

ABSTRACT

An Energy Management System for electric vessels is described, based on a Model Predictive Control (MPC) with Anticipative Action. The electric ship has a power system composed of a hydrogen fuel cell generator, a battery storage system, a propulsion system, an auxiliary load module, and a command system. The controller defines the power allocated among the vessel's power system components. The MPC design uses a Linear Parameter-Varying (LPV) model to approximate the nonlinear dynamics of the vessel's power system and components. To improve the performance of the LPV-MPC, an additional predictor is included, based on data-driven Machine Learning. This is included in the LPV-MPC so the future predicted trajectory of the reference signals can be estimated to improve the allocation of power. The reference trajectory is generated using a Neural Network trained to estimate the future power demand determined by representative ship manoeuvres. A simple baseline Rule-based (RB) strategy was compared with the basic LPV-MPC and with the data-driven LPV-MPC that includes the prediction generated by the Neural Network.

INTRODUCTION

The reduction of emissions and pollution has become a major goal of marine companies in recent times. In the automotive field, the use of batteries and electric motors is often considered the most Controllers Comparison: Performance Indices effective and economically sustainable solution for cars and small vehicles, but in other transportation sectors, different technologies have been considered. Those in the maritime transportation field have considered hydrogen-based energy generation as a very suitable approach to decarbonization and the zero-emission ship transport goal. A Fuel Cell (FC) powered vessel and ship power system control problem is considered. The power system sources include a FC and a battery storage system. The propulsion system load and the auxiliary loads are to be supplied by the available power provided by the energy sources. The control problem is the design of the power allocation algorithm, termed the Energy Management System (EMS). The design of the EMS with different types of power sources and several loads can be using different control policies. These include simple Rule-based methods involving a set of IF-THEN statements, and advanced optimization-based policies such as the Equivalent Consumption Minimization Strategy (ECMS). A Rule-based (RB) EMS was considered as the baseline EMS control approach for the vessel's power system for comparison with the LPV-MPC-based solutions. Two LPV-MPC designs were considered. To decrease the degree of suboptimality due to the use of the LPV modelling approach, a data-driven or Machine Learning (ML) based prediction algorithm was introduced in one solution. A Neural Network (NN) was designed to provide the ML and compute the future power demand for the propulsion system. This prediction sequence was then introduced within the LPV-MPC to enhance the prediction ability. The predicted reference signal adds a form of anticipative action or preview action.

GOALS

- Design and development of an MPC for FC-fuelled vessel
- Training and validation of a ML-based prediction module to improve MPC performances
- Testing in simulation environment the different controllers develop and evaluate improvements given by the proposed MPC-ML control system with respect to baseline Rules-Based and standard MPC policies

METHODS

The optimization problem for the MPC-based EMS is formulated with a quadratic cost-function subject to affine constraints:

$$\min_{\Delta u_j} \sum_{i=1}^{N_p} \|Q(y_{k+i|k} - r_{k+i|k})\|_2^2 + \sum_{j=1}^{N_u} \|R(\Delta u_{k+j-1})\|_2^2$$

$$s.t. \quad x_{k+i+1|k} = Ax_{k+i|k} + B_{k+i|k}u_{k+i}$$

$$y_{k+i|k} = Cx_{k+i|k}$$

$$T_{k+i} = Dx_{k+i|k} + Eu_{k+i}$$

$$x_{k|k} = \hat{x}_k$$

$$u_{k+i+1} = u_{k+i} + \Delta u_{k+i+1} \quad \text{for } i \leq N_u$$

$$u_{k+i+1} = u_{k+i} \quad \text{for } i > N_u$$

$$\Delta u_{k+i} \in \mathbb{D}, u_{k+i} \in \mathbb{U}, y_{k+i} \in \mathbb{Y}, N_p \geq N_u$$

and N_p denotes the prediction horizon, N_u is the control horizon, Q and R are the weights on output magnitude and input rate, $\Delta u_{k+j|k}$ is the vector of control increments, and $x_{k+i|k}$ is the prediction of the state at time $k+i$ based on information available at time k . The vector $r_{k+i|k}$ represents the reference signal and is considered constant over the prediction horizon in the LPV-MPC approach:

$$r_{k+i|k} = [\Delta m_{H_2}^r(k), SoC^r(k), P_{fc}^r(k), P_b^r(k), P_T^r(k)]^T$$

To improve the prediction capabilities of the LPV-MPC, reduce the suboptimality of the solution, and increase the control performance, a so-called previewing approach (also termed anticipative action) is considered to include the predicted reference signal $P_T^r(k+i)$ within the LPV-MPC cost function. In this work, the total reference power to be allocated is given by the sum of the command and auxiliary load systems as indicated in Eq. (18). Because the total torque demand is mainly related to the command signal power demand, the future reference signal is approximated by:

$$P_T^r(k+i) = \hat{P}_{cmd}(k+i) + P_a(k)$$

The auxiliary load demand power is then considered constant over the prediction horizon whereas the command power demand $\hat{P}_{cmd}(k+i)$ is predicted by the data-driven algorithm trained to estimate the signal over the considered horizon.

RESULTS

The performance of the RB and basic LPV-MPC policies are now compared with the LPV-MPC with ML solution (given by combining the NN predictor with the LPV-MPC) and performance indices are shown in Table 1 and the battery State-of-Charge in Figure 8 compared with the LPV-MPC and baseline RB designs. The performance of the RB controller is limited due to the simplicity of the policy. It provides good results in terms of fuel consumption and battery degradation but reduces the lifetime of the FC due to the large oscillations affecting the FC reference power. This is shown in the FC stress performance which is larger than for MPC. Compared with the baseline RB policy, the LPV-MPC reduces the hydrogen consumption by 13.68%, with a fuel cell stress reduction of 99% whereas the battery degradation increases by an order of magnitude. The LPV-MPC with ML solution provides an improvement similar to basic LPV-MPC, such that hydrogen consumption reduces by 15.79%, the FC stress decreases by 99.97% but the battery degradation index worsens. However, hydrogen fuel cell degradation is more important economically.

RESULTS

The most interesting result is given by the LPV-MPC with ML controller relative to the basic LPV-MPC. The LPV-MPC with ML controller provides a reduction in FC degradation of 62.5% with respect to the basic LPV-MPC performance, together with a reduction of battery stress of 2.32% and a reduction of hydrogen consumption of 2.5%. Both battery and FC powers allocated by the different controllers satisfy their constraints on the magnitude, and the battery *SOC* remains within its prescribed bounds. This is because of the constraint-handling ability of the LPV-MPC-based EMS to consider the physical and logical limits of the plant as shown in Figure 1.

Table 1. Controllers Comparison: Performance Indices

Controller	$m_{H_2}[kg]$	$m_L[kg]$	$D_b (\times 10^5)$
RB	0.95	90.73	0.30
MPC	0.82	0.08	2.59
MPC-AI	0.80	0.03	2.53

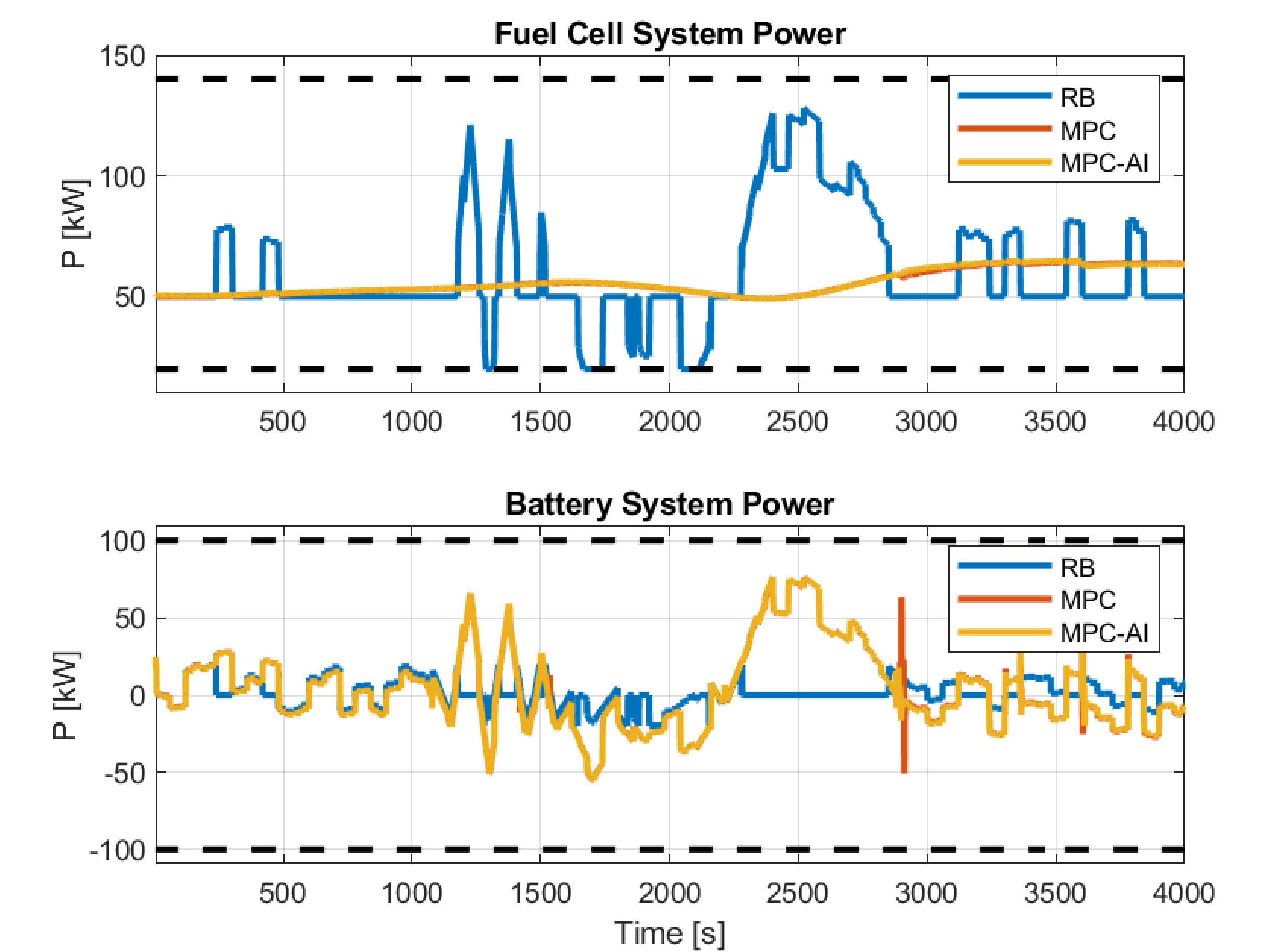


Figure 1. Power Control Signals Comparison

CONCLUSIONS

A Model Predictive Control (MPC) Energy Management System (EMS) for a Fuel Cell (FC) powered vessel that was also equipped with a battery energy storage system was presented. A baseline Rule-based (RB) EMS was first developed for comparison purposes. An EMS based on a model based LPV-MPC was then developed to optimally control the vessel taking into account various constraints. A Machine Learning (ML) algorithm based on a Neural Network (NN) was then developed to predict the propulsion power demand. This NN predictor was combined with the model based LPV-MPC, and the performance of the AI assisted LPV-MPC was improved over the baseline and basic LPV-MPC. That is, the EMS power consumption was reduced and the fuel cell degradation was improved. Future research will consider the design and testing of the proposed LPV-MPC combined with ML, and apply it to high-fidelity models for more complex integrated ship power systems.