Distributed MPC for Cost-Optimal Control of FC-Battery Shipboard Microgrids

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***Abstract*—The electrification of ship power systems plays a center role in the mobility transition towards sustainable transport solutions. It allows the integration of various power sources, energy storage systems, and intermittent generation. The integration of an increasing number of components with distinct characteristics shapes the notion of a shipboard microgrid which benefits from a modular approach in its design to reduce costs and uncertainties. DC distribution facilitates the modular design by simplifying the control, and, combined with power electronics interfaces, increases the controllability of power flows in the system. To handle the increasing system complexity, this work proposes a distributed and predictive control approach, addressing the modular topology of future shipboard power systems and leveraging load power forecasting. Investigations show that a distributed, predictive energy management reaches a similar performance as a centralized implementation. For a modular shipboard power system, the proposed method decreases both fuel and degradation costs with increasing performance gains for longer prediction horizons.**

***Index Terms*—Shipboard DC microgrid, Energy Management, MPC, Distributed Control, Fuel Cells.**

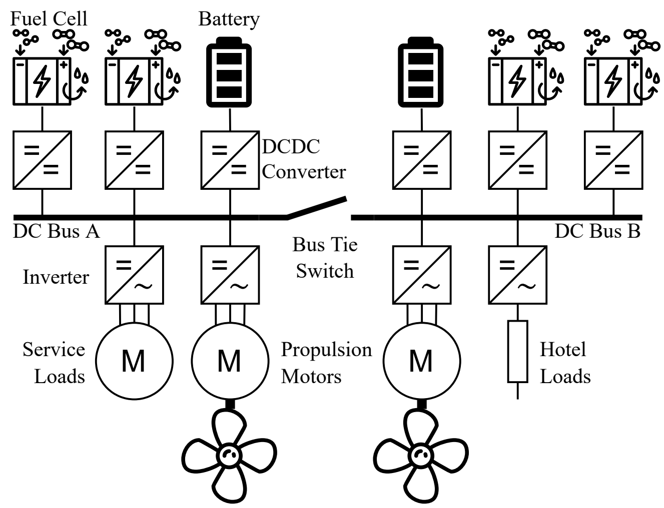

Fig. 1. Modular FC-Battery Shipboard DC Microgrid with four FC modules and two battery modules

I. Introduction

The design of marine vessels sees a shift towards the electrification of the shipboard power system. An increased amount of different technologies is integrated into the system, such as fuel cells (FCs) [1], energy storage systems (ESSs) [2], intermittent power generation, and electric propulsion [3], with a trend towards modularization and distribution of generation and storage units [4]. The increased system complexity makes the coordination of all energy resources a key challenge. DC distribution technology is receiving interest as a solution to tie all different components together into a shipboard DC microgrid [5], [6]. Equipped with power electronics interfaces, the increased complexity of the shipboard microgrid can be met with the high controllability of power flows.

This work aims at the minimization of the operational cost of hydrogen FC-based shipboard power systems (SPSs). The main drivers are the fuel cost and stack replacement cost due to degradation. The energy management strategy (EMS) can be realized as a centralized optimization, assuming full knowledge of parameters and states of all components [7]. However, such a solution requires careful parameterization, a high computational burden, and lacks scalability and resilience towards faults [8]. An alternative lies in the shift towards a distributed architecture. The advantages of distributed control for hybrid systems are shown by [9]. A multi-agent distributed control for the fuel consumption minimization with multiple diesel generators is investigated by [10]. Distributed state-of-charge (SoC)-management of ESSs in shipboard microgrids is addressed by [11]. Further, an instantaneous optimization fails to properly account for dynamic costs and excludes insights on future disturbances, for which model predictive control (MPC) is a common solution [12].

This work proposes a distributed, model-predictive approach for the cost-optimal energy management in DC shipboard power systems with a modular FC-battery power system topology. To this end, we derive a distributed implementation of an optimization-based energy management which allows the integration of multiple power system components and an adaptation to individual characteristics. In addition, the inclusion of load predictions in a predictive energy management allows for the anticipation and avoidance of increased operating costs due to dynamic operation. The proposed method is compared to a centralized MPC to evaluate the effect of the altered control architecture on the energy management performance.

The remainder of this paper is organized as follows. Section II derives the proposed approach for the distributed equivalent consumption minimization strategy (ECMS) and MPC for the control of modular FC-battery DC SPS and presents algorithms for the implementation in local and centralized controllers. In Section III, the performance of centralized and distributed energy management strategies as well as the performance of predictive control for different prediction and optimization horizons are evaluated. Finally, Section IV reviews the contributions made in this work and gives an outlook on future research activities on this topic.

II. Power System Control

We consider a shipboard DC microgrid whose primary equipment is comprised of FCs, batteries, and power-controlled loads. Power generation and energy storage systems are connected to the DC bus via DC-DC converters, whereas loads are interfaced via inverters, as shown in Fig. 1. The power system model follows the approach described in [7].

This study focuses on the energy management task, whereas fast-acting ESSs are utilized to stabilize the DC bus voltage, compensating fast power fluctuations, as in [13]. This section introduces a generalized approach for the distributed optimization of the energy management in SPS. Consequently, the local optimization problems for FC and battery modules, and the system wide optimization problems are described. Finally, algorithms for an instantaneous and predictive distributed energy management are presented.

A. Problem Formulation

We consider a shipboard power system with a set M of distributed units, whose power output can be controlled. Each unit $m \in M$ has an individual cost function $f_m(p_m, x_m)$ where p_m is the unit's power output and x_m a vector of states influencing its cost function. The power system is subject to disturbances, posed by power loads and intermittent generation, which can be aggregated as a scalar p_{load}. Considering only one time instant k, the energy management's goal is to minimize the total cost of power generation while meeting the power balance constraints:

$$\min_{p_{m,k}} \sum_{m \in M} f_m(p_{m,k}, x_{m,k}) \quad s.t. \sum_{m \in M} p_{m,k} = p_{load,k} \tag{1}$$

This optimization problem is separable via dual decomposition [14], such that each unit solves a local optimization problem given a fixed Lagrange multiplier μ:

$$\min_{p_m} f_m(p_m, x_m) - \mu p_m, \forall m \in M \tag{2}$$

A central coordinator is required to adjust μ, functioning as a system wide price, to satisfy the power balance constraint.

B. Local Optimization Problems

We consider a power system equipped with a set of FCs I and a set of batteries J that make up all distributed generation ($I \cup J = M$). Each individual cost is a function of the system's parameters, states, and control inputs. Additionally, every component is subject to individual constraints, most notably on the power output, power gradient, and battery SoC. The operating cost of a FC module i is a function of its power level and power gradient, and incorporates both fuel costs as well as cost for the operation-dependent cell degradation. We formulate the costs as a time discrete function with an optimization time period Δt. Given the power $p_{i,k}$ of module i at time k as a state, the cost function for transitioning to $p_{i,k+1}$ at the next time instant is

$$f_i(p_{i,k+1}, p_{i,k}) = \\ k_{2,i}p_{i,k+1}^2 + k_{1,i}p_{i,k+1} + k_{0,i} + k_{d,i}(\Delta t(p_{i,k+1} - p_{i,k}))^2 \tag{3}$$

where $k_{x,i}$ are module-specific coefficients. Fig. 2 shows exemplary static cost curves of a new and an aged FC module.

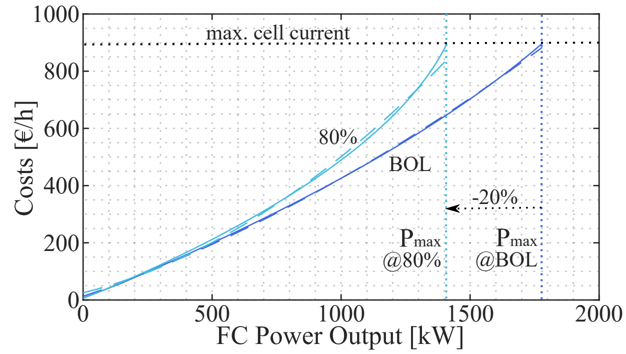

Fig. 2. Cost Model (solid) and Quadratic Approximation (Dashed) for PEMFC at BOL (blue) and 80% SoH (turquoise)

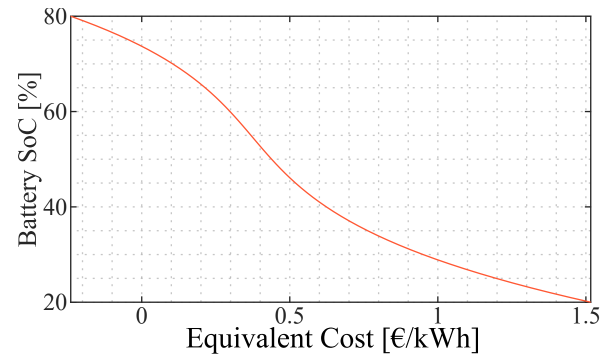

Fig. 3. SoC-dependent equivalent cost of stored energy

Similar to a conventional ECMS-approach [15], the stored energy in an ESS is assigned an SoC-dependent equivalent cost. Fig. 3 shows an exemplary case of the equivalent value of stored energy. With this, we define the cost function of a battery as

$$f_j(p_{j,k+1}, \xi_{j,k}) = \lambda(\xi_{j,k})(p_{j,k+1} + k_{2,j}p_{j,k+1}^2) \tag{4}$$

Using the local cost functions for FC and battery modules, a distributed ECMS can be derived via dual decomposition.

Each FC module has an optimal power output $p_i^*(\mu)$ solving its local optimization problem for the next time step $k+1$:

$$\max_{p_{i,k+1}} \mu p_{i,k+1} - f_i(p_{i,k+1}, p_{i,k}) \tag{5}$$

The equivalent problem for a battery module yields $p_j^*(\mu)$:

$$\max_{p_{j,k+1}} \mu p_{j,k+1} - f_j(p_{j,k+1}, \xi_{j,k}) \tag{6}$$

All modules have convex cost functions, i.e., p_i^* and p_j^*, and accordingly their sum, are monotonously increasing over μ:

$$\sum_{i\in I} \frac{dp_i^*}{d\mu} + \sum_{j\in J} \frac{dp_j^*}{d\mu} > 0 \tag{7}$$

C. Price Adjustment

The Lagrange multiplier μ acts as a virtual market price in the SPS. Due to the convexity of local functions, μ can be adjusted via a gradient descent approach until the power balance constraint is fulfilled. I.e., we can find an equilibrium with an optimal Lagrange multiplier μ^* where the sum of all distributed power generation is equal to the load:

$$\sum_{m\in M} p_m^*(\mu^*) - p_{load} = 0 \tag{8}$$

A generic FC-battery power system topology and the distribution of local and global optimization tasks is shown in Fig. 4. From the system perspective, the type and state of each unit is irrelevant as this information is included in the bids from each module. Hence, for the system level optimization it is sufficient to adjust μ^* iteratively until either a convergence criterion is fulfilled or a maximum number of iterations is reached. The price adjustment algorithm, as shown in Algorithm 1, is embedded in a central controller that broadcasts μ and sends a trigger signal to request power bids from all distributed modules. The parameter k_μ represents the step width for the price adjustment, ε is the convergence tolerance, and it and it_{max} are iteration counter and maximum number of iterations, respectively. Upon receiving a Trigger signal, each distributed unit updates its power bid according to Algorithm 2.

D. Predictive Optimization

Using time-series forecasting to predict the future load [7], [16], a set of predictions $\hat{p}_{load,k} \forall k = [1,..,N]$ with prediction horizon N can be obtained. An expansion of the local optimization problems over a series of discrete time intervals allows the optimization over the prediction horizon:

$$\max_{p_{i,k+1}} \sum_{k=0}^{N-1} \mu_{m,k} p_{i,k+1} - f_i(p_{i,k+1}, p_{i,k}) \tag{9}$$

$$\max_{p_{j,k+1}} \sum_{k=0}^{N-1} \mu_{m,k} p_{j,k+1} - f_j(p_{j,k+1}, \xi_{j,k}) + \lambda(\xi_{j,N}) E_{j,N} \tag{10}$$

where $E_{j,N}$ is the terminal battery energy, and $p_{i,0}$ and $\xi_{j,k}$ denote the FC power and battery SoC at time of optimization, respectively. Instead of a single market price, a vector of prices $\mu_{m,k} \forall k = [1,..,N]$ is needed here. The distributed MPC is solved iteratively following Algorithms 1 and 2, which are adapted to handle vectors instead of scalars. Each $\mu_{m,k}$ is adjusted individually for time instance k until each module bids a discrete power trajectory such that the power balance constraint is fulfilled at each time instance. Accordingly, an individual market price is established at each time instance. The initialization of μ starting a new optimization is realized by an index shift, assigning $\mu_k = \mu_{k+1} \forall k = [1,..,N-1]$.

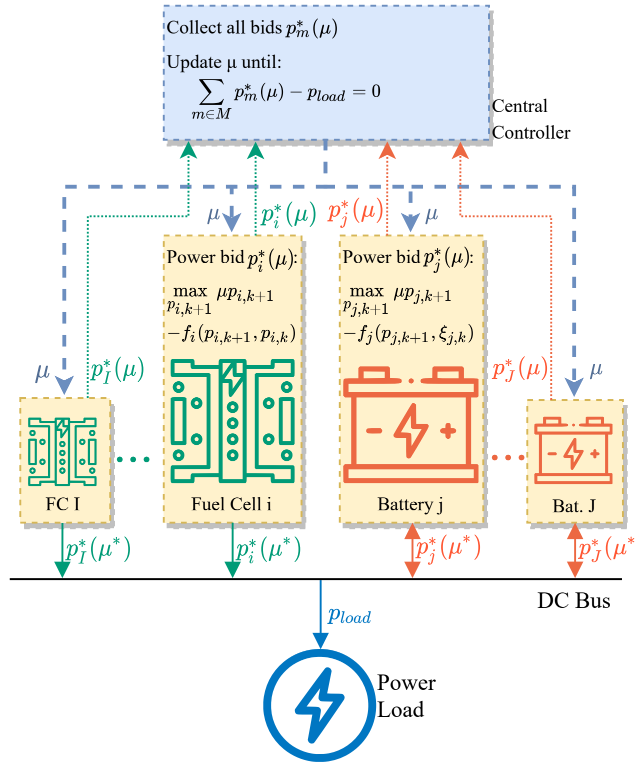

Fig. 4. Control architecture for distributed optimization of modular FC-battery power system via price adjustment

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Algorithm 1 Price adjustment by central controller

Input: p_m^*, p_{load}
if New Optimization **then**
  $it \leftarrow 0$
  $\mu \leftarrow \mu_{m,prev}$ {Start with Previous Equilibrium Price}
  Send Trigger
  return
end if
$P_{err} \leftarrow \sum_{m\in M} p_m^* - p_{load}$
if $P_{err} \le \varepsilon$ **or** $it > it_{max}$ **then**
  Stop Trigger {Converged or Max. Iterations Reached}
  return
end if
$it \leftarrow it + 1$
$\mu \leftarrow \mu + k_\mu P_{err}$ {Adjust Price}
Send Trigger
return
Output: μ, Trigger

Algorithm 2 Local bidding by distributed controllers

Input: μ, Trigger

if Trigger **then**

  $p_m^* \leftarrow \arg(\max \mu p_m - f_m((p_m), x_m)$ {Bid of Unit m}

end if

Output: p_m^*

TABLE I
SIMULATION AND OPTIMIZATION PARAMETERS

Parameter	Description	Value
T_{sim}	Simulation step size	1 s
T_{com}	Communication step size	0.1 s
T_{opt}	Optimization step size	5 s
T_{mpc}	MPC optimization interval	30 s
N_{mpc}	Optimization horizon	30
ε	Constraint tolerance (ECMS;MPC)	1;10 kW
it_{max}	Maximum iterations	45

E. Implementation

The distributed ECMS and MPC algorithms and the power system simulation are implemented in Matlab/Simulink. The various tasks of the simulation and control algorithms are running at different time steps, as shown in I. The simulation of the physical system is running at $T_{sim} = 1\,\text{s}$. Each optimization instance is initiated with a time period T_{opt}. The MPC optimizes over N_{mpc} discrete intervals with a time width of T_{mpc}. Each iteration of the distributed ECMS or MPC is completed at a rate of T_{com}. The maximum number of iterations it_{max} is set such that an optimization instance is finished before the next optimization is triggered. To reduce the delay caused by a high number of iterations, all modules' power references are updated already during the optimization using the intermediate power bids of the unconverged optimization.

III. Investigations

We investigate a tugboat, for which operational data and its power system design are available and described in [7]. The measurements have been cleaned and parsed into distinct mission profiles. For evaluating the performance of different strategies, we simulate the power system operation for 16 representative missions and accumulate the estimated cost for hydrogen and for degradation. In this section, several investigations show how the performance of the centralized and distributed approaches compares, and how predictive control can improve on the performance of instantaneous optimization.

A. Central vs Distributed

Initially, we consider a power system with one FC and one battery. [7] describes the power system design and a centralized ECMS and MPC for this case. The aim is to compare the performance of the centralized ECMS and MPC from [7] with the distributed strategies proposed in this study.

Fig. 5 shows the accumulated cost for hydrogen and cell degradation over the 16 simulated mission profiles. It can be seen that the centralized and distributed implementations of the ECMS yield almost identical results, which shows that the distributed EMS does not compromise the control performance. The distributed MPC even yields a slightly improved performance, which can be explained with minor differences in the optimization algorithm. The distributed implementation allows for the formulation of multiple problems of low complexity, yet the complete optimization problem can be highly complex and represent the real system more accurately than a single, centralized problem with less complexity.

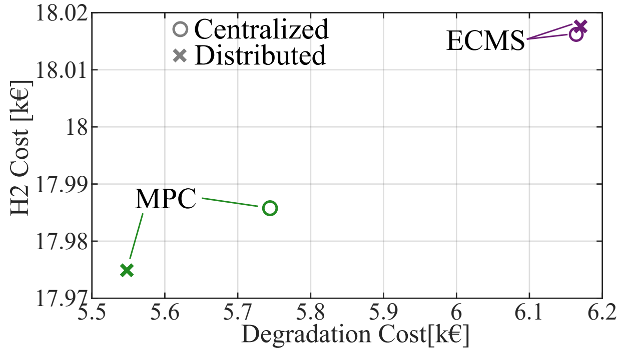

Fig. 5. Hydrogen and degradation costs for all mission profiles with centralized versus distributed implementations of ECMS and MPC

TABLE II
FC AND BATTERY PARAMETERS OF MODULAR POWER SYSTEM

Parameter	Description	Value
$P_{fc,A}$	Max. power FC A at BOL	1780 kW
$SoH_{fc,A}$	State-of-health of FC A	100 %
$P_{fc,B}$	Max. power FC B at BOL	1780 kW
$SoH_{fc,B}$	State-of-health of FC B	80 %
$P_{fc,C}$	Max. power FC C at BOL	445 kW
$SoH_{fc,A}$	State-of-health of FC A	85 %
$P_{fc,D}$	Max. power FC D at BOL	445 kW
$SoH_{fc,D}$	State-of-health of FC D	95 %
$E_{bat,A}$	Energy capacity battery A	1000 kWh
$R_{i,A}$	Inner resistance battery A	6.1 mΩ
$E_{bat,B}$	Energy capacity battery B	250 kWh
$R_{i,B}$	Inner resistance battery B	12.2 mΩ

B. Modular System Layout

Next, we consider a system layout that reflects the modular design of modern, zero-emission SPS. The power system is equipped with four FC systems and two battery energy storage systems. Each FC system has an individual power rating and aging state, influencing its polarization curve. Each battery has an individual capacity and differs in cell-specific internal resistance. Accordingly each unit's cost function is unique, which should be reflected in its operation. The parameters of the system components are listed in Table II.

The results of one exemplary mission profile using the distributed MPC are shown in Fig. 6. It can be seen that the FCs operate according to their respective marginal cost curves, whereas the power gradients are kept relatively low (Fig. 6b). Among the batteries, the SoCs are kept balanced while it is evident that battery B, which has a lower resistance relative to its capacity than battery A, is used more dynamically (Fig. 6c). The evolution of the optimal price in Fig. 6d gives

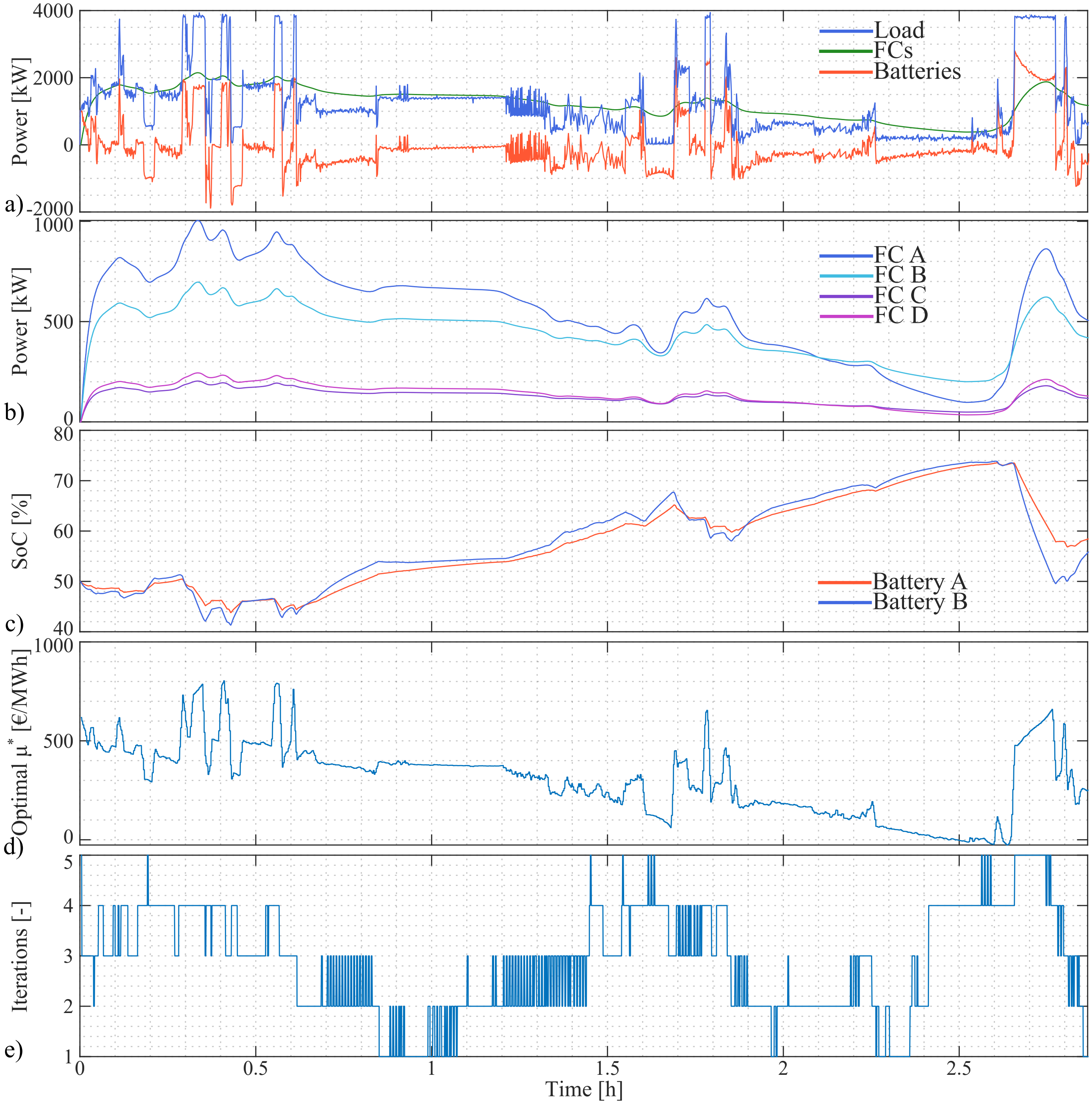

Fig. 6. Exemplary results for one mission profile with distributed MPC showing a) the total power split, b) FC power per module, c) battery SoC per module, d) the optimal price, e) iterations required for solving the optimization.

an indication of the marginal energy cost at a given point in time. The bids for time instances over the prediction horizon additionally give an indication of the future cost. The latter can potentially serve as an input for the load management. Finally, Fig. 6e shows that the number of iterations required for completing each optimization is low, meaning that the needed data traffic and computational effort is quite low.

The distributed ECMS and MPC, as well as a distributed filter-based controller with $60\,\mathrm{s}$ low-pass filter from [17] are simulated over multiple missions. The accumulated costs for the different strategies, split into hydrogen and degradation costs are shown in Fig. 7. Results show that both optimization-based strategies significantly improve over the filter-based benchmark. The MPC further improves the hydrogen consumption slightly and the degradation significantly.

A reliable load forecast over $15\,\mathrm{min}$ has been proven possible in [7]. To estimate the potential benefits of an increased prediction horizon, Fig. 8 shows the costs with MPC for varying prediction horizons. The results show that the performance improves with an increasing prediction and optimization horizon. The differences are quite small between horizons of $5\,\mathrm{min}$ and $15\,\mathrm{min}$. However, higher horizons

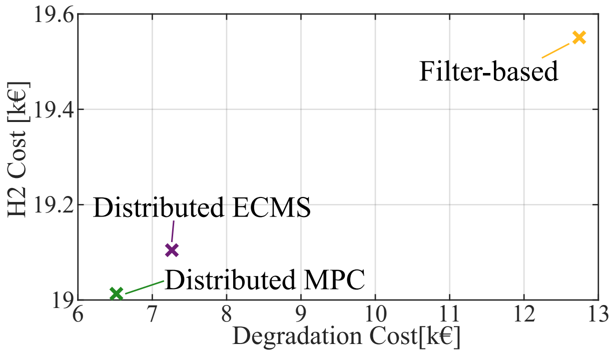

Fig. 7. Accumulated hydrogen and degradation costs with filter-based control, distributed ECMS, and distributed MPC

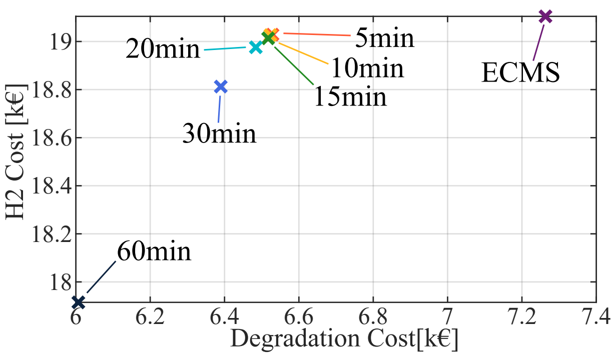

Fig. 8. Accumulated hydrogen and degradation costs for distributed MPC with different prediction horizon

promise significant gains for this specific case study. This highlights the importance of long prediction horizons for improving the operational efficiency of modular SPS.

IV. Conclusions

Considering the increasing focus on modularity in shipboard power systems, the architecture and algorithms of the power system control and energy management must follow this trend and in turn become modular. This facilitates the integration of novel technologies, such as zero-emission power generation and storage systems. The way to achieve this is a shift from a centralized towards a distributed control architecture. Dual decomposition and predictive control allow for a flexible and and cost-optimized power dispatch, coordinated via a virtual market price. Results show the real-time applicability of the proposed predictive, distributed energy management approach and hint at possible gains that can be achieved by extending the load prediction horizons up to one hour.

Future work will focus on the flexible operation of modular power system topologies using distributed control. This covers parameter adaptation to changes in a component's characteristics as well as changes in the system topology. Additional focus will be on the price adaptation mechanism, exploring its convergence behavior, the inclusion of non-convex modules, and more complex decision-making. Experimental validation of the embedded controllers and their communication in real-time is intended to showcase the method's applicability.

Acknowledgment

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