engine (ICE)-based system and, related to this, to minimize the exhaust emission [KPB11].
In this context recent research works distinguish between offline optimization, which regard to the system behavior for a complete time interval, and online optimization, which are designed from the controller's point of view, and are updated at each time step of the system operation.
For offline control optimization using a previously known load profile Bellman's Dynamic Programming approach [Bel12, RGB10] and Global Optimization methods such as genetic algorithms [PIzGV01] are common methods and lead to feasible solutions. Dynamic Programming methods are used to calculate the optimal control

trajectory based on the complete information of the the system dynamics and load profile for the total time interval. In [FQ06] the power split of a parallel hybrid vehicle with a two-stage control is optimized with a Dynamic Programming algorithm. For stochastically uncertain systems both methods can be adapted. Hereby, the Dynamic Programming method can be enlarged to a so-called Stochastic Dynamic Programming (SDP) algorithm. Online capable methods are typically based on the optimal control principle [PG10, MFCS10], model-based [SG07] or rule-based [HSDS07], or sub-optimal [vKdJS08] approaches.
The evaluation of the performance of these algorithms have to be considered in the context of the underlying load profile. A number of methods for the determination and the design of power and energy management algorithms are given in literature. The simpliest methods for the realization of power and energy management of these systems are rule-based methods [HSDS07]. Hereby, the control is realized by a set of boolean or fuzzy rules, which are previously defined for different operation states of the power train.
In [CWL+08], a rule-based power management of a series-parallel hybrid electric vehicle is shown, switching between six operation modes, whereas in [HSDS07] five operation modes are applied. The shown advantage of these approaches is the small computational effort and thus the simple applicability within real-time applications. On the other hand, these approaches only lead to sub-optimal results. Alternative methods base upon neural networks or fuzzy-logic. In [LL09] and [JLK05], fuzzy logic-based power flow control methods are applied on a fuel cell/battery-based series hybrid vehicle to manage the power split between the components. For the application of fuzzy logic-based methods, membership functions are defined for each system state to be considered. The resulting power flow control is determined by the identified degrees of membership with the related controller rules. In [LXH+09] a fuzzy logic power management for a hybrid bus, consisting of a fuel cell system and nickel metal hydrate batteries is introduced. The key advantage of fuzzy logic-based approaches is the simplicity, the easy adaptivity, and the low computational effort. It is shown that, dependent on the driving cycle chosen, an improvement of the fuel efficiency to up to 12.6% can be achieved. In [HJ04] a fuzzy logic-based control applying only control loops based on the identified operational state is compared to a model-based approach, which includes knowledge of the power train system as well. In further studies, algorithms are applied, which receive the control strategy from efficiency maps [FSR09] or system models of the power train [Boy06], to minimize the fuel consumption of the system. Hereby, in [FSR09], the efficiency map of a fuel cell system is applied to choose the operation point of a fuel cell system dependent on the load power determined. In [Boy06], the control rules are stated for an ICE/battery-based HEV by power loss calculations based on system models of the power train system. Another widely usedmethod are different types of optimal controllers. In this context in [KKJ+05] and [SBG04] fuel and electric energy minimization algorithms are given for parallel hybrid electric vehicles based on a combustion engine and a battery pack. An optimal control approach of a fuel cell/battery-based hybrid

vehicle power train with an optimal state feedback is shown in [HYZG08]. Hereby, the assumption of a linear system model is used and the knowledge of the driving cycle is integrated to the optimization. For rule-based and optimal control-based power flow control algorithms, a typically used approach is the usage of the ECMS (equivalent consumption minimization strategy) to give an equivalent description of the different energy sources and to convert the global optimization problem to a local one and thus to receive a simplier online formulation [GS07].

In [RPSG05] and [MRS05] an online-ECMS-based power management is introduced for a fuel cell/supercapacitor-powered VW Jetta model. In [KKJ+05] a simulation study is presented, where a conventional algorithm is compared with a quadratic programming and dynamic programming solution, whereas the approach of [SBG04] is based on the equivalent consumption minimization strategy (ECMS). In a comparative study descibed in [BBA06], a vehicle power train system with an ICE and a battery system is introduced, where the motor torque split is optimized with respect to the minimal fuel consumption for a given driving cycle. This optimization is realized with two optimal control methods, i.e. the adaptive equivalence strategy, which is based on the ECMS method, and the mixed integer quadratically constrained linear program (MI-QCLP), where the optimal control policy is achieved by the solution of a quadratic subproblem. It is shown that both methods are principally applicable for real-time applications but also highly sensitive to prediction errors.

In [PR07], for a parallel hybrid power train consisting of an ICE an electric motor, three approaches are compared to each other. Hereby, a rule-based control, an adaptive equivalent fuel consumption minimization strategy (A-ECMS) and a H_∞-based energy management are compared to each other.

Another possibility to realize the power flow control is the usage of an instantaneous optimal controller. In [KR11], an instantaneous optimal control approach is applied for a single-mode, power-split system of a hybrid electric vehicle power train, which is based on an ICE and a battery. Hereby, a combined approach consisting of a target generation based on the Pontryagin's minimum principle and a target tracking based on a linear quadratic regulator is applied to realize the optimal power split between the ICE and the battery. Other research projects focus on the optimization of the individual component control. In [HSZM09] an optimal fuel cell control approach based on a Radial Basis Function (RBF) neural network approach combined with an optimization based on nonlinear programming (NLP) is shown. Hereby, the control goal of minimizing the stack current flow is used. In [Nie08] a control optimization is realized by a model predictive controller. In [VSP06] a fuel cell system is controlled by a MPC-based algorithm to avoid fuel cell oxygen starvation, to prevent air compressor surge and choke, and to simultaneously match an arbitrary level of current demand. The usage of MPC-based methods [GP11, BRP+10] in the context of power flow control approaches can be seen as a compromise between offline and online methods. For the application of these methods, the usage of a prediction algorithm is typically required.

The control performance of MPC-based approaches depend on the prediction performance of those algorithms. Algorithms based on previous velocity measurements are common methods to be applied for the prediction of the velocity trajectory in combination with the control strategy within automotive applications. Hereby typically GPS-based methods [GMST07] or track-based prediction based on the recent trajectory [CB11] are applied.
Considering these aspects, the implementation of prediction algorithms into model predictive control algorithms as e.g. described in [BRP+10] and [RBC+10] appears to be a suitable combination of the methods described.
Since the optimization methods described are typically based on given or known load profiles. For powertrain systems, these load profiles are typically defined e.g. by driving cycles described by time dependent trajectories of the velocity or the power demand. For unknown driving cycles typically prediction algorithms are applied. Aside from heuristic approaches [Wil09] typically online optimized strategies are applied to realize predictive power flow control strategies. One promising prediction strategy in this context is based on the knowledge of former velocity trajectories to provide approximate information about the expected future load profile [CB11].
In the following chapters, based on the methods stated here, the power flow control problem will be discussed and applied with respect to a multiobjective consideration of the problem. Therefor, in chapter 2, fundamental information to hybrid electric power trains as applied within this thesis are stated. Based on the experimental environment as described in chapter 3, the power flow control problem will be stated in chapter 4 and different methods will be developed, discussed, and applied in chapter 5 within simulation and experimental investigation.

2 Hybrid electric power trains and power conversion systems

A typical application field of hybrid electric powertrains are automotive systems. But there are also other application fields for hybrid electric powertrains e.g. in industrial applications or in aircraft components [ZMB+10].

2.1 Components and topologies of hybrid electric powertrain systems and related modeling approaches

Typically, hybrid electric powertrain systems consist of power sources (e.g. fuel cells, generators), power sinks (e.g. motors, other electrical loads) and storage elements (e.g. batteries, supercapacitors) [Cha07,GS07]. Especially for the realization of power flow control strategies, electric power conversion components as e.g. DC/DC converters [Gar02], rectifiers, inverters are required.
An important aspect for the design is the choice of the topological structure of the components within the powertrain system. Typically, some topological structures are more suitable for large ranges whereas others have a better suitability for the realization of larger peak power during operation. The reasons usually result from technical restrictions as e.g. the time constants of the dynamical behavior of a DC/DC converter of the hybrid topology.
Details, especially regarding the modeling of the dynamical behavior of power train systems and its components are described e.g. in [GS07].
An important aspect for the design of a power train is the topological structure of its components. In [NPA06] different topological structures of fuel cell/battery-based hybrid electric power trains are introduced and discussed for typical driving cycles. Hereby, it becomes clear that the choice of the topology depends on the design targets and that no topology can completely fulfil all of these targets since the different requirements are oftenly conflicting to each other. Typically, each topology has a different efficiency and power availability. As a consequence, some topologies are more suitable for e.g. long range driving cycles whereas others can better cope with e.g. large acceleration phases. In this context, an experimental study is provided in [OXL+06], where two topologies and the related energy management strategies of fuel cell/battery hybrid busses are compared to each other. Hereby, bus A is equipped with a fuel cell system, which is connected with a lead acid battery to an energy hybrid (i.e. the Range Extender topology) structure. Bus B is propulsed by a power hybrid topology (i.e. the Full Hybrid topology) consisting of a fuel cell system and a nickel metal hydrate battery. The related topological structures are depicted in Figure 2.1. The two busses are compared to each other in a bus cycle and a constant speed testing. The related results are depicted in Figure 2.2.

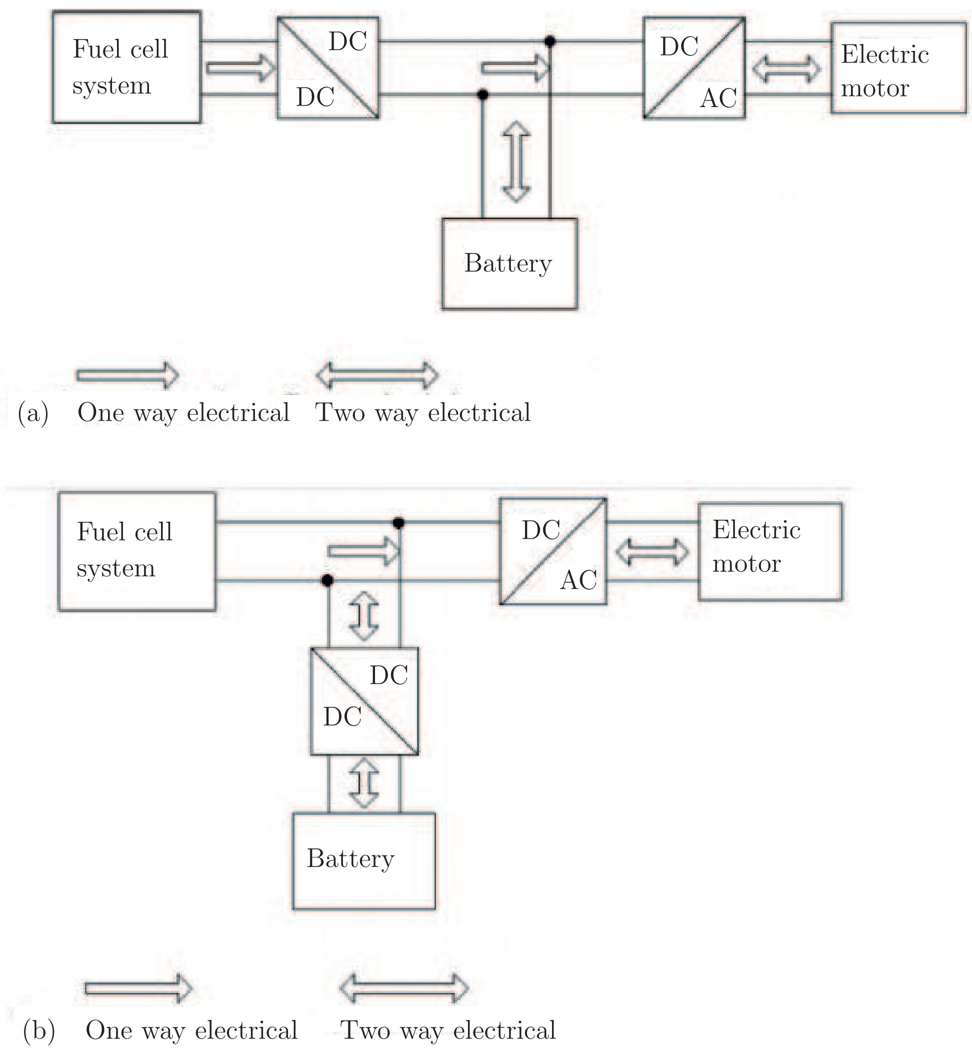
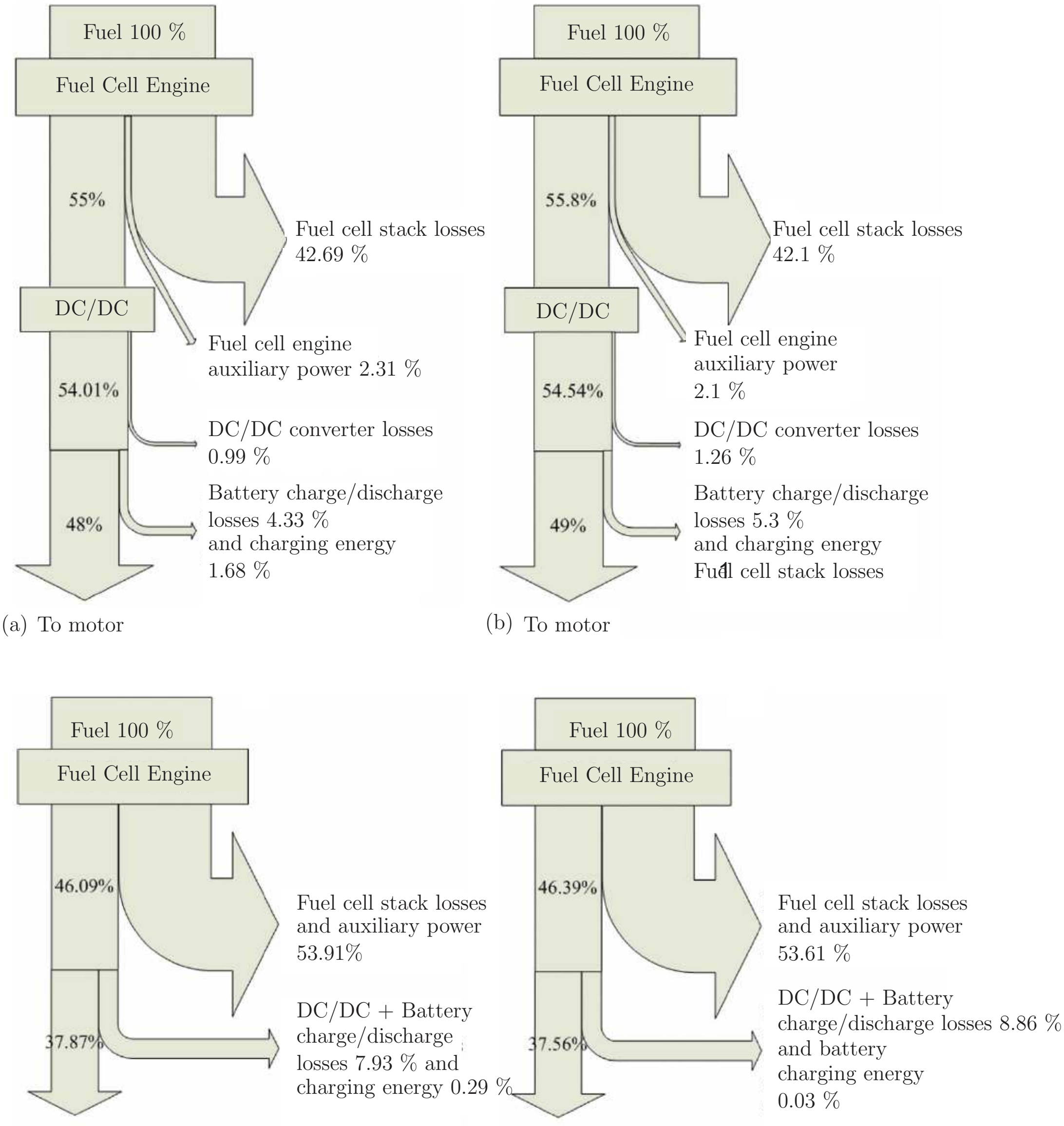


Figure 2.1: Topologies applied: Energy hybrid structure (top) and power hybrid structure (bottom) [OXL+06]

In this example the strengths of each topology becomes clear. Whereas bus A can achieve a better energy efficiency result of 55% in comparison of 46% of bus B, for suddenly increasing power demand in acceleration phases, the topology of bus B leads to better results and thus also has a better effect on the system's drivability.
In the following, four typical topologies are introduced and compared. These topologies are typically applied in hybrid electric power train systems and particularly occur in serial hybrid vehicles, fuel cell hybrid vehicles, and purely electrically driven vehicles.
The topologies are demonstrated using the example of a fuel cell/supercapacitor-based power train system. But the principal relations can also be transfered to



(a) To motor (b) To motor (c) To motor (d) To motor

Figure 2.2: Energy flow diagram of: fuel cell bus A in cycles testing (a), fuel cell bus A in 40 km/h constant speed testing (b), fuel cell bus B in cycles testing (c),fuel cell bus B in 40 km/h constant speed testing (d) [OXL+06]

arbitrary other system components e.g. battery-based systems, combustion engines etc.

2.1.1 Topology A: Basic topology

The simplest topological conception is realized by the connection of all energy sources and the drive motor to a system bus as illustrated in Figure 2.3.

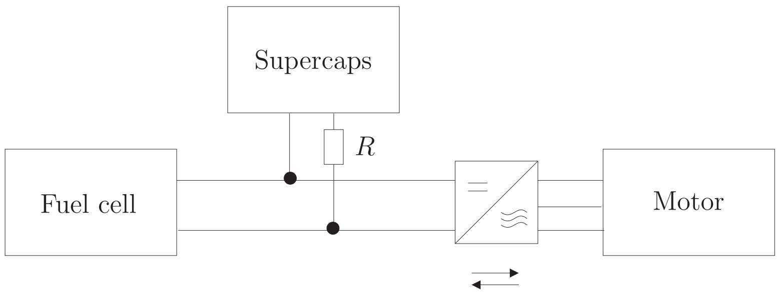


Figure 2.3: Topology A: Basic topology of a hybrid electric system (without DC/DC converter) [Özb10]

During the operation, the supercapacitors are charged by the primary energy source (here: fuel cell system) or by the current flow of the brake energy recovery until their voltage levels are equal. The fuel cell system and the supercapacitors are directly connected to the motor to supply it.
The advantage of this structure is its simple setup, the low control effort and no loss by DC/DC converters. The supercapacitors can be used in addition to the fuel cell system to supply the motor. The recovered braking energy can directly be stored into the supercaps without control delay.
On the other hand, the disadvantages of this structure are that, caused by the lack of a DC/DC converters, the bus voltage can not be controlled. For this reason, the motor voltage and the charging and discharging of the supercaps can only indirectly be influenced, which limits the application of a power and energy management to the control of the fuel cell and the motor. For the same reason, the operation of the motor within a suitable operation point can not be guaranteed and the control of the power split between the supply of the fuel cell system and supercapacitor can not be realized.

2.1.2 Topology B: Range Extender (Energy Hybrid Topology)

The Range Extender topology is a widely used powertrain structure in series hybrid electric vehicles. In this topology, the electric power flow of the primary energy source (here: the fuel cell system) can be controlled by a monodirectional DC/DC-converter.

The term Range Extender describes the capability of the system of enlarging the range of a power source (here: supercaps) with the usage of a second one (here: the fuel cell system). The related sketch is illustrated in Figure 2.4.

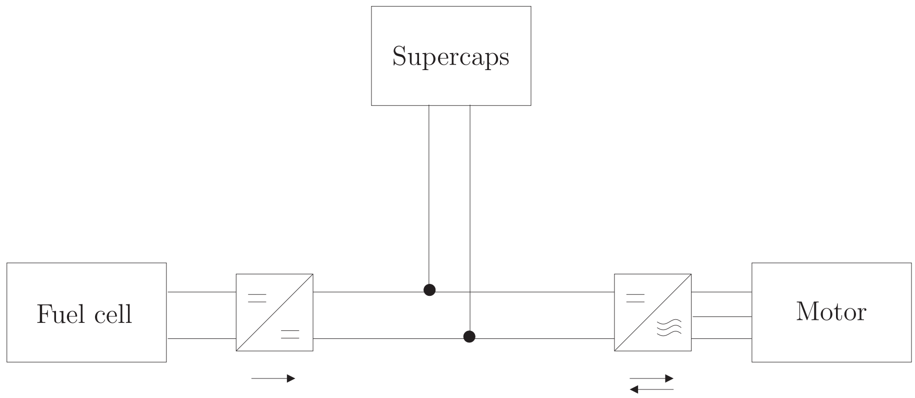


Figure 2.4: Topology B: Range Extender topology with a fuel cell system, supercaps, and a DC/DC converter [Özb10]

The charging and discharging of the supercapacitors can be defined with the application of the control of the monodirectional DC/DC converter. Hereby, the fuel cell power can be kept at a constant level dependent on the dimensioning of the components and the load profile. In this topology the bus voltage is equal to the supercap voltage and the motor voltage. The main advantage of this topology is that the fuel cell sytem can be controlled to operate continuously in an energy-efficient operation point. Due to the fact that only a single DC/DC converter is applied, the typical energy losses are comparatively small. For this reason, this topology is oftenly used to increase the power train system's efficiency and thus the range (Energy Management). The direct connection of the supercapacitors and the motor allows a fast supply and braking energy recovery.
The disadvantage is that the bus voltage can only be influenced by the state of charge of the supercapacitors. This also means that a variation of the motor voltage, which can be necessary dependent on the load profile, can only be realized very slowly. Additionally, this topology does not allow to control the power split between fuel cell system and supercapacitors.

2.1.3 Topology C: Full Hybrid (Power Hybrid Topology)

A further topology is the Full Hybrid topology illustrated in Figure 2.5. Hereby, the primary energy source (here: the fuel cell system) is connected directly to the bus. By the application of a bi-directional DC/DC controller the charge/discharge of the supercaps can directly be influenced. By the control of the bus voltage the power ratio of the fuel cell power on the system power can be influenced as well.

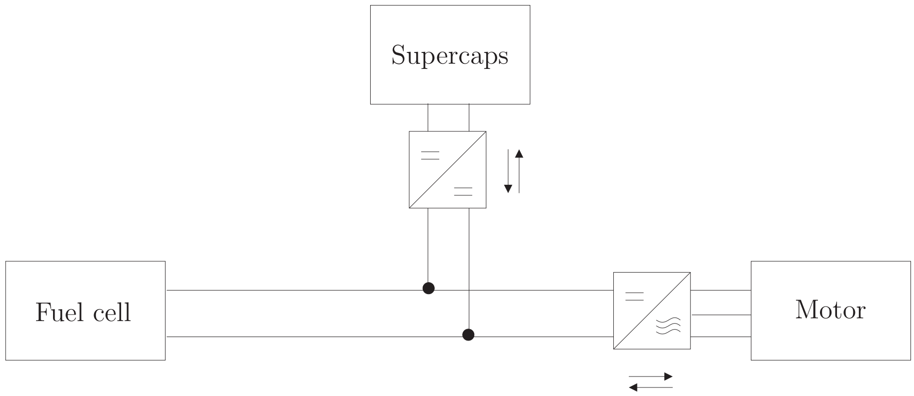


Figure 2.5: Topology C: Full Hybrid Topology with bi-directional DC/DC Converter for the charge/discharge of the supercaps [Özb10]

The bus voltage can be controlled directly with this topology, which can be an advantage for the dynamic behavior of the drive motor. For this reason, this topology is typically applied for power management tasks to improve the drivability of the system. But on the other hand, a disadvantage is that the direct connection of the motor power and the fuel cell power can cause large current gradients effecting an accelarated aging of the fuel cell system.

2.1.4 Topology D: Extended Hybrid

For the Extended Hybrid Topology, as shown in Figure 2.6, two DC/DC converters are applied, which allows a more flexible control of the current flows within the power train structure and thus the power flow control can better be adapted to the different driving situations [NPA06].

The large flexibility of this topology is possible since the usage of two DC/DC controllers enables the system to control the bus voltage directly and almost independently from the fuel cell size and the state of charge of the supercaps. However, due to the complexity of the system and possible undesired effects caused by the interaction between the directly linked DC/DC converters (e.g. current oscillation), the controller design is a challenging task. A disadvantage of the Extended Hybrid topology is that the usage of two DC/DC converters in this system topology causes relatively large energy losses. Furthermore, the integration of a powertrain with this structure especially for the usage in automotive applications causes larger volume,

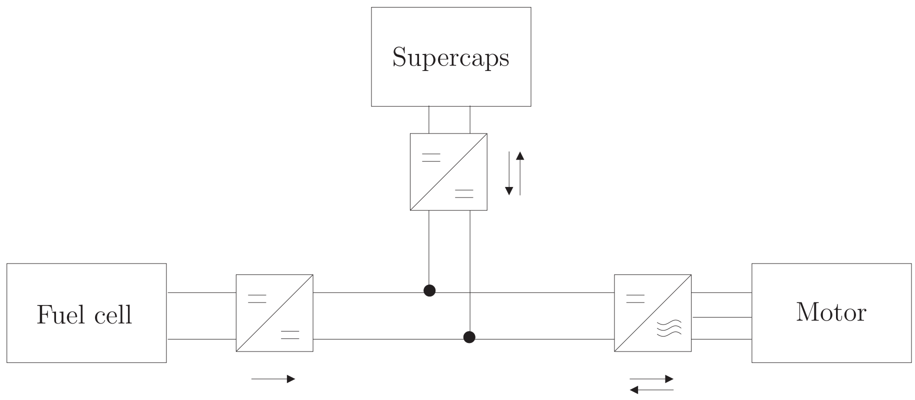


Figure 2.6: Topology D: Extended Hybrid topology with DC/DC converters, fuel cell system, and supercaps [Özb10]

weight, and purchase costs of the system.
In [TRD09] this topological principle is applied for hybrid system consisting of a fuel cell with two storage elements, i.e. a super capacitor system and a battery system. Heeby, as a control approach, a rule-based algorithm is integrated. For a similiar power train system with fuel cell, battery and supercapacitor, in [ZPM+11] a flatness-based and a fuzzy logic-based control approach are applied and compared to each other.

2.1.5 Discussion

It can be concluded that the usage of DC/DC controllers allows a better control of the power split and can be used to allow the operation of the fuel cell and the motor in a more efficient operation point. Hereby, for the control of the charge and discharge of storage elements, a bi-directional DC/DC converter is required, whereas for the additional control of the fuel cell current flow, a simplier monodirectional DC/DC controller is sufficient. On the other hand, the usage of DC/DC converters, especially bi-directional ones, lead to larger energy losses since of their typically small efficiency. A disadvantage of the usage of a bi-directional DC/DC converter might be a more challenging control problem to manage the charge and the discharge of the storage elements during boost and recovery operations. To sum up, the choice of a suitable topological architecture is depend on the operation points of the components, which is directly dependent on the load profile (driving cycle) applied to the power train system. Detailed studies are provided e.g. in [ÖS08, Özb10].

2.2 Performance properties of hybrid electric power train systems

As stated in [GS07], the optimization of hybrid electric power train systems, which includes both, the design and dimensioning as well as the control strategies, base upon the optimization of a cost function J. In the simpliest case, this is the minimization of the fuel mass m_f consumed during a time period $t = [t_0, t_E]$ in dependency of the system input $u(t)$ with the resulting cost function

$$J = \int_{t_0}^{t_E} \dot{m}_f(t, u(t))dt, J \rightarrow \text{Min.} \tag{2.1}$$

This cost function can also be applied for effects, which indirectly depend on the fuel mass, such as the emmission of pollutant, so that Eq. 2.1 can be generalized as

$$J = \int_{t_0}^{t_E} L(t, u(t))dt, J \rightarrow \text{Min.} \tag{2.2}$$

In hybrid electric power trains typically different types of energy are used. For the integration of the SOC of the electric storage to the related cost function, a simple way is to integrate a soft constraint by penalizing deviations between the initial and the final energy stored. Applying a penalty term ϕ to Eq. 2.2, the so-called charge-sustaining performance index

$$J = \phi(\Delta SOC) + \int_{t_0}^{t_E} L(t, u(t))dt \tag{2.3}$$

can be obtained. The penalty parameter can typically be written in quadratic form as

$$\phi_{quad}(\Delta SOC) = \alpha(SOC(t_0) - SOC(t_e))^2 \tag{2.4}$$

or in linear form

$$\phi_{lin}(\Delta SOC) = \alpha(SOC(t_0) - SOC(t_e)). \tag{2.5}$$

The quadratic form penalizes the target SOC independent of the sign of the deviation, whereas for the linear expression, the charging and the discharging can be considered in a different way. For the linear case, the charging and discharging can be integrated to the cost function considering the SOC rate during the time interval as

$$J = \int_{t_0}^{t_E} (L(t, u(t)) + \alpha \dot{SOC}(t))dt. \tag{2.6}$$

Hereby, the weighting parameter α can principally be chosen arbitrarily, according to the regulatory standard SAE J1711, $\alpha = 38$ kWh per gallon of gasoline is recommended.

The usage of a piecewise-linear penalty function, distiguishing between discharging (α_{dis}) and charging (α_{chg}), as

$$\phi_{lin}(\Delta SOC) = \begin{cases} \alpha_{dis}(SOC(t_0) - SOC(t_e)), & SOC(t_e) > SOC(t_0) \\ \alpha_{chg}(SOC(t_0) - SOC(t_e)), & SOC(t_e) < SOC(t_0) \end{cases} \tag{2.7}$$

directly leads to the equivalent consumption minization strategy (ECMS) formulation. Based upon these typically used expressions (as stated e.g. in [GS07]), in the context of this thesis, further performance properties with respect to drivability and aging are considered as well. Therefor, in section 4.1, the underlying relations and especially the resulting requirement for the power flow control are discussed and, resulting from this, a performance measurement and evaluation scheme is developed in section 4.2. These schemes are used for the realization of the control optimization schemes as described in chapter 5.

2.3 Component sizing and control design of hybrid electric powertrain systems

For the design of these systems the planning of the system architecture as well as the control design have to be considered. Hereby the application of optimization approaches play an important role.
Classical approaches for the optimization of hybrid electric powertrain systems deal with the component choice and its sizing. In [Gue05] some basic realization steps are explained for a fuel cell-based hybrid electric vehicle. Hereby, typically, the design is mainly based on static and quasi-static load demand assumptions. In [Hen08] the sizing of a combined storage system consisting of a battery and a supercapacitor is discussed. Hereby, the minimizion of the life-cycle costs of the battery is achieved by the integration of the supercapacitors.
An generalized optimization strategy for the element sizing of hybrid electric power trains is presented in [dRAB09]. Hereby, a formulation based on energy hubs is used with three basic elements, i.e. direct connections, converters, and storages. The

idea is to define the energy hubs as interfaces between producers, consumers, and the transportation infrastructure. For the consideration of dynamic influences, the system behavior in time and frequency domain and especially the transient behavior of the system has to be considered. Hereby, especially control aspects are a central point. For this reason, in recent years, the control optimization has become an important research field. A combined consideration of sizing and control aspects of hybrid electric power trains is shown in [KP07]. For the dynamical considerations, power flow control algorithms of hybrid electric powertrain systems, such as e.g. power management, energy management, and lifetime management, are key issues, which are discussed in the following.

2.4 Component aging within hybrid electric powertrain systems

Another aspect is the minimization of component aging effects of hybrid electric powertrains by the usage of control algorithms.

The aging of components in the context of hybrid electric powertrain systems has become a growing research area in recent years. In this field many publications deal with the investigation of aging mechanisms especially occuring in fuel cell [HJRW09, Zha08, Liu06] or battery systems [LSG+10, MFSF09, RHG+04, MOGR09]. The implementation of aging effects within a battery management system is discussed e.g. in [Kai07]. These aging processes of system components can be influenced by the design of the system but they can also be considered in dependency on the operating conditions. In [HJRW09] and [BBB+05] typical influences on aging-related performance losses of fuel cell systems are experimentally identified and compared to each other. Main aging effects within fuel cell systems during transient operation are summarized in [Özb10]. Hereby, it becomes clear that the operation dependent lifetime of fuel cell systems is mainly limited by its membrane [CWY+06], where mechanical, thermal, and catalyst degradation occur. Hereby, for mechanical degradation (cracks, tears, punctures, and pinholes), impulsion pressure by hydrogen, water, and air are comparatively minor causes, whereas main contributions are humidity and temperature cycles, since these cause large stress changes [HSZ+06]. Thermal degradation is mainly caused by hot-spots in the membrane which leads to local water evaporation and causes pinholes within the membrane. These pinholes lead to increased hydrogen crossover, i.e. crossing of hydrogen atoms without reaction with the oxygen atoms, which leads to smaller efficiency or may lead to further damage by the reaction of hydrogen (burning) [CZT+07]. Catalyst degradation occurs by platinum dissolution, carbon-support corrosion, and platinum sintering [YY07]. Further details are provided in [YSMH09]. By these effects, a loss of electrochemical surface area on the active layer of the membrane electrode assembly is caused. As a consequence of these and further studies [MFF+08, SYG07], transient and cyclic fuel cell operation leads to a faster degradation compared to stationary operation. Thus, stationary operation should be preferred for the fuel cell system. Additionally, an increased deterioration also occurs by the operation of fuel cells for a long time duration near their power limit, since this is also related to a large current flow dynamics. It can be concluded that the usage of comparatatively small fuel cells (i.e. with a small power range) has to be avoided. As a consequence, for the power flow control of a hybridized power train system with respect to an increased fuel cell lifetime, the fuel cell system should be applied for a supply of a stationary power demand at its nominal operation point, whereas peak powers should be realized by a secondary power source with a high power capability such as e.g. supercapacitors. Related investigation results are provided e.g. in [ÖS08].

3 Experimental emulation of hybrid electric powertrains

The development of power trains and their power flow control is typically realized by model-based considerations, simulation-based studies as well as experimental investigation. Hereby, modeling approaches are used to gain a detailed understanding of the system structure and its dynamical behavior, whereas the experimental investigation is an important part for the validation of the dynamical models and for the proof of the applicability of e.g. a chosen control approach especially within systems with a complex structure, a nonlinear dynamical behavior, or uncertain system parameters. The experimental investigation of power train system is typically realized with usage of Hardware-in-the-Loop (HiL) test rigs. There is a large number of Hardware-in-the-Loop concepts for the experimental evaluation of hybrid electric and hybrid hydraulic power train systems. Disadvantages of classical setups are the higher costs and the worse adaptability of hardware components. Another problem is the deterioration and large energy and fuel consumption of the components especially during the testing process. For this reason, the experimental evaluation of power trains by emulation systems is a promising method in order to overcome these problems. Hereby a physical system is replaced with a surrogate dynamical system based on realtime models.
As shown e.g. in [Özb10], [MOS09], and [MOS10], a fuel cell/supercapacitor-based Hardware-in-the-Loop (HiL) test rig is build up at the Chair of Dynamics and Control at the University of Duisburg-Essen. The experimental environment is shown in Figure 3.1.

3.1 Overview

In the context of electric and hybrid electric power train systems principally two emulator concepts can be distinguished. Pseudo-emulators use actual electric components of a different sizing. In [MPV$^+$09] this scaling is realized based on the implementation of a buck converter, in [OIQ05] an amplification of the dynamical behavior of a fuel cell is carried out by a Switching Mode Power Supply (SMPS). In [PB09] a networked hybrid electric vehicle power train Hardware-in-the-Loop (HiL) system is presented, where, among others, dissimilarly sized components of a fuel cell system and a battery are included. Hereby the scaling effects of the components are modeled by dimensionless variables defined by Buckingham's Pi Theorem as introduced in [Buc14].
In constrast, the classical emulator concepts use controlled power supply systems and power sinks based on dynamical models to replace the regarded electric component. In the field of hybrid electric power trains especially emulator applications of fuel cell systems are of special interest. In [GBBM11], a DSP-based electrical

Figure 3.1: Fuel cell/supercapacitor-based Hardware-in-the-Loop (HiL) test rig ([Özb10], [MOS09], [MOS10])

structure for the emulation of a fuel cell system is introduced, which focusses on the complex dynamical behavior of the system and can also be adapted to the emulation of supercapacitor systems. Further examples for fuel cell emulation are shown in [PB11] and [SAY10].
Another typical example for the application of electrical emulation algorithms is the consideration of battery systems as described e.g. in [PLC03].
Furthermore, the integration of the components into a power train structure is widely used. In [WSS11], a hybrid power train emulator based on a physical engine and a hydrostatic dynamometer is introduced. The control of the engine speed and the torque applied by the dynamometer are determined by a simultaneous simulation of a power train structure. The disadvantage of the described electrical power train emulation systems is that they mainly focus on the dynamic behavior of individual components and neglect the interdependences between them.
The emulation of hydraulic power train system is also a commonly used method. In [CA03] the load emulation of an Earthmoving Vehicle Powertrain is realized by three hydraulic load units. Another example is the Augmented Earthmoving Vehicle Powertrain Simulator (AEVPS) for the study of mobile electrohydraulic powertrains as described e.g. in [DASM11]. The disadvantage of hydraulic test rig systems is the

need of more effort to set up the experimental structure and its adaptation to changing requirements.
For this reason, the use of hydraulic electric analogy models is a suitable method to investigate the dynamical behavior of systems by using surrogate models. Some fundamental considerations in this context are provided by [Sch54] and analoguous units are compared to each other. There are also research projects using this analogy for modeling and diagnosis. In [RJ12], a hydraulic electric analogy model is used for the modeling and simulation of a cardiovascular system. In [LH06] an electrical surrogate model is applied for the fault location within a hydraulic powerline structure. Using these considerations, the emulation of hybrid hydraulic power train systems using electric power train topologies becomes obvious.

In the context of this thesis, this test rig is modified and generalized for the emulation of general hybrid power train topologies and electric energy conversion systems. Based on the principles stated before an emulator system of a range extender topology is set up as a HiL environment. Its schematic setup is shown in Figure 3.2.

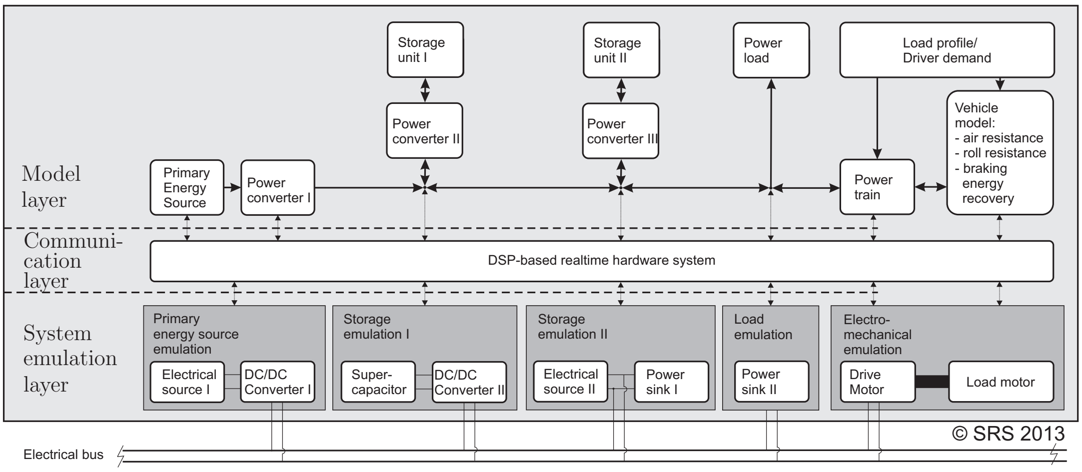


Figure 3.2: Power train emulation structure of a hybrid power train topology

Its operation is based on a three-layer-structure. In the model layer the dynamic behavior of the electric components is stated. During the operation a simultaneous simulation is carried out and the results are sent via a DSP-based realtime hardware system in the communication layer to the electrical hardware components of the power train topology within the system emulation layer. The emulation layer consists of four hardware emulation groups. The primary energy source emulation is realized by a controlled electrical source, which emulates a primary electric source and a combined voltage-current-controlled monodirectional DC/DC converter. The short-time electric storage unit is realized by an ultracapacitor package. The topology can be completed by further storage units, e.g. physical or emulated battery systems.

The drive train, which is supplied by the electric components and whose dynamical behavior is dependent on the influence of the driver behavior and the mechanical properties of the vehicle, is emulated by a speed-controlled electric drive motor, which is capable of recovering electric energy during braking maneuvers, and a load motor. This torque-controlled load motor is coupled with the drive motor via a common axle. It is supplied by an external grid and applies external torques to the drive motor resulting from simultaneous simulation results of air and roll resistance or braking maneuvers. The topology and the experimental environment are depicted in Figure 3.2.

The emulation includes also the experimental investigation of the influence of power flow control algorithms. The emulation is based on controlled elementary power train components, which can be used as surrogate electric components. The modular structure of the system allows a good adaptability depending on the system requirements.

The related HiL test rig environment is shown in Figure 3.3.

Figure 3.3: HiL test rig for power train emulation

In the following, the usage of emulation concepts for different hybrid power train systems such as a hybrid electric, a hybrid hydraulic, and a Wind Energy Conversion System are discussed and their results are presented.

3.2 Emulation of a hybrid electric power train system

At first, a vehicle model with a hybrid electric power train system is considered. This power train consists of a fuel cell system, applied as a primary energy source. Additionally, a supercapacitor system is used as an intermediate storage. These components are arranged in a range extender configuration and are connected to a common bus. They supply an electric motor, which is capable of regenerating electric energy during breaking. The system topology is shown in Figure 3.4.

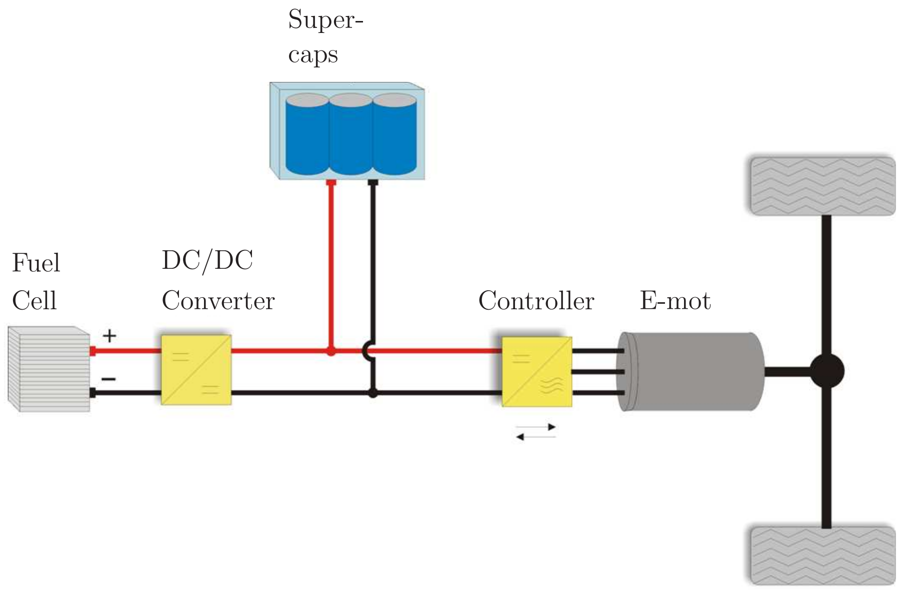


Figure 3.4: Topology of the hybrid electric power train system [Özb10]

For simplicity, the charging dynamics of the supercapacitors is assumed as linear with

$$U_{SC} = \frac{1}{C} \int I_{SC} \; dt, \tag{3.1}$$

with the capacity C, the current flow I_{SC}, and the voltage U_{SC} assumed as propotional to the SOC of the supercapacitors. The control of the electric power flows within the topology is realized by a compound voltage/current-controlled DC/DC converter as

$$\begin{bmatrix} U_{Bus} \\ I_{Bus} \end{bmatrix} (k+1) = f(U_{Bus}(k), I_{Bus}(k), s_{DCDC}(k)), \tag{3.2}$$

with U_{Bus} and I_{Bus} describing the voltage and current at the outflow of the DC/DC converters and the control signal s_{DCDC}.

For the power flow control of the power train two control algorithms are included. The first one controls the current flow of the monodirectional DC/DC converter (Power converter I / DC/DC converter I as depicted in Figure 3.2). Hereby the SOC of the supercapacitors are controlled to be constant. Secondly, a driver model is included for the control of the vehicle speed depending on the reference speed, given by a driving cycle. The related emulation structure is depicted in Figure 3.5.

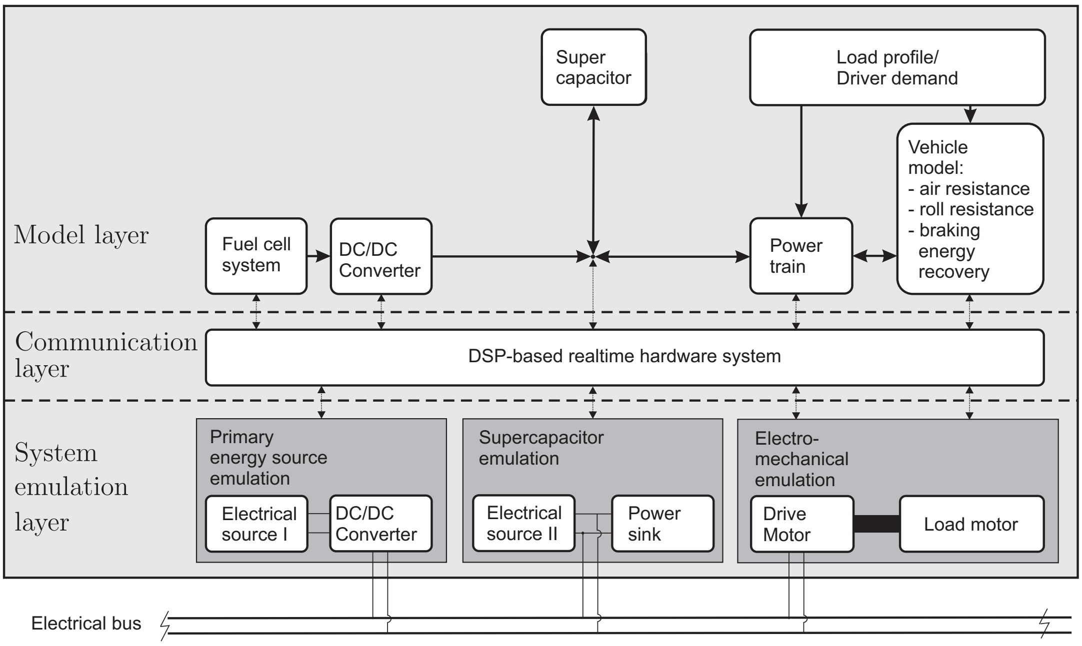


Figure 3.5: Emulation structure of the power train topology of the hybrid electric vehicle

The experiments are conducted using the ECE driving cycle as a load profile. For the hybrid electric power train the focus is on the control and emulation of the current flow by using the power flow control algorithms mentioned.
The emulated current flows of the DC/DC converter and the charging current of the supercapacitors, emulated by the electric power sink, are depicted in Figure 3.6. In both cases a good coincidence between model behavior and emulation can be achieved.

The electro-mechanic emulation of the vehicle motor is realized by the motor unit, containing drive motor and load motor. Hereby the rotational speed of the electric power train model relates to the rotational speed of the emulator motor, whereas the electric current flow of the emulator motor, which depends on the load applied is equivalent to the motor current of the electric model. For the motor, the related current flow and the rotational speed of the model and the emulation are shown in Figure 3.7.

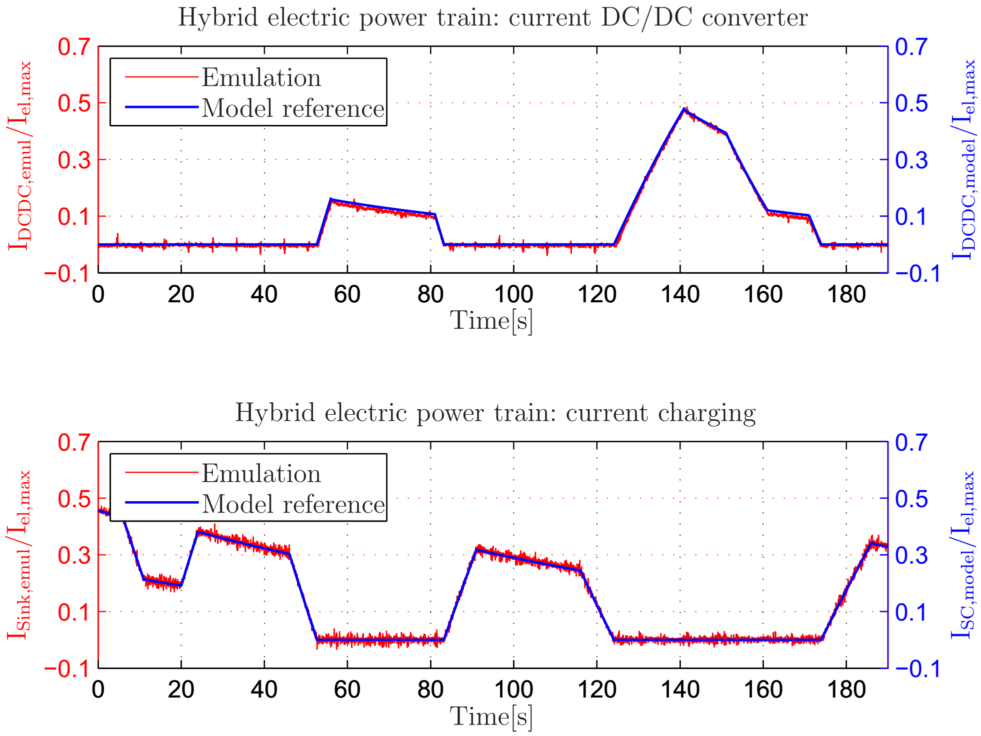


Figure 3.6: Current flows of the DC/DC converter (top) and charging current of the supercapacitors (bottom)

It becomes clear that also for the requirements of this application example, a good emulation performance can be achived.

3.3 Emulation of a hybrid hydraulic power train system

A second experimental application example is the emulation of a hybrid hydraulic power train system, whose components are arranged in a series hybrid configuration. This system consists of an combustion engine, which drives a pump unit of a hydraulic manifold system. Included in this system is a hydro motor and a hydraulic accumulator, which is used as an intermediate storage system. Details and a comparison further topological architectures are provided e.g. in [DCLC13].

A series hybrid hydraulic which is shown in Figure 3.8 is modelled for the emulation. This topology contains an axial piston pump and motor, a bladder type accumulator, a pressure relief valve, and an internal combustion engine. Since in this topology there is no direct mechanical connection between engine and vehicle drive train, the engine and the hydro motor can be controlled independently. The transmission ratio

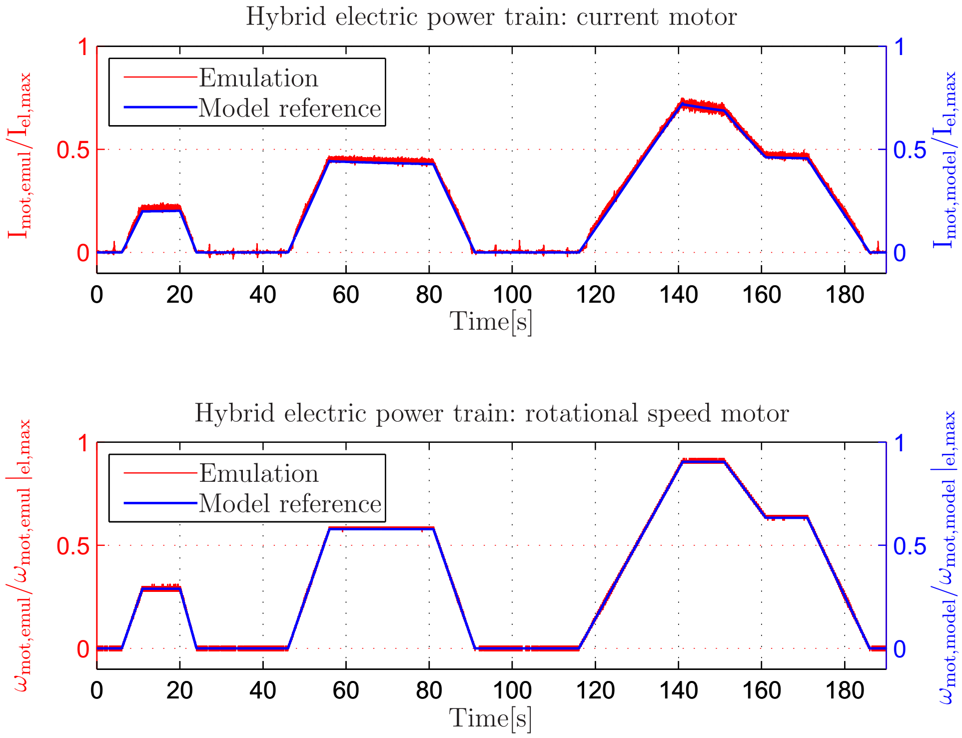


Figure 3.7: Motor current flows (top) and rotational speed motor (bottom)

between engine and vehicle is defined by multiplication of pump and motor displacement ratio. By changing the displacement of both pump and motor continuously, transmission ratio changes continuously and wide spread transmission ratio are realizable.

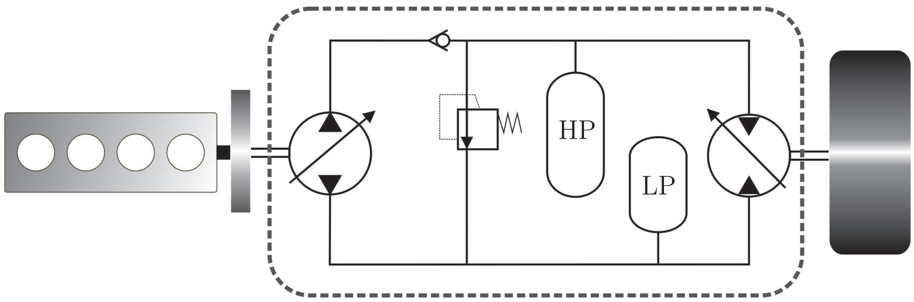


Figure 3.8: Topology of the hybrid hydraulic power train system (e.g. [PBF92a, PBF92b, DCLC13])

The longitudinal vehicle dynamics is assumed as identical to the hybrid electric power train. The fuel consumption is calculated using a quasi-stationary look-up table of the engine and the brake, which is based on the engine torque and velocity used as inputs. High frequent power changes of the engine are neglected for these considerations.

Additionally, a quasi-static model of the bent axis piston pump and motor are applied in this topology. It contains their volumetric and mechanical efficiency in relation to pressure, displacement, and velocity of the pump or the motor. The relation between mechanical and fluidic characteristics is given by

$$\begin{aligned} T &= \frac{p\,Q}{\omega} \\ \omega &= \frac{Q}{xD}. \end{aligned} \tag{3.3}$$

Hereby, T denotes the motor torque, p the pressure difference between input and output of the pump and motor, Q the hydraulic flow, ω the rotational velocity, x the displacement ratio, and D the maximum volumetric displacement. Additionally, ahe volumetric and mechanical efficiency of pump and motor are presented e.g. in [PBF92a, PBF92b]. For simplicity, the real efficiency data map of pump and motor are applied here. Generally, the efficiency has a direct relation with the pump and motor displacement and reverse relation with the load.

The bladder type accumulator is used for two purposes. First, it damps the pressure deviation in the system high pressure line and second, it is the temporary source of energy in the system for braking energy recovery. Two accumulators namely high and low pressure accumulators are connected to the high and low pressure line respectively. There are two different accumulator models included. One model considers energy losses, and the other one is an adiabatic model. Using the adibatic model of the accumulator the power change $\dot{P}$ is represented as

$$\dot{P} = -\frac{Qp^2}{C_{acc}}, \tag{3.4}$$

where C_{acc} is the accumulator constant depending on the initial gas volume. The state of charge (SOC) as a normalized energy level in the accumulator is

$$SOC = \frac{p - p_{min}}{p_{max} - p_{min}}, \tag{3.5}$$

in which p_{max} and p_{min} are the maximum and minimum pressure within the accumulator.
For the emulation of the hybrid hydraulic power train with the electric components of the emulation system, the system outputs of the hybrid hydraulic power train system are transformed among the relations of the electric hydraulic analogy model

Table 3.1: Analogy between electric and hydraulic system properties [Sch54]

Electric	Hydraulic
potential	potential
current flow	charge/discharge
resistance	resistance
inductance	inertance
capacitance	capacitance
generator	pump
series scheme	series scheme

described in [Sch54]. Hereby, among others, the analogy of the electric and hydraulic units listed in Table 3.1 are described.

For the emulation of the hybrid hydraulic power train the electric hydraulic analogy model is used, as mentioned before. The related emulation structure is illustrated in Figure 3.9.

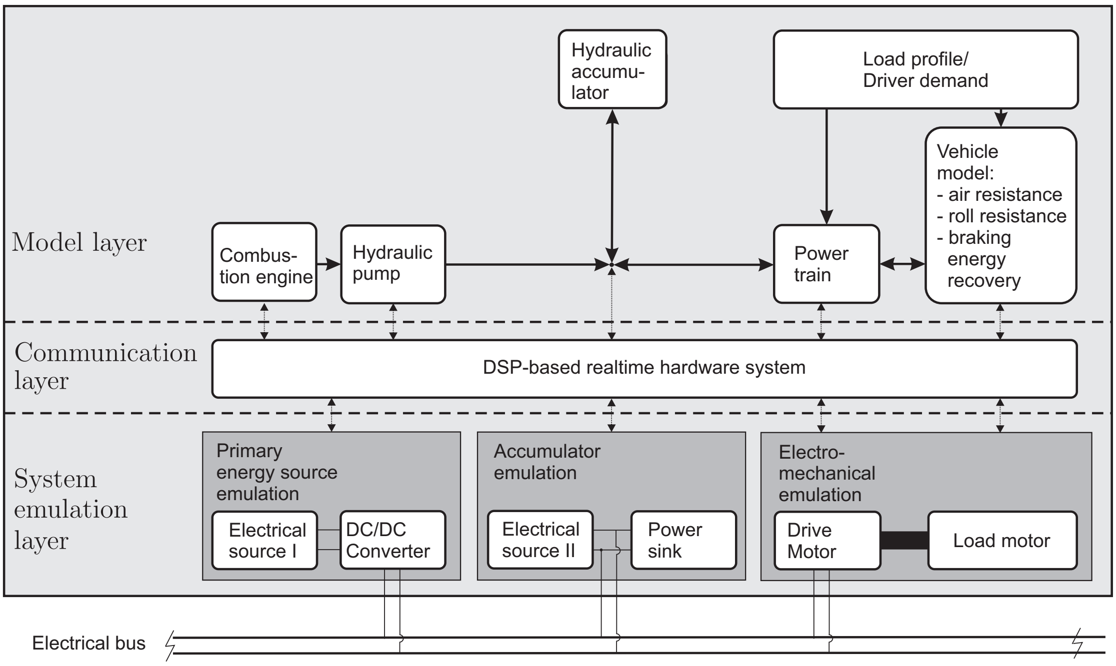
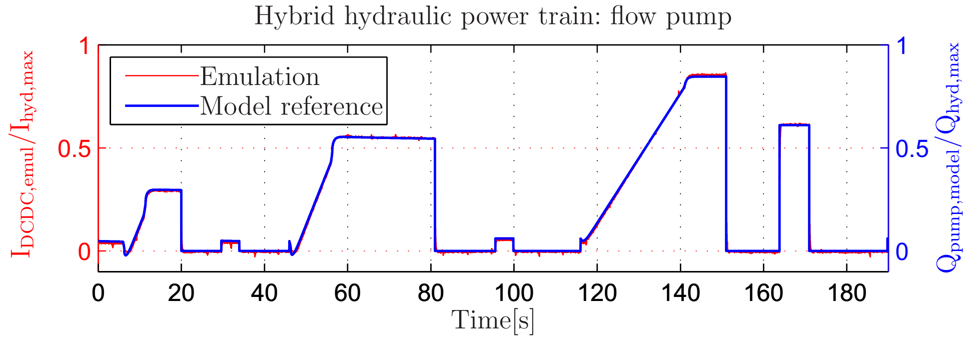


Figure 3.9: Emulation structure of the power train topology of the hybrid hydraulic vehicle

This example is focussed on the hydraulic flows, which can be emulated by equivalent electrical current flows of a proportional magnitude. The hydraulic flow rate of the pump is hereby emulated with the scaled electric current outflow of the DC/DC converters of the emulator, whereas the emulation of the charging flow of the hydraulic accumulator is realized with the electric power sink. The simulated hydraulic flows of the pump and the accumulator and the related electric emulator current flows are depicted in Figure 3.10. It becomes clear that a good coincidence between simulation results and measurement can also be achieved.



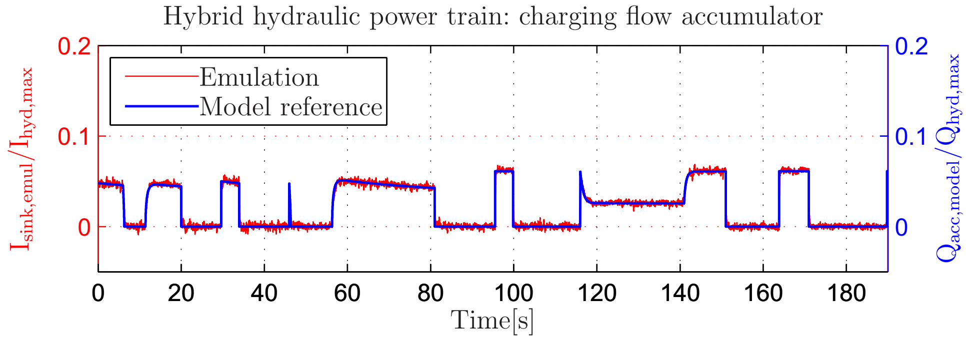


Figure 3.10: Current flows of the DC/DC converter (top) and charging current of the supercapacitor (bottom)

Accordingly, for the hydro-mechanical emulation of the hydromotor the rotational speed is emulated with the rotational speed of the driving motor, whereas the emulation of the hydraulic flowrate is realized by an equivalent electric current flow. The related hydraulic flow and the rotationals speed of the motor is shown in Figure 3.11.

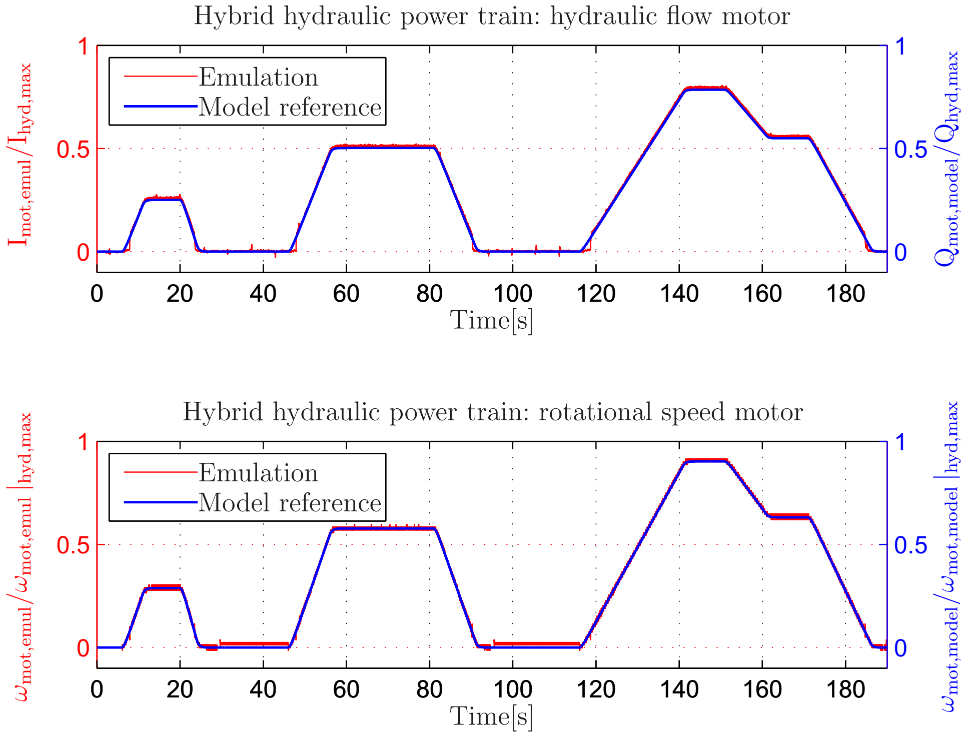


Figure 3.11: Motor current flows (top) and rotational speed of the motor (bottom)

Also for the emulation of the signals required for this application example, a good coincidence can be achieved. It can be concluded that the emulation of the interaction flows between the components of hybrid electric and hybrid hydraulic power train topologies can be suitably realized by emulator systems based on electric components. The same holds for the emulation of electro-mechanical and hydro-mechanical relation by electro-mechanical motors. Nevertheless, it has to be taken into consideration that the results demonstrated can only be seen as initial test result for the specific experimental environment described.

3.4 Emulation of a wind energy conversion system

Wind energy as a clean and renewable energy has attracted a lot of attention. However, some technical problems still remain, out of which, the most important one is to increase the efficiency of energy generation. The classical strategy of operating with variable wind speed is to control pitch angle and generator torque by different classical or modern control strategies [SBG04, BBM06] in order to get the rated power. This limits the power to the rated level by high wind speed and takes the maximal low power generation during low wind speed. Therefore, the energy lost at high wind speed is non-negligible. In the following, a control concept for wind energy converter system combining the traditional wind turbine control with power management is shown. The goal of the power management is to increase the efficiency of wind turbine by taking the maximal power at every wind speed using generator torque control and compensating the low energy generation at low wind speed with the extra energy generated at high wind speed over the rated energy for rated output power, if possible. There exist three sub controllers: the pitch control, the generator torque control, and the energy flow control for the energy storage.

In addition to the wind turbine and its components, the usage of an electric grid with electricity consumption as well as an intermediate storage element is assumed. The storage element equalizes fluctuations of the flows by storing electric energy for peak load case and delivering in low energy cases. The power flow within this electrical network between generator, storage element, and grid is controlled by a converter system. Further details as well as a suitable controller structure design stabilizing the grid voltage are shown in [LMMS13]. The structure of the WECS is depicted in Figure 3.12. For experimental evaluation, the models of the related Wind

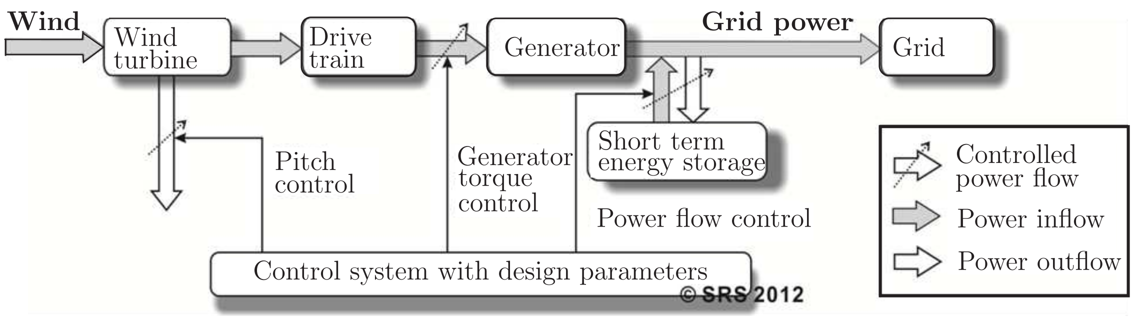


Figure 3.12: Structure of the considered hybrid WECS [LMMS13]

Energy Conversion System (WECS) as well as the intermediate storage system are integrated into a power train emulation system. Hereby, the results of the electric power flow control approach is emulated with the usage of a test rig environment. The emulator system consists of two controllable power sources, refering to the generator and storage energy delivered and two power sinks emulating the grid load as well as the energy stored in the storage elements. The components are connected to each other in a suitable topology. The resulting emulator operation structure of the WECS is illustrated in Figure 3.13.

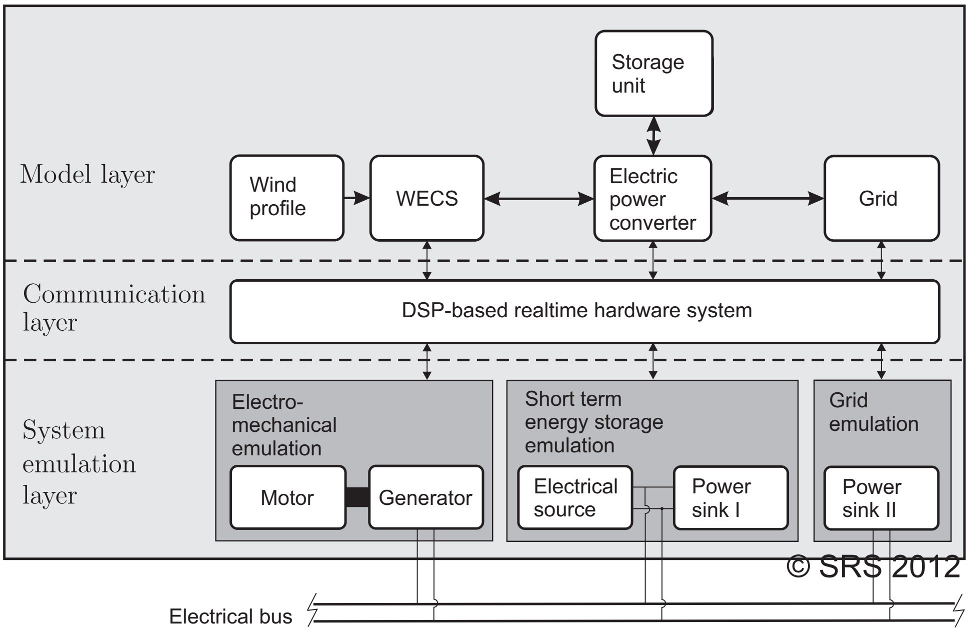


Figure 3.13: Power train emulation structure of a WECS [LMMS13]

The model layer contains the dynamic power train component models mentioned before and is connected with a realtime hardware system of the communication layer. In this layer the resulting electric powerflows to be realized within the system emulation layer are calculated. The related signals are transmitted to the electric hardware of the system emulation layer. In the context of this contribution this system emulator layer is built up by three main parts. These elements are connected to a common electric grid. For the electro-mechanical emulation part, two electric motors are mechanically coupled via a common axle. Hereby, a speed-controlled drive motor, being used as a generator, is applied to supply the components of the electric topology. The other motor, the torque-controlled load motor, applies mechanical torques to the drive motor. These are related to the mechanical loads of the WECS caused by the wind loads. Secondly, a further emulation part uses a programmable electrical source and a power sink to realize the electric flows of the electric converter and the energy storage. The third emulation part realizes the electric load profile being applied on the electric grid. For the operation a pre-defined load profile is applied to the grid of the system. The operation of the WECS including the pitch control is based on a predefined wind profile as shown in Figure 3.14.

The WECS and the storage topology are connected together and the electric grid is assumed as an external electric load. The dynamics of the electric components

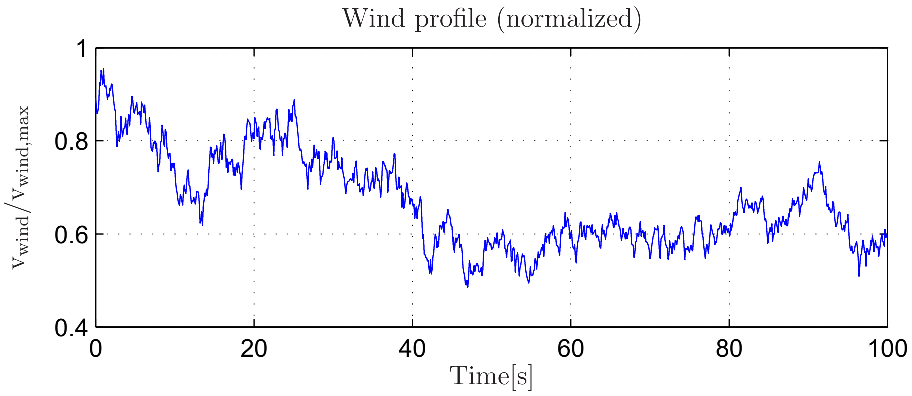


Figure 3.14: Wind profile applied to the system [LMMS13]

including their control are obtained through a simultaneous simulation, whereas the electric flows between them are emulated by controllable electric units.

For the electromechanical emulation the reference values of rotational speed of the WECS and the resulting electric power are applied to the electric motors. The expected demand is calculated from the simulation of the WECS model. For the integration with the system emulation layer, a combined speed and torque control is realized. The results obtained for the rotational speed emulation is shown in Figure 3.15.

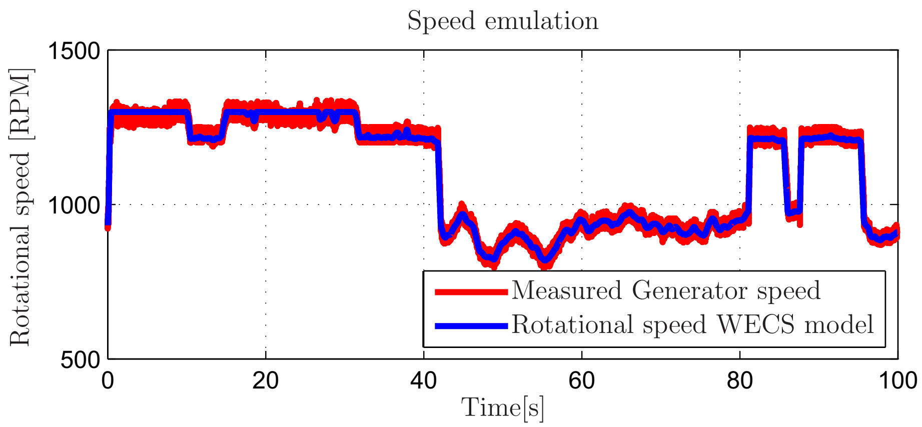


Figure 3.15: Speed emulation of the WECS [LMMS13]

The related emulation of the electrical power generated by the WECS is depicted in Figure 3.16.

It becomes clear that both the rotational speed and the measured motor power (with diminished sensor noise) closely follow the reference signals resulting from the

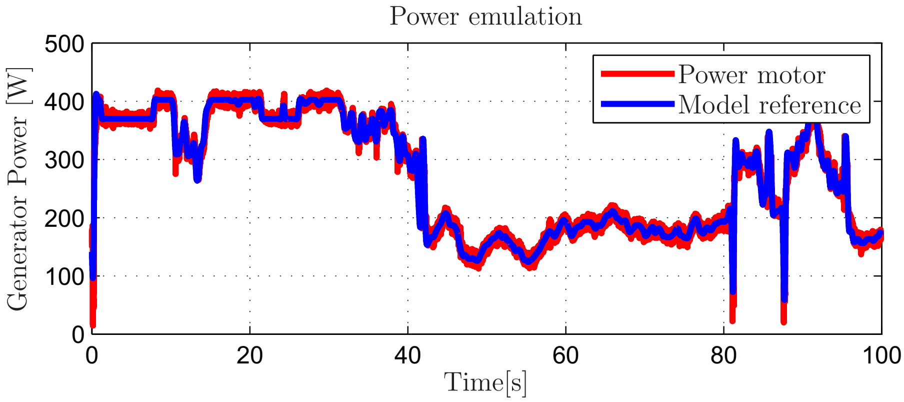


Figure 3.16: Power emulation of the WECS [LMMS13]

WECS model. Thus, the principle applicability of the emulation concept and the test-rig becomes clear under the introduced conditions. However, for a more detailed investigation and thus for the application of more complex structures it will be necessary to add more detailed system models and further power train components.

3.5 Discussion

The emulation structure, which is set up by electric power sources, sinks, and power conversion elements, allows a more generalized view to power train and electric energy conversion structures regarding them as power sources, sinks and transmission elements. Additionally, as shown, the motor unit can be applied as an electro-mechanical conversion system, applied both as a motor and a generator. The experimental results of the initial tests show that using this emulation structure, different topological structures can be integrated. Thus, it can be concluded that for the system structures under the conditions introduced this is principally applicable for the experimental investigation of the power flow control approaches, which will be introduced in the following chapters. However, the applicability within real-time applications also depends on the complexity of the power train models and the related computational effort required.

4 Power flow control algorithms of hybrid electric powertrains

As discussed, the sizing of the power train components and the power flow control within the system structure are important aspects for the development of hybrid electric power trains systems. In this context, in recent years, a large number of optimization approaches of hybrid electric powertrains are published in the context of related research projects. Typical design optimization approaches investigate the influence of the component sizing on the fuel consumption. Other sources define relations between geometrical sizes using scaling theorems.
The disadvantage of the methods optimizing only the sizing, is that it only considers static and quasi-static influences regarding mainly the stationary behavior of the system. For considering transient and cyclic effects, the influence of dynamic effects have to be considered as well. This also includes the consideration of the influence of control algorithms on the system, especially the power flow control of the power train.
The task of power flow control algorithms is to control the electric powerflow within the topology between the system components and thus the determination of the electric or mechanic power split between different power sources or storages. This can be realized by the usage of energy transmission elements as e.g. DC/DC controllers [Gar02]. Another possibility is the control of the system components directly. In [OWMS13] and [Özb10], different fuel cell control appraches are compared to each other. Hereby, the input mass flow is controlled sepatately to minimize the pressure difference between anode and cathode. In the context of hybrid electric powertrain systems the electric powerflow control of these systems is a central task and plays an important role in recent years' research work e.g. in automotive applications.
An overview about typical power flow control methods and strategies in the context of automotive power train systems is given e.g. in [Mur08] and [Ott07].
In [GS07], the optimization problem for the fuel minimization of parallel hybrid vehicles is detailed. According to the authors, power flow control strategies can be classified to causal controllers, which are based on the measured or identified load profile, and non-causal controllers, where additional information is required. Hereby, non-causal controllers require detailed knowledge of the driving conditions e.g. by a previously given driving cycle or a prediction algorithm, whereas causal controllers can also be applied within non-predictable driving profiles.
Another classification of the authors is the distinction among heuristic, optimal, and suboptimal controllers. Hereby, heuristic controllers are mostly based on Boolean or fuzzy rules based e.g. on the driving speed, vehicle acceleration, required power etc., whereas optimal and suboptimal controllers are based on the formulation of a cost function.
In the following, the influences of power flow control approaches on the dynami-

cal behavior and thus the performance of power trains is considered and related optimization approaches are discussed.

4.1 Basics of the power flow control within hybrid electric power trains

Typical power flow control algorithms within hybrid electric power train systems are power and energy management. A large number of research projects deal with power and energy management problems. Hereby, energy management algorithms typically relate to range or efficiency oriented control algorithms, whereas power management algorithms are more related to the capability of the power train of providing peak power or large accelerations.
In [Ros07] a modular tri-shell hierarchical structure is applied and a separate control of the long-term energy management, the power management with fast decision requirements, and the power electronics to control the power interfacing circuit is distinguished. As discussed, the power flow control can also be applied with respect to the maximization of the reliability and hence its the component lifetime.
As stated in [Özb10], the power flow control can be distinguished between power management, energy management, and lifetime management, which can also be distinguished by their time-horizon.
In the context of this thesis, power management is considered as the drivibility-oriented control, energy management as the approaches aiming at the improvement of the fuel economy and thus the minimization of the total energy consumption, and lifetime management relates to the control maximizing the component's life time. Considering the time horizons of the related control approaches, power management typically refers to a short-term, energy management to a middle-term, and life time management to a long-term control strategy.
As shown in Figure 4.1 these methods can be realized as integral parts of the power flow control of the power train system.

Taking the different control goals of the power flow control into consideration, in the context of this thesis the control strategy of the electric flow can be considered as a multiobjective problem. Based on this, an optimization approach has to be carried out with respect to previously given topological structures.

4.1.1 Power Management

The objective of the power management is to maximize the capability of a system of delivering a peak power for a short time interval. Therefore, typically the required energy has to be delivered by a source or storage with large power capability such as supercapacitors, lithium-ion batteries etc. Large power demands typically occur

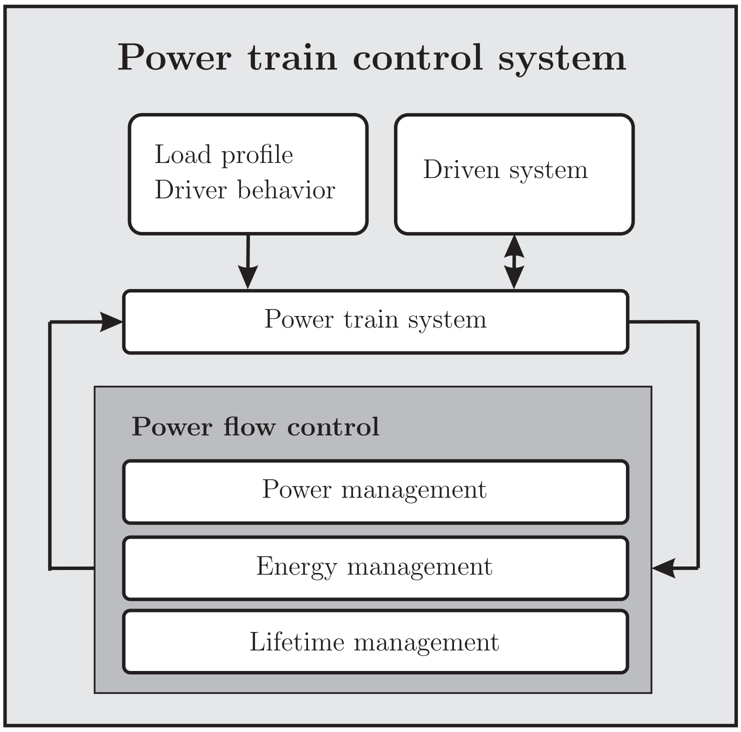


Figure 4.1: Scheme of a power train control structure

during strong acceleration maneuvers. A good indicator to evaluate the performance of the power management is the tracking of the predefined load profile. This property is comparable to the drivability in vehicle applications.

4.1.2 Energy Management

Energy management of hybrid electric power trains of vehicles aims at the maximization of the fuel economy, the energy efficiency of the system, or the minimization of the fuel/energy consumption and hence contributes to the range of the system with respect to time or distance. In hybrid electric power trains, this is typically related to the fuel consumption of an energy source such as e.g the hydrogen consumption of a fuel cell system or the fuel consumption of a combustion engine. Additionally, in the case of the usage of one or more storage elements (e.g. accumulators, supercapacitors etc.), their discharge has to be considered as well. A typical method to combine these energy consumption, is the ECMS method, as discussed e.g. in [GS07]. Hereby, methods to provide an equivalent discription of the different energy sources are provided. Aside from the operation of the power sources and storage element at the maximum efficiency, the total energy management performance can also be improved by the maximization of the energy recovery e.g. during braking maneuvers. This aspect can lead to the necessity to operate the power train system at a different operation point. Thus, if applied within an optimization framework, the optimization goal of the energy management is to maximize the fuel economy of the power train system.

4.1.3 Lifetime Management

In [RS96, SR97, SRMP98] the Safety and Reliability Control Engineering (SRCE) concept is introduced. Hereby, the relation between operation and reliability characteristics of a system is discussed. This concept is detailed and demonstrated using the examples of electric supply systems [Söf99a] and mechanical systems with vibration [Söf99b, Söf99c]. The main idea of the concepts is to apply the influence of system aging mechanisms for the development of a suitable control policy for the maximization of the system reliability and hence also for the total component lifetime.
In the context of this thesis, this basic idea is applied in a simplified manner to integrate the main component aging mechanisms during their operation into the power flow control algorithms. Hereby, the application of lifetime management techniques is demonstrated with respect to the aging of fuel cell systems. Therefore, main aging mechanisms as discussed in section 2.4, are used and thus an aging-oriented control of the electric power flows within the topological structure is realized using lifetime management-based algorithms. In this context, the objective of the lifetime management is to avoid operation states which causes large aging [Özb10]. In the context of this thesis, the alternating power output, especially with large frequency, is considered as main aging aspect to be considered within the development of lifetime management algorithms for the operation of fuel cell-based power trains.

4.2 Performance measurement and evaluation

As discussed before, in the context of this thesis, a multiobjective power flow control approach, considering power management, energy management, and lifetime management is developed. The central properties of the power train system related to these objectives are the drivability of the system, the fuel economy in accordance to the ECMS considerations, and the deterioration of individual system components (here applied to the example of fuel cell aging).

The evaluation of the power flow control can be performed on the basis of several performance criteria. In the following, the example of a fuel cell/supercapacitor-based hybrid electric power train is used to demonstrate its performance properties with respect to the drivability of the system, the fuel economy and the occurance of faster deterioration of the fuel cell system during transient operation is presented.

As described in [MOS14], the drivability of the power train system can be evaluated considering the load profile as a demanded reference signal and the capability of the system to fulfil it. Typical examples of reference signals are load profiles based on the power demand or a speed reference as it is typically applied in driving cycles. Hereby a poor drivability can be identified at a large difference between the reference profile and the measured values as shown in Figure 4.2 using the example of a speed reference.

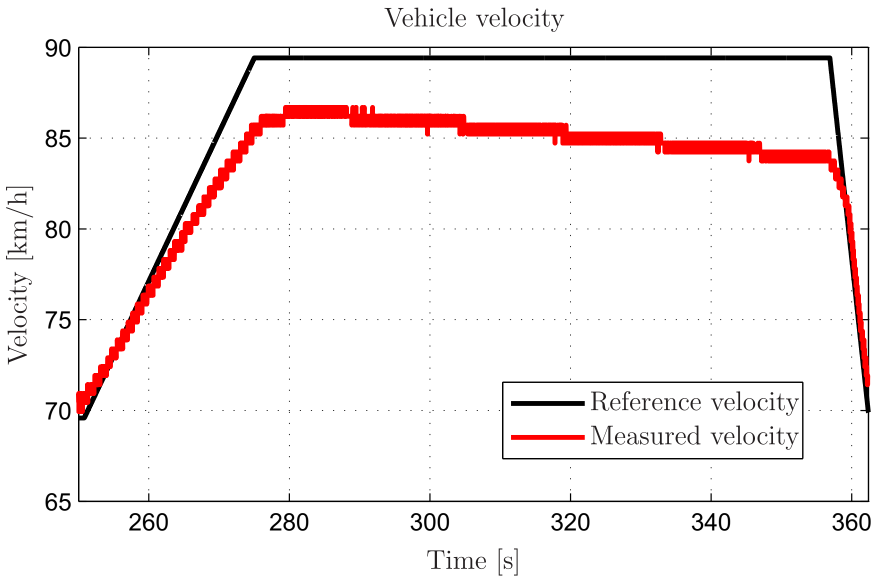


Figure 4.2: Reference and measured vehicle velocity [MOS14]

Taking this into consideration, an evaluation parameter denoting the power availability of the system and, thus the drivability, can be defined as a function of this difference, e.g. using the IAE (*integral absolute error*) with

$$P_{driv} = f_1\left(\int_t |v_{ref} - v_{meas}|\, dt\right). \tag{4.1}$$

It becomes clear that a large value correlates with a poor drivability of the system to fulfil a demanded load profile. In Figure 4.3 typical values of the IAE between reference and actual velocity in dependency on the reference bus voltage are shown.

These deviations principally occur at low bus voltages since the capability of the drive motor of providing large electric power strongly decreases at lower supply voltages. As illustrated in Figure 4.4 a lower bus voltage limit can be defined where this effect typically occurs if undershooted.

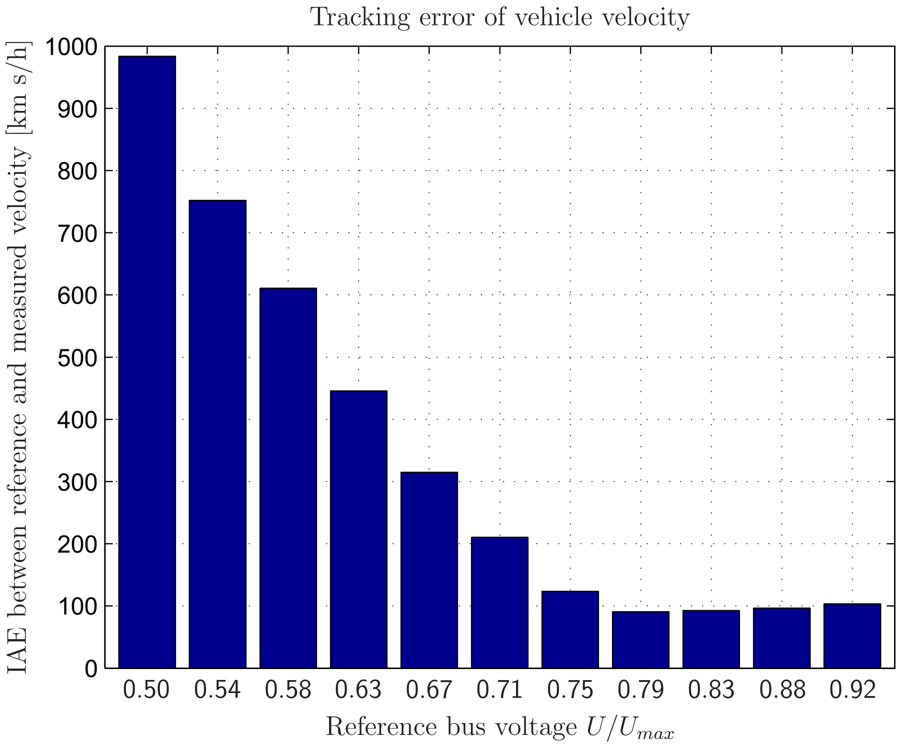


Figure 4.3: Integral absolute error (IAE) of the measured velocity dependent on the reference bus voltage [MOS14]

Secondly, the fuel economy of the system can be determined by measuring the hydrogen consumption of the fuel cell system and the discharge of the energy storage (here: supercapitors) during the driving cycle. Herefrom the performance parameter P_{econ} evaluating the system's fuel economy can be determined by

$$P_{econ} = V_{H_2} + f_2(SOC_{init}, SOC_{final}), \tag{4.2}$$

where V_{H_2} denotes the measured consumption of hydrogen and $f(SOC_{init}, SOC_{final})$ a function to calculate the amount of hydrogen to even up the difference between the final state of charge SOC_{final} and the initial state of charge SOC_{init} of the energy storage.

Furthermore, deterioration mechanisms on the fuel cell system are evaluated by the third parameter P_{det}. It is based on the assumption that high frequent and large magnitude changes in the fuel cell power increase the component's aging as described e.g. in [Zha08] and discussed in section 2.4. Thus, a highpass filter is applied to determine the high frequent power changes and a suitable function f_3 is applied to quantify its magnitude. The resulting parameter is calculated by

$$P_{aging} = f_3((P_{FC,filt}(t))), \tag{4.3}$$

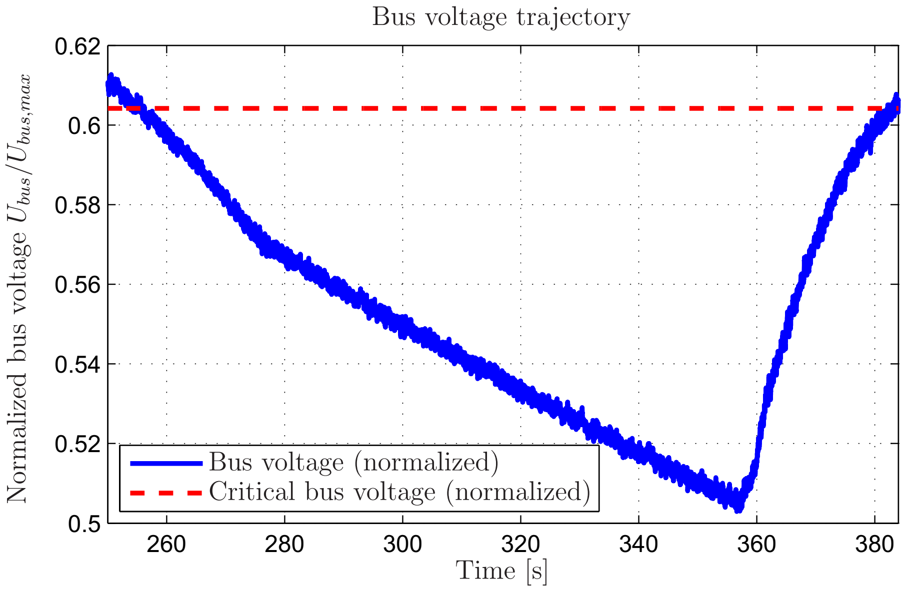


Figure 4.4: Relative bus voltage during driving profile of Figure 4.2 [MOS14]

using the highpass-filtered fuel cell power $P_{FC,filt(t)}$.

Applying the evaluation parameters described before, the total system performance P_{total} can be defined. Therefor the parameters P_{driv}, P_{econ}, and P_{det} are weighted by

$$P_{total} = \sqrt{\lambda_1 \; P_{driv}^2 + \lambda_2 \; P_{econ}^2 + \lambda_3 \; P_{det}^2}. \tag{4.4}$$

Here λ_1, λ_2, and λ_3 denote weighting coefficients predefined by the user.

4.3 Experimental comparison of power flow control algorithms

The requirement for the realization of the power flow control algorithms as an integrated power management, energy management, and lifetime management approach leads to a multiobjective control approach. Hereby, a suitable method for the evaluation, and, based on this, an optimization with respect to the performance criteria of Eq. 4.1-4.3 is required. Using the example of a hybrid electric powertrain system this consideration leads to the problem to analyze the control performance with respect to the performance properties in dependency of a given load profile (here: the previously defined driving cycle). For principle consideration, the relations are shown by the usage of simple control algorithms.

4.3.1 Power flow control algorithms considered

In the following, three typical power flow control algorithms (denoted by PCA I, PCA II, PCA III) and their influence on the system behavior are presented. These algorithms can be denoted as modified rule-based algorithms. Hereby the first approach describes a classical rule-based controller whereas the other ones consider quantitative measurements of the system states as well. In contrast to classical approaches, known from the literature and mentioned before, the three control approaches are designed to cope with multiple conflicting objectives and can be designed by the related parameters. The usage of an additional system model for this adaption is not required for the evaluation.

The methods demonstrated in the following are a two position controller (Bang-Bang Control) of the primary energy source, a current rate limitation-based controller, and controller which regulates the bus voltage to a constant value.

4.3.1.1 Power flow control algorithm PCA I: Maximal power of primary energy source for low state-of-charge of the energy storage

The objective of the first power flow control algorithm is to control the primary energy source in a way that it operates at maximal power if the state of charge of the storage element has been fallen below a previously defined threshold. This algorithm can be considered as a typical example of a rule-based controller. For its realization the state-of-charge of the energy storage is identified using its nonlinear system relations (system voltage dependent on the electric current inflows and outflows). So a comparison to the predefined SOC limitation is performed and a two-level control (maximal power or idle operation) of the primary energy source can be realized. The static switching behavior is briefly illustrated in Figure 4.5. Hereby the reference power of the primary energy source (here: the fuel cell system) is controlled dependent on the identified SOC. This critical SOC is applied as a control parameter of the power flow control and can be varied during the experiments.

The principal ideas hereby are to provide a fast reaction of the system to critical discharges of the storage element and on the other hand to save the primary source if not necessarily needed. Thus the goal is to improve the power availability of the system, also in case of comparatatively high required loads. The advantage of this approach is that critically low states-of-charge of the energy storage can be overcome comparibly fast, so that the capability of the motors to deliver larger electric power is improved. On the other hand, this approach has two disadvantages. In many cases, operating at maximal power is related to a non-optimal efficiency, which increases the fuel consumption of the system. Another important aspect is that the fast switching between maximal power an stand-by operation causes high power

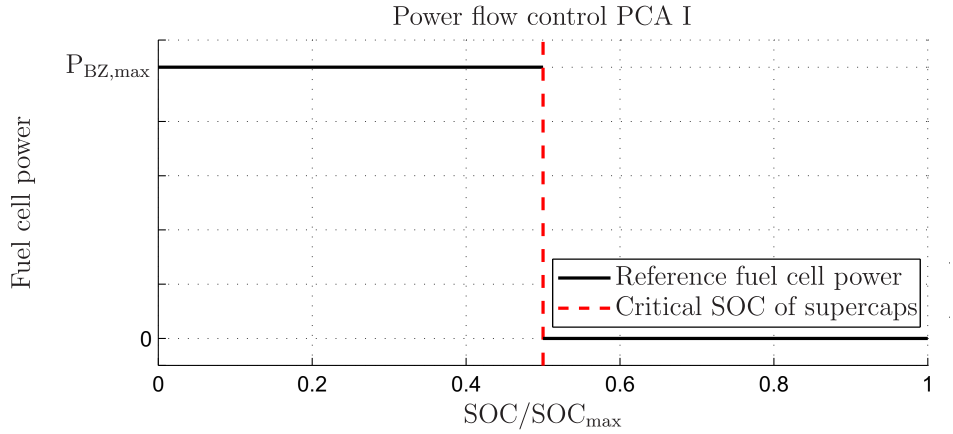


Figure 4.5: Switching strategy in PCA I [MOS14]

slopes, which, in many power sources (especially fuel cell systems) leads to a faster aging and deterioration process [Zha08], as discussed before.

4.3.1.2 Power flow control algorithm PCA: Power management guided by a reference voltage level

In the second power management approach the energy flow is controlled by a reference voltage level of the electric intermediate system. This is typically realized by the application of controllable converters. For the control the system voltage (bus voltage) level is monitored and compared to the reference voltage. In contrast to the rule-based algorithm PCA I the numerical values of the control error and its proportional, integral and differential relations are considered for the determination of the control input as well. A typical example showing the effect of the control is illustrated in Figure 4.6. For this algorithm the reference voltage level can be varied and thus be applied as a control parameter.

This power management is applied using the reference voltage level defined for a typical load profile. The measured voltages of the intermediate system during the operation is considered in comparison. Compared to the PCA I algorithm, the power rates of the primary energy source are typically smaller for this algorithm since the control leads to a smoother trajectory and fewer switching of the electric current. As a result, a smaller effect on the component aging is expected. Dependent on the electric power demand on the system, it has to be defined, which aspect has a positive influence. The reduction of a generator voltage can have a positive effect on the capability of the system of recovering electric energy, whereas an increase of the motor voltage can improve the drivability concerning the supply of peak power.

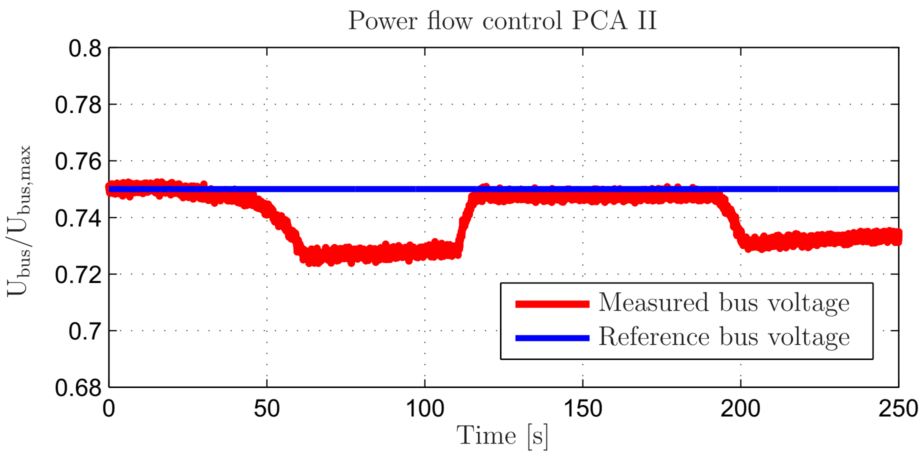


Figure 4.6: Principle of PCA II [MOS14]

4.3.1.3 Power flow control algorithm PCA: Principle/Goals Power management guided by current control

The third power management method deals with the control of the electric current flow [LD04]. Based on the monitored voltages and current flows of the primary energy source and the system bus respectively, the operation and thus the power flow of the primary energy source is influenced in the way that its current rate is limited to a maximal rate $P_{ratelim,i}$. Hereby a direct influence on the power trajectory of the energy source and the charging/discharging of the storage elements becomes clear. In Figure 4.7 the effect of current rate limitation on the fuel cell operation is illustrated.

The advantage of this method is that the direct influence of the algorithm on the current flow can increase the system safety and can especially reduce the aging mechanisms on the individual components (here: the fuel cell system) by the minimization of the specific current-related influence.

4.3.2 Experimental evaluation

The algorithms are evaluated with respect to drivability, fuel economy, and component lifetime. For the system evaluation, the performance parameters, as stated in Eqs. 4.1-4.3, are applied.

The experimental evaluation is realized on a fuel cell/supercapacitor-based hybrid electric powertrain system, which is mentioned in chapter 3. Details of this power train test-rig are described e.g. in [Özb10], [MOS09], and [MOS10]. Hereby, the fuel cell system is applied as a primary electric energy source and the supercapacitors as

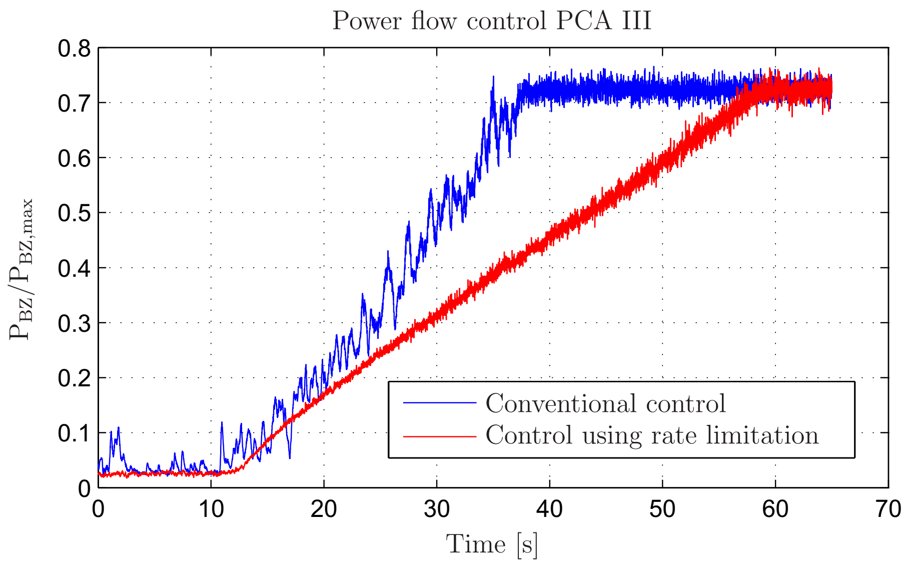


Figure 4.7: Power flow control, classical and with limitation of current gradient [MOS14]

an intermediate electric storage element. The system components are arranged in a Range Extender topology as shown in Figure 4.8

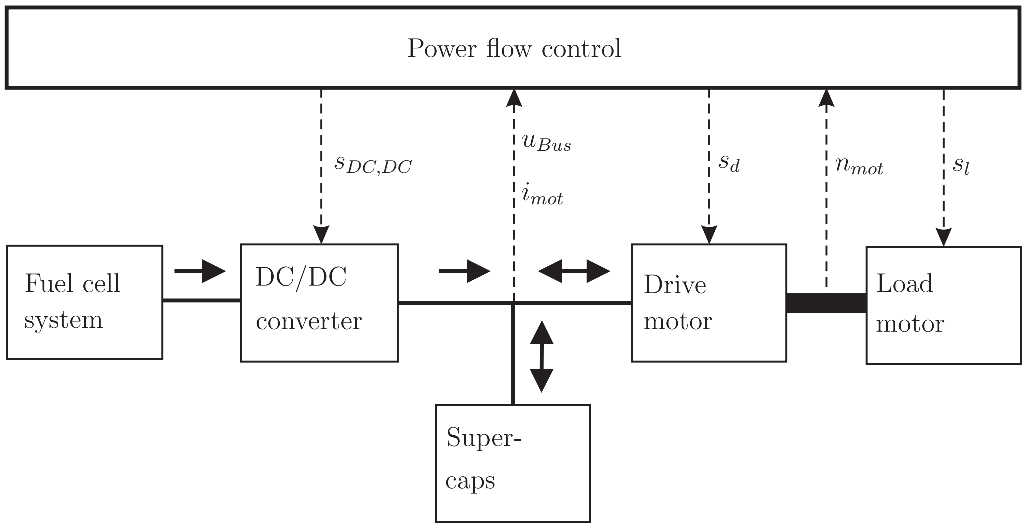


Figure 4.8: Topology of the powertrain system [MOS09, MOS10]

These components supply an electric drive motor. This motor is speed-controlled and capable of regenerating electric energy while operating as a generator. The control is realized by the drive motor signal s_d. The current flow of the fuel cell system to the supercapacitors and the drive motor is controlled by a monodirectional DC/DC converter, which is controlled by the signal $s_{DC,DC}$. To apply external forces on the system as they occur e.g. by air and roll resistance of a vehicle or during braking maneuvers, a torque-controlled load motor is mechanically coupled via a common axle to the drive motor, which is controlled by the signal s_l. The control of the components of this power train and thus the power flow control algorithms are realized by a DSP-based realtime hardware system. Hereby, the measurement of the bus voltage u_{Bus}, the motor current i_{mot}, and the rotational speed of the motor n_{mot} are essential measurements.

The algorithms are demonstrated for the EUDC and the ECE cycle, as shown in Figure 4.9.

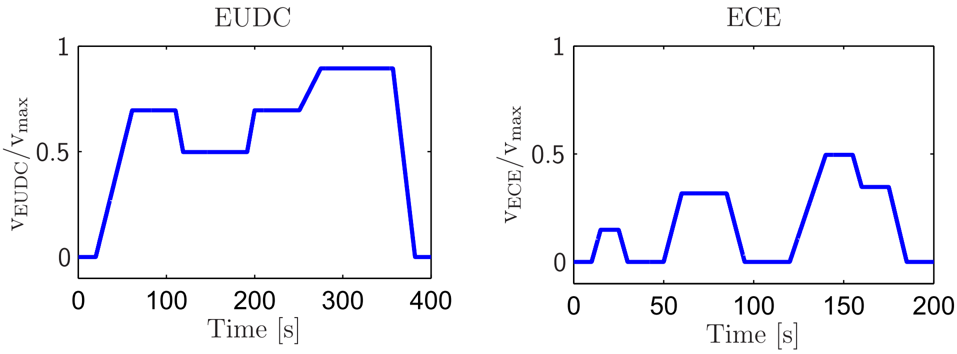


Figure 4.9: Driving cycles applied: EUDC (left plot), ECE (right plot)

For the realization of driving cycles at the test rig, a motor control system has been applied. Hereby, for the drive motor speed control is used. The speed control is realized by the implementation of a driver model determining the reference speed. The load motor is controlled by torque control. Therefore, a vehicle model is used to determine the resistance torque applied to the drive motor using the current measurement as illustrated in Figure 4.10.

The related results of the three power management approaches in dependency on the control parameter chosen are shown in Figs. 4.11 and 4.12 for each driving cycle. Hereby, for each figure, in the upper plot the tracking error for the evaluation of the drivability and the energy consumption (combined hydrogen coonsumption and supercapacitor discharge) are depicted, whereas the lower bar plot denotes the aging-related parameter.

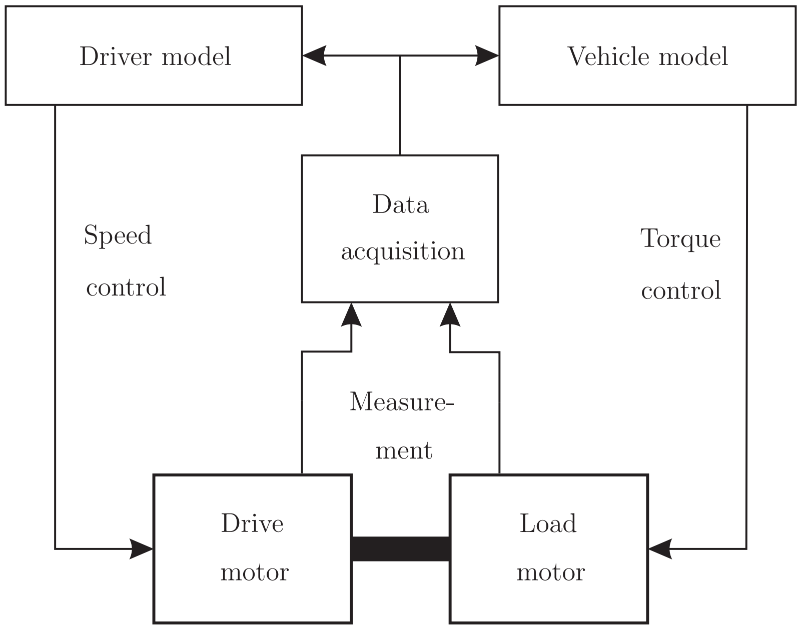
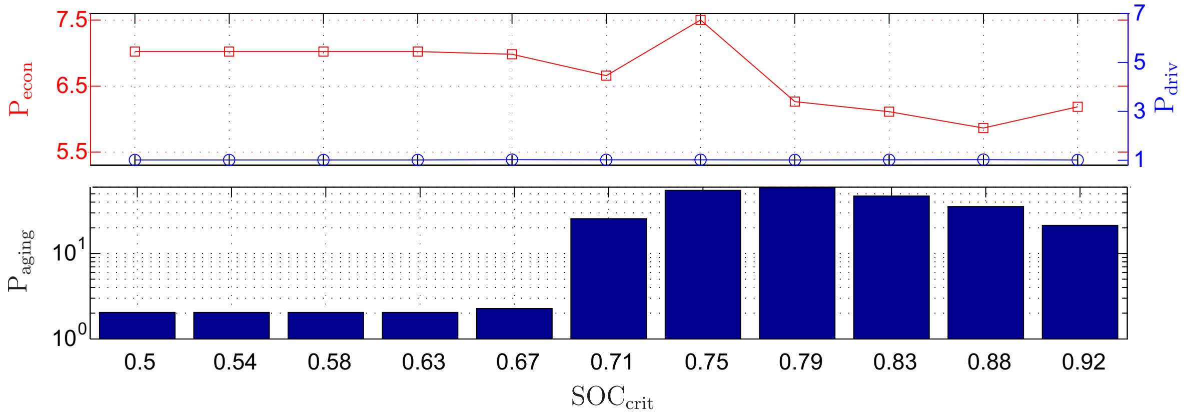
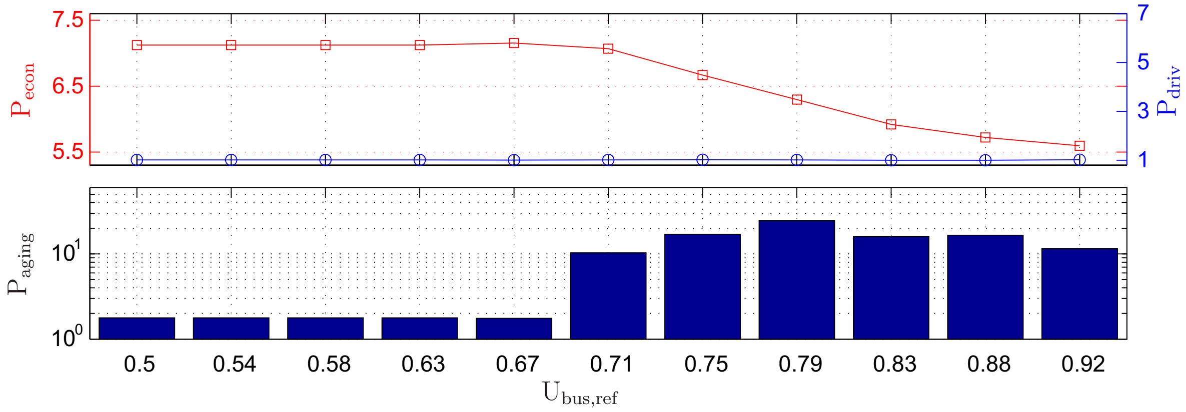


Figure 4.10: Scheme of the control of the motors [MOS09, MOS10]

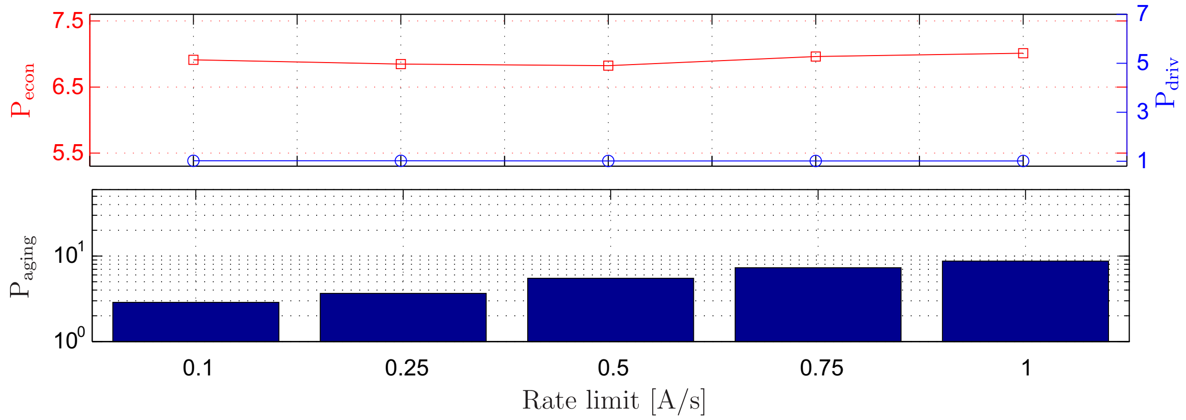
For the ECE (Figure 4.11) there are only small tracking errors for all approaches. The reasons are that there are only small acceleration phases during the operation and a smaller energy amount required so that the discharge of the supercapacitors is small and hence the motor performance losses are only small. For the PCA I approach, the largest energy consumption (hydrogen comsumtion and discharge of the supercapacitors) is observed at a control parameter of 0.75. The largest aging parameter value occur for 0.79. In both cases, the reason is that in this operation range a comparably frequent change of the fuel cell operation between idle and full power operation occurs, which leads to transient operation and hence to both larger energy consumption an aging. For PCA I and PCA II, the fuel economy becomes better for larger values. Additionally, only small aging is observed for small control values since the fuel cell mainly operates in idle mode. From the results of PCA III (rate limitation) only a small influence on drivability and fuel economy can be seen, but, as expected, there is a clear relation for the aging parameter.
For the EUDC, a similiar behavior for large values can be observed for the fuel economy. Since this driving cycle is a faster track with larger acceleration phases, the total energy amount is much higher and hence the discharge of the supercapacitors is larger. As mentioned, this has a negative influence on the performance of the drive motor. For this reason, for smaller control values of PCA I and PCA II, the tracking error significantly increases. Directly related to the tracking error is also the smaller energy consumption, which is related to the smaller speed and acceleration during the driving cycle. For the aging parameter, also maximum values are achieved for



(a) PCA I during driving cycle ECE

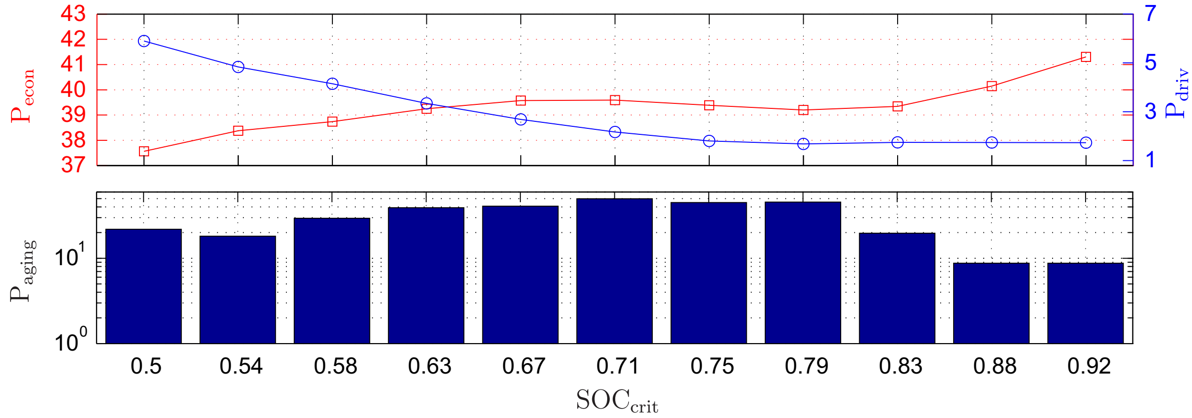


(b) PCA II during driving cycle ECE

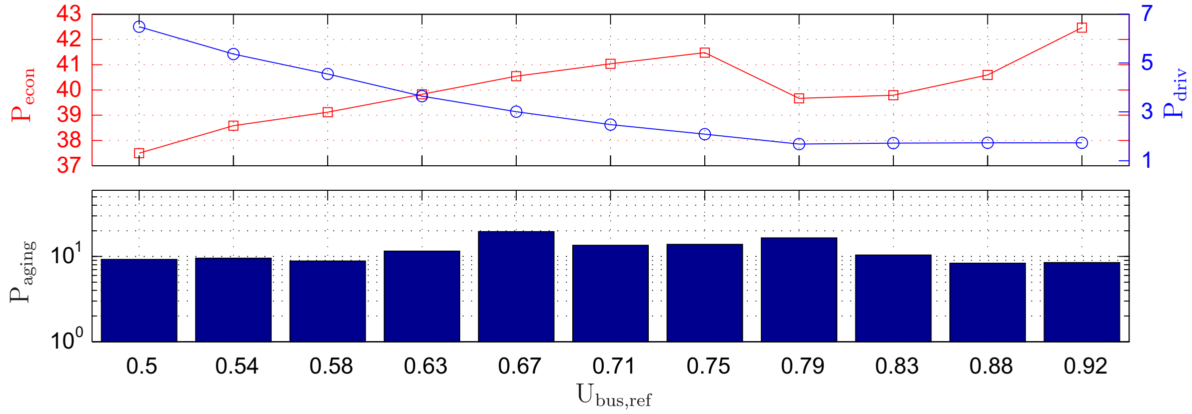


(c) PCA III during driving cycle ECE

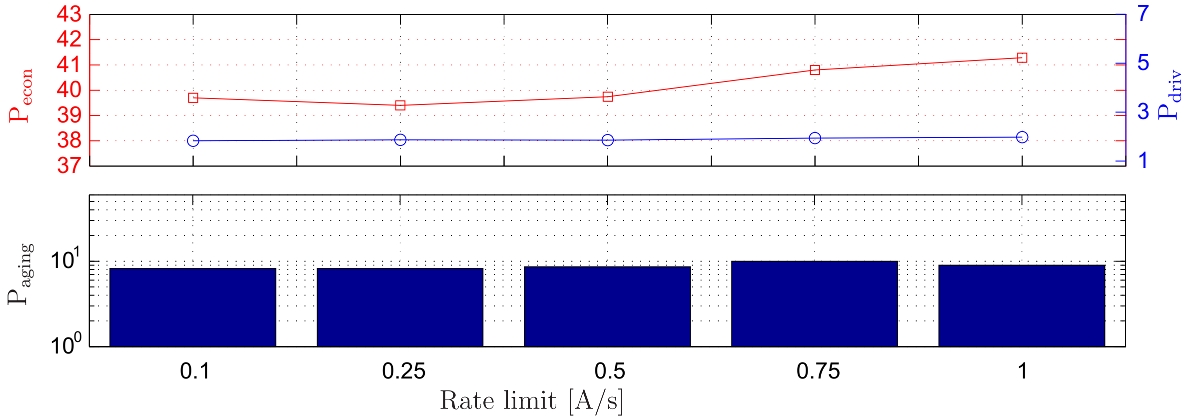
Figure 4.11: Results for driving cycle ECE [MOS09, MOS10]



(a) PCA I during driving cycle EUDC



(b) PCA II during driving cycle EUDC



(c) PCA III during driving cycle EUDC

Figure 4.12: Results for driving cycle EUDC [MOS09, MOS10]

medium control values. The influence of the rate limit of PCA III on the aging can also be observed for this driving cycle, but its relative influence is smaller.
From the results it becomes clear that there are many influences on the operation performance of the power train. Additionally, this performance is strongly dependent on the driving cycle applied. So, independent on the details of the results, it becomes clear that the usage of optimization algorithms for the power, energy, and lifetime management algorithms becomes obvious. Related algorithms and their application within offline and experimental applications will be introduced and discussed in the following chapters.

5 Optimization of power flow control algorithms

As shown by the results of section 4.3, there are complex nonlinear relations and interdependencies between the different components of the power train system. It becomes clear that different control strategies have multiple influences on different system performance properties. Another aspect is that the results also significantly depend on the driving cycle used. Taking this into consideration, the application of optimization algorithms becomes obvious. For the improvement of the performance of the power flow control within hybrid electric power train systems, the usage of optimization algorithms is a typical suitable technique. As described in chapter 4, there is a large number of methods in literature dicussing optimization methods in the context of power flow control algorithms. Hereby, it is distinguished between offline and online methods. The usage of offline optimization methods is a common methodology to achieve suitable benchmark solutions for the evaluation of power flow control algorithms. Hereby, the optimized trajectories are based on given system dynamics and load profiles. Online methods are designed for the implementation within an experimental environment. Hereby, for real-time applications, an important aspect is the computatial effort required. For this reason, in this context, suboptimal results are typically accepted as sufficient.
In the following, three types of control optimization methods are applied. Since different system performance properties as well as the consequences to the different power flow control levels, i.e. power management, energy management, and lifetime management, are considered, a multiobjective problem formulation becomes necessary also for the optimization algorithms.
At first, parameter optimization techniques are applied for the control optimization, which include searching algorithms. These methods are implemented and applied within an embedded experimental power train emulation environment and within an optimization loop including simulation, evaluation and search algorithm. Hereby, for the embedded online optimization approach, with the Golden Section search method, a simplified method is used, whereas the offline optimization approach applies a more sophisticated Genetic Algorithm (GA)-based searching algorithm. After that, the power flow control optimization based on Dynamic Programming (DP) and Model Predictive Control (MPC) is applied, which are both for the direct optimization of the control input. Hereby, the DP-based optimization is realized completely offline assuming the driving cycle to be previously known, whereas the MPC-based approach is realized using a preceeding horizon. Hereby, the approach is combined with a prediction algorithm of the load profile. Finally, an Instantaneous Optimality (IO)-based power flow control approach is applied, which consists of a combined identification and prediction algorithm and a lookup-table set up by a database of different offline-optimized solutions. According to [GS07] this method can be considered as time-invariant feedback controller.

5.1 Power flow control optimization based on parameter optimization

For the power flow control of a power train system with a given or repeated load profile and a previously known system structure, i.e. in parametrized form, the optimization algorithm is typically realized by the usage of searching algorithms. This searching algorithm is based on an intermediate system evaluation, which is realized by the cost function defined in Eq. 4.4. Based on the results of section 4.3, this can be achived by an iterative process during the experimental process. For experimental applications with a repeated load profile, an embedded optimization method of the system can be realized by this method. Dependent on the complexity of the system, it is suitable to use suitable searching methods. The related results are based on [MS11b, SOM10, MOS14]. A typical simple searching algorithm to achieve an optimal solution iteratively, is the Golden Section method. For simplicity reasons, the cost function is assumed to be convex here.
For offline parameter optimization and with the knowledge of the dynamical behavior of the system (in parameterized form) as well as the load profile, the usage of evolutionary algorithms as e.g. Genetic Algorithms (GA) is a widely used method. The related optimization structure can be realized by the combination of the system simulation process with an evaluation, and, based on this, a searching strategy to find the optimal parameters of the system structure (e.g. system parameters, control parameters etc.). These results are based on [MSS11, MWS11, MS11a]. Due to their comparatively complex structure, these methods are more time consuming than the embedded-online methods stated before, but due to their sophisticated searching strategies in combination with the more detailed information of the system behavior, principally a better performance and a better avoidance of e.g. local extrema can be expected.
In the following, the application of the embedded online and the offline optimization method are demonstrated using the example of the fuel cell/supercapacitor-based hybrid electric power train as introduced before. For the demonstration of the embedded-online optimization, an experimental approach with an iterative searching algorithm is used. The offline optimization is demonstrated in section 5.1.2, and the Genetic Algorithm (GA)-based optimization approach of the parametrized control and sizing structure is applied. For both cases, the cost function of the underlying optimization problem is achieved by the evaluation parameters as stated in Eq. 4.1-4.3.

5.1.1 Embedded-online power flow control optimization using Golden Section search

Nonlinear parameter optimization methods are typically realized by iterative searching processes. For the usage within experimental applications, the computational effort plays an essential role. A rather simple method with a small computational effort is a searching algorithm based on Golden Section. A detailed description of this method and its aspect within multiobjective optimization problems is given e.g. in [VTS12]. This method is used in the following for the iterative optimization of the control parameters of the power flow control algorithms.

5.1.1.1 Golden Section Search

As described in [MOS14], the Golden Section Search algorithm is applied within an embedded optimization process and thus within an iterative process based on the intermediate evaluation of the power flow control algorithm. Hereby, the goal is to determine during an experiment the optimal control parameters with respect to the total system performance.

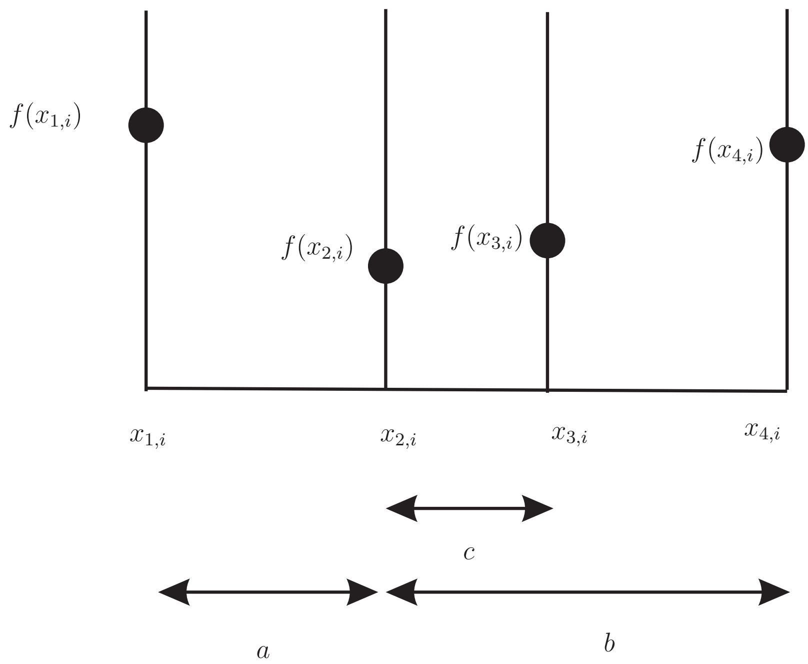


Figure 5.1: Scheme of the Golden Section Search algorithm (according to [VTS12])

For every iteration step i, four values $x_{1,i}, x_{2,i}, x_{3,i}, x_{4,i}$ are defined within a predefined interval as shown in Figure 5.1. For a,b, and c the relation

$$\frac{c}{a} = \frac{a}{b} = \varphi = \frac{2}{1+\sqrt{5}} \approx 0.618 \tag{5.1}$$

is given, where φ is the so called *golden ratio*.

Determining the minimal value

$$min_i \;=\; min(f(x_{1,i}), f(x_{2,i}), f(x_{3,i}), f(x_{4,i})) \tag{5.2}$$

the values $x_{1,i+1}, x_{2,i+1}, x_{3,i+1}, x_{4,i+1}$ of the following iteration step $i+1$ are calculated by

$$\begin{array}{ll} \text{case } 1 : (min_i = x_{2,i}) & \text{case } 2 : (min_i = x_{3,i}) \\ x_{1,i+1} = x_{1,i} & x_{1,i+1} = x_{2,i} \\ x_{2,i+1} = x_{1,i} + \varphi\ a & x_{2,i+1} = x_{3,i} \\ x_{3,i+1} = x_{2,i} & x_{3,i+1} = x_{2,i} + \varphi\ b \\ x_{4,i+1} = x_{3,i} & x_{4,i+1} = x_{4,i} \end{array} \tag{5.3}$$

and the relating minimal value by

$$min_{i+1} \;=\; min(f(x_{1,i+1}), \ldots, f(x_{4,i+1})). \tag{5.4}$$

The algorithm is implemented to the experimental setup and the power flow control approaches PCA I-III are applied. Based on the related control parameters $x_{1..4,i}$ the related function values $f(x_{1..4,i}$ are calculated by an evaluation according to Eqs. 4.1-4.4. Based on these results, an iterative optimization is realized based on the Golden Section approach.

5.1.1.2 Optimization results

The experimental realization as well as the evaluation of the power flow control algorithms are performed at the HiL test rig of the fuel cell/supercap-based hybrid electric power train introduced before. Results comparing the different power flow control strategies show that the control parameters mainly effect the relating evaluation criteria [MOS09]. In extension to these previous investigations the results of an online-optimization introduced in section 5.3 are given in the sequel. The realization of the method is performed using the golden section search algorithm for the optimization of the control parameters of each of the power flow control algorithms.

PCA I For the first experimental series, the PCA I strategy is applied. This strategy is determined by the usage of the reference state of charge SOC_{Ref} of the energy storage as a control parameter as illustrated in Figure 4.5. Hereby, a SOC value of 1 refers to a fully charged storage. The iteration steps of the optimization process are shown in Figure 5.2 on the left side. As described before, each iteration step i consists of 4 experimental cycles j.

After each iteration step, the performance parameter P_{total} of the values $x_{j,i}, j = 1, 2, 3, 4$ is calculated and new values $x_{j,i+1}, j = 1, 2, 3, 4$ are set using the approach

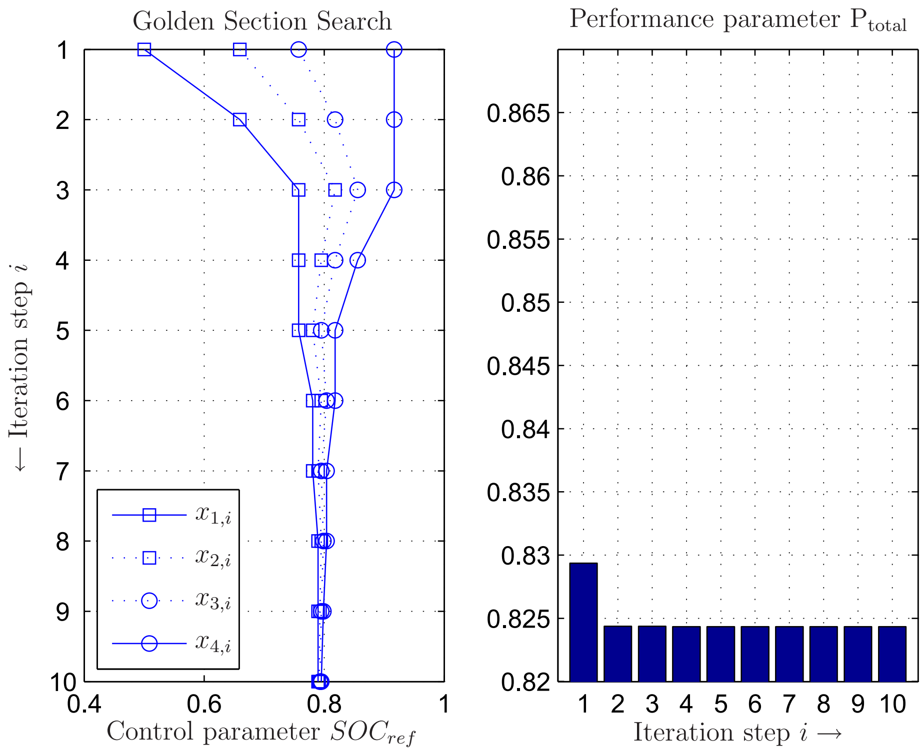


Figure 5.2: Optimization steps applying PCA I. Left: Iteration steps of the control parameters, Right: Evaluation results (small values refer to better performance) [MOS14]

described before. From the performance parameter P_{total}, after each iteration step, the cycle with the best performance, i.e. the lowest cost function value, is monitored. As shown on the right side of Figure 5.2, it becomes clear that after few iteration steps the algorithm converges. The resulting control value of 0.79 is comparible to results of comparatative investigations [MOS09].

PCA II For the same experimental conditions and using the same initial values as before, the optimization algorithm is applied on the PCA II strategy. Therefore, the ratio between the reference bus voltage $U_{Bus,Ref}$ and the maximal bus voltage $U_{Bus,Max}$ (related to a fully charged storage) is used as a control value. In Figure 5.3 the results of the optimization steps are shown.

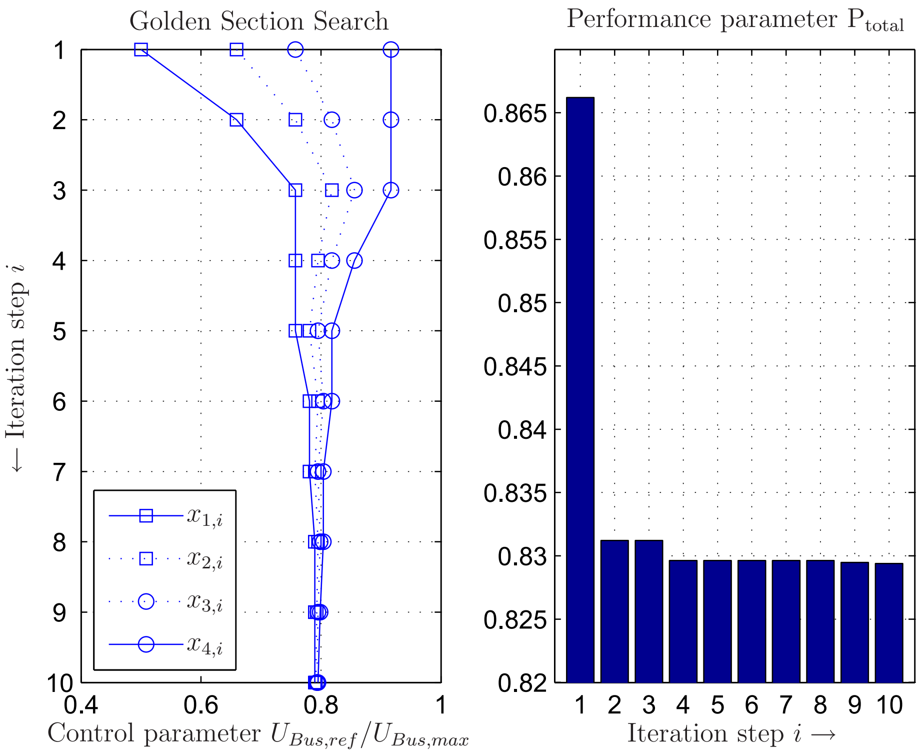


Figure 5.3: Optimization steps applying PCA II. Left: Iteration steps of the control parameters, Right: Evaluation results (small values refer to better performance) [MOS14]

It becomes clear that despite of the different power flow control algorithm and the energy flows, an optimum is achived at 0.78, which is also located near to the value determined in comparative studies [MOS09].

PCA III The third power flow control algorithm, conducted under the same experimental conditions described, applies the ratio of the rate limitation parameter $P_{ratelim,i}$ and the maximal rate limitation $P_{ratelim,i,max}$ of the current flow as control variable. The usage of a rate limitation leads on the one hand to a smoother power trajectory of the fuel cell system, which has a positive influence on the component aging and the fuel economy. On the other hand it prolongates the reaction of the system to low SOC of the supercapacitor system and thus worsens the capability of the motors to fulfil a given load profile and, related to this, the power availability of the system. The results of the optimization of this power management parameter achieved after a few iteration steps is shown in Fig 5.4. The resulting final parameter of 0.25 is comparable to the optimal result of comparable experiments [MOS09].

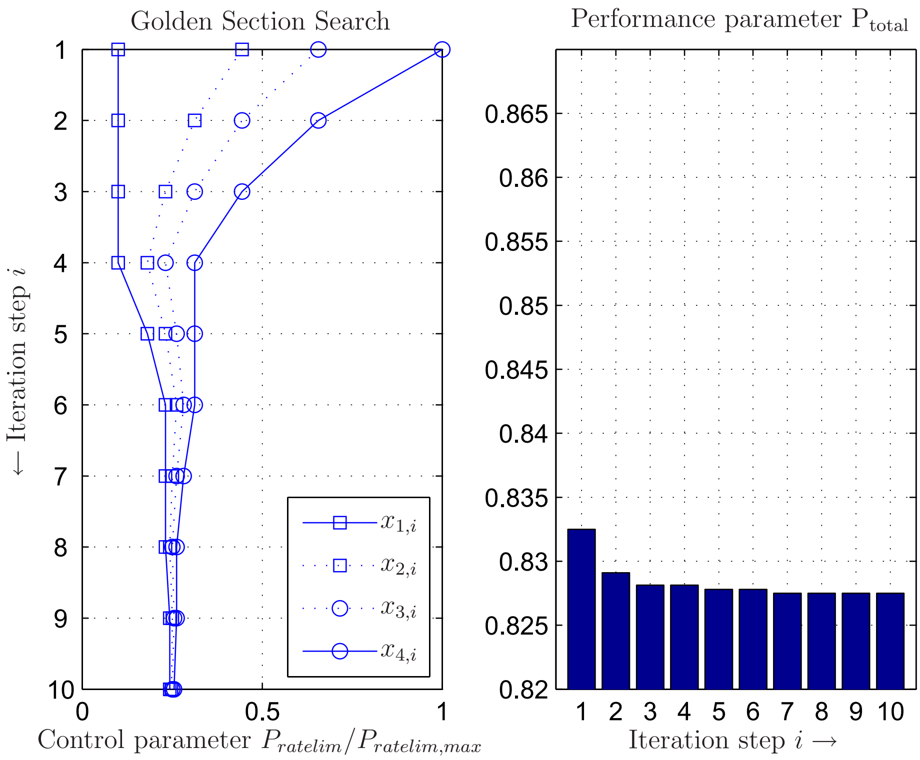


Figure 5.4: Optimization steps applying PCA III. Left: Iteration steps of the control parameters, Right: Evaluation results (small values refer to a better performance) [MOS14]

5.1.1.3 Discussion

For each power flow control approach, it can be shown that the optimization leads to a feasible result after a few iteration steps. In these experiment, the results are received without a detailed knowledge of the chosen driving cycle.

For a final evaluation of the method it has to be stated that the approach is sensitive to the chosen weighting factors. Another set of weighting parameters may lead to different results.

The results show that the approach is applicable for the power management optimization and the shown specific results can be applied for a principal introduction to the systematic consideration and evaluation of typical design conflicts and their numerical optimization applying multidimensional parameter arrays. As shown in [Zen13], this approach can easily be enlarged to an arbitrary number of optimization variables by the usage of an multidimensional search space. Comparable results from simulation studies show the applicability in other driving cycles e.g. with a repeating start-stop character [ÖS08]. Further aspects and details in this context are stated in [MS11b, SOM10, MOS14] and [Özb10]. A disadvantage of this method, though is the limited applicability if the cost function can not be assumed as convex. In this case, more sophisticated searching algorithms are required.

5.1.2 Offline power flow control optimization with Global Optimization methods

As shown before, embedded online optimization methods are suitable to be applied within an experimental environment. But due to their typically simple structure, it is only suitable for simple optimization problems. A better optimization performance can be achieved with more sophisticated searching algorithms and a more detailed knowledge of the system behavior. For such optimization problems, Global Optimization (GO) methods are commonly applied. Since these methods are more time consuming, they are typically applied for offline optimization problems. In the context of this thesis, the concept of the offline power flow control optimization is realized by the integration of the dynamic simulation of the power train dynamics into the Global Optimization framework using a loop structure containing the system model, the evaluation, and the searching algorithm, which is exemplified with a Genetic Algorithm (GA)-based algorithm. The modular structure allows a better adaptability of the approach to other system models or searching algorithms. The results presented in this section are based on [MWS11] and [MS11a]. Hereby, in [MWS11], it is additionally shown on the example of a magnetic bearing system that the combination of a Genetic Algorithm (GA)-based optimization loop and an unscented H_∞-Controller leads to suitable optimization results also for systems with uncertain parameters.

5.1.2.1 Optimization loop

Classical parameter optimization approaches as described e.g. in [RSM08] are typically realized integrating the system models into the optimization structure. The disadvantage hereby is that detailed and precise models of the typically nonlinear behavior are explicitly required. Dependent on the grade and character of nonlinearity, the complexity of the system topology, the constraint conditions of the physical parameters as well as the actuating signals of the system, and coupling effects caused by the interaction between the system components, the complexity of the system models can be increased significantly.

To overcome these problems, in this thesis, for the optimization algorithm, a loop structure is applied. Therefore, a parameterized system and control structure is assumed and some key properties of the system are analyzed based on the dynamic behavior during the operation to set up the optimization algorithm. Hereby, the load profile is assumed to be known. A typical structure of such a loop is shown in Figure 5.5.

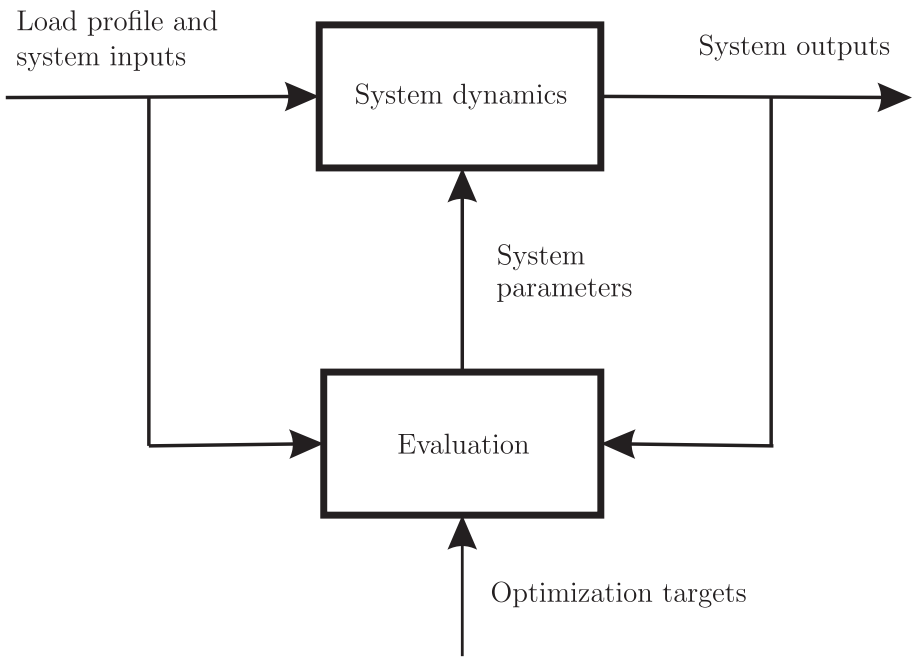


Figure 5.5: Scheme of the optimization loop [MWS11, MS11a]

Hereby, the input-output behavior of the system is evaluated in dependency of the optimization targets and the load profile. For the evaluation process, the system dynamics is analyzed and certain properties are described by the definition of performance parameters. The performance parameters generated in this way are used to update the system and the control parameters in order to optimize the system properties with respect to the previously defined targets.
Hereby, dependent on the dynamical behavior of the regarded system, the evaluation of the system performance during the operation has to be realized with respect to predefined conditions. Based on the system performance, the optimization is realized iteratively by the application of suitable search algorithms. Searching algorithm are a central aspect in global optimization problems as e.g. genetic algorithms for the determination of the optimal solution. The advantage of the methods of the global optimization compared to classical optimization methods is that they are, firstly, almost independent from the initial conditions of the parameters and, secondly, that they are less sensitive to local extrema.
The search algorithms are based on typical methods of the global optimization methods as described e. g. in [HB10, Sol98]. A similiar method applied in the context of a process control optimization in described in [EVAB07].
The evaluation of the dynamical behavior of the hybrid electric powertrain system is realized by the usage of the performance parameters of Eq. 4.1-4.3 evaluating the

discussed properties of the dynamic behavior of the system. To achieve the evaluation of the global system performance, these parameters have to be weighted in a suitable way. Depending on the values achieved, the parameters of the systems and thus the operation point of the system have to be adapted iteratively to get the optimal operation point.

5.1.2.2 Modeling of the hybrid electric power train

For the application of the optimization loop, a dynamical model of the power train system has to be integrated. As power train system, the fuel cell/supercapacitor-based hybrid electric power train in range extender topology, shown in Figure 3.4 is used. Hereby, the modeling of the system dynamics is based on a modified system model of [Özb10] .

The dynamic behavior of the system, which contains the two motors, a fuel cell system, the supercapacitors, and a DC/DC converter, is described by a discrete-time nonlinear state space model. Hereby, the two motors are modeled as a unit with the motor input u_{mot}, which contains the control signals s_d, s_l of the drive motor and the load motor. The system structure of the motors is assumed as a Hammerstein system containing a static nonlinearity and a LTI system connected in series. The state vector is built up by the motor current i_{mot} and the motor speed n_{mot}.

Hence, the resulting dynamic behavior of the motor unit is described by

$$x_{mot}(k+1) = \begin{bmatrix} i_{mot} \\ n_{mot} \end{bmatrix}_{(k+1)} = f_1(u_{mot}(k), x_{mot}(k)), u_{mot}(k) = \begin{bmatrix} s_d \\ s_l \end{bmatrix}_{(k)} . \quad (5.5)$$

The supercapacitors of the power train system can approximately be described by a LTI discrete-time state space model as

$$x_{SC}(k+1) = A_{SC}\ x_{SC}(k)\ +\ B_{SC}\ u_{SC}(k). \quad (5.6)$$

Hereby, the bus voltage U_{Bus} is defined as the state of the supercap model ($x_{SC} = U_{Bus}$) and the supercap current i_{sc} as system input ($u_{SC} = i_{sc}$). In the range extender topology, for the DC/DC converter current flow, the relation

$$i_{sc} = i_{DC,DC}(s_{DC,DC}) - i_{mot}\ , \quad (5.7)$$

with the output current of the DC/DC converter $i_{DC,DC}(s_{DC,DC})$, the motor current i_{mot}, and the control signal of the DC/DC converter $s_{DC,DC}$ holds.

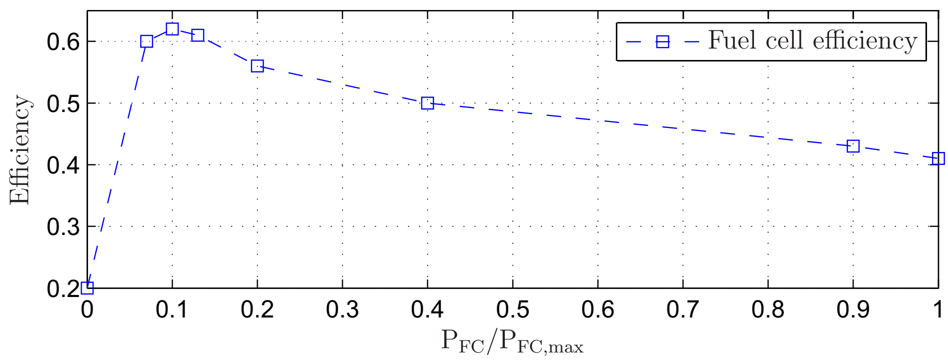


Figure 5.6: Fuel cell efficiency dependent on the power [MSS12]

Hereby, a nonlinear relation between $i_{DC,DC}$ and the control signal $s_{DC,DC}$ of the DC/DC converter can be defined.
The fuel consumption of the fuel cell system can be defined considering the fuel cell voltage and current. In this context, the typical relations between fuel cell power and efficiency as shown in Figure 5.6 are of specific interest.

The model relations of the fuel cell system are defined based on the principal relations described in [PSP04]. Taking this into consideration, the fuel consumption can be determined by

$$\dot{V}_{H_2} = f_2(u_{FC}, i_{FC}, t). \tag{5.8}$$

For simplicity reasons, additional power losses e.g. for the cooling of the system are neglected in this context.
For the validation of the models, the behavior of the power train system models is compared with experimental measurements at the power train test rig. Hereby, as load profile, the EUDC driving cycle is applied. The measured signal inputs of the DC/DC converter $s_{DC,DC}$, the drive motor s_D, and the load motor s_L during the cycle are used as inputs of the models as well as the test rig components. The resulting outputs of the system model, containing the motor speed n_{mot}, the motor current i_{mot} and the bus voltage U_{Bus} have been compared to the measured data.
As it is shown in Figure 5.7, there is a good coincidence between simulation and measured signals of the system.

Since its applicability is shown, in the following, the power train model is integrated into the optimization loop.

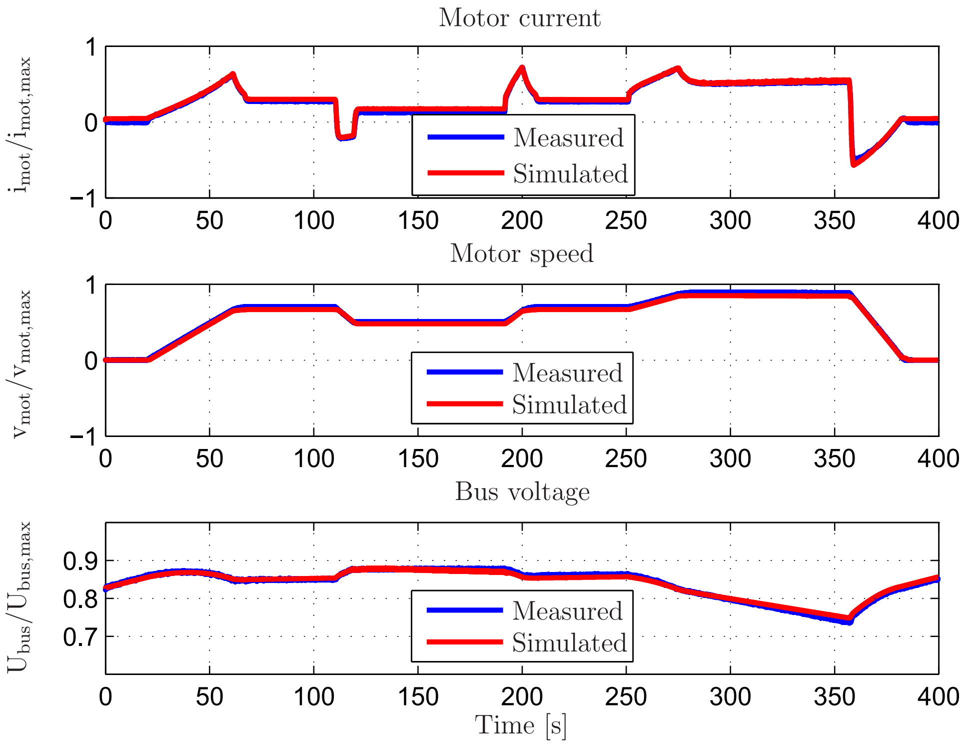


Figure 5.7: Validation of the system applying an EUDC driving cycle

5.1.2.3 Sizing and power flow control parameter optimization of a fuel cell/supercapacitor-based hybrid electric power train

For the power train system mentioned, the parameter optimization with global optimization methods is discussed. Therefore, in the following, the optimization with respect to the fuel performance, the drivability, and the fuel cell aging with respect to the design parameters is shown. For simplicity reasons and to allow a better visualization, this problem is demonstrated with two design parameters, i.e. the supercap sizing (denoted by its capacity C) and the reference bus voltage $U_{Bus,ref}$. But the functional principle is also valid for an arbitrary number of design parameters, dependent on the complexity and the related computational effort. The influences of these parameters on the system performance properties is received by simulation using the EUDC as a load profile. For the visualization of the relations, the parameter space is equidistantly discretized by an 30-by-30-sized grid. Hereby, all system performance properties are regarded seperately.

For the evaluation of the fuel economy of the power train, the hydrogen consumption as well as the supercap discharge during the operation have to be considered, in accordance to the ECMS formulation, as mentioned. The relations with respect to the parameters mentioned are shown in Figure 5.8.

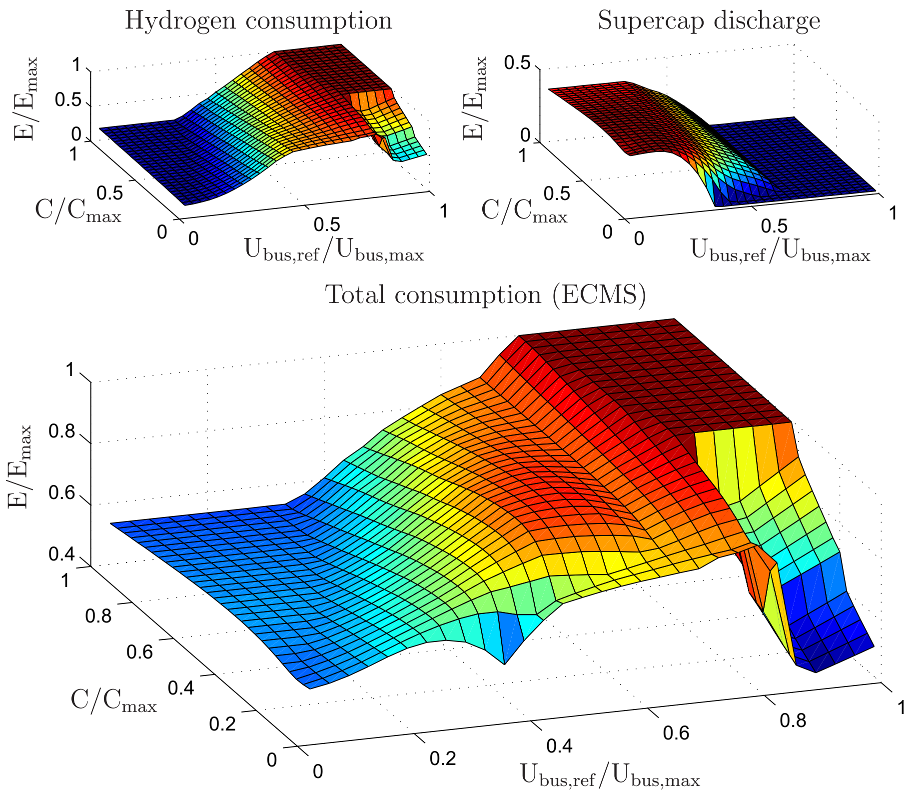


Figure 5.8: Fuel economy of the power train system, a) hydrogen consumption (top left), b) supercapacitor discharge (top right), c) total energy consumption (bottom)

For the fuel consumption, it is shown that a larger reference voltage $U_{Bus,ref}$ leads to a smaller discharge of the supercapacitors since the bus voltage is directly related to its SOC. Thus, this control setting leads to a larger electric current inflow into the supercapacitors. Additionally, it can be seen, that smaller values leads to a smaller total energy consumption. But as it will be shown in the following, the different properties are typically conflicting each other.
For the drivability evaluation, the deviation (IAE) between reference velocity and actual velocity of the vehicle is considered. The relations on the operation parameters are depicted in Figure 5.9.

For this property, it is shown that larger deviations and hence worse drivability occur in the case of small and large values of the reference bus voltage ($U_{Ref}/U_{Ref,max} < 0{,}4$ and $U_{Ref}/U_{Ref,max} > 0{,}8$) and small supercapacitor's sizing ($C/C_{Max} < 0{,}5$). The reason is that a power train with a small storage is not capable of delivering large power amount (e.g. for strong acceleration maneuvers) since the supercapacitors will be discharged faster. The large deviations for large reference control values and small component size is caused by the need of a fast switching between mechanical

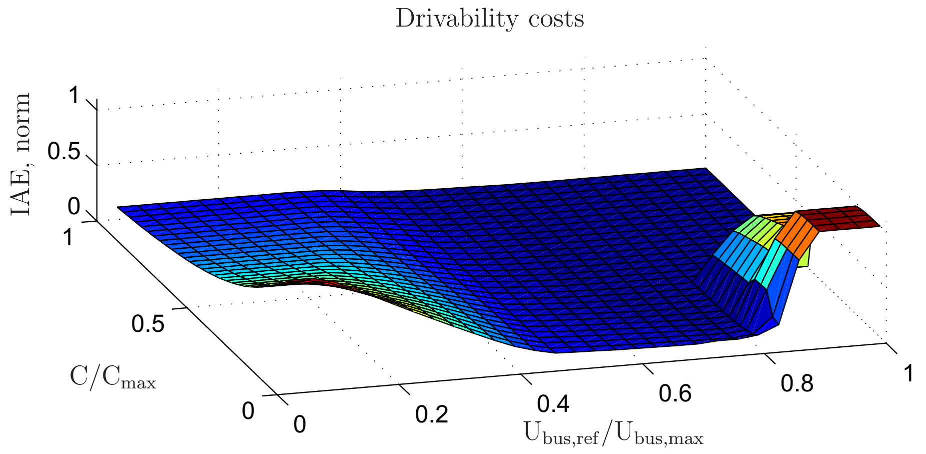


Figure 5.9: Speed deviation for drivability consideration

brake and braking energy recovery since the energy recovery is not possible in the case of fully charged supercapacitors. For the evaluation of the fuel cell aging, which is dependent of the high frequent power changing, the relations are depicted in Figure 5.10.

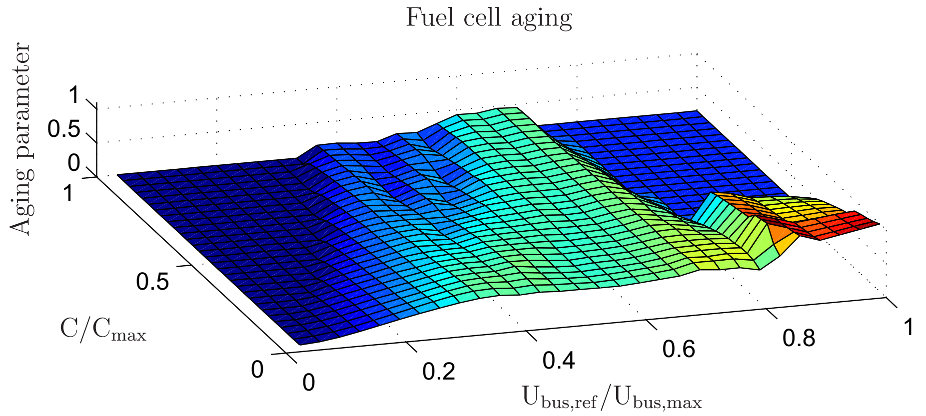


Figure 5.10: Fuel cell aging

Hereby, especially for middle-sized values of the reference bus voltage, an accelerated aging bahavior can be expected. This is caused by the frequently occuring change of the current flow of the fuel cell system whereas for small or large parameter settings it mainly operates in idle or steady-state operation, which are both more component saving operation modes. The resulting total performance of the system is determined by a weighted sum as described in Eq. 4.4.
As mentioned, the optimization of the parameters is realized by an optimization loop using Genetic Algorithms. The results, demonstrated with the initial and final parameters, are shown in Figure 5.11.

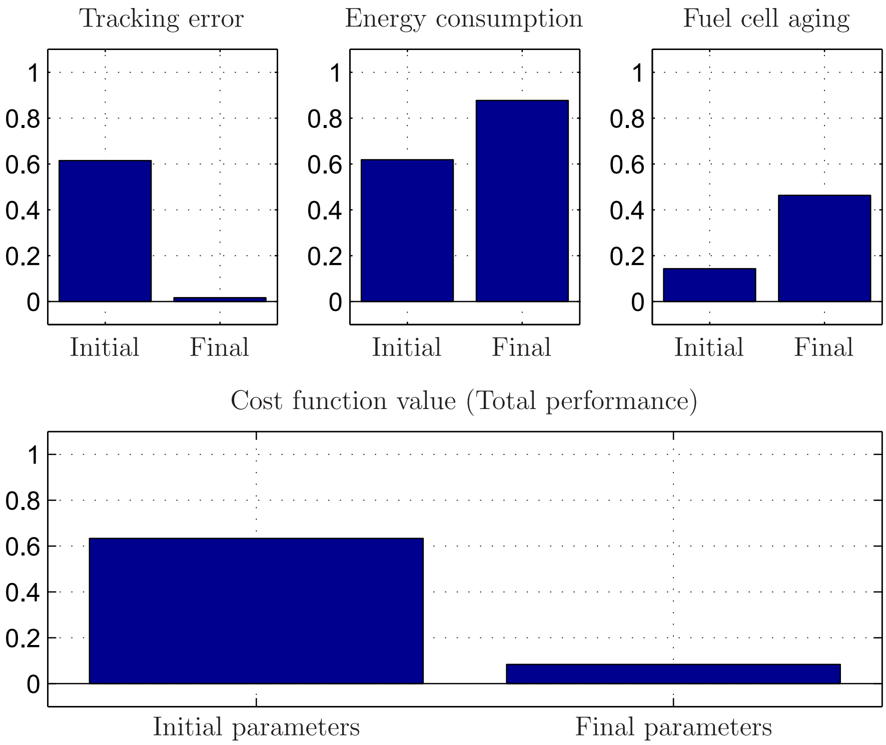


Figure 5.11: Genetic Algorithm (GA)-based optimization: Initial and final performance of the individual properties (top) and the total performance (bottom)

For this parameter settings, the chosen weighting factors, and the applied driving cycle, the optimization leads to a strong improvement of the drivability Figure 5.11, top left, with a slight increase of the energy consumption and aging. As shown in the lower plot the total performance is significantly improved.
In Figure 5.12, the relations between the parameter setting and the total cost function is shown.

The parameter settings for the initial and final parameter setting of the optimization algorithm are shown and the feasiblity of the result becomes clear.

5.1.2.4 Discussion

As it is shown, the Genetic Algorithm (GA)-based approach is applicable for the offline optimization of parametrized system and control structures for given load profiles. The advantage of this approach is that it can easily be adapted to different power train models, cost functions, and searching algorithms, since the searching algorithms only depend on the cost function values and not on the details of the

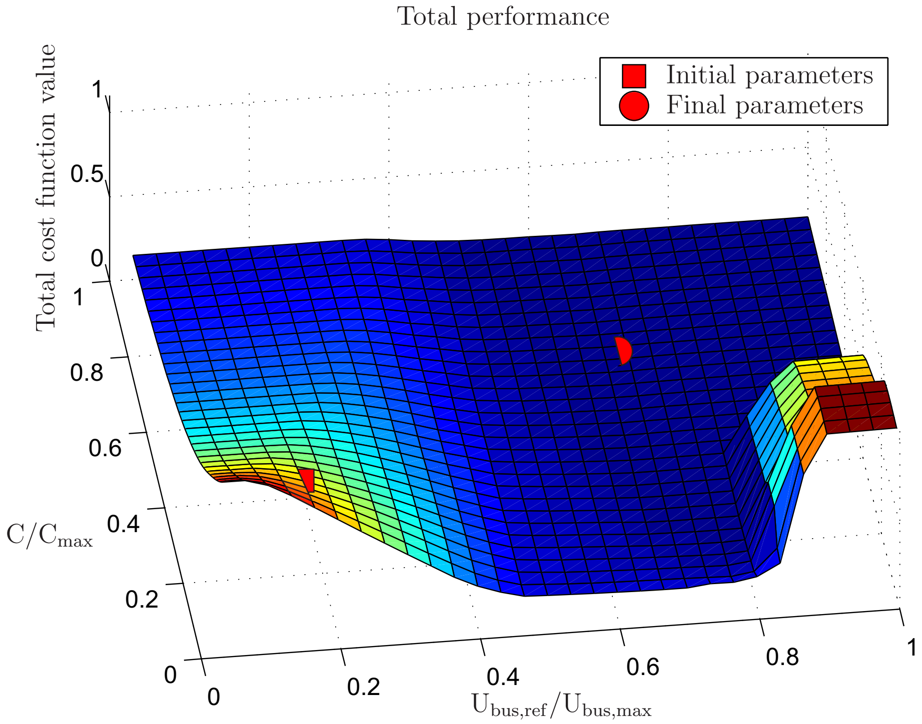


Figure 5.12: Total performance

models applied. A comparable method, applying a NSGA II-based optimization for a hybrid electric and a hybrid hydraulic power train, is introduced in [KMMS13]. Also the number of design variables, including the required constraints, can easily be adapted. A disadvantage of this method is the large computational effort and thus the large time required for the optimization. Furthermore, this method has only a limited suitability to influence the control trajectory directly. The related integration of such an algorithm is possible, but requires a large number of variables and thus increases the computational efforts intensively. For the direct optimization of the control trajectory, approaches based on Dynamic Programming (DP) and Model Predictive Control (MPC) as introduced in the following section, are more suitable.

5.2 Control optimization based on Dynamic Programming (DP) and Model Predictive Control (MPC)

In the preceding sections, the system and control parameter operation within an simulation and experimental environment are discussed. Hereby, a given system structure in parameterized form is assumed and the optimization procedure is only

related to the quantaties of the parameter values and thus the the controller signals are only influenced indirectly.
Another possibility is the direct optimization of the control trajectory. Typical direct optimization methods are Dynamic Programming (DP) and Model Predictive Control (MPC) [GS07]. Hereby, the Dynamic Programming (DP) method is suitable for the model-based offline optimization of the power flow control trajectory with previously known driving cycles. In [PBMG06], a typical Dynamic Programming (DP)-based algorithm for a generalized series hybrid electric vehicle is introduced, which optimizes the power split between the combustion engine and the storage system. The dynamic programming method is particularly used to obtain a reference trajectory for the performance evaluation of e.g. suboptimal online control algorithms as stated before. As a typical offline optimization method, the Dynamic Programming algorithm, comparable to the previously discussed Global Optimization (GO)-based optimization, requires the model of the system dynamics and the data on the driving cycle of the complete operation time interval.
The Model Predictive Control (MPC) method uses a comparable optimization algorithm (direct optimization) but in this case the optimization is carried out for a preceeding prediction horizon with a predefined length. Thus, this control method can be considered as a compromise solution between pure online methods, which consider the instantaneous measurements, and offline optimization algorithms, which are based on the knowledge of the complete time interval. For the usage of a Model Predictive Controller, the integration of a prediction algorithm is required to receive a suitable estimation of the load profile.
From this consideration, a system conception as shown in Figure 5.13 results.

In the following, two methods for a load profile prediction are discussed. Based on the prediction, a Model Predictive Control Algorithm is applied on the fuel cell/supercapacitor-based hybrid electric power train system mentioned. Therefor, the power train model of section 5.1.2.2 is integrated into the algorithm and the cost function of Eq. 4.4 is used.

5.2.1 Load profile prediction

The performance of a Model Predictive Controller strongly depends on the load profile prediction. In literature, the prediction of vehicle speed is a widely discussed topic as e.g. in [KDG+12, CB11]. In the context of this thesis it is assumed that the vehicle speed is continous with small local changes in the acceleration. Thus, it is assumed for the upcoming workload load profile that it can approximately be predicted by the inclusion of the recent load profile (here: velocity) measurements. This can be realized by a horizon length defining the number of preceeding measurements for the prediction. Hereby, as described in [MSS12, MS12b, MS12a], a short horizon can better include recent changes but is also more sensitive to measurement noise.

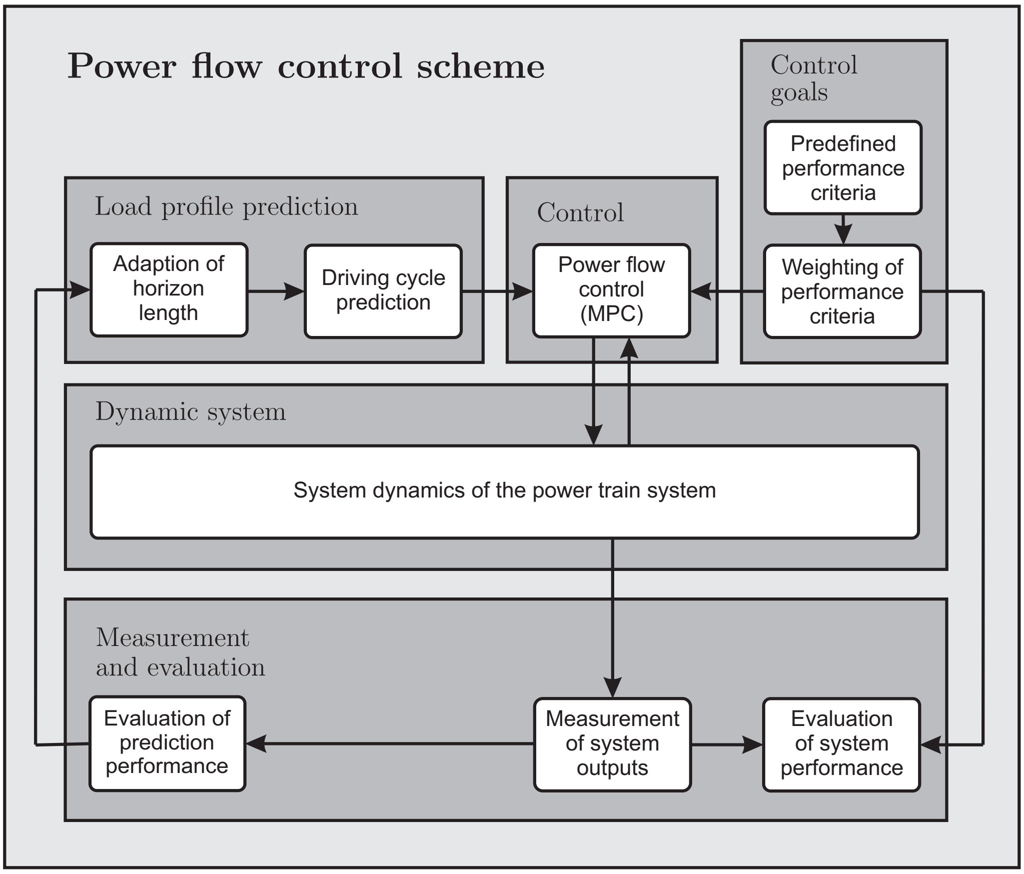


Figure 5.13: Conception of the MPC-based power flow control

In the following, two approaches are introduced for the prediction based on this assumption. The first one is an algorithm based on an Artificial Neural Network (ANN) as applied in [MSS12] and the other one is based on a polynomial approach as introduced in [MS12b, MS12a], which is based on an adaptive number of preceeding measurements included to the prediction algorithm.

5.2.1.1 Load profile prediction by ANN

As shown in [MSS12], with the knowledge and identification of the load profile of the former time periods a prediction of the trajectory for the following time steps can be realized.
Therefor, an algorithm based on an artificial neural network (ANN) is applied. Hereby, the information about the measured trajectory of inherent system states is applied to identify the velocity profile of the near past and thus a prediction for the expected load profile for the future time steps is realized.

Due to its advantages concerning memory requirement RNN has been chosen as the identifier in the module perception and interpretation here.
As summerized in [MSS12], the training of ANN can be realized by the usage of different learning algorithms like backpropagation (BP) through time, recurrent BP, dynamic BP, and real-time recurrent learning (RTRL) etc. [CF98]. Due to the fact that the synaptic weights of the fully connected recurrent network can be adjusted with RTRL in real time [Hay99], RTRL is selected as the learning algorithm which can make the realization the online identification achievable. In order to improve the identification and prediction abilities, dynamic recurrent neural networks (DRNN) based on the RNN with RTRL, is applied for multi-step-ahead prediction [PRA00]. In the following, the detailed algorithm and the application examples will be demonstrated for a discrete-time system description. Hereby, the previous measurements of the load profile are used as an input of the DRNN, and, based on this, the prediction of the future load profile is calculated as an output. The layout of DRNN is illustrated in Figure 5.14. The network applied consists of three layers, i.e. an input

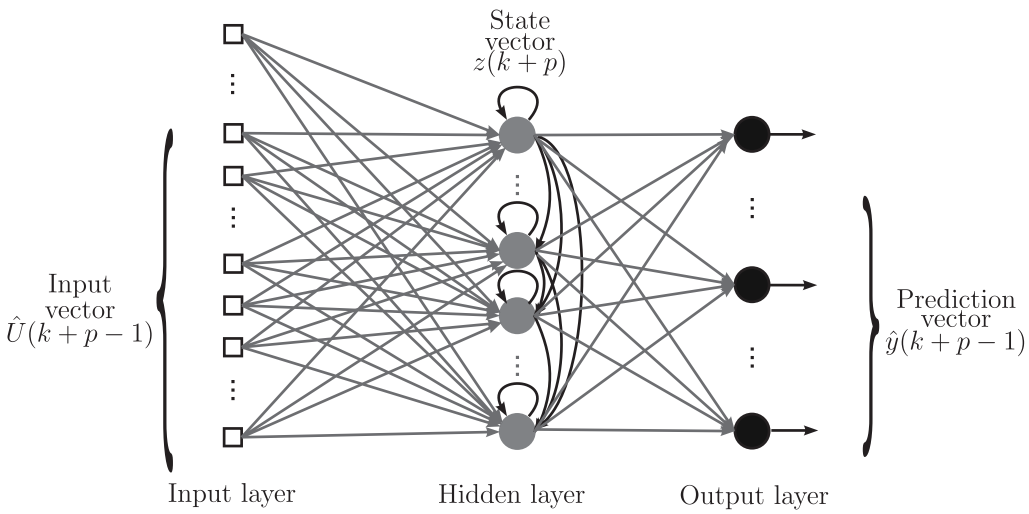


Figure 5.14: Dynamic recurrent neural network architecture utilized as p-step-ahead predictor [MSS12], see [PRA00]

layer, a nonlinear hidden layer, and a linear output layer [PRA00]. The recursive relation between the input vector and the prediction vector of DRNN is calculated by

$$\begin{aligned}\hat{y}(k+p) \quad = \quad & f(\hat{y}(k+p-1), \hat{y}(k+p-2), \ldots, \\ & y(k), \ldots, y(k-n), \\ & u(k), \ldots, u(k-m)).\end{aligned} \tag{5.9}$$

Hereby, $\hat{y}(\cdot)$ denote the estimated outputs of the DRNN, whereas $u(\cdot)$ and $y(\cdot)$ are the measured inputs and outputs. The parameter k is the current time step, p the multi-step prediction horizon and n and m denote the number of the past steps including the influences of the system inputs and outputs. The p-step-ahead predictor is proposed in vector form as

$$\begin{cases} x(k+p) &= F(W_{22}z(k+p-1) \\ &\quad +W_{12}\hat{U}(k+p-1)+b_2), \\ \hat{y}(k+p) &= W_{23}z(k+p)+b_3, \end{cases} \tag{5.10}$$

where $x(k+p)$ denotes the state vector, $F(\cdot)$ a squashing function, W_{ij} the weighting matrices between the i^{th} and j^{th} layer, and b_j are the bias vector of the j^{th} layer. For the learning algorithm of DRNN, a gradient descent procedure is applied to compute the weight changes [PRA00]. The related gradients are calculated by

$$\begin{aligned} \Delta W_{ij} &= -\eta \sum_{k=t+1}^{t+w_s} \left(\frac{\partial E(k)}{\partial W_{ij}}\right), \\ \Delta b_j &= -\eta \sum_{k=t+1}^{t+w_s} \left(\frac{\partial E(k)}{\partial b_j}\right), \end{aligned} \tag{5.11}$$

where η is the learning rate, w_s a possibly moving window for the prediction horizon, t is the first time step of the moving window, and $E(k)$ is the error given by

$$E(k) = (\hat{y}(k) - y(k))^2 \tag{5.12}$$

with the output vector of the real system $y(k)$. A more detailed description of the used approach can be found in [PRA00].
The prediction algorithm is applied to the second stage of the US06 driving cycle as illustrated in Figure 5.15.

The ANN-based algorithm as described, is applied to predict the load profile, i.e. the velocity demand of the system. Hereby, the passed velocity measurements are used as inputs and the predicted next step as an output of the net. For the training of the prediction algorithm the load profile is repeated several times. Dependent on the number of past information of the velocity a prediction trajectory is determined.

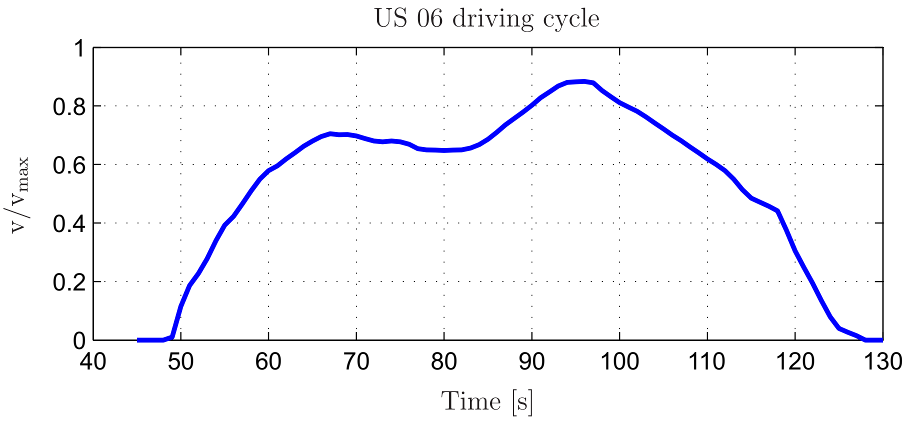


Figure 5.15: US06 driving cycle (second stage) applied for the prediction and optimization algorithm

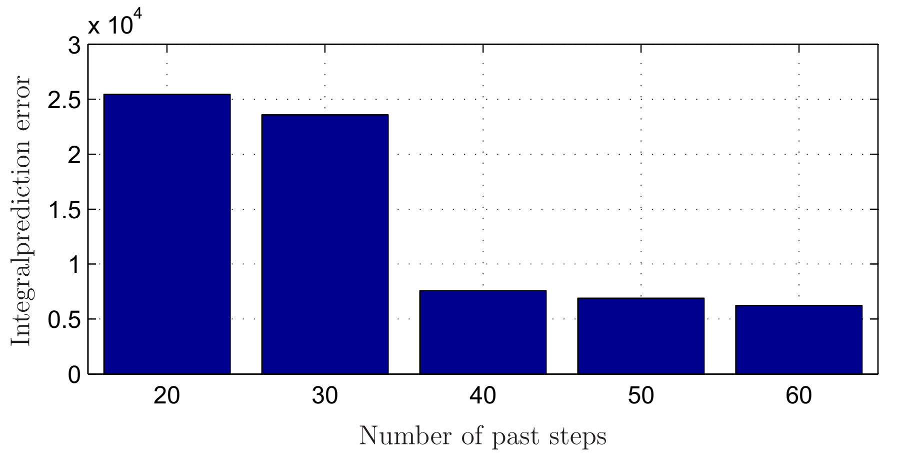


Figure 5.16: Prediction error dependent on past load profile information [MSS12]

The performance of the prediction depends on the number of former load profile information. Thus, the integral prediction error depends on the number of the past steps included, as shown in Figure 5.16.

It becomes clear that the choice of the number of information included has a significant influence on the prediction performance. Further details are described in [MSS12].

5.2.1.2 Online polynomial-based load profile prediction with variable horizon

The usage of ANN for the prediction of driving cycles as described in section 5.2.1.1 leads to suitable results in offline simulations but a disadvantage with respect to

experimental applicability is the large computational effort for the training of the network. Another problem is its fixed structure, which doesn't allow to adapt the prediction parameters as e.g. the backsight horizon length. To realize a good compromize between a good prediction accuracy and robustness against measurement noise, the application of a polynomial-based prediction approach with an adaptive backsight horizon length is introduced in [MS12b] and [MS12a].
The usage of the measurements of past trajectories is a common method for the prediction of the velocity trajectory in automotive applications [CB11]. The prediction algorithm applied in the following, uses specific features of the past trajectory measured over predefined time horizons. Dependent on the prediction performance determined, for each time step the length of the horizon, i.e. the number of past measurements included for the prediction, is adapted. The new suggested point in this context is that, for the prediction of the load profile of a time horizon t_p, a shorter horizon (here denoted by t_1) can better include recent changes of the load profile, whereas a longer horizon (denoted by t_2) is less sensitive to small disturbances or small high frequent changes of the velocity required. In Figure 5.17 the prediction approach is demonstrated using the example of two predicted velocity trajectories v_1 and v_2 dependent on the number of past measurements included.

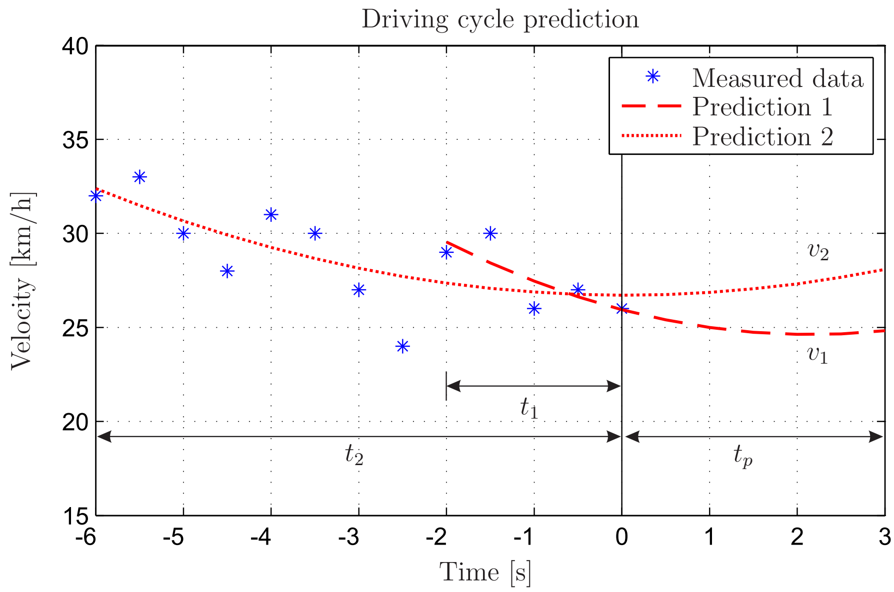


Figure 5.17: Driving cycle prediction dependent on horizon length [MS12b, MS12a]

As illustrated, the prediction of the load profile velocity can significantly vary dependent on the length of the horizon, i.e. the number of past measurement data included. Due to the advantages and disadvantages of the horizon lengths on the prediction performance the usage of an adaptive time horizon dependent on the performance determined for the previously determined prediction is applied. Hereby

the coincidence of the previous prediction with the actual velocity as well as a comparison between the velocity prediction algorithms with another prediction (e.g. t_1 etc.) are applied to adapt the horizon length for the next time step.
Thus, the resulting horizon length t_i is determined by the relation

$$t_i(t) = h(v_{meas}(t), v_i(t + t_p), t_1(t + t_p), v_1(t + t_p), \dots), \tag{5.13}$$

with the predicted velocity $v_i(t + t_p)$ and the measured actual velocity v_{meas}, which is necessary to determine the prediction error of the algorithm.
In Figure 5.18, the application of this prediction algorithm on the second stage of the US06 driving cyle is shown. Additionally, the prediction error of the algorithm and the varying horizon length t_i are illustrated for this cycle.

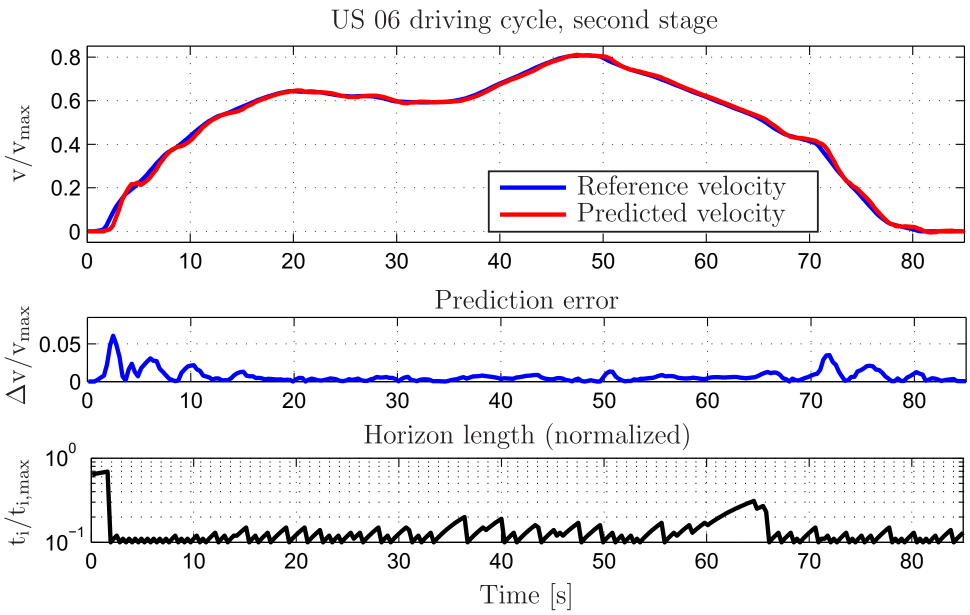


Figure 5.18: Prediction algorithm applied to the US06 driving cycle (second stage)

It becomes clear that the horizon length t_i will be increased if there is a small prediction error and thus good coincidence between predicted and measured velocity for a time period and it will be decreased in the case of large deviations.

5.2.2 MPC-based power flow optimization

Based on the prediction algorithms described, a model predictive algorithm is applied for the realization of the control optimization. Model predictive controllers are optimization-based methods for the feedback control.

The general optimal control problem of a Model Predictive Control (MPC)-based approach with a given prediction horizon length N can be stated as

$$\underset{u(0),\dots,u(N-1)}{min} J(x,u) = \sum_{k=0}^{N-1} y(x(k),u(k)), \tag{5.14}$$

with the cost function J, the system state x, the control input u, and the system output y. Further details and algorithms are described e.g. in [GP11, Wan09].
As described in [GS07], two typical methods for the integration of the system dynamics into the optimization problem are:

1. Stating the system dynamics in a time-discrete state description as

$$\dot{x}(t) = f(t, x(t), u(t)) \tag{5.15}$$

with the resulting optimization problem for each time step Δt

$$u(t, x(t)) = arg\ \underset{u}{min}\ J(t + \Delta t, x(t) + \dot{x}(t, x(t), u(t)))\ \Delta t. \tag{5.16}$$

2. Introduction of a Hamiltonian function

$$H(x, \lambda, u, t) = J(x, u, t) + \lambda^T\ F(x, u, t) \tag{5.17}$$

to be minimized at each time interval. Hereby, $J(x, u, t)$ denotes the cost function of the system with respect to the system properties and $F(x, u, t)$ the constraint function, which contains the system differential equations.
In both cases, the cost function J considering the weighted system properties (drivability, fuel performance, component aging) is stated by the introduced performance parameters of Eq. 4.1-4.3.
In this context, two important aspects for the performance and applicability of an MPC approach are the prediction performance and the computational effort of the algorithm.

In the following, the MPC-based optimization is demonstrated applying the Hamiltonian-based optimization approach, which is introduced in [MS12a]. As load profile prediction algorithm, the online polynomial-based approach is used here. But as it is shown in [MSS12] and [MS12b], the MPC approach based on the state description leads to comparable results and computational effort.
Based on Eq. 5.17, the equations of the system costates (also called *adjoint states*) are determined by

$$\dot{\lambda}_i = -\frac{\partial H}{\partial x_i}. \tag{5.18}$$

Additionally, for the input trajectory the necessary optimality condition given by

$$u = arg\ \min_{u}\ H(x, \lambda, u, t) \tag{5.19}$$

has to be fulfilled.
The problem introduced can be considered as a boundary value problem. Hereby, for each state and costate variable, either an initial or a final value has to be defined as

$$\begin{array}{rclcrcl} x_1(t_0) & = & x_{0,1} & \vee & x_1(t_f) & = & x_{f,1} \\ & \vdots & & & & \vdots & \\ x_i(t_0) & = & x_{0,i} & \vee & x_i(t_f) & = & x_{f,i} \\ \lambda_1(t_0) & = & \lambda_{0,1}, & \vee & \lambda_1(t_f) & = & \lambda_{f,1} \\ & \vdots & & & & \vdots & \\ \lambda_j(t_0) & = & \lambda_{0,j}, & \vee & \lambda_j(t_f) & = & \lambda_{f,j}. \end{array} \tag{5.20}$$

For the implementation of the input constraints the usage of a smoothing function, as proposed in [AK12], is included. Hereby, a saturation function $SAT(s)$ with

$$SAT(s) = \begin{cases} s_{max}, & s > s_{max} \\ s, & s_{min} \leq s \leq s_{max} \\ s_{min}, & s < s_{min} \end{cases} \tag{5.21}$$

is included with respect to a parameter s to be limited by its maximum s_{max} and its minimum s_{min}. The saturation function is approximated by a smoothing function

$$\begin{aligned} SAT(s, \nu) \;\; = \;\; & 0.5 \left(\sqrt{\nu + (s - s_{min})^2} - \sqrt{\nu + (s - s_{max})^2} \right) \\ & + \text{mean}(s_{min}, s_{max}), \end{aligned} \tag{5.22}$$

which depends on the smoothing parameter ν. The dependency of the smoothing function with respect to the parameter ν, is depicted in Figure 5.19.

The results of the MPC are compared with a conventional controller and also with a globally optimal solution determined by dynamic programming for a known load profile. For the conventional control approach, the velocity is determined by a driver model and the current flow through the DC/DC converter is controlled by a PI-controller regarding the bus voltage U_{bus} of the system.
In Figure 5.20 the three approaches, i.e. the conventional controller, the MPC-based controller, and the solution based on Dynamic Programming are compared to each other showing the behavior of the hydrogen consumption (upper plot), the energy

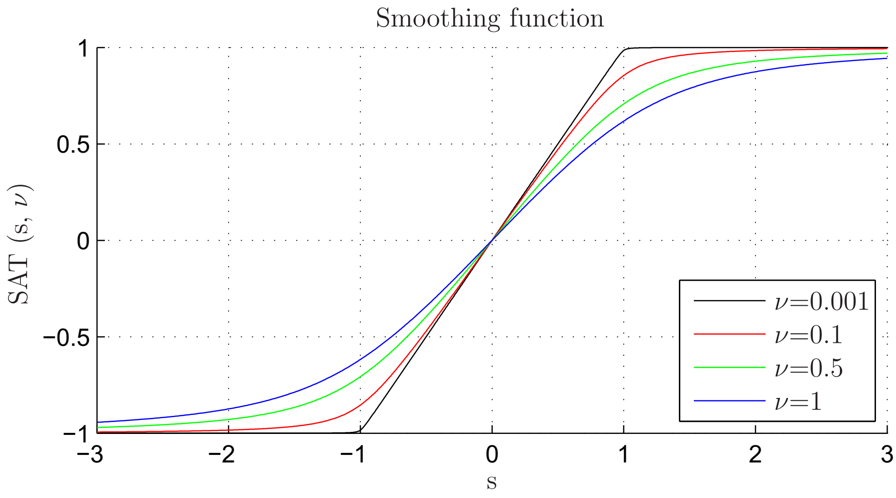


Figure 5.19: Approximation of the input constraints by a smoothing function (Here: s_{max}=1 and s_{min}=-1) [MS12a]

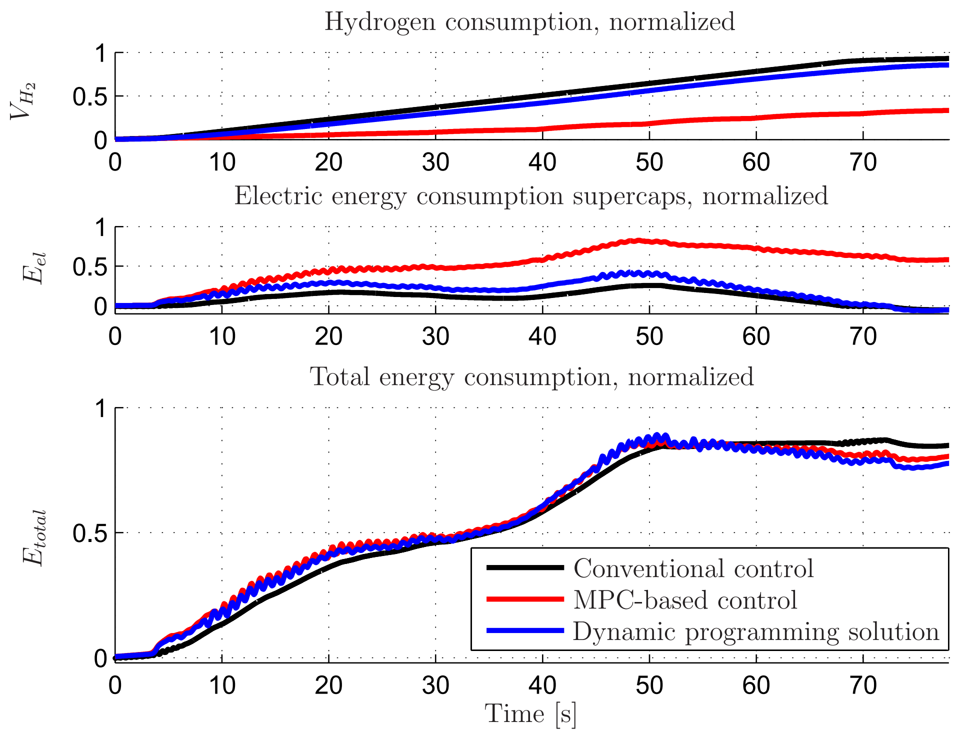


Figure 5.20: Energy consumption of the system dependent on the controller applied [MS12a]

delivered by the supercaps (middle plot), and the resulting total energy consumption.

It can be seen that the MPC-based solution leads to better results for the total energy consumption in comparison to the conventional approach. By using the suggested method, the hydrogen consumption is decreased and instead of this more power is delivered by the supercaps. The reason hereby is that the optimization is only realized for a comparably short time horizon. The better efficiency of the conventional controller during acceleration phases (5 s-25 s, 40 s-50 s) is caused by the fact that the driver model causes time delays for the velocity tracking which on the other hand also causes a worse performance during braking/regeneration phases (20 s-35 s, 50 s-75 s).
For the velocity tracking errors used to determine the drivability of the system the related results are depicted in Figure 5.21.

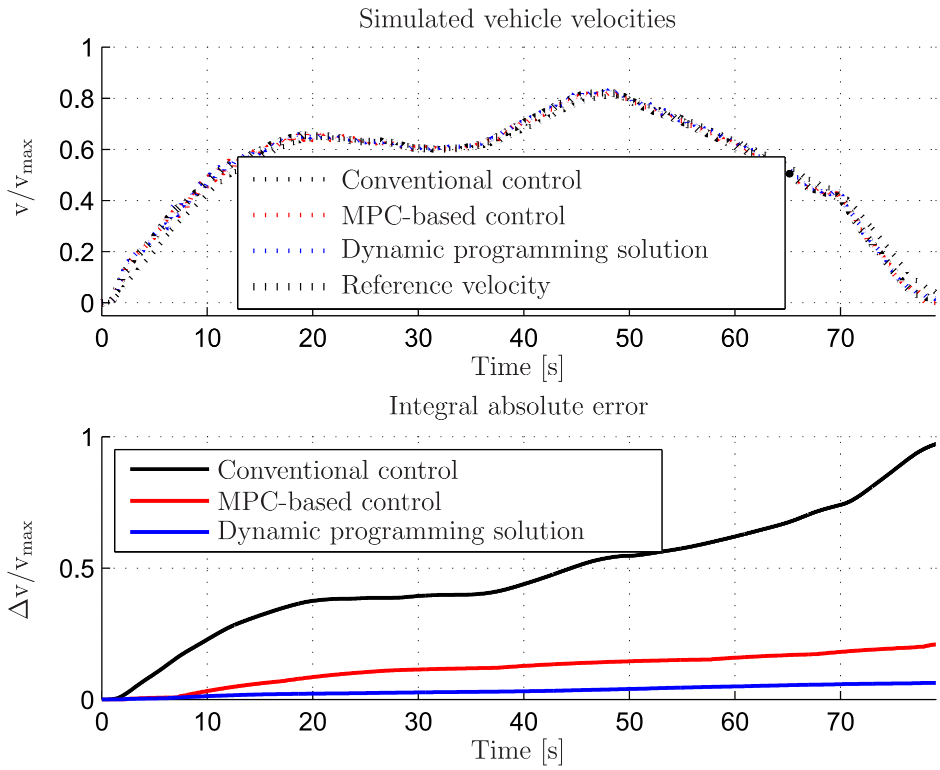


Figure 5.21: Velocity tracking errors of the system dependent on the controller applied

It should be noted that the MPC-based approach realizes control optimization only for a predefined prediction horizon. Hereby optimal results within a local time horizon possibly leads to a worse global performance of the system (if considered for

the total time interval). Besides, the MPC-based algorithm strongly depends on the performance of the prediction algorithm, i.e. a worse performance of the load profile prediction also leads to a worse control performance. The Dynamic Programming approach realizes the control optimization for the complete time interval so that these local effects are avoided.
In Figure 5.22 the related results are illustrated using the performance parameters introduced before. Hereby, small radii denote better system performances. It is shown that the introduced MPC-based method leads to an improvement for drivability and fuel economy with a slight worsening for the fuel cell aging.

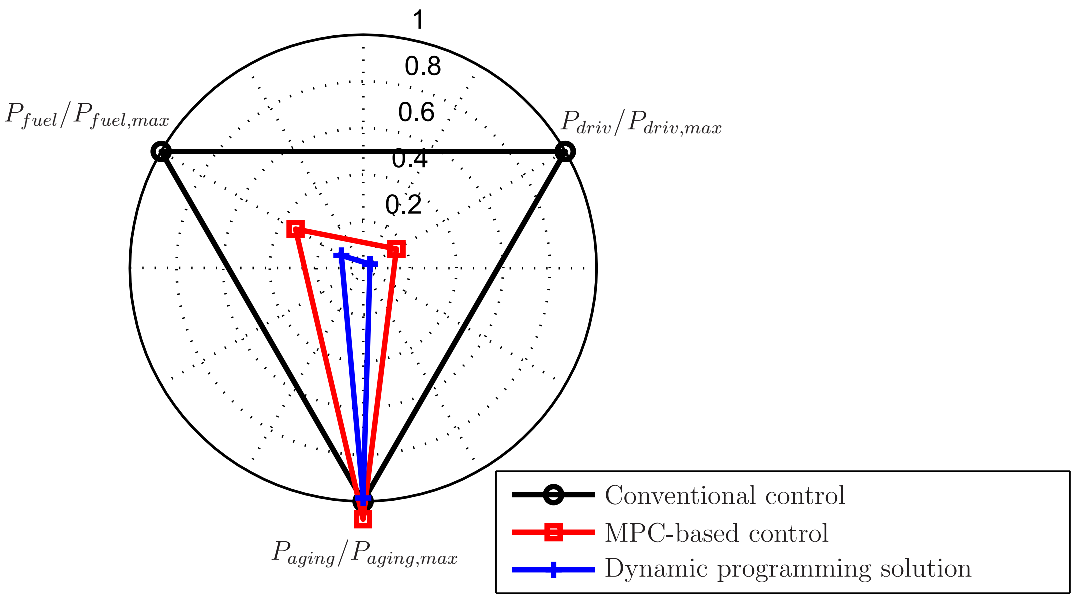


Figure 5.22: System properties for the approaches regarded

Hereby the worse drivability (described by P_{driv}) of the MPC-based approach mainly results from the prediction error of the related algorithm. The conventional controller uses a driver model-based velocity control, which leads to a comparibly large time delay between the reference and the actual velocity of the system. The large fuel consumption (described by P_{fuel}) is due to the load profile independent control of the fuel cell system and the fact that there are intervals in which the fuel cell has to be operated in full power operation, which causes a worse score for the fuel cell economy. The increase of the fuel consumption of the MPC-based approach in comparison to the Dynamic Programming (DP)-based solution is caused by the fact that the fuel economy is only optimized for a rather short time interval which leads to the problem that an unexpected increase of the load profile afterwards requires a larger energy amount and thus an operation of the fuel cell within a less efficient working point. The comparibly good influence of the conventional controller on the

component aging (P_{aging}) is caused by the fact that the time delay of the controller (which has a negative influence on the drivability) also causes a smooth trajectory of fuel cell current i_{FC} and thus less high frequenz oscillations.
For the total performance of the system as shown in Figure 5.23, which is determined by the weighting of the three parameters according to Eq. 4.4, it can be shown that the MPC-based method leads to an improvement compared to conventional approaches and gives results in vicinity of the Dynamic Programming (DP)-based global optimal solution.

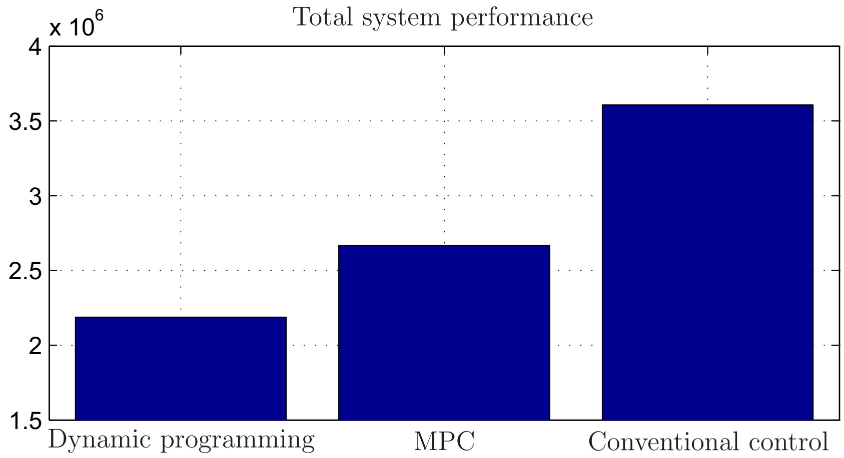


Figure 5.23: Total system performance parameters of the approaches

The embedding of driver behavior models as e.g. shown in [SWSF13] is a helpful method to receive results. Hereby, the coupling of a power train test rig with a driver simulator is an obvious technical solution.

5.3 Instantaneous optimality-based power flow control

With the considerations taken before a prediction and an evaluation algorithm are integrated into the control structure. By this, the algorithm can be applied for a shorter time inteval. As shown, the usage of Model Predictive Controllers leads to suitable results. Model Predictive Controllers are principally real-time applicable, but their performance strongly depends on the complexity of the model and the optimization algorithm included. Typically, for systems with a complex nonlinear structure and time-comsuming numerical optimization algorithms, they have only a limited applicabilty for experimental applications.
To overcome this problem, in the context of hybrid electric vehicles, online-based power flow control methods are commonly applied. In this context, rule-based methods based on Boolean or fuzzy rules involving various system variables are commonly used power flow control methods [GS07]. Most of these methods are designed

to minimize the fuel consumption of a vehicle in order to increase the system's efficiency or to minimize the exhaust emmission of e.g. combustion engines. In [BAC09], a rule-based energy management of a Toyota Prius model is introduced with the goal is to increase the range of the vehicle. This approach covers 4 engine operation modes and 5 energy management rules. Also based on a Toyota Prius model, in [KR11], a rule-based power split algorithm is compared to an instantaneous optimization approach. The instantaneous optimization approach consists hereby of a target generation algorithm based on Pontryagin's minimum principle and a target tracking algorithm based on a Linear Quadratic Regulator (LQR). In [SRA11], a rule-based algorithm for a Hybrid Solar Vehicle (HSV) is introduced and compared to an optimal electric generator scheduling, which is realized by Genetic Algorithms and Dynamic Programming.

A disadvantage of these methods is the limited applicability for multiobjective optimization problems. Additionally, predictional information can only be integrated to a small grade. For this reason, the integration of a database containing offline optimized trajectories is an obvious solution. In this context, at least two important aspects have to be considered. At first, a sufficiently accurate identification of the system state is needed and secondly, a suitable prediction algorithm, especially for the load profile is required. Based on the results of these algorithms, a data base containing optimal solutions of standardized load profile sections with respect to different system states can be included.

In this section, these principles will be shown using the example of a fuel cell/supercapacitor-based hybrid electric vehicle power train. Based on the optimal control trajectories of standardized driving cycle segments within different system states, a power flow control is realized and the results are stored in a multidimensional database. In comparison to the instantaneous optimal control shown in [KR11], the maps for the target generation are also based on the instant velocity and acceleration of the vehicle, in adddition to the SOC of the energy storage. This allows the avoidance of an extra target tracking approach.

Two algorithms for the identification of the system state as well as the prediction of the expected load profile are used to realize this concept. For experimental validation, the control concept is integrated into a power train emulation system. Hereby, the data of the database are integrated to the power flow control system by the usage of a lookup table.

To realize the optimization, the performance parameters evaluating drivability, fuel economy, and lifetime, which are stated in Eqs. 4.1-4.3, are used. For safety reasons, an overcharge of the supercapacitors has to be avoided. On the other hand, the operation with low SOC of the supercapacitors leads to a worse power suppy and thus to a worse performance of the motor and also may lead to a failure of auxiliary systems. For this reason, SOC values in vicinity of the upper and lower boundary have to be avoided. In the context of this application, this is realized by the integration of a soft constraint defining a penalty term P_{pen}, which is added to the cost function. This term is defined by

$$P_{pen} = \begin{cases} \beta_1(SOC_{SC} - SOC_{upper}) & \text{if } SOC_{SC} > SOC_{upper}, \\ \beta_2(SOC_{lower} - SOC_{SC}), & \text{if } SOC_{SC} < SOC_{lower} \end{cases} . \tag{5.23}$$

Hereby, SOC_{upper} denotes the predefined upper and SOC_{lower} the lower threshold for the supercapacitor's SOC during the operation.
The applicability of this approach is demonstrated in Figure 5.24.

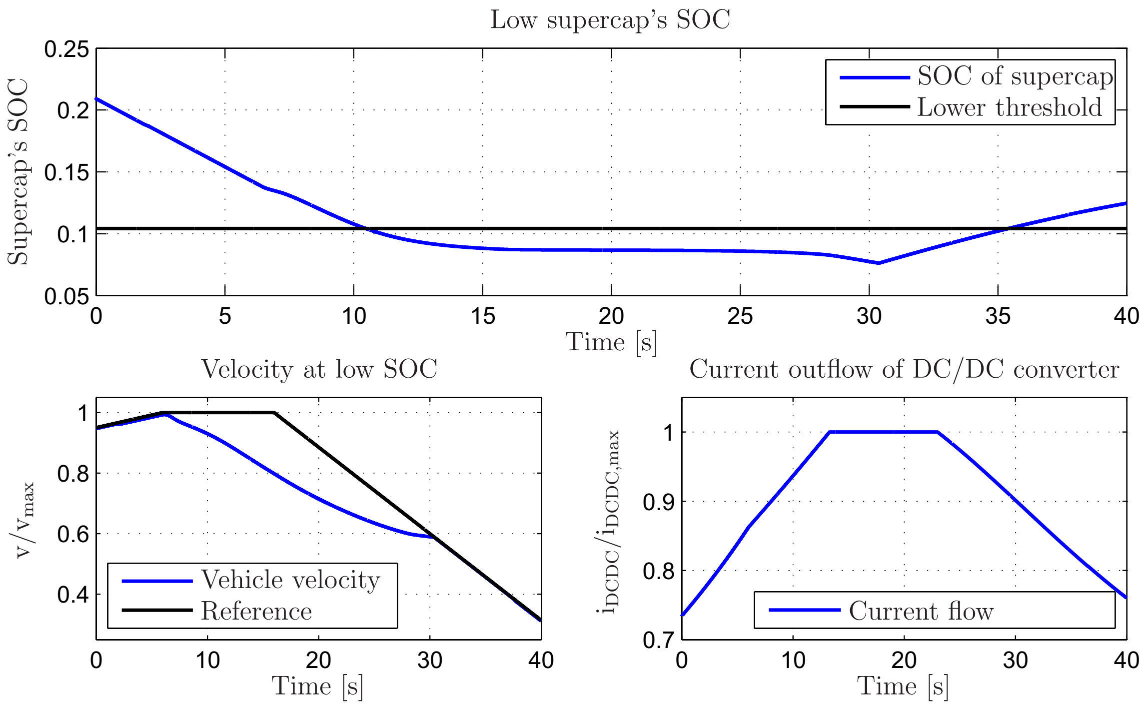


Figure 5.24: Power train operation at low supercap's SOC

Hereby, the power train system is operated at low supercap's SOC. In the case of the SOC dropping below the threshold SOC_{lower}, the penalty parameter P_{pen} is added to the cost function. As shown in the lower plots, this leads to a reduction of the vehicle velocity (bottom, left) to reduce the further energy consumption and an immediate increase of the current outflow of the DC/DC-Converter (bottom, right) to charge the supercapacitors. A comparible result is also achieved for SOC values near the upper threshold. These operation results are achieved in accordance to the optimal solution, which is demonstrated in the following.

Taking these aspects and the performance properties of Eqs. 4.1-4.3 into consideration, the total system performance and hence the cost function J of the optimization problem results to

$$J = \lambda_1 \; P_{driv} + \lambda_2 \; P_{eff} + \lambda_3 \; P_{aging} + P_{pen}, \tag{5.24}$$

with the weighting parameters λ_1, λ_2, and λ_3.
Based on the relations stated, a database for the optimal control trajectory at different operation points is calculated with an offline optimization algorithm. Hereby, a set of standardized driving cycle segments is defined. Hereby, for each load profile, a constant acceleration $a_1 \dots a_{n1}$ is assumed within a time interval $t = [t_1, t_2]$. Each acceleration value is combined with an initial vehicle velocity $v_{0,1} \dots v_{0,n2}$ and a given initial supercap's SOC $SOC_{0,1} \dots \; SOC_{0,n3}$. Thus, for this application, a three-dimensional array, dependent on the three parameters, results. For each parameter combination, an optimal Dynamic Programming solution is determined for the time interval. These solutions are arranged to a database of optimal input trajectories for the usage within the control system. The idea here is to provide an optimal control input for a load situation, which is defined by the instantaneous velocity, acceleration, and SOC. The functional principle is illustrated in Fig 5.25.

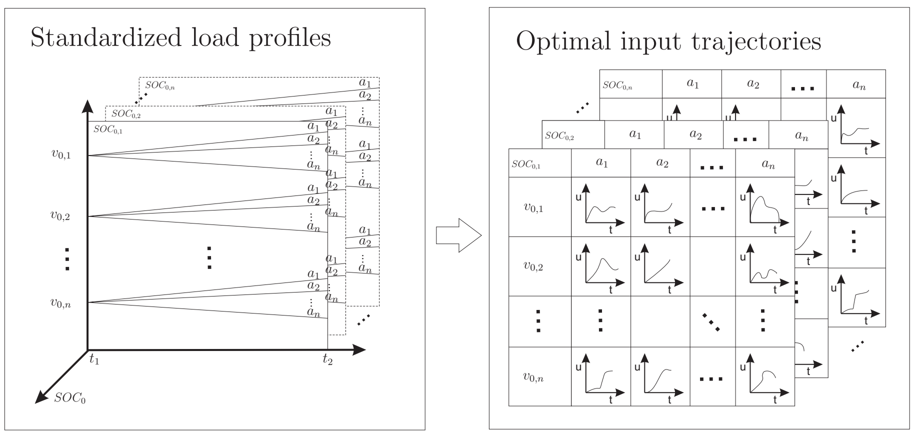


Figure 5.25: Data base of optimal control trajectories

As mentioned, this multidimensional data base is suitable to realize an instantaneous optimal control without a target tracking approach.

5.3.1 Integration of the power flow control algorithms into the power train emulation system

Based on the model relations, the prediction algorithm, and the DP-based control map, the operation of the system under the influence of a defined load profile is

simulated and the electric flows are determined.
Based on the aforementioned considerations, the structure of the resulting total system structure is shown in Fig 5.26.

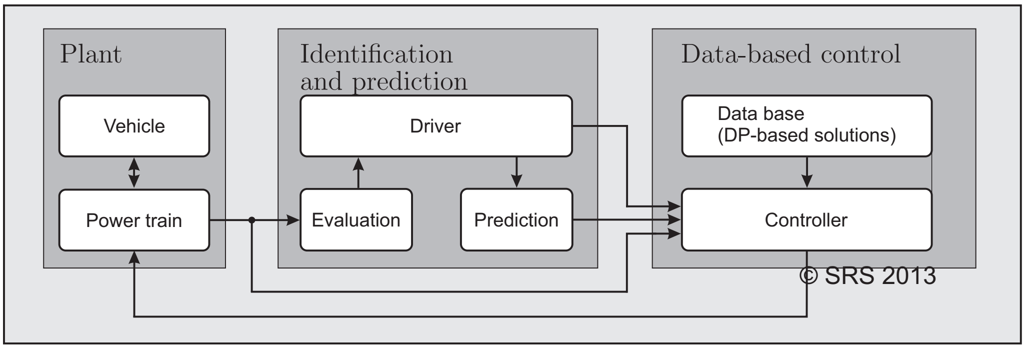


Figure 5.26: Control structure of the hybrid electric power train system

The approach is experimentally evaluated using the modified New European Driving Cycle (NEDC) (Figure 5.27) as a load profile.

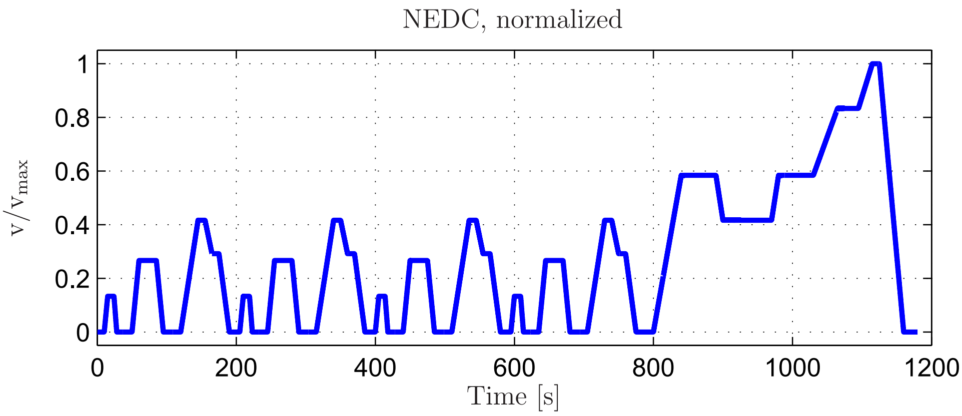


Figure 5.27: Load profile (normalized NEDC)

The approach is compared to a classical PI-controller, regulating the supercap voltage to a constant reference SOC. As a reference, a Dynamic Programming solution over the total time interval is applied. This solution is based on a detailed previous knowledge of the system behavior and the load profile.
In the following, first, the applicability within the test rig environment is shown and a performance evaluation will be given.

5.3.2 Emulation results

As mentioned, an electromechanical emulation is performed by the motors, and the emulation of the electric current flows is realized by the usage of the electric

components (power supply system, electric loads, DC/DC converter).
To evaluate the electromechanical emulation performance, the related measurements of the motors are monitored and compared to the model behavior. Hereby, the measured rotational speed of the motors of the emulation test rig is compared with the simulated angular velocity of the related models. In Figure 5.28, the comparison of the two outputs is shown.

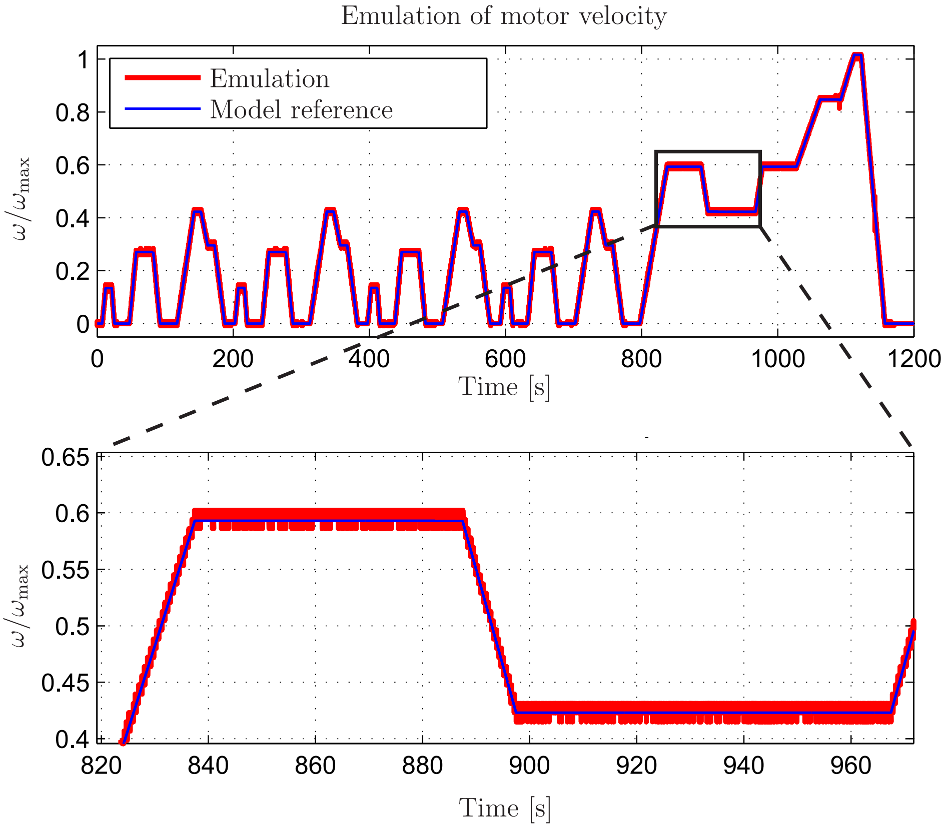


Figure 5.28: Mechanical emulation of the motors

A good coincidence between the simulation signals and measurement signals from the emulation is achieved.
For the current emulation of the electric supply structur of the hybrid electric power train, the simulated components are replaced by controllable electric surrogate components such as a power source for the emulation of the fuel cell system, a combined power source and load to emulate the supercapacitors, and a controlled monodirectional DC/DC converter.
The related power train emulation structure resulting from the considerations of chapter 3 is depicted in Figure 5.29.

Hereby, the motor current is based on the related model behavior whereas the current flow of the DC/DC converter is emulated by a physical DC/DC converter.

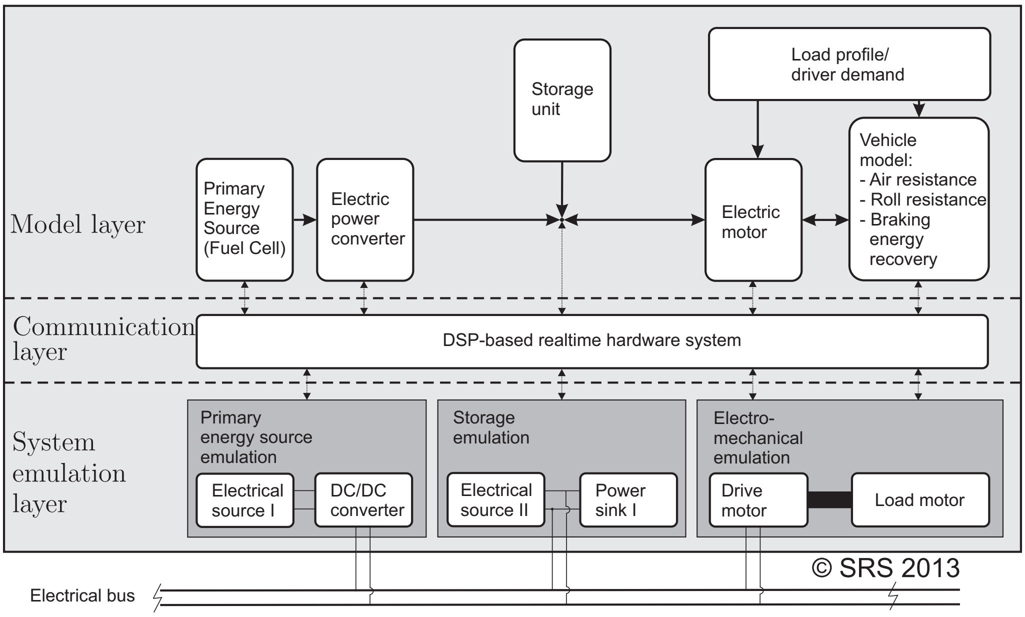


Figure 5.29: Power train emulation structure

The behavior of the supercapacitor system is emulated by two components. Hereby, the supercap current inflows during the charging process are emulated by an electric power sink, whereas the supercap current outflows during discharging are experimentally realized by an electric power supply device. The related results are depicted in Figure 5.30.

It becomes clear that all current flow measurements closely follow to their reference behavior achieved by the power train component models.

5.3.3 Performance comparison

For the instantaneous optimality (IO)-based power flow control approach mentioned, the system performance with respect to drivability, fuel economy and component aging of the fuel cell system is evaluated and compared to a classical controller, whose functional principle is set to regulate the supercap voltage to a constant desired SOC with a PI controller and an additional second PI controller regulating the vehicle speed dependent on the measurement and its deviations from the driving cycle. These approaches are compared to a reference approach, applying a Dynamic Programming solution with respect to the complete time interval. Hereby, the DP solution is based on a previous knowledge of the system dynamics and the driving cycle.
In Figure 5.31, the results for the drivability considerations of the three control approaches is shown. Hereby, for each approach, the absolute velocity deviation

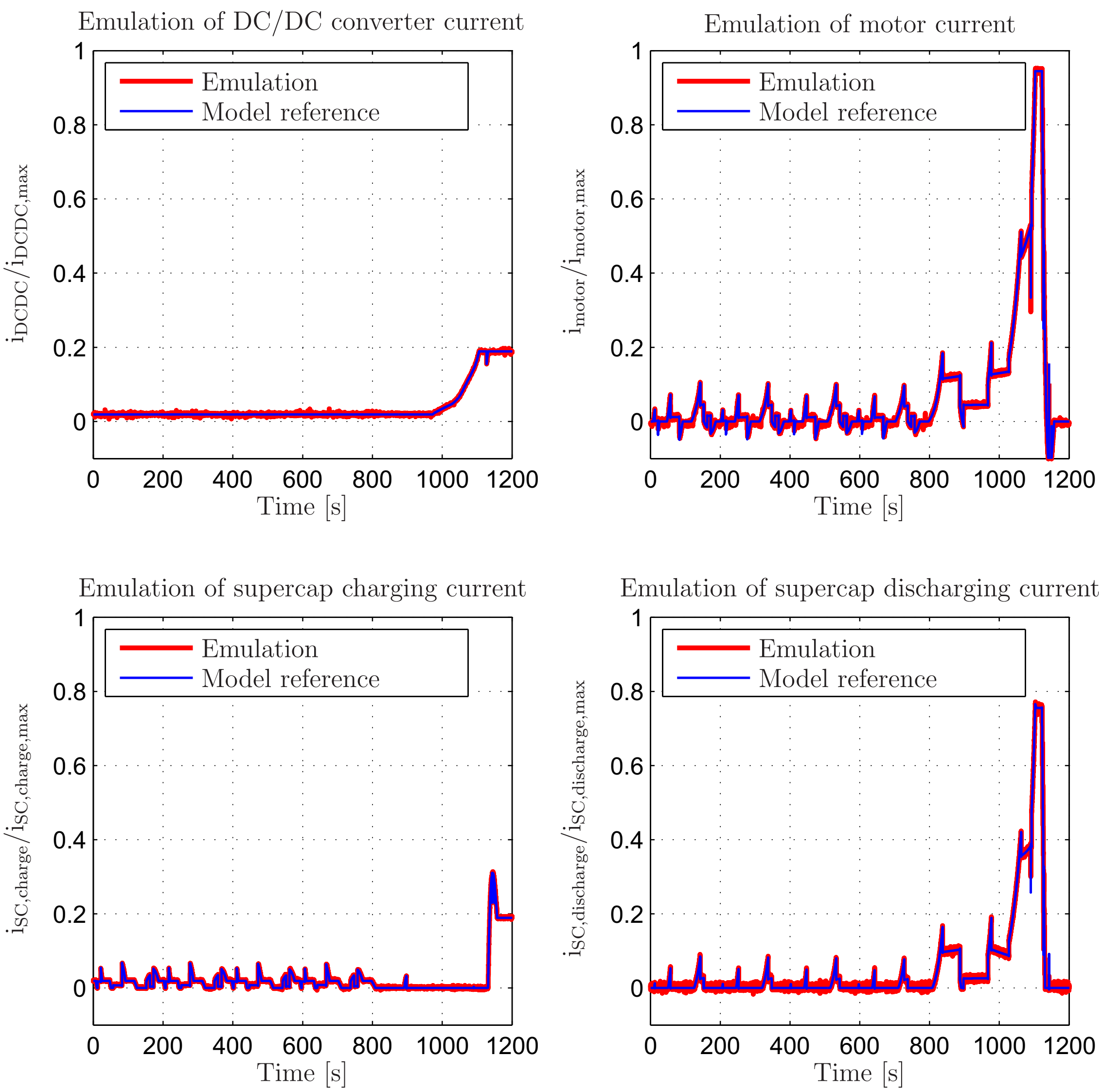


Figure 5.30: Current flow emulation of the components

between reference and actual velocity is determined (middle plot) and the accumulated deviation is calculated (bottom plot). It becomes clear that the instantaneous optimal controller is closely related to the Dynamic Programming solution.

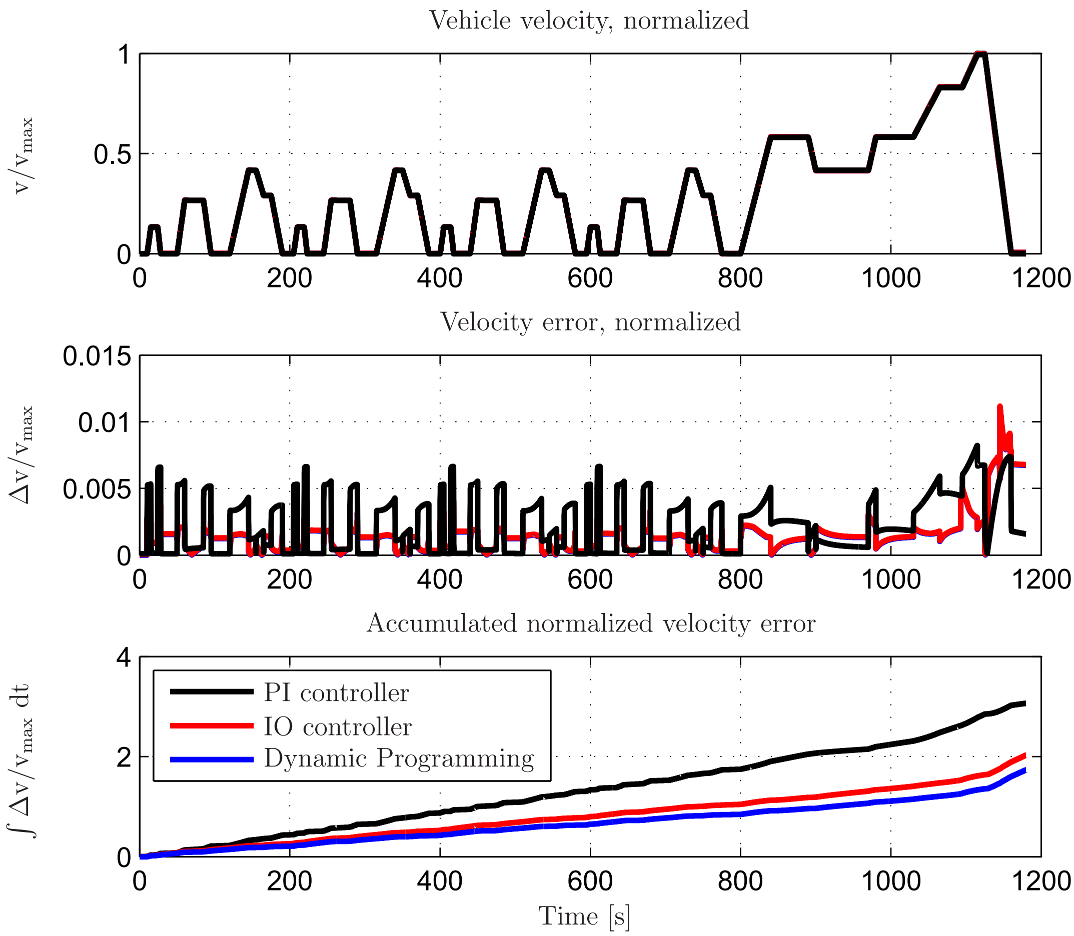


Figure 5.31: Drivability considerations

The fuel economy results are despicted in Figure 5.32. They focus to hydrogen consumption and supercap discharge and the resulting total performance according to the ECMS formulation.

It can be seen that the hydrogen consumption achieved by the PI controller-based power flow control algorithm is slightly smaller then the other ones. This result is directly related to the worse drivabilty of the system, i.e. the capability of the algorithm of fulfilling the acceleration peaks of the load profile. Hereby, it becomes clear that the drivability and the fuel economy are conflicting properties.
For the determination of the fuel cell aging, the measured fuel cell power is high-pass-filtered and the resulting measurement signal is accumulated. As shown in Figure 5.33 the new approach can (in comparison to the PI controller) significantly reduce the aging behavior of the fuel cell system close to the Dynamic Programming solution.

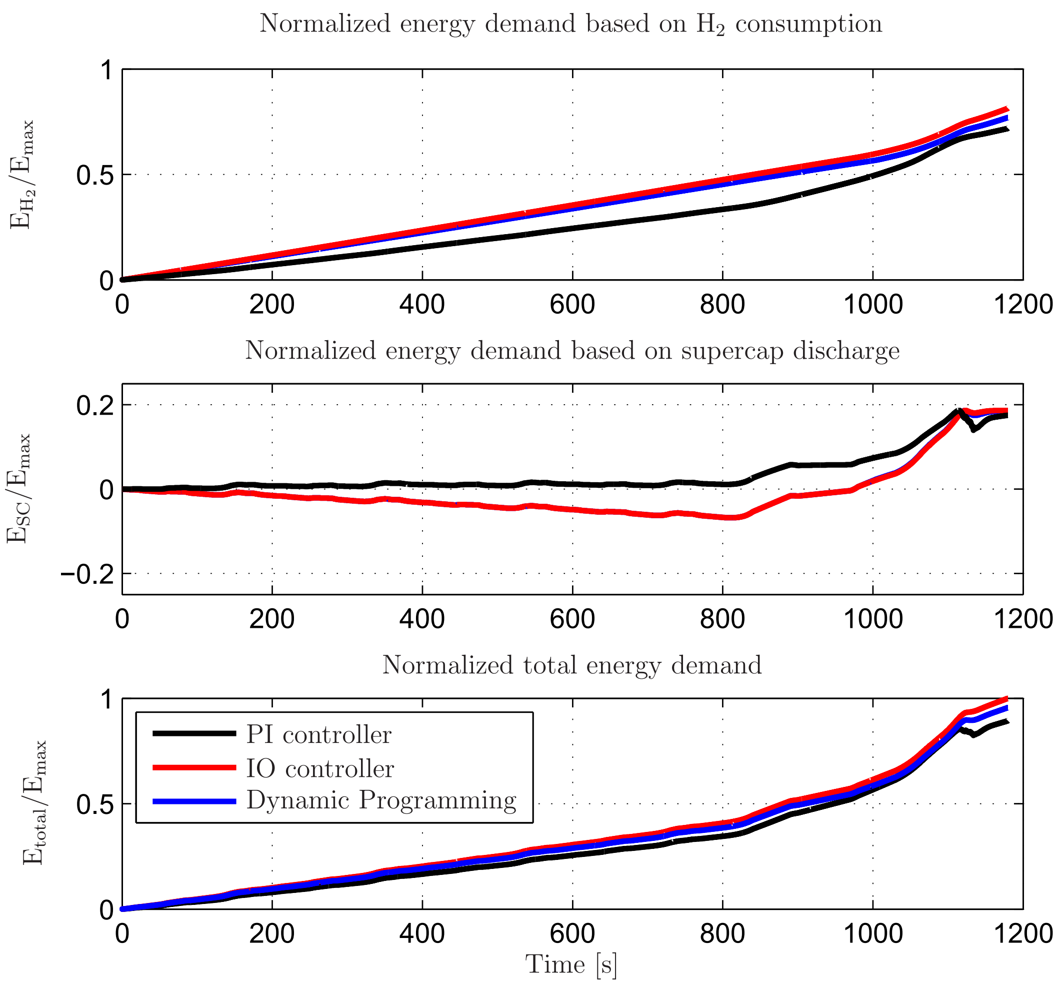


Figure 5.32: Fuel economy considerations

In Figure 5.34, the three evaluation parameters considering the drivability, the fuel economy, and the fuel cell aging, as described in Eqs. 4.1, 4.2, and 4.3, are compared to each other. It becomes clear that the instantaneous optimality (IO)-based power flow control algorithm leads to a significant improvement. The results are close to those of the Dynamic Programming solution.

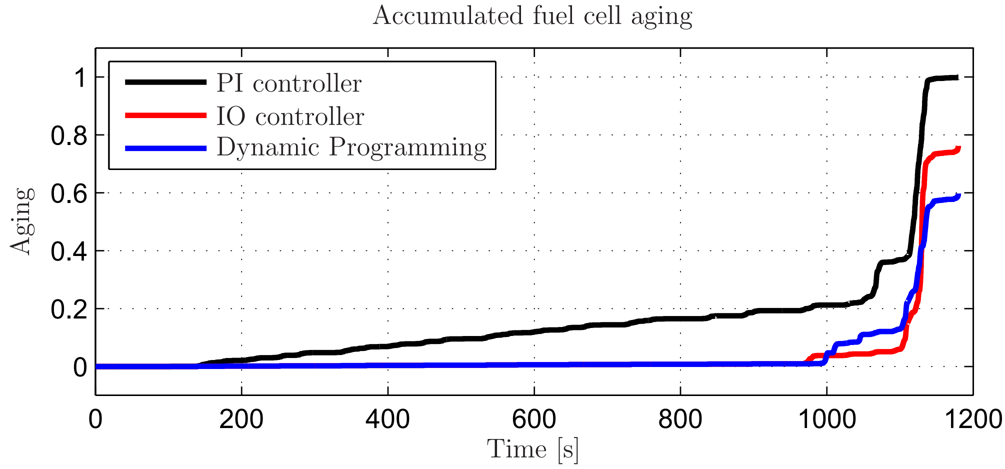


Figure 5.33: Aging considerations

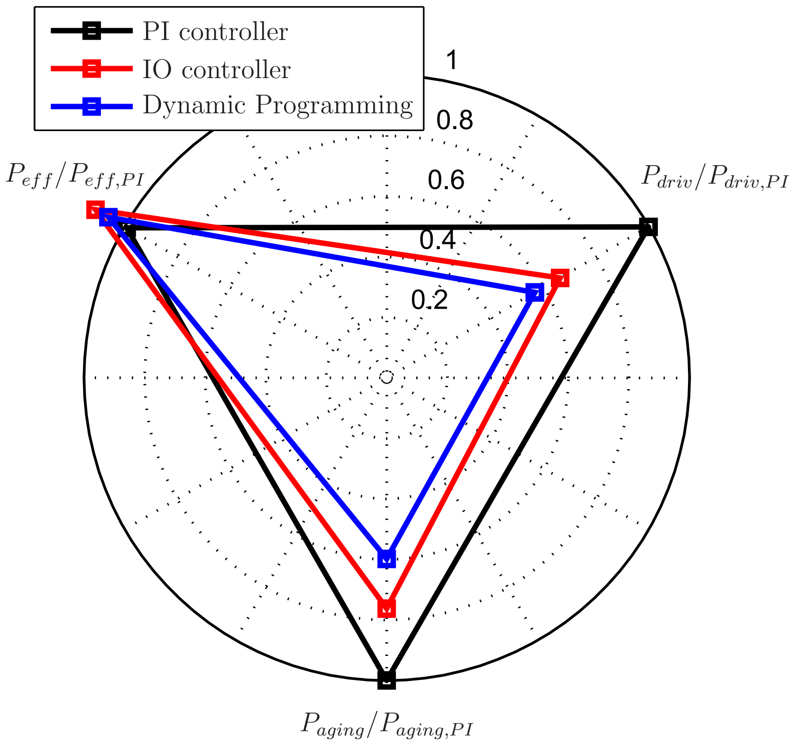


Figure 5.34: Performance parameters of the approaches

For the consideration of the total performance, the weighted sum of the performance parameters, i.e. the cost function value (including the penalty parameter P_{pen}), as stated in Eq. 5.24, is used. As it can be seen from Figure 5.35, a good result close to the Dynamic Programming solution can be obtained for the Instantaneous Optimality (IO)-based power flow control algorithm.

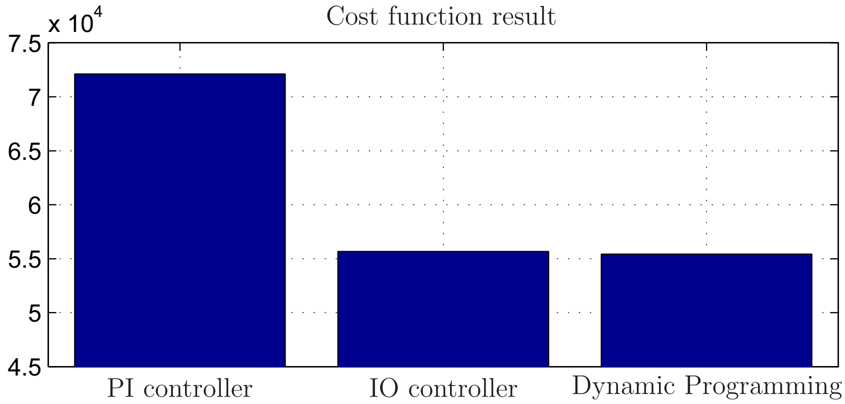


Figure 5.35: Total performance (cost function values) of the approaches

5.3.4 Discussion

The results of the instantaneous optimality (IO)-based power flow control algorithm show a good applicability within real-time applications and an improved performance compared to classical rule-based power flow control algorithms especially for multiobjective control problems. However, the applicability of this approach depends depends on two aspects. First, the size of the database and the related lookup tables considerably influences the computational effort required. This effect can be reduced by a sophisticated access to the database, but especially large multi-dimensional matrices leads to an significant increase of the computational time. A second point is the structure of the data within the database. Since the implementation to the power train cntrol system is realized by lookup tables, which also require the interpolation between previously defined operation points, a sufficiently smooth distribution of the control values within the database is required. Especially for multidimensional databases, this has to be proven in advance.

6 Summary and Outlook

6.1 Conclusion

In this thesis, the power flow control and its optimization is discussed and applied within simulation and experimental environments . For experimental application and validation, a methodology for the emulation of the operation and the power flow control of hybrid electric power trains is introduced. For the control, the aspects of drivability, fuel performance, and component aging are considered seperately, and a multiobjective optimization and hence an integrated approach containing power management, energy management, and limetime management is developed and applied.
Dependent on the system structure and requirements, different optimization methods for the power flow control optimization are introduced and the related results are presented. From the results, the strengths and weaknesses of the methods considered, as depicted in Table 6.1, become clear.

	Parametrization/ dimensioning	Applicable for realtime/ experimental applications	Optimization of control trajectories	Multiobjective applicability	Independent on previous load profil knowledge
Global Optimization (GO)	++	−	o	++	-
DP-based optimization	o	-	++	+	-
Heuristic optimization	+	o	o	+	o
MPC-based optimization	o	o	+	+	+
IO-based optimization	o	+	+	+	+
Classical rule-based approaches	o	++	o	o	+

Table 6.1: Comparison of the control optimization methods

Hereby, the sophisticated searching algorithms of the Global Optimization (GO)-based approaches make them suitable for parameter optimization within dimensioning problems within parameterized given system or controller structures. These algorithms oftenly also include methodes for the solution of multiobjective optimization problems. The large computational effort, however, does not allow the application within experimental application with a fast changing dynamics or for a fast reaction. The optimization of the control trajectory is possible, but this requires the definition of a comparibly large chromosome structure, which might lead to a long computational time. Since it consideres a complete time interval for the optimization, it has only limited applicability without a previous knowledge of the load profile. For this reason, this method is a good method for the application within offline-optimization problems with a given parameterized system and controller structure.
For the optimization of control trajectories for a given system dynamics and load profile, a Dynamic Programming (DP)-based solution leads to the best performance and can thus be considered as a suitable method for the generation of reference solutions. As shown, for this method, also the implementation of multiobjective approaches is possible by a suitable definition of its cost function. The disadvantage of this methos is that the large computational effort and thus the required computational time do not allow the application within most experiment environments. Also the implementation of real-time identification algorithms is rarely possible using this method since it typically consideres a complete time interval as well. The application within parametrization problem is possible but requires a comparibly large effort. For this reason, this method are suitable for offline optimization problems of control trajectories within given system structures and load profiles.
Heuristic methods such as the Golden Section Search method introduced can be used within experimental environments. Its comparably simple search algorithms allows a shorter computational time but does not necessarily guarantee a convergence of the optimization process. It can be considered as a compromize solution between the fast but unflexible classical rule-based methods and the Global Optimization methods with comparible large optimization performance but long computational time and effort. As shown, the heuristic optimization methods is suitable for the application within environments without a detailed system knowledge, if a repeated load profile can be assumed. In this environment, it can be applied for an iterative adaption of the control parameters.
Approaches based on the Model Predictive Controller (MPC) can also be seen as compromize solutions between online and offline methods since this method requires less computational time than the offline optimization methods but has a more detailed view on the system properties than the online methodes. Its control structure is designed for the optimization of the control trajectory and the inclusion of prediction algorithms make it independent of a previous knowledge of a load profile. Due to the preceding horizon, this method can also be applied within online applications. The integration within experimental applications depends on the complexity of the

system and thus from the required computational effort. On the other hand, for the solution and optimization of parametrization problems the MPC is not a suitable method.
For real-time applications, the classical rule-based methods and the Instantaneous Optimality (IO)-based power flow control method can be applied. Whereas the IO-based method uses look-up-tables with pre-optimized trajectories as well as a prediction algorithm, classical rule-based approaches typically use a small number of system states where the operation rules are defined. The information of the IO-based method are based on a Dynamic Programming (DP)-based optimization, whereas those of the classical rule-based methods are typically set up by experience. This aspect makes the total performance and the multiobjective applicability of the IO-based optimization better, whereas classical rule-based methods require less computational effort and are thus easier to be implemented within real-time applications.

6.2 Contributions

Within this thesis, a number of optimization approaches are investigated with respect to the power flow control of hybrid electric power train systems.
Hereby, a contribution to a conceptual development of a multiobjective optimal power flow control algorithms within hybrid electric power trains is presented. The idea of this multi-objective focus is to distinguish between power management, energy management, and lifetime management of the power train, which depend on the system properties to be considered and the time scale regarded. In the context of this thesis the focus is to include the evaluation results based on simulations and experimental applications.
The implementation of heuristic search algorithms as well as genetic algorithms within simulation and experimental environments is realized to optimize the multi-objective power flow control algorithms of the hybrid electric power train systems. The advantage of this method is to realize these systems without a detailed knowledge of their dynamical behavior. As shown, in the case of a repeated load profile, this optimization can also be applied without its consideration.
For the experimental evaluation of hybrid electric power train structures, a concept of an emulation structure is introduced, developed, and experimentally realized. This structure allows a modular setup and thus the realization of different system topologies for both hybrid electric power train system and the related electric energy conversion systems. Since the electric components are used as sources, sinks, and power converters, their application allows the emulation of arbitrary electric power train components as well as a general power train consideration. The implementation of electric hydraulic analogy models even allows the emulation of hybrid hydraulic power train systems. As shown, this can be realized with an accurate emulation performance.
The implemention of predictional algorithms into the power flow control algorithms

allows the adaptation to the expected load profile and hence to a related driver behavior. Aside from the model-based algorithms especially the experimental algorithms lead to additional options. By the usage of these kind of algorithms it is also possible to connect the power train system to a driving simulator for the inclusion of human drivers.
The implementation of a knowledge-base, based on optimal input trajectories determined by the Dynamic Programming approach, into the power flow control of the power train allows the implementation of offline-optimized control inputs into an experimental environment and guarantees a better performance than e.g. classical rule-based algorithms.

6.3 Outlook

Future work in this field could be the application of the methods demonstrated for other power train systems e.g. those based on combustion engines or Lithium-Ion batteries. In this context the emulation test rig developed in the context of this thesis can be applied for the further topologies.
Robust control algorithms can be developed to deal with prediction errors and model parameter uncertainties. In this context, in [MWS11], the application of a Global Optimization-based optimization loop in combination with an unscented H_∞-Controller is demonstrated for a magnetic bearing system.
The implementation of more sophisticated search algorithms for the Global Optimization-based optimization and the Embedded-Online Optimization may lead to faster results and to a better applicability also for non-convex cost functions.
Further steps in future will be the implementation of more detailed aging models into the lifetime management. Hereby, especially online-capable methods for the determination of the State-of-Health (SOH) of different system components will be a challenging task.
In future, the implementation of improved prediction algorithms will lead to a better performance. Hereby learning algorithms and models including the driver behavior can be applied as well. The implementation of detailed driver models can help to adapt the methods for individual driver behavior especially if the system is coupled with a driving simulator. In the same context, the implementation into real driver situation, i.e. steering a vehicle on a road, can be considered as well. To do so, more information about the driving situation is required to realize a suitable power flow control.

Another field is the consideration of multiple power trains and driving simulators in a competitive or cooperative environment as e.g. multiple vehicles on the road, overtaking maneuvers etc. Hereby, further information, e.g. received by car-to-car-communication devices or GPS-based data, can be included as well.

Literature

[Age13] European Environment Agency. Annual european union greenhouse gas inventory 1990-2011 and inventory report 2013, 2013. Available at: www.eea.europa.eu/publications/european-union-greenhouse-gas-inventory-2013, last visited: July 27th 2013.

[AK12] S. N. Avvakumov and Yu. N. Kiselev. Boundary Value Problem for Ordinary Differential Equations with Applications to Optimal Control. *CMC Department, Moskow State Lomonosov University, Moskow, Russia, See also URL* http://oc.cmc.msu.ru/download/22/ BVP_1_Avv_Kis.pdf *(22th March 2012)*, 2012.

[AM07] J. Auer and J. Miller. Ultracapacitor-based energy management strategies for eCVT hybrid vehicles. In *IET Automotive Electronics, 3rd IET Conference*, Warwick, UK, 2007.

[AP02] R. Apter and M. Präthaler. Regeneration in Hybrid Vehicles. In *Proc. of the IEEE 55th Vehicular Technology Conference*, Birmingham, AL/USA, 2002.

[BAC09] H. Banvait, S. Anwar, and Y. Chen. A Rule-Based Energy Management Strategy for Plug-in Hybrid Electric Vehicle (PHEV). In *American Control Conference (ACC)*, St. Louis/MO, USA, 2009.

[BBA06] R. Beck, A. Bollig, and D. Abel. Comparison of two Real-Time Predictive Strategies for the Optimal Energy Management of a Hybrid Electric Vehicle. In *E-COSM - Rencontres Scientifiques de l'IFP*, 2006.

[BBB+05] M. Broussely, Ph. Biensan, F. Bonhomme, Ph. Blanchard, S. Herreyre, K. Nechev, and R.j. Staniewicz. Main Aging Mechanisms in Li-ion Batteries. *Journal of Power Sources*, 146:90–96, 2005.

[BBM06] F. D. Bianchi, D. Battista, and R. J. Mantz. *Wind Turbine Control Systems: Principles, Modelling and Gain Scheduling Design.* Springer Verlag, 2006.

[Bel12] R. Bellman. The Theory of Dynamic Programming. *Mathematical Programming*, 131(1-2):131–161, February 2012.

[Boy06] S. J. Boyd. *Hybrid Electric Vehicle Control Strategy Based on Power Loss Calculations.* PhD thesis, Virginia Polytechnic Institute and State University, Blacksburg/Virginia, USA, 2006.

[BRP+10] C. Bordons, M.A. Ridao, A. Pérez, A. Arce, and D. Marcos. Model Predictive Control for power management in hybrid fuel cell vehicles. In *Vehicle Power and Propulsion Conference (VPPC)*, Lille, France, September 2010.

[Buc14] E. Buckingham. On physically similar systems; illustrations of the use of dimensional equations. *Physical Review*, 4:345–376, 1914.

[Bun12] Deutsche Bundesbank. The price of crude oil and its impact on economic activity in the industrial countries, 2012. Available at: www.bundesbank.de/Redaktion/EN/Downloads/Publications/Monthly_Report_Articles/2012/2012_06_oil.pdf, last visited: July 28th 2013.

[CA03] D. Carter and A. Alleyne. Load Modeling and Emulation for an Earthmoving Vehicle Powertrain. In *Proc. of American Control Conference (ACC)*, Denver, CO, USA, June 2003.

[CB11] O. Cassebaum and B. Bäker. Predictive Supervisory Control Strategy for Parallel HEVs using Former Velocity Trajectories. In *Vehicle Power and Propulsion Conference (VPPC)*, Chicago, IL, USA, September 2011.

[CBL08] K. Chen, A. Bouscayrol, and W. Lhomme. Energetic Macroscopic Representation and Inversion-based Control: Application to an Electric Vehicle with an Electrical Differential. *Journal of Asian Electric Vehicles*, 6(1):1097–1102, June 2008.

[CF98] T. W. S. Chow and Y. Fang. A recurrent neural-network-based real-time learning control strategy applying to nonlinear systems with unknown dynamics. *IEEE transactions on industrial electronics*, 45:151–161, 1998.

[Cha07] C. C. Chan. The State of the Art of Electric, Hybrid, and Fuel Cell vehicles. *Proc. of the IEEE*, 95(4):704–718, April 2007.

[Com93] European Community. Towards sustainability - a european community programme of policy and action in relation to the environment and sustainable development, 1993. Available at: www.ec.europa.eu/environment/archives/env-act5/pdf/5eap.pdf, last visited: July 27th 2013.

[CWL+08] S. Chen, L. Wang, C. Liao, L. Wan, and X. Lu. Realization of an energy management strategy for a series- parallel hybrid electric vehicle. In *IEEE Vehicle Power an Propulsion Conference (VPPC)*, Harbin, China, 2008.

[CWY+06] A. Collier, H. Wang, X. Z. Yuan, J. Zhang, and D. P. Wilkinson. Degradation of polymer electrolyte memranes. *Journal of Hydrogen Energy*, 31(13):1838–1854, 2006.

[CZT+07] X. Cheng, J. Zhang, Y. Tang, C. Song, J. Shen, and D. Song. Hydrogen crossover in high-temperature PEM fuel cells. *Journal of Power Sources.*, 167(1):25–31, 2007.

[DASM11] T. O. Deppen, A. G. Alleyne, K. A. Stellson, and J. J. Meyer. Model Predictive Control of an electro-hydraulic powertrain with energy storage. In *Proc. of the ASME 2011 Dynamic Systems and Control Conference (DSCC 2011)*, Arlington, VA, USA, October 2011.

[DCLC13] Z. Du, K. L. Cheong, P. Y. Li, and T. R. Chase. Fuel Economy Comparison of Series, Parallel, and HMT Hydraulic Hybrid Architectures. In *Proc. of 2013 American Control Conference (ACC)*, Washington, D.C. / USA, June, 17-19 2013.

[DOW00] J. Dixon, M. Ortúzar, and E. Wiechmann. Regenerative Braking for an Electric Vehicle, Using Ultracapacitors and a Buck-Boost Converter. In *17th Electric Vehicle Symposium (EVS'17)*, Montreal, Canada, 2000.

[dRAB09] A. J. del Real, A. Arce, and C. Bordons. Optimization strategy for element sizing in hybrid power systems. *Journal of Power Sources*, 193(1):315–321, 2009.

[ERWL05] A. Emadi, K. Rajashekara, S. Williamson, and S. M. Lukic. Topological Overview of Hybrid Electric and Fuel Cell Vehicular Power System Architectures and Configurations. *IEEE Transactions on Vehicular Technology*, 54(3):763–770, 2005.

[EVAB07] J. A. Egea, D. Vries, A. A. Alonso, and J. B. Banga. Global Optimization for Integrated Design and Control of Computationally Expensive Process Models. *Ind. Eng. Chem. Res.*, 46(26):9148–9157, 2007.

[FQ06] L. Fang and S. Qin. Optimal control of parallel hybrid electric vehicles based on theory of switched system. *Asian Journal of Control*, 8(3):274–280, 2006.

[FSR09] D. Feroldi, M. Serra, and J. Riera. Energy management strategies based on efficiency map for fuel cell hybrid vehicles. *Journal of Power Sources*, 190(2):387–401, 2009.

[GA07] M. Garcia Arregui. *Theoretical study of a power generation unit based on the hybridization of a fuel cell stack and ultracapacitors*. PhD thesis, L'Institute National Polytechnique de Toulouse, L'Universite de Toulouse, Toulouse, France, 2007.

[Gar02] O. Garcia. *DC/DC-Wandler für die Leistungsverteilung in einem Elektrofahrzeug mit Brennstoffzellen und Superkondensatoren.* PhD thesis, ETH Zürich, Zürich, Switzerland, 2002.

[GBBM11] F. Gao, B. Blunier, D. Bouquain, and A. Miraoui. Modes Based DC Power Source Emulator for Electrical and Hybrid Electrical Vehicles Drive Train Tests. In *Proc. of IEEE Vehicle Power an Propulsion Conference (VPPC 2011)*, Chicago, IL, USA, 2011.

[GDH00] X. Guillaud, P. Degobert, and J. P. Hautier. Modeling, control, and causality: the causal ordering graph. In *Proc. of 16th IMACS World Congress*, Lausanne, Switzerland, 2000.

[GK13] S. Gonsrang and R. Kasper. Simulation Study of Energy Flow in Electric Vehicles with Range Extender. In *11. Magdeburger Maschinenbau-Tage*, Magdeburg, Germany, September, 25-26 2013.

[GMST07] J. Gonder, T. Markel, A. Simpson, and M. Thornton. Using GPS Travel Data to Assess the Real World Driving Energy Use of Plug-In Hybrid Electric Vehicles (PHEVs). In *Transportation Research Board (TRB) 86th Annual Meeting*, Washington, D.C., USA, 2007.

[GP11] L. Grüne and J. Pannek. *Nonlinear Model Predictive Control - Theory and Algorithms.* Springer London Dordrecht Heidelberg New York, 2011.

[GS07] L. Guzzella and A. Sciarretta. *Vehicle propulsion systems: Introduction to Modeling and Optimization.* Springer-Verlag, Berlin Heidelberg, 2007.

[Gue05] M. B. Guenther. *Modelling and Design Optimization of Low Speed Fuel Cell Hybrid Electric Vehicles.* PhD thesis, University of Victoria, 2005.

[Hay99] S. Haykin. *Neural networks.* Prentice Hall International, Inc., New Jersey, USA, 1999.

[HB10] E. M. T. Hendrix and G. T. Boglárka. *Introduction to nonlinear and Global Optimization.* Springer Verlag, 2010.

[Hen08] W. Henson. Optimal battery/ultracapacitor storage combination. *Journal of Power Sources*, 179(1):417–423, 2008.

[Her10] F. Herb. *Alterungsmechanismen in Lithium-Ionen-Batterien und PEM-Brennstoffzellen und deren Einfluss auf die Eigenschaften von daraus bestehenden Hybrid-Systemen.* PhD thesis, University of Ulm, 2010.

[HFNJ09] F. Herb, A. Frank, C. Nitsche, and A. Jossen. Optimierung der Regelung zwischen Brennstoffzelle und Batterie in Bezug auf Komponentenalterung. *at-Automatisierungstechnik*, 57(1):40–47, 2009.

[HJ04] J. Hellgren and K. Jonasson. *Comparison of Two Algorithms for Energy Management of Hybrid Powertrains*. PhD thesis, Chalmers University of Technology, Sweden und Lund University, Sweden, Göteborg and Lund, Sweden, 2004.

[HJ07] J. Hellgren and E. Jonasson. Maximisation of brake energy regeneration in a hybrid electric parallel car. *International Journal of Electric and Hybrid Vehicles*, 1(1):95–121, 2007.

[HJRW09] F. Herb, A. Jossen, S. Reiff, and M. Wöhr. Investigation of Li-battery and Fuel Cell aging in FC hybrid car model. In *Eleventh Grove Fuel Cell Symposium*, London, 2009.

[HSDS07] T. Hofman, M. Steinbuch, R. van Druten, and A. Serrarens. Rule-based energy management strategies for hybrid vehicles. *Int. J. Electric and Hybrid Vehicles*, 1(2):71–94, 2007.

[HSZ+06] X. Huang, R. Solasi, Y. Zou, M. Feshler, K. Reifsnider, D. Condit, S. Burlatsky, and T. Madden. Mechanical endurance of polymer membrane and PEM fuel cell durability. *Journal of Polymer Science. Part B. Polymer physics.*, 44(16):2346–2357, 2006.

[HSZM09] J. Hasikos, H. Sarimveis, P.L. Zervas, and N.C. Markatos. Operational optimization and real-time control of fuel-cell systems. *Journal of Power Sources*, 193(1):258–268, 2009.

[HYZG08] Y. Haitao, Z. Yulan, S. Zechang, and W. Gang. Model-based power control strategy development of a fuel cell hybrid vehicle. *Journal of Power Sources*, 180(2):821–829, 2008.

[IINP06] I. V. Ion, I. C. Ionita, D. Negoita, and S. Paraschiv. The Profitableness of Hybrid Solar Vehicles (HSV). In *International Workshop on Hybrid and Solar Vehicles*, University of Salerno, Salerno, Italy, 2006.

[JLK05] K.-S. Jeong, W.-Y. Lee, and C.-S. Kim. Energy management strategies of a fuel cell/battery hybrid system using fuzzy logics. *Journal of Power Sources*, 145(2):319–326, 2005.

[Jon02] K. Jonasson. *Analysing Hybrid Drive System Topologies*. PhD thesis, Lund University, Lund, Sweden, 2002.

[Kai07] R. Kaiser. Optimized battery-management system to improve storage lifetime in renewable energy systems. *Journal of Power Sources*, 168(1):58–65, 2007.

[KDG+12] S. Kermani, S. Delprat, T. M. Guerra, R. Trigui, and B. Jeanneret. Predictive energy management for hybrid vehicle. *Control Engineering Practice*, 20(4):408–420, 2012.

[KKJ+05] M. Koot, J. T. B. A. Kessels, B. de Jager, W. P. M. H. Heemels, P. P. J. van den Bosch, and M. Steinbusch. Energy Management Strategies for Vehicular Electric Power Systems. *IEEE Transactions on Vehicular Technology*, 54(3):771–782, 2005.

[KMMS13] M. Karbaschian, M. Marx, B. Moulik, and D. Söffker. Multiobjective NSGA II-based control optimization of hydraulic and electric hybrid propulsion systems with respect to their dynamic behavior in time domain. In *ATK - Antriebstechnisches Kolloquium*, Aachen/Germany, 2013.

[KP07] M.-J. Kim and H. Peng. Power Management and Design Optimization of Fuel cell/ Battery Hybrid Vehicles. *Journal of Power Sources*, 165(2):819–832, 2007.

[KPB11] D. Kum, H. Peng, and N. K. Bucknor. Supervisory Control of Parallel Hybrid Electric Vehicles for Fuel and Emission Reduction. *Journal of dynamic systems, measurement, and control*, 133(6):061010.1–061010.10, 2011.

[KPF+05] E. Karden, S. Ploumen, B. Fricke, T. Miller, and K. Snyder. Energy storage devices for future hybrid electric vehicles. *Journal of Power Sources*, 54(3):763–770, 2005.

[KPS07] G. H. Kim, A. Pesaran, and R. Spotnitz. A three-dimensional thermal abuse model for lithium-ion cells. *Journal of Power Sources*, 170:476–489, 2007.

[KR75] D. Karnopp and R. Rosenberg. *System dynamics: a unified approach.* J. Wileys & sons., 1975.

[KR11] N. Kim and A. Rousseau. Comparison between Rule-Based and Instantaneous Optimization for a Single-Mode, Power-Split HEV. In *Proc. of SAE World Congress*, Detroit/MI, USA, April, 12-14 2011.

[LD04] S. Liu and R. A. Dougal. Design and Analysis of a Current-Mode Controlled Battery/Ultracapacitor Hybrid. In *39th IAS Annual Meeting*, Seattle, USA, 2004.

[LH06] K. Lin and K. E. Holbert. Extension of Power Line Fault Location Techniques to Pressurized Line Diagnostics. In *38th North American Power Symposium, NAPS 2006.*, 2006.

[Liu06] D. Liu. *Durability Study of Proton Exchange Membrane Fuel Cells via Experimental Investigations and Mathematical Modelling.* PhD thesis, Virginia Polytecnic Institute and State University, Blacksburg, Virginia/USA, 2006.

[LL09] C.-Y. Li and G.-P. Liu. Optimal fuzzy power control and management of fuel cell/battery hybrid vehicles. *Journal of Power Sources*, 192(2):525–533, 2009.

[LMMS13] Y. Liu, M. Marx, B. Moulik, and D. Söffker. Experiment-based simulation and optimization on wind powertrain systems based on power flow emulation. In *Conference for Wind Power Drives (CWD)*, Aachen, Germany, March 2013.

[LP08] J. Liu and H. Peng. Configuration, Sizing, and Control of Power-Split Hybrid Vehicles. In *Proc. of 9th International Symposium on Advanced Vehicle Control (AVEC)*, Kobe, Japan, 2008.

[LSG+10] J. Liu, A. Saxena, K. Goebel, B. Saha, and W. Wang. An adaptive Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-ion Batteries. In *Annual Conference of the Prognostics and Health Management Society*, 2010.

[LXH+09] X. Li, L. Xu, J. Hua, X. Lin, J. Li, and M. Ouyang. Power management strategy for vehicular-applied hybrid fuel cell/battery power system. *Journal of Power Sources*, 191(2):542–549, 2009.

[MFCS10] S. J. Moura, H. K. Fathy, D. S. Callaway, and J. L. Stein. A Stochastic Optimal Control Approach for Power Management in Plug-In Hybrid Electric Vehicles. In *IEEE Transactions on Control Systems Technology*, 2010.

[MFF+08] S. Maass, F. Finsterwalder, G. Frank, R. Hartmann, and C. Merten. Carbon support oxidation in PEM fuel cell cathodes. *Journal of Power Sources.*, 176(2):444–451, 2008.

[MFSF09] S. J. Moura, J. C. Forman, J. L. Stein, and H. K. Fathy. Control of Film Growth in Lithium Ion Battery Packs via Switches. In *2nd Annual Dynamic Systems and Control Conference*, Hollywood, CA, USA, October 12-14 2009.

[MOGR09] V. Marano, S. Onori, Y. Guezennec, and G. Rizzoni. Lithium-ion Batteries Life Estimation for Plug-in Hybrid Electric Vehicles. In *Vehicle Power and Propulsion Conference (VPPC)*, Dearborn/MI, USA, 2009.

[MOS09] M. Marx, M. Özbek, and D. Söffker. Comparison and Evaluation of Power Management approaches applied to a Fuel Cell-based Hybrid HIL Powertrain. In *7th Workshop on Advanced Control and Diagnosis ACD 2009*, Zielona Góra, Poland, 2009.

[MOS10] M. Marx, M. Özbek, and D. Söffker. Power Management Investigations on a Fuel Cell-based Hybrid HiL Powertrain. In *SAE 2010 World Congress, April 2010*, Detroit, MI, USA, April 2010.

[MOS14] M. Marx, M. Özbek, and D. Söffker. Powermanagement of a hybrid electric powertrain system - aspects of design, power flow control, and optimization targets. *International Journal of Powertrains (IJPT) - (submitted, publication scheduled in 2014).*, 2014.

[MPV+09] G. Marsala, M. Pucci, G. Vitale, M. Cirrincione, and A. Miraoui. A prototype of a fuel cell PEM emulator based on a buck converter. *Applied Energy*, 86(10):2192–2203, 2009.

[MRS05] M. Musardo, G. Rizzoni, and B. Staccia. A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management. In *Proc. of the 44th IEEE Conference on Decision and Control, and the European Control Conference 2005*, Sevilla, Spain, 2005.

[MS11a] M. Marx and D. Söffker. Integrated Optimization of the Powermanagement System of a Hybrid Electric Powertrain System. In *7th IEEE Vehicle Power and Propulsion Conference (VPPC)*, Chicago, IL, USA, September 2011.

[MS11b] M. Marx and D. Söffker. Online powermanagement optimization of a fuel cell-based hybrid electric powertrain. *Proc. of Appl. Math. Mech. (PAMM)*, 11(1):827–828, December 2011.

[MS12a] M. Marx and D. Söffker. A new optimal power and energy management approach applied to a fuell cell/spercap-based hybrid-powertrain system. In *Joint Conference MOVIC and ASME DSCC (Dynamic Systems and Control Conference)*, Ft. Lauderdale, FL, USA, Oct. 17-19 2012.

[MS12b] M. Marx and D. Söffker. Optimization of the powerflow control of a hybrid electric powertrain including load profile prediction. In *The 8th IEEE Vehicle Power and Propulsion Conference IEEE (VPPC 2012)*, Seoul, Korea, 2012.

[MSS11] M. Marx, O. Sacher, and D. Söffker. Integrated design and optimization of a complex nonlinear hybrid electric powertrain including simulations in time domain. *Proc. Appl. Math. Mech. (PAMM)*, 11(1):825–826, December 2011.

[MSS12] M. Marx, X. Shen, and D. Söffker. A Data-Driven Online Identification and Control Optimization Approach Applied to a Hybrid Electric Powertrain System. In *Proc. 7th Vienna International Conference on Mathematical Modelling (MATHMOD 2012)*, Vienna, Austria, February 2012.

[Mur08] Y. L. Murphey. Intelligent Vehicle Power Management - An Overview. *Studies in Computational Intelligence (SCI)*, 132:169–190, 2008.

[MWS11] M. Marx, C. Wei, and D. Söffker. Optimization of Complex Dynamic Systems with Respect to their Behavior in Time and Frequency Domain. In *Proc. ASME 2011 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference (IDETC/CIE)*, Washington D.C., USA, August 28-31 2011.

[Nie08] J. Niemeyer. *Modellprädiktive Regelung eines PEM-Brennstoffzellensystems*. PhD thesis, Universität Karlsruhe (TH), 2008.

[NPA06] S. M. Naylor, V. Pickert, and D. J. Atkinson. Fuel cell drive train systems - driving cycle evaluation of potential topologies. In *Vehicle Power and Propulsion Conference (VPPC)*, Windsor, UK, September 2006.

[OIQ05] M. Ordonez, M. T. Iqbal, and J. E. Quaicoe. A Novel Fuel Cell Simulator. In *Proc. of 36th IEEE Power Electronics Specialists Conference 2005 (PESC '05)*, St. John's, Nfld., Canada, 2005.

[ÖS08] M. Özbek and D. Söffker. Modeling and Simulation of a Fuel Cell-based Hybrid Powertrain. In *IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA)*, Beijing, China, 2008.

[ÖS09] M. Özbek and D. Söffker. About the system design of a Fuel-cell SuperCap hybrid powertrain. In *Proc. ASME 2009 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference (IDETC/CIE)*, San Diego, CA, USA, 2009.

[Ott07] J. Ottoson. *Energy Management and Control of Electrical Drives in Hybrid Electric Vehicles*. PhD thesis, Lund University, Lund, Sweden, 2007.

[OWMS13] M. Özbek, S. Wang, M. Marx, and D. Söffker. Modeling and control of a PEM fuel cell system: A practical study based on experimental defined component behavior. *International Journal of Process Control*, 23(3):282–293, March 2013.

[OXL+06] M. Ouyang, L. Xu, J. Li, L. Lu, D. Gao, and Q. Xie. Performance Comparison of two Fuel Cell Hybrid Buses with different Powertrain and Energy Management Strategies. *Journal of Power Sources*, 163(1):467–479, 2006.

[PB09] M. D. Petersheim and S. N. Brennan. Scaling of hybrid-electric vehicle powertrain components for Hardware-in-the-loop simulation. *Mechatronics*, 19(7):1078–1090, October 2009.

[PB11] M. D. Petersheim and S. N. Brennan. Real-time and Power Hardware-in-the-loop Simulation of PEM Fuel Cell Stack System. *Journal of Power Electronics*, 11(2):1–1, March 2011.

[PBB06] Zs. Preitl, P. Bauer, and J. Bokor. Fuel Consumption Optimization for Hybrid Solar Vehicle. In *International Workshop on Hybrid and Solar Vehicles*, University of Salerno, Salerno, Italy, 2006.

[PBF92a] A. Pourmovahed, N. H. Beachley, and F. J. Fronczak. Modeling of a Hydraulic Energy Regeneration System - Part I: Analytical Treatment. *Journal of Dynamic Systems, Measurement, and Control*, 114:155–159, March 1992.

[PBF92b] A. Pourmovahed, N. H. Beachley, and F. J. Fronczak. Modeling of a Hydraulic Energy Regeneration System - Part II: Experimental Program. *Journal of Dynamic Systems, Measurement, and Control*, 114:160–165, March 1992.

[PBMG06] L. V. Pérez, G. B. Bossio, D. Moitre, and G. O. García. Optimization of power management in an hybrid electric vehicle using dynamic programming. *Mathematics and Computers in Simulation*, 73(1-4):244–254, 2006.

[PG10] L. V. Pérez and G. O. García. State Constrained Optimal Control Applied to Supervisory Control in HEVs. *Oil & Gas Science and Technology*, 65(1):191–201, 2010.

[PIzGV01] A. Piccolo, L. Ippolito, V. zo Galdi, and A. Vaccaro. Optimisation of energy flow management in HEVs via genetic algorithms. In *IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, 2001.

[PLC03] C. Park, J. Liu, and P. H. Chou. B#: A Battery Emulator and Power-Profiling Instrument. In *Proc. of Low Power Electronics and Design (ISLPED 03)*, Irvine, CA, USA, August 2003.

[PR07] P. Pisu and G. Rizzoni. A comparative Study of Supervisory Control strategies for Hybrid Electric Vehicles. *Control Systems Technology, IEEE Transactions on*, 15(3):506–518, 2007.

[PRA00] A. G. Parlos, O. T. Rais, and A. F. Atiya. Multi-step-ahead prediction using dynamic recurrent neural networks. *Neural Networks*, 13:765–786, 2000.

[PSP04] J. T. Pukrushpan, A. G. Stefanopolou, and H. Peng. *Control of Fuel Cell Power Systems: Principles, Modeling, Analysis, and Feedback Design.* Springer, 2004.

[RBC+10] G. Ripaccioli, D. Bernardini, S. Di Cairano, A. Bemporad, and I.V. Kolmanovsky. A stochastic model predictive control approach for series hybrid electric vehicle power management. *American Control Conference (ACC)*, 2010.

[RGB10] C. Romaus, K. Gathmann, and J. Böcker. Optimal Energy Management for a Hybrid Energy Storage System for Electric Vehicles Based on Stochastic Dynamic Programming. *IEEE Vehicle Power and Propulsion Conference (VPPC)*, 2010.

[RHG+04] P. Ramadass, B. Haran, P. M. Gomadam, R. White, and B. N. Popov. Development of First Principles Capacity Fade Model for Li-Ion Cells. *Journal of the Electrochemical Society*, 151(2):A196–A203, 2004.

[RHWP03] P. Ramadass, B. Haran, R. White, and B. N. Popov. Mathematical modeling of the capacity fade of Li-ion cells. *Journal of Power Sources*, 123:230–240, 2003.

[RJ12] S. Ravanshadi and M. Jahed. Introducing a Distributed Model of the Hearth. In *The Fourth IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*, Roma, Italy, June 2012.

[Ros07] L. C. Rosario. *Power and Energy Management of Multiple Energy Storage Systems in Electric Vehicles.* PhD thesis, Department of Aerospace Power & Sensors, Cranfield University, DCMT Shrivenham, Swindon, Wiltshire, UK, 2007.

[RPSG05] P. Rodatz, G. Paganelli, A. Sciarretta, and L. Guzzella. Optimal power management of an experimental fuel cell/supercapacitor-powered hybrid vehicle. *Control Engineering Practice*, 13(1):41–53, 2005.

[RS96] U.-K. Rakowsky and D. Söffker. Verknüpfung von Methoden der Regelungstheorie und der technischen Zuverlässigkeit zur Modellierung dynamischer Systeme. *VDI Berichte*, 1282:753–763, 1996.

[RSM08] G. Rousseau, D. Sinoquet, and Y. Milhau. Constrained optimization of energy management for a mild-hybrid vehicle. *Oil & Gas Science and Technology*, 62(4):623–634, 2008.

[SAY10] A. S. Samosir, M. Anwari, and A. H. M. Yatim. A simple PEM Fuel Cell Emulator using Electrical Circuit Model. In *Proc. of 9th International Power & Energy Conference (IPEC 2010)*, Singapore, October 2010.

[SBDS05] J. Schiffer, O. Bohlen, R. W. de Doncker, and K. Y. Sauer, D. U.and Ahn. Optimized energy management for fuelcell-supercap hybrid electric vehicles. In *IEEE Conference in Vehicle Power and Propulsion*, pages 341–348, 2005.

[SBG04] A. Sciarretta, M. Back, and L. Guzzella. Optimal control of parallel hybrid electric vehicles. *IEEE Transactions on Control Systems Technology*, 12(3):352–363, 2004.

[SBS06] W. Steiger, T. Böhm, and B.-G. Schulze. Direkthybrid - eine Kombination von Verbrennungsmotor mit einem elektrischen Getriebe. In *15. Aachener Kolloquium Fahrzeug- und Motorentechnik*, Aachen, Germany, 2006.

[Sch54] J. C. Schönfeld. Analogy of hydraulic, mechanical, acoustic and electric systems. *Applied Scientific Research B*, 3(2):417–450, 1954.

[Scr07] J. T. Scruggs. Multi-objective optimization of regenerative damping systems in vibrating structures. In *Proc. of 2007 American Control Conference (ACC)*, New York City / USA, July, 11-12 2007.

[Söf99a] D. Söffker. Regelungstechnische Methoden zur überwachung technischer Komponenten und zur lebensdaueroptimierten Betriebsführung in der Stromerzeugung. *VDI-GET (Hrsg.): Technische Konzepte zur Kostendämpfung in der Stromerzeugung. VDI-Berichte 1474*, pages 199–213, 1999.

[Söf99b] D. Söffker. Überwachung, Diagnose und lebensdaueroptimierte Betriebsführung schwingungsfähiger Maschinen - Teil 1: Prinzipvergleich bestehender modellgestützter und signalanalytischer Verfahren am Beispiel der Wellenrissdetektion bei Turborotoren. *VDI-EKV Schwingungstagung, Frankenthal, 27./28. Mai 1999, in: VDI-Berichte 1466*, pages 609–626, 1999.

[Söf99c] D. Söffker. Überwachung, Diagnose und lebensdaueroptimierte Betriebsführung schwingungsfähiger Maschinen - Teil 2: Entwicklung lebensdauer- und belastungsabhängiger Ausfallraten im SRCE-Konzept. *VDI-EKV Schwingungstagung, Frankenthal, 27./28. Mai 1999, in: VDI-Berichte 1466*, pages 627–638, 1999.

[SG07] A. Sciaretta and L. Guzzella. Control of hybrid electric vehicles. *IEEE Control Systems Magazine*, 4:60–70, 2007.

[Sol98] D. P. Solomatine. Genetic and other global optimization algorithms - comparison and use in calibration problems. In *Proc. 3rd Intern. Conference on Hydroinformatics, 1021-1028*, Copenhagen, Denmark, 1998.

[SOM10] D. Söffker, M. Özbek, and M. Marx. Powermanagement eines hybridelektrischen Antriebs - Auslegung, Optimierung und Leistungsregelung. *at-Automatisierungstechnik*, 58(10):580–589, 2010.

[SPA07] A. Schneuwly, M. Prummer, and J. Auer. Neue Energiespeicherkonzepte im Kraftfahrzeug. In *VDI-Berichte Nr. 2000*, 2007.

[SR97] D. Söffker and U.-K. Rakowsky. Perspectives of monitoring and control of vibrating structures by combining new methods of fault detection with new approaches of reliability engineering. In *12th ASME Conference on Reliability, Stress Analysis, and Failure Prevention*, Virginia Beach, VA, USA, 1997.

[SRA11] M. Sorrentino, G. Rizzo, and I. Arsie. Analysis of a rule-based control strategy for on-board energy management of series hybrid vehicles. *Int. J. Control Engineering Practice, 1433-1441*, May 2011.

[SRMP98] D. Söffker, U. K. Rakowsky, C. Müller, and O. H. Peters. Perspektiven regelungs- und zuverlässigkeitstheoretischer Methoden zur überwachung dynamischer Systeme aus sicherheitstechnischer Sicht. *at-Automatisierungstechnik*, 46:295–301, June 1998.

[SWSF13] D. Söffker, J. Wang, S. Schiffer, M., Marx, and X. Fu. Know your options - Interfacing consequences and forecasted performance analysis: A concept for the novel type of information system KYO-ICPA. In *12th IFAC/IFIP/IFORS/IEA Symposium on Analysis, Design, and Evaluation of Human-Machine Systems*, Las Vegas/NV, USA, August 11-15 2013.

[SYG07] Y. Shao, G. Yin, and Y. Gao. Understanding and approaches for the durability issues of Pt-based catalysts for PEM fuel cell. *Journal of Power Sources.*, 171(2):558–566, 2007.

[TKT06] U. Troelzsch, O. Kanoun, and H.-R. Tränkler. Characterizing aging effects of lithium ion batteries by impedance spectroscopy. *Electrochimica Acta*, 51:1664–1672, 2006.

[TRD09] P. Thounthong, S. Raël, and B. Davat. Energy management of fuel cell/battery/supercapacitor hybrid power source for vehicle applications. *Journal of Power Sources*, 193(1):376–385, 2009.

[UN92] UNO United Nations. United nations framework convention on climate change, 1992. Available at: www.unfccc.int/resource/docs/convkp/conveng.pdf, last visited: July 27th 2013.

[UN98] UNO United Nations. Kyoto protocol to the united nations framework convention on climate change, 1998. Available at: www.unfccc.int/resource/docs/convkp/kpeng.pdf, last visited: July 27th 2013.

[VBR06] I. Valero, S. Bacha, and E. Rulliere. Comparison of energy management controls for fuel cell applications. *Journal of Power Sources*, 156(1):50–56, 2006.

[vKdJS08] T. van Keulen, B. de Jager, and M. Steinbuch. An Adaptive Sub-Optimal Energy Management Strategy for Hybrid Drive-Trains. In *Proceedings of the 17th World Congress of the International Federation of Automatic Control*, Seoul, Korea, July 2008.

[VSP06] A. Vahidi, A. Stefanopoulou, and Huei Peng. Current management in a hybrid fuel cell power system: A model-predictive control approach. *Control Systems Technology, IEEE Transactions on*, 14(6):1047–1057, 2006.

[VTS12] D. A. G. Vieira, R. H. C. Takahashi, and R. R. Saldanha. Multicriteria optimization with a multiobjective golden section line search. *Mathematical Programming*, 131(1-2):131–161, February 2012.

[Wag04] A. Wagener. *Adaptives Energiemanagement für einen Pkw-Antrieb mit dezentraler Reglerstruktur*. PhD thesis, Fakultät für Ingenieurwissenschaften, Universität Ulm, Ulm, Germany, 2004.

[Wan09] L. Wang. *Model Predictive Control System Design and Implementation Using MATLAB*. Springer Verlag, London, 2009.

[Wil09] A. Wilde. *Eine modulare Funktionsarchitektur für adaptives und vorausschauendes Energiemanagement in Hybridfahrzeugen*. Doctoral thesis, Technische Universität München, Germany, 2009.

[WSS11] Y. Wang, X. Song, and Z. Sun. Hybrid powertrain control with a rapid prototyping research platform. In *Proc. of American Control Conference (ACC)*, Twin Cities, MN, USA, 2011.

[XHL+08] L. F. Xu, J. F. Hua, X. F. Li, Q. F. Meng, J. F. Li, and M. F. Ouyang. Control Strategy Optimization of a Hybrid Fuel cell Vehicle with Braking Energy Regeneration. In *Vehicle Power and Propulsion Conference (VPPC)*, Harbin, China, September 2008.

[YKM11] H. Yu, M. Kuang, and R. McGee. Trip-oriented Energy Management Control Strategy for Plug-in Hybrid Electric Vehicles. In *50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC)*, Orlando, FL, USA, December 2011.

[YSMH09] N. Yousfi-Steiner, Ph. Moçotéguy, and D. Hissel. A review on polymer electrolyte membrane fuel cell catalyst degradation and starvation issues - causes, consequences, and diagnostic for mitigation. *Journal of Power Sources.*, 194(1):130–145, 2009.

[YY07] X. Yu and S. Ye. Recent advances in activity and durability enhancement of Pt/C catalytic cathode in PEMFC-Part II. *Journal of Power Sources.*, 172(1):145–154, 2007.

[Özb10] M. Özbek. *Modeling, Simulation, and Concept Study of a Fuel Cell-based Hybrid Powertrain.* PhD thesis, University of Duisburg-Essen, 2010.

[Zha08] J. Zhang. *Fuel Cell Electrocatalysts and Catalysts Layers.* Springer, London, 2008.

[ZMB+10] H. Zhang, F. Mollet, S. Breban, C. Saudemont, B. Robyns, and R. Meuret. Hybrid Storage and Dissipation Systems based Power Management Strategies in a local DC Power Distribution system of more electric aircraft. In *Proc. of the 27th International Congress of the Aeronautical Sciences (ICAS 2010)*, Nice, France, September, 19-24 2010.

[ZPM+11] M. Zandi, A. Payman, J.-P. Martin, S. Pierfederici, and D. Davat. Energy Management of a Fuel Cell/Supercapacitor/Battery Power Source for Electric Vehicular Applications. *IEEE Transacions in Vehicular Technology*, 60(2):433–438, 2011.

The thesis is based on the results and development steps presented in the following previous publications :

[DMKS09] K.-U. Dettmann, M. Marx, K. Kashi, D., Nissing, and D. Söffker. Concept and Components for Disturbance Decoupling and Energy Harvesting. In *Proc. of ASME 2009 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference (IDETC/CIE)*, pages 863–868, San Diego, CA, USA, 2009.

[KMMS13] M. Karbaschian, M. Marx, B. Moulik, and D. Söffker. Multiobjective NSGA II-based control optimization of hydraulic and electric hybrid propulsion systems with respect to their dynamic behavior in time domain. In *ATK - Antriebstechnisches Kolloquium*, Aachen/Germany, 2013.

[LMMS13] Y. Liu, M. Marx, B. Moulik, and D. Söffker. Experiment-based simulation and optimization on wind powertrain systems based on power flow emulation. In *Conference for Wind Power Drives (CWD)*, Aachen, Germany, March 2013.

[MOS09] M. Marx, M. Özbek, and D. Söffker. Comparison and Evaluation of Power Management approaches applied to a Fuel Cell-based Hybrid HIL Powertrain. In *7th Workshop on Advanced Control and Diagnosis ACD 2009*, Zielona Góra, Poland, 2009.

[MOS10] M. Marx, M. Özbek, and D. Söffker. Power Management Investigations on a Fuel Cell-based Hybrid HiL Powertrain. In *SAE 2010 World Congress, April 2010*, Detroit, MI, USA, April 2010.

[MOS14] M. Marx, M. Özbek, and D. Söffker. Powermanagement of a hybrid electric powertrain system - aspects of design, power flow control, and optimization targets. *International Journal of Powertrains (IJPT) - (submitted, publication scheduled in 2014).*, 2014.

[MS11a] M. Marx and D. Söffker. Integrated Optimization of the Powermanagement System of a Hybrid Electric Powertrain System. In *7th IEEE Vehicle Power and Propulsion Conference (VPPC)*, Chicago, IL, USA, September 2011.

[MS11b] M. Marx and D. Söffker. Online powermanagement optimization of a fuel cell-based hybrid electric powertrain. *Proc. of Appl. Math. Mech. (PAMM)*, 11(1):827–828, December 2011.

[MS12a] M. Marx and D. Söffker. A new optimal power and energy management approach applied to a fuell cell/spercap-based hybrid-powertrain system. In *Joint Conference MOVIC and ASME DSCC (Dynamic Systems and Control Conference)*, Ft. Lauderdale, FL, USA, Oct. 17-19 2012.

[MS12b] M. Marx and D. Söffker. Optimization of the powerflow control of a hybrid electric powertrain including load profile prediction. In *The 8th IEEE Vehicle Power and Propulsion Conference IEEE (VPPC 2012)*, Seoul, Korea, 2012.

[MSS11] M. Marx, O. Sacher, and D. Söffker. Integrated design and optimization of a complex nonlinear hybrid electric powertrain including simulations in time domain. *Proc. Appl. Math. Mech. (PAMM)*, 11(1):825–826, December 2011.

[MSS12] M. Marx, X. Shen, and D. Söffker. A Data-Driven Online Identification and Control Optimization Approach Applied to a Hybrid Electric Powertrain System. In *Proc. 7th Vienna International Conference on Mathematical Modelling (MATHMOD 2012)*, Vienna, Austria, February 2012.

[MWS11] M. Marx, C. Wei, and D. Söffker. Optimization of Complex Dynamic Systems with Respect to their Behavior in Time and Frequency Domain. In *Proc. ASME 2011 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference (IDETC/CIE)*, Washington D.C., USA, August 28-31 2011.

[OWMS13] M. Özbek, S. Wang, M. Marx, and D. Söffker. Modeling and control of a PEM fuel cell system: A practical study based on experimental defined component behavior. *International Journal of Process Control*, 23(3):282–293, March 2013.

[SOM10] D. Söffker, M. Özbek, and M. Marx. Powermanagement eines hybridelektrischen antriebs - auslegung, optimierung und leistungsregelung. *AT - Automatisierungstechnik*, 58(10):580–589, 2010.

[SWSF13] D. Söffker, J. Wang, S. Schiffer, M., Marx, and X. Fu. Know your options - Interfacing consequences and forecasted performance analysis: A concept for the novel type of information system KYO-ICPA. In *12th IFAC/IFIP/IFORS/IEA Symposium on Analysis, Design, and Evaluation of Human-Machine Systems*, Las Vegas/NV, USA, August 11-15 2013.

In the context of the research projects at the Chair of Dynamics and Control the following student theses have been supervised by Matthias Marx and Univ.-Prof. Dr.-Ing. Dirk Söffker. Development steps and results of the research projects and the student theses are integrated to each other and hence are also part of this thesis.

[Cha12] Hailin Chao. Modern Motors and Generators. Bachelor Thesis, October 2012.

[Che12] Yinhua Chen. Evaluation and Comparison of Hydraulic and Electric Hybrid Vehicles. Bachelor Thesis, September 2012.

[Ras11] Sabrina Raspopov. Künstliche neuronale Netze in Python mit Schwerpunkt auf Modellbildung und Mustererkennung. Bachelor Thesis, November 2011.

[Sac11] Oliver Sacher. Modellbildung und Regelung bei rekuperationsfähigen hybridelektrischen Antriebssystemen mit Hilfe von neuronalen Netzen. Project Thesis, May 2011.

[Sch10] Ester Schürr. MPC-basierte optimale Regelung eines PEM-Brennstoffzellensystems. Diploma Thesis, June 2010.

[Sus12] George Susan. Moderne Energiespeicher und aktuelle Entwicklungen. Bachelor Thesis, July 2012.

[Win12] Jens Winkler. Optimierung technischer Systeme mit evolutionären Algorithmen in Python. Diploma Thesis, March 2012.

[Yan09] Dapeng Yang. Deployment of a Predictive Hydraulic Force Control in an Automotive Appication using a Vehicle Roll Model. Master Thesis, September 2009.

[Zen13] Yang Zeng. Optimale Leistungsflussregelung bei hybridelektrischen Antriebsstrukturen: Simulationen und experimentelle Realisierung. Master Thesis, March 2013.