Toward Holistic Energy Management Strategies for Fuel Cell Hybrid Electric Vehicles in Heavy-Duty Applications

By Thomas Rudolf[ID], Tobias Schürmann[ID], Stefan Schwab[ID],
and Sören Hohmann[ID], *Member IEEE*

ABSTRACT | The increasing need to slow down climate change for environmental protection demands further advancements toward regenerative energy and sustainable mobility. While individual mobility applications are assumed to be satisfied with improving battery electric vehicles (BEVs), the growing sector of freight transport and heavy-duty applications requires alternative solutions to meet the requirements of long ranges and high payloads. Fuel cell hybrid electric vehicles (FCHEVs) emerge as a capable technology for high-energy applications. This technology comprises a fuel cell system (FCS) for energy supply combined with buffering energy storages, such as batteries or ultracapacitors. In this article, recent successful developments regarding FCHEVs in various heavy-duty applications are presented. Subsequently, an overview of the FCHEV drivetrain, its main components, and different topologies with an emphasis on heavy-duty trucks is given. In order to enable system layout optimization and energy management strategy (EMS) design, functionality and modeling approaches for the FCS, battery, ultracapacitor, and further relevant subsystems are briefly described. Afterward, common methodologies for EMSs are structured, presenting a new taxonomy for dynamic optimization-based EMSs from a control engineering perspective. Finally, the findings lead to a guideline toward holistic EMSs, encouraging the co-optimization of system design, and EMS development for FCHEVs. For the EMS, we propose a layered model predictive control (MPC) approach, which takes velocity planning, the mitigation of degradation effects, and the auxiliaries into account simultaneously.

KEYWORDS | Component degradation; co-optimization; energy management strategies; fuel cell hybrid electric vehicles (FCHEVs); heavy-duty applications; holistic approaches; proton exchange membrane fuel cell (PEMFC).

I. INTRODUCTION

Environmental protection is in demand to slow down climate change and stimulates the developments of sustainable technologies, in particular, in the transportation domain [1], [2]. Therefore, a significant trend has been emerging to research into innovative approaches for renewable technologies with a strong interest in electric mobility [3]. Over the last decades, a rising variety of hybrid electric vehicles (HEVs) as a combination of electric drives with internal combustion engines (ICEs), as well as pure BEVs, have become available for individual traffic,

satisfying an initial demand for regenerative and locally emission-free mobility [4].

While HEVs play a role in the transition toward wide electric mobility, shortcomings of BEVs remain. This includes a limited driving range in comparison to HEVs and the additionally needed charging infrastructure. The requirement of sufficient mileage per battery charge for individual mobility seems to be met by BEVs through research and future development of battery technologies, which leads to higher gravimetric and volumetric energy density. In contrast, for heavy-duty and long-haul trucks, the available battery technology may be insufficient in regard to the combination of high power and long distances forming challenging requirements. In addition, the demand for fast charging to minimize the overall trip time and high component durability are more prevalent in this application field and act as economic constraints. Here, the deployment of FCS technology as the main energy source may be a favorable solution for heavy-duty vehicles due to the high gravimetric energy density of hydrogen and the ability for fast refueling. While challenges, such as large-scale hydrogen production, distribution, storage infrastructure, and the handling of hydrogen in infrastructural and vehicle fuel storage systems, still remain [5], fuel cell (FC) vehicles have a viable chance in high-energy applications [6].

The use of additional energy and power buffering technologies, such as batteries or ultracapacitors, is motivated by the restricting power dynamics in FCSs and brings advantages toward the fuel cell hybrid electric vehicle (FCHEV) drivetrain. However, an FCHEV drivetrain with multiple sources and loads of high energy or power, such as in FCHEVs for heavy-duty applications, presents a highly complex system. Therefore, Das *et al.* [7] emphasize the need for improved control strategies as an enabling technology for FCHEVs concerning regenerative braking and the transient power supply of the FCS. Hence, FCHEVs necessitate a more holistic EMS approach to account for the prevailing complexity and the additional degrees of freedom (DOFs).

A. FCHEV in Heavy-Duty Applications

Applications and prototypes of FCHEV in the heavy-duty domain already range from public transportation with buses [8]–[10], heavy-duty trucks [6], [11], rail bound trams and trains [12]–[16], maritime applications [17]–[19], and construction machines [20]. Moriarty and Honnery [21] proclaim that FCHEVs may be superior to BEVs for the heavy-duty transport sector, and the impact of hydrogen in this domain is likely not to decrease in the future. Instead, it may be the future alternative in the transportation domain [22].

FC technology, power systems, and their application in the transport sector have been thoroughly studied in the literature (see [23]–[25]). For the next quarter-century, a sharp increase in their applications is expected [26].

Thereby, the utilization of emission-free produced hydrogen is seen as a crucial factor for paving the way to a wide reduction of CO_2 in transit and transportation [6], [27]–[29]. Considering hydrogen production and storage, Singh *et al.* [24] present a broad overview, including a safety ranking of fuels and a comparison to the storage and infrastructure of carbon fuels. Furthermore, the FCHEV drivetrain system costs are modeled and analyzed [30], pointing out production costs of the proton exchange membrane fuel cell (PEMFC) as a key point for wide adoption in transportation applications. Ribbau *et al.* [31] conducted a study in public transportation with FC hybrid electric buses showing the advantage of lower operating costs compared to diesel buses when regarding the energy consumption per mileage. However, to achieve general competitiveness with conventional buses, there are still present challenges and barriers to overcome [32].

Designing an FCHEV drivetrain comes along with challenges to the energy storage sizing and placement for heavy-duty applications [33], [34]. Nevertheless, its technological feasibility has already been shown for medium-sized and heavy-duty trucks since the requirements regarding range, payload, power, and fuel economy can be met [35], [36]. However, the system durability for long-life applications, especially due to FCS lifetime, is still a great concern [35], [37]. Thus, forecast of degradation regarding cyclic loads has been studied and may be a bottleneck for commercial adoption in certain heavy-duty fields [38]. Miller *et al.* [16] point out heavy-duty specific issues regarding heat transfer in the FCS, as well as shock loads and steep power transients during drivetrain operations. These drawbacks in FCHEVs for heavy-duty applications call for an intelligent and predictive EMS. Thus, system efficiency and degradation as the main challenges can be taken into account simultaneously.

B. Contribution and Structure

This work is based on a broad literature review and focuses on FCHEVs for heavy-duty applications in the transportation domain. It aims to provide an extensive understanding of the design and development of EMSs for the FC hybrid drivetrain and motivates the future research direction to holistic EMSs. For this purpose, it contributes relevant approaches and aspects toward dynamic optimization-based EMSs for FCHEVs in heavy-duty applications from a system-and-control-engineering point of view. An individual review of the developments and challenges in the operation or control of single components, such as FCs, power electronics (PEs), or electric machines (EMs), is not in the scope of this article.

For the design and development of EMSs, a general system overview of the FCHEV drivetrain and its topologies is presented in Section II. In regard to model-based strategies and system optimization, the modeling approaches of relevant subsystems, components, and their dynamic behavior with an emphasis on the recent research regarding degradation and wearing effects for FCSs and batteries

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

are elaborated in Section III. Afterward, a thorough presentation of the current research in regard to methodologies for EMSs of hybrid drivetrains is given and structured in Section IV. Thereby, the challenges, constraints, and opportunities for EMS design are pointed out, and a new taxonomy for dynamic optimization-based methods is proposed. Section V focuses on the scientific path toward holistic EMSs in FCHEVs combining the findings in Sections II–IV. Thereby, the potential of holistic strategies for heavy-duty and long-haul trucks is highlighted.

II. SYSTEM OVERVIEW

FCHEV drivetrains consist of a combination of at least two energy storages or converters. The hydrogen tank in combination with the FCS acts as the primary energy source, while energy buffer storages contribute to the hybrid characteristics. For a comprehensive overview, the reader is referred to [39] and [40], which also describes different components and motor types. Das *et al.* [7] give a thorough survey of the FCHEV drivetrain, various energy storage systems (ESSs), and topologies for FCHEVs that are in the focus of the contribution. Furthermore, several types of FCs and their characteristics are described and evaluated in terms of applicability in FCHEVs [7].

In this article, FC hybrid electric trucks are discussed as a fitting example system of the FCHEV drivetrain in heavy-duty applications. The later presented EMSs are adaptable to various applications or drivetrain topologies and can be complemented with specific components or requirements. FCHEV technology provides a high efficiency on low loads and the possibility of local zero emissions when using pure hydrogen without preceding reformers [41].

A. FCHEV Drivetrain

In Fig. 1, an FCHEV drivetrain topology of a heavy-duty truck is depicted. The drivetrain comprises the FCS with preceding hydrogen fuel tank (H_2 tank system) and an electric high voltage bus (HV bus) with connected ESSs, which act as buffers. Widely used electric ESSs in HEVs are batteries and ultracapacitors, which are operated bidirectional offering degrees of freedoms (DOFs) for an EMS. The ESSs supply the dc/ac-inverter [power electronics (PE)] and, subsequently, the EM, as well as the mechanical drivetrain with power. The mechanical drivetrain may comprise transmissions in form of a gear box (GB) with the respective mechanical advantage (MA) in order to cover a wide torque range in heavy-duty applications.

The FCS consists of one or more FC stacks with serially connected cells and various auxiliaries for the operation, such as pumps for hydrogen, atmospheric oxygen, moistening and dewatering subsystems, and a cooling cycle for the heat losses. Thus, the high efficiency of single laboratory FCs or stacks is reduced in favor of a stable operation and the ability to be precisely controlled with regard to the demanded power. The prevalent FC technology are PEMFCs for applications with requirements
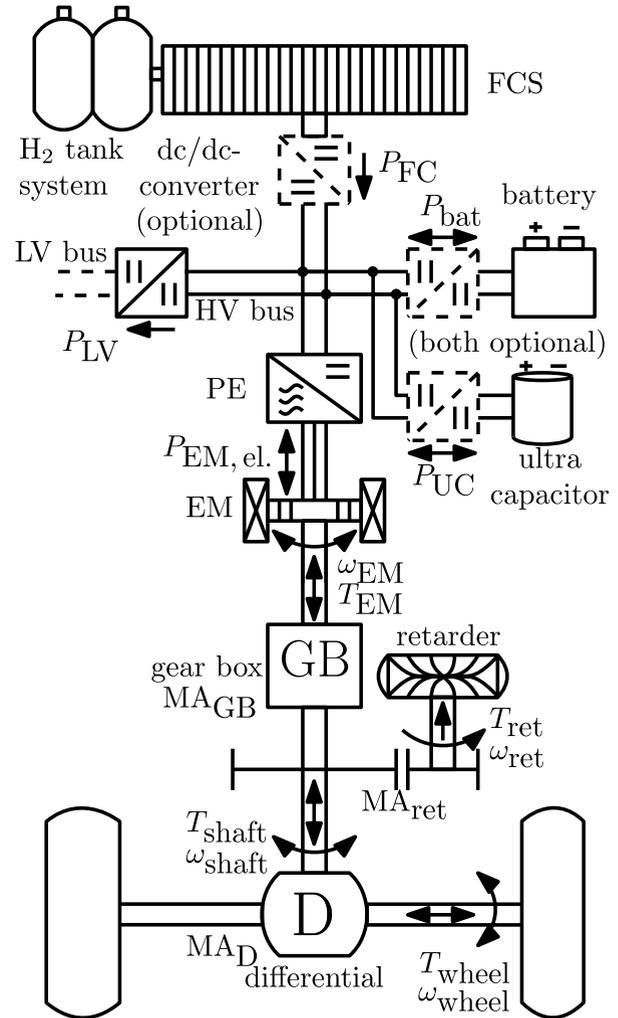

Fig. 1. *FC hybrid drivetrain of a heavy-duty truck with its electrical and mechanical domains, including a retarder as hydrodynamic brake.*

regarding compact systems and comparably low operating temperatures. In addition, the fast startup time and a high power density of PEMFCs are favorable for transportation applications [5]. Therefore, PEMFCs are exclusively considered in this work.

The electric powertrain voltage levels, e.g., the ESS voltages, can be separated from the main dc-link (HV bus) by inserting dc/dc-converters. Therefore, additional flexibility can be provided if needed and voltage levels can be stabilized more easily. However, this comes along with costs regarding the system efficiency. In general, the use of dc/dc-converters at the ESSs is optional, and the resulting topologies are of ongoing research [7].

Auxiliaries for specialized applications, safety functions, or comfort features exist across the various voltage levels of the power network. High-power auxiliaries, such as compressors for the braking system in heavy-duty applications, air conditioning, or cooling cycles, are
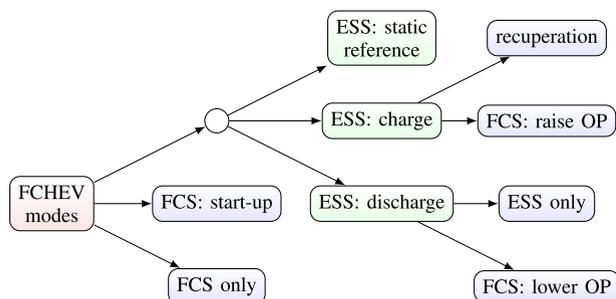
Fig. 2. *Example of drivetrain modes for operation in an FCHEV with effects to the ESSs (green).*

Fig. 3. *Qualitative Sankey diagram of an FCHEV energy flow during boost mode.*

mostly operated from the higher voltage bus (HV bus). Since these auxiliaries are significant power consumers, it may be beneficial to consider them in the developing process of the EMS. Furthermore, trailers can be connected to the vehicle power network, e.g., in freight transport, and should be considered as relevant energy consumers. In conclusion, the vehicle power network is a complex system, and complexity may even be further growing due to highly automated and assisted driving applications comprising a multitude of sensors and computational units.

The mechanical drivetrain is very dependent on the specific application and may comprise various braking systems and sometimes additional ESSs, such as flywheels [7]. For heavy-duty applications, it is necessary to minimize the use of the friction braking system; thus, components, such as retarders, are used, which dissipate the braking power to a fluid. During regenerative braking in heavy-duty vehicles, the occurring high-power levels must often be distributed across different braking systems in the mechanical drivetrain as well since the currents of the EM, PEs, and electric ESSs are limited.

During drivetrain operation, various modes with respect to different energy flows are needed to fulfill a specific driving or application task. For an FCHEV, a wide variety of drivetrain modes can be derived in this regard. Fig. 2 shows the operating modes ranging from single energy source operation of the FCS across specialized powertrain modes, such as the startup of the FCS at the beginning of the operation up to strategic decisions concerning ESS states, such as the control of battery state of charge (SOC).

For intended charging of the ESSs, the operating point (OP) of the FCS can be raised to supply energy in addition to the demand for the driving task. Vice versa, for an explicit discharge of the ESSs, the FCS can be lowered while simultaneously drawing more power from the battery or ultracapacitor. Further operating modes may be a power boost by supplying the drivetrain with all storages for a temporary overdrive of the inverter (PE) and the EM or the regenerative braking (recuperation) loading the ESSs with dissipated kinetic energy of the vehicle and, thus, decelerating.
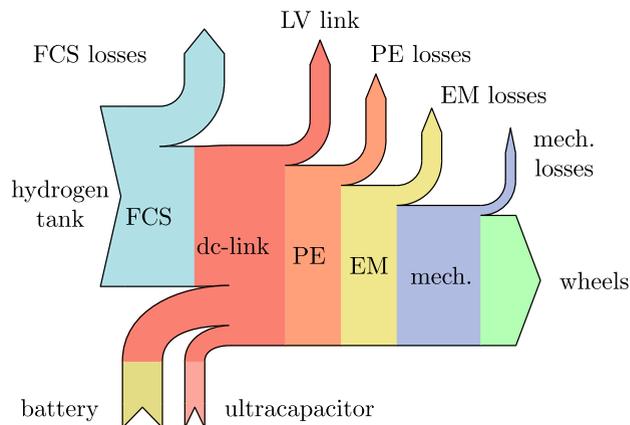
In Figs. 3–5, Sankey diagrams depict the energy flow between components along with the drivetrain in a qualitative manner. Here, a subset of operation modes, namely boosting, ESS loading by raising the FC OP, and regenerative braking in an FCHEV drivetrain, is visualized. These modes are implicitly and explicitly used in EMSs. While operating in the propulsion mode in Figs. 3 and 4, the FCS provides electric energy to the dc-link from its hydrogen tank with losses regarding the FCS auxiliaries. The additional ESSs, namely battery and ultracapacitor, are connected to the dc-link. The electric energy is distributed to the internal low-voltage (LV) link, as well as the electric drive of the PE and the EM with losses (PE losses and EM losses). The mechanical (mech.) (see Figs. 3–5) drivetrain leads the power with additional losses (mech. losses) through the wheels to surmount the driving resistances.

During the boost mode, all ESSs supply the vehicle high voltage dc-link with energy (see Fig. 3), whereas a raised FCS OP contributes to charging the battery and ultracapacitor (see Fig. 4). In contrast, Fig. 5 shows an inverted energy flow originating from the kinetic vehicle energy and resulting in the charging of the ESSs.
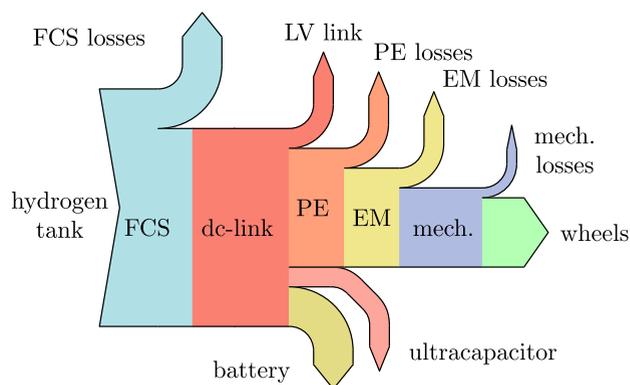

Fig. 4. *Qualitative Sankey diagram of an FCHEV energy flow during a raised OP of the FCS.*
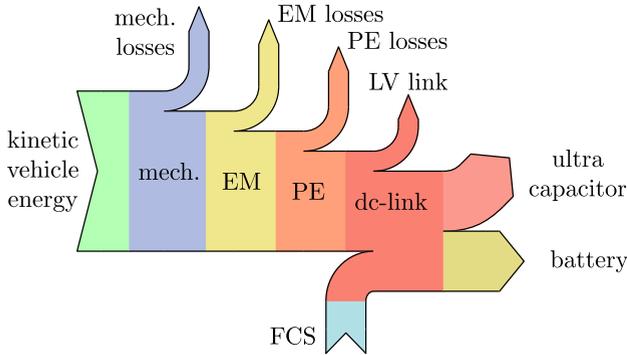
This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

Fig. 5. *Qualitative Sankey diagram of an FCHEV energy flow for regenerative braking.*

B. Electric Powertrain Topologies in FCHEV

FCHEVs are solely energy sourced from the electric power network. The term powertrain topology describes the types and placement and the structural interactions of the components used in the network of the electric powertrain. The employed ESSs contribute differently to the network depending on their energy capacity and their dynamic response to power demands or their buffering capability. In Fig. 6, a schematic power distribution Φ_P, subject to the electric power load dynamics $P(t)$ with load frequencies ν_P and the prevalent maximum load frequency $\nu_{P,\max}$, is depicted.

The FCS is the dominant ESS and covers the electric base load at lower load frequencies. The battery and ultracapacitor support the electric powertrain as buffering energy supplies for highly dynamic loads and at high total electric loads. Furthermore, they store energy from regenerative braking operation [43]. The highest power dynamics are buffered by the dc-link capacitor at very low absolute power values. In [42], ultracapacitors in single dc/dc-converter topology of an FCHEV are used as a buffer for high-frequency loads. Subsequently, this topology design technique can be used to further adapt a drivetrain according to the load profile of its application. Various topologies have been studied aiming to further increase fuel efficiency by enhancements with additional or fewer components [40]. In [44], ESSs and the role of bidirectional dc/dc-converters are described in detail.

However, the more flexibility is added through additional components, such as dc/dc-converters, the higher the monetary costs and power losses due to these components are. In [7], a comprehensive study regarding FCHEV topologies is presented, discussing single-stage and multistage dc bus topologies and pointing out possible advantages of the single-stage topology. Thereby, the single-stage advantage is reasoned with simplicity and higher system efficiency. Though, dc/dc-converters bring the needed flexibility for intelligent EMSs in special applications, such as demanding heavy-duty trucks. Thus, the developed EMS has to take advantage of this flexibility in order to justify the additional costs and losses.

C. Topology Optimization and Dimensioning

For leveraging hybrid energy storage systems (HESSs) in an intelligent EMS, a dedicated topology design in combination with a precise dynamic model of the total topology and components are needed for the EMS development. Decisions are usually based on an extensive simulation and development framework, supporting the static designing and dimensioning process with accurate physical models of the drivetrain and the ESSs [39]. The prevalent questions are as follows.

- Which components have to be used?
- Which components should be added for the needed flexibility in regard to the specific application?
- How should these components be dimensioned?
- What are the resulting system constraints?

A static optimization is often used to guarantee a general fulfillment of the expected load profiles in driving cycles. However, this does not imply an efficient or low-wear operation of the drivetrain in the target application or in combination with the operating EMS. Therefore, studies have been conducted toward the combination of static optimization with an underlying optimization of the EMS to further optimize the vehicle's global efficiency [45]. The framework comprises an outer loop varying the component size and an inner loop that relies on dynamic programming (DP) and full knowledge of the future driving cycle to assess the performance of the chosen component sizes. In [10] and [46], similar frameworks are described for the simultaneous optimization of the component sizing, EMS parameterization, and the powertrain hybridization. This combined approach of the powertrain and the EMS design is called co-optimization.

Furthermore, co-optimization goals are mitigation of component degradation and the optimization of auxiliary and its placement, especially in demanding applications, such as heavy-duty trucks and goods transportation with high energy consumption by auxiliaries [47]. An intelligent combination and sizing of different ESSs reduce fast transients of the PEMFC and battery cur-
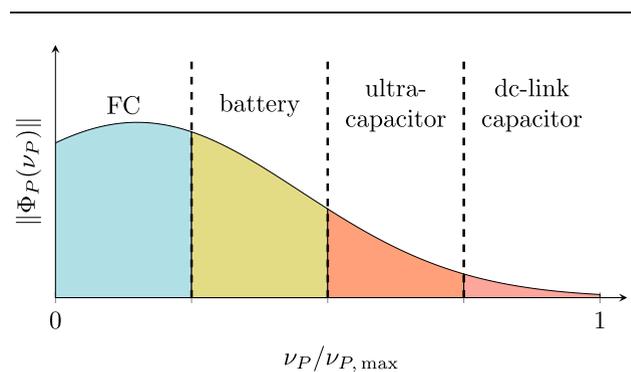

Fig. 6. *Schematic power prevalence to load bandwidth in regard to the dominant ESS, adapted and extended from its appearance in [42].*

rents, contributing to slower degradation [48]–[50]. Here, Hu *et al.* [49] compare a battery-only approach with an HESS approach for an FC hybrid electric bus by applying an optimization-based and health-conscious design framework. The systematic analysis regarding fuel economy and degradation effects leads to the optimal dimensioning of the ESSs for power demands and regenerative braking with respect to different driving patterns [51]. Comparing several EMS approaches while optimizing the ESS size, Song *et al.* [52] conclude that the application of an HESS with a battery and an ultracapacitor along with an adequate EMS results in reduced life-cycle costs. Thereby, a dynamic battery degradation model is used in order to compare the effects of various ESS sizes and EMS approaches. Another optimization framework for FCHEV, which also takes battery lifetime into account, is given in [53].

In conclusion, the combination of a static development framework [39] and co-simulation of the intended EMS in a hybrid co-optimization framework is highly recommended and contributes toward a more holistic development process [49], [52], [53].

III. SYSTEM MODELING

Facilitating holistic EMS approaches, accurate modeling of electrical, mechanical, thermal, and aging behavior is needed, in particular, for intelligent and suitable problem formulation regarding dynamic optimization-based methods. In this section, models describing the physical behavior of the FCS, batteries, and ultracapacitors are depicted. Here, the emphasis is put on the recent literature regarding aging and degradation processes that are key aspects for the durability of FCHEVs. Furthermore, mechanical and thermal models in regard to the drivetrain of FCHEVs are briefly presented.

For further studies, Guzzella and Sciarretta [54] give a comprehensive overview of the modeling of electric and nonelectric vehicle propulsion systems focusing on quasi-static and dynamic models for various components in the electrical and mechanical powertrains. The recent development of degradation and aging models for lithium-ion batteries and FCs is elaborated and summarized in [50]. Advantages and disadvantages for various modeling approaches are depicted in a clear manner in order to enable a reasonable choice of particular models for health-conscious EMSs or prognostics and health management. In [55] and [56], extensive studies on modeling approaches for battery cells, FCs, a wide range of other storage technologies, and components of the mechanical powertrain for BEVs, HEVs, and FCHEVs are elaborated.

A comprehensive source for drivetrain and vehicle models or driving cycles, including FCHEV components, is offered by the *ADVISOR* toolbox for MATLAB, developed up to the early 2000s (see [57] and [58]). The simulation toolbox is widely used in the development of FCHEVs [59], [60]. Further development has been made with the vehicle simulation and development framework
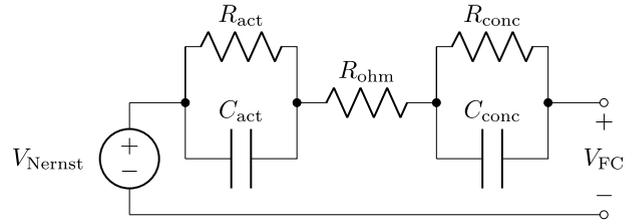

Fig. 7. *Equivalent circuit diagram of the PEMFC voltage V_{FC} with its ohmic behavior and RC elements for the activation and concentration polarization effects based on [54].*

Autonomie [61], which is used for simulations regarding energy consumption and performance of FCHEVs (see [28]). However, there are efforts toward comparable simulation frameworks [62].

A. Models of Energy Sources

In the following, the most relevant technologies of ESSs for FCHEVs, namely FCSs, batteries, and ultracapacitors, and their key characteristics for energy and power supply are presented. The contribution to the dynamic power supply of each presented ESS in the frequency domain is depicted in Fig. 6. Further descriptions for various energy storage technologies for electric vehicle applications and classification in regard to the underlying physical principles are given in [44], [55], and [63].

1) Fuel Cell System: In contrast to batteries and ultracapacitors, which are presented subsequently, an FC is not an energy storage but an energy conversion technology. The fundamental working principle and characteristics of different FCs are described in [18] and [23]. In general, PEMFC has advantages over other FC types for the application in transportation and is, therefore, the mainly used and researched technology. A PEMFC converts hydrogen (mostly stored in a tank) and oxygen in a chemical reaction into electricity and the byproducts, heat and water vapor. (Heat and water vapor are the byproducts.) Since there are no reaction products, such as CO_2, NO_x, or soot in the chemical conversion process, PEMFCs, directly sourced from an H_2 tank (see Fig. 1), are regarded as locally emission-free and clean electric power sources. The FCS comprises various pumps, compressors, and heat-transfer devices that are mandatory auxiliaries for the operation of the FC. These auxiliaries for operation and the produced heat are the main losses responsible for the mitigation of the FC efficiency. Nevertheless, compared to ICE, FCs excel in a superior efficiency from tank to wheel.

The fundamental specifications of FCs as energy sources are a high specific energy density but low dynamics in transient power demands (see Fig. 6). The low power dynamic of an FC is particularly caused by the operation of the FCS, including various pumps and compressors. In Fig. 7, the most relevant physical phenomena limiting the transient power supply are depicted in an exemplary
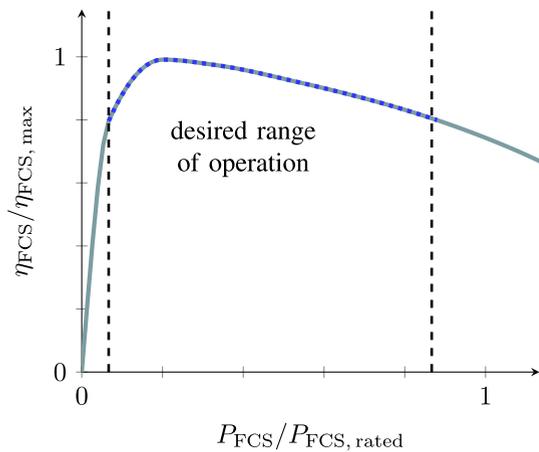
This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

Fig. 8. *Qualitative characteristic curve of the relative efficiency of an FCS in relation to its rated output power.*

equivalent circuit diagram. Thereby, V_{Nernst} describes the open-circuit voltage of the FC in regard to the Nernst equation describing the fundamental correlation to varying temperature or pressure. The parameters R_{act}, C_{act}, R_{ohm}, R_{conc}, and C_{conc} quantify the voltage losses for the activation polarization V_{act}, ohmic losses V_{ohm}, and concentration polarization V_{conc}, respectively [54]. These voltage losses occur over the operation region of the FC. Favorably, the FCS is operated in the ohmic region, which is marked as the desired range of operation in Fig. 8 [39]. Besides the low dynamics, the FCS needs some time to warm up until it is fully operational. This behavior has to be taken into consideration in the design process of HESSs for FCHEVs [39]. For efficient operation of the FCS by the EMS in the initial heating-up and further starts and stops while driving, precise modeling is needed [7].

FCSs suffer from degradation processes causing reduced efficiency over operation time and a limited lifetime. Therefore, the intelligent operation of the FCS has to be addressed by the EMS in order to mitigate degradation and meet durability requirements, which are of particular importance in demanding heavy-duty applications. Jouin *et al.* [64] elaborate the state-of-the-art prognostics and health management for FCs and, in particular, PEMFCs for application in transport systems. Due to the limited lifetime of FCs, a better understanding of wearing processes resulting in optimized operation is needed for the competitiveness of FCHEVs.

The mechanisms of PEMFC degradation and physical and chemical phenomena have been studied besides various modeling approaches. The effects of gas, heat, and water management on PEMFC degradation are analyzed in [65] and [66], while strategies to mitigate these wearing effects mainly caused by cyclic loads are derived [66]. A behavioral model for PEMFCs based on a static modeling approach, which takes into account the activation phenomenon at the cathode and the anode, and a dynamic model part based on an electrical equivalent circuit, is developed

in [67]. The proposed model is fit and validated with experimental data from long-term tests. Hereby, electrochemical impedance spectroscopy (EIS) and polarization curve measurements are applied to update the model parameters regularly. Further efforts in the analysis of the degradation phenomena and aging modeling for health assessment of PEMFC are presented in [68]. Critical components and power losses in the FCS are identified and modeled in a holistic framework for prognostics. Moreover, variations, the trend of parameters, and characteristic measurements allow for estimations of aging and degradation effects. Further developments in modeling and diagnosis for PEMFC are based on multivariate statistical methods for diagnosis [69], neural networks (NNs) for black-box modeling [70], or linear subspace identification methods for fault detection and isolation with a Kalman filter [71].

2) Battery: Applied in an adequate operation region regarding temperature, power demand, and discharging or charging currents, batteries provide a durable and safe power supply with little efforts for maintenance [72]. In order to ensure safe and effective operation, battery management systems determine the battery states and request necessary measures, such as current limitation or thermal control [73]. As the capacity of single cells in battery packs varies due to production or aging deviations, active balancing algorithms are applied to maintain full storage potential [74].

Through their chemical compounds, battery technologies reveal differences in specific power, specific energy, durability, efficiency, temperature dependence, and costs. To fulfill the requirements of the electric propulsion system, a reasonable choice of the battery technology for FCHEVs in heavy-duty applications is needed [55], [75]. Lead-acid, lithium-ion, and nickel-based batteries are the commonly used technologies. Due to the highest specific power and energy density, lithium-ion batteries are most relevant for application in vehicular propulsion. Accurate measurement and estimation of battery states, such as voltage, SOC, temperature, or state of health (SOH), are the key factors for efficient management of battery cells and correct consideration in the EMS [73].

The dynamic modeling of the battery cell voltage V_{cell} is usually based on equivalent circuit diagrams, such as in Fig. 9 [72]. The included parameters V_{OC}, R_0, R_1, C_1, R_2, and C_2 are fit for particular battery cells utilizing data from EIS measurements [76]. Considering and emphasizing different physical phenomena of batteries, various equivalent circuit diagrams have been developed. In order to improve the battery model fidelity for varying temperatures, the parameters V_{OC}, R_0, R_1, and C_1 may be adaptive to temperature and SOC changes, as presented in [77]. In addition, battery models are extended with approaches to consider the battery lifetime [78]. With respect to the form of EIS measurements, alternative dynamic modeling approaches, such as fractional models based on *RQ*
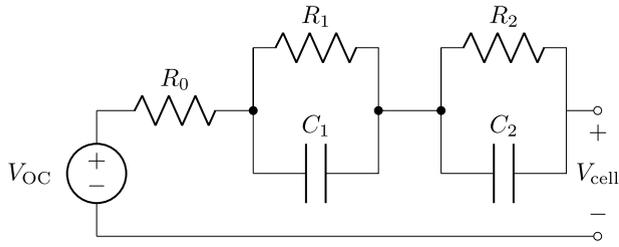
This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

Fig. 9. *Equivalent circuit diagram of a battery and the resulting cell voltage V_cell of the open circuit.*

elements instead of *RC* elements, are studied [79]. The advantages of these more detailed models are a higher precision in voltage and current prediction but may lead to an increased effort due to adequate parameterization and higher computational efforts for the EMS. Nevertheless, the precision of battery models with *RC* elements, such as in Fig. 9, is usually suitable for consideration in the EMS in a well-tempered battery system.

Considering the durability of batteries, aging and degradation effects are a major concern in recent research and development with BEVs, HEVs, and FCHEVs in mind [50]. Adapting an aging model based on accumulated charge throughput, Marano *et al.* [80] study the wearing effects on lithium-ion batteries. The proposed aging model takes overcharging, temperature, and depth of discharge as weighting factors represented in a severity map into account. Regarding aging models for lithium-ion batteries, a classification in two categories is proposed. On the one hand, physical–chemical models are used to describe the inner mechanisms of each battery cell. The overall aging and degradation process is divided into various aspects of the electrochemical cell architecture [81]. On the other hand, empirical models simplify the aging process to the main aspects. By fitting the parameters, which describe these main physical relations of cell aging, with the aid of experimental data, empirical models are adapted to a particular cell category. In order to develop a control-oriented battery aging model suitable for real-time optimization, Tang *et al.* [82] adapted a semiempirical model that is based on a generic aging model presented in [83]. Further research in the field focuses on models of battery packs [84] and frameworks for the onboard estimation of the battery lifetime [85].

3) Ultracapacitor: The physical working principle of ultracapacitors offers the highest specific power density compared to batteries and FCs [86]. In contrast, the energy density is relatively low and the main focus of recent research efforts [55]. Therefore, ultracapacitors are deployed in FCHEVs for transient power demands in regenerative braking or hard accelerating (see Fig. 6). The exemplary equivalent circuit model in Fig. 10 comprises the capacity C, the parallel resistance R_{EPR}, and the series resistance R_{ESR}, which depict the electric storage

capability, the self-discharging losses, and the efficiency losses in charging and discharging, respectively [56], [87]. Contrary to FCs and batteries, for the dynamic modeling of ultracapacitors, no additional time constants, such as *RC* elements, are used in this model representation.

Besides their high power density, ultracapacitors excel in a long lifetime and the independence of temperature. Due to their simple physical working principle, no maintenance and no management system for effective and safe operation are needed. As the output voltage V_{UC} is directly dependent on the SOC, ultracapacitors are usually employed with a dc/dc-converter to the HV bus (see Fig. 1). If no dc/dc-converter is applied, the ultracapacitor works like a dc-link capacitor with improved energy storage capability [7].

B. Mechanical and Thermal Models

1) Mechanical Loads: For an accurate reference generation and prediction of the demanded torque from a road profile, depending on the system, road, and environment parameters, a driving load model is needed [88]. These models are, in particular, needed for predictive EMSs and take friction, point mass propelling forces, the air drag, road slopes, and rolling resistances into account. They are extended by decelerating forces to model regenerative braking by EM recuperation, friction braking, or the hydrodynamic retarder in heavy-duty road applications. Mechanical load models, the influence of the drivetrain inertia by the EMs, GBs, or wheels are thoroughly presented in [39], while a reduced model for an optimal control design is used in [88].

2) Hydrodynamic Braking and Retarder: In heavy-duty applications, braking systems are of exceptional interest due to the large vehicle mass and the inertial momentum. For longer braking phases during travel, permanent friction braking, which would result in heavy wearing effects and overheating, is strongly avoided. Thus, hydrodynamic braking systems are used to dissipate kinetic energy into heat, e.g., by using a Föttinger fluid coupling for the conversion, which is further dissipated in a cooling cycle [89]. An exemplary integration of a hydrodynamic retarder as an additional braking system is shown in Fig. 1. Fluid
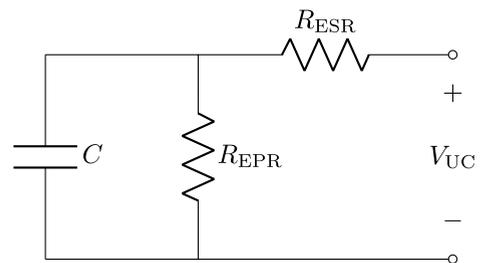

Fig. 10. *Equivalent circuit diagram of an ultracapacitor with equivalent series and parallel resistances R_ESR and R_EPR.*
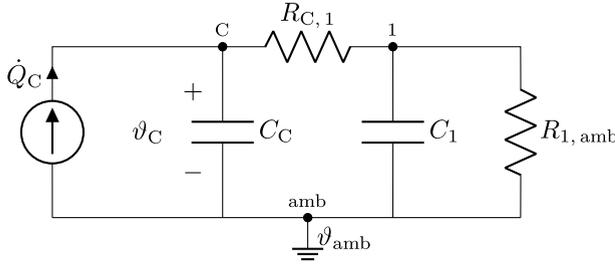
This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

Fig. 11. *Equivalent circuit diagram for the thermal behavior of a component (C) with the temperature ϑ_C and the thermal capacity C_C.*

couplings in the retarder create a braking torque T_{ret}, which is quadratic to the impeller rotational velocity ω_{ret} and can be further increased by the power of five by the parameter of the rotor's diameter d_{ret}. The braking torque is also proportional to the fluid density ρ_{fluid}, as well as further constructional parameters k_{ret}, and is described by

$$T_{ret} = k_{ret} \cdot d_{ret}^5 \cdot w_{ret}^2 \cdot \rho_{fluid}.$$

With respect to the fluid, parameters change dynamically and have to be taken into account in the system design and the EMS.

3) Thermal Modeling: The component tempering, e.g., in the FC operation phases, or in the fulfillment of the battery temperature sweet spot, and the control of cooling cycles, have a great influence on the overall system efficiency and degradation effects in the FCHEV drivetrain. In Fig. 11, an exemplary equivalent circuit diagram describing the thermal behavior of a general component (C) is depicted.

The heating power $\dot{Q}_C$ of the component increases the temperature ϑ_C as it loads the thermal capacity C_C. Subsequently, the heat is conducted across the component casing with the thermal capacity C_1. The ambient temperature ϑ_{amb} determines the thermal reference point across the system. The heat conduction between the reference points $\{C, 1, amb\}$ is modeled with the resistances $R_{C,1}$ and $R_{1,amb}$.

The placement of a cooling cycle is subject to the design of the individual system. In the study of Bauer *et al.* [90], a cooled battery storage is described as a lumped mass heat capacity $C_{th,bat}$ with a dynamic model of the battery temperature ϑ_{bat}

$$\dot{\vartheta}_{bat} = \frac{1}{C_{th,bat}} \cdot (P_{loss\,bat} + \dot{Q}_{amb} + \dot{Q}_{cool}).$$

Thereby, the dynamic battery temperature $\dot{\vartheta}_{bat}$ depends on the electric power losses of the battery $P_{loss\,bat}$, the ambient heat emission $\dot{Q}_{amb}$, and the heat emission $\dot{Q}_{cool}$ into a cooling cycle. The authors optimize the energy for battery tempering versus drivetrain efficiency.

This lumped-sum approach is widely used in the literature to factor in thermal dependencies. For example, Cheng *et al.* [9] design a model-based temperature control for a city bus as a part of its EMS.

IV. METHODOLOGIES FOR EMS

Efficient operation of FCHEVs is strictly related to intelligent and accurate design of the EMS. Up to the present, much research work regarding EMSs with respect to the mechanical drivetrain of heavy-duty trucks has been conducted, e.g., efficient gear switching for heavy-duty trucks [91], [92]. Reviews and surveys on a broad range of EMS methodologies for hybrid vehicles are presented in [93]–[97], while recent reviews focus on health-conscious [50] or learning-based [60] methods for EMSs. Thereby, the developed methodologies for the EMS in HEVs can be adapted and transferred to a promising application in the EMS for FCHEVs.

The optimization for a high system efficiency by an intelligent power split is the primary task of the EMS for FCHEVs [3]. However, respecting the degradation processes of the FCS and ESSs for an increased lifetime [50] and low total cost of ownership (TCO) is crucial for economic competitiveness [6]. Therefore, the combination of multiple optimization objectives to simultaneously account for both an efficient operation and a minimum degradation is the key challenge for further research. Additional challenges for heavy-duty applications are robust energy supply for safety-related components and auxiliaries, as well as the managing of component temperatures across the system. Furthermore, the problem formulations often show nonlinear and even mixed-integer characteristics for approaches with combined objectives. Thus, real-time optimization of the EMS is exceptionally challenging due to the resulting high computational efforts.

On the other hand, combining these objectives for EMS design brings opportunities due to increased flexibility around the thermal management, auxiliaries, and the driving strategy. Taking advantage of this potential is important for EMS development but is in need of comprehensive system knowledge. These approaches benefit from information about future component behavior and driving cycle. Thus, predictive optimization and dynamic weighting of the multiple objectives lead to a superior system operation than optimizing separated subproblems with possibly contradicting objectives.

With a multiobjective optimization approach, the problem dimensionality increases and is subject to the different domains. Thereby, each controlled subsystem introduces dedicated input variables to the optimization problem, e.g., the power split factors of the ESSs, the FCS OP, or the vehicle velocity. Switching components, such as a GB (see Fig. 1), add additional problem dimensionality and complexity and often lead to mixed integer programming (MIP).

Problem complexity of EMSs in FCHEVs is further increased by the constraints that arise. These constraints
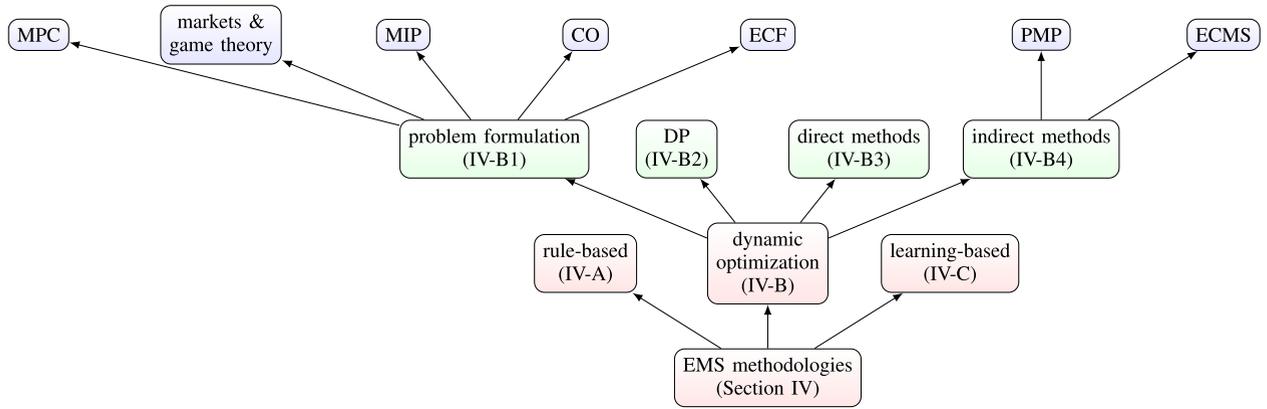
Fig. 12. *Classification of EMS methodologies and structuring of Section IV with root methodologies (red), grouping for dynamic optimization-based methodologies (green) and further subdivisions (blue).*

comprise the FCS power dynamics, the thermal limits of components, restricted ESS capacities, or the maximum power of the PEs, as well as the EMs, among others. In terms of the driving strategy, this constrains the propulsion power and the regenerative braking for the FCHEV. In contrast, the occurring limitations mitigate the degradation and wearing effects through lower thermal stress and damped peak powers.

Taking the complexity of FCHEVs into consideration, EMSs are usually designed as a hierarchical supervisory control, which is responsible for the high-level decisions [98], [99]. High-level decisions are used as references, e.g., for the voltage levels, the power demands, the SOC, or the velocity of the vehicle. The resulting set points are applied by underlying control loops on the component level, e.g., classic PID control [48], differential flatness-based controllers [100], advanced control methods [101], or dynamic evolution control for continuously updated control laws [102].

In the following, rule-, dynamic optimization-, and learning-based strategies in the literature are successively presented and discussed. The presented EMSs are applied to different HEVs or FCHEVs that differ in technologies, topologies, or application sector. Nevertheless, the considered problem of energy management with multiple objectives and requirements is comparable. Hence, the described approaches may give valuable insights and hints for possible EMS problem solving regarding FCHEVs in heavy-duty applications. In contrast to previous works and reviews, we propose a new classification of dynamic optimization-based approaches for the EMS, oriented around optimal control, and depicted in Fig. 12. The classification of optimization-based methods is proposed in categories based on [103] and [104], namely DP, direct methods, and indirect methods. Furthermore, we add learning-based methods as a new category, which may be a promising field for future research activities regarding EMSs [60].

A. Rule-Based Strategies

Rule-based control strategies are a simple and easy to implement methodology to control power distribution and power flow within FCHEVs in real time [7], [95]. Generally, rule-based control strategies are divided into deterministic rule-based strategies (applying fixed rules and thresholds) and fuzzy rule-based strategies (based on fuzzy set theory [105]).

For the implementation, neither deterministic nor fuzzy rule-based approaches need an underlying model. Therefore, both methodologies are suitable for the control of complex and strongly nonlinear systems as FCHEV powertrains combining electrical, mechanical, chemical, and thermal domains. Especially in drivetrains with multiple DOFs due to different energy buffers, such as batteries and ultracapacitors, heuristic approaches have been dominant in recent years as stated by Ansarey *et al.* [106]. Furthermore, the computational efficiency makes rule-based approaches ideal for fast integration in real-time applications [107]. Hence, referring to the state of the art, rule-based approaches are widely applied in many production vehicles [94]. A comprehensive and comparative study of various rule-based EMSs for an HESS comprising a PEMFC, a battery, and an ultracapacitor is presented in [108].

Since one reason for nonoptimal control performance is the fixed rules and nonaccurate thresholds, current development and research focus on the adaption, tuning, and optimization of these parameters in rule-based control strategies. Hereby, the fundamental parameters are adjusted in terms of driving cycle, powertrain characteristics, and various vehicle states [108], [109]. Taking these adjustments into account, today's implementation and adaption of rule-based approaches for a particular FCHEV are time-consuming and complex processes. These processes include, but not limited to, off-line optimization of parameters [109]–[113], instantaneous optimization of OPs [114], [115], real-time optimization in a restricted search

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

space [116], driving cycle recognition [59], [117]–[119], and driving cycle prediction [120].

1) Deterministic rule-based strategies: They are commonly implemented via lookup tables and state machines. The thermostat strategy is the simplest control strategy. With this strategy, the FCS always operates around its most efficient OP and is switched on or off to maintain battery SOC. In [121], the durability of FCs in a plug-in FCHEV is enhanced by applying a novel FC configuration, which works at fixed OPs. A thermostat control approach with the ON–OFF switching of three FCs and hysteresis is developed aiming at a reduced operation time of the FCs. In [122], the advantages of a blended thermostat and a power follower strategy are used for the control of a hybrid city bus. Extensions of the thermostat approach are often based on efficiency maps for the FC operation, including the most efficient OPs [123].

In the frequency-based strategy, a low-pass filter or wavelet transform is used to split the traction power demand in components of low and high frequencies [14], [124], [125]. Low-frequency demands will be covered by the FC, while high-frequency components with steep power transients are covered by the battery or the ultracapacitor. Therefore, on the one hand, demanding transients of the FCS and, on the other hand, high currents of the battery are mitigated leading to higher fuel economy and an increased battery and FC lifetime, respectively. An equivalent power distribution in the frequency domain for FCHEVs with FC, battery, and ultracapacitor as the HESS is shown in Fig. 6. Applying a frequency-based approach with cascaded control loops, Azib *et al.* [42] illustrate the effectiveness of a simple HESS comprising a PEMFC and an ultracapacitor for FCHEVs.

2) Fuzzy logic control (FLC): These systems are based on fuzzy set theory introduced by Zadeh [105] and are usually grounded on human expertise, existing heuristics, or engineering intuition. While fuzzy rule-based strategies are deterministic as well, they have emerged as a dedicated class of rule-based strategies in the literature due to significant differences in the approach. The development of an FLC system is composed of membership functions for input and output variables and fuzzy rules mapping input sets onto output sets. In a fuzzy rule-bused controller, three steps are performed.

1) In the fuzzification, the input variables are assigned to fuzzy input sets by corresponding membership functions.
2) In the inference, with the aid of predefined fuzzy rules, these fuzzy input sets are mapped to fuzzy output sets.
3) In the defuzzification step, to get applicable output values, the inverse fuzziness step is applied in which quantified output variables are computed from fuzzy output sets via membership functions.

A thorough overview of the FLC, its mathematical theory, and general applications and adaptations is given in [126]. In [127], classification and comparison of various EMSs are presented. The review focuses on fuzzy rule-based control strategies categorized in conventional, adaptive, and predictive FLC methods.

Conventional fuzzy rule-based EMSs for power distribution, allocation, or electric-assisted control in FCHEVs are studied in [128]–[130]. In order to achieve two partly contradicting objectives, an adaptive neural fuzzy inference system is implemented and trained with data from two different controllers in [131]. Another implementation of FLC with machine learning is studied in [132]. With the help of the machine learning algorithm Learning Optimal Power Sources (LOPPS), a fuzzy rule-based controller for varying power demands and vehicle states is developed. In [133], an adaptive FLC with the ability to compensate different vehicle operating states and uncertainties is presented. The proposed controller is composed of a fuzzy neural network (FNN) as the main controller. With respect to multiobjective optimization in [43], a basic fuzzy rule-based strategy for FCHEVs is adapted considering various driving cycles. In [134], membership functions for input, output, and fuzzy rules are adapted via off-line optimization with respect to specific driving cycles.

B. Dynamic Optimization-Based Strategies

In contrast to the prior presented rule-based strategies, profound system knowledge and accurate models are often necessary for dynamic optimization-based approaches. This is usually considered as a white-box approach in the optimization field. However, as an example for black-box approaches, learning-based strategies are presented in Section IV-C, which may also have optimization character included in the process of learning approximations. Dynamic optimization-based strategies solve an optimization problem by calculating an optimal solution that minimizes a set of objective functions. The objective function set can be weighted to quantify the importance of certain criteria or goals. Further objectives, external information about the future driving cycle, or internal information about system states may be added to the designed objective function set. Hence, dynamic optimization-based strategies are easier to scale or adapt than rule-based strategies, though the application of optimization-based approaches is often connected to high computational efforts for solving the optimization problem and calculating the control input [96], [104], [135]. Besides the objective function set, constraints to input or state variables provide the opportunity to restrict the optimal solution to a feasible set.

With respect to the problem formulation, system modeling, input and output variables, and the considered optimization horizon, substantially differing optimization problems occur. Considering the different properties of optimization problems, we propose three categories as a new taxonomy for dynamic optimization-based approaches in EMSs, namely DP, direct methods, and indirect methods, based on [103] and [104]. For each class of

optimization methods, there are various algorithms for the numerical calculation of the optimal control inputs. The goal is to find the optimal solution of the provided objective function set with respect to constraints, either algebraic, numeric, or in the form of the computational power. As there is a wide range of solvers, open-sourced and proprietary, which compile the problem in a provided language and compute matching sets of solutions, interfacing the optimization problem to a software solver is often the first step. Here, the solver interface frameworks, YALMIP [136] and CasADI [137], provide a convenient way for fast implementation with various external solvers. Solvers differ depending on the characteristics of the problem formulation, the optimization methodology, and the computational effort. Problem properties, such as differentiability, convexity, boundedness, or mixed-integer, substantially influence the choice of suitable solving algorithms.

1) Problem Formulation for Optimization: Regarding optimization problems, the problem formulation as the first step has been an important research field in mathematics, computer science, and engineering. In the following, various approaches for the problem formulation, such as MPC, convex optimization (CO), MIP, market-based and game-theoretic methods, and equivalent consumption factor (ECF), are introduced.

Model predictive control (MPC) is a popular and widely applied advanced control methodology. In general, MPC is defined by four properties [138].

1) A dynamic optimization problem is formulated, and the arising objective function is solved in every time step, yielding the next optimal control variable.
2) The behavior of the controlled system is predicted by an internal system model with respect to the control variables.
3) The optimization problem has to be solved with respect to constraints on control or state variables or both.
4) MPC uses a moving or receding horizon to predict the system behavior. Therefore, optimal control variables for a predefined planning horizon are calculated, whereas only the first control variable is applied to the system. Afterward, the MPC gets the measured or estimated feedback from the system and repeats the procedure for the next time step, while the horizon is moving forward in time.

The simple handling of constraints in optimization problems is one advantageous characteristic of MPC. Taking the depicted properties into account, MPC is a particularly suitable approach for EMSs in FCHEVs, which allows for simple handling of constraints and real-time capable implementation. Thereby, a real-time capable implementation of the MPC is achievable by adjusting the step size in discrete-time optimization problems or the prediction horizon in order to reduce computational efforts. Regarding the varying power demands with high peak power requirements in heavy-duty applications, the MPC is able to compensate the slow power dynamics of the FCS by adding power from the battery and the ultracapacitor. Thus, the MPC takes advantage of the peak power capabilities of the HESS in FCHEVs (see Fig. 6) by planning an adequate power split between the ESSs over the moving horizon [139]. In [20] and [140], a stochastic model predictive control (SMPC) is implemented for the optimization of the fuel economy. As the input of the SMPC, the future velocity or the mechanical load is forecast by a Monte Carlo method based on a Markov chain. The SMPC performance in the overall system shows a slightly increased fuel consumption compared to the global optimization approach using DP with the ground truth of the future velocity. A blended EMS comprising an MPC and a rule-based approach for the operation of an HESS is developed and evaluated in [141]. In [47], recent MPC algorithms for EMSs are classified in terms of prediction methods for the driving cycle forecast (as in [135] and [142]) and with respect to the applied models. Finally, a comprehensive list of factors affecting the MPC performance and the current challenges for MPC approaches in the EMS are summarized [47].

The arising optimization problem of an MPC is usually solved by direct methods, e.g., quadratic programming (QP) [142], as well as indirect methods [143]. An approach based on an MPC for FCHEVs that switches between driving modes for propulsion and braking is proposed in [88]. In order to allow the effective exploitation of elevation information and to reduce fuel consumption, Lattemann *et al.* [144] proposed an MPC for a heavy-duty truck that varies the speed in a predefined speed band around a preset speed.

Market-based and game theoretic methods are designed to imitate and simulate human behavior in certain situations, which are modeled as a business process, negotiation, game, or auction. In recent research, the methods of market and game theory are transferred to other domains where interaction between humans, machines, or humans and machines happens. In [145], the game theory is used to develop a novel EMS taking multiple objectives and interaction with the driver into account. Despite the problem formulation as a noncooperative game between driver and vehicle, experimental validation demonstrates good characteristics in drivability and efficient fuel consumption. Gielniak and Shen [146] propose an EMS based on game theory for an FCHEV with respect to the objectives drivetrain efficiency and vehicle performance. Thereby, the ESSs, namely an FC, a battery, and an ultracapacitor, are designed as the players that maximize their payoffs [146].

Mixed integer programming (MIP) results from discrete integer control variables, such as gear choices in the GB of the mechanical drivetrain or switching component states included in the problem formulation [3], [92]. A holistic approach, taking advantage of the DOFs in the system operation, namely vehicle velocity, gear shifting, and torque split, is extensively studied in [147]. An integrated

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

MPC approach for simultaneous velocity planning and an EMS for FCHEVs yielding to an MIP is proposed in [148].

With growing system complexity or nonlinear problems, the MIP complexity grows disproportional due to combinatorial states and permutations but remains viable as an EMS design approach [3]. Caux *et al.* [3] describe a derivative-free optimization approach for an FC drivetrain with two types of ESSs, addressing additional ultracapacitors. The authors transfer the drivetrain model into a data-driven linear MIP approach with a combinatorial formulation. The need for further research regarding robustness in the case of changing FC efficiency characteristics is suggested [3].

Convex optimization (CO) is an approach to problem formulation with an advantageous characteristic that enables derivative-based solving algorithms to effectively find the global optimum. If the optimization problem is convex and feasible, the calculated solution is guaranteed to be the global optimum. In contrast to CO problems, nonconvex optimization problems may have multiple feasible local optima. Thus, the complexity of finding the global optimum is significantly increased, and as a result, convexity is desirable for optimization problem design. Unfortunately, CO problems with convex objective function sets and at the same time convex constraints are rare. Especially, nonlinear functions and constraints, such as obtained by EMSs for FCHEVs, lead to nonconvex problems. Convexification of nonconvex optimization problems leads to approximated and potentially oversimplified problems. As the nonlinear functions of components and systems describe their exact characteristics and behavior, simplified optimization problems lead to less accurate and possibly infeasible solutions. Comprehensive studies regarding CO for a wide range of technical problems are presented in [149]. The application of CO in the EMS for FCHEVs is studied in [51]. The design of CO problems and the approaches for convexification in the field of electric mobility are addressed by Egardt *et al.* [150].

The *equivalent consumption factor (ECF)* is originally used to, respectively, compare the electrical and the chemical energy of the battery with an ICE and is proposed in [151]. Applying this factor reduces the dimension of the optimal control problem as the battery charge is compared to fuel consumption and, thereby, substituted. As a transfer to the application in FCHEVs, the mass flow of hydrogen $\dot{m}_{H_2}$ is conditioned in regard to an FCS efficiency lookup table and using the gasoline equivalent lower heating value (LHV) h_{LVH, H_2} of hydrogen [106]

$$\dot{m}_{H_2} = \frac{P_{FC}}{\eta_{FC}(P_{FC}) \cdot h_{LVH, H_2}}$$

with P_{FC} as the FC power and η_{FC} as the dependent FC efficiency. The ECF approach needs a thorough parameterization, also depending on the driving cycle, and can suffer from suboptimal behavior in terms of wide power demand variation. Thus, an intelligent adaption is needed to achieve improved optimization results [152]. Recent literature for the application of the ECF in various approaches of equivalent consumption minimization strategys (ECMSs) for FCHEVs is presented in Section IV-B4.

2) Dynamic Programming: DP is an optimization methodology developed by Bellman who applied it to solve optimal control problems. The basic principle is the decomposition of the global optimization problem into subproblems. The subproblems can be regarded as branches that are sequentially solved. Finally, a path through the branches is leading to the optimal solution. In order to reduce the computational burden, the principle of optimality is used to cut some of the nonoptimal branches. Thereby, the principle of optimality states that, in the branch leading to the optimal solution, every subproblem has to be optimal itself. In general, DP suffers from the curse of dimensionality, which describes the fact that an additional optimization variable yields a significantly increased complexity of the optimization problem [153].

DP is mostly used in order to find the global optimal solution for evaluation and benchmarking [106], [135], [147], [154]. For this purpose, a noncausal problem formulation is used as the full *a priori* knowledge about the driving cycle and route information is assumed. Another purpose is the adaption of real-time capable approaches, such as rule-based strategies by the parameters derived from off-line optimization with DP. This procedure is suitable for complex optimization problems in terms of nonlinear FC performance or high-dimensional problems [155]. In [156], a comprehensive overview on optimization-based control strategies for energy-efficient driving with an emphasis on DP is elaborated. For further reference, Bertsekas [153] provides a thorough overview of DP approaches, methodologies, and implementations for optimal control problems. The extension of DP by introducing stochastic variables in the optimization problem leads to stochastic dynamic programming (SDP). The stochastic input variables are applied in order to include uncertain information, such as future driving patterns in the problem formulation [157].

For an efficient numerical solution of DP, search algorithms, such as A⋆, B⋆, or D⋆, as well as backtracking, or branch-and-bound algorithms, are applied. Another class of solving algorithms is summarized as stochastic search approaches. The stochastic search uses probabilistic strategies mostly motivated by nature to find the optimal solution. Commonly known algorithms, which are applied and adopted to a wide range of problems in the EMS design, are genetic algorithm (GA) [158], particle swarm optimization (PSO) [59], [159], simulated annealing (SA) [98], or the bees algorithm [134].

3) Direct Methods: In direct methods, a continuous dynamic optimization problem is approximated through discretization in the time domain, which subsequently yields a static optimization problem with discrete-time optimization variables [103]. In contrast, in direct

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

collocation methods, both the control variables and the state variables are replaced by discrete variables [103]. Direct methods are usually deployed by solving optimal control problems arising from MPC approaches. Here, the discretization of control variables in time over the moving horizon leads to static optimization problems that are iteratively solved. The quality of the obtained solution depends on the parameterization, solving algorithm, and the conditioning of the optimal control problem. Furthermore, control variable parameterization methods suffer from nonlinear inequality constraints, as they arise in EMS problems of FCHEVs [160]. Yielding strongly nonconvex optimization problems, these inequality constraints cause various local optima that are often far from the global solution (see CO in Section IV-B1).

In order to overcome these drawbacks of control variable parameterization methods, Pérez and García [161] propose an EMS approach based on direct collocation methods (or direct transcription). Another approach, applying direct collocation methods to deal with the arising constraints in control and state variables, is presented in [162]. In [163], a direct collocation approach for a multiobjective EMS for FCHEVs is studied.

For several static optimization problems, there are efficient solving algorithms. In regard of available derivatives, derivative-based solving algorithms, such as Newton's method, the quasi-Newton method, sequential quadratic programming (SQP), or Broyden–Flechter–Goldfarb– Shanno algorithm (BFGS) surpass derivative-free algorithms. For additional consideration of boundaries, active-set methods and interior-point methods are applied. Unfortunately, in most algorithms, it is not guaranteed that the global optimum is obtained. Heuristics to solve optimization problems without analytical knowledge of the derivatives are derivative-free methods, such as the simplex algorithm for linear optimization problems or the Nelder–Mead method and other pattern search algorithms applicable for nonlinear problems [122].

4) Indirect Methods: Indirect methods make use of the necessary conditions for an optimal solution [104]. Approaches are usually based on the calculus of variations and derive formulations of the solution for an optimal control problem. For simple optimization problems, a closed-form solution is achievable. Regarding the complex and nonlinear optimization problems linked to EMSs for FCHEVs, an analytical solution is often not possible for the desired objectives [95]. Thus, numerical solutions with shooting techniques or direct collocation are needed [103].

Pontryagin's minimum principle (PMP) is the most widely applied indirect method approach because of its capability to cope with the arising constraints in EMS optimization problems [156]. Because PMP redefines the original optimal control problem into a local optimal control problem that is easier to solve, it allows no guarantees of optimality [160]. Ambühl *et al.* [164] derive an explicit solution from a simplified hybrid powertrain model to leverage PMP with a motor power-dependent piecewise Hamiltonian function for optimization with input constraints.

In [165], an EMS based on PMP is introduced, which takes battery aging and minimizing fuel consumption into account. The approach makes use of a factor map for quantification of several aging effects occurring in particular vehicle-operating conditions. Various research works study PMP for EMSs with respect to a wide range of objectives and constraints [53], [82], [90].

In addition to the ECF introduced in Section IV-B1, the *equivalent consumption minimization strategy (ECMS)* approach simplifies the original optimal control problem to local optimization problems that are solvable with less computational effort. The fundamental ECMS is based on instantly available information. Therefore, deployment of ECMS results in a reformulated optimal control problem, which facilitates real-time applicability [166]. Serrao *et al.* [160] highlight the equivalence of PMP and ECMS analytically and state that, assuming a CO problem, PMP, and, hence, the ECMS yields the optimal solution. The ECMS methodology is also extendable to other combinations of ESSs in various HESSs for FCHEVs [167], [168]. Furthermore, a combination of energy and thermal management based on ECMS is implemented and validated in [169]. Emphasizing component lifetime, recent developments apply and extend ECMS methodology for health-conscious degradation minimization [50].

As the ECF is fixed for the instantaneous local optimal control problem, ECMS suffers from suboptimal behavior in a global sense. In order to overcome these disadvantages of the ECMS regarding the fixed ECF, extensive development and research address the intelligent adaptation of the ECF. These intelligent adaptation approaches include global optimization for the driving cycle, on the one hand, and online adaptation based on state estimation and prediction or recognition of driving patterns, on the other hand [7], [50], [95], [152], [170]. Further research efforts facilitating the online adaptation of the ECMS approach, initially proposed in [168], are presented in [170]. In order to estimate the SOH of ESSs, an unscented Kalman filter approach is developed and validated.

For an ECMS in FCHEVs, a time-dependent objective function J as the integral over the sum of the provided power by the fuel mass flow $\dot{m}_{\text{fuel}}$ and a fuel equivalent function ψ is formulated

$$J = \int_{t_0}^{t} \dot{m}_{\text{fuel}}(\mathbf{u}) + s \cdot \psi(\Delta\text{SOC}, \mathbf{u}) d\tau.$$

Here, the equivalent fuel consumption of a further ESS ψ represents a battery (see [135], [160], and [171]). Thus, ψ is dependent on the charging state difference ΔSOC and is multiplied with the ECF $s \in \mathbb{R}$ for equivalence weighting.

C. Learning-Based Strategies

Sutton and Barto [172] distinguish three categories of learning methods, namely supervised, unsupervised, and

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

reinforcement learning (RL). Hereby, supervised learning describes methods that learn behavior based on given rules or labels. After the training with the labeled data, supervised learning algorithms are able to apply these rules to new data. Here, the challenge is to apply the rules to known situations and adequately extrapolate the rules for unknown data or situations. In order to implement adaptive fuzzy rule-based strategies, supervised learning approaches are applied and validated for EMSs in [131]–[133]. Furthermore, in [117] and [118], a learning vector quantization network for driving cycle recognition is developed. In [173], driving modes are switched based on the detection of the driving behavior with long short-term memory in a recurrent neural network (RNN). In contrast to supervised learning, unsupervised learning is used to identify structures or patterns in unlabeled data.

The third category, RL, differs from both aforementioned learning methods. RL is the process of learning by interaction with the environment based on instantaneous rewards and a value function that considers estimated rewards. A comprehensive introduction of RL and its characteristics is elaborated in [172]. In the act of learning, RL approaches try to maximize their reward and, hence, solve an optimization problem. However, in contrast to dynamic optimization-based methods, RL does not apply an explicit and constant model as a representation of its environment. As a result, RL is, in general, very adaptive to changes in its environment. In recent years, RL has been an emerging and popular technology [172], and thus, its applications have been studied in a wide range of domains. Hu *et al.* [60] highlight applications of RL in EMSs and give an overview of current research efforts and future prospects. The authors distinguish RL methods for EMSs into two categories, pure RL [174] and blended approaches combining RL with forecasting information [175], [176] or MPC [177]. In [178], a multiobjective-based EMS with RL is developed. The proposed EMS is updated at discrete times with respect to a divergence factor. First approaches with RL for EMSs in FCHEVs are studied in [179].

V. TOWARD HOLISTIC APPROACHES

In Sections I–IV, recent research efforts and the state-of-the-art concerning applications, the system design, the system modeling, and EMS methodologies in regard to FCHEVs for heavy-duty applications have been presented. This section is intended to combine the different aspects and give a guideline for the development of FCHEVs starting with the system design, over EMS considerations, up to the verification and validation process with an emphasis on heavy-duty trucks.

A. Co-Optimization in the Powertrain and EMS Design

The first step in the system design is the definition and assessment of requirements for the intended use. For heavy-duty and long-haul trucks, requirements comprise, in particular, the torque, the payload, the range, and the durability. Regarding the economic competitiveness, further aspects that have to be considered are the initial investment and the life-cycle costs contributing to the TCO. Thereby, life-cycle costs involve efficient operation and maintenance efforts. Based on the weighted requirements, various decisions regarding technologies, topologies, and component sizing have to be made. Several options concerning ESSs for a suitable HESS are presented in Section II. In terms of heavy-duty applications, the combination of an FC, a battery, and an ultracapacitor is advantageous in order to meet the peak power requirements for acceleration or deceleration via regenerative braking under payload condition [49]. The usage of PEs as the dc/dc-converter to connect the ESSs in the dc-link (see Fig. 1) is always a tradeoff between the additional costs, the losses, the weight, and the flexibility for the subsequent EMS design.

Thereby, a strong coupling between the system design and the layout, on the one hand, and the EMS, on the other hand, is pointed out. Thus, the iterative co-optimization and the simultaneous development of the system and the EMS are crucial for capable and competitive FCHEVs. As the system design for heavy-duty applications is of even higher complexity, a suitable framework for the iterative co-optimization is necessary [49], [53]. This framework comprises a simulation environment with precise models for components and characteristic driving cycles. While the co-optimization for the system design takes place offline, the computational burden plays a subordinate role [45]. Hence, the use of complex component models to ensure the necessary performance of the drivetrain and high demands for the durability of heavy-duty and long-haul trucks is advisable. The basis for durable operation is already set in the early development stage with the crucial choices regarding the applied technologies of ESSs, their dimensioning, and the overall powertrain topology (see Fig. 1). Because optimal topology and component dimensioning are varying for changing requirements in terms of intended range and payload, the ambitious development of a comprehensive co-optimization framework definitely pays off in the long term.

B. Holistic Energy Management Strategies

Future information on the driving cycle and power demands is usually utilized in order to find the optimal solution and unleash the full potential of EMSs. Therefore, most presented methodologies for the EMS incorporate some form of prediction or driving cycle recognition in order to intelligently adapt static parameters, thresholds, or rules while driving [95]. With respect to long time scales, tour forecasting concerning the hydrogen tank system and the battery SOC may improve the overall energy efficiency and reduce the component stress. Thereby, a new trip can be started with a fully loaded battery and ultracapacitor while having a lower hydrogen tank pressure at

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

the end of the former trip. This enables a moderate startup regarding power and dynamic electric load for the FCS by primarily using battery and ultracapacitor as energy supply during the first minutes of operation.

For shorter horizons in terms of the next minutes of driving, the information about the route profile, the weather, traffic lights, and the traffic congestion is important to consider in a holistic EMS. This information affects the planning of velocity and regenerative braking phases directly, as well as it influences the battery SOC and the power split planning in the HESS implicitly. At present, some information regarding the route profile, the weather, and the nearby traffic is already available from onboard sensors and navigation systems [47]. Moreover, further improvements and the dissemination of intelligent transportation systems with vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication will increase the availability of information [96]. In order to cope with uncertainties and disturbances, recent research addresses forecasting and prediction of the velocity or driving patterns via stochastic methods, such as the Markov chain Monte Carlo method [140], [142], [157], [180] or suitable postprocessing with filter approaches [140]. Regarding the different horizons of the prediction, the MPC approach is a promising methodology for intelligent EMS taking advantage of future information [47], [96]. In order to overcome the still prevalent computational limitations, a layered design comprising various methodologies for the arising subproblems and the customized modeling is promising [88], [116]. The combination of advantages with respect to the presented rule-, dynamic optimization-, and learning-based methodologies in a holistic EMS is seen to be an encouraging path [60], [177]. This holistic approach addresses the many subproblems with a blended and layered MPC strategy.

For heavy-duty trucks, velocity planning plays a significant role as the payloads, and therefore, the inertial momentum is high. With longitudinal planning in automated or assisted driving, a balanced velocity and acceleration profile is achievable, which has positive influences on the system efficiency and degradation effects regarding the whole drivetrain and, in particular, the FC and the battery [72]. Hence, adapting velocity and acceleration profiles with a holistic EMS reveals major advantages in terms of an efficient operation and further mitigation of wearing effects [148]. Thus, combining the velocity planning and the power split decisions is the key aspect toward a holistic EMS with the highest potential.

Another important factor is the operation of auxiliaries. Heavy-duty trucks, in general, and FCHEVs, in particular, have a noticeable power consumption by auxiliaries [181], [182]. Thus, intelligent auxiliary management in the EMS is highly recommendable [47], [183]. Using thermal capacities in cooling cycles and a flexible operation of auxiliaries as virtual power plants adds DOFs to the EMS and, thereby, offers the possibility to balance the power consumption of the system. Energy from recuperation

phases and at high battery SOCs can be consumed by auxiliaries and may subsequently prevent the need for this energy at a later time when power may be rare due to a high driving load. Summarizing, intelligent usage of auxiliaries, in particular, for heavy-duty trucks increases the system efficiency and durability.

While the proposed holistic EMS and velocity planning imply balanced power consumption and mitigate power transients, a health-conscious operation of the FC and the battery is already included [50], [68], [72]. However, for heavy-duty applications that have demanding requirements concerning the strongly varying power supply with prominent peak powers, accurate monitoring of the FC and the battery is needed to ensure longevity [49]. Thereby, a changing health status of ESSs can be taken into account in the EMS objective function at an early stage, which reduces further damage to the ESS through a reduced peak or highly dynamic power loads by an intelligent power split. Hereby, the proposed MPC approach for the EMS allows for an online adaption of constraints, which facilitates the health-conscious ESS operation.

C. EMS Verification and Validation

For a thorough testing of the chosen system layout and the EMS, methodologies and algorithms are mostly verified against a broad variety of driving cycles in simulations [43]. In later stages, they are validated in laboratory hardware-in-the-loop (HiL) environments, such as roller dynamometers or FC test benches [100], software-in-the-loop (SiL) testing, and further evaluated in the field. In order to facilitate a successful co-optimization of the system design and the EMS for heavy-duty applications, specific driving cycles for the intended use and payloads are necessary. Particularly, the precise reproduction of load cycle dynamics and load peaks is an important factor in testing the system topology, component dimensioning, and the intended EMS for heavy-duty trucks. A promising approach may be the application of statistical data representing real driving behavior in order to analyze long-term wearing and degradation effects of the FC and the battery [80], [184]. Furthermore, driving cycles can be altered in regard to slope profiles of interest, as well as new high or average speeds to test edge-cases and limitations of the FCHEV and the EMS design and increase the test coverage [185]. Including specific driving cycles and complex models for verification and validation within an iterative co-optimization framework for the system layout and the EMS design guarantees a structured and sustainable development process.

VI. C O N C L U S I O N

In this article, a comprehensive review regarding FCHEVs for heavy-duty applications has been presented ranging from a system overview and modeling of drivetrain components to EMS methodologies. The enumeration of prototypes in Section I regarding FCHEVs in heavy-duty

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

applications for a wide range of domains has illustrated the capability of the PEMFC as the power supply for transport systems. A brief description of the drivetrain topology and models of the main components in Sections II and III has given insights into relevant FCHEV characteristics. Hereby, the emphasis has been put on the recent research work regarding the modeling of wearing and degradation effects for the FCS and the battery, as there is a strong interest and need for the lifetime optimization of these components in FCHEVs [50].

The EMS methodologies in Section IV have been classified in three categories: rule-based, dynamic optimization-based, and learning-based. We have suggested a new taxonomy for the dynamic optimization-based approaches from a methodical perspective in the categories DP, direct methods, and indirect methods, respectively. This new taxonomy corresponds to the findings of Serrao *et al.* [160] who point out the equivalence between PMP and ECMS analytically, which are subgroups of the indirect methods.

While recent research efforts are focusing on single problems of optimization, the co-optimization of the drivetrain topology and the component dimensioning in combination with the EMS development are important to be addressed. In order to successfully improve FCHEV performance, we propose a comprehensive co-optimization framework for system layout and simultaneous EMS design. With this ambitious framework, system and control engineers are able to pay attention to the coupled decisions regarding technology, topology, and sizing, on the one hand, and an application-suitable and intelligent EMS, on the other hand. Thereby, the development framework may comprise precise models describing the complex FCHEV system for heavy-duty trucks and specific driving cycles for verification and validation. For the development of a holistic EMS, a hierarchical MPC approach seems to be promising. The MPC seamlessly allows the inclusion of external and internal information and the adaption to constraints in order to facilitate health-conscious operation, especially for the FCS and the battery. For an efficient and durable FCHEV, great potentials are expected by simultaneous optimization of the velocity planning, the auxiliary management, and the thermal management, as well as the power split between the FC, the battery, and the ultracapacitor. For this purpose, reliable information about the future route profile, power demands, and environmental parameters is crucial. This information can be extracted from onboard sensors, navigation systems, or the communication with vehicles (V2V) and the infrastructure (V2I). To conclude, a comprehensive framework for co-optimization with an intelligent holistic EMS approach may contribute significant improvements to heavy-duty FCHEVs to be highly competitive in transport applications. ∎

REFERENCES

[1] C. E. Sandy Thomas, "Transportation options in a carbon-constrained world: Hybrids, plug-in hybrids, biofuels, fuel cell electric vehicles, and battery electric vehicles," *Int. J. Hydrogen Energy*, vol. 34, no. 23, pp. 9279–9296, Dec. 2009.

[2] A. Emadi, "Transportation 2.0," *IEEE Power Energy Mag.*, vol. 9, no. 4, pp. 18–29, Jul./Aug. 2011.

[3] S. Caux, Y. Gaoua, and P. Lopez, "A combinatorial optimisation approach to energy management strategy for a hybrid fuel cell vehicle," *Energy*, vol. 133, pp. 219–230, Aug. 2017.

[4] C. C. Chan, "The state of the art of electric, hybrid, and fuel cell vehicles," *Proc. IEEE*, vol. 95, no. 4, pp. 704–718, Apr. 2007.

[5] A. Alaswad, A. Baroutaji, H. Achour, J. Carton, A. Al Makky, and A. G. Olabi, "Developments in fuel cell technologies in the transport sector," *Int. J. Hydrogen Energy*, vol. 41, no. 37, pp. 16499–16508, 2016.

[6] E. Çabukoglu, G. Georges, L. Küng, G. Pareschi, and K. Boulouchos, "Fuel cell electric vehicles: An option to decarbonize heavy-duty transport? Results from a Swiss case-study," *Transp. Res. D, Transp. Environ.*, vol. 70, pp. 35–48, May 2019.

[7] H. S. Das, C. W. Tan, and A. H. M. Yatim, "Fuel cell hybrid electric vehicles: A review on power conditioning units and topologies," *Renew. Sustain. Energy Rev.*, vol. 76, pp. 268–291, Sep. 2017.

[8] K. Simmons, Y. Guezennec, and S. Onori, "Modeling and energy management control design for a fuel cell hybrid passenger bus," *J. Power Sources*, vol. 246, pp. 736–746, Jan. 2014.

[9] S. Cheng, C. Fang, L. Xu, J. Li, and M. Ouyang, "Model-based temperature regulation of a PEM fuel cell system on a city bus," *Int. J. Hydrogen Energy*, vol. 40, no. 39, pp. 13566–13575, 2015.

[10] L. Xu, C. D. Mueller, J. Li, M. Ouyang, and Z. Hu, "Multi-objective component sizing based on optimal energy management strategy of fuel cell electric vehicles," *Appl. Energy*, vol. 157, pp. 664–674, Nov. 2015.

[11] H. Lee, S. Nakasaku, T. Hirota, Y. Kamiya, Y. Ihara, and T. Yamaura, "Analysis of energy consumption and possibility of further reduction of a fuel cell garbage truck," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 1876–1881.

[12] W. Zhang, J. Li, L. Xu, and M. Ouyang, "Optimization for a fuel cell/battery/capacity tram with equivalent consumption minimization strategy," *Energy Convers. Manage.*, vol. 134, pp. 59–69, Feb. 2017.

[13] J. P. Torreglosa, F. Jurado, P. García, and L. M. Fernández, "Hybrid fuel cell and battery tramway control based on an equivalent consumption minimization strategy," *Control Eng. Pract.*, vol. 19, no. 10, pp. 1182–1194, 2011.

[14] Q. Li, W. Chen, Z. Liu, M. Li, and L. Ma, "Development of energy management system based on a power sharing strategy for a fuel cell-battery-supercapacitor hybrid tramway," *J. Power Sources*, vol. 279, pp. 267–280, Apr. 2015.

[15] P. Fragiacomo and P. Francesco, "Energy performance of a fuel cell hybrid system for rail vehicle propulsion," *Energy Procedia*, vol. 126, pp. 1051–1058, Sep. 2017.

[16] A. R. Miller, K. S. Hess, D. L. Barnes, and T. L. Erickson, "System design of a large fuel cell hybrid locomotive," *J. Power Sources*, vol. 173, no. 2, pp. 935–942, 2007.

[17] L. van Biert, M. Godjevac, K. Visser, and P. V. Aravind, "A review of fuel cell systems for maritime applications," *J. Power Sources*, vol. 327, pp. 345–364, Sep. 2016.

[18] J. J. de-Troya, C. Álvarez, C. Fernández-Garrido, and L. Carral, "Analysing the possibilities of using fuel cells in ships," *Int. J. Hydrogen Energy*, vol. 41, no. 4, pp. 2853–2866, Jan. 2016.

[19] A. M. Bassam, A. B. Phillips, S. R. Turnock, and P. A. Wilson, "Development of a multi-scheme energy management strategy for a hybrid fuel cell driven passenger ship," *Int. J. Hydrogen Energy*, vol. 42, no. 1, pp. 623–635, Jan. 2017.

[20] T. Li, H. Liu, and D. Ding, "Predictive energy management of fuel cell supercapacitor hybrid construction equipment," *Energy*, vol. 149, pp. 718–729, Apr. 2018.

[21] P. Moriarty and D. Honnery, "Prospects for hydrogen as a transport fuel," *Int. J. Hydrogen Energy*, vol. 44, no. 31, pp. 16029–16037, 2019.

[22] E. Ogungbemi, T. Wilberforce, O. Ijaodola, J. Thompson, and A. G. Olabi, "Selection of proton exchange membrane fuel cell for transportation," *Int. J. Hydrogen Energy*, Jul. 2020, doi: 10.1016/j.ijhydene.2020.06.147.

[23] O. Z. Sharaf and M. F. Orhan, "An overview of fuel cell technology: Fundamentals and applications," *Renew. Sustain. Energy Rev.*, vol. 32, pp. 810–853, Apr. 2014.

[24] S. Singh *et al.*, "Hydrogen: A sustainable fuel for future of the transport sector," *Renew. Sustain. Energy Rev.*, vol. 51, pp. 623–633, Nov. 2015.

[25] M. El Hannach, P. Ahmadi, L. Guzman, S. Pickup, and E. Kjeang, "Life cycle assessment of hydrogen and diesel dual-fuel class 8 heavy duty trucks," *Int. J. Hydrogen Energy*, vol. 44, no. 16, pp. 8575–8584, 2019.

[26] B. Tanç, H. T. Arat, E. Baltacıoğlu, and K. Aydın, "Overview of the next quarter century vision of hydrogen fuel cell electric vehicles," *Int. J. Hydrogen Energy*, vol. 44, no. 20, pp. 10120–10128, 2019.

[27] H. C. Frey, N. M. Rouphail, H. Zhai, T. L. Farias, and G. A. Gonçalves, "Comparing real-world fuel consumption for diesel-and hydrogen-fueled transit buses and implication for emissions," *Transp. Res. D, Transp. Environ.*, vol. 12, no. 4, pp. 281–291, 2007.

[28] D.-Y. Lee, A. Elgowainy, A. Kotz, R. Vijayagopal, and J. Marcinkoski, "Life-cycle implications of hydrogen fuel cell electric vehicle technology for medium-and heavy-duty trucks," *J. Power Sources*,

vol. 393, pp. 217–229, Jul. 2018.

[29] F. Liu, F. Zhao, Z. Liu, and H. Hao, "The impact of fuel cell vehicle deployment on road transport greenhouse gas emissions: The China case," *Int. J. Hydrogen Energy*, vol. 43, no. 50, pp. 22604–22621, 2018.

[30] S. T. Thompson *et al.*, "Direct hydrogen fuel cell electric vehicle cost analysis: System and high-volume manufacturing description, validation, and outlook," *J. Power Sources*, vol. 399, pp. 304–313, Sep. 2018.

[31] J. Ribau, R. Viegas, A. Angelino, A. Moutinho, and C. Silva, "A new offline optimization approach for designing a fuel cell hybrid bus," *Transp. Res. C, Emerg. Technol.*, vol. 42, pp. 14–27, May 2014.

[32] T. Hua *et al.*, "Status of hydrogen fuel cell electric buses worldwide," *J. Power Sources*, vol. 269, pp. 975–993, Dec. 2014.

[33] J. Kast, R. Vijayagopal, J. J. Gangloff, and J. Marcinkoski, "Clean commercial transportation: Medium and heavy duty fuel cell electric trucks," *Int. J. Hydrogen Energy*, vol. 42, no. 7, pp. 4508–4517, 2017.

[34] J. Kast, G. Morrison, J. J. Gangloff, R. Vijayagopal, and J. Marcinkoski, "Designing hydrogen fuel cell electric trucks in a diverse medium and heavy duty market," *Res. Transp. Econ.*, vol. 70, pp. 139–147, Oct. 2018.

[35] J. Marcinkoski, R. Vijayagopal, J. Kast, and A. Duran, "Driving an industry: Medium and heavy duty fuel cell electric truck component sizing," *World Electr. Vehicle J.*, vol. 8, no. 1, pp. 78–89, Mar. 2016.

[36] J. J. Gangloff, J. Kast, G. Morrison, and J. Marcinkoski, "Design space assessment of hydrogen storage onboard medium and heavy duty fuel cell electric trucks," *J. Electrochem. Energy Convers. Storage*, vol. 14, no. 2, May 2017, Art. no. 021001.

[37] N. Macauley, M. Watson, M. Lauritzen, S. Knights, G. G. Wang, and E. Kjeang, "Empirical membrane lifetime model for heavy duty fuel cell systems," *J. Power Sources*, vol. 336, pp. 240–250, Dec. 2016.

[38] M. Moein-Jahromi, M. J. Kermani, and S. Movahed, "Degradation forecast for PEMFC cathode-catalysts under cyclic loads," *J. Power Sources*, vol. 359, pp. 611–625, Aug. 2017.

[39] M. Ehsani, *Modern Electric, Hybrid Electric, Fuel Cell Vehicles*, 3rd ed. Boca Raton, FL, USA: CRC Press, 2018.

[40] K. V. Singh, H. O. Bansal, and D. Singh, "A comprehensive review on hybrid electric vehicles: Architectures and components," *J. Mod. Transp.*, vol. 27, no. 2, pp. 77–107, Jun. 2019.

[41] A. M. Bassam, A. B. Phillips, S. R. Turnock, and P. A. Wilson, "An improved energy management strategy for a hybrid fuel cell/battery passenger vessel," *Int. J. Hydrogen Energy*, vol. 41, no. 47, pp. 22453–22464, Dec. 2016.

[42] T. Azib, O. Bethoux, G. Remy, C. Marchand, and E. Berthelot, "An innovative control strategy of a single converter for hybrid fuel cell/supercapacitor power source," *IEEE Trans. Ind. Electron.*, vol. 57, no. 12, pp. 4024–4031, Dec. 2010.

[43] S. Ahmadi, S. M. T. Bathaee, and A. H. Hosseinpour, "Improving fuel economy and performance of a fuel-cell hybrid electric vehicle (fuel-cell, battery, and ultra-capacitor) using optimized energy management strategy," *Energy Convers. Manage.*, vol. 160, pp. 74–84, Mar. 2018.

[44] S. F. Tie and C. W. Tan, "A review of energy sources and energy management system in electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 20, pp. 82–102, Apr. 2013.

[45] S. Ebbesen, "Optimal sizing and control of hybrid electric vehicles," Ph.D. dissertation, Dept. Mech. Process Eng., ETH Zürich, Zürich, Switzerland, 2012.

[46] M.-J. Kim and H. Peng, "Power management and design optimization of fuel cell/battery hybrid vehicles," *J. Power Sources*, vol. 165, no. 2, pp. 819–832, Mar. 2007.

[47] Y. Huang, H. Wang, A. Khajepour, H. He, and J. Ji, "Model predictive control power management strategies for HEVs: A review," *J. Power Sources*, vol. 341, pp. 91–106, Feb. 2017.

[48] P. Thounthong, S. Raël, and B. Davat, "Energy management of fuel cell/battery/supercapacitor hybrid power source for vehicle applications," *J. Power Sources*, vol. 193, no. 1, pp. 376–385, Aug. 2009.

[49] X. Hu, L. Johannesson, N. Murgovski, and B. Egardt, "Longevity-conscious dimensioning and power management of the hybrid energy storage system in a fuel cell hybrid electric bus," *Appl. Energy*, vol. 137, pp. 913–924, Jan. 2015.

[50] M. Yue, S. Jemei, R. Gouriveau, and N. Zerhouni, "Review on health-conscious energy management strategies for fuel cell hybrid electric vehicles: Degradation models and strategies," *Int. J. Hydrogen Energy*, vol. 44, no. 13, pp. 6844–6861, Mar. 2019.

[51] X. Hu, N. Murgovski, L. M. Johannesson, and B. Egardt, "Optimal dimensioning and power management of a fuel cell/battery hybrid bus via convex programming," *IEEE/ASME Trans. Mechatronics*, vol. 20, no. 1, pp. 457–468, Feb. 2015.

[52] Z. Song, H. Hofmann, J. Li, J. Hou, X. Han, and M. Ouyang, "Energy management strategies comparison for electric vehicles with hybrid energy storage system," *Appl. Energy*, vol. 134, pp. 321–331, Dec. 2014.

[53] C. Liu and L. Liu, "Optimal power source sizing of fuel cell hybrid vehicles based on Pontryagin's minimum principle," *Int. J. Hydrogen Energy*, vol. 40, no. 26, pp. 8454–8464, Jul. 2015.

[54] L. Guzzella and A. Sciarretta, *Vehicle Propulsion Systems*. Berlin, Germany: Springer, 2013.

[55] M. A. Hannan, M. M. Hoque, A. Mohamed, and A. Ayob, "Review of energy storage systems for electric vehicle applications: Issues and challenges," *Renew. Sustain. Energy Rev.*, vol. 69, pp. 771–789, Mar. 2017.

[56] M. A. Hannan, F. A. Azidin, and A. Mohamed, "Hybrid electric vehicles and their challenges: A review," *Renew. Sustain. Energy Rev.*, vol. 29, pp. 135–150, Jan. 2014.

[57] K. B. Wipke, M. R. Cuddy, and S. D. Burch, "ADVISOR 2.1: A user-friendly advanced powertrain simulation using a combined backward/forward approach," *IEEE Trans. Veh. Technol.*, vol. 48, no. 6, pp. 1751–1761, Nov. 1999.

[58] T. Markel *et al.*, "Advisor: A systems analysis tool for advanced vehicle modeling," *J. Power Sources*, vol. 110, no. 2, pp. 255–266, 2002.

[59] J. Wu, C.-H. Zhang, and N.-X. Cui, "Fuzzy energy management strategy for a hybrid electric vehicle based on driving cycle recognition," *Int. J. Automot. Technol.*, vol. 13, no. 7, pp. 1159–1167, 2012.

[60] X. Hu, T. Liu, X. Qi, and M. Barth, "Reinforcement learning for hybrid and plug-in hybrid electric vehicle energy management: Recent advances and prospects," *IEEE Ind. Electron. Mag.*, vol. 13, no. 3, pp. 16–25, Sep. 2019.

[61] *Autonomie–Vehicle System Tool*. Accessed: Jan. 19, 2021. [Online]. Available: https://www.autonomie.net/expertise/Autonomie.html

[62] Y. Chen *et al.*, "A SystemC-AMS framework for the design and simulation of energy management in electric vehicles," *IEEE Access*, vol. 7, pp. 25779–25791, 2019.

[63] C. Mi and M. A. Masrur, *Hybrid Electric Vehicles: Principles and Applications With Practical Perspectives*. Hoboken, NJ, USA: Wiley, 2017.

[64] M. Jouin, R. Gouriveau, D. Hissel, M.-C. Péra, and N. Zerhouni, "Prognostics and health management of PEMFC—State of the art and remaining challenges," *Int. J. Hydrogen Energy*, vol. 38, no. 35, pp. 15307–15317, 2013.

[65] F. Nandjou, J.-P. Poirot-Crouvezier, M. Chandesris, J.-F. Blachot, C. Bonnaud, and Y. Bultel, "Impact of heat and water management on proton exchange membrane fuel cells degradation in automotive application," *J. Power Sources*, vol. 326, pp. 182–192, Sep. 2016.

[66] P. Pei and H. Chen, "Main factors affecting the lifetime of proton exchange membrane fuel cells in vehicle applications: A review," *Appl. Energy*, vol. 125, pp. 60–75, Jul. 2014.

[67] E. Lechartier, E. Laffly, M.-C. Péra, R. Gouriveau, D. Hissel, and N. Zerhouni, "Proton exchange membrane fuel cell behavioral model suitable for prognostics," *Int. J. Hydrogen Energy*, vol. 40, no. 26, pp. 8384–8397, Jul. 2015.

[68] M. Jouin, R. Gouriveau, D. Hissel, M.-C. Péra, and N. Zerhouni, "Degradations analysis and aging modeling for health assessment and prognostics of PEMFC," *Rel. Eng. Syst. Saf.*, vol. 148, pp. 78–95, Apr. 2016.

[69] J. Hua, J. Li, M. Ouyang, L. Lu, and L. Xu, "Proton exchange membrane fuel cell system diagnosis based on the multivariate statistical method," *Int. J. Hydrogen Energy*, vol. 36, no. 16, pp. 9896–9905, Aug. 2011.

[70] M. Buchholz and V. Krebs, "Dynamic modelling of a polymer electrolyte membrane fuel cell stack by nonlinear system identification," *Fuel Cells*, vol. 7, no. 5, pp. 392–401, Oct. 2007.

[71] M. Buchholz, M. Eswein, and G. V. Krebs, "Modelling PEM fuel cell stacks for FDI using linear subspace identification," in *Proc. IEEE Int. Conf. Control Appl. (CCA)*, Piscataway, NJ, USA, Sep. 2008, pp. 341–346.

[72] J. Schmalstieg, S. Käbitz, M. Ecker, and D. U. Sauer, "A holistic aging model for Li(NiMnCo)O$_2$ based 18650 lithium-ion batteries," *J. Power Sources*, vol. 257, pp. 325–334, Jul. 2014.

[73] L. Lu, X. Han, J. Li, J. Hua, and M. Ouyang, "A review on the key issues for lithium-ion battery management in electric vehicles," *J. Power Sources*, vol. 226, pp. 272–288, Mar. 2013.

[74] M. Caspar, T. Eiler, and S. Hohmann, "Systematic comparison of active balancing: A model-based quantitative analysis," *IEEE Trans. Veh. Technol.*, vol. 67, no. 2, pp. 920–934, Feb. 2018.

[75] M. Beaudin, H. Zareipour, A. Schellenberglabe, and W. Rosehart, "Energy storage for mitigating the variability of renewable electricity sources: An updated review," *Energy Sustain. Develop.*, vol. 14, no. 4, pp. 302–314, Dec. 2010.

[76] M. Schönleber and E. Ivers-Tiffée, "Approximability of impedance spectra by RC elements and implications for impedance analysis," *Electrochem. Commun.*, vol. 58, pp. 15–19, Sep. 2015.

[77] T. Huria, M. Ceraolo, J. Gazzarri, and R. Jackey, "High fidelity electrical model with thermal dependence for characterization and simulation of high power lithium battery cells," in *Proc. IEEE Int. Electr. Vehicle Conf.*, Mar. 2012, pp. 1–8.

[78] M. Chen and G. A. Rincon-Mora, "Accurate electrical battery model capable of predicting runtime and I-V performance," *IEEE Trans. Energy Convers.*, vol. 21, no. 2, pp. 504–511, Jun. 2006.

[79] M. Eckert, L. Kölsch, and S. Hohmann, "Fractional algebraic identification of the distribution of relaxation times of battery cells," in *Proc. 54th IEEE Conf. Decis. Control (CDC)*. Piscataway, NJ, USA, Dec. 2015, pp. 2101–2108.

[80] V. Marano, S. Onori, Y. Guezennec, G. Rizzoni, and N. Madella, "Lithium-ion batteries life estimation for plug-in hybrid electric vehicles," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Piscataway, NJ, USA, Sep. 2009, pp. 536–543.

[81] S. J. Moura, J. L. Stein, and H. K. Fathy, "Battery-health conscious power management in plug-in hybrid electric vehicles via electrochemical modeling and stochastic control," *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 3, pp. 679–694, May 2013.

[82] L. Tang, G. Rizzoni, and S. Onori, "Energy management strategy for HEVs including battery

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

life optimization," *IEEE Trans. Transport. Electrific.*, vol. 1, no. 3, pp. 211–222, Oct. 2015.

[83] J. Wang *et al.*, "Cycle-life model for graphite-LiFePO$_4$ cells," *J. Power Sources*, vol. 196, no. 8, pp. 3942–3948, Apr. 2011.

[84] A. Cordoba-Arenas, S. Onori, and G. Rizzoni, "A control-oriented lithium-ion battery pack model for plug-in hybrid electric vehicle cycle-life studies and system design with consideration of health management," *J. Power Sources*, vol. 279, pp. 791–808, Apr. 2015.

[85] S. Onori, P. Spagnol, V. Marano, Y. Guezennec, and G. Rizzoni, "A new life estimation method for lithium-ion batteries in plug-in hybrid electric vehicles applications," *Int. J. Power Electron.*, vol. 4, no. 3, pp. 302–319, 2012.

[86] A. Khaligh and Z. Li, "Battery, ultracapacitor, fuel cell, and hybrid energy storage systems for electric, hybrid electric, fuel cell, and plug-in hybrid electric vehicles: State of the art," *IEEE Trans. Veh. Technol.*, vol. 59, no. 6, pp. 2806–2814, Jul. 2010.

[87] M. Uzunoglu and M. S. Alam, "Dynamic modeling, design and simulation of a PEM fuel cell/ultra-capacitor hybrid system for vehicular applications," *Energy Convers. Manage.*, vol. 48, no. 5, pp. 1544–1553, 2007.

[88] R. Meyer, R. A. DeCarlo, P. H. Meckl, C. Doktorcik, and S. Pekarek, "Hybrid model predictive power flow control of a fuel cell-battery vehicle," in *Proc. Amer. Control Conf.*, Jun. 2011, pp. 2725–2731.

[89] Y. Jia, "Dynamic simulation research of hydrodynamic retarder in brake process," in *Proc. Int. Conf. Transp., Mech., Electr. Eng. (TMEE)*, Dec. 2011, pp. 1193–1196.

[90] S. Bauer, A. Suchaneck, and F. P. León, "Thermal and energy battery management optimization in electric vehicles using Pontryagin's maximum principle," *J. Power Sources*, vol. 246, pp. 808–818, Jan. 2014.

[91] S. Terwen, M. Back, and V. Krebs, "Predictive powertrain control for heavy duty trucks," *IFAC Proc. Volumes*, vol. 37, no. 22, pp. 105–110, Apr. 2004.

[92] S. Terwen, "Vorausschauende Längsregelung schwerer lastkraftwagen," *Schriften des Instituts für Regelungs-und Steuerungssysteme, Karlsruher Institut für Technologie*. Karlsruhe, Germany: KIT Scientific Publishing, 2010.

[93] A. Sciarretta and L. Guzzella, "Control of hybrid electric vehicles," *IEEE Control Syst.*, vol. 27, no. 2, pp. 60–70, Apr. 2007.

[94] S. G. Wirasingha and A. Emadi, "Classification and review of control strategies for plug-in hybrid electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 60, no. 1, pp. 111–122, Jan. 2011.

[95] P. Zhang, F. Yan, and C. Du, "A comprehensive analysis of energy management strategies for hybrid electric vehicles based on bibliometrics," *Renew. Sustain. Energy Rev.*, vol. 48, pp. 88–104, Aug. 2015.

[96] C. M. Martinez, X. Hu, D. Cao, E. Velenis, B. Gao, and M. Wellers, "Energy management in plug-in hybrid electric vehicles: Recent progress and a connected vehicles perspective," *IEEE Trans. Veh. Technol.*, vol. 66, no. 6, pp. 4534–4549, Jun. 2017.

[97] A. Panday and H. O. Bansal, "A review of optimal energy management strategies for hybrid electric vehicle," *Int. J. Veh. Technol.*, vol. 2014, pp. 1–19, Jan. 2014.

[98] J. P. Trovão, P. G. Pereirinha, H. M. Jorge, and C. H. Antunes, "A multi-level energy management system for multi-source electric vehicles—An integrated rule-based meta-heuristic approach," *Appl. Energy*, vol. 105, pp. 304–318, May 2013.

[99] Z. Yu, D. Zinger, and A. Bose, "An innovative optimal power allocation strategy for fuel cell, battery and supercapacitor hybrid electric vehicle," *J. Power Sources*, vol. 196, no. 4, pp. 2351–2359, Feb. 2011.

[100] P. Thounthong, S. Pierfederici, J.-P. Martin, M. Hinaje, and B. Davat, "Modeling and control of fuel cell/supercapacitor hybrid source based on differential flatness control," *IEEE Trans. Veh. Technol.*, vol. 59, no. 6, pp. 2700–2710, Jul. 2010.

[101] M. Ortuzar, J. Moreno, and J. Dixon, "Ultracapacitor-based auxiliary energy system for an electric vehicle: Implementation and evaluation," *IEEE Trans. Ind. Electron.*, vol. 54, no. 4, pp. 2147–2156, Aug. 2007.

[102] A. S. Samosir and A. H. M. Yatim, "Implementation of dynamic evolution control of bidirectional DC–DC converter for interfacing ultracapacitor energy storage to fuel-cell system," *IEEE Trans. Ind. Electron.*, vol. 57, no. 10, pp. 3468–3473, Oct. 2010.

[103] M. Diehl, H. G. Bock, H. Diedam, and P.-B. Wieber, "Fast direct multiple shooting algorithms for optimal robot control," in *Fast Motions in Biomechanics and Robotics* (Lecture Notes in Control and Information Sciences), vol. 340, M. Diehl and K. Mombaur, Eds. Berlin, Germany: Springer, 2006, pp. 65–93.

[104] M. Werling, *Optimale Aktive Fahreingriffe: Für Sicherheits-und Komfortsysteme in Fahrzeugen*. Munich, Germany: Oldenbourg Wissenschaftsverlag, 2017.

[105] L. A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965.

[106] M. Ansarey, M. Shariat Panahi, H. Ziarati, and M. Mahjoob, "Optimal energy management in a dual-storage fuel-cell hybrid vehicle using multi-dimensional dynamic programming," *J. Power Sources*, vol. 250, pp. 359–371, Mar. 2014.

[107] N. Sulaiman, M. A. Hannan, A. Mohamed, E. H. Majlan, and W. R. Wan Daud, "A review on energy management system for fuel cell hybrid electric vehicle: Issues and challenges," *Renew. Sustain. Energy Rev.*, vol. 52, pp. 802–814, Dec. 2015.

[108] S. N. Motapon, L.-A. Dessaint, and K. Al-Haddad, "A comparative study of energy management schemes for a fuel-cell hybrid emergency power system of more-electric aircraft," *IEEE Trans. Ind. Electron.*, vol. 61, no. 3, pp. 1320–1334, Mar. 2014.

[109] J. Peng, H. He, and R. Xiong, "Rule based energy management strategy for a series–parallel plug-in hybrid electric bus optimized by dynamic programming," *Appl. Energy*, vol. 185, pp. 1633–1643, Jan. 2017.

[110] Y. Zhu, Y. Chen, G. Tian, H. Wu, and Q. Chen, "A four-step method to design an energy management strategy for hybrid vehicles," in *Proc. Amer. Control Conf.*, vol. 1. Piscataway, NJ, USA, Jun./Jul. 2004, pp. 156–161.

[111] A. Boukehili, Y. T. Zhang, Q. Zhao, C. Q. Ni, H. F. Su, and G. J. Huang, "Hybrid vehicle power management modeling and refinement," *Int. J. Automot. Technol.*, vol. 13, no. 6, pp. 987–998, 2012.

[112] L. Tribioli, M. Barbieri, R. Capata, E. Sciubba, E. Jannelli, and G. Bella, "A real time energy management strategy for plug-in hybrid electric vehicles based on optimal control theory," *Energy Procedia*, vol. 45, pp. 949–958, 2014.

[113] S. Ahmadi and S. M. T. Bathaee, "Multi-objective genetic optimization of the fuel cell hybrid vehicle supervisory system: Fuzzy logic and operating mode control strategies," *Int. J. Hydrogen Energy*, vol. 40, no. 36, pp. 12512–12521, Sep. 2015.

[114] Y.-J. Huang, C.-L. Yin, and J.-W. Zhang, "Design of an energy management strategy for parallel hybrid electric vehicles using a logic threshold and instantaneous optimization method," *Int. J. Automot. Technol.*, vol. 10, no. 4, pp. 513–521, Aug. 2009.

[115] B. Škugor, J. Deur, M. Cipek, and D. Pavković, "Design of a power-split hybrid electric vehicle control system utilizing a rule-based controller and an equivalent consumption minimization strategy," *Proc. Inst. Mech. Eng., D, J. Automobile Eng.*, vol. 228, no. 6, pp. 631–648, 2014.

[116] R. Koubaa and L. Krichen, "Double layer metaheuristic based energy management strategy for a fuel cell/ultra-capacitor hybrid electric vehicle," *Energy*, vol. 133, pp. 1079–1093, Aug. 2017.

[117] R. Langari and J.-S. Won, "Intelligent energy management agent for a parallel hybrid vehicle—Part I: System architecture and design of the driving situation identification process," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 925–934, May 2005.

[118] J.-S. Won and R. Langari, "Intelligent energy management agent for a parallel hybrid vehicle—Part II: Torque distribution, charge sustenance strategies, and performance results," *IEEE Trans. Veh. Technol.*, vol. 54, no. 3, pp. 935–953, May 2005.

[119] S.-I. Jeon, S.-T. Jo, Y.-I. Park, and J.-M. Lee, "Multi-mode driving control of a parallel hybrid electric vehicle using driving pattern recognition," *J. Dyn. Syst., Meas., Control*, vol. 124, no. 1, pp. 141–149, Mar. 2002.

[120] Y. Yokoi *et al.*, "Driving pattern prediction for an energy management system of hybrid electric vehicles in a specific driving course," in *Proc. 30th Annu. Conf. IEEE Ind. Electron. Soc.*, Piscataway, NJ, USA, Nov. 2004, pp. 1727–1732.

[121] H. Zhang, X. Li, X. Liu, and J. Yan, "Enhancing fuel cell durability for fuel cell plug-in hybrid electric vehicles through strategic power management," *Appl. Energy*, vol. 241, pp. 483–490, May 2019.

[122] M. Kim, D. Jung, and K. Min, "Hybrid thermostat strategy for enhancing fuel economy of series hybrid intracity bus," *IEEE Trans. Veh. Technol.*, vol. 63, no. 8, pp. 3569–3579, Oct. 2014.

[123] D. Feroldi, M. Serra, and J. Riera, "Energy management strategies based on efficiency map for fuel cell hybrid vehicles," *J. Power Sources*, vol. 190, no. 2, pp. 387–401, 2009.

[124] Y. Kim, T.-K. Lee, and Z. Filipi, "Frequency domain power distribution strategy for series hybrid electric vehicles," *SAE Int. J. Alternative Powertrains*, vol. 1, no. 1, pp. 208–218, 2012.

[125] Y. Kim, A. Salvi, J. B. Siegel, Z. S. Filipi, A. G. Stefanopoulou, and T. Ersal, "Hardware-in-the-loop validation of a power management strategy for hybrid powertrains," *Control Eng. Pract.*, vol. 29, pp. 277–286, Aug. 2014.

[126] D. Driankov, H. Hellendoorn, and M. Reinfrank, *An Introduction to Fuzzy Control*. Berlin, Germany: Springer, 1993.

[127] F. R. Salmasi, "Control strategies for hybrid electric vehicles: Evolution, classification, comparison, and future trends," *IEEE Trans. Veh. Technol.*, vol. 56, no. 5, pp. 2393–2404, Sep. 2007.

[128] D. Gao, Z. Jin, and Q. Lu, "Energy management strategy based on fuzzy logic for a fuel cell hybrid bus," *J. Power Sources*, vol. 185, no. 1, pp. 311–317, Oct. 2008.

[129] S. G. Li, S. M. Sharkh, F. C. Walsh, and C. N. Zhang, "Energy and battery management of a plug-in series hybrid electric vehicle using fuzzy logic," *IEEE Trans. Veh. Technol.*, vol. 60, no. 8, pp. 3571–3585, Oct. 2011.

[130] G. Shi, Y. Jing, A. Xu, and J. Ma, "Study and simulation of based-fuzzy-logic parallel hybrid electric vehicles control strategy," in *Proc. ISDA*, A. Abraham and Y. Chen, Eds. Los Alamitos, CA, USA: IEEE Press, Oct. 2006, pp. 280–284.

[131] M. Mohebbi, M. Charkhgard, and M. Farrokhi, "Optimal neuro-fuzzy control of parallel hybrid electric vehicles," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Piscataway, NJ, USA, Sep. 2005, pp. 252–256.

[132] Z. Chen, M. Abul Masrur, and Y. L. Murphey, "Intelligent vehicle power management using machine learning and fuzzy logic," in *Proc. IEEE Int. Conf. Fuzzy Syst. (IEEE World Congr. Comput. Intell.)*, Piscataway, NJ, USA, Jun. 2008, pp. 2351–2358.

[133] W. Dazhi, Y. Jie, Y. Qing, W. Dongsheng, and J. Hui, "Estimation and control of hybrid electric

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Rudolf *et al.*: Toward Holistic Energy Management Strategies for FCHEVs in Heavy-Duty Applications

vehicle using artificial neural networks," in *Proc. 2nd IEEE Conf. Ind. Electron. Appl.*, Piscataway, NJ, USA, May 2007, pp. 35–40.

[134] M. Derakhshan and K. H. Shirazi, "Optimized fuzzy controller for a power–torque distribution in a hybrid vehicle with a parallel configuration," *Proc. Inst. Mech. Eng., D, J. Automobile Eng.*, vol. 228, no. 14, pp. 1654–1674, 2014.

[135] D. Ambühl, "Energy management strategies for hybrid electric vehicles," Ph.D. dissertation, Dept. Mech. Process Eng., ETH Zürich, Zürich, Switzerland, 2009.

[136] J. Lofberg, "YALMIP : A toolbox for modeling and optimization in MATLAB," in *Proc. IEEE Int. Conf. Robot. Autom.*, Taipei, Taiwan, Sep. 2004, pp. 284–289.

[137] J. A. E. Andersson, J. Gillis, G. Horn, J. B. Rawlings, and A. Diehl, "CasADi: A software framework for nonlinear optimization and optimal control," *Math. Program. Comput.*, vol. 11, no. 1, pp. 1–36, 2019.

[138] M. Morari, F. Borrelli, and A. Bemporad, *Predictive Control for Linear and Hybrid Systems*. Cambridge, U.K.: Cambridge Univ. Press, 2017.

[139] R. T. Bambang, A. S. Rohman, C. J. Dronkers, R. Ortega, and A. Sasongko, "Energy management of fuel cell/battery/supercapacitor hybrid power sources using model predictive control," *IEEE Trans. Ind. Informat.*, vol. 10, no. 4, pp. 1992–2002, Nov. 2014.

[140] S. Xie, H. He, and J. Peng, "An energy management strategy based on stochastic model predictive control for plug-in hybrid electric buses," *Appl. Energy*, vol. 196, pp. 279–288, Jun. 2017.

[141] S. Zhang, R. Xiong, and F. Sun, "Model predictive control for power management in a plug-in hybrid electric vehicle with a hybrid energy storage system," *Appl. Energy*, vol. 185, pp. 1654–1662, Jan. 2017.

[142] S. Di Cairano, D. Bernardini, A. Bemporad, and I. V. Kolmanovsky, "Stochastic MPC with learning for driver-predictive vehicle control and its application to HEV energy management," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 3, pp. 1018–1031, May 2014.

[143] M. Back, S. Terwen, and V. Krebs, "Predictive powertrain control for hybrid electric vehicles," *IFAC Proc. Volumes*, vol. 37, no. 22, pp. 439–444, 2004.

[144] F. Lattemann, K. Neiss, S. Terwen, and T. Connolly, "The predictive cruise control—A system to reduce fuel consumption of heavy duty trucks," *SAE Trans., J. Commercial Vehicles*, vol. 113, pp. 139–146, Jan. 2004.

[145] C. Dextreit and I. V. Kolmanovsky, "Game theory controller for hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 2, pp. 652–663, Mar. 2014.

[146] M. J. Gielniak and Z. J. Shen, "Power management strategy based on game theory for fuel cell hybrid electric vehicles," in *Proc. IEEE 60th Veh. Technol. Conf.*, Piscataway, NJ, USA, Sep. 2004, pp. 4422–4426.

[147] G. Heppeler, M. Sonntag, and O. Sawodny, "Fuel efficiency analysis for simultaneous optimization of the velocity trajectory and the energy management in hybrid electric vehicles," *IFAC Proc. Volumes*, vol. 47, no. 3, pp. 6612–6617, 2014.

[148] H. Zheng, J. Wu, W. Wu, and Y. Wang, "Integrated motion and powertrain predictive control of intelligent fuel cell/battery hybrid vehicles," *IEEE Trans. Ind. Informat.*, vol. 16, no. 5, pp. 3397–3406, May 2020.

[149] S. Boyd, S. P. Boyd, and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[150] B. Egardt, N. Murgovski, M. Pourabdollah, and L. Johannesson Mardh, "Electromobility studies based on convex optimization: Design and control issues regarding vehicle electrification," *IEEE Control Syst.*, vol. 34, no. 2, pp. 32–49, Apr. 2014.

[151] G. Paganelli, T. M. Guerra, S. Delprat, J.-J. Santin, M. Delhom, and E. Combes, "Simulation and assessment of power control strategies for a parallel hybrid car," *Proc. Inst. Mech. Eng., D, J. Automobile Eng.*, vol. 214, no. 7, pp. 705–717, Jul. 2000.

[152] C. Sun, F. Sun, and H. He, "Investigating adaptive-ECMS with velocity forecast ability for hybrid electric vehicles," *Appl. Energy*, vol. 185, pp. 1644–1653, Jan. 2017.

[153] D. P. Bertsekas, *Dynamic Programming and Optimal Control* (Athena Scientific Optimization and Computation Series), vol. 3, 3rd ed. Belmont, MA, USA: Athena Scientific, 2005.

[154] P. Pisu and G. Rizzoni, "A comparative study of supervisory control strategies for hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 15, no. 3, pp. 506–518, May 2007.

[155] D. Fares, R. Chedid, F. Panik, S. Karaki, and R. Jabr, "Dynamic programming technique for optimizing fuel cell hybrid vehicles," *Int. J. Hydrogen Energy*, vol. 40, no. 24, pp. 7777–7790, Jun. 2015.

[156] A. Sciarretta, G. De Nunzio, and L. L. Ojeda, "Optimal ecodriving control: Energy-efficient driving of road vehicles as an optimal control problem," *IEEE Control Syst.*, vol. 35, no. 5, pp. 71–90, Oct. 2015.

[157] T. Fletcher, R. Thring, and M. Watkinson, "An Energy Management Strategy to concurrently optimise fuel consumption & PEM fuel cell lifetime in a hybrid vehicle," *Int. J. Hydrogen Energy*, vol. 41, no. 46, pp. 21503–21515, 2016.

[158] A. Poursamad and M. Montazeri, "Design of genetic-fuzzy control strategy for parallel hybrid electric vehicles," *Control Eng. Pract.*, vol. 16, no. 7, pp. 861–873, Jul. 2008.

[159] Z. Chen, R. Xiong, and J. Cao, "Particle swarm optimization-based optimal power management of plug-in hybrid electric vehicles considering uncertain driving conditions," *Energy*, vol. 96, pp. 197–208, Feb. 2016.

[160] L. Serrao, S. Onori, and G. Rizzoni, "ECMS as a realization of Pontryagin's minimum principle for HEV control," in *Proc. Amer. Control Conf.*, Piscataway, NJ, USA, Jun. 2009, pp. 3964–3969.

[161] L. V. Pérez and G. O. García, "State constrained optimal control applied to supervisory control in HEVs," *Oil Gas Sci. Technol.-Revue de l'Institut Français du Pétrole*, vol. 65, no. 1, pp. 191–201, 2010.

[162] R. Dosthosseini, A. Z. Kouzani, and F. Sheikholeslam, "Direct method for optimal power management in hybrid electric vehicles," *Int. J. Automot. Technol.*, vol. 12, no. 6, pp. 943–950, Nov. 2011.

[163] Y. Liu, J. Li, Z. Chen, D. Qin, and Y. Zhang, "Research on a multi-objective hierarchical prediction energy management strategy for range extended fuel cell vehicles," *J. Power Sources*, vol. 429, pp. 55–66, Jul. 2019.

[164] D. Ambühl, O. Sundström, A. Sciarretta, and L. Guzzella, "Explicit optimal control policy and its practical application for hybrid electric powertrains," *Control Eng. Pract.*, vol. 18, no. 12, pp. 1429–1439, Dec. 2010.

[165] L. Serrao, S. Onori, A. Sciarretta, Y. Guezennec, and G. Rizzoni, "Optimal energy management of hybrid electric vehicles including battery aging," in *Proc. Amer. Control Conf.*, Jun. 2011, pp. 2125–2130.

[166] L. Serrao, S. Onori, and G. Rizzoni, "A comparative analysis of energy management strategies for hybrid electric vehicles," *J. Dyn. Syst., Meas., Control*, vol. 133, no. 3, May 2011.

[167] L. Xu, J. Li, J. Hua, X. Li, and M. Ouyang, "Optimal vehicle control strategy of a fuel cell/battery hybrid city bus," *Int. J. Hydrogen Energy*, vol. 34, no. 17, pp. 7323–7333, Sep. 2009.

[168] H. Li, A. Ravey, A. N'Diaye, and A. Djerdir, "A novel equivalent consumption minimization strategy for hybrid electric vehicle powered by fuel cell, battery and supercapacitor," *J. Power Sources*, vol. 395, pp. 262–270, Aug. 2018.

[169] J. Lescot, A. Sciarretta, Y. Chamaillard, and A. Charlet, "On the integration of optimal energy management and thermal management of hybrid electric vehicles," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2010, pp. 1–6.

[170] H. Li, A. Ravey, A. N'Diaye, and A. Djerdir, "Online adaptive equivalent consumption minimization strategy for fuel cell hybrid electric vehicle considering power sources degradation," *Energy Convers. Manage.*, vol. 192, pp. 133–149, Jul. 2019.

[171] C. Musardo, G. Rizzoni, Y. Guezennec, and B. Staccia, "A-ECMS: An adaptive algorithm for hybrid electric vehicle energy management," *Eur. J. Control*, vol. 11, nos. 4–5, pp. 509–524, Jan. 2005.

[172] R. S. Sutton and A. Barto, *Reinforcement Learning: An Introduction* (Adaptive Computation and Machine Learning), 2nd ed. Cambridge, MA, USA: MIT Press, 2018.

[173] M. Haubmann, D. Barroso, C. Vidal, L. Bruck, and A. Emadi, "A novel multi-mode adaptive energy consumption minimization strategy for P1-P2 hybrid electric vehicle architectures," in *Proc. IEEE Transp. Electrific. Conf. Expo (ITEC)*, Piscataway, NJ, USA, Jun. 2019, pp. 1–6.

[174] Y. Hu, W. Li, K. Xu, T. Zahid, F. Qin, and C. Li, "Energy management strategy for a hybrid electric vehicle based on deep reinforcement learning," *Appl. Sci.*, vol. 8, no. 2, p. 187, Jan. 2018.

[175] C. Liu and Y. L. Murphey, "Power management for plug-in hybrid electric vehicles using reinforcement learning with trip information," in *Proc. IEEE Transp. Electrific. Conf. Expo (ITEC)*, Piscataway, NJ, USA, Jun. 2014, pp. 1–6.

[176] T. Liu, X. Hu, S. E. Li, and D. Cao, "Reinforcement learning optimized look-ahead energy management of a parallel hybrid electric vehicle," *IEEE/ASME Trans. Mechatronics*, vol. 22, no. 4, pp. 1497–1507, Aug. 2017.

[177] G. Williams *et al.*, "Information theoretic MPC for model-based reinforcement learning," in *Proc. IEEE Int. Conf. Robot. Automat. (ICRA)*, Piscataway, NJ, USA, May/Jun. 2017, pp. 1714–1721.

[178] R. Xiong, J. Cao, and Q. Yu, "Reinforcement learning-based real-time power management for hybrid energy storage system in the plug-in hybrid electric vehicle," *Appl. Energy*, vol. 211, pp. 538–548, Feb. 2018.

[179] R. C. Hsu, S.-M. Chen, W-Y. Chen, and C.-T. Liu, "A reinforcement learning based dynamic power management for fuel cell hybrid electric vehicle," in *Proc. Joint 8th Int. Conf. Soft Comput. Intell. Syst. (SCIS) 17th Int. Symp. Adv. Intell. Syst. (ISIS)*. Piscataway, NJ, USA, 2016, pp. 460–464.

[180] C. Sun, X. Hu, S. J. Moura, and F. Sun, "Velocity predictors for predictive energy management in hybrid electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 3, pp. 1197–1204, May 2015.

[181] H. Khayyam and A. Bab-Hadiashar, "Adaptive intelligent energy management system of plug-in hybrid electric vehicle," *Energy*, vol. 69, pp. 319–335, May 2014.

[182] S. Onori, L. Serrao, and G. Rizzoni, *Hybrid Electric Vehicles*. London, U.K.: Springer, 2016.

[183] T. Romijn, M. Donkers, J. Kessels, and S. Weiland, "Receding horizon control for distributed energy management of a hybrid heavy-duty vehicle with auxiliaries," *IFAC-PapersOnLine*, vol. 48, no. 15, pp. 203–208, 2015.

[184] P. Ahmadi, S. H. Torabi, H. Afsaneh, Y. Sadegheih, H. Ganjehsarabi, and M. Ashjaee, "The effects of driving patterns and PEM fuel cell degradation on the lifecycle assessment of hydrogen fuel cell vehicles," *Int. J. Hydrogen Energy*, vol. 45, no. 5, pp. 3595–3608, 2020.

[185] D. Ambuhl and L. Guzzella, "Predictive reference signal generator for hybrid electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 58, no. 9, pp. 4730–4740, Nov. 2009.

ABOUT THE AUTHORS

Thomas Rudolf received the M.Sc. degree from the Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany, in 2017. He studied electrical engineering and information technology, with a focus on dynamic systems and automation, at KIT and the Chalmers University of Technology, Gothenburg, Sweden.

Since 2018, he has been a Research Associate with the FZI Research Center for Information Technology, Karlsruhe, where he is working on the fields of energy management in hybrid vehicles and maneuver planning for highly automated driving.

Tobias Schürmann received the M.Sc. degree in electrical engineering and information technology from the Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany, in 2014.

Since 2015, he has been a Research Associate with the FZI Research Center for Information Technology, Karlsruhe, where he is working on the fields of vehicle power network topologies and distributed control.

Stefan Schwab received the M.Sc. degree in electrical engineering and information technology from the Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany, and the University of Newcastle, Callaghan, NSW, Australia, in 2012, and the Ph.D. degree with a focus on guaranteed verification of dynamic system from KIT in 2019.

He is currently the Department Manager and the Research Group Leader of the Department Control in Information Technology (CIT) at the FZI Research Center for Information Technology, Karlsruhe.

Sören Hohmann (Member, IEEE) received the bachelor's and master's degrees from the Technical University of Braunschweig (TU Braunschweig), Braunschweig, Germany, and the École nationale supérieure d'électricité et de mécanique, Nancy, France, during (1992–1997), the Ph.D. degree, with a thesis on nonlinear time-discrete control systems, in 2002, and the Diploma degree in electrical engineering, with a specialization in control technology, from the University of Karlsruhe (TH Karlsruhe), Karlsruhe, Germany.

He was with BMW, Munich, Germany, where he was the Head of the development of advanced braking systems and series development of integrated vehicle dynamics controls (ICM) and sensors. He was the Head of the advance and series development of active safety systems. Since Autumn 2010, he has been the Head of the Institute of Control Systems, Karlsruhe Institute of Technology (KIT), Karlsruhe. Since April 2015, he has been a member of the Board of Scientific Directors of the FZI Research Center for Information Technology, Karlsruhe. He is currently an Elected Deputy Spokesperson of the KIT Information Systems Technologies Center (KCIST), and an Elected Member of the Council for Research and Promotion of Young Scientists (CRYS) of KIT.