SHIP PROPULSION PLANT PERFORMANCE ASSESSMENT USING AN ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Nowadays, more than in the past, the attention towards the environmental impact of shipping has gained great interest. In particular, several international rules were issued to set new standards in terms of ship energy efficiency and emissions. Most of the actual worldwide fleets are not compliant with the new standards, and it is unthinkable that ship-owners will replace the existing ships with new buildings in a short time. According to this, the retrofit of either the propulsion plant or auxiliary system is the good compromise choice. The first task that the designer has to face is the evaluation of the actual propulsion plant performance to detect where to act. On the view of this, the authors present two different approaches to identify the performance of an existing ship propulsion plant equipped with a four-stroke diesel engine and a controllable pitch propeller. The first approach is the standard approach, relying on the static performance assessment of the required power and fuel consumption, starting from the design data of the hull and machinery, not always available several years past ship fabrication. The second approach is based on the application of an artificial neural network, trained using the results of sea trials. Ship speed, shaft revolution speed, pitch angle, engine torque and fuel consumption have been recorded, then part of the data have been used as a training set for the artificial neural network, and the remaining as a validation set to compare the two approaches. The main idea is to evaluate the best strategy, in term of developing time and accuracy, to obtain the global, even if static, evaluation of the propulsion plant performance, with the final aim to have a handy tool to be used to assess potential energy saving solutions. Eventually, a comparison between the two methodologies and sea trials is shown and critically discussed.

1. INTRODUCTION

The prediction of fuel consumption fuel rate gained major interest in the last decade for several reasons. Firstly, a higher awareness of the maritime field in the environmental impact of the shipping leads to find new eco-friendly solutions. Secondly, the evergreen attention of the ship owners to the operating cost (mainly the fuel consumption). Thirdly, strict rules issued by the international maritime organization [10,11] affect existing ships limiting their pollutant emissions [3,4] and force ship-owners to find efficient ship management strategies. In the view of this, a tool able to predict in real time the fuel consumption could be helpful to detect potential inefficiency and to suggest alternative operating solutions. This is the main motivation that led the authors to develop, and test on a real case study, a data-driven approach not widely used in maritime field: artificial neural network. To understand the benefit of such kind of approach, a comparison with a traditional design and performance prediction method is presented.

2. STATIC APPROACH

The several propulsion elements (engine, gearbox, bearing, propulsor) that contribute to the global energy efficiency of the vessel need to be modelled to evaluate their efficiency. A steady-state approach has been used to obtain reliable results in a relatively simple way. In the following, the methods adopted to model the engine, propeller and transmission line are presented.

The first element to be modelled is the main engine. In particular, the knowledge of fuel consumption on the whole set of engine working points is a crucial aspect. The manufacturer data are implemented with a statistical evaluation of the engine efficiency and fuel consumption according to a procedure developed in [2]. The specific fuel consumption q_s, and consequently the engine efficiency η_{Eng}, is assessed using a polynomial surface, which form is reported as follows:

$$q_s\,(N,P_b) = \sum_{i=1}^{4}\sum_{j=1}^{4} P_{ij}\; N^i\; {P_b}^j \qquad (1)$$

Where P_{ij} are the coefficients of the polynomial, obtained through the analysis of several fuel consumption data related to different four-stroke diesel engines [14].

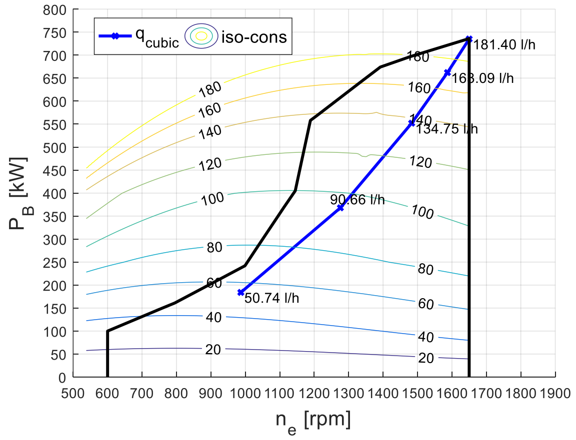

Figure 1. Engine Fuel Consumption map.

The propeller performances are evaluated using open water characteristics, thanks to which it is possible to evaluate the thrust coefficient K_T and torque coefficient K_Q depending on both the advance coefficient J and the propeller pitch angle φ.

$$T = K_T(J,\varphi)\,\rho\, n^2\, D^4$$
$$T = K_T(J,\varphi)\,\rho\, n^2\, D^4$$

(2)

$$Q_O = K_Q(J,\varphi)\,\rho\, n^2\, D^5$$

Where ρ is the seawater density, D is the propeller diameter and n is the shaft line revolution regime. Among the several methods that could be used to evaluate the propeller characteristics, the Wageningen series [13] was chosen for its simplicity (Figure 2). The propeller is modelled based on its design values of pitch to diameter ratio, diameter, number of blades and expanded area ratio.

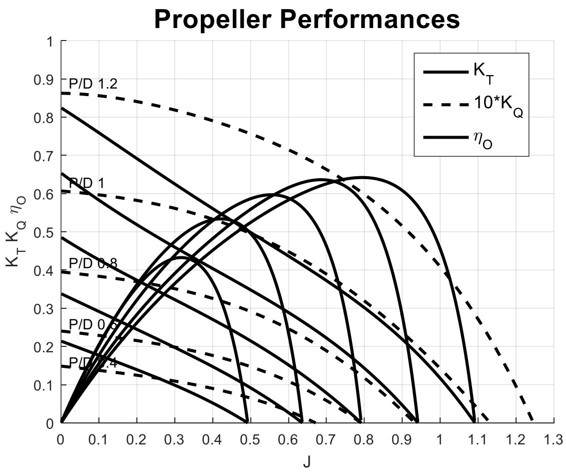

Figure 2. Propeller Open Water Characteristics

The ship drag and the propulsive coefficient are modelled using three different methods: towing tank tests available, Holtrop regression and the series presented in [8], suitable for trawlers and tug. A comparison of the ship drag is presented in Fig. 6.

As it is possible to note, van Oortemersen results present a hump not feasible for a trawler. As reported in [12], this could be charged to some typos present in the original paper.

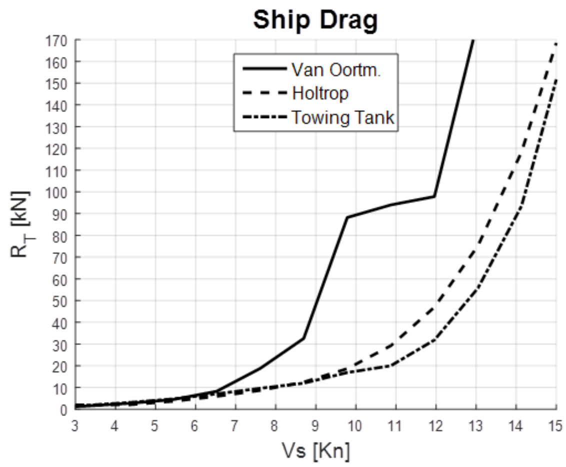

Figure 3. Ship Drag Comparison.

3. SEA TRIAL

3.1 CASE STUDY

The research Vessel "G. Dallaporta" was built in 2001, and now it is used to support advanced Italian Research Council research in several maritime fields, from engineering to biology. This vessel mainly operates in the Mediterranean Sea, and its steel hull is shaped like a fishing vessel, as the majority of the research activities are related to fisheries [7]. The propulsion system of R/V "G. Dallaporta" is composed by the main diesel engine, a reduction gearbox and a controllable pitch propeller (CPP) in the nozzle. An electric generator is also coupled with the main engine through a power take-off. Thus, in standard condition, the main engine is the only power source.

The electric generator provides electric power for all the services (light onboard, hotel, navigation instrumentation, etc.). Such electrical load is almost constant.

Another power take-off is coupled with a hydraulic pump, for hydraulic users such as winches, cranes, and other deck machinery.

The vessel is also provided of an auxiliary generator, which is a redundancy of the main engine for all the electric and hydraulic loads. A picture of this research vessel is reported in Figure 4, whereas its main characteristics in Table 1.

Figure 4. The R/V “G. Dallaporta”.

Table 1. Main parameters and characteristics of the R/V “G. Dallaporta”

Length overall (LOA)	35.0 m
Length between perpendiculars (LBP)	30.7 m
Gross tonnage	286 GT
Displacement	312 tons
Main engine	Wärtsilä UD25V12 - 810 kW
Auxiliary Engine	Caterpillar 3306 - 170 kVA
Propulsion system	Controllable picth propeller in Nozzle - Diameter 1.78 m
Crew	7 members + 11 researchers

Several scientific instrumentations and systems, for the complete data collection, support the research activity onboard.
Vessel’s position, course, speed are monitored with a FURUNO digital GPS which is connected to several instruments. The vessel is also equipped with an ATLAS DOLOG 22 for measuring the speed over the seabed.
Load cells are installed to measure the resistance of the different gears. The propulsion system of the vessel is equipped with measurement system by Hoppe Marine, for the assessment of fuel consumption (fuel meters are installed both on the feed and the return line) [1], the torque delivered to the propeller, and the shaftline revolutions are continuously sampled during different activities.
Sea trials have been carried out in the Adriatic Sea during three consecutive days in summer. During the trials, two operating conditions have been tested: trawling and free navigation. Both the states have been tested at different ship speeds, with several propeller pitch and engine revolution speed combinations. For the sake of shortness, only free navigation results are presented in this paper. The whole measured dataset is reported on the engine diagram, as shown in Figure 5, and covers most of the engine’s operating conditions. Figure 6 presents the steady-state values for each trial configuration in free navigation.

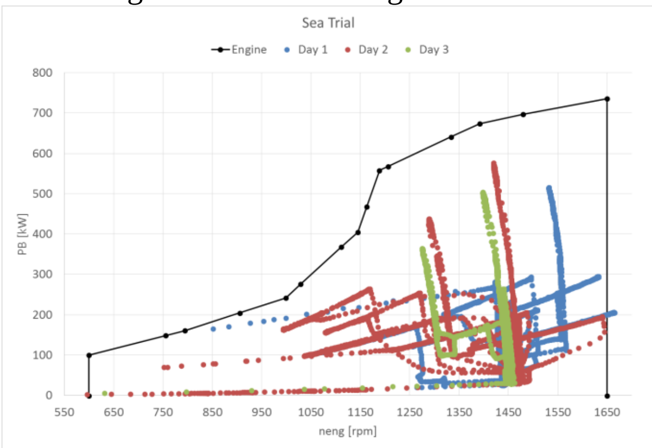

Figure 5. Sea trial summary.

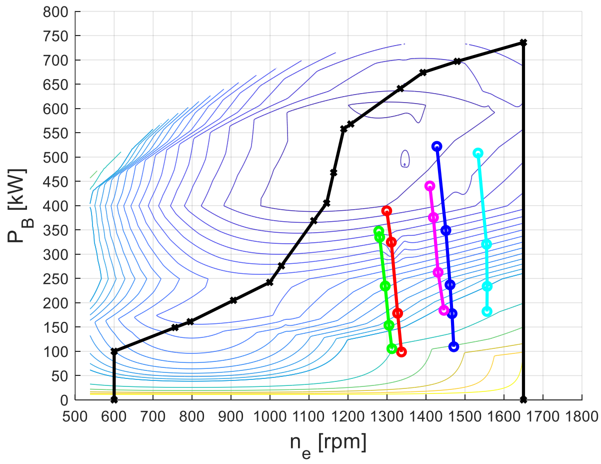

Figure 6. Synthesis of engine mapping.

4. ARTIFICIAL NEURAL NETWORK ANALYSIS

This section presents a machine learning approach to fuel consumption prediction based on artificial neural networks (ANN). Machine learning, or learning from data, generically refers to all those computation techniques that aim to fit models on data, i.e. that try not to describe the relationships between input and output data by equations, but from the dataset itself. An ANN is a computational tool inspired by the architecture of biological systems. It is based on simple computational units called neurons: they are basically composed by a linear part, which makes a weighted summation of the neuron inputs adding a constant value (bias), and a nonlinear part, called "activation function", which saturates the neuron output within a defined range according to a proper nonlinear law (e.g. hard limit function, sigmoid, hyperbolic tangent). Neurons are organised in layers: every input and output variable of the network is associated with a neuron in the input and output layer, respectively. Input and output layers are separated from each other by one or more non-linear hidden layers. Each neuron of the i^{th} layer receives the inputs from the neurons of the previous layer, and it fires his output values to the neurons of the next layer: there is no feedback and information flows from the input to the output layer. This architecture is called "Feed Forward Back Propagation Network" (FFBP), or "Multi-Layer Perceptron". It can be shown that a hidden layer FFBP with sigmoid activation function is a universal regressor [9]. The main feature of ANNs is their self-programming attitude. The neuron weights are determined by a learning algorithm, which iteratively updates the weight values aiming to minimise the error between ANN output and target values on a known set of data samples. Further details on ANNs basics and learning theory can be found in [9], while some applications to marine engineering problems are presented in [5,15,6].

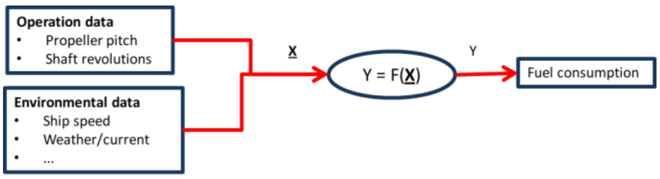

Figure 7. Synthesis of the problem structure

In this paper, a single layer ANN has been trained on the experimental data to predict the fuel consumption based on the following predictors:

- Propeller pitch
- Shaft revolutions
- Ship's speed
- Wind speed and direction

The problem structure is synthesized in Figure *7*. The available dataset is composed of 3896 experimental measures (Figure 8): data have been normalized in [0; 1] and randomly split into training data (70%) used by the training algorithm for learning, validation data (15%) used for the algorithm's stopping criterion, and testing data (15%) used to evaluate the network performance once it has been trained. This is the usual practice to avoid both what are called "overfitting" and "over validation" in favour of network generalisation.

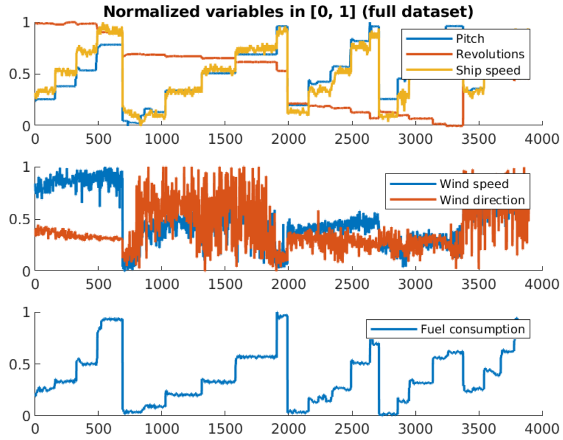

Figure 8. Sea Trial results in the time domain

5. RESULTS

In this section, a comparison between experiments and calculated data are reported, both static and neural network approaches are analysed.

5.1 STATIC APPROACH

The results of the traditional model-based prediction are presented in Figure 9, where the fuel consumption in [l/h] is reported on the y-axis, versus the trial number.

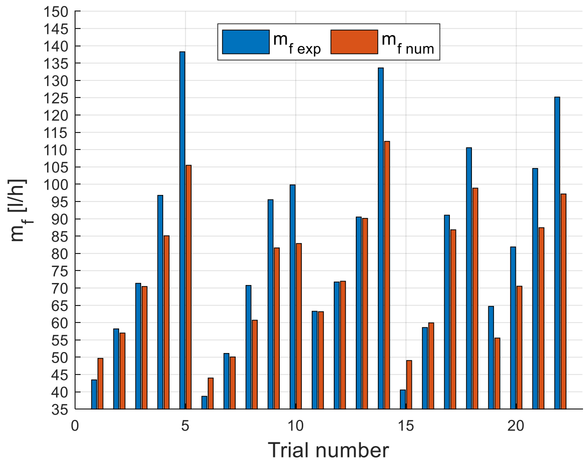

Figure 9. Experiments vs Sea trials.

Notice that the static approach shows a good agreement with experimental data in most of the trials, mainly at partial engine loads. On the contrary, significant errors up to 40% are observed at high engine loads. The average percentage error is about 6%.

5.2 ARTIFICIAL NEURAL NETWORK

The artificial neural network described in section 4 has been trained with good results, that can be summarised in a mean squared error (MSE) of about 2.6E-4 on the testing data. The prediction of the entire dataset, including training, validation and testing data, is shown in Figure 10, The same figure shows the percentage error on the predicted variable, which is always less than 5% and with a mean absolute value of about 0.5%.

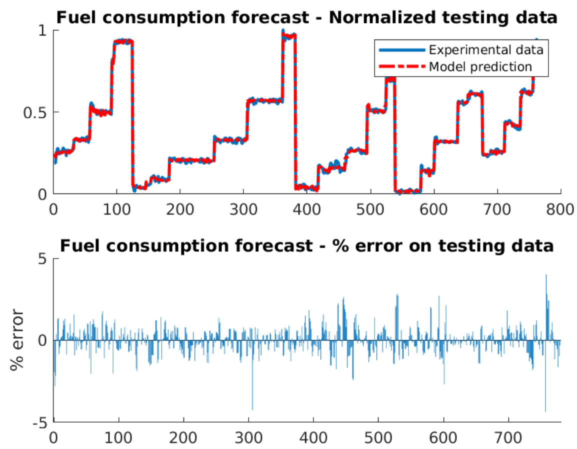

Figure 10. ANN prediction and performance.

5. CONCLUSIONS

In the paper, two different approaches to identify the performance of an existing ship propulsion plant equipped with a four-stroke diesel engine and a controllable pitch propeller have been presented. The first approach is based on the static performance assessment of the required power and fuel consumption; the second aims to predict the same quantity by using a data-driven approach, based on an artificial neural network. The network has been trained, validated and tested using the dataset coming from sea trials.

The first approach showed an acceptable precision in the prediction of the overall fuel consumption, with a mean error of about 6% (compatible with the accuracy of the engine manufacturer's datasheets). However, the maximum prediction error is about 40%. The main weaknesses of this approach are the long development time compared with the ANN and the considerable amount of information needed to model the whole propulsion plant.

The ANN showed good prediction performance, predicting fuel consumption with an average error of 0.5%.

The proposed method could be useful for fuel consumption minimisation, relying on the ANN to assess the fuel consumption, either in steady-state or transient conditions, in real time, based on the conditions measured during navigation, and using optimisation techniques to find the optimal operating setup. Eventually, the ANN can be retrained and updated during navigation when new experimental measures are available.

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