

Model Predictive Control for Hybrid Diesel-Electric Marine Propulsion ^{*}

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Abstract: In this work, the problem of energy management strategies in hybrid diesel-electric marine propulsion systems is investigated with the implementation of two types of Model Predictive Controllers. The system behavior is described by models based on system identification as well as on first-principles. These models were used for the design of linear and adaptive predictive controllers respectively. The controllers were successfully tested at HIPPO-1 testbed, at the Laboratory of Marine Engineering, evaluating diverse strategies for disturbance rejection, system stability, and operation of the plant within desirable limits.

Keywords: hybrid marine engine, predictive control, λ control, transient operation

1. INTRODUCTION

Strict emission regulations imposed by legislation authorities (e.g. International Maritime Organization-IMO) make marine engine manufacturers to look for new opportunities for emissions reduction. One promising technology for emissions reduction and fuel efficiency enhancement is hybridization, i.e. usage and coordination of more than one energy sources used for propulsion.

This research work tackles the problem of energy management strategies (EMS) in hybrid diesel-electric marine propulsion systems, without any battery storage capacity. Such a system decides in real time the amount of power delivered at each time constant by the energy sources present in the experimental marine power train. Objectives are to investigate a) the interaction between the power sources and b) the feasibility of the hybrid configuration to achieve reduced exhaust emissions and improved fuel consumption during transient loading operation. This could lead to diesel engine downsizing as is the case in the "modern" point of view in marine propulsion.

Usually, the engine control units contain a certain amount of single closed-loops, with many look up tables in order to achieve closed-loop control of the multi-parametric

and strongly non-linear engine behavior, Ripaccioli et al. [2009]. Today, a more sophisticated and complicated control method is needed: one that continuously decides the operation point of the plant, while enforcing the operating constraints and optimizing the energy consumption, in terms of fuel and electric energy consumption.

Several strategies for power management have been applied so far, including dynamic programming, stochastic dynamic programming, equivalent fuel consumption minimization and model predictive control (MPC). Of the many advanced control design methodologies, MPC seems to be the most capable to handle multi-variable processes, satisfy constraints, deal with long time delays and utilize plant response disturbance knowledge. MPC has been used in a broad range of applications, such as diesel engine control, del Re et al. [2009], Ortner and del Re [2007], Adachi et al. [2009], Hybrid Electric Vehicles, Ripaccioli et al. [2009], etc.

Usually the objective of the EMS is to minimize fuel consumption. In the work presented here, the control problem is recast in an alternate way so as to track λ reference while ensuring that certain constraints, like NO_x and fuel consumption are met.

2. SYSTEM DESCRIPTION AND MODELING

2.1 Experimental Facility

The hybrid propulsion powertrain HIPPO-1 test bed at Laboratory of Marine Engineering, NTUA (LME) (seen in Fig. 1) consists of an internal combustion engine (ICE) in parallel connection to an electric machine (EM). As such, the rotational speeds of ICE and EM are identical, whereas the supplied torques add together. The desired

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torque demand is applied through a water brake dynamometer.



Fig. 1. The hybrid diesel-electric test bed (HIPPO-1) at LME.

The prime mover is a production-type, CATERPILLAR 6-cyl. 10-liter, four-stroke, in-line marine diesel engine with electronically controlled unit fuel injection, turbocharged, with a rated power output of 425 kW at 2300 rpm. The ICE is coupled to a standard 3-phase asynchronous induction motor, with a rated power of 112 kW. The EM is connected to a frequency inverter unit, enabling the torque output regulation of the EM. The electrical power needed to drive the EM is through the grid of the Laboratory; any produced electrical power can be dumped to a pack of installed braking resistors. The dynamometer has a load capacity of 1200 kW, with maximum speed at 4000 rpm. The cost for the hybridization is similar to the cost of the ICE.

The whole test bed is controlled and monitored in real time by a dSpace DS1103 controller board, programmed under the Matlab/Simulink environment. Measurements present in the test bed include: NOx/oxygen, soot emissions (PM) in terms of exhaust gas opacity, fuel mass flow, turbocharger speed, torque and speed, intake manifold pressure. The NOx/oxygen sensor is the automotive-standard NGK SmartNOx wide range linear λ sensor installed 1 m downstream from the ICE turbine.

The control goal is to moderate the load of the diesel engine by inserting power from the electric motor to the system. This helps to reduce the engine emissions (NOx, PM), especially during load transients, caused by e.g., rough seas, variation in electricity demand on-board or maneuvering. As engine emissions are not typically measured in production engines, a standard variable has to be determined that reflects emission level and can be easily obtained. In case of combustion engines, this variable is the λ value expressing the in cylinder air-fuel ratio (AFR) over the stoichiometric AFR. Although λ is not a measure of emissions itself, it is still a reliable estimate of them, as illustrated in Guzzella and Onder [2004].

2.2 Models from Identification

With the use of engine identification datasets multiple kinds of models were identified, according to their input-output attributes.

In the identification, the system parameters that individually affect the λ value and that are independent from each other have been considered, so as to find the exact relation between each parameter and the λ value during the modeling procedure, Alberer and Anderson [2012]. Eventu-

ally three experiments were designed and performed, as illustrated in Fig. 2: each time changing the total torque demand ($Load$), the engine speed (SE) or the electric motor frequency inverter command (u_{cmd}). For every parameter a Pseudo-Random Binary Sequence (PRBS) signal of appropriate bias and amplitude was applied. Data from each experiment was splitted for the identification and validation process, as shown in vertical sessions in Fig. 2.

The identification data were merged in order to find the model with the best average fit on the three data series.

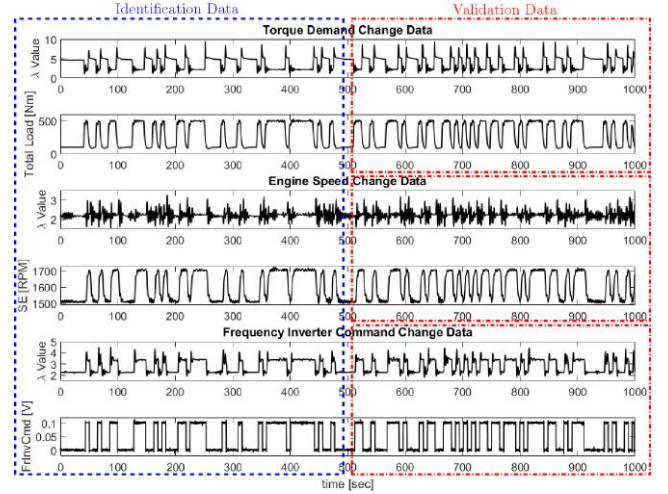


Fig. 2. Identification and validation data sets.

For identification process algorithm N4SID was used in order to find the A_i, B_i, C_i terms of each model which describes the engine transient dynamics during step loading as suggested for multi-variable systems, Ljung [2015].

A linear MISO model for λ output was identified, which considers the command to the frequency inverter (u_{cmd}) and the deviation of engine speed from its reference ($dSE = SE - SE_{Ref}$) as inputs, as described in (1).

$$\dot{\mathcal{X}}_1 = A_1 \mathcal{X}_1 + B_1 [u_{cmd} \ dSE]^T; \quad \lambda = C_1 \mathcal{X}_1 \quad (1)$$

The external load is not typically measured in marine engines; thus it is not included in the above equation. Speed deviation is also the disturbance which forces the ECU of the engine to inject more or less fuel in order to maintain the engine speed, accelerate or slow down, according to the Speed Reference (SE_{Ref}).

Engine emissions and consumption models were also modeled at the operating point of $SE = 1600 \text{ rpm}$ as a function of intake manifold pressure (MAP), SE and λ . NOx and Fuel Oil Consumption (FOC) models depending on the fundamental engine measurements were extracted from the available measured data, as described in (2), (3). As PM formation is complex, similar linear models proved unsuccessful to describe its dynamic behavior; thus it was not considered in the present work.

$$\dot{\mathcal{X}}_2 = A_2 \mathcal{X}_2 + B_2 [\lambda \ MAP]^T; \quad NOx = C_2 \mathcal{X}_2 \quad (2)$$

$$\dot{\mathcal{X}}_3 = A_3 \mathcal{X}_3 + B_3 [MAP \ SE]^T; \quad FOC = C_3 \mathcal{X}_3 \quad (3)$$

As the above models are depending on measurements that are changing with the application of u_{cmd} , an internal

MAP model, as described by (4) is needed in order to reduce the prediction error of the MPC internal model (5).

$$\dot{\mathcal{X}}_4 = A_4 \mathcal{X}_4 + B_4 [u_{cmd} \ SE]^T; \quad MAP = C_4 \mathcal{X}_4 \quad (4)$$

Finally, the MISO models were combined to make a MIMO model, as shown in (5) and used in MPC design. The fitting of the MIMO model to validation data is shown in Fig. 3.

$$\dot{\mathcal{X}}_5 = \begin{bmatrix} A_1 & 0 & 0 & 0 \\ B_2 C_1 & A_2 & 0 & B_2 C_4 \\ 0 & 0 & A_3 & B_3 C_4 \\ 0 & 0 & 0 & A_4 \end{bmatrix} \begin{bmatrix} \mathcal{X}_1 \\ \mathcal{X}_2 \\ \mathcal{X}_3 \\ \mathcal{X}_4 \end{bmatrix} + \begin{bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \end{bmatrix} \begin{bmatrix} u_{cmd} \\ dSE \\ SE \\ \lambda \\ MAP \end{bmatrix} \quad (5)$$

$$[\lambda \ NOx \ FOC]^T = diag[C_1 \ C_2 \ C_3 \ 0] \mathcal{X}_5$$

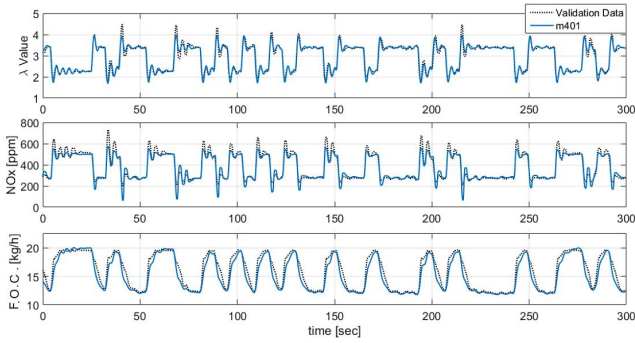


Fig. 3. Fitting of MIMO model to the validation data.

2.3 First Principles Model

The first principles model of the diesel-electric powertrain was based on Heywood [1988]. As the dynamics of the electric motor are significantly faster than those of a diesel engine, the motor was modeled as a first-order transfer function with a time constant. The overall hybrid engine model is summarized in Samokhin and Zenger [2014]. The outcome was a nonlinear model which was validated with data from experiments at LME. As it is computationally heavy for the optimizer when running online, a linear approximation was used for the adaptive predictive controller design. Fig. 4 shows the comparison of the measured and modeled λ values at constant powertrain speed and load transients (constant torque demand and electric motor dynamics are excited by the PRBS signal).

2.4 Linearization

In order to improve the accuracy of the predictions, the model is linearized online at each sampling interval around the systems trajectory $x(t)$, $u(t)$. The linearization of the nonlinear model is computed using the first order Taylor series expansion and the so-called small perturbation method. For better understanding of the system from the control point of view, the physical equations are rewritten in terms of state variables, by introducing vectors for the state $x \in \mathbb{R}^5$, input $u \in \mathbb{R}^1$ and measured outputs $y \in \mathbb{R}^1$ as

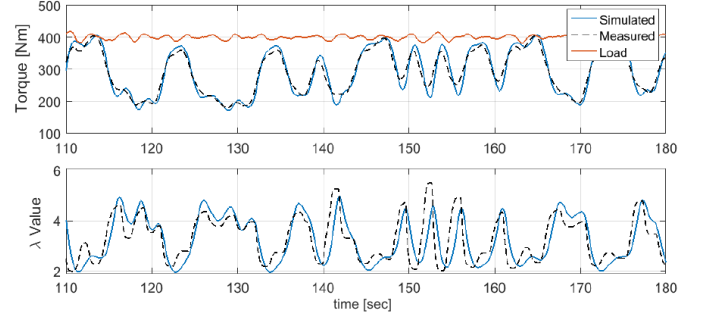


Fig. 4. Fit of the first-principles model to the validation data.

$$x = \left[\begin{array}{c|c} \underbrace{MAP \ p_{exh} \ P_{compr} \ SE}_{ICE \ states} & \underbrace{T_{EM}}_{EM \ state} \end{array} \right]^T \quad (6)$$

$u = u_{cmd} \rightarrow$ control input
 $y = \lambda \rightarrow$ measured output

3. CONTROL SYSTEM DESIGN

Two different cases were studied; standard linear constrained (MPC) and adaptive MPC (A-MPC) respectively.

3.1 MPC design

The λ value is controlled by changing the u_{cmd} . Speed deviation is treated as measured disturbance.

The MPC calculates the future control sequence that minimizes a performance index related to the optimized goals subject to the equations of dynamic models of the system and the constraints, Maciejowski [2000]. Then it applies the first element of the computed sequence. The process is repeated at the next time step by moving the prediction horizon one step forward.

For the solution of the optimization problem, quadratic programming (QP) is used which tries to minimize the cost function over the prediction horizon (7) by computing the N_u optimal sequence of the u_{cmd} moves within the Control Horizon (N_u), Bemporad et al. [2015].

$$\min_{(z_k, \varepsilon)} \sum_{i=1}^p \left\{ \frac{w_\lambda}{s_\lambda} [\lambda_{Ref}(k) - \hat{\lambda}(k+i|k)] \right\}^2 + \sum_{i=0}^{p-1} \left\{ \frac{w_{\Delta u}}{s_u} \Delta u(k+i|k) \right\}^2 + \rho_\varepsilon \varepsilon_k^2, \quad (7)$$

s.t. $u_{min} \leq u(k+i|k) \leq u_{max}$
 $NOx(k+i|k) \leq NOx_{max} + \varepsilon_k V_{NOx}$
 $FOC(k+i|k) \leq FOC_{max} + \varepsilon_k V_{FOC}$
 $\varepsilon_k \geq 0$

where k is the current control interval, z_k is the optimization process decision, given by $z_k^T = [u(k|k)^T \ u(k+1|k)^T \ \dots \ u(k+p-1|k)^T]^T$, p is the number of prediction intervals, $\lambda_{Ref}(k)$ describes the reference value for λ value at current control interval, while $\hat{\lambda}(k+i|k)$ is the predicted value of λ at i th prediction horizon step. $u(k+i|k)$ is the optimal

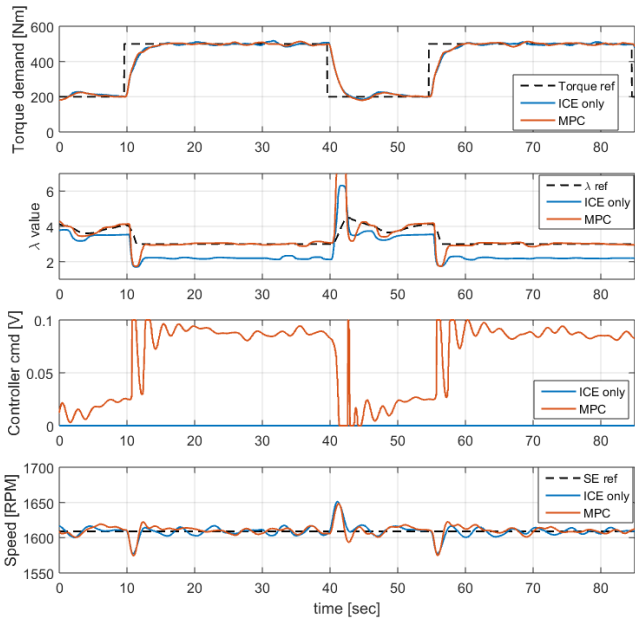


Fig. 6. Torque demand, λ values, controller command, and speed disturbance, in step loading experiments with MPC.

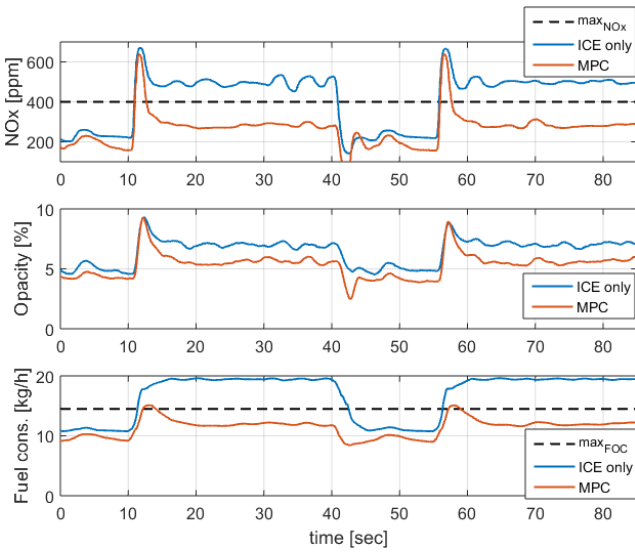


Fig. 7. Effect of the hybrid operation on NO_x , exhaust opacity, and fuel consumption, in step loading experiments with MPC.

a stronger command during the transient phenomenon, leading to a decrease of the emission pollutants.

In Fig. 7, the impact of the hybrid powertrain on the produced NO_x , exhaust gas opacity and fuel consumption, as compared to the conventional setup can be seen. During the load application the engine speed drops, causing the increment in fuel command, which eventually causes a NO_x spike. Engine Speed variation (faster reaction than λ) which is utilized as disturbance input in the MPC, causes the controller to react and give the maximum available command. However, due to the electric motor torque limit as well as the dynamics of the fueling, the NO_x spike cannot be avoided at 12 s. (and at 57 s.).

It can be noted that with the hybrid setup, MPC reduces NO_x content by 40 % during steady state and by almost 10 % during the transient. Regarding the measured exhaust gas opacity, MPC behavior leads to a reduction of 25 % when compared to the conventional powertrain for the same loading scenario. Finally, it can be seen that the fuel consumption of the conventional powertrain is around 20 kg/hr, while with MPC it is reduced by 40 %.

Adaptive MPC A-MPC design produces a smoother command profile, as it can be seen in Fig. 8. The power split, between the diesel engine and the electric motor is shown in the first subplot of the figure, with red and blue lines respectively. It is expected that A-MPC performs better against MPC; In our case this is not clearly shown, as at this loading case the linear model performs adequately without the need for a non-linear approach and A-MPC.

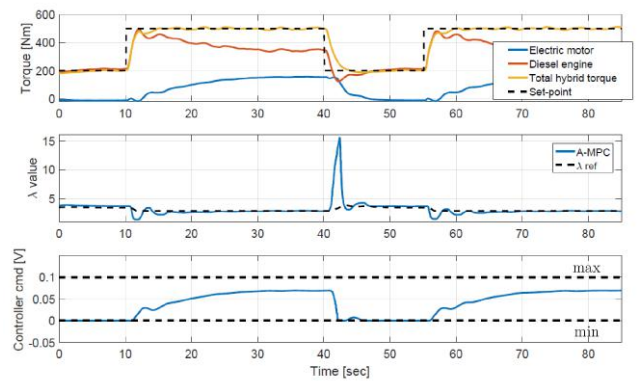


Fig. 8. Torque demand, λ value, and controller command, in step loading experiments with A-MPC. Speed is constant at 1600 rpm (not shown).

4.2 Propeller loading

The second type of testing was done when the engine was operated according to the propeller curve law (i.e. the power demand is a cubic function of the propeller rotational speed). In this mode, speed and load varied simultaneously, as shown in Fig. 9.

In propeller loading, the different capabilities of the two controllers were exploited. At time = 20 s, a change in the dynamics of both controllers can be observed. In the A-MPC case the command reduces until a zero value, at the end of the transient, while in the MPC case the command continues to provide the required electric torque, so as to keep the diesel engine operation within the maximum NO_x and fuel consumption limits.

Specifically in Fig. 10, where the corresponding values of emission pollutants and fuel consumption are presented, it can be noted that the MPC operates the plant successfully close to the imposed fuel consumption limit, managing to keep the consumption under the maximum line, while A-MPC, which is unconstrained, follows a different control strategy.

However, the advantage of A-MPC is the fact that it can make the prediction of the plant behavior according

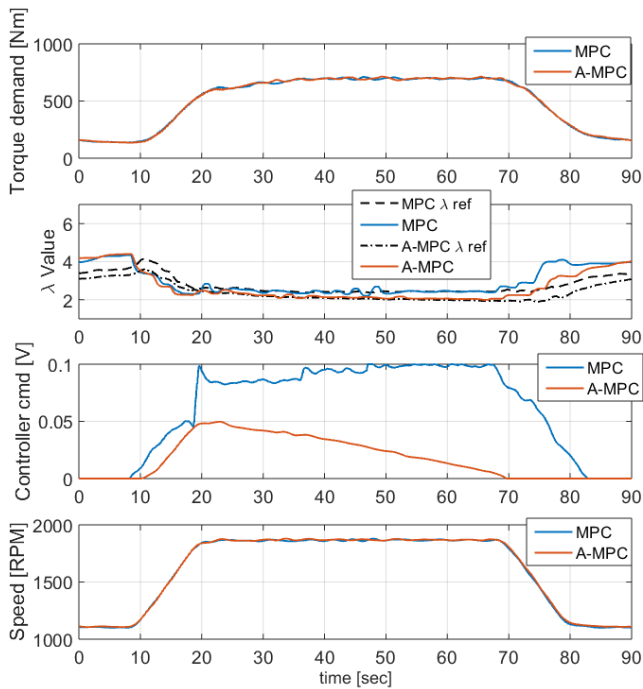


Fig. 9. Torque and speed variation, λ values, and controller command, in propeller loading experiments, MPC vs A-MPC.

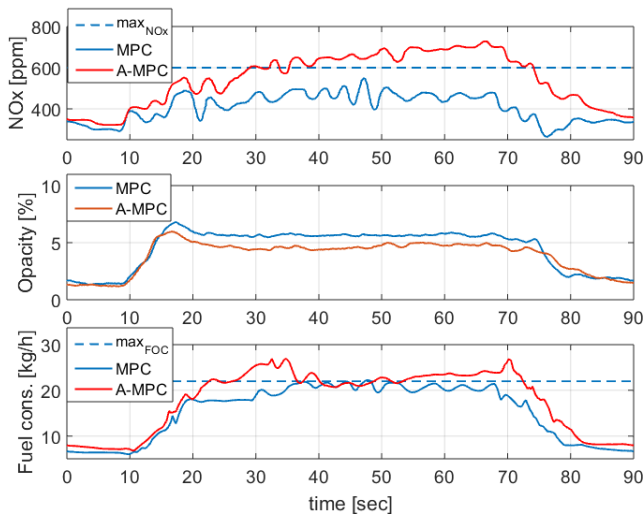


Fig. 10. Effect of the hybrid operation on NO_x , exhaust opacity, and fuel consumption, in propeller loading experiments, MPC vs A-MPC..

to a model describing the current operating point of the engine, which is a beneficial feature for a system operating at different points from those of the nominal model, as it happens with MPC.

5. CONCLUSIONS AND FURTHER WORK

In this work, the goal was to establish an energy management strategy for a hybrid diesel-electric marine propulsion system. For this, predictive controllers with different capabilities were designed and implemented: a standard MPC and an adaptive MPC.

The modeling procedure for MPC was straight forward: identification experiments provided models for controller design. A-MPC model is based on first-principles; therefore it requires on-line linearization at each sampling interval.

The performance of the two controllers was verified experimentally under realistic operating conditions on the hybrid diesel-electric testbed at LME. Results showed the efficient control of the plant during transient operation, in terms of reduction of gas emissions and fuel consumption improvement, while successfully handling input and output constraints.

Although the two proposed controllers tracked the λ reference in a similar way, their commands were drastically different, as MPC has to cope also with constraints.

Future work with the Explicit-MPC, where the QP problem is solved off-line and stored in look-up tables, will allow for a different type of implementation of the power-split control strategy.

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